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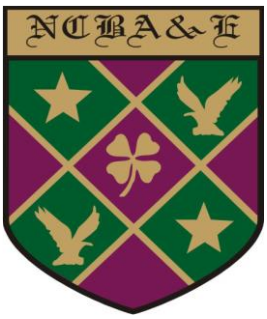

INTELLIGENT DIAGNOSIS OF CHRONIC DISEASE AND TREATMENT USING GOLD NANO THERMO ROBOT (GNTR) EMPOWERED WITH SOFT COMPUTING APPROACHES

BY

ZAHID HASAN

DOCTOR OF PHILOSOPHY
IN
COMPUTER SCIENCE

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NATIONAL COLLEGE OF BUSINESS ADMINISTRATION & ECONOMICS

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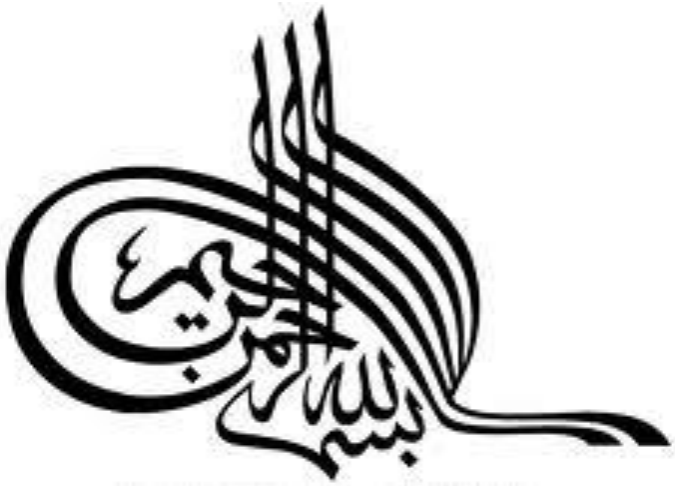
A dissertation submitted to
School of Computer Science

In Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY
IN
COMPUTER SCIENCE

February, 2023



In the name of ALLAH,
The Most Beneficial,
Most Merciful,

AUTHOR'S DECLARATION

I, **Zahid Hasan hereby** state that my Ph.D. thesis titled **"Intelligent-Diagnosis of Chronic- Disease and Treatment Using Gold - Nano Thermo- Robot (GNTR) Empowered with Soft-Computing Approaches"** is my work and has not been submitted previously by me for taking any degree from this university, **National College of Business Administration & Economics, (NCBA&E), Lahore** or anywhere else in the country/world.

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February, 2023

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I solemnly declare that the research work presented in the thesis titled **"Intelligent Diagnosis of Chronic Disease and Treatment Using Gold Nano Thermo Robot (GNTR) Empowered with Soft Computing Approaches "** is solely my research work with no significant contribution from any other person. Small contribution/help whenever taken has been duly acknowledged and that complete thesis has been written by me.

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This is to certify that research work presented in the thesis, entitled **"Intelligent Diagnosis of Chronic Disease and Treatment Using Gold Nano Thermo Robot (GNTR) Empowered with Soft Computing"** was conducted by **Mr. Zahid Hasan** under the supervision of **Dr. Sagheer Abbas** and Co-Supervision of **Dr. Muhammad Adnan Khan**.

No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the **School of Computer Science** in partial fulfillment of requirements for the degree of Doctor of Philosophy in the field of **Computer Science**, School of **Computer Science**, National College of Business Administration & Economics, Lahore.

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DEDICATION

This dissertation is affectionately dedicated to my parents, with special acknowledgment to my mother, whose unwavering encouragement and vision guided me through the completion of my studies and contributed significantly to the attainment of this degree. A heartfelt dedication is extended to my devoted wife, who consistently prioritized my well-being, offering prayers and steadfast support during challenging times. I extend a warm dedication to my son and daughter, whose prayers were a source of strength and inspiration throughout every phase of my academic journey.

Finally, a profound expression of gratitude and dedication goes to my soon-to-be wife, whose unconditional love and guidance were instrumental in my accomplishments. I am deeply thankful for the unwavering support and prayers from my entire family, which played a crucial role in my academic success.

I Love You All!

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First and foremost, I extend my gratitude to Almighty Allah for providing me with the physical and mental strength, energy, motivation, and invisible support necessary to complete this work. It is through His will that I have undertaken and completed this thesis, and I am grateful for His blessings that facilitated significant support from various individuals.

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Thank you all.

SUMMARY

Innovations in the diagnosis and treatment of chronic illnesses have been made possible by recent developments in medical technology. The combination of Gold Nano Thermo Robots with soft computing methodologies is one such ground breaking invention that produced an intelligent system that has the potential to revolutionize healthcare. Gold Nano Thermo Robots are tiny tools made to precisely travel the human body and target locations with heat using their special heat-generating abilities. These robots are very adaptive and have the capacity for complex decision-making when paired with soft computing, which includes diverse computational techniques inspired by the human brain. Gold Nano Thermal-Robots can detect and track minute molecular changes within the body during diagnostics because of this synergistic approach. These robots can detect early symptoms of chronic illnesses including cancer, cardiovascular problems, and neurological ailments because of their sophisticated sensors and imaging capabilities. The robot's ability to comprehend complicated data patterns is made possible by soft computing approaches, which improves diagnostic precision and lowers false-positive rates. Gold Nano Thermo Robots (GNTRs) can now tailor treatment plans for specific patients because of the incorporation of soft computing. The robots can create specialized treatment regimens by digesting enormous volumes of patient data, including genetic data, medical history, and real-time physiological reactions. These strategies may include the administration of medications, the use of certain thermal treatments, or even the stimulation of the body's own healing processes. Gold Nano Thermo Robots (GNTRs) are now equipped with the ability to customize treatment plans for specific patients because of the integration of soft computing. The robots can create individualized treatment regimens by analyzing enormous volumes of patient data, including genetic data, medical history, and real-time physiological reactions. These strategies might include the administration of medications, the use of certain thermal treatments, or even the stimulation of the body's own healing processes.

The capability of this intelligent system to continually learn and adapt is one of its main advantages. The Gold Nano Thermo Robots (GNTRs) may continuously improve their diagnostic and therapeutic capacities using machine learning algorithms and nanotechnology approaches, adjusting to the particulars of each patient, and keeping up with the most recent advances in medical science, which is better as compared to the previous approaches.

LIST OF TABLES

Table 1: Results for Removal of Pectoral Muscle 141

Table 2: Results for breast muscle segmentation 139

Table 3: Results for Breast Muscle Segmentation 140

Table 4: Results of comparison of Pectoral Muscle Removal 140

Table 5: Results for Removal of Pectoral Muscle **Error! Bookmark not defined.**

Table 6: Results Comparison of Breast aner Detection 141

Table 7: Diagnostic Results **Error! Bookmark not defined.**

Table 8: Comparative Analysis of Treatment Response Between Temperature Limit & Thermal Therapy Duration 159

Table 9: Comparative Analysis Between Required radius of GNTRS and Tumor Depth During Penetration 161

LIST OF FIGURES

Figure No.	Title	Page

Figure 1: Technologies Involved in the Field of Medicine 22
Figure 2: Distribution of malignancies according to the geographic area of residence of the patients in Pakistan. Dec.1994 to Dec.2020 23
Figure 3: Distribution of malignancies in top 10 countries with the 24
Figure 4: Applications of Gold Nano Particles **Error! Bookmark not defined.**
Figure 5: Proposed Model of Gold Nano Thermo Robot (GNTR) 34
Figure 6: The Roles of Artificial Intelligence.....38
Figure 7: The Responsibilities of Artificial Intelligence 40
Figure 8: Data Flowing from a Previous Layer to a Unit in the Successive Layer. 50
Figure 9: Proposed Model of Gold Nano Thermo Robot (GNTR) 88
Figure 10: Proposed Methodology of the Research Study 89
Figure 11: A Schematic Depiction of a Convolutional Neural Network 90
Figure 12: Forward Propagation 91
Figure 13: Forward Propagation and Back Propagation 91
Figure 14: Methodology of Coulomb Explosion.....92
Figure 15: Features of the Concatenation Network.....95
Figure 16: A Process of Filtering out Noise in Digital Mammogram Images 96
Figure 17: Edge Detection Process in Digital Mammogram Images 97
Figure 18: (a) Input image section of rectangular window around the cancer tumor. 98
Figure 19: Proposed Block Diagram of Proposed Methodology 103
Figure 20: Proposed Block Diagram of Proposed Methodology of GAN 104
Figure 21: Proposed Block Diagram GAN Back Propagation Technique 105
Figure 22: The Architecture of Generative Adversarial Network.....106
Figure 23: Proposed Block Diagram GAN, Real or Fake Out Put Procedure 108
Figure 24: Flow Chart of GAN, Real or Fake Out Put Procedure 110
Figure 25: Proposed Design Methodology of GNTRs..... **Error! Bookmark not defined.**
Figure 26: Discretization mesh of proposed Gold Nano Thermo Robot (GNTR) 116
Figure 27: Discretization mesh of Gold Rode of GNTR.....116
Figure 28: Proposed Inter Body Communication Network Architecture.....120
Figure 29: Schematic coulomb explosion procedure flowchart **Error! Bookmark not defined.**
Figure 30: Procedure of Coulomb Explosion.....125

Figure 31: Explicit Method stencil 128
Figure 33: a). FTCS scheme, b). BTCS scheme, c). Crank Nicolson 131
Figure 32: Flow Chart of Heat Control System..... **Error! Bookmark not defined.**
Figure 34: Visual Inflection Regions on Our Breast Cancer Seg Datasets 143
Figure 35: Curve for SVM Classifier, ROC analysis for breast cancer classifier with 80 % - 20 % training and testing set splitting in (a) SVM classifier AUC 95.65 %, (b) SVM classifier AUC 75.00 %, (c) SVM classifier AUC 93.49 %, SVM classifier AUC 93.49 ..... **Error! Bookmark not defined.**
Figure 36:(a): Input Normal mammogram images, (b): Filtering process, (c): Segmentation, (d): Input Normal Images (e): Filtering process, (f) Comparison Net Results. No Difference Seen in (a, b, c, d, e). 144
Figure 37: (a): Input abnormal mammogram images, (b): Filtering process, (c): Segmentation, (d): Input abnormal Images (e): Filtering process, (f) Comparison Net Results. Difference Seen in (a, b, c, d, e) and diagnosis the disease. 145
Figure 38: (a) Described the relationship between size of GNTR, tumor viability and hyperthermia in first panel, (b) Described the relationship between time duration temperature availability and laser fluency in second panel; (c) Described the relat ..... **Error! Bookmark not defined.**
Figure 39: Control temperature actions between different nodes of GNTRs at steady state time 1800 s. ..... **Error! Bookmark not defined.**
Figure 40: Control Temperature Actions Between Different Nodes of GNTRs at Steady State Time 2700 s. ..... **Error! Bookmark not defined.**
Figure 41: Control Temperature Actions between Different Nodes of GNTRs at Steady State Time 2520 s. 149
Figure 42: Control Temperature Behavior Between Different Nodes of Gold Nano Rode of GNTR Using Mat Lab Software. 150
Figure 43: Different Temperature Behavior with Different Time Interval for the Treatment of Breast Tumors ..... **Error! Bookmark not defined.**

LIST OF ABBREVIATION

Abbreviation	Description
ITS	Intelligent Transportation System
ICT	Information and Communication Technology
IoT	Internet of Things
ML	Machine Learning
Ion MT	Internet of Nano Medical Things
NDN	Nano Devices Network
AI	Artificial Intelligence
ISR	Intelligent Signal Routing
AI	Artificial Intelligence
ANDMS	Advanced Nano Devices Management System
RFID	Radio Frequency Identification
UHF	Ultra-High Frequency
DSRC	Dedicated Short Range Communication
VHF	Very High Frequency
MMS	Medical Management System
HCS	Heat Control System
ICT	Information and Communication Technology
IT	Information Technology
IaaS	Infrastructure as a Service
PaaS	Platform as a Service
SaaS	Software as a Service
PSTN	Public Switched Telephone Network
LAN	Local Area Networks
RIP	Routing Information Protocol
OSPF	Open Shortest Path First
EIGRP	Enhanced Interior Gateway Routing Protocol
ISP	Internet Service Providers
ML	Machine Learning
SVM	Support Vector Machine

Abbreviation	Description
MMS	Medical Management System
HCS	Heat Control System
CNN	Convolutional Neural Network
ICT	Information and Communication Technology
IT	Information Technology
NPV	Negative Predictive Value
LR+ ve	Likelihood Positive Ratio
LR-ve	Likelihood Negative Ratio
FPR	False Positive Rate
PPV	Positive Predictive Value
FNR	False Negative Rate
TNR	True Negative Rate
TPR	True Positive Rate
DNN	Deep Neural Network
AS	Autonomous Systems
ISP	Internet Service Providers
ML	Machine Learning
SVM	Support Vector Machine
DF	Data Fusion
DNN	Deep Neural Network
MF	Membership Functions
OBU	On Board Unit
WSN	Wireless Sensor Nodes
NFC	Near Field Communication
ANN	Artificial Neural Network
GNTR	Gold Nano Thermo Robot
SNDMS	Smart Nano devices Management System
UBI	Usage Based Insurance
ANN	Artificial Neural Network

Abbreviation	Description
LS	Level of Services
QoS	Quality of Service
LBS	Location Based Services
SLP	Simultaneous Localization and Planning
SDN	Software Defined Networking
PrivaaS	Privacy as a Service
DQaaS	Data Quality as a Service
TP	True Positive
FP	False Positive
TN	True Negative
FN	False Negative

TABLE OF CONTENTS

AUTHOR'S DECLARATION ..... **iv**
PLAGIARISM UNDERTAKING ..... **v**
CERTIFICATE OF APPROVAL ..... **vi**
DEDICATION ..... **vii**
ACKNOWLEDGMENT ..... **viii**
SUMMARY ..... **ix**
LIST OF TABLES ..... Error! Bookmark not defined.
LIST OF FIGURES ..... **xi**
LIST OF ABBREVIATION ..... **xiii**
CHAPTER 1 INTRODUCTION **21**
1.1 Nanotechnology **25**
1.1.1 Applications of Nanotechnology in the Domain of Healthcare **26**
1.1.2 Drug Delivery **27**
1.1.3 Cancer Therapy **27**
1.1.4 Imaging Agents **27**
1.1.5 Diagnostics **28**
1.1.6 Vaccines **28**
1.1.7 Regenerative Medicine **28**
1.1.8 Neuroscience **28**
1.1.9 Wound Healing **28**
1.1.10 Targeted Therapy **28**
1.1.11 Drug Resistance Mitigation **29**
1.1.12 Gene Therapy **29**
1.1.13 Dental Healthcare **29**
1.1.14 Artificial Organs **29**
1.1.15 Remote Monitoring **29**
1.2 Nanorobots **30**
1.2.1 Applications of Nanorobots in the Domain of Healthcare **30**
1.2.2 1.2.2 Targeted Drug Delivery **30**
1.2.3 1.2.3 Surgery and Tissue Repair **31**
1.2.4 1.2.4 Diagnostics Agent **31**
1.2.5 1.2.5 Targeted Detection of Bacterial and Viral Infections **31**
1.2.6 1.2.6 Drug Monitoring and Release Agent **31**
1.2.7 1.2.7 Nanomedicine for Neurological Disorders **31**
1.2.8 1.2.8 Blood Cleansing **31**
1.2.9 1.2.9 Immune System Enhancement **31**
1.2.10 1.2.10 Vascular Health **32**
1.2.11 1.2.11 Organ Preservation **32**
1.3 PROPOSED GOLD NANO THERMO ROBOT **32**

1.3.1 1.3.1 PROPOSED DESIGN OF GOLD NANO THERMO ROBOTIC SYSTEM 33
1.3.2 1.3.2 Morphology of Proposed Gold Nano Thermo Robot 33
1.3.3 1.3.3 Key Components of Gold Nano Robots 34
1.3.4 1.3.4 Discrete Mesh Process 35
1.3.5 1.3.5 Gold Nanoparticles 35
1.3.6 1.3.6 Surface Modifications 35
1.3.7 1.3.7 Navigation Systems 35
1.3.8 1.3.8 Drug Delivery Systems 35
1.3.9 1.3.9 Sensors Network 36
1.3.10 1.3.10 Control Systems 36
1.3.11 1.3.11 Communication Mechanisms 36
1.3.12 1.3.12 Imaging Agents 36
1.3.13 1.3.13 Heat Control Mechanisms 36
1.3.14 1.3.14 Safety Features 36
1.3.15 1.3.15 Biodegradability 36
1.3.16 1.3.16 Energy Sources 37
1.3.17 1.3.17 WORKING PRINCIPLE of Proposed Gold Nano Thermo Robots 37
1.4 Diagnostic Section 38
1.4.1 1.4.1 Artificial Intelligence 38
1.4.2 1.4.2 Soft Computing 40
1.4.3 1.4.3 key components of Soft Computing 41
1.4.4 1.4.4 Applications of Soft Computing 41
1.4.5 1.4.5 Machine learning 42
1.5 Working Principles of Machine Learning Technique 44
1.5.1 1.6.1 Data Collection 44
1.5.2 1.6.2 Data Preprocessing 44
1.5.3 1.6.3 Feature Engineering 45
1.5.4 1.6.4 Data Splitting 45
1.5.5 1.6.5 Model Selection 45
1.5.6 1.6.6 Training the Model 45
1.5.7 1.6.7 Evaluation, after training 45
1.6 Hyperparameter Tuning fine-tunes the model's hyperparameters to optimize its performance. 45
1.7 Computer Vision 46
1.7.1 1.8.1 Deep Machine Learning Models 46
1.7.2 1.8.2 Medical Image Processing 47
1.7.3 1.8.3 Medical Image Processing Steps 47
1.8 How Deep Machine Learning Diagnosis the Chronic Diseases 52
1.8.1 1.9.1 Image Input 53
1.8.2 1.9.2 Convolutional Layers 53
1.8.3 1.9.2 Pooling Layers 53
1.8.4 1.9.2 Fully Connected Layers 53
1.8.5 1.9.3 Training 53
1.8.6 1.9.4 Transfer Learning 54
1.8.7 1.9.5 Interpretability 54
1.8.8 1.9.6 Validation and Testing 54
1.8.9 1.9.7 Deployment 54

1.8.10 1.9.8 Generative Adversarial Networks 54
1.8.11 1.9.9 Data Collection and Preprocessing 55
1.8.12 1.9.10 GAN Architecture Design 55
1.8.13 1.9.11 Data Splitting 55
1.8.14 1.9.12 GAN Training 55
1.8.15 1.9.13 Hyperparameter Tuning 55
1.8.16 1.9.14 Validation and Monitoring 56
1.8.17 1.9.15 Generation of Synthetic Images 56
1.8.18 1.9.16 Integration with Diagnosis Model 56
1.8.19 1.9.17 Diagnosis Model Training 56
1.8.20 1.9.18 Model Evaluation 56
1.8.21 1.9.19 Deployment and Clinical Use 56
1.9 Fusion 57
1.9.1 1.10.1 Data Fusion 57
1.9.2 1.10.2 Feature-Level Data Fusion 57
1.9.3 1.10.3 Multiple Data Sources 57
1.9.4 1.10.4 Feature Extraction 57
1.9.5 1.10.5 Integration 57
1.9.6 1.10.6 Enhanced Information 58
1.9.7 1.10.7 Applications of Feature-Level Data Fusion 58
1.10 EMERGING TRENDS IN CLOUD COMPUTING 59
1.10.1 1.11.1 Services of Cloud Computing 59
1.10.2 1.11 .10 Deployment Models for Cloud Computing 60
1.11 Edge Computing 61
1.11.1 1.11.1 Applications of Edge Computing in Healthcare 61
1.12 Treatment Section 62
1.12.1 1.12.1 CONVENTIONAL TREATMENT METHODS 62
1.12.2 1.12.1 Intelligent Therapeutic Nano system 63
1.12.3 1.12.2 Gold Nanoparticles 64
1.12.4 1.12.3 Properties of Gold Nanoparticles: 65
1.13 Coulomb Explosion 66
1.13.1 1.13.1 Ionization 66
1.13.2 1.13.2 Accumulation of Charges 67
1.13.3 1.13.3 Repulsion Dominance 67
1.13.4 1.13.4 Rapid Disruption 67
1.13.5 1.13.5 Coulomb Explosion Imaging 67
1.13.6 1.13.6 Absorption of Laser Energy 68
1.13.7 1.13.7 Electron-Ion Recombination 68
1.13.8 1.13.8 Vibrational and Rotational Excitation 68
1.14 Hypothermia Treatment 68
1.14.1 1.14.1 Local Hyperthermia 69
1.14.2 1.14 .2 Patient Preparation 69
1.14.3 1.14 .3 Heat Application 69
1.14.4 1.14 .4 Regional Hyperthermia 69
1.14.5 1.14 .5 Treatment Setup 69
1.14.6 1.14 .6 Heat Distribution 69
1.14.7 1.14 .7 Monitoring 70
1.14.8 1.14 .8 Mechanisms of Action 70
1.15 Heat Control System 71

1.16 Interbody Communication Network of a Nano Therapeutic Robotic system 72
1.16.1 1.16 .1 Working Roles of Ion MT for Nano Therapeutic System (GNTRs) 72
1.17 The "See and Treat" Technique 75
1.18 Nanomedicine 75
1.18.1 1.18.1 Key Aspects of Nanomedicine 75
1.19 Research Gap 78
1.20 MOTIVATION 78
1.21 PROBLEM STATEMENT 79
1.22 RESEARCH OBJECTIVES 80
1.23 RESEARCH QUESTIONS 80
1.24 CONCLUSION 81
CHAPTER 2 LITERATURE REVIEW 82
2.1 Conclusion 87
CHAPTER 3 PROPOSED METHODLOGY 88
GOLD NANO THERMO ROBOT (GNTR) 88
CHAPTER 3 94
PROPOSED DIAGNOTIC METHODLOGY 94
(BASE PAPER MODEL) 94
3.1 PROPOSED METHODOLOGY 94
3.1.1 MEDIA FILTERING 95
3.1.2 EXTRACT OF BREAST REGION 96
3.1.3 3.1.2 GENERATIVE ADVERSARIAL NETWORKS 101
CHAPTER 4 PROPOSED TEATMENT METHODLOGY 113
4.1 Design Methodology of Proposed Gold Nano Thermo Robot (GNTR) 113
4.1.1 Morphology of Proposed Gold Nano Thermo Robot (GNTR) . 113
4.1.2 4.1.2 Key Components of Proposed Gold Nano Thermo Robot (GNTR) 114
4.1.3 4.1.3 Discrete Mesh Process of Proposed GNTR 115
4.1.4 4.1.4 Complex Internal Discretize Mesh Process of Proposed GNTRs 115
4.1.5 4.1.5 Mechanism of action of Proposed GNTRs Error! Bookmark not defined.
4.1.6 4.1.6 Inter Body Communication Network 117
4.1.7 4.1.7 Role of Ion MT for Nano Therapeutic System 118
4.1.8 4.1.8 Coulomb Explosion Procedure 120
4.1.9 4.1.9 Schemes for Heat Control System 123
4.1.10 4.1.10 Mathematical Model 125
4.1.11 4.1.11 Pseudo Code 132
CHAPTER 5 134
SIMULATION RESULTS AND DISCUSSION Error! Bookmark not defined.
5.1 Results And Discussion of Diagnostic Stage 134
5.1.1 5.1.1 Performance Evaluation 134

5.2 5.2 Segmentation Result..... Error! Bookmark not defined.
5.2.1 5.2.1 Breast Cancer Dataset / Kaggle 135
5.2.2 5.2.2 Experimental Settings.....135
5.2.3 Structure Measure $S\alpha$ 136
5.3 Results And Discussion of Treatment Stage 144
5.23 5.3.1 Complex Physical Effects of the Coulomb Explosion Procedure on the Surface of Proposed Gold Nano Thermo Robot (GNTR) ..... Error! Bookmark not defined.
5.3.1 CORRELATIONS between tumor size and required radius of GNTRs.....152
5.3.2 5.4.1 BEST FIT SCENARIO.....152
5.3.3 Effective Treatment Responses.....153
5.4 Discussion.....155
CHAPTER 6: CONCLUSION 165
CHAPTER 7: LIMITATIONS & FUTURE WORK.....167
REFERENCES.....168

CHAPTER 1

INTRODUCTION

Intelligent diagnosis and treatment of chronic-diseases can be achieved using nanotechnology, -which offers several advantages over traditional diagnostic and treatment methods. Furthermore, being a rapidly expanding field that combines nanotechnology and medicine to advance the application of nanoscale materials and devices to improve disease diagnosis, treatment, and prevention whereas lowering the possible side effects associated with traditional chemotherapy or radiation therapy, nanomedicine has revolutionized the pharmaceutical industry in several ways. Novel diagnostic methods, particularly biosensors and imaging agents, that have high sensitivity and specificity enabling identifying illnesses before they occur have been made possible by nanomedicine [1]. These diagnostic techniques can enable patients' individualized treatment programs and offer immediate updates on the course of their diseases. By permitting the targeted and controlled release of therapeutic substances, lowering side effects, and increasing the effectiveness of treatment, nanomedicine has transformed and created new opportunities for regenerative medicine in the pharmaceutical domain [2]. According to **Figure 1**, nanomedicine is an interdisciplinary field of research that combines the study of medicine with the study of nanotechnology, involving nanobiotechnology, molecular medicine, biochemistry, material science, nanoanalytical probes, and biochips, to create novel therapeutic and diagnostic approaches.

Chronic diseases, often characterized by their prolonged and persistent nature, pose significant challenges for medical sciences and healthcare systems worldwide. These conditions encompass a diverse range of illnesses, including cardiovascular diseases, diabetes, cancer, and neurodegenerative disorders [2]. The challenges lie in their multifaceted and complex etiology, which often involves a combination of genetic, environmental, and lifestyle factors. Unlike acute diseases, chronic conditions require long-term management and care, demanding a comprehensive understanding of disease progression and personalized treatment strategies. Additionally, the subtle onset and slow progression of chronic diseases can make early detection and accurate diagnosis challenging, potentially leading to delayed interventions, and compromised patient outcomes.

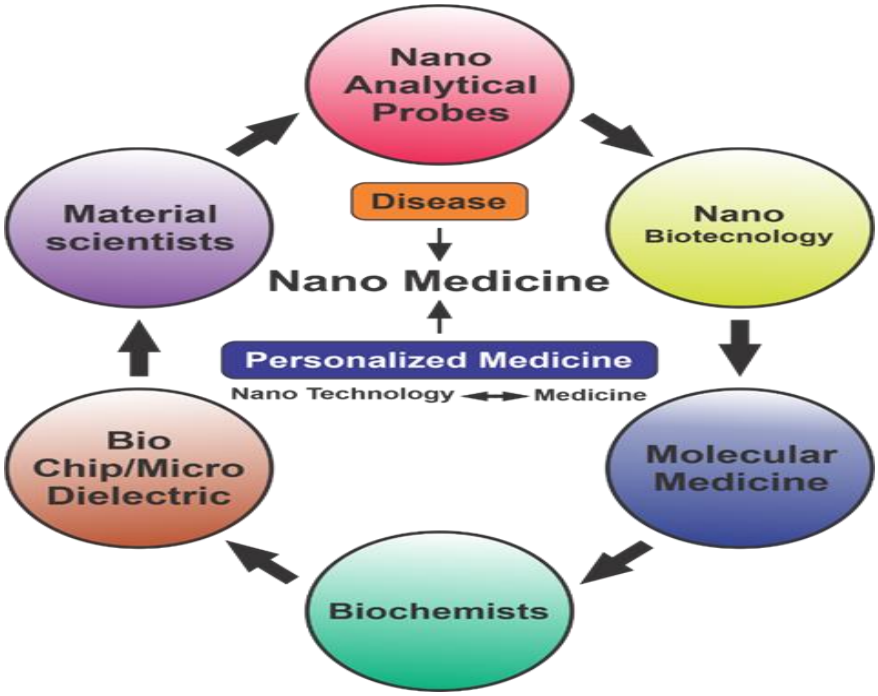


Figure 1: Technologies Involved in the Field of Medicine

Furthermore, the economic burden associated with chronic diseases, from prolonged healthcare costs to reduced workforce productivity, highlights the urgent need for innovative approaches that can address these challenges head-on and offer improved solutions for prevention, diagnosis, and treatment. Furthermore, the gradual onset and subtle progression of symptoms can lead to delayed diagnosis, allowing the diseases to advance to advanced stages before intervention. Inadequate early detection tools, limited understanding of disease mechanisms, and the need for personalized treatment strategies further exacerbate the challenges. Addressing these complexities demands a comprehensive and multidisciplinary approach that integrates advances in medical research, technology, and patient care to develop effective strategies for managing and combating chronic diseases. Cancer of the breast is still one of the most frequent diseases among women globally, which emphasizes how critical it is to comprehend and treat this terrifying health issue. The astounding 2.26 million new instances of breast cancer recorded in women in 2020 alone brought attention to the startling frequency of the disease in the medical community [1]. In addition to posing a serious risk to women's health, this illness necessitates coordinated efforts to enhance treatment outcomes through improved knowledge, early identification, and medical research.

Breast cancer has -become a noticeable health -concern in Pakistan, standing -out among numerous worldwide nations. Statistics show that nearly one in every nine women in Pakistan are -at risk of facing breast- cancer. While developed-

countries commonly report more cases of breast cancer, the mortality- rate due to this condition is higher in developing nations.

Internationally, it is approximated that around 700,000 women are diagnosed with breast cancer each year, with almost 300,000 succumbing to the -disease. The involvedness of breast -cancer, with its multiple and often indefinite- causes, makes complete avoidance challenging [1]. Conversely, the key to modifying the effect lies in early revealing, as identifying breast cancer in its initial stages can substantially decrease mortality rates among women.
From December 1994 to December 2021, the Shaukat Khanum Memorial Cancer Hospital and Research Centre ("SKMCH& RC") trust and its associated centres provided the regional breast cancer statistics [1]. The pie diagram in Figure 2. below provides a graphic depiction of the distribution of cancer cases among all provinces of Pakistan, as well as in Afghanistan, Azad Kashmir, and other nearby nations.

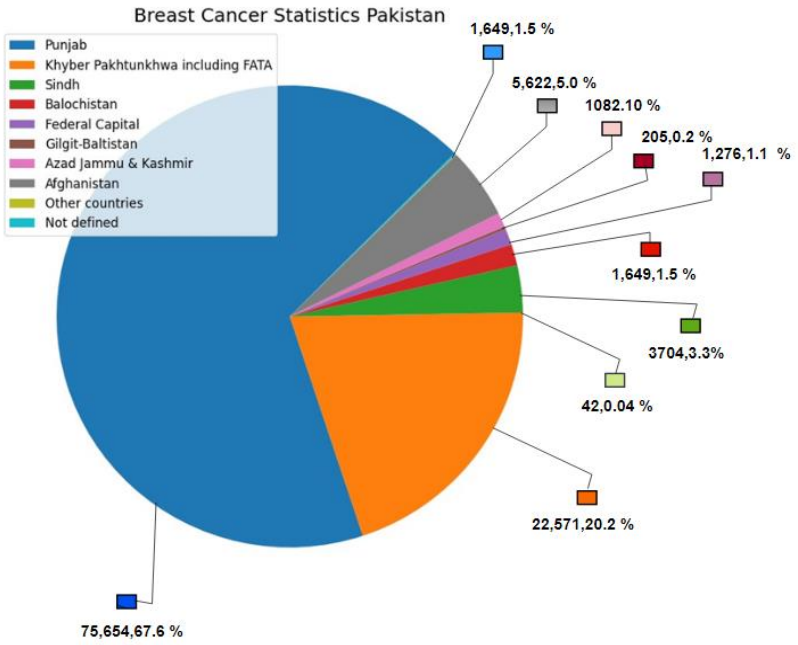


Figure 2: Spreading of malignancies conferring to the geographic zone of residence of the affected role in Pakistan. 2/12/1994 to 2/12/2020

Chronic diseases, characterized by their long-lasting nature and often complex aetiology, pose a significant burden on global healthcare systems and patients' quality of life. Conventional diagnostic and treatment approaches often lack the precision required to address the unique intricacies of each patient's condition. In response to this challenge, researchers and engineers have been diligently working to develop innovative solutions that leverage emerging technologies [3].

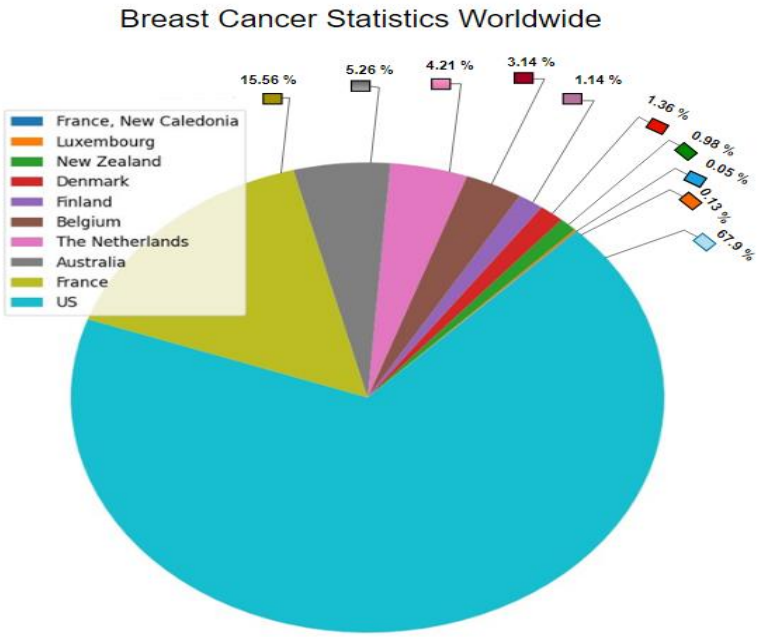


Figure 3: Spreading of malignancies in topmost Ten states with the maximum rates of breast cancer global among ladies in 2020.

The World Cancer Research Fund International is the source of the global breast cancer data. [1]. The pie diagram in Figure shows the data of the top ten nations in the world with the highest incidence of breast cancer in women in 2020. 3. Technological developments in medicine have completely changed how chronic illness is identified and treated, launching the field of precision medicine and opening the door to more individualized and efficient healthcare options.
One of the most intriguing and transformative innovations in this domain is the integration of nanotechnology approaches with soft computing techniques [4]. This amalgamation of cutting-edge nanotechnology, robotics, and sophisticated computational methods has paved the way for intelligent and targeted diagnosis and treatment of chronic diseases. As we stand at the cusp of a new era in healthcare, where the marriage of nanotechnology, robotics, and computational intelligence holds the key to unlocking unparalleled advancements in chronic disease management, it is imperative to comprehensively understand the multifaceted landscape of intelligent diagnosis and treatment by using soft computing approaches. By edge cutting technologies it has now become to synthesis of innovation has the potential to reshape the healthcare landscape, ushering in an era of personalized, precise, and effective interventions that offer renewed hope to millions of individuals grappling with chronic diseases.

Nanotechnology, with its ability to manipulate and engineer materials at the atomic and molecular scale, has opened possibilities for developing highly targeted and minimally invasive medical interventions. Concurrently, robotics has advanced to incorporate intricate mechanical designs and precise control mechanisms, enabling the creation of highly dexterous and adaptable medical devices. Soft computing, on

the other hand, encompasses various computational techniques that mimic human decision-making processes, such as neural networks, genetic algorithms, and fuzzy logic. When combined, these technologies form a synergistic framework that can enhance the accuracy, efficiency, and personalized nature of diagnosing and treating chronic diseases. In response to these challenges, researchers and scientists have turned to nanotechnology and robotics to develop innovative tools capable of operating at the cellular and molecular levels. The Gold Nano Thermo Robotic System is proposed to develop in this study to fulfil these challenges. The proposed Nano medical device, characterized by its miniature size and remarkable manoeuvrability, holds the potential to revolutionize the way chronic diseases are diagnosed and treated. These Nano systems can navigate through the intricate biological landscape of the human body, accessing remote or hard-to-reach areas with unprecedented precision. What truly sets these Gold Nano Thermo Robotic System apart is their integration with soft computing techniques. Soft computing encompasses a range of computational methodologies, including artificial neural networks, genetic algorithms, fuzzy logic, and machine learning, which excel at processing complex and uncertain information. Machine learning algorithms play a significant role in the diagnosis of chronic diseases by analysing large amounts of data, identifying patterns, and assisting healthcare professionals in making more accurate and timely decisions. These algorithms leverage computational power to process complex information and extract valuable insights from various types of medical data, ultimately aiding in early detection, risk assessment, and personalized treatment planning. By harnessing the power of soft computing, these proposed Gold Nano Thermo Robotic System can analyse vast amounts of patient-specific data, adapt to dynamic physiological conditions, and make intelligent decisions in real-time. The study is divided into two phases. First is diagnostic phase and second is treatment phase. Advancements in medical technology have significantly transformed the landscape of healthcare, offering innovative solutions for the diagnosis and treatment of chronic diseases. Among these groundbreaking technologies, the integration of Gold Nano Thermo Robotic System empowered with soft computing stands out as a promising approach. This convergence of nanotechnology, robotics, and computational intelligence has paved the way for a new era of precision medicine, enabling more accurate, efficient, and personalized management of chronic health conditions [1].

1.1 Nanotechnology

Nanotechnology is a cutting-edge field that involves manipulating and engineering materials and devices at the nanoscale, which is typically between 1 and 100 nanometres. At this tiny level, the fundamental building blocks of matter exhibit unique properties and behaviours that differ from their macroscale counterparts. Scientists and engineers working in nanotechnology utilize these

properties to create groundbreaking innovations with widespread applications. In nanotechnology, researchers design and control matter at the molecular and atomic levels, allowing them to construct nanomaterials, nanodevices, and nano systems with incredible precision [5]. This precision enables the development of smaller, more efficient, and highly functional structures and products across a wide range of disciplines.

Nanotechnology has transformative potential in various sectors, including electronics, where it can lead to faster and more energy-efficient microchips and displays. In medicine, it offers the promise of targeted drug delivery, advanced imaging techniques, and novel therapies, revolutionizing healthcare. Additionally, nanomaterials can enhance the performance of batteries and solar cells, leading to more efficient energy production and storage. Furthermore, nanotechnology has applications in materials science, enabling the creation of stronger, lighter, and more durable materials. Environmental and clean energy solutions, such as water purification and pollution remediation, are also benefiting from nanotechnology. Additionally, the discipline contributes to the creation of nano sensors and nanoelectromechanical devices (NEMS), which find use in transportation, communication, and detection [6].
Nevertheless, there are moral, security, and legal issues brought up by the quick development of nanotechnology. Careful evaluation and control are required due to concerns about the possible toxicity of certain nanomaterials and their effects on the environment and human health. Despite these challenges, nanotechnology holds great promise for addressing some of society's most pressing issues and driving innovation in nearly every facet of modern life [8].

1.1.1 Applications of Nanotechnology in the Domain of Healthcare

Nanotechnology has brought about transformative applications in the field of healthcare, offering innovative solutions to various medical challenges. Here are some key applications of nanotechnology in healthcare:

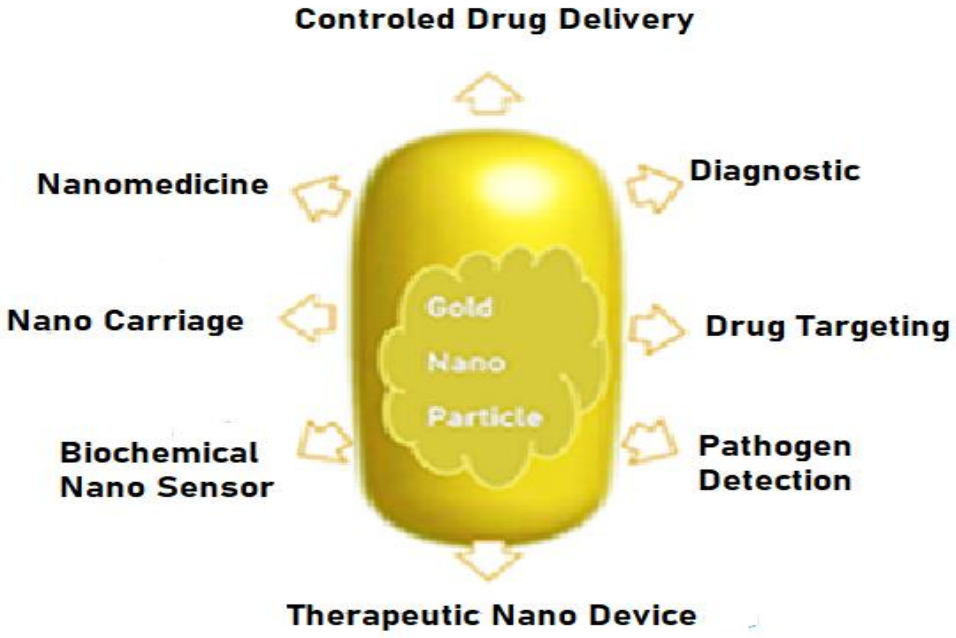


Figure 4: Uses for Nanoparticles of Gold

1.1.2 Drug Delivery

Nanoparticles and nanocarriers can be designed to encapsulate drugs, genes, or therapeutic agents. These nanoscale carriers enable precise drug targeting, controlled release, and improved bioavailability. They can deliver medications directly to affected cells or tissues, minimizing side effects, and enhancing treatment efficacy [7].

1.1.3 Cancer Therapy

Nanoparticles can selectively target and deliver cancer drugs to tumor sites, minimizing damage to healthy tissues. This approach reduces side effects and allows for higher drug concentrations at the tumour, improving cancer treatment outcomes.

1.1.4 Imaging Agents

Nanoparticles with imaging agents (e.g., quantum dots) enable highly sensitive and specific imaging of tissues and cells. This can aid in early disease detection, tracking disease progression, and guiding surgical procedures.

1.1.5 Diagnostics

Nanotechnology has enabled the development of highly sensitive and rapid diagnostic tests. Nanoscale sensors and probes can detect disease biomarkers, viruses, or bacteria with exceptional precision. This has implications for point-of-care diagnostics and personalized medicine.

1.1.6 Vaccines

Nanoparticle-based vaccine formulations can enhance the immune response and improve vaccine stability. They are being explored for various infectious diseases, including COVID-19.

1.1.7 Regenerative Medicine

Nanomaterials can be used to scaffold tissue engineering and regenerative medicine approaches. They facilitate cell growth and tissue regeneration, offering potential solutions for organ transplantation and tissue repair [6].

1.1.8 Neuroscience

Drug delivery to the brain and neural interface are two areas where nanotechnology is involved. It can advance neurological disease therapies and deepen our knowledge of how the brain works.

1.1.9 Wound Healing

Nanomaterials and dressings can promote faster wound healing by delivering growth factors and antimicrobial agents. They also help reduce scarring.

1.1.10 Targeted Therapy

Nanoparticles can be functionalized to target specific cells or tissues. This approach is particularly valuable in treating diseases like Alzheimer's, where targeting beta-amyloid plaques is crucial [7].

1.1.11 Drug Resistance Mitigation

Nanotechnology can help address antibiotic resistance by improving the delivery of antimicrobial agents and developing innovative treatments.

1.1.12 Gene Therapy

Nanoscale carriers can deliver genetic material to correct or replace faulty genes. This has potential applications in treating genetic disorders and certain diseases.

1.1.13 Dental Healthcare

Nanomaterials are used in dental applications for remineralization, anti-bacterial coatings, and drug delivery to oral tissues.

1.1.14 Artificial Organs

Nanotechnology is advancing the development of artificial organs and prosthetics with improved biocompatibility and functionality.

1.1.15 Remote Monitoring

Nano sensors can be used to remotely monitor vital signs and detect biomarkers in real time. This is valuable for continuous health monitoring and early disease detection.

1.1.16 Nanomedical Robots

Nanomedical robots are a broader category that encompasses not only nanorobots, but also other nanoscale tools and devices used for medical purposes. This includes nanoparticles designed for drug delivery, imaging agents, or even nano sensors that can detect biomarkers for diseases. They can enhance the accuracy of diagnostics, improve drug efficacy, and reduce side effects. In practice, these nanoscale technologies offer several advantages [10]. They can improve the precision of medical treatments, reduce collateral damage to healthy tissues, and enhance the effectiveness of therapies. Moreover, they have the potential to enable entirely new approaches to healthcare, such as early disease detection at the molecular level or personalized medicine tailored to an individual's unique genetic profile.

However, it's crucial to acknowledge that as of my last knowledge update in September 2021, these technologies were still predominantly in the experimental and preclinical stages. Developing safe and effective nanorobots and nanomedical robots for clinical use involves overcoming significant challenges, including ensuring biocompatibility, addressing potential toxicity issues, and navigating regulatory hurdles [9].

Nevertheless, ongoing research and development in this field holds great promise for revolutionizing healthcare by ushering in an era of highly targeted, minimally invasive, and personalized medical interventions. As technology advances, the healthcare community will continue to investigate the capability applications and benefits of nanorobots and nanomedical robots in addressing various health challenges [45].

1.2 Nanorobots

Nanorobots and nanomedical robots are cutting-edge technologies with transformative potential in the healthcare domain. These miniature machines, often just a few nanometres in size, are designed to operate at the molecular or cellular level, allowing for precise and targeted interventions within the human body [50]. Nanorobots are typically autonomous or semi-autonomous devices with the ability to perform various tasks, such as drug delivery, tissue repair, or even diagnostics. They can navigate through the bloodstream, seek out specific cells or pathogens, and execute predefined functions. For instance, they might deliver chemotherapy drugs directly to cancer cells, sparing healthy tissue, or clear arterial blockages.

1.2.1 Applications of Nanorobots in the Domain of Healthcare

Nanorobots performs several major jobs in the healthcare domain. Few are described below.

1.2.2 Targeted Drug Delivery

Drugs can be delivered using nanorobots to target bodily regions or cells. The therapeutic effectiveness of pharmaceuticals is increased and adverse effects are reduced because to this focused drug administration. For instance, they could precisely administer chemotherapy medications to cancer cells while preserving healthy tissue [51].

1.2.3 Surgery and Tissue Repair

Nanorobots could perform microsurgery at the cellular or molecular level. They might be used for repairing damaged tissues, removing blood clots, or even assisting in nerve regeneration.

1.2.4 Diagnostics Agent

Nanorobots equipped with sensors and imaging capabilities can be used for early and precise disease detection. They could identify biomarkers associated with various diseases, including cancer, infections, or neurodegenerative disorders [56].

1.2.5 Targeted Detection of Bacterial and Viral Infections

Nanorobots could target and eliminate pathogenic microorganisms, such as bacteria or viruses. They might be programmed to detect and neutralize infections, contributing to the development of highly effective antimicrobial treatments.

1.2.6 Drug Monitoring and Release Agent

In chronic conditions, nanorobots could continuously monitor drug levels in the body and adjust drug delivery accordingly. This could optimize treatment regimens and improve patient outcomes.

1.2.7 Nanomedicine for Neurological Disorders

Nanorobots could navigate the intricate neural pathways and assist in the treatment of neurological disorders like Alzheimer's disease or Parkinson's disease by delivering therapeutic agents to specific brain regions [7].

1.2.8 Blood Cleansing

Nanorobots might be designed to filter and cleanse the bloodstream, removing toxins, pathogens, or excess substances, which could be beneficial in conditions like sepsis or kidney disease.

1.2.9 Immune System Enhancement

Nanorobots could stimulate or modulate the immune system's response, enhancing the body's ability to fight infections or combat diseases like cancer.

1.2.10 Vascular Health

Nanorobots may help maintain vascular health by clearing arterial blockages, repairing damaged blood vessels, or preventing the formation of blood clots.

1.2.11 Organ Preservation

In organ transplantation, nanorobots might be used to preserve organs during transport, reducing the risk of damage and extending the window for successful transplantation.

1.3 PROPOSED GOLD NANO THERMO ROBOT

The GNTRs is an innovative medical technology designed to combat cancer through a two-phase approach: diagnostic and treatment. During the therapy phase, it uses an advanced heat management system to accurately control temperatures between 38°C and 45°C, which is an essential range for killing cancerous cells. This temperature range is achieved through a process known as Coulomb explosion, which releases controlled bursts of energy, ultimately leading to the destruction of cancerous tissue [1].

The treatment phase begins with the activation of the GNTRs. These nanorobots are equipped with gold nanoparticles that have unique properties, particularly their ability to efficiently convert external energy into heat. They are steered to the tumor site by a mix of active targeting (surface changes that assure precise attachment to cancerous cells) and passive targeting (taking advantage of the improved permeability and retention effect) as they travel through the circulation. Compared to conventional cancer therapies, the GNTRs has significant benefits due to its capacity to carry out this therapy phase with such accuracy. It lowers the possibility of unintentional harm to healthy cells, lessens side effects, and improves the general efficacy of cancer therapy [3]. This novel strategy shows the promise of gold nanoparticles, controlled release of nanoparticles, and nanotechnology as a viable route in the ongoing fight against cancer.
This innovative approach represents a promising avenue in the ongoing battle against cancer, showcasing the potential of nanotechnology, gold nanoparticles, and controlled heat therapy to revolutionize cancer care and improve patient outcomes. Conversely, it's key to note that while this concept holds great promise, practical implementation and safety considerations require extensive research, testing, and validation before clinical adoption [1].

1.3.1 PROPOSED DESIGN OF GOLD NANO THERMO ROBOTIC SYSTEM

GNTRs are cutting-edge nanoscale devices designed to perform precise tasks within the human body, particularly in the field of medicine [1]. These tiny robots are equipped with various elements and functionalities that enable them to navigate, diagnose, and treat various medical conditions. In the world of nanomedicine, GNTRs have emerged as a promising innovation with a range of critical elements. GNTRs represent a remarkable fusion of nanotechnology, medicine, and robotics. Their multifaceted elements enable them to carry out precise and minimally invasive procedures, such as targeted cancer treatment. While still largely in the research and development phase, these innovative robots hold immense potential for revolutionizing healthcare by offering highly targeted therapies with minimal side effects [56].

1.3.2 Morphology of Proposed GNTRs

The (GNTRs) being suggested are crafted from gold, a crucial material known for its ability to transmit electrical signals within the body. Furthermore, gold has the capacity to absorb and subsequently release heat in a regulated manner. The application of gold compounds as potential anticancer agents has gained significant attention, and gold nanoparticles (AuNPs) are extensively employed in cancer research [60].

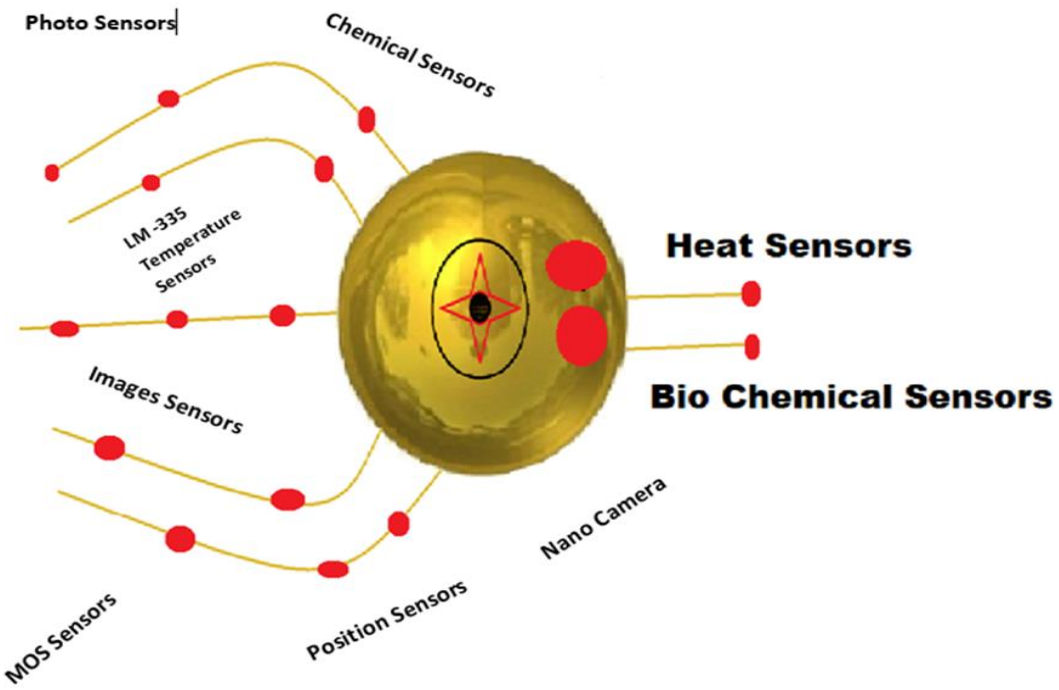


Figure 4: Proposed Model of Gold Nano Thermo Robot (GNTR)

The outstanding properties of the suggested Nano robots, including as surface enhanced, Raman spectroscopy, surface plasma resonance, controlled fusion, and the changeable surface shape, all contribute to biological safety and stability and are advantageous to diagnosis and therapy procedures [63]. As seen in Figure 5 [1], the form and architecture of these nanorobots are modeled after the structures of unicellular biological organisms such as Chlamydomonas, guaranteeing effective employment fulfillment.

1.3.3 Key Parts of GNTRs

A Nano computer that is in charge of carrying out predefined duties, storing and deciphering signals and external stimuli, communicating with other Nano computers, and identifying external authority mechanisms is included in the proposed Nano robot [67]. A navigational network is connected into the patient's body to track every nanorobot's movement and provide accurate topographical data. Numerous Nano instruments, involving a Nano camera, temperature sensor, image sensor, position device, biochemical sensor, timer instrument, heat transducer device, and heat storing device are all part of this cutting-edge Nano gadget. The precise location of Nanorobots inside the body may be determined

thanks to the Nano camera. Interfacial components, power monitor, sensors devices, and communications actuators are used in the building of these nanorobots. **Figure 5** [1] depicts the GNTR model that is suggested.

1.3.4 Discrete Mesh Process

Figure 4, illustrates a gold rod of the GNTRs as an illustration of how the discretization process splits the physical environment into a limited number of discrete points or networks of nodes. The partial differential equation (PDE) is then replaced by a collection of equations that construct connections throughout the actual values of the unknown quantity at the points in the process. These equations are referred to as difference equations due to how they express the difference in the unknown quantity's values between one point and its surrounding point. Different equations are the names provided for these formulas. For a **1D** heat equation, the physical domain is a gold nanorod, which is a straight line. The discretization method divides this gold nanorod into a finite number of points, or nodes, as seen in **Figure 5**. Every node is assigned a value for the unknown temperature, and the heat equation is transformed into a collection of differential equations which correspond to the high temperature at neighbouring nodes [7].

1.3.5 Gold Nanoparticles

At the heart of these robots are gold nanoparticles, often chosen for their unique properties. Gold nanoparticles efficiently convert external energy into heat, making them ideal for controlled hyperthermia-based treatments. They serve as the heat source for therapeutic applications [9].

1.3.6 Surface Modifications

The surface of these nanoparticles is often modified to enhance their stability, biocompatibility, and targeting capabilities. Functional groups or molecules can be attached to the surface for specific interactions with biological entities, such as cancer cells.

1.3.7 Navigation Systems

GNTRs rely on various navigation mechanisms to move within the body. This can include passive targeting, where they exploit the enhanced permeability and retention (EPR) effect to accumulate at disease sites, or active targeting, achieved through ligand-receptor interactions.

1.3.8 Drug Delivery Systems

Some GNTRs are designed to carry and release therapeutic agents, such as drugs or genetic material, to the targeted areas. This enables both localized treatment and a reduction in systemic side effects.

1.3.9 Sensors Network

To ensure precise navigation and effective treatment, these robots may include sensors for detecting biological cues or markers in their microenvironment. These sensors provide real-time information for decision-making.

1.3.10 Control Systems

GNTRs are equipped with control systems that regulate their actions. These systems can be pre-programmed or, in more advanced iterations, may have adaptive and autonomous capabilities, responding to changing conditions [67].

1.3.11 Communication Mechanisms

In some cases, these robots communicate with external devices or systems for remote monitoring and control. This can include wireless communication or the transmission of data to healthcare providers.

1.3.12 Imaging Agents

To aid in diagnostics and monitoring, GNTRs may incorporate imaging agents. These agents enhance visibility in medical imaging modalities such as MRI, CT scans, or ultrasound.

1.3.13 Heat Control Mechanisms

Perhaps the most critical element for therapeutic applications, these robots feature heat control systems. These systems precisely regulate temperature within the desired therapeutic range (e.g., 38°C to 45°C) to induce hyperthermia or thermal ablation of target cells, such as cancer cells [67].

1.3.14 Safety Features

Safety mechanisms are essential to prevent unintended damage to healthy tissues. These may include fail-safes, feedback loops, and algorithms that ensure the robot's actions remain within safe parameters.

1.3.15 Biodegradability

To ensure biocompatibility and eventual elimination of robots from the body, they may be designed to degrade or be eliminated through natural bodily processes.

1.3.16 Energy Sources

GNTRs require an energy source to function. This can include external energy sources, such as magnetic fields or light, or they may harvest energy from their surroundings.

1.3.17 WORKING PRINCIPLE of Proposed GNTRs

The proposed GNTRs represent a groundbreaking approach to the diagnosis and treatment of chronic diseases [47]. These nanoscale robots are designed with multifaceted functionalities that revolutionize healthcare. The working principle of these robots begins with their introduction into the patient's bloodstream, guided either passively through the enhanced permeability and retention effect or actively through specific targeting molecules. Once at the disease site, these robots utilize their advanced sensors and imaging capabilities to perform highly precise diagnostics, detecting biomarkers, cellular abnormalities, or tissue anomalies [1].

For treatment, these robots employ gold nanoparticles as therapeutic agents, activated through controlled energy sources. The gold nanoparticles efficiently convert external energy into heat, enabling the robots to regulate temperature within a therapeutic range, typically 38°C to 45°C. This precisely controlled hyperthermia triggers a cascade of therapeutic effects. In the case of cancer, it leads to the selective destruction of malignant cells, sparing healthy tissues from harm. The robots' heat control systems ensure that temperatures remain within this critical window, optimizing treatment efficacy while minimizing collateral damage [11].

These robots can also be customized to deliver targeted therapies, such as drugs or genetic materials, directly to the affected cells, minimizing systemic side effects. Their biodegradable components ensure their safe elimination from the body after treatment.

The proposed Gold Nano Thermo Robots combine diagnostic and therapeutic functionalities within a single nanoscale platform, offering a minimally invasive, highly precise, and personalized approach to the diagnosis and treatment of chronic diseases. Their working principle integrates advanced sensing, imaging,

heat control, and therapeutic capabilities to potentially revolutionize the landscape of healthcare and improve patient outcomes for chronic diseases [12].

1.4 Diagnostic Section

The first stage of our research is known as the diagnostic section and its explained in detail below.

1.4.1 1.4.1 Artificial Intelligence

AI has become an invaluable tool for scientists across various disciplines. Its ability to process, analyze, and make predictions from data, coupled with advancements in machine learning and deep learning, has accelerated scientific progress and opened new frontiers of discovery [19].

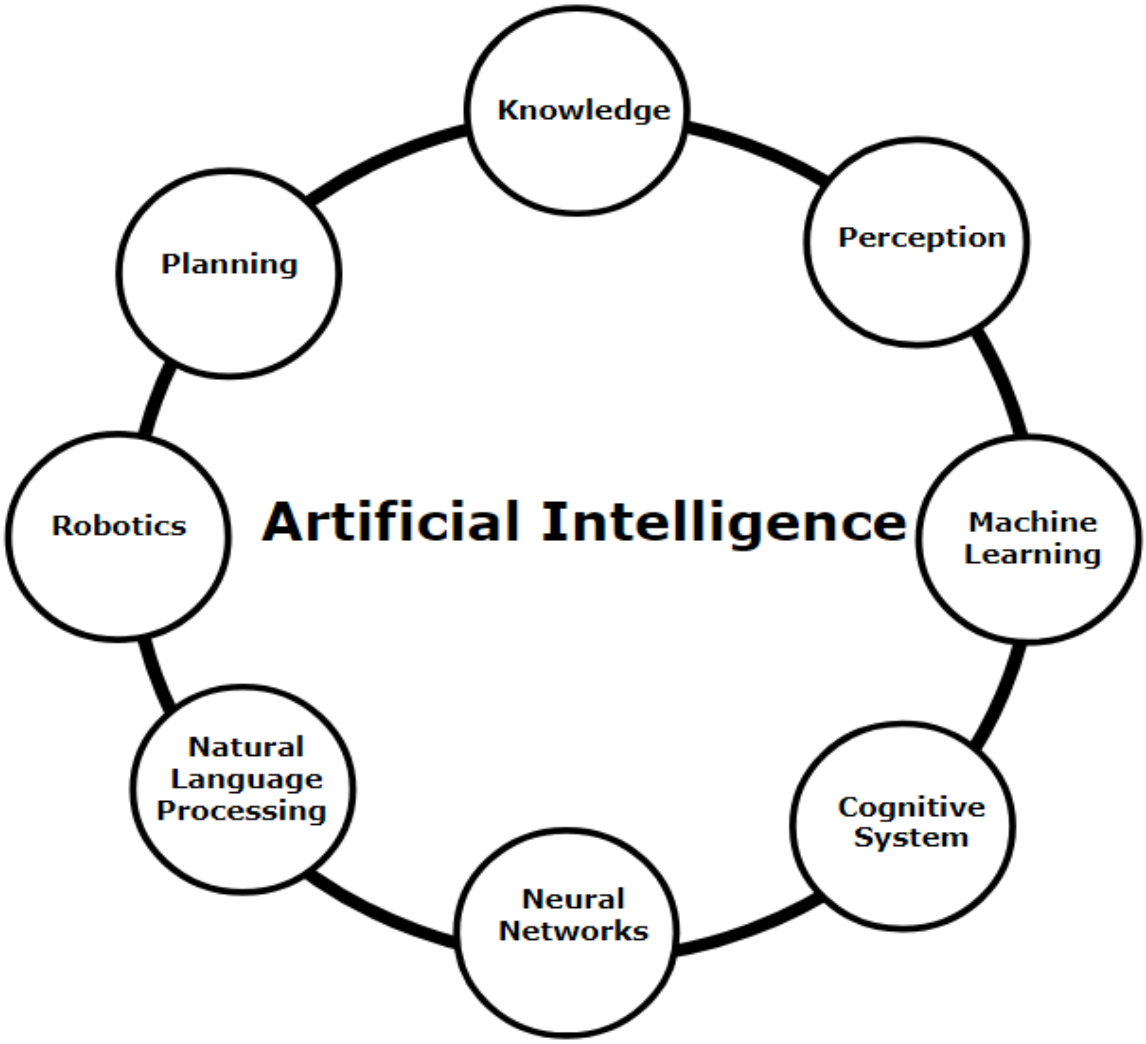


Figure 5: The Roles of Artificial Intelligence

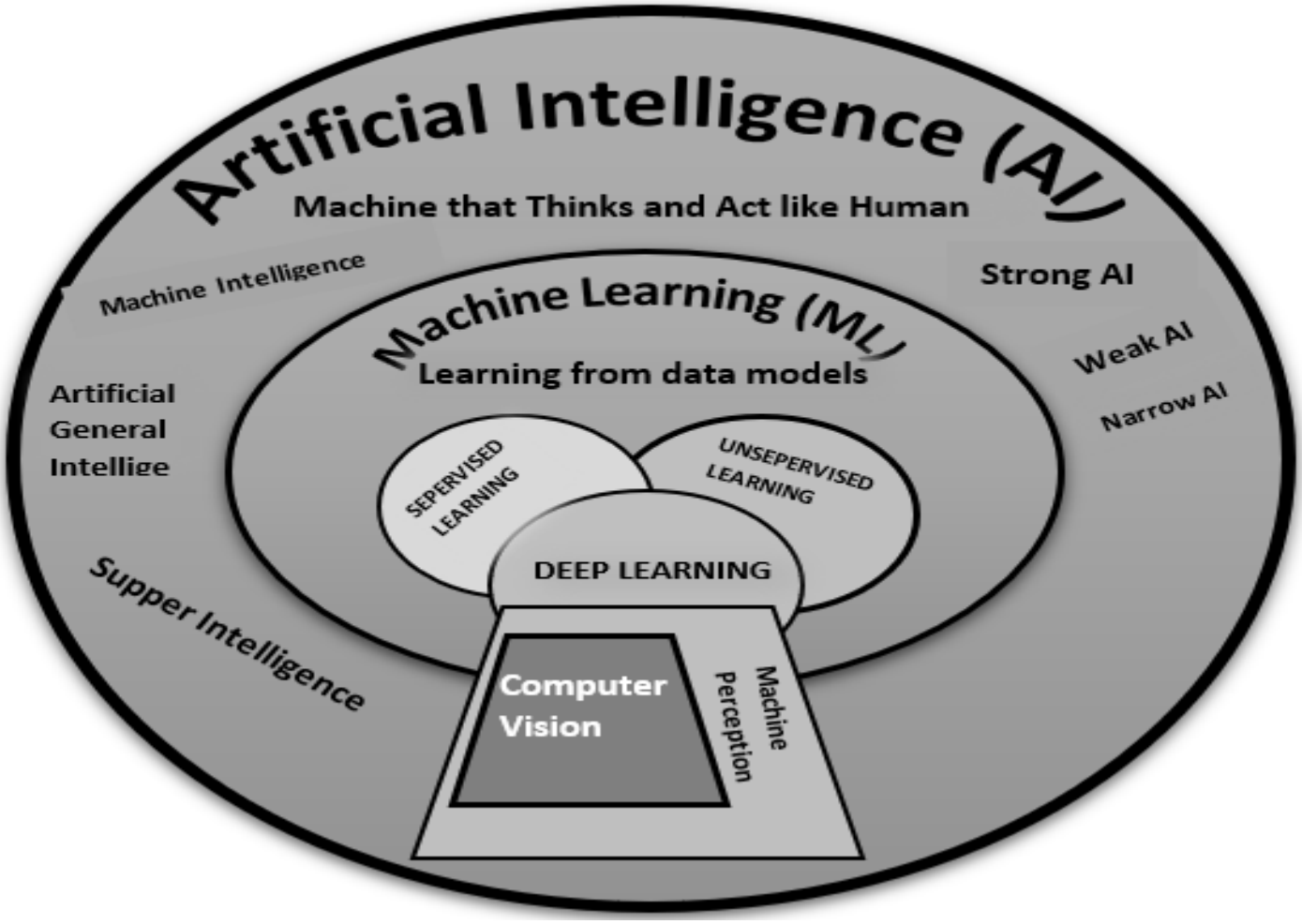
To guarantee that the advantages of AI are used responsibly and ethically, it is crucial to address ethical issues, data protection, and responsible AI use as the technology's influence in science rises [20]. Artificial intelligence (AI) has emerged as a key component of the contemporary period, bringing about significant changes in several fields. Its accomplishments and importance are astounding and continue to influence our world in many ways.

- Neural Networks
- Planning
- Machin Learning
- Natural Language Processing
- Perception
- Robotics and Automation
- Knowledge
- Scientific Experimentation
- Cognitive System

AI algorithms are exceptionally skilled at processing and analyzing vast datasets, which is crucial in scientific research. AI-driven data analysis helps scientists uncover patterns, trends, and insights in fields such as genomics, astronomy, climate science, and social sciences. It accelerates drug discovery by simulating and predicting the behavior of molecules and their interactions with biological systems. This reduces the time and cost associated with developing new pharmaceuticals and aids in the interpretation of medical imaging, such as MRI and CT scans, to assist in disease diagnosis. Machine learning models can also predict disease risks and outcomes based on patient data. It is instrumental in analyzing genomic and proteomic data, facilitating [21]. The roles Artificial Intelligence Sphere and the involved techniques genetic research, personalized medicine, and the identification of potential disease markers are described in **Figure 6**. Now it has become possible to simulations and models assist in designing new materials with desired properties, advancing fields like materials science and nanotechnology [68].

In the domain of robots and autonomous systems are used in scientific research for tasks such as sample collection in extreme environments, exploring the depths of the ocean, and studying extraterrestrial environments. AI-powered natural language processing (NLP) tools help scientists process and extract information from scientific literature, making it easier to stay up to date with research developments and now could be possible to optimize experimental designs and automate laboratory processes, increasing the efficiency and reproducibility of experiments. AI-driven simulations are crucial for modeling complex systems in fields like physics, chemistry, and climate science [49].

AI has become an invaluable tool for scientists across various disciplines. Its ability to process, analyze, and make predictions from data, coupled with advancements in machine learning and deep learning, has accelerated scientific progress and



opened new frontiers of discovery. However, as AI's role in the scientific world grows, it is essential to address ethical considerations, data privacy, and the responsible use of AI to ensure its benefits are harnessed ethically and effectively [22].

Figure 6: The Responsibilities of Artificial- Intelligence

1.4.2 Soft Computing

Soft computing is a subfield of artificial intelligence (AI) and computational intelligence that focuses on the development of algorithms and techniques inspired by the human brain’s work. It is called "soft" computing to contrast it

with "hard" computing, which typically deals with precise, mathematical methods and algorithms [22]. Soft computing, on the other hand, deals with methods that can handle uncertainty, imprecision, and incomplete information, making it suitable for solving complex real-world problems where traditional computing approaches may fall short. Soft computing is a paradigm of computing that addresses problems involving uncertainty, imprecision, and complexity by drawing inspiration from human cognitive processes and combining various computational techniques [23]. It is a valuable approach for solving real-world problems where traditional deterministic methods may be inadequate. The functions and responsibilities are explained in **Figure 7**.

1.4.3 key components of Soft Computing

1) **Neural Networks**: These computer models are based on the architecture and operations of the human brain. They are made up of data-driven, networked nodes called neurons. Neural networks find use in pattern recognition, classification, regression, and other domains. 2) **Evolutional Algorithms:** These optimization strategies draw inspiration from the natural selection process [26]. Swarm intelligence, evolutionary programming, and genetic algorithms are a few of them. These algorithms are used to resolve challenging search and optimization issues.**3) Fuzzy Logic:** A mathematical paradigm known as fuzzy logic allows values to be partially or imprecise rather than rigidly binary (true or false), thereby addressing ambiguity. It is especially helpful in contexts like control systems and decision-making when conventional logic might not be able to offer definitive solutions. **4) Probabilistic Reasoning:** To manage uncertainty and make judgments based on probability, probabilistic reasoning is frequently included into soft computing techniques. In this context, probabilistic graphical models and Bayesian networks are frequently employed. **5) Machine Learning** : The field of soft computing includes a range of machine learning methods, such as clustering algorithms, support vector machines, and reinforcement learning. Computers can learn from data and become more efficient over time thanks to these techniques.6) Hybrid Approaches: To construct hybrid systems, soft computing frequently combines many of the aforementioned components' techniques[27]. **Figure 7** provides a detailed explanation of these hybrid systems, which may successfully solve difficult challenges by leveraging the strengths of many approaches.

1.4.4 Applications of Soft Computing

1). **Control Systems**, Fuzzy logic controllers and neural network-based controllers are used in industrial automation, robotics, and process control to handle imprecise and dynamic environments. **2)**. **Pattern Recognition**, Neural

networks and other soft computing techniques are used for image and speech recognition, natural language processing, and handwriting recognition. **3). Data Mining**, soft computing is employed for extracting valuable insights and patterns from large datasets, enabling businesses to make data-driven decisions. **4). Financial Forecasting**, Fuzzy logic and neural networks are used to predict financial market trends and make investment decisions. **5). Medical Diagnosis**, soft computing techniques assist in medical diagnosis and decision support systems, where uncertainty and imprecision are common [29].

1.4.5 Machine learning

Computer systems could learn and make predictions or choices without explicit programming thanks to a subset of artificial intelligence called machine learning. By using data to train algorithms, it enables them to recognize patterns and reach well-informed conclusions. Numerous industries, including healthcare, banking, self-driving cars, and recommendation systems, employ machine learning. Applications like language translation, fraud detection, and illness diagnosis are powered by it [27]. Deep learning and neural networks are driving advances in fields like image identification and natural language processing as technology moves forward. The future of technology and decision-making is being shaped by machine learning's capacity to conclude data.

1.4.5.1 Types of Machine Learning

A variety of methodologies and various types are included in machine learning, each aimed at addressing certain tasks and learning scenarios [20]. Machine learning practitioners can pick the best method for their particular issue and dataset from a variety of machine learning types that cater to distinct use cases and learning scenarios. The following list includes the main categories of machine learning.

1.4.5.1.1 Supervised Learning

In supervised learning, an algorithm is trained on a labelled dataset in which each input data point has a corresponding output or target label assigned to it. The primary aim is to obtain an understanding of the mapping from input to output, making it suitable for tasks like regression (e.g., forecasting chronic illnesses) and classification (e.g., spam email detection).

1.4.5.1.2 Unsupervised Learning

In unsupervised learning, the training process occurs with unlabeled data, requiring the algorithm to discover patterns or structures inherent in the data itself. Typical techniques employed include clustering (such as grouping similar customer profiles) and dimensionality reduction.

1.4.5.1.3 Semi Supervised Learning

Both types of machine learning components are combined in semi-supervised learning. It makes use of both a significant amount of unlabeled data and a modest amount of annotated data. When collecting labelled data is costly or time-consuming, this method is essential.

1.4.5.1.4 Reinforcement Learning

The goal of reinforcement learning is to teach agents how to make a series of choices in a dynamic environment to maximize a cumulative reward. It is often utilized in recommendation systems, autonomous cars, robotics, and gaming [30].

1.4.5.2 Deep Learning

Deep learning is a branch of machine learning that makes use of multi-layered neural networks, or deep neural networks. It has made major advancements in AI possible and is excellent at jobs like speech recognition, imagine identification, and natural language processing.

1.4.5.3 Transfer Learning

Training a model for a specific assignment and then modifying it for a similar but distinct task is known as transfer learning. When labelled data for the target task is scarce or fine-tuning pre-trained models is achievable, it is advantageous [30].

1.4.5.4 Online Learning (Incremental Learning)

Online learning is appropriate for situations where data streams are constantly changing since it updates a model as new data becomes available. Applications such as fraud detection and recommendation systems use it.

1.4.5.5 Self -Supervised Learning

In self-supervised learning, the algorithm creates its own labels based on the input data, making it a subset of unsupervised learning. It is frequently applied in natural language processing, where the model is trained to anticipate words that are absent from phrases [32].

1.4.5.6 Instance-Based Learning

The foundation of instance-based learning is the memorization of the training set and the prediction of future instances based on how well they resemble the previously stored examples. An example of such algorithm is KNN.

1.4.5.7 Ensemble Learning

In ensemble learning, multiple machine-learning models are integrated to maximize overall performance and reduce overfitting. Techniques like Gradient Boosting and Random Forests are often used in ensemble learning [31].

1.5 Working Principles of Machine Learning Technique

The iterative process of learning from data, generating predictions, assessing performance, and improving models to get better outcomes over time is the foundation of machine learning. Machine learning models may tackle a variety of problems, from image recognition and natural language processing to recommendation systems and autonomous decision-making, by generalizing from the training statistics to generate estimates on novel, unseen data [29].

1.5.1 Data Collection

Machine learning begins with the collection of applicable data. These statistics can be arrived from numerous resources, including sensors , databases, text documents , images, or any another form of structured or unstructured information.

1.5.2 Data Preprocessing

Raw data is often noisy and may contain errors or missing values. Information preprocessing engages cleaning, transforming, and preparing information for evaluation. This consists of tasks like data cleaning, feature extraction, and normalization.

1.5.3 Feature Engineering

Feature engineering is the method of selecting and transforming the most appropriate attributes (features) from the dataset. Effective feature engineering can notably impact the implementation of a machine learning model [28].

1.5.4 Data Splitting

The collection of data is employed for constructing a set for learning, an evaluation set, and occasionally a set for validation. Although the training collection is utilized to train the model using machine learning, the testing set is employed for assessing its outcome.

1.5.5 Model Selection

Select a machine learning model or technique that is suitable for the current task. The kind of problem, the properties of the data, and the intended results determine which model is best. Neural networks, decision trees, support vector machines, and other models are commonly used.

1.5.6 Training the Model

During the training phase, the chosen model modifies its internal parameters to learn from the training data. The objective is to reduce the discrepancy between the target values and the predictions made by the simulation [32].

1.5.7 Evaluation, after training

The testing dataset is used to evaluate the model's performance and determine how accurate the predictions are. Among the common assessment measures are accuracy, F1-score , recall, mean-squared error and precision.

1.6 Maximize the Model’s Performance

Cross-validation-like approaches are frequently used in this phase to prevent either under- or overfitting. Deployment: After a model is trained to a high degree of satisfaction, it may be used to generate predictions or judgments in a real-world application. This might entail employing the model to automate processes or incorporating it into a software system [45]. Monitoring and Maintenance: To ensure that machine learning models continue to function well in dynamic contexts, continuous monitoring is necessary. To keep models

accurate, they might need to be periodically retrained with fresh data. Loop of Feedback The model may be further improved by considering feedback from its predictions and results. A feedback loop like this is necessary for ongoing development.

1.7 Computer Vision

The goal of the artificial intelligence (AI) field of computer vision is to give machines the ability to see and comprehend visual data from their environment in a manner similar to that of the human visual system. It entails creating models and algorithms that can process and analyze data from photos or videos, extract relevant information, and make judgments using that information. Applications for computer vision are many and span many different sectors, including the medical field. Combining computer vision with nanorobotic systems and nanotechnology technologies can result in novel and very accurate diagnostic and treatment approaches in the context of healthcare and the detection of chronic illnesses. Highly individualized treatment programs based on unique patient data may be made possible by the combination of nanotechnology and computer vision [47].An innovative approach to healthcare is the combination of computer vision, nanorobotic systems, and nanotechnology methods. It presents the possibility of less intrusive therapies, earlier and more precise identification of chronic illnesses, and better patient outcomes. It's crucial to remember that this topic is still in its experimental phases and that obstacles about technology, regulations, and ethics surrounding the manipulation of nanoscale objects within the human body may prevent practical implementations [48].

1.7.1 Deep Machine Learning Models

Open neural network exchange ONNX runtime can be used to deploy and execute deep learning models for medical image segmentation tasks. It ensures that these models can be readily integrated into medical imaging systems, making it easier for healthcare professionals to use them for diagnosis and treatment planning. The choice of ONNX runtime for medical image segmentation in chronic disease diagnosis is driven by its advantages in model interoperability, performance optimization, and ease of deployment. It allows medical institutions to leverage the latest advances in deep learning without the need to rebuild models or develop custom deployment solutions. ONNX runtime ensures that the models can be efficiently executed on a variety of hardware, from desktop workstations to specialized medical imaging equipment, enhancing

the accuracy and efficiency of chronic disease diagnosis and treatment planning. ONNX Runtime is used in image processing and medical image segmentation for chronic disease diagnosis because of its model compatibility, performance optimization, cross-platform support, scalability, and interoperability. It helps ensure that deep learning models can be efficiently deployed and utilized in healthcare applications, ultimately improving the accuracy and effectiveness of chronic disease diagnosis and treatment [47].

1.7.2 Medical Image Processing

Medical image processing techniques are essential to diagnose chronic illnesses using medical images. Using these methods, medical pictures are manipulated and analyzed to obtain useful data that can help with chronic illness monitoring and diagnosis. These diagnosis-processing approaches are crucial to increase the precision, effectiveness, and consistency of illness detection and monitoring in chronic disorders. These methods help medical practitioners make wise choices and provide better patient care. It's crucial to remember that the precise image processing techniques and algorithms applied might change based on the kind of chronic illness and the imaging modality being utilized [43].

1.7.3 Medical Image Processing Steps

1.7.3.1 Image Acquisition

A variety of modalities, including computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and positron-emission tomography (PET), are commonly used to get medical pictures. Getting high-quality medical images is the initial stage in image processing [41].

1.7.3.2 Preprocessing

Noise Reduction: Medical images often contain noise, which can interfere with diagnosis. Image processing techniques like filtering are used to reduce noise and enhance image quality.

1.7.3.3 Contrast Enhancement

Adjusting image contrast can help visualize structures and abnormalities more clearly.

1.7.3.4 Image Registration

In cases where multiple images or modalities are used for diagnosis, image registration aligns them to facilitate comparisons.

1.7.3.5 Segmentation

Segmentation is the process of dividing an image into regions or objects of interest. In medical imaging, this can include identifying and outlining specific structures, organs, or lesions.
Region Growing, Thresholding, and Watershed algorithms are commonly used for segmentation tasks.

1.7.3.6 Feature Extraction

Following segmentation, pertinent attributes or traits are taken out of the interest regions. Size, shape, texture, and intensity are a few examples of these attributes. To describe and quantify the irregularities that have been found, feature extraction is essential.

1.7.3.7 Pattern Recognition

Machine learning and pattern recognition techniques can be applied to classify and diagnose chronic diseases based on extracted features.
Neural networks, support vector machines, and decision trees are some common algorithms used for this purpose.

1.7.3.8 3D Image Processing

In some cases, medical images are three-dimensional (3D), such as CT or MRI scans. 3D image processing techniques are used to analyze volumetric data and extract information from multiple image slices [26].

1.7.3.9 Visualization

Visualization tools are employed to present processed medical images in a way that is comprehensible to healthcare professionals. This includes 2D and 3D rendering and interactive visualization.

1.7.3.10 Quantitative Analysis

Quantitative analysis involves measuring and analyzing specific parameters within medical images. For example, measuring the size of tumors or monitoring changes in tissue density over time.

1.7.3.11 Computer-Aided Diagnosis (CAD)

CAD systems integrate image processing techniques with machine learning to provide automated or semi-automated assistance to radiologists and clinicians in disease detection and diagnosis.

1.7.3.12 Integration with Clinical Data

Medical images are often combined with clinical data, such as patient history and laboratory results, for a more comprehensive diagnosis.

1.7.3.13 Reporting and Communication

The processed images and diagnostic findings are typically reported and communicated to healthcare professionals for clinical decision-making.

1.7.3.14 Longitudinal Analysis

For chronic diseases that require monitoring over time, image processing can track disease progression and treatment efficacy through longitudinal analysis.

1.7.3.15 Training a Deep Neural Network

There are many crucial phases involved in training a Deep Neural Network (DNN) for medical image processing. First, a tagged dataset comprising medical imaging, such as CT scans, MRIs, and X-rays, is gathered. Preprocessing is done on these photos to guarantee uniformity and get rid of noise. Convolutional neural networks (CNNs) are the most common type of DNN design, and they are built to extract pertinent characteristics from the pictures. The network becomes capable of automated diagnosis during training when it learns to link these properties to the associated medical problems. A loss function that measures the difference between the expected output and the ground truth labels serves as the process's guidance. To reduce this loss, optimization procedures such as stochastic gradient descent are used to iteratively alter the network's

parameters[24].The network is trained until it achieves acceptable performance, which is usually verified using a different dataset. Due to a lack of medical data, transfer learning—where previously trained models are adjusted for particular medical tasks—is also frequently used. After being taught, the DNN may be used to analyze medical images accurately and effectively, assisting with patient care, diagnosis, and treatment planning. Ensuring the safety and dependability of the model in practical healthcare applications requires regular upgrades and continuous evaluation.

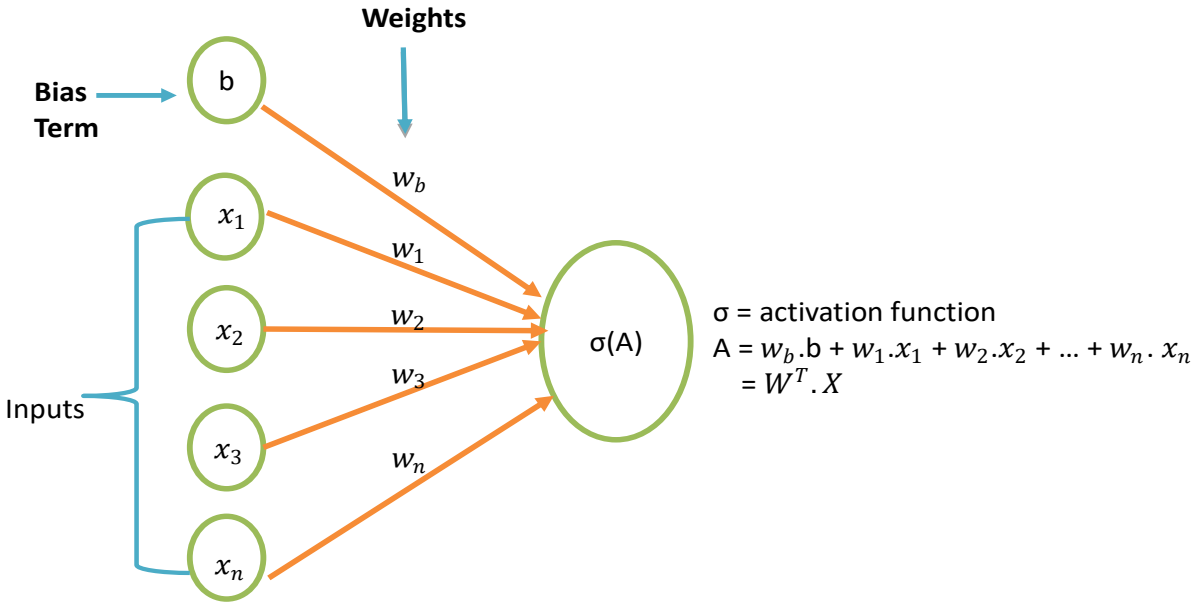


Figure 7: Data Flowing from a Previous Layer to a Unit in the Successive Layer.

1.7.3.16 Deep Learning Algorithms

A particular category of artificial intelligence (AI) methods known as deep learning algorithms for medical image processing make use of deep neural networks to analyze and interpret medical images. Because these algorithms may help doctors diagnose illnesses, plan treatments, and track patients' progress, they have become more important in the healthcare sector [23]. These are some essential elements of medical image processing deep learning algorithms.

1.7.3.17 Key Aspects of Deep Learning Algorithms

1.7.3.17.1 Convolutional Neural Networks

Most of the deep learning algorithms used in medical image processing are based on CNNs. Their purpose is to automatically identify patterns and identify characteristics in medical photos. CNNs are made up of many layers of pooling and convolutional processes that aid in capturing hierarchical representations of the image data [21].

1.7.3.17.2 Transfer Learning

It is typical practice to use transfer learning since labelled medical picture resources are few. Medical imaging tasks are best suited for pre-trained CNN models, which were trained on extensive general image datasets (like ImageNet) [22]. With this method, the performance on medical pictures is enhanced by utilizing the learned characteristics from wider image sets.

1.7.3.17.3 Architectural Variations

Different architectural variations of CNNs, such as U-Net, Dense Net, and Res Net, are tailored to specific medical image processing tasks. For example, U-Net is often used for image segmentation tasks, while other architectures may be more suitable for classification or detection.

1.7.3.17.4 Image Segmentation

Deep learning algorithms are widely used for image segmentation in medical applications. They can precisely delineate and segment regions of interest within images, such as tumors, organs, or blood vessels. This is crucial for treatment planning and monitoring disease progression [34].

1.7.3.17.5 Object Detection

Object detection algorithms based on deep learning can identify and localize abnormalities or specific structures within medical images. For instance, they can detect lesions in mammograms or polyps in endoscopy images.

1.7.3.17.6 Classification

Deep learning models are used for disease classification by assigning labels to medical images based on their content. For example, they can classify X-rays as normal or abnormal or identify specific diseases, like diabetic retinopathy in retinal images [31].

1.7.3.17.7 Data Augmentation

To address the issue of limited labeled medical data, data augmentation techniques are used to artificially increase the dataset size. This comprises applying various transformations (e.g., rotations, flips, scaling) to the existing images to build new variations.

1.7.3.17.8 Model Interpretability

It is important to guarantee that deep learning models in medical image processing are interpretable. To build confidence among medical practitioners, researchers are creating methods to clarify the reasoning behind a model's specific predictions.

1.7.3.17.9 Validation and Regulatory Compliance

Deep learning algorithms for medical image processing require rigorous validation to ensure their safety and efficacy. Compliance with healthcare regulations and standards, such as FDA guidelines, is paramount when deploying these algorithms in clinical settings.

1.7.3.17.10 Real Time Processing

Real time or else near real time processing capabilities are essential for certain medical applications, such as surgical assistance and point-of-care diagnostics. Optimizing deep learning models for speed and efficiency is a critical consideration [23].

1.8 How Deep Machine Learning Diagnosis the Chronic Diseases

CNNs are a formidable class of deep learning algorithms applied extensively in medical image processing for the diagnosis of chronic diseases. CNNs are particularly well-suited for this task due to their ability to automatically learn and extract meaningful features from medical images. CNNs have recognized to be highly successful in medical image processing for chronic disease diagnosis. They can assist healthcare providers by offering fast and accurate assessments, helping with early detection, treatment planning, and patient management [22]. However, it's essential to continue improving these models, ensuring their interpretability, and adhering to regulatory standards to ensure patient safety and clinical utility. How CNNs are applied in the diagnosis of chronic diseases using medical imaging the procedure is as follows:

1.8.1 Image Input

CNNs take medical images as input, such as X-rays, CT scans, MRIs, or histopathology slides. These images can offer detailed information about the internal configurations and conditions of a patient's body, making them valuable for disease diagnosis.

1.8.2 Convolutional Layers

CNNs contain of numerous layers, including convolutional layers, which are responsible for feature extraction. In the context of medical image processing, these layers learn to identify relevant patterns and structures in the images. For instance, in chest X-rays, they may learn to detect lung nodules or abnormalities [23].

1.8.3 Pooling Layers

Pooling layers preserve the most crucial information while reducing the spatial dimensions of feature maps. As a result, the network may become less computationally taxed and more resilient to changes in the amount and location of images.

1.8.4 1.9.2 Fully Connected Layers

After feature extraction, CNNs typically take in fully connected layers that perform classification or regression tasks. In the case of disease diagnosis, these layers are responsible for determining the presence, severity, or type of chronic disease based on the learned features.

1.8.5 1.9.3 Training

CNNs are trained using labeled medical image datasets. Radiologists or healthcare experts annotate the images to indicate the presence or absence of specific chronic diseases. During training, the network learns to minimize the difference between its predictions and the ground truth labels by adjusting its internal parameters through backpropagation and optimization techniques like stochastic gradient descent [37].

1.8.6 Transfer Learning

Since there is not enough labelled data in medical image analysis, transfer learning is frequently used. It is possible to optimize pre-trained CNN models for use in medical applications. These models have been trained on extensive picture datasets. Performance can be greatly improved by applying information from general image domains to medical image processing [27].

1.8.7 Interpretability

Interpretability is crucial in medical image processing. Researchers are working on techniques to make CNNs more interpretable by visualizing the regions of an image that contribute to a particular diagnosis or decision. This helps clinicians understand and trust the model's outputs.

1.8.8 Validation and Testing

Trained CNN models are rigorously validated on separate datasets to assess their accuracy, sensitivity, specificity, and other performance metrics. Testing on newfound, unseen data ensures that the model generalizes well to different patient populations.

1.8.9 Deployment

Once validated, CNN models can be employed in clinical settings to assist healthcare professionals. They can provide automated preliminary assessments, highlight potential areas of concern, and aid in the identification and monitoring of chronic diseases such as cancer, cardiovascular diseases, or neurodegenerative conditions [40].

1.8.10 Generative Adversarial Networks

(GANs) are a class of deep learning models consisting of two neural networks, a generator, and a discriminator, that work together in a competitive manner. GANs can be applied in medical image processing for the diagnosis of chronic diseases by generating synthetic medical images that can help improve the robustness of disease detection models or augment limited datasets. Here's a step-by-step procedure for using GANs in this context:

1.8.11 Data Collection and Preprocessing

Gather a large dataset of medical images related to chronic disease of interest, such as X-rays, CT scans, or MRIs. Ensure proper labeling or annotation of the images, indicating the presence or absence of the disease.

1.8.12 GAN Architecture Design

TO create a GAN architecture designed especially for the creation of medical images. The generator network creates synthetic medical pictures by using random noise as input. Conversely, the discriminator network distinguishes between actual (from the dataset) and artificial pictures.

1.8.13 Data Splitting

Divide the dataset into training, validation, and testing sets. The training set is used to train the GAN, while the validation set is used to monitor the training process and avoid overfitting. The testing set remains separate for final evaluation.

1.8.14 GAN Training

To train the GAN in an adversarial fashion, with the discriminator's goal being an accurate classification of a picture as genuine or fake and the generator's goal being the generation of images that are indistinguishable from actual ones. Through backpropagation, the generator and discriminator networks are updated repeatedly. Employ loss functions to direct the training process, such as binary cross-entropy. GANs can boost the diagnostic model's overall performance and improve the model's capacity to identify disease-related patterns by incorporating GAN-generated synthetic pictures into the training dataset [45]. This will ultimately lead to more precise diagnosis of chronic diseases and improved patient care.

1.8.15 Hyperparameter Tuning

Test with different hyperparameters, involving the learning rates, batch sizes, and architectural choices, to optimize the GAN's execution.

1.8.16 Validation and Monitoring

Continuously monitor the GAN's training using the validation set to prevent issues like mode collapse or poor convergence. Adjust training parameters or architecture as needed.

1.8.17 Generation of Synthetic Images

Once the GAN is trained and validated, use the generator network to generate synthetic medical images. Generate a diverse set of synthetic images that represent both normal and disease-related patterns.

1.8.18 Integration with Diagnosis Model

Incorporate the synthetic images into the dataset used for training a diagnostic model, such as a CNN. Mix real and synthetic data to create a farther robust dataset for disease diagnosis.

1.8.19 Diagnosis Model Training

Train a diagnostic model (e.g., CNN) using the augmented dataset, which now includes synthetic images. Use the same labels or annotations from the original dataset for disease diagnosis.

1.8.20 Model Evaluation

Evaluate the diagnostic model's performance using the separate testing dataset. Measure metrics like accuracy, sensitivity, specificity, and area under the ROC curve to assess the model's ability to diagnose the chronic disease [42].

1.8.21 Deployment and Clinical Use

Once the diagnostic model demonstrates satisfactory performance, it can be deployed in a clinical setting to aid in the diagnosis of chronic diseases. Healthcare professionals can use the model to analyze medical images and provide more accurate and efficient diagnoses.

1.9 Fusion

Fusion is the procedure of combining multiple sources of data, information, or knowledge to produce more comprehensive, accurate, and actionable insights. It's a fundamental concept in various fields, including data science, artificial intelligence, remote sensing, and information analysis [34].

1.9.1 Data Fusion

Data fusion is a specific form of fusion that focuses on combining data from multiple sources to provide a more complete and accurate representation of a phenomenon or situation. Data fusion aims to overcome the limitations of individual data sources and enhance the quality and reliability of the resulting information. There are several levels of data fusion, with feature-level data fusion being one of them[42].

1.9.2 Feature-Level Data Fusion

Feature-level data fusion involves the integration of information extracted from multiple data sources at the level of individual features or attributes. In other words, it combines specific characteristics or measurements from different sources to create a more informative and comprehensive dataset.

1.9.3 Multiple Data Sources

In feature-level data fusion, you start with multiple data sources, each providing information about the same or related phenomena. These sources can be sensors, devices, databases, or any systems generating data.

1.9.4 Feature Extraction

From each data source, you extract relevant features or attributes that represent specific aspects of the phenomenon of interest. These features could be numerical values, categorical labels, or any measurable properties.

1.9.5 Integration

A single dataset is created by combining the characteristics that were derived from each data source. Many methods, including concatenation, averaging, weighting, and more sophisticated machine learning algorithms, can be used to accomplish this integration [34].

1.9.6 Enhanced Information

The result of feature-level data fusion is a combined dataset that contains a richer set of features, often with reduced redundancy and improved accuracy. This enhanced dataset can provide a more comprehensive understanding of the phenomenon being studied.

1.9.7 Applications of Feature-Level Data Fusion

1.9.7.1 Remote Sensing

In satellite imaging analysis, information from several sensors is combined at the feature level to provide more detailed pictures that may be utilized for environmental monitoring and land cover categorization.

1.9.7.2 Sensor Networks

Data from many sensors (such as temperature, humidity, and motion) may be combined at the feature level in Internet of Things (IoT) applications to give a comprehensive picture of a smart environment.

1.9.7.3 Medical Diagnosis

Feature level data fusion is used in healthcare to association data from different diagnostic tests (e.g., MRI, CT scans, blood tests) to improve the accuracy of disease diagnosis.

1.9.7.4 Financial Analysis

In financial markets, data from various sources, such as stock prices, economic indicators, and news sentiment, can be fused at the feature level to develop more accurate predictive models.

1.9.7.5 Security and Surveillance

In security systems, data from different sensors (e.g., cameras, motion detectors) can be fused at the feature level to enhance threat detection and situational awareness.

1.10 EMERGING TRENDS IN CLOUD COMPUTING

A technological paradigm known as "cloud computing" entails providing computer services and resources online. Pay as you-go cloud service providers offer hardware and software that people and companies may access and use instead of owning and managing physical assets. In the current digital era, cloud computing has emerged as a key technology that supports a multitude of services and applications, ranging from artificial intelligence and machine learning to site hosting and data storage [46]. It has completely changed how people and companies use and manage IT resources, giving them scalability, affordability, and agility in a world where connections are growing.

1.10.1 Services of Cloud Computing

1.10.1.1 On-Demand Resources

Cloud providers offer a vast pool of computing resources, including virtual machines, storage, databases, and more. Users can provision and use these resources as needed, scaling them up or down to accommodate changing requirements.

1.10.1.2 Accessibility

Users may access their data and apps from a variety of devices, including computers, smartphones, and tablets, thanks to cloud services, which are available from any location with an internet connection.

1.10.1.3 Cost Efficiency

Cloud computing excludes the require for upfront capital expenditures on hardware and software. Consumers pay just for the resources they consume, which can lead to cost savings.

1.10.1.4 Scalability

Cloud services can easily scale to meet changing demands. Whether an organization needs to accommodate increased website traffic, process large datasets, or run complex simulations, cloud resources can be provisioned as required**.**

1.10.1.5 Flexibility

Numerous services are available on cloud platforms, including Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS). The degree of management and control that users need is up to them.

1.10.1.6 Reliability and Availability

Best cloud service companies guarantee excellent availability and uptime. Since data is frequently duplicated across several data centers, there is less chance that hardware failures could lead to loss of information.

1.10.1.7 Security

Cloud companies make significant investments in security protocols to safeguard infrastructure and data. On the other hand, users are also in charge of protecting their information and applications in the cloud [58].

1.10.1.8 Automatic Updates

Operator load is reduced since cloud providers usually handle patch management and software upgrades.

1.10.2 Deployment Models for Cloud Computing

1.10.2.1 Public Cloud

A third-party provider of cloud services owns and manages the resources, and several clients share the same infrastructure. AWS, Azure from Microsoft, and GCP (Google Cloud Platform) are a few instances.

1.10.2.2 Private Cloud

Resources might be hosted on-site by an outside supplier or dedicated to a particular enterprise. Although private clouds may have higher upfront expenses, they offer more control and security.

1.10.2.3 Hybrid Cloud

This architecture integrates public and private clouds, enabling the sharing of apps and data between them. It preserves control over sensitive data while providing scalability and flexibility.

1.10.2.4 Community Cloud

Multiple organizations with shared interests (e.g., healthcare providers or government agencies) use a community cloud to share resources.

1.10.2.5 Service Models

Service models are the foundation of cloud computing. Regarding service delivery, there are three fundamental models to consider:

- Infrastructure as a Service (IaaS)
- Platform as a Service (PaaS)
- Software as a Service (SaaS)

1.11 Edge Computing

Edge computing is a distributed computing paradigm that, as opposed to depending on a centralized cloud-based system, moves processing and data storage closer to the point where data is generated, or the "edge" of the network. This strategy seeks to lower latency, speed up reaction times, save bandwidth, and raise the general level of data processing proficiency. Applications that need real-time or almost real-time data processing and decision-making are especially well-suited for edge computing. Edge computing is a game-changing technology with many uses, especially in the medical field. It is an essential part of contemporary healthcare systems, enhancing patient care and healthcare delivery due to its capacity to analyze data at or near the source, decrease latency, improve security, and facilitate real-time decision-making [59].

1.11.1 Applications of Edge Computing in Healthcare

1.11.1.1 Remote Patient Monitoring

Healthcare providers can collect and analyze patient data (e.g., vital signs, ECG readings) in real-time, enabling quick detection of health issues and reducing the need for frequent hospital visits.

1.11.1.2 Telemedicine

Real-time video consultations and diagnostic image processing can occur at the edge, enhancing the quality of virtual healthcare services.

1.11.1.3 Surgical Robotics

Edge computing supports precise, low-latency control in robotic surgery, reducing the risk of errors.

1.11.1.4 Wearable Health Devices

Wearables like fitness trackers and medical sensors can process data locally and send only relevant information to the cloud, conserving battery life and reducing latency.

1.12 Treatment Section

The second section of our research study is the treatment section. The working rules and responsibilities of the treatment section have been described below as.

1.12.1 1.12.1 CONVENTIONAL TREATMENT METHODS

Conventional treatment methods in medicine, including.

- Surgery
- Chemotherapy
- radiation therapy

These methods have been the cornerstone of healthcare for decades. Surgery involves physically removing tumors or affected tissues, while chemotherapy and radiation therapy aim to kill or inhibit the growth of cancer cells. While these approaches have saved countless lives and remain vital in many cases, they have

notable limitations. Surgery can be invasive, carries risks of infection and complications, and may not be suitable for all patients. Chemotherapy often leads to significant side effects, including nausea and immune system suppression. Radiation therapy can damage surrounding healthy tissues. Moreover, conventional treatments do not always offer precise targeting of diseased cells, leading to collateral damage and potential long-term health issues. As a result, there is a growing concern in developing innovative therapies like targeted drug delivery and minimally invasive procedures to overcome these limitations and improve patient outcomes [67].

1.12.2 Intelligent Therapeutic Nano system

An intelligent therapeutic nano system designed for the diagnosis and treatment of chronic diseases marks a groundbreaking advancement in the field of medical science. Chronic diseases, with their often complex and long-term nature, pose a significant challenge to healthcare systems worldwide. In response to this challenge, the convergence of nanotechnology and healthcare has given rise to a new paradigm of precision medicine. These intelligent nano systems, operating at the nanoscale, have been meticulously engineered to not only diagnose chronic diseases with unprecedented accuracy but also to deliver targeted treatments directly to affected cells or tissues. By incorporating sophisticated sensors and responsive mechanisms, they can detect subtle disease biomarkers or physiological changes, enabling early diagnosis and intervention [54]. Moreover, their ability to precisely deliver therapeutic agents, such as drugs or genetic therapies, holds the potential to mitigate the progression of chronic diseases and improve patient outcomes. As we delve into the details of these intelligent therapeutic nano systems, it becomes evident that they represent a beacon of hope in the relentless battle against chronic illnesses, offering the prospect of early detection, precise treatment, and ultimately, an enhanced quality of life for countless individuals affected by these conditions [52].

The intelligent therapeutic nano systems for the diagnosis and treatment of chronic diseases signifies a transformative leap forward in the realm of medical science and healthcare. Chronic diseases, characterized by their persistent and often progressive nature, pose a significant global health challenge, accounting for a substantial portion of healthcare expenditures and impacting the quality of life of millions. In response to this critical healthcare need, the convergence of nanotechnology and medicine has yielded a revolutionary approach to address chronic diseases.

These intelligent nano systems, operating at the remarkably tiny nanoscale, represent a marvel of precision and sophistication. They have been meticulously engineered to serve a dual purpose: first, for highly accurate and early diagnosis, and second, for precisely targeted treatment. To achieve the former, these nano

systems often incorporate advanced sensing capabilities. They can detect even the subtlest disease biomarkers or physiological alterations within the body, providing the potential for early diagnosis when intervention is most effective [56].

However, it is in their therapeutic capabilities that these nano systems truly shine. Equipped with the ability to deliver therapeutic agents, such as drugs or genetic therapies, with pinpoint accuracy, they offer an unprecedented level of precision in treatment. Unlike traditional treatments that may affect healthy tissues and lead to side effects, intelligent therapeutic nano systems can direct their payloads exclusively to the affected cells or tissues, minimizing collateral damage and enhancing treatment efficacy.

Consider, for instance, their application in cancer therapy. These nano systems can be programmed to recognize and target cancer cells specifically, sparing healthy cells from the toxic effects of chemotherapy. In the context of neurodegenerative diseases, they may traverse the formidable blood-brain barrier to deliver therapies directly to affected areas. In the realm of genetic disorders, they hold the promise of delivering gene-editing tools to correct faulty genes at the source [57].

As we delve deeper into the intricacies of these intelligent therapeutic nano systems, it becomes increasingly evident that they offer a beacon of hope in the relentless battle against chronic illnesses. By combining early, precise diagnosis with finely tuned treatments, they have the potential to mitigate disease progression, improve patient outcomes, and ultimately enhance the quality of life for countless individuals grappling with chronic conditions. The chapters that follow will explore the remarkable capabilities, design principles, ethical considerations, and practical applications of these nano systems, shedding light on the transformative potential they bring to the field of healthcare [61].

1.12.3 Gold Nanoparticles

Gold atoms are collected into nanoscale-sized particles known as gold nanoparticles. Because of their tiny size and high surface area-to-volume ratio, they have special optical, electrical, and chemical characteristics. Gold nanoparticles' numerous uses in diagnosis and therapy have drawn considerable interest from a variety of industries, including medicine. Healthcare research on gold nanoparticles is still ongoing because of its potential to transform therapy and diagnosis. Though these applications seem very promising, it's vital to remember that they are still in the early stages of development, and more study and clinical studies are required to properly understand their safety and effectiveness in the practice of medicine [8].

1.12.4 Properties of Gold Nanoparticles:

The properties of gold nano particles to solve medical problems are explained below.

1.12.4.1 Size and Shape Control

The size and form of gold nanoparticles—such as spheres, rods, or shells—can be carefully manipulated to affect their characteristics and uses. Plasmon Vibration on the Surface (SPR): Due to a phenomenon called surface plasmon resonance, gold nanoparticles have special optical characteristics such as high light absorption and scattering. By modifying the size and form of the nanoparticle, the SPR peak could be modified [12].

1.12.4.2 Biocompatibility

Gold nanoparticles are generally considered biocompatible and well-tolerated by the human body, making them suitable for medical applications.
Surface Functionalization: Their surfaces can be modified with various molecules, such as antibodies, peptides, or drugs, to enhance their specificity and functionality.

1.12.4.3 Biosensors

Gold nanoparticles are used in biosensors to detect specific biomolecules, such as proteins, DNA, and RNA. When functionalized with ligands or antibodies, they can bind to target molecules, leading to changes in their optical properties that can be detected, enabling sensitive and rapid diagnostics.
Imaging: Gold nanoparticles can enhance medical imaging techniques like computed tomography (CT), magnetic resonance imaging (MRI), and photoacoustic imaging. They serve as contrast agents, improving the visualization of tissues and tumors [15].

1.12.4.4 Point-of-Care Testing

Gold nanoparticle-based lateral flow assays are employed in point-of-care tests for infectious diseases, pregnancy, and drug testing due to their simplicity and rapid results.

1.12.4.5 Drug Delivery

Drugs, genes, or other medications can be delivered to certain target areas in the body through gold nanoparticles. Precision medication delivery is made possible by surface changes and size control, which lowers adverse effects and increases therapeutic efficacy.

1.12.4.6 Photothermal Therapy (PTT)

When exposed to near infrared (NIR) light, gold nanoparticles can convert the absorbed energy into heat, selectively destroying cancer cells or pathogens. This technique is known as photothermal therapy and shows promise in cancer treatment.

1.12.4.7 Radiation Therapy Enhancement

Gold nanoparticles increase the effectiveness of radiation therapy (radiotherapy) by increasing the absorption of ionizing radiation, thereby improving tumor cell killing while minimizing damage to healthy tissue.

1.12.4.8 Photodynamic Therapy (PDT)

Gold nanoparticles can enhance photodynamic therapy by acting as carriers for photosensitizers. When exposed to light, the photosensitizers generate reactive oxygen species that selectively destroy cancer cells. Gene Therapy: Gold nanoparticles are used in gene delivery systems, facilitating the introduction of therapeutic genes into target cells for gene therapy applications [47].

1.13 Coulomb Explosion

The Coulomb explosion is a phenomenon that happens when particles or ions with high charges are exposed to a strong electric field. The word "explosion" denotes the quick and violent disruption of the particles caused by the electrostatic force between charged particles, which is referred to as the "Coulomb" force. The following actions are usually included in the Coulomb explosion procedure.

1.13.1 Ionization

Initially, a sample of atoms or molecules is ionized, meaning one or more electrons are removed from the particles, resulting in the formation of positively charged ions. This can be achieved using various techniques, such as intense laser pulses or high-energy electron beams. The generation of heat in Coulomb explosion experiments can vary depending on the definite experimental setup, the nature of the charged particles involved, and the energy sources used to initiate the process. Additionally, the generation of heat can have both intended and unintended consequences, and researchers carefully control and monitor these effects to achieve their experimental objectives safely and accurately [63].

1.13.2 Accumulation of Charges

The ionized particles are then exposed to a strong electric field, either from an external source or due to the presence of other charged particles in the vicinity. The electric field causes the ions to experience a force proportional to the magnitude of their charge, leading to the accumulation of more charge on the particles.

1.13.3 Repulsion Dominance

As the charge on the ions increases, the repulsive forces between them become more significant. The electrostatic repulsion tries to push the ions away from each other since like charges repel each other.

1.13.4 Rapid Disruption

When the electric field is strong enough and the charges on the ions are sufficiently large, the repulsive forces become dominant over the intermolecular or interatomic forces holding the particles together. As a result, the ions start to rapidly move away from each other, leading to a violent disruption of the sample [89].

1.13.5 Coulomb Explosion Imaging

In many cases, Coulomb explosion is used as a diagnostic technique to investigate the structure and dynamics of molecules or clusters of atoms. For example, in molecular imaging, the sample is ionized, and the resulting Coulomb explosion is captured using imaging detectors. By analyzing the trajectories and momenta of the exploded fragments, scientists can reconstruct the initial

structure and properties of the sample. Coulomb explosion has applications in various fields, including physics, chemistry, and materials science, where it provides valuable insights into the behavior of charged particles and the structure of complex systems at the atomic and molecular level.

1.13.6 Absorption of Laser Energy

In some Coulomb explosion experiments, the initial ionization of the sample is achieved using intense laser pulses. When the laser interacts with the sample, it imparts its energy to the charged particles, leading to an increase in their kinetic energy. This increase in kinetic energy corresponds to an increase in temperature. The absorbed laser energy can be converted into thermal energy, resulting in a localized heating of the sample [87].

1.13.7 Electron-Ion Recombination

During Coulomb explosion, highly charged ions experience strong repulsive forces that drive them away from each other. As the ions move apart, they may eventually recombine with free electrons present in the vicinity. This process of electron-ion recombination releases energy in the form of photons or heat. The released heat can contribute to the overall temperature rise in the system.

1.13.8 Vibrational and Rotational Excitation

In some cases, the initial ionization and Coulomb explosion may result in the production of highly excited molecular or atomic species. These excited states often have excess energy in the form of vibrational or rotational energy. As the excited species relax back to their ground states, they can release this excess energy in the form of heat, contributing to the overall temperature increase.

1.14 Hypothermia Treatment

Hyperthermia is a medical treatment that involves heating specific areas of the body or the entire body to temperatures higher than normal body temperature (typically between 40°C to 45°C or 104°F to 113°F). It is used as an adjunctive therapy for the treatment of breast cancer and other types of cancer. Hyperthermia can be applied locally, regionally, or systemically, depending on the treatment goals and the patient's condition. Hyperthermia for breast cancer is typically administered by a specialized medical team with experience in cancer

treatment [85]. The specific approach, equipment, and treatment plan may vary based on individual patient factors and the clinical context. Patients considering hyperthermia therapy for breast cancer should consult with their oncologists to determine the most appropriate treatment strategy for their condition.

1.14.1 Local Hyperthermia

Local hyperthermia targets a specific area or tumor within the breast. It is often used in conjunction with other cancer treatments, such as radiation therapy or chemotherapy. Here's how it works:

1.14.2 Patient Preparation

The patient is positioned on a treatment table, and temperature sensors are placed in and around the breast area to monitor temperature accurately.

1.14.3 Heat Application

Heat is applied to the tumor or the affected breast using various methods, such as microwave, radiofrequency, or ultrasound devices. These devices generate heat and raise the temperature of the tumor to the desired therapeutic range [83].

Treatment Duration: The duration of the hyperthermia session can vary but typically lasts less than an hour.

1.14.4 Regional Hyperthermia

Regional hyperthermia involves heating larger areas or regions of the body. It is often used when breast cancer has spread to nearby lymph nodes or tissues.

1.14.5 Treatment Setup

External applicators, such as microwave or radiofrequency devices, are carefully positioned around the affected breast and surrounding areas.

1.14.6 Heat Distribution

These applicators generate heat that is distributed regionally to encompass the breast and nearby lymph nodes.

1.14.7 Monitoring

Continuous monitoring of temperature and patient vital signs is crucial to ensure safe and effective treatment.

1.14.8 Mechanisms of Action

Hyperthermia for breast cancer treatment works through several mechanisms:

1.14.8.1 Direct Tumor Damage

Elevated temperatures directly damage and kill cancer cells by disrupting their cellular structures and functions.

1.14.8.2 Enhanced Sensitivity

Heat makes cancer cells more sensitive to radiation therapy and certain chemotherapy drugs, enhancing the effectiveness of these treatments.

1.14.8.3 Increased Blood Flow

Hyperthermia causes blood vessels to dilate (expand), improving blood flow to the tumor. This can enhance the delivery of oxygen and nutrients to cancer cells, increasing the effectiveness of treatment.

1.14.8.4 Immune Response

Heat can stimulate the immune system to recognize and attack cancer cells more effectively.

1.14.8.5 Treatment Planning

Treatment planning for hyperthermia is carefully tailored to the patient's specific condition, including the type and stage of breast cancer. The medical team determines the target temperature, treatment duration, and frequency of hyperthermia sessions.

1.14.8.6 Side Effects

Hyperthermia treatments may have side effects, including skin redness, discomfort, or burns in the treated area. These effects are typically temporary and manageable. The medical team closely monitors the patient during and after each session to address any adverse reactions promptly [82]. Overtreatment can have side effects such as skin redness, discomfort, or burning sensation in the treated area. These side effects are generally temporary and manageable. The treatment team closely monitors the patient during and after each session to address any complications immediately.

1.14.8.7 Integration with Other Treatments

Hyperthermia is often used as part of a multimodal treatment approach. It may be combined with surgery, radiation therapy, chemotherapy, or immunotherapy to maximize its benefits in breast cancer treatment.

1.15 Heat Control System

The proposed technique for the treatment of chronic diseases like breast cancer involves a heat control system that specifically targets patient-specific breast tumors. A heat control system involves heating specific areas of the body or the entire body to temperatures higher than normal body temperature (typically between 40°C to 45°C or 104°F to 113°F). It is used as an adjunctive therapy for the treatment of breast cancer and other types of cancer. The goal is to concentrate heat at the position of the tumor while minimizing heat levels in surrounding healthy tissues. This is achieved through the optimization of phase excitations of heat generated by the coulomb explosion of gold nanoparticles. In this technique, gold nanoparticles are used to generate heat [70]. These nanoparticles are introduced into the body, specifically targeting the breast tumor. When exposed to certain frequencies of electromagnetic waves, the gold nanoparticles undergo a coulomb explosion, releasing heat in the process. By controlling the phase excitations of the applied electromagnetic waves, the heat can be concentrated at the tumor site. To determine the optimal heat levels required at the tumor position, a thermal analysis is conducted. This analysis helps calculate the scaling factor of the gold nanoparticles' excitation amplitudes, which in turn determines the amount of heat generated. By adjusting these excitation amplitudes, the desired temperature at the tumor position can be achieved. A closed-loop procedure is implemented to ensure that no negative impacts occur on the surrounding healthy tissues. This means that feedback

mechanisms are in place to continuously monitor and control the heat levels throughout the treatment process [73]. This feedback helps maintain the temperature within the tumor region while minimizing thermal damage to healthy tissues. The proposed technique has been validated through research in the areas of breast cancer and fetal tumors using control hyperthermia. The results of these studies demonstrate the effectiveness and feasibility of the proposed technique in targeting and treating breast tumors while minimizing the impact on healthy tissues.

1.16 Interbody Communication Network of a Nano Therapeutic Robotic system

The concept of an interbody communication sensors network in a therapeutic nanorobotic system used for the diagnosis and treatment of chronic diseases involves the integration of nanoscale sensors and devices within the human body to enable real-time monitoring, data exchange, and precise therapeutic interventions. This network serves as a vital component in the management of chronic diseases, allowing for personalized and targeted treatments.
Chronic diseases often require long-term management, and this nanorobotic system offers a promising approach to enhance the precision and effectiveness of treatment. It allows for early detection of disease progression, immediate intervention, and continuous monitoring, ultimately improving the quality of life for patients living with chronic conditions. While this technology is still in the realm of research and development, its potential to transform chronic disease management is significant [44].

1.16.1 Working Roles of Ion MT for Nano Therapeutic System (GNTRs)

1.16.1.1 Nanorobotic Agents

These are tiny robotic devices or nanoparticles designed to perform specific tasks within the body, such as drug delivery, tissue repair, or diagnostics. In the context of chronic disease treatment, they are engineered to detect and respond to disease markers, deliver medications, or perform other therapeutic functions [42].

1.16.1.2 Distributed Sensors

Nanoscale sensors are strategically placed throughout the body, either as standalone devices or integrated into the nanorobotic agents. These sensors can detect various biomarkers associated with chronic diseases, such as glucose levels for diabetes or specific proteins for cancer.

1.16.1.3 Data Collection

The sensors continuously collect data on the patient's health and the progression of the chronic disease. This data includes information on biomarker levels, tissue conditions, or physiological parameters relevant to the disease in question.

1.16.1.4 Interbody Communication Network

The sensors are interconnected through a communication network that allows them to share data with each other and with external monitoring and control systems. This network can operate wirelessly, using technologies like Bluetooth or even at the nanoscale, through molecular communication [44].

1.16.1.5 Real-Time Monitoring

The interbody communication network enables real-time monitoring of disease progression. For example, in the case of diabetes, nano sensors can monitor glucose levels and transmit data to external devices or healthcare providers.

1.16.1.6 Data Analysis

The collected data is analyzed by external systems or onboard processing units within the nanorobotic agents. Advanced algorithms can interpret this data to assess disease severity, predict flare-ups, or trigger therapeutic interventions.

1.16.1.7 Targeted Therapeutics

Based on the data received from the sensors, the nanorobotic agents can be programmed to deliver targeted therapies. For instance, if a sensor detects a spike in cancer biomarkers, the nanorobots can release anti-cancer drugs specifically at the tumor site.

1.16.1.8 Feedback Loop

The system operates in a feedback loop, with continuous data collection, analysis, and therapeutic interventions. This loop ensures that treatment is adapted and optimized in response to the dynamic nature of chronic diseases.

1.16.1.9 Remote Control

Healthcare providers or patients themselves can have remote access to the system through external devices like smartphones or computers. They can monitor the patient's condition and adjust treatment parameters as needed [56].

1.16.1.10 Personalized Care

The interbody communication sensors network enables highly personalized care. Treatment strategies can be tailored to the individual's specific disease profile, optimizing outcomes, and minimizing side effects.

1.16.1.11 A Framework for Innovation, The Internet of Nano Medical Things

The Internet of Nanomedical Things (Ion MT) is a concept that extends the principles of the Internet of Things (IoT) to the field of nanomedicine. It involves the integration of nanoscale devices, sensors, and systems into a networked framework to enable advanced diagnostics and treatment for chronic diseases. When applied to a nano-therapeutic robotic system, the Ion MT offers innovative and highly precise solutions for managing chronic conditions [56]. The Ion MT, when combined with nano-therapeutic robotic systems, offers a revolutionary approach to managing chronic diseases. It provides early detection, personalized treatment, and continuous monitoring, ultimately improving patient outcomes and quality of life [61]. While this technology is still in the research and development stage, its potential to transform healthcare for chronic disease management is promising. The main functions for nano therapeutic robotic system are discussed in below as

- Sensors for Data Collection
- Real-time Data Collection
- Data Transmission
- Data Analysis and Interpretation
- Treatment Customization
- Remote Monitoring
- Precision Medicine
- Early Detection and Prevention

- Patient Empowerment

1.17 The "See and Treat" Technique

The "**see and treat"** method hinges on the nano robot machine's ability to identify the tumor and administer therapy in real-time. As the device navigates through the body, it uses imaging and molecular markers to locate the cancerous tissue. Once the tumor is pinpointed, the nano robot device initiates hyperthermia therapy by generating controlled heat at the tumor site. The beauty of this technique lies in its precision. Conventional cancer therapies, including systemic chemotherapy or surgery, can seriously affect organs and healthy tissue. By minimizing collateral harm and concentrating the therapeutic heat where it is most required, the "see and treat" strategy, in contrast, ensures superior results. Additionally, the patient's vital signs are continually monitored by the integrated system during the whole process. ECG sensors monitor heart rate and rhythm stability, blood pressure nano sensors track respiratory and circulatory parameters, and nano pulse oximetry devices measure blood pressure. The device may instantly modify the therapy if any abnormalities are found, ensuring the patient's safety and well-being.

1.18 Nanomedicine

The use of nanotechnology to the diagnosis, treatment, and prevention of illness is known as nanomedicine. It creates new medical applications by using the special qualities and powers of materials and technology at the nanoscale (usually between 1 and 100 nanometers). By enabling earlier illness detection, more focused and targeted therapies, and enhanced drug delivery systems, nanomedicine has the potential to completely transform the healthcare industry [47]. The field of nanomedicine is still developing, which opens up new avenues for enhancing patient outcomes and overall quality of life.

1.18.1 Key Aspects of Nanomedicine

The importance of aspects of nanomedicine in medical research has been explained as below:

1.18.1.1 Drug Delivery

One of the most significant applications of nanomedicine is in drug delivery. Nanoparticles, such as liposomes, micelles, and dendrimers, can be engineered to encapsulate drugs and transport them to specific target sites in the body [47]. This targeted drug delivery reduces side effects and enhances the therapeutic effectiveness of medications.

1.18.1.2 Diagnostics Tool

Nanotechnology enables the development of highly sensitive diagnostic tools. Nanoscale sensors and imaging agents can detect biomarkers or abnormalities at an early stage, allowing for more accurate disease diagnosis. Quantum dots and gold nanoparticles are examples of nanomaterials used in diagnostics.

1.18.1.3 Targeted Therapy

Nanomedicine has made significant strides in cancer treatment. Nanoparticles can be designed to selectively accumulate in tumor tissues, improving the precision of radiation therapy or chemotherapy while minimizing damage to healthy cells. This approach is known as "targeted therapy."

1.18.1.4 Regenerative Medicine

Since nanotechnology produces materials and scaffolds at the nanoscale for tissue engineering and regeneration, it contributes to regenerative medicine. These substances can guide tissue regeneration and cell proliferation by imitating the extracellular matrix [49].

1.18.1.5 Vaccines

Nanoparticle-based vaccines have been developed to enhance the immune response. These vaccines can improve vaccine stability, increase antigen presentation, and provide a more effective immune response.

1.18.1.6 Gene Therapy

Nanoparticles can be used to deliver therapeutic genes to specific cells, offering prospective treatments for genetic disorders and other diseases at the genetic level.

1.18.1.7 Antibacterial Agents

Nanomaterials like silver nanoparticles have shown promise as antibacterial agents, with the ability to combat drug-resistant bacteria.

1.18.1.8 Neuroscience

Nanotechnology is used to develop nanoscale devices for studying and manipulating neural systems. These devices can help understand brain functions and potentially treat neurological disorders.

1.18.1.9 Personalized Medicine

Nanomedicine can be tailored to an individual's specific genetic and physiological characteristics, allowing for personalized treatments and drug dosages.

1.18.1.10 Safety and Ethics

The development and use of nanomedicine also increases important moral and safety considerations, such as potential toxicity of nanomaterials, regulatory oversight, and privacy concerns.

1.18.1.11 no Sensors Network

The network of nano sensors represents a state-of-the-art technology platform designed to monitor and analyze a variety of materials at the nanoscale level, transforming our ability to collect data and make informed decisions across multiple domains. These networks consist of a variety of sensors, including thermal sensors, chemical sensors, nano cameras, photosensors, heat storage nanodevices, position sensors, image sensors, position sensors, timer sensors, and biochemical sensors. You can find them. Nano cameras are multifunctional nanoscale devices with unique capabilities, while photosensors capture light intensity and wavelength. Thermally stored nanodevices can store and release thermal energy on demand. Location, image, and position sensors provide spatial information, while time sensors provide precise timing and synchronization. Biosensors provide insight into biological processes at the molecular level. Together, these nano sensors enable data collection with unprecedented accuracy, enabling breakthroughs in healthcare, environmental monitoring, materials science, and many other areas. The Nano sensor network Interactions between nano sensors play an important role in the establishment of sophisticated nanomedical nano systems [52]. This system harnesses the power of nanotechnology to precisely deliver therapeutic agents to the targeted cells or tissues, while monitoring them.

1.19 Research Gap

Most of the existing research works focus only on the implementation of traditional methods for the diagnosis and treatment of chronic diseases, typically including radiation therapy, hormone therapy, surgery, and chemotherapy. The conventional diagnosis approaches do not produce fast, exact, and accurate results, and in the meantime, they have very serious side effects. With the advent of advanced technologies, it has now become possible to overcome all limitations, as discussed above. So, the present research article addresses the gap that is not present in existing conventional methods and discovers a new way to solve the problem for medical applications. However, at the initial stage of installation, some diseases are difficult to treat, but after applying new methods and designing the best technologies, the results can be much better than in existing case studies. The foremost motivation of the proposed research work is to implement the proposed GNTRs made of gold nanoparticles at low cost for all individuals in society to treat and diagnose breast cancer diseases safely and quickly at an early stage without damaging the neighboring healthy cells of the organs.

1.20 MOTIVATION

Nanomedicine represents the future of healthcare, a place where science and technology come together, and we can revolutionize the diagnosis and treatment of chronic diseases. With smart nanomedical devices powered by the awesome power of soft computing, we are on the cusp of a transformational era in healthcare. We Imagine a world where diseases will not only be treated but intelligently diagnosed early long before symptoms appear. Nanorobots, with their small but powerful tools, can make this vision a reality. Armed with soft computing, these little warriors can move through our complex biological systems with unparalleled precision in nanorobotics, size does not reduce the effect. It magnifies that, working at the cellular and molecular level, nanomedical devices will hold the promise of accuracy in diagnosing chronic diseases. They will quickly analyze vast amounts of data and will make decisions in real-time, offering hope to those suffering from once-unmanageable statistics is computing, with machine learning algorithms and artificial intelligence, delivers these miracles of antiherpetic systems that will provide the mental ability to learn and improve. They will ensure the good and the bad. Developed with the patient, treatment plans will be modified to be more effective. The combination of nanotechnology and soft computing will open a new frontier in personalized medicine. Each patient is a unique case study, and treatment plans will be tailored precisely to their needs. Gone are the days of monotherapy; Now, we are ushering

in an era of healthcare that is as unique as the person it serves. Nanorobots will transcend traditional boundaries.

The proposed nanotherapeutic system is a testament to our pioneering spirit and our commitment to shaping the future of healthcare. It will represent a thrilling journey into the realm of innovation and scientific exploration, where we seek to merge cutting-edge technology with the deepest human desire and the conquest of chronic diseases.

1.21 PROBLEM STATEMENT

The diagnosis and treatment of chronic disease is a complex and challenging task that requires a combination of multiple diagnostic and therapeutic methods and technologies. The chronic disease detection techniques and modalities are usually limited and small in range. The existing diagnostic and therapeutic procedures are uncomfortable, painful, high costs, inter-spectator variability in image clarification, and low understanding in detecting and treating chronic diseases in impenetrable biological dead tissues. Consequently, there is a strong demand for inexpensive and effective auxiliary modalities that can address these constraints. To address this challenge, it is proposed to design a state-of-the-art hybrid nano-intelligent therapeutic device, the "Gold Nano Themo Robot" (GNTR), that has nano-digital cameras and nano-sensors and devices that move in the body's tissues to get real-time data in the form of images from the current cancer tumor size and then send the data to the medical dataset. The proposed GNTRs will act as nanomedicines that can be used for automated diagnosis and treatment of chronic diseases. To diagnose and analyze medical images of the disease by using an autonomous intelligent segmentation method based on convolutional neural networks. This proposed nano therapeutic nano intelligent device works in two sections. One section will be used for diagnostic purposes and the second section is used for treatment purposes. In the **Diagnostic Section**, the proposed GNTR uses deep machine learning approaches for diagnosis the chronic diseases. Medical image segmentation acts as a critical role in the classical identification methods of chronic diseases. In this study a novel intelligent diagnostic method is proposed, for the examination of tumors in the brain. We proposed a model called the "Gold Nano Thermo Robot" (GNTR) that has nano-digital cameras and nano-sensors that move in the body's tissues to get real-time data in the form of images from the current tumor size and then send the data to the medical dataset. To diagnose and analyze visual images of the disease by using an autonomous intelligent segmentation method based on convolutional neural networks. In the second **Treatment Section**, the proposed GNTR model also treats the cancer tumor based on controlling hyperthermia, developing a **"Heat Control System"** that will work as heat therapy. It works on the "**SEE and TREAT**

"technique by controlling the intensity of heat using the magical properties of coated spherical gold nanoparticles.

1.22 RESEARCH OBJECTIVES

The major objective of the proposed research is to introduce Gold Nano Thermo Robots (GNTRs) to provide state of the arts performance in the domain of pharmaceuticals, ensuing basic robotic thermometric parameters by combining multi sensing techniques. These nano machines are designed to be small enough to penetrate cells and deliver medication directly to the affected area, minimizing the risk of side effects associated with traditional treatments. To accomplish the following objectives, Gold Nano Thermo Robots (GNTRs) are designed.

- To design a novel GNTRs can accurately diagnose chronic diseases using advanced technologies such as artificial intelligence, biomedical deep machine learning algorithms convolutional neural network and image processing techniques.
- To novel proposed GNTRs are made of gold metal to be small enough to penetrate cells of organ and deliver medication directly to the affected area, minimizing the risk of side effects associated with traditional treatments.
- The proposed GNTRs can generate heat, store heat, transfer heat, can control heat, and have targeted approach to diagnosis and treatment of chronic diseases**.**
- To controlling the intensity of heat in the range of 38 C^0 to 45 C^0, using proposed heat control system to treat the cancer cells without effecting the neighboring healthy cells**.**
- To investigate the role of robotic thermometric parameters in breast cancer treatment and to identify the most important parameters for guiding the combined treatment of Radio Therapy (RT) and Chemotherapy (CT) with Heat Therapy (HT).

1.23 RESEARCH QUESTIONS

Subsequent research questions are being introduced for this research.

- How could the proposed GNTRs work for intelligent diagnosis of chronic diseases empowered with nano sensors, nano camera, nano device

network-enabled nano devices be entangled with the interbody communication network and deep machine learning techniques for provide more efficient and better accurate diagnosis results?

- How could treat the targeted chronic disease effectively by saving the surrounding healthy cells of the ill organ by using novel technique Heat Control System of proposed GNTR.

1.24 CONCLUSION

This chapter discusses an introduction to the novel intelligent diagnosis and treatment nano intelligent therapeutic device known as GNTR)s empowered with nanotechnologies and soft computing approaches. Artificial intelligence (AI) and nanotechnologies approaches are modern approaches to information technology and have made significant developments in the field of diagnosing and treatment of chronic diseases and helping medical physicians. It revolutionized the capabilities of machines by enabling them to mimic human intelligence and perform tasks that typically demand human-like cognitive abilities. AI-powered devices and apps. enable remote monitoring of patients with chronic diseases. These tools can track vital signs, glucose levels, or medication adherence, sending real-time data to healthcare providers. AI can then analyze this data and alert physicians to any concerning trends or deviations. In the same era, the Internet of Nano Medical Things (Ion MT) emerges as a next-generation bio-analytical tool that combines network-linked biomedical devices with a software application for advancing human health [44].

Conventional and ordinary diagnosis and treatment methods have a clear drawback since they are unable to handle unexpected and unpredictable new health issues. It is becoming more complicated to keep up with and deliver the appropriate solutions for healthcare at a constantly rising rate of new health problems. The accurate diagnosis and treatment methods should be further developed considering increasing new health challenges [47].

CHAPTER 2

LITERATURE REVIEW

In this portion, many studies have examined the mechanics of nanorobots in this part, providing a thorough examination of the essential factors influencing their operation and their uses in the field of medicine. The goal is to learn more about the potential implications of these nanorobots in the diagnosis and treatment of intricate medical issues. The author [61] has published research on the use of nanorobots in medicine, highlighting their utility in quick, real-time settings for illness diagnosis and treatment. The current state of medicine requires a tool that can identify and provide precise information about a wide range of illnesses quickly, and since nanorobots can identify and cure illnesses inside the human body, they have been recommended as a possible treatment [74]. The research emphasizes that to process input data and analyze findings within, deploying nanorobots requires the integration of artificial intelligence techniques, such as neural network systems. A media access control (MAC) architecture can make this integration easier while also improving result accuracy and enabling online analysis. According to the paper, the use of nanorobots in healthcare might completely transform the industry by providing accurate, quick, and effective illness detection and treatment. A case study utilizing magnetic control systems and micro-robotic technology to handle certain medical situations has been carried out to assess this suggested approach [72]. To solve this problem, a three-dimensional clinical database was used to create a real-time simulation that enables the integration of communicating nanorobots in fundamental parts. This simulation provides a regulated setting [45]. Subsequent filtering processes eliminate artifacts, labels, and markers from the binary mask, resulting in a refined mask containing only the breast region. However, a limitation of this technique is identified: the use of a fixed grayscale intensity level of 18 may lead to

over-segmentation of the breast region due to low-intensity pixels near the skin-air interface in mammograms falling below the threshold. The rigidity of using a fixed intensity level raises concerns about the accuracy of breast region segmentation. In a related study, Authors [34] propose an alternative automated method for breast region segmentation in mammograms. While specific details of this technique are not provided, the mention of an "automatic technique" suggests an exploration of dynamic or adaptive thresholding methods to enhance the precision of breast region segmentation. Both approaches underscore the ongoing efforts within the literature to develop automated methods for accurately delineating the breast region in mammograms. As accurate identification of abnormalities within breast tissue is crucial for breast cancer detection, advancements in segmentation techniques significantly contribute to improving the overall efficacy of mammographic analysis [50].

Various studies have explored the potential of using Generative Adversarial Networks (GANs) for cancer diagnosis. GANs, constructed akin to object-oriented programming, employ classes and objects as domain representations in image segmentation, as depicted in Figure 4. A recommended best practice for GAN architecture development is the creation of a specification document in straightforward terms. This document should encompass the ontology's objective, users, use cases, formality level, and scope, ensuring it is concise, free of duplication, and maintains partial completeness and actual meanings and relationships within the domain [19]. **In Figure 3**, the authors [26] present a general methodology for developing a GAN architecture. Image segmentation emerges as a potent tool for enhancing cancer diagnosis and treatment by facilitating improved organization and knowledge sharing within the domain. Once a deep machine learning algorithm is developed, it can support cancer diagnosis in various ways [30]. For instance, a knowledge-based system utilizing deep machine learning algorithms can be constructed to reason about a patient's symptoms, suggesting potential diagnoses or treatment options [27]. Image segmentation contributes to knowledge sharing among medical professionals, providing a common language and structure for discussing cancer and related concepts. Researchers [39] have developed an ontology, wherein domain experts identify key concepts and relationships, representing them as classes and object properties. Breast cancer algorithms utilizing deep machine learning represent different aspects, including risk factors, symptoms, diagnosis, and treatment options [36].

Traditional medical diagnostic systems were limited in analyzing quantitative aspects of medical data, lacking a comprehensive understanding of the patient's condition. Recent advancements focus on more comprehensive diagnostic systems considering qualitative aspects such as patient history, lifestyle factors, and social determinants of health, aiming for personalized medical diagnosis and treatment [41]. Nanorobots are identified as promising applications of nanotechnology in medical sciences, particularly in dentistry. Nanorobots show potential in enhancing accuracy,

predictability, safety, and treatment quality in dental applications, ranging from teeth cleaning to complex surgeries [27]. Precision targeting using nanorobots provides advantages in the treatment of chronic illnesses like breast cancer, including less intrusive treatments, quicker healing periods, and better patient outcomes [32].

The authors discussed the difficulties in using robotics and magnetic control systems in the medical area [32]. Although promising, extensive biomedical applications need to address technological restrictions. To ensure safety and effectiveness in medical applications, chemical characteristics must be considered and evaluated throughout the creation of nanorobots, in addition to real-time simulations and sensing devices [46]. An apparatus for controlling epidemic diseases using nanorobots and a satellite monitoring system is described, highlighting the necessity of advanced control systems to guarantee accurate movement [37]. The use of nanorobots in medical diagnostics has led to advanced improvements, as demonstrated by their ability to reduce operating hazards, and carry out difficult tasks on a tiny scale [35]. The authors [32] examine the most current developments in nanorobotic technology in their study, with an emphasis on how these technologies may be used to identify and cure illnesses that affect the human body. The article emphasizes how nanorobots may be used to cure cancer with intense radiation and analyze people's DNA. It emphasizes the necessity of adding more targets for identifying different illnesses in the body while acknowledging that these technologies are still in the testing stage. To successfully eradicate illnesses, the essay emphasizes the significance of administering medications at specific times using noninvasive ways. Furthermore, the application of nanotechnology enables prompt treatment of any adverse consequences.

The researchers [64] proposed a cancer therapy technique called hyperthermia (HT), which entails heating cancerous tissues to temperatures between 40°C and 43°C, which is higher than the average body temperature. Benefits from this approach have been shown, improving the efficacy of other cancer treatment techniques including chemotherapy (CT) and radiation therapy (RT). The researchers [104] provide a different strategy for treating breast cancer by positing that high temperatures can draw temperature-sensitive chemotherapy medicines, maximizing their efficacy in the region of interest and reducing their toxicity in healthy tissues [106]. Elevating body tissue temperature from 40°C to 43°C is the main objective of examinations on hyperthermia. Increasing temperature beyond a certain point may cause the proteins in cancerous cells to become denatured, which would kill the cancerous cells. Thermal ablation is a method that may be used as a stand-alone therapy if the temperature threshold of 43°C is exceeded [104]. Increasing the temperature of malignant tissues to 40°C to 43°C is another hyperthermia therapeutic approach for breast cancer that the researchers investigate [80]. The authors of the study examine how human breast cancer cell lines are affected by heat [89]. The study shows that temperature and the length of hyperthermic exposure have a major impact on cell viability. By using microwave radiation to raise the temperature of breast cancer cells to a therapeutic level, the researchers treat malignant tissues using microwave hyperthermia. Treatments for microwave hyperthermia include linear antenna arrays

[80]. An electric diode is used in another study [97] to monitor temperature in an intrusive manner that might not be appropriate for application in human breasts [69]. Even though microwave hyperthermia appears to be a promising cancer therapy modality, more investigation is required to provide non-invasive and efficient techniques for temperature monitoring during treatment [73]. The researchers expanded Fenn's work on microwave hyperthermia in their study by conducting a clinical study [88]. Local anesthesia is used to numb the breast, and a sensor catheter is inserted to monitor the electric field and temperature during hyperthermia treatment. This approach allows for more precise and non-invasive temperature monitoring, with results indicating that hyperthermia treatment is safe and effective in reducing tumor size. The study demonstrates the potential of using microwave hyperthermia as an adjuvant therapy in breast cancer treatment [87].

The authors [88] detail methods and objectives aimed at optimizing the delivery of hyperthermia treatment to cancerous tissue while minimizing harm to healthy tissue. They employ a trust-region framework, a mathematical optimization technique that iteratively solves sub-problems within a specified region [75]. In another context, the authors [80] highlight medical image processing as an evolving and challenging field, with a specific focus on the processing of MRI images. The lungs, integral to the respiratory system, comprise various parts such as the trachea, clavicle, carina, right atrium, left ventricle, right hemi diaphragm, left hemi diaphragm, and cost phrenic angle **Figure 4**. Chest X-ray (CXR) serves as a common diagnostic practice for various respiratory diseases due to its cost-effectiveness compared to other medical imaging techniques. Lung segmentation plays a pivotal role in reducing computational complexity for lung-related illness identification when computations are confined to lung sections. It is particularly crucial for identifying diseases like pneumonia [86] and tuberculosis [98], [90]. Numerous publications emphasize the significance of lung segmentation before further processing [23], including its application in COVID-19 detection. A variety of methods have been employed for lung segmentation in CXR images, categorized into conventional procedures and deep learning-based methods. Conventional procedures encompass rule-based techniques [34], pixel classifier-based methods [22], deformable models, and hybrid approaches [31], [32]. Deep learning-based methods fall into two broad groups: discriminative models like U-net [33] and generative models such as autoencoders and generative adversarial networks (GANs). While GANs are widely known for image production, they are also employed for segmentation [24], [34], [31], [29]. The authors of [35] introduce a variant of GANs called hybrid fusion networks for generating synthetic MRI image modalities, addressing concerns related to missing modalities. This work [23] demonstrates that the presented network surpasses state-of-the-art synthesis networks in terms of accuracy [24]. For image registration, an unsupervised adversarial similarity network is presented [29], showcasing its ability to train without using ground truth and achieve state-of-the-art outcomes on brain MRI images. The authors of [39] train a GAN framework to segment liver images, while in [32], GAN is taught to generate lung

nodules. Results indicate that supplementing data using GANs can improve overall segmentation outcomes, particularly when training data is limited. Brain MR and CT images are employed in their studies [26], and a methodology for generating CT images from input MRI images is suggested [29]. An issue of hazy CT images is addressed, presenting a loss function to alleviate this concern. The creation of CXR and their segmented masks is demonstrated [43], emphasizing that image quality is compromised when pairs are formed compared to generating CXR images alone [41]. Although GANs have been extensively developed for various applications, they have not been specifically designed for lung image segmentation, highlighting an area for potential exploration.

During their study, the researchers clarified that although nanorobots are small, readily recognizable, and manageable devices, they have accuracy issues that prevent them from integrating seamlessly with AI-based methodologies [39]. Limitations exist when integrating artificial intelligence (AI)-based methods with nanorobots in biomedical applications [34]. The study of the literature provides a thorough examination of the use of nanorobots in the medical field, including their possible uses, limitations, and difficulties [35]. However, nanorobots are useful in many biomedical applications and are more affordable than wearable technology. They also have a quicker identifying speed. The researchers' goal is to give a thorough knowledge of how nanorobots might aid in the diagnosis and treatment of a variety of medical diseases through the examination of numerous factors [36]. The proposed methodology involves the utilization of Otsu's thresholding technique for extracting the breast region in mammograms. Subsequently, a combination of Canny edge detection and straight-line approximation is applied to estimate the boundary of the pectoral muscle. Finally, Local Binary Patterns (LBF) are extracted from both normal and abnormal breast tissues. These extracted LBF features are employed to train a Support Vector Machine (SVM) for classifying normal and abnormal breast tissues. This approach integrates multiple image processing techniques to enhance the accuracy of breast region extraction, estimation of the pectoral muscle boundary, and the subsequent classification of breast tissues based on extracted features using SVM.

To our best knowledge, there is currently no existing study that presents a practical application for the diagnosis and treatment of breast cancer utilizing a Gold Nano Thermo Robot specifically engineered and treated with gold nanoparticles, incorporating advanced sensor technologies such as heat sensors, position sensors, location ensors, and more. Furthermore, there is a lack of comparative analysis regarding the heat intensity generated through the coulomb explosion process. Additionally, to regulate the heat intensity, we propose the development of a heat control system based on mathematical equations, enabling the maintenance of temperatures within the range of 35°C to 45°C. This temperature range has been established in various-research studies as effective in eradicating cancer cells [36]. The absence of such research is noted throughout the entire literature review, and this research endeavor aims to fill this notable gap.

2.1 Conclusion

The literature study makes it clear that most research findings don't offer a complete answer for using nanorobotic systems to enable intelligent diagnosis and therapy. Our work fills this gap by introducing the GNTRs, a therapeutic and diagnostic nano-intelligent system that provides comprehensive treatments for chronic disorders. This cutting-edge nano-robotic technology is very promising and might completely transform medical procedures, especially in the intricate areas of diagnosis and therapy. By reviewing the body of current research, scientists want to identify areas that need more investigation to improve the effectiveness and security of nanorobotic technology. Interestingly, there is a dearth of information in the literature about the fabrication procedure needed to integrate nanorobots with AI-based methods [23]. This work's main goal is to introduce a dual-functional nanotechnology-based diagnostic and therapeutic system. Creating a classification model to distinguish between benign and malignant breast cancer is the main goal of the first module. This model successfully classifies breast cancer tumors as either malignant or benign using clinical data by combining ontology and case-based reasoning. To treat tumors located in the breast medium, the second module focuses on heat treatment, which does away with the requirement for intricate optimization techniques. We present our idea, the Gold-Nano Thermo-Robot, which is intended to control therapy as well as diagnostic processes. This study compiles data in favor of using thermometric parameters, particularly in the context of hyperthermia (HT) therapy, in the treatment of breast cancer. The incorporation of thermometric factors has potential for improving treatment results [35].

To find the best way to use these characteristics in the treatment of breast cancer as well as figure out how to incorporate them into clinical practice, more study is necessary. Recognizing that all nanotechnology interventions involving materials and devices at the atomic and molecular scale need stringent testing with specific restrictions is crucial.

CHAPTER 3

PROPOSED METHODLOGY

GOLD NANO THERMO ROBOT (GNTR)

The functioning of the Gold-Nano Thermo-Robot (GNTR) is delineated into two primary components: Diagnostic and Treatment. The integration of nano smart devices, nano cameras, and intelligent sensors is essential to form and synchronize the elements necessary to accomplish the goals outlined in the novel GNTR model. The methodology of GNTR, as illustrated in **Figure 9,** encompasses five distinct phases, with each phase undertaking a specific and unique role.

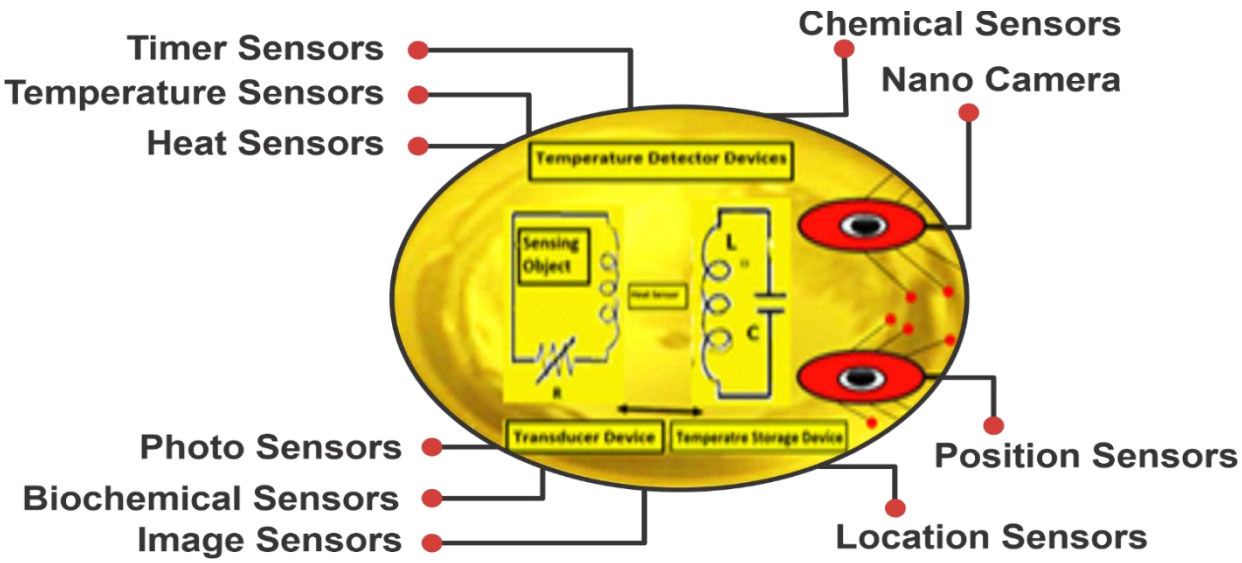


Figure 8: Proposed Model of Gold Nano Thermo Robot (GNTR)

2.1 Phase1 Integrated Sensor Plate form:

In Phase 1, an integrated sensors platform is established, encompassing various sensors such as actuators, heat sensors, chemical sensors, micro or nano video cameras, biosensors, and signal receivers and transmitters. These sensors collectively have the capability to perceive and gather information about the given situation. The output

information obtained from **Phase 1** is then transmitted as input information to **Phase 2**

for further processing.

2.2 Phase 2 Data Pre-Processing Platform:

Figure 9: Proposed Methodology of the Research Study

Following the accumulation of data in Phase 1, the obtained output information is transmitted to **Phase 2,** referred to as the Data Preparation Platform. In this phase, various steps are undertaken to process the raw data, including data cleaning, data discretization, data integration, data accuracy assessment, data reduction, and ensuring data completeness. After these procedures, further actions are initiated, such as feature extraction,

segmentation, post-processing, training, and testing, culminating in evaluation and performance analysis. The process of data preparation, often termed data engineering, is of paramount importance as it significantly influences the outcomes of the research.

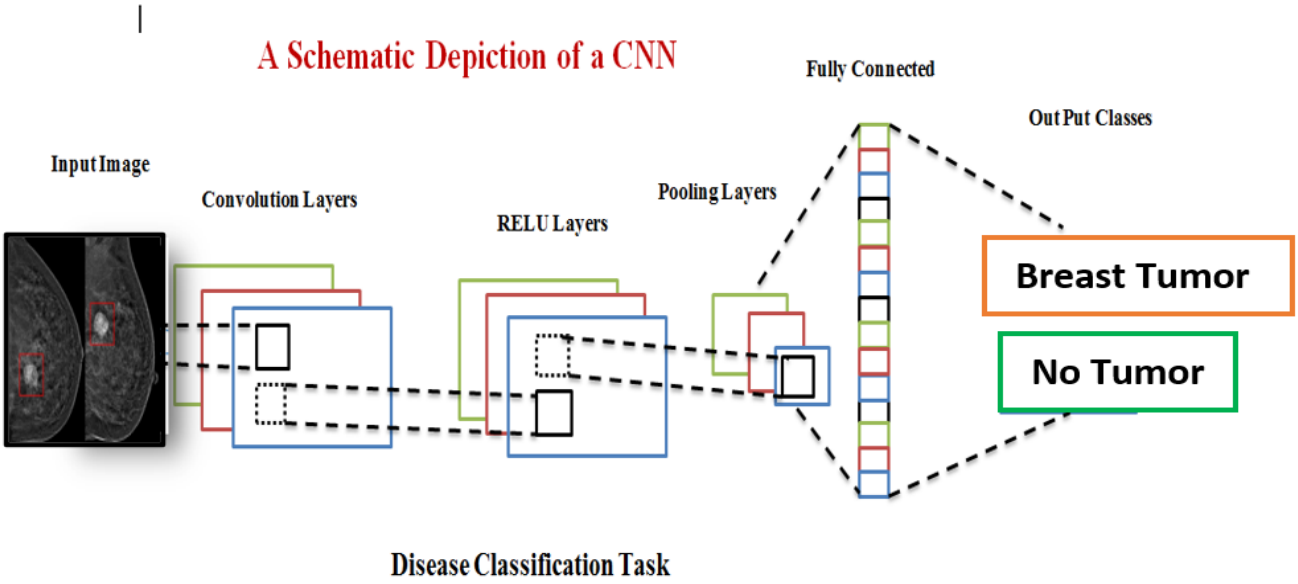


Figure 10: A Schematic Depiction of a Convolutional Neural Network

2.3 Phase 3 Platform of Deep machine Learning

The foundation of this research work lies in the deep machine learning platform, which is instrumental in predicting diseases through advanced techniques within the realm of deep machine learning. This phase encompasses two sub-phases: the training phase and the testing phase. The post-processed image data output serves as input for **Phase 3**. **Figure 11**. Architecture of the Convolutional Neural Network (CNN)In **Phase 3,** the architecture of the Convolutional Neural Network (CNN) is crafted, comprising multiple layers. When an image is introduced as input, it traverses through convolution layers, normalization layers, and pooling layers. The sequence may vary, and the design of the network requires specific thresholds for elucidation.

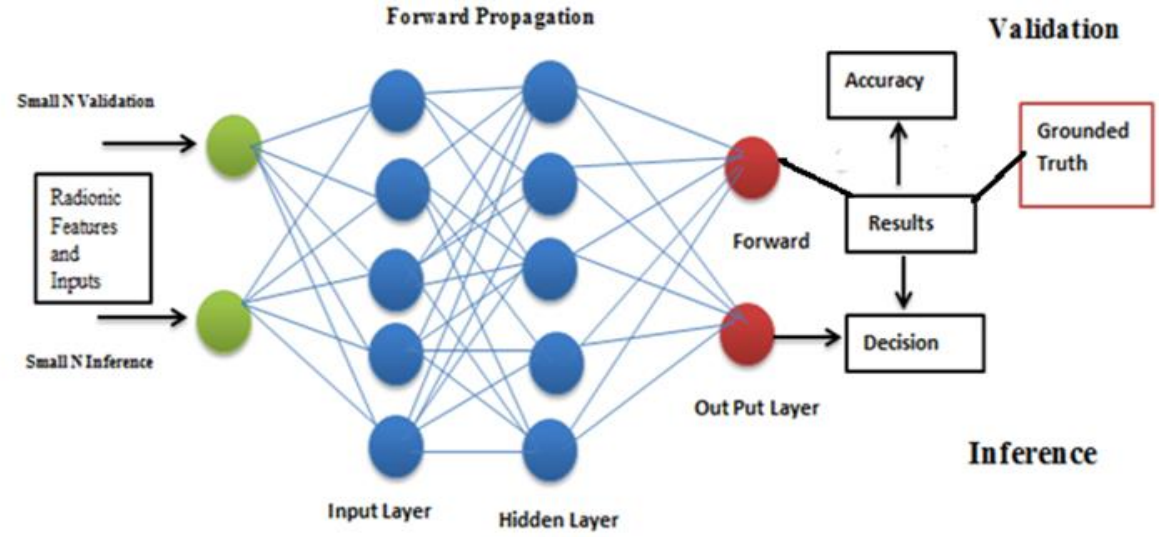


Figure 11: Forward Propagation

During the training phase, the model is trained over a set number of epochs using digital images. The training process involves backward propagation and weight updates. Once the training is complete, the algorithm employs a feed-forward approach for trial images, ultimately leading to the network predicting scores. Filters, also known as weights, features, or kernels, play a crucial role. Initially set randomly, these weights undergo adjustments and updates, essentially allowing the system to learn these specific weights through the process.

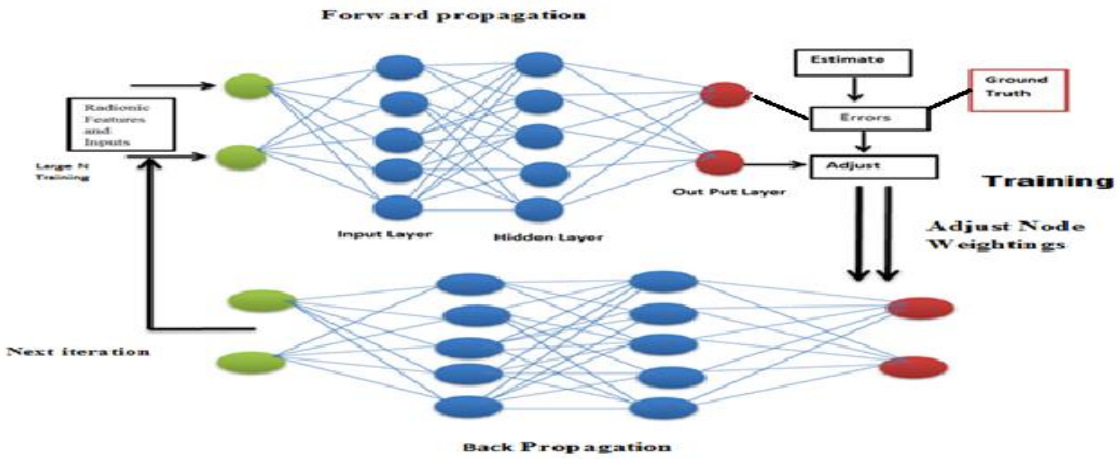


Figure 12: Forward Propagation and Back Propagation

2.4 Phase 4 Platforms of Mathematical Operations:

After the output of **Phase 3** then the turn comes **Phase 4.** This is the mathematical modeling platform. Here real-world problems convert into well defend math problems and then convert into governing the required differential equations and find the solutions of model behaviour.

2.5 Phase 5 Platform of Treatment:

In the final phase, **Phase 5**, termed the treatment platform, the proposed model involves the utilization of a Heat Control System for treating severe infections while safeguarding the adjacent healthy cells surrounding tumours. It is recognized that cancer cells are susceptible to destruction at 42°C. Consequently, this study aims to regulate the temperature precisely at 42°C, employing various mathematical methods such as the Finite Difference Method, Finite Element Method, and Crank Nicolson Method.

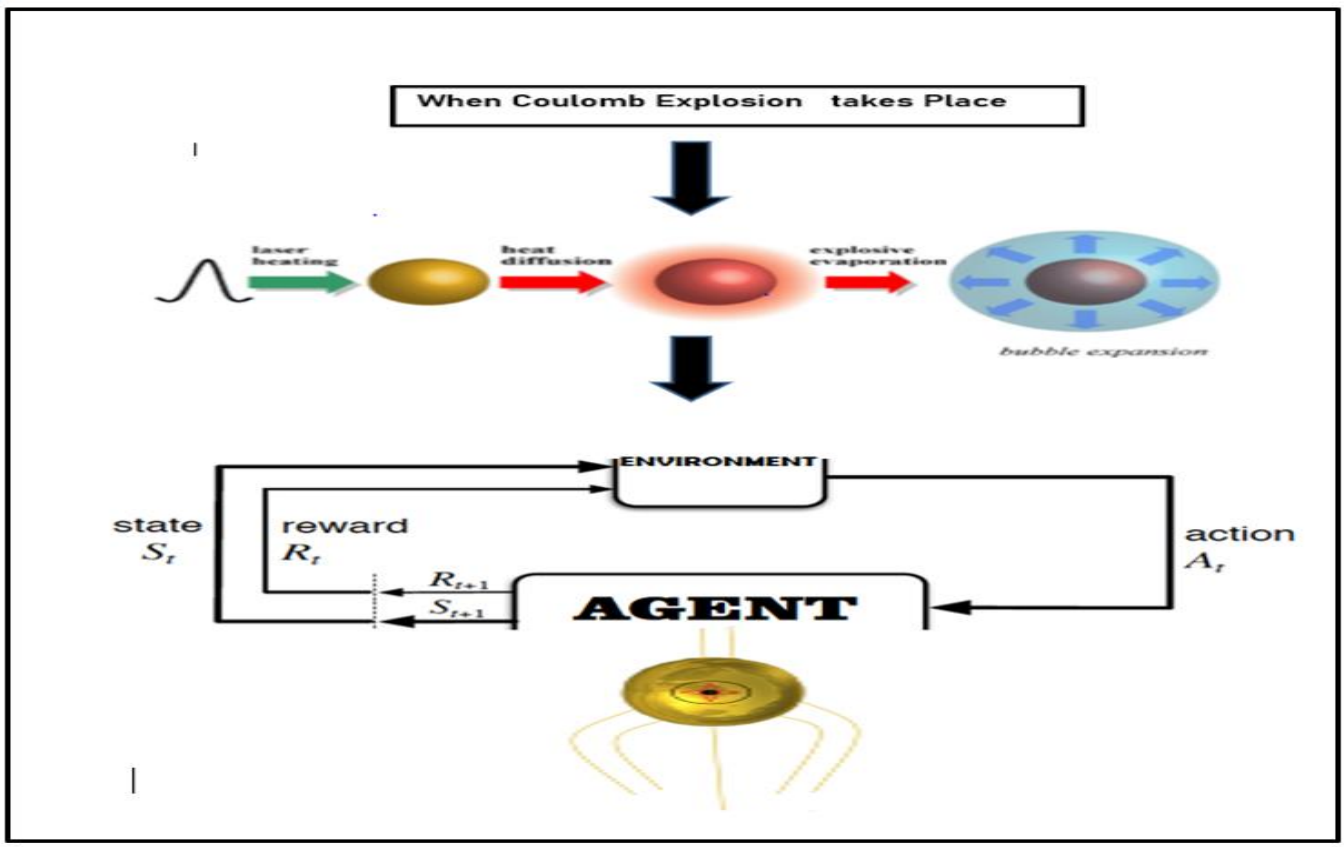


Figure 13: Methodology of Coulomb Explosion

According to this method, when brief laser pulses with a femtosecond time scale are applied to gold nanospheres at the centre of another sphere (with a radius of 1 μm), they

explode coulombically. The multiphoton ionization, electron-electrons interactions, and electron-photon excitation relaxations within the gold nanoparticles' Surface Plasmon Resonance (SPR) spectrum region are what cause this explosion. As a result of absorbing many photons, the gold particles are stimulated to higher electronic states, which causes a sharp temperature rise. When the temperature increases to the point where nonlinear effects are observed, tiny bubbles appear along with the production of shock and acoustic waves. The absorbed photon energy is subsequently transformed into thermal energy by the gold atoms' quick relaxation. By cautiously controlling the amount of heat released, this energy can be used to treat fatal illnesses. To manage this regulated heat for therapeutic purposes, the **"Heat-Control-System"** that is being presented is needed.

2.6 Conclusion

The proposed GNTR methodology requires rigorous testing and validation through preclinical and clinical trials to ensure safety and efficacy before clinical implementation. This methodology consists of five basic phases. Each phase starts after successfully completing the previous phase. After successfully diagnosis the chronic disease, the treatment phase starts. Apply mathematical models to understand and optimize treatment parameters. Treatment Platform with Heat Control System (38°C to 42°C).

CHAPTER 3

PROPOSED DIAGNOTIC METHODLOGY

(BASE PAPER MODEL)

In this research work, an article under review process by Zahid et al., 2023, to automatic diagnosis of chronic disease. This research proposed an automatic breast segmentation and cancer tumor diagnosis using GNTRs based GAN and SVM algorithms in Mammograms. Breast cancer has become one of the most globally significant medical problems for which medical science will have to find a solution. Medical scientists and researchers all over the world are investigating fast diagnostic techniques for this deadly disease. Recently, many artificial intelligence-based approaches have been used for breast cancer detection. This paper introduces a new approach to diagnostics using the GNTRs, empowered with deep learning techniques endowed in nanomedicine [59].

3.1 PROPOSED METHODOLOGY

The block diagram displayed in Figure 15 depicts the methods that we used in this investigation. Firstly, we used median filtering to reduce the amount of noise in the mammography. The Otsu approach is then used to create a binary mask by setting a threshold for the mammography [86]. The breast area is covered by this binary mask along with labels and other artifacts. Connected component labeling is used to get rid of these labels and artefacts. The breast area of the original mammography is then extracted using the binary mask that results. We identify the pectoral muscle's position in the next stage. Then, to locate the pectoral muscle's border and make its removal easier, a straight-line approximation and Canny-edge detection combination is employed. After that, to locate the pectoral muscle's border and make its removal easier, a straight-line approximation and Canny-edge detection combination is used. Furthermore, a variety of attributes are taken from the normal and pathological breast tissues' Gray-Level Co-occurrence Matrix (GLCM). The last step is to train a support vector machine (SVM) to identify breast cancer in the mammography. Mammogram screening is the main and most popular approach for early breast cancer diagnosis.

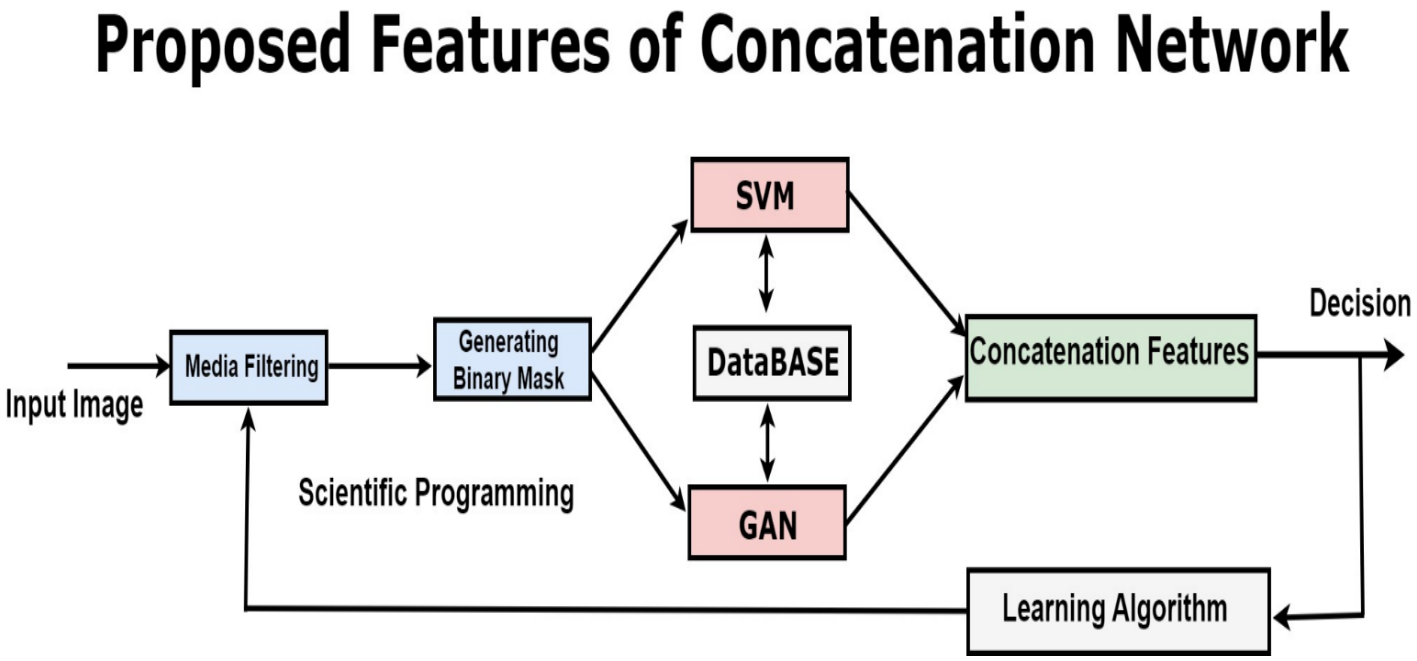


Figure 14: Features of the Concatenation Network

This method stands out as the most dependable and economical way to spot early warning indicators of breast cancer. A mammogram, or detailed greyscale picture of the breast region, is obtained with the use of a specific low-dose x-ray imaging method in mammography. Digital mammograms are widely used in Computer-Aided Detection (CAD) systems since they provide a better dynamic contrast of breast tissue than traditional screen film mammograms [37]. These computerized analytical systems (CADs) use digital mammography to identify possible breast cancerous spots. Nowadays, a lot of radiologists depend on the results these technologies produce for thorough assessment. This study aims to provide an easy procedure for separating the breast area, removing the pectoral muscle, and detecting breast cancer in mammography. Utilizing the Mini-Mammographic Diagnostic Imaging Analysis Society (Mini-MIAS) database, the whole process has been validated.

3.1.1 MEDIA FILTERING

The noise reduction procedure is important when analyzing digitized mammograms for Computer-Aided Detection (CAD) methods. Low-intensity noise can be detected in the vicinity of the breast region's skin-air contact in mammography. Furthermore, there are times when mammography scans have scratch artefacts as well.

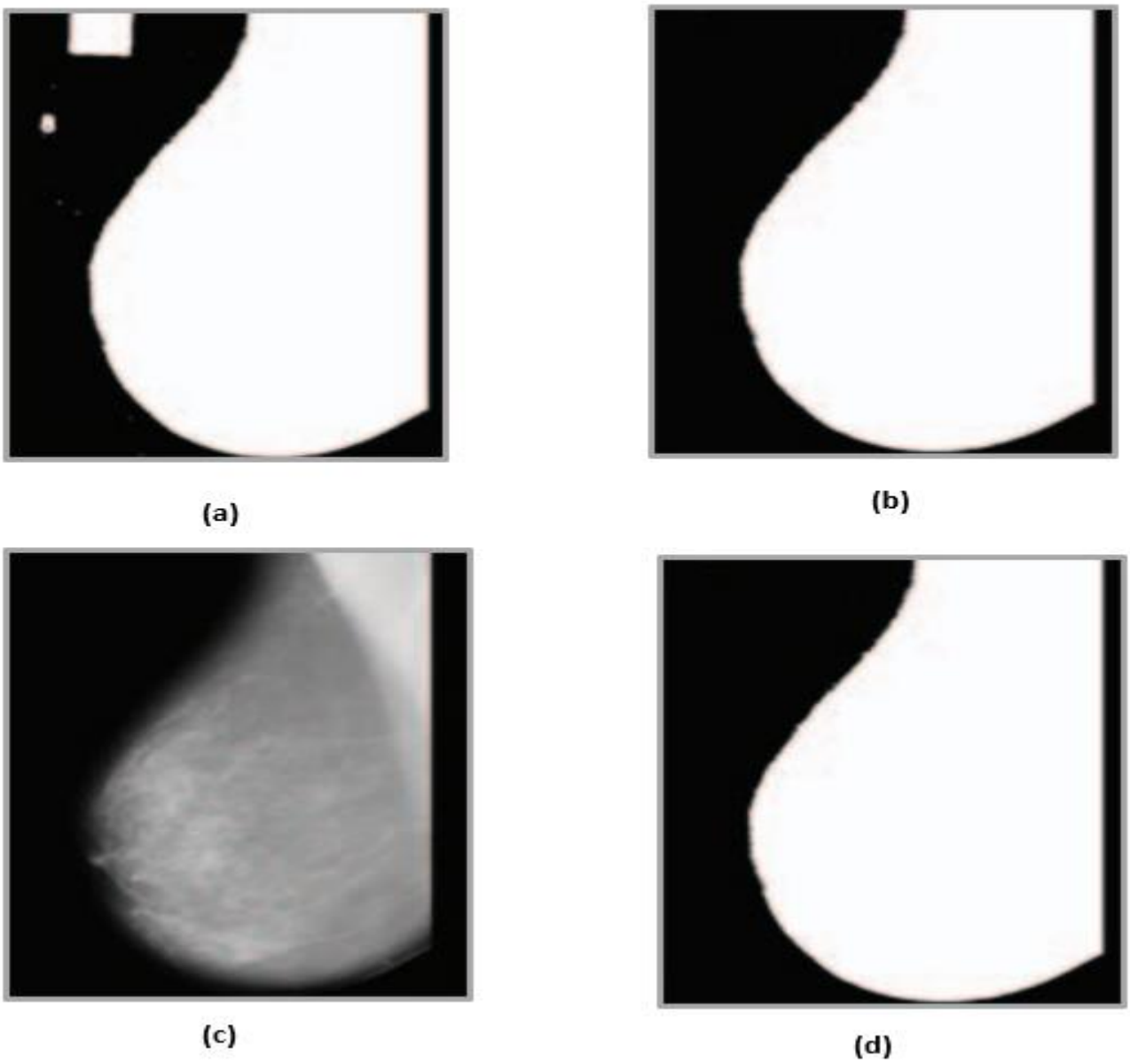


Figure 15: A Process of Filtering out Noise in Digital Mammogram Images

Regarding noise reduction, a nonlinear median filter with a 3*3 window size was selected. These pixels are sorted in ascending order utilizing a median filter-specified size from each pixel's neighborhood, or I_((x,y)) in the picture. The median value in the sorted array is then replaced with the value of the image pixel. I_((x,y)).

3.1.2 EXTRACT OF BREAST REGION

1) Generating of Binary Mask:

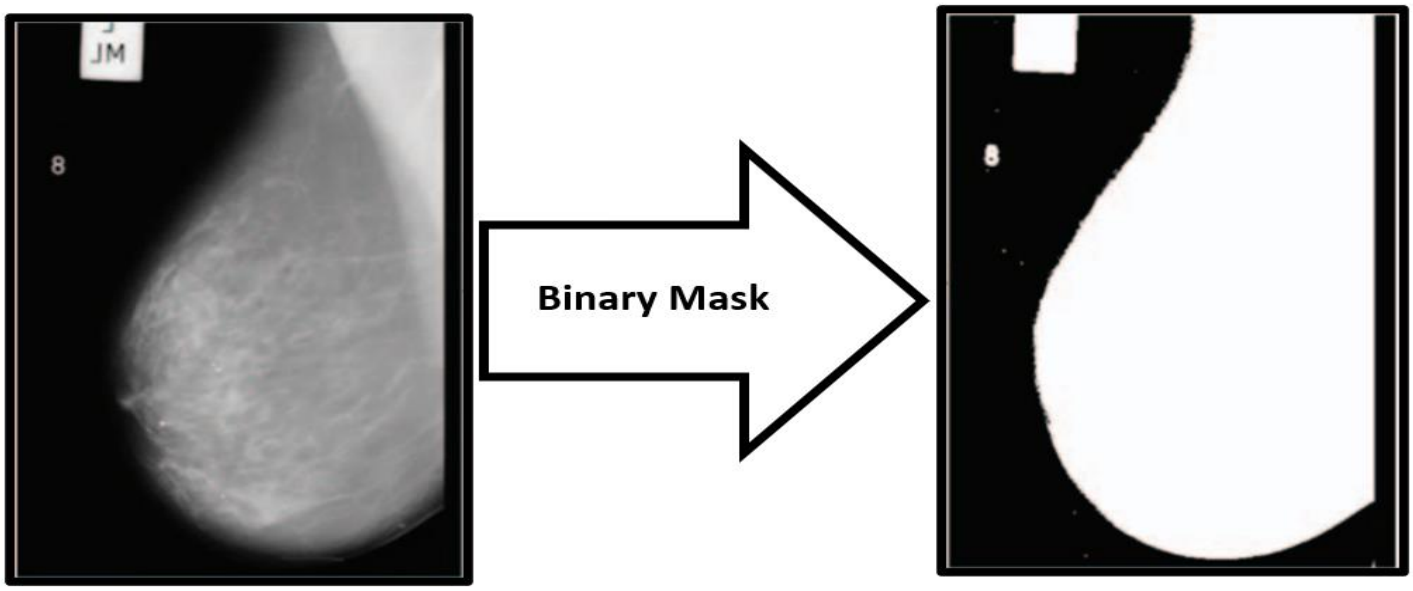


Figure 16: Edge Detection Process in Digital Mammogram Images

Mammograms frequently contain numerous artefacts, undesired labels, and markers. The Otsu approach was used to apply a thresholding step to the mammography to separate the breast area. The Otsu method establishes a global threshold value to differentiate pixels in the foreground from their background. Since the Otsu technique maximizes interclass variance and minimizes intraclass variation, the threshold value it determines is regarded as ideal. As seen in Figure 16. (A) Label and marker were present in the binary mask. (b) To extract the biggest breast cancer, connected-component labelling is carried out. (d) Binary mask. (b) has dilated (c) The source image is The whole mammography was divided into 16 different classes using the Otsu technique, multiplied with (d) extract-breast-region in the suggested way. Each class was identified by a between-class variance.

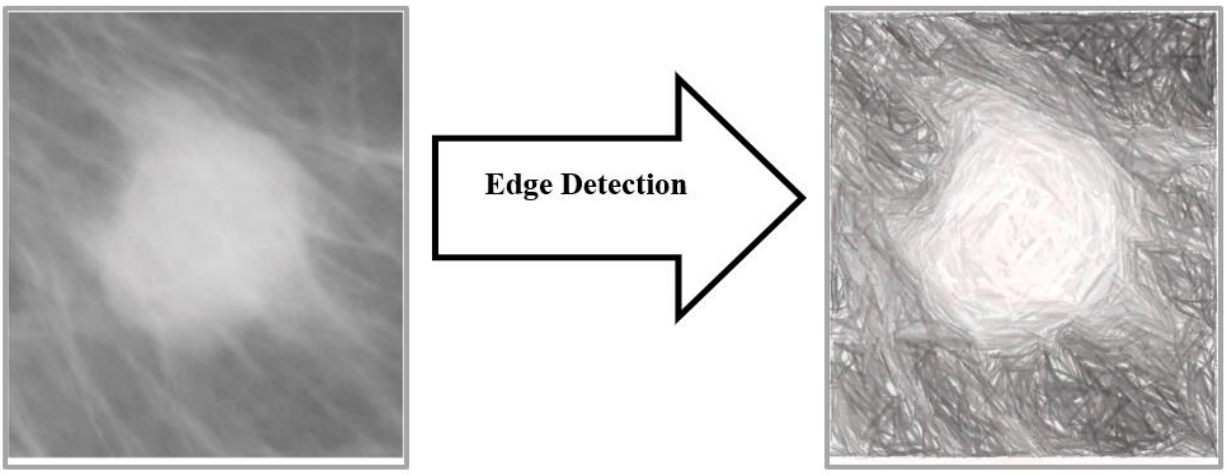


Figure 17: (a) Input image section of rectangular window around the cancer tumor.

proposed approach, the Otsu method was utilized to partition the entire mammogram into 16 distinct classes, each characterized by a between-class variance. $\mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3, \ldots \ldots \ldots \ldots \mathbb{C}_{16}$ and defined as

$$\sigma BW^2 = \sum_{t=1}^{16} P_t \left(m_{t-m_G} \right)^2 \qquad (1)$$

Where σBW^2 is involving class variance, P_t is the cumulative probability that pixel fits to t^{th} class, m_t is mean pixel intensity of t^{th} class, m_G is the average pixel intensity of entire mammogram. Equation (1) is optimized as,
$t_1^*, \ t_2^*, \ t_3^*, \ t_4^*, \ \ldots\ldots\ldots \ t_{16}^* = \text{argmax}_t \ \sigma BW^2 \ (t_1^*, \ t_2^*, \ t_3^*, \ t_4^*, \ \ldots\ldots\ldots . t_{16}^*)$
After wards, the lowest value of threshold t_1^* obtained with Otsus method was used to binaries a mammogram. The output of this stage is presented in **Figure 18**.

2) Connected Component Labeling:

In the next section, we go over how to use connected component labeling (CCL) to recover the breast region from the created binary mask. As the breast area depicted in **Figure 18**, is the largest connected component in the binary mask, our goal is to separate this main linked component from the binary mask. To do this, we applied CCL on the binary mask and then extracted the most connected component, which is illustrated in **Figure 17**. The binary mask that is produced now just covers the breast area. The border of the breast region is refined by dilatation of this mask with the application of morphological operators. The breast area of the mammography is then successfully isolated and extracted by multiplying this mask elementwise with the noise-suppressed mammogram [98].

3) Removal of Pectoral Muscle

The brightest region located in the top-left or top-right of the MLO (Medio-Lateral Oblique) image of mammography is known as the pectoral muscle. Since the pectoral muscle's brightness level is like that of malignant tissues, removing it is essential for an accurate diagnosis of breast cancer. However, this work is difficult since the pectoral muscle border is partially visible in some mammograms because it is surrounded by brilliant fibro-globular tissues. To overcome this difficulty, we provide a technique that uses straight-line approximation in combination with the detection of canny edges to detect the pectoral muscle boundary in its entirety. To make sure the pectoral muscle is moved to the top-left corner, all-left-aligned mammograms in the database are first horizontally flipped [21]. The border of the pectoral muscle is then located using a Canny-edge detection technique, as shown in Figure 16(b). The remaining pectoral-muscle border is estimated by drawing a straight line between the ends.

A (x1, y1) and B (x2, y2), described by the equation:

$$y - y_1 = \frac{y_2 - y_1}{x_2 - x_1} * (x - x_1) \qquad (2)$$

The pectoral muscle surround using canny-edge detection is displayed in Figure 16(b), and the remaining pectoral muscle boundary can be calculated using a straight line in Figure 16(c).

4) Feature Extraction

To determine the traits of malignant tissues, we first removed the pectoral muscle from the breast area and then extracted features from both aberrant and normal breast tissues. Although a few feature-extraction techniques have been put forward in the literature, our methodology made use of the Gray-Level Co-occurrence Matrix (GLCM). The occurrence of various combinations of pixel intensities in a picture is described by GLCM. As shown in Figure 5, our method involved selecting a window surrounding the malignant tissue that measured 201 by 201 pixels. The image's pixel values were scaled to integer values between 0 and 3 prior to the creation of the GLCM. After that, four GLCM matrices with angles of 45, 45, 90, and 90 degrees were produced. Each GLCM matrix yielded the following properties: contrast, correlation, energy, and homogeneity. These features were combined to create a feature vector with dimensions of 1x16. These features were taken from tissues that were malignant and healthy. Lastly, using the attributes that were collected, our methods used support vector machines (SVMs) to classify breast tissues as either normal or malignant [23].

5) Support Vector Machine Based Classification

The GLCM characteristics that were acquired in the previous stages are classified using Support Vector Machines (SVM). Using a linear separator inside a feature space, SVM uses linear discrimination to divide features into two or more different groups. The separator corresponds to a hyperplane with m-1 dimensions if the feature space has m dimensions. Here is how the linear discriminant function is expressed:

$$f(x) = SGN\ (w^T x + b) \quad (3)$$

Where, $w^T x = \sum_{j=1}^{m} w_{j,} x_{j,}$

$x_{j,}$ is a feature vector of j^{th} example,

W represents a weight vector, while b denotes a biased value. In this case, the sign function returns +1 labels for arguments larger than 0 and returns -1 for augments smaller than 0. W and b in the SVM are changed so that the following requirements are complied with:

$$\text{Min } \eta = \frac{1}{2} w^T w$$

Such as $w^T x_i + b \leq -1\ \forall$ i s.t $y_i = -1$

$$w^T x_i + b \geq -1\ \forall \text{ i s.t } y_i = +1$$

In this context, the variable "y" signifies the output label. The SVM classifier is known for its robustness, establishing an optimal boundary between features of positive and negative classes. For our study, the SVM toolbox in MATLAB was employed, utilizing a linear kernel for training. Determining the maximum Area Under the Curve (AUC) value from the trained classifier's Receiver Operating Characteristic (ROC) curve allowed for the optimization of the misclassification rate. Because they can learn the mapping from one domain to another, GANs are often used to generate realistic data. In our study, a given input mammography picture is trained to produce a segmented mask using the GAN's generator. By using the adversarial loss measure to update the generator, the discriminator discerns between the produced mask and the ground truth. Creating masks for the input mammography pictures that are as realistic as feasible in comparison to the ground truth masks is the goal. Five distinct discriminators designated as **D1, D2, D3, D4, and D5**, respectively—are used to train and assess the model. The suggested model can get dice scores of 0.9740 and IOU scores of 0.943 on the mammography picture dataset, according to experimental

results. These scores are better than earlier stated state-of-the-art results. These findings demonstrate the effectiveness of this method for identifying breast cancer in females, making it a viable tool for further medical diagnosis. The suggested method for identifying and removing breast cancer infections from patients' mammography pictures is described in this study [41]. The fundamental ideas of image processing—segmentation, volume estimation, visualization, morphological operations, media filtering, and binary mask generation—are all incorporated into this system. **Figure 19,** shows the concatenation features network of the SVM and GAN algorithms. We use a particular technique, which is depicted in **Figure 20,** with a block diagram. The first step in reducing noise in a mammography is to use median filtering. Thereafter, a binary mask is created by applying Otsu's approach to determine a threshold for the mammography. The breast area, related labels, and other artifacts are all included in this mask [43]. Connected component labeling is used to get rid of these labels and artifacts. The breast area is then extracted from the original mammography using the binary mask that is produced. **Figure 21,** provides an explanation of the GAN backpropagation technique. The location of the pectoral muscle is determined at the fourth stage. After that, the pectoral muscle's border is identified using a straight-line approximation and Canny-edge detection technique, which makes it easier to remove. Furthermore, a variety of characteristics are taken from the normal and pathological breast tissues' Gray-Level Co-occurrence Matrix (GLCM). Lastly, GAN with Support Vector Machine (SVM) are trained to identify breast cancer in mammography images.

3.1.1 GENERATIVE ADVERSARIAL NETWORKS

3.1.1.1 A Generative Adversarial Network (GAN) model comprises

Generator, denoted as G, and a Discriminator, denoted as D. G takes in a random noise vector as input and endeavors to generate data that aligns with the distribution of real data. Meanwhile, the role of D is to authenticate the data by discerning whether it is genuine or generated (fake). Various experiments were conducted using diverse datasets. The proposed methodology has been explained in **Figure 20** [35].

3.1.1.2 GENERATOR ARCHITECTURE

The implementation involves Generative Adversarial Networks (GANs) with a generator network structured in an encoder-decoder style. This design retains a similar architecture for the generator, allowing for the natural utilization of noise code. The encoder functions as a multi-layered neural network, extracting features from the input image. In the initial layers, it captures local features, progressing to extract more global information in deeper layers. The encoder down samples the input until a bottleneck is reached, marking the transition to decoder up-sampling [23].Within the first four layers of our generator G, input down-sampling occurs, facilitating feature learning.

The fifth layer serves as the bottleneck, initiating the up-sampling process to reconstruct the image, as depicted in **Figure 5**. Notably, our architecture does not rely on random noise, as it learns to disregard it, leading to a lack of improvement in results. Additionally, the generator incorporates skipping connections, akin to those used in U-Net, to enhance its performance [34].

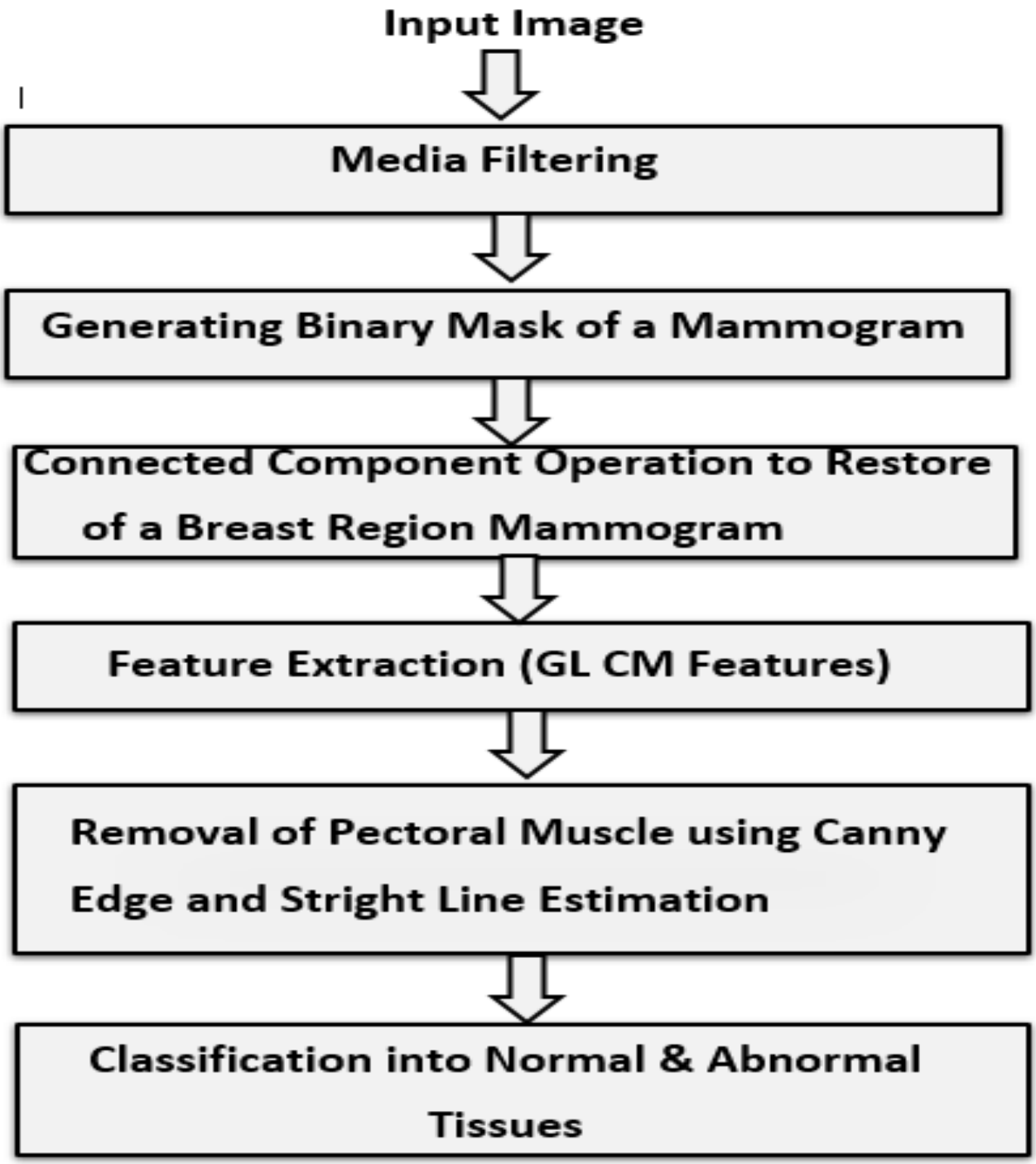


Figure 18: Proposed Block Diagram of Proposed Methodology

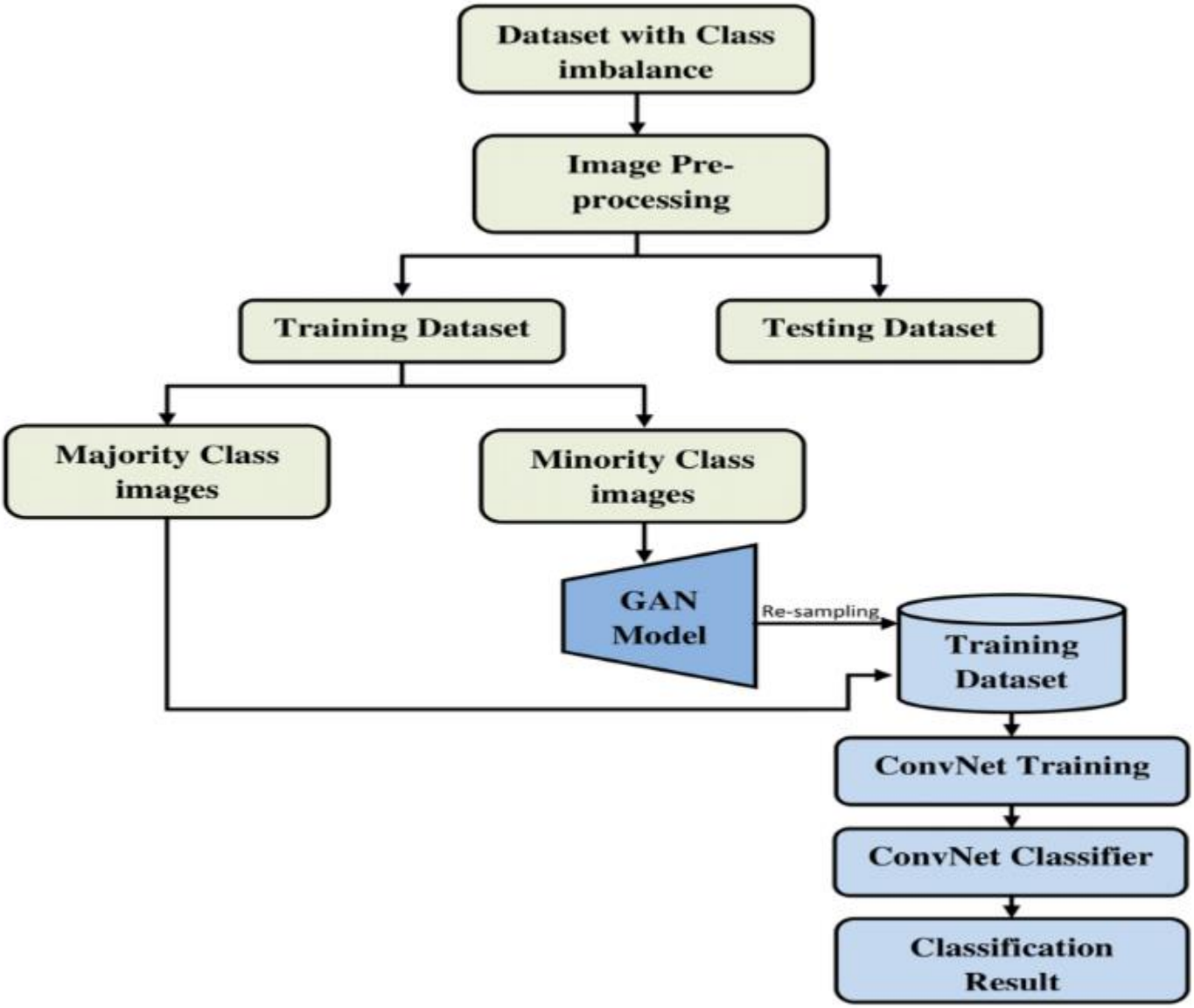


Figure 19: Proposed Block Diagram of Proposed Methodology of GAN

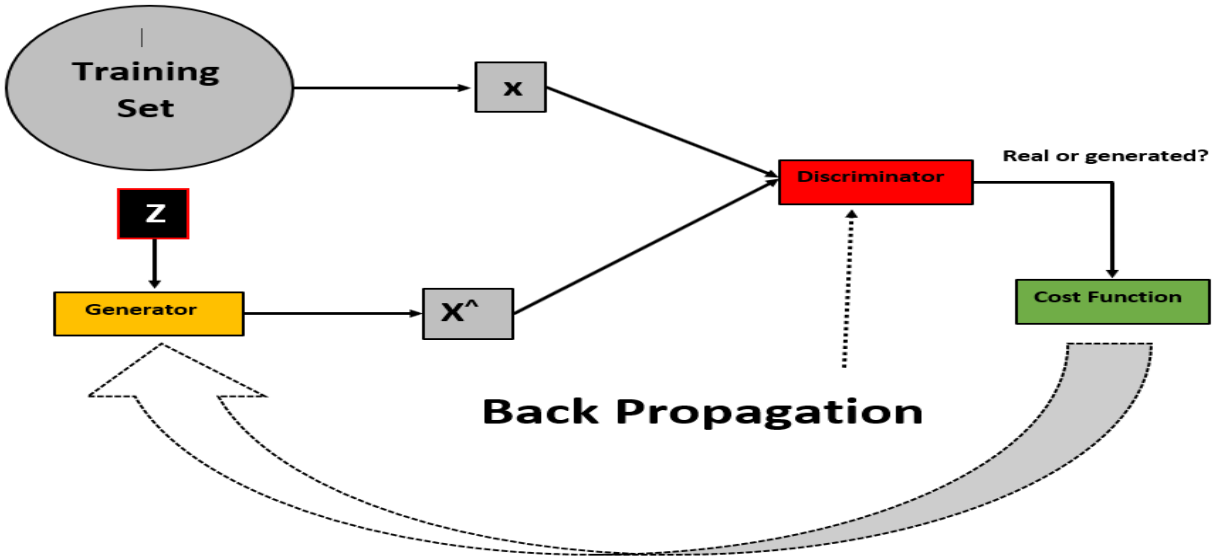


Figure 20: Proposed Block Diagram GAN Back Propagation Technique

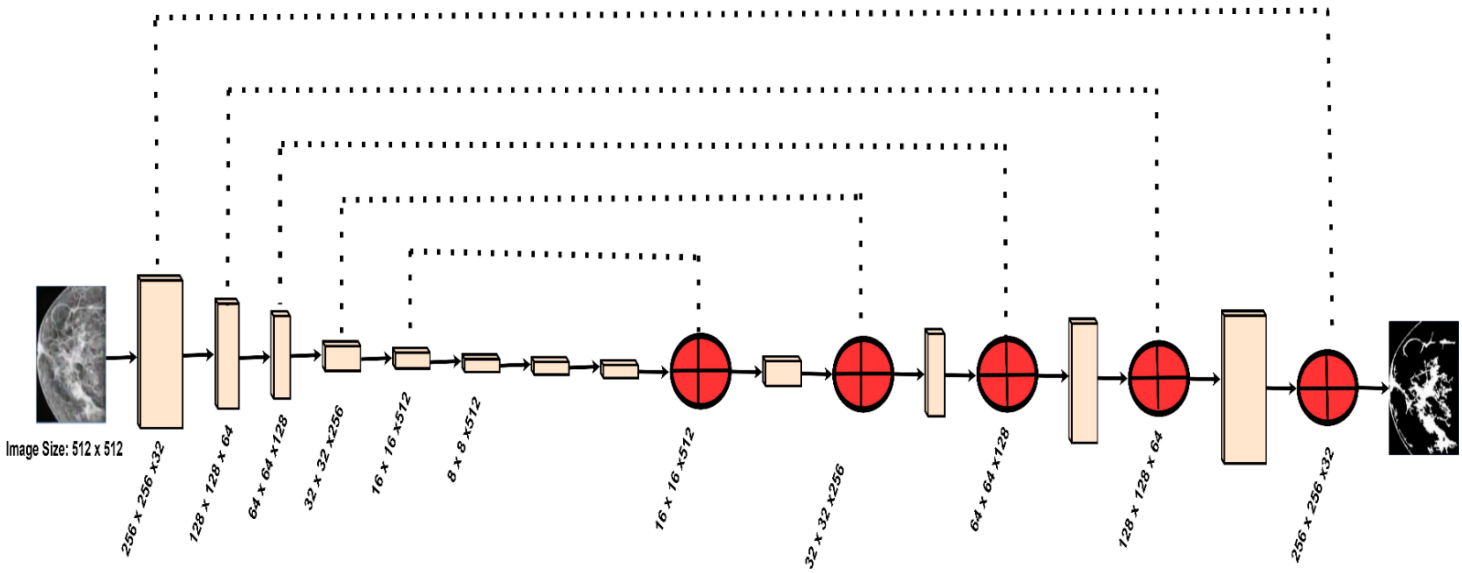


Figure 22. Proposed Block Diagram GAN, Generator and Discriminator Procedure

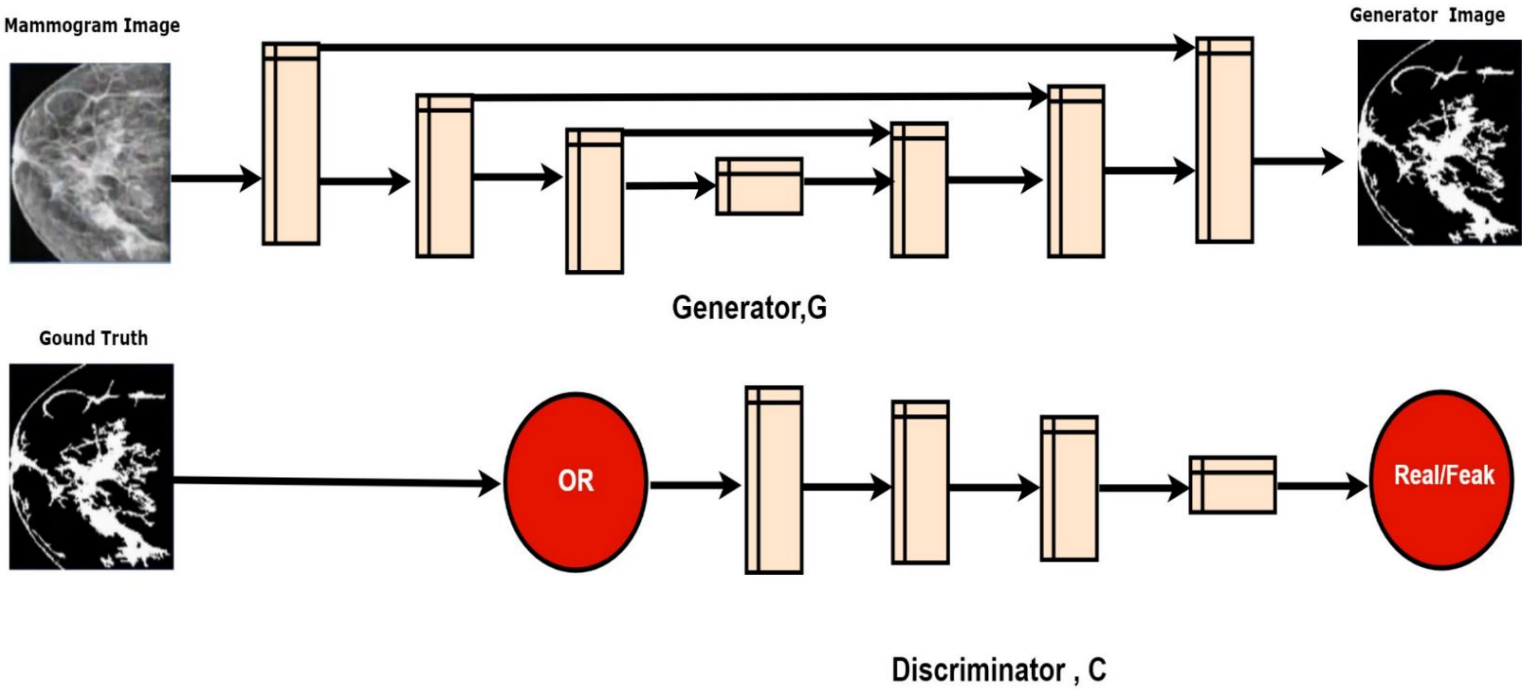


Figure 23: The Architecture of Generative Adversarial Network

Figure 'G' depicts the architecture of our GAN, detailing the composition of our generator. This generator uses a network architecture resembling a U-net for converting a given mammography picture to the appropriate binary mask. The diagram's blocks each represent a layer of the network, where the input picture is down-sampled up to the Centre layer, where up-sampling starts. A noteworthy feature is the use of skip connections, which help to maintain the image's morphology. Reference provides further information on these connections. Conversely, 'D' represents our discriminator network, which is a simple convolutional neural network system. This discriminator performs binary classification using either the generator-generated picture or the ground truth image as input [20]. The discriminator produces binary results that indicate if the input image is categorized as '0' (fake image) or '1' (genuine image). In 22 Figure. The input of the generator's design is a 512 × 512 × 1 pixel image. A down sampling procedure is used for this input, gradually decreasing its dimensions to 16 × 16 × 512. The up-sampling stage starts after the down-sampling. Until the bottleneck layer is reached, the number of filters in each down sampling layer increases while their individual dimensions drop. The illustration's dot lines indicate the existence of skip connections, which are essential for maintaining the image's morphology. In the end, an output picture is created with the same dimensions as the input—that is, -512 × 512 × 1.

3.1.1.3 SKIP CONNECTIONS

The incorporation of skip connections from U-Net is integral to our design, serving to maintain the morphology of the generated images and mitigate the risk of vanishing gradients. Originally introduced in residual networks, skip connections prove valuable by enabling the direct transfer of error gradients between layers of the decoder and encoder. This mechanism enhances generalization capabilities within the network. Following the discussion on skip connections, the subsequent section delves into various types of discriminators employed in this study.

3.1.1.4 DISCRIMINATOR

The approach we employ uses a deep convolutional neural network as the discriminator, which is intended to identify input photos as real or fraudulent [35]. The convolution batch normalization activation pattern is followed by the network architecture. The lung mask (picture) produced by the generator network, or the lung mask derived from the ground truth can be sent to the discriminator. The discriminator's job is to classify every image as real or fake. The discriminator is used in two configurations: image discriminator and patches discriminator. How they handle the input is where they diverge most. Making predictions based on the complete image, the image discriminator converts the input image to a single scalar output. The patch discriminator, on the other hand, separates the input picture into several patches and associates each patch with a single scalar output. On patches of size-N × N pixels, predictions are produced independently, with no overlap across patches. The findings of each patch are averaged to produce the final categorization. Patch discriminators, which assume patch and pixel independence, effectively model the input image as a Markov random field. Patches discriminators, so the theory goes, deal with problems like fuzzy images that come from failures at high frequencies, like edges. Patch discriminators also have the benefit of requiring fewer parameters than whole image discriminators, resulting in a reduction in computational time, and working well for processing any size of extremely big image. Figure 23 depicts the discriminator's overall structure.

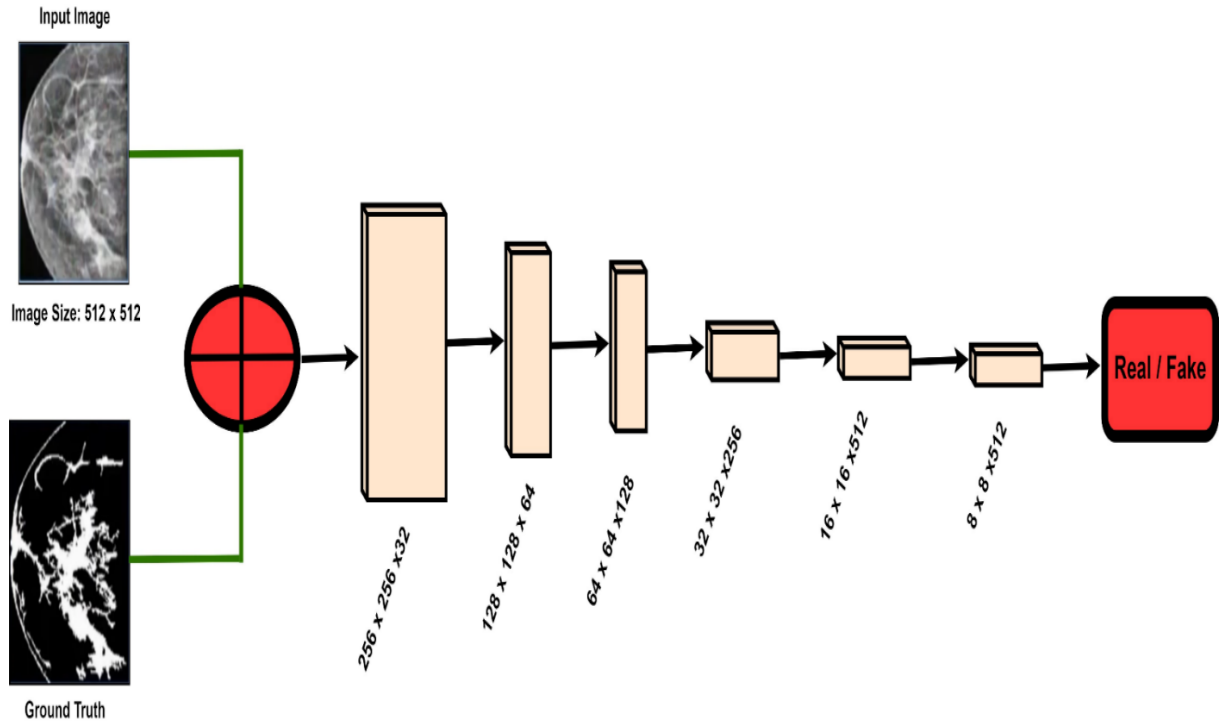


Figure 24: Proposed Block Diagram GAN, Real or Fake Out Put Procedure

The concatenated mask image and the matching mammography image are inputs into the Discriminator D4 architecture. The discriminator moves from low-level features in the first layers to high-level features in the last layers as it attempts to extract features at each layer [27]. A prediction that indicates whether the input is categorized as real (representing a mask from the ground truth) or false (representing a mask created by the generator) is the discriminator's final output. **Figure 23** provides an explanation of the discriminator network and generator network block diagrams.

3.1.1.5 DISCRIMINATOR D1

The discriminator moves from low-level features in the first layers to high-level features in the last levels as it attempts to extract features at each layer. A prediction indicating whether the input is categorized as real (representing a mask from the ground truth) or false (representing a mask created by the generator) is the discriminator's final output. Put more simply, the discriminator stated above also known as Pixel GAN is a neural network built specifically for picture analysis. It focuses especially on assigning a '1' or '0' to each pixel in an image. This is an explanation of its organization.

3.1.1.5.1 Patch Size:

The discriminator examines the image pixel by pixel, with a patch size of 1 × 1 pixels. This means it evaluates each pixel individually.

3.1.1.5.2 Layers:

Four layers compose up the discriminator, an input layer, three concealed levels, and the last output layer.

3.1.1.5.3 Activation Functions:

Certain portions of the network employ distinct activation functions. The sigmoid activation function is used in the final output layer, which squashes the output values between 0 and 1. The leaky ReLU (Rectified-Linear-Unit) activation function is used for the hidden layers. When the input is negative, Leaky ReLU permits a slightly non-zero gradient, which aids in the network's training [27].

3.1.1.5.4 Classification Process:

The main task of this discriminator is to classify each pixel in the input image as either belonging to class '1' or '0'. The '1' and '0' represent different categories or characteristics the model is trying to distinguish. Prediction: The final prediction for the entire image is made by taking the average of the results obtained for each individual pixel. This means that the model considers the collective information from all pixels to arrive at an overall classification for the entire image [29].

3.1.1.5.5 DISCRIMINATOR D2

In the case of the second discriminator, it follows a structure known as patch GAN, which uses a patch size of 16×16 pixels. The network architecture consists of convolutional layers followed by batch normalization and rectified linear unit (ReLU) activation, and it has a total of five hidden layers.
The key distinction between patch GAN and Pixel GAN lies in their prediction targets. Unlike Pixel GAN, which focuses on classifying individual pixels, patch GAN predicts patches of the image, each of size N×N, where N is determined such that N^2 equals 16 (in this case, N = 4). This means the discriminator assesses and categorizes image patches instead of individual pixels. The final prediction for the entire image is then determined by averaging the predictions made for all the patches present in the input image. In essence, the model considers the collective

information from these patches to arrive at an overall classification for the entire image [31].

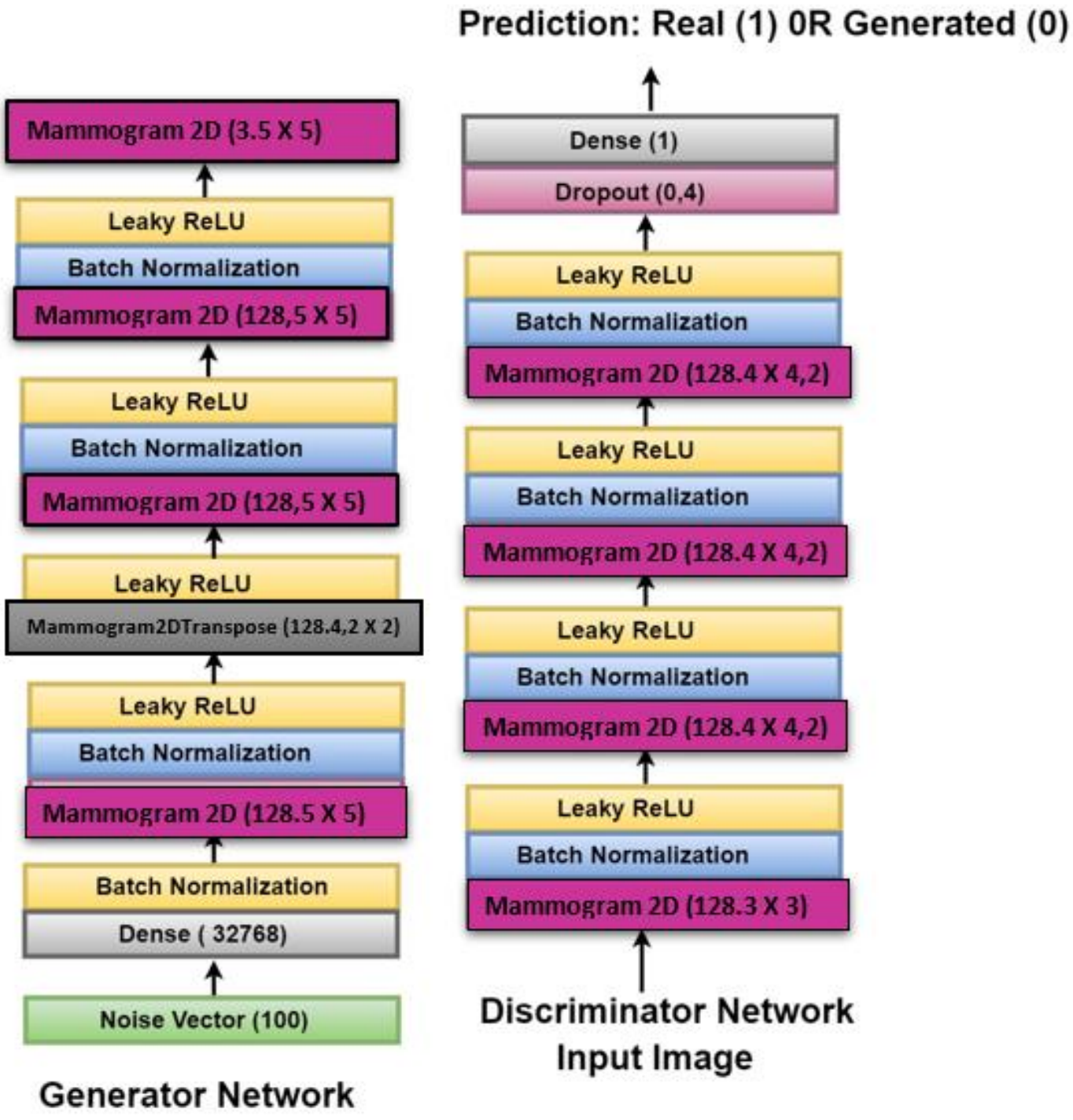


Figure 25: Flow Chart of GAN, Real or Fake Out Put Procedure

3.1.1.6 DISCRIMINATOR D3

In the case of the third discriminator, the patch size is not fixed but rather ranges from 16 × 16 to 70 × 70 pixels. This variation in patch size is a deliberate design choice. In research and literature, it has been observed that a patch size of 70 × 70 pixels tends to yield better results. This is because a larger patch size, like 70 × 70, can encompass global features of the image. The advantage of using a 70 × 70 patch size is that it allows the model to capture broader contextual information and global patterns within the image. Despite this increased coverage, the number of parameters involved is reduced compared to considering the entire image. This reduction in parameters is beneficial as it helps manage computational complexity and resource requirements while still achieving effective analysis of global image features [33].

3.1.1.7 DISCRIMINATOR D4

In the fourth discriminator, a different approach is taken by utilizing a full image discriminator. This means that the final prediction is derived by considering the entire image, rather than breaking it down into patches. The network architecture for this discriminator comprises one input layer, five hidden layers structured as convolution batch normalization real, and a final output layer.

3.1.1.8 Model Architectures

The generator is divided into eight blocks, with four 3 × 3 convolutional layers that use batch renormalization and are followed by either an upscaling or downscaling layer. Convolutions with a stride of two are used in the downscaling layers, which are then followed by dropout, batch normalization, and leaky ReLU. Conversely, upscaling layers include dropout, batch-renormalization, leaky ReLU, and deconvolution with a stride of 1/2. As stated before, we include skip connections in the generator. We use a 1 x 1 convolutional layer for feature transfer across blocks, just as the Res Net method. The discriminator uses a Dense-Net design, with four transition layers and four dense blocks. Four convolutional layers make up each dense block, which ends with a dropout layer. Dropout's ability to effectively avoid overfitting is the primary factor in the choice to use it at the last layer [34].

3.1.1.8.1 Optimization:

We utilize the standard approach to improve our networks: we update one gradient-decent step on D, then one step on G. The model was trained to employ **algorithm 1**.

Algorithm 1: Training algorithm for our model

Input: gradient penalty coefficient δ, Adam Parameter $\alpha, \gamma_1, \gamma_2$, *batch size k, input image* x_i
Input: discriminator parameter φ_0, generator Parameter α_0

While α not converged do
  for t = 1,2,3…… do
    for i = 1,2, 3, ……., k do
      Sample real data x_j, random noise from Eq. (1), random number $\in \sim \mu(0.1)$;
      $x_g = G_\theta(Z, x_j)$;
      $\hat{x} = \in x_i + (1-\in) x_g$;
      L^i = Eq. (4) + Eq. (5);
    end
    $\varphi \leftarrow$ Adam ($\nabla_\rho \varphi \frac{1}{k} \sum_{i=1}^{k} D_\varphi(x_g)$), $\rho, \alpha, \gamma_1, \gamma_2$);
  end
  Sample batch of laten variable $\{ Z_i \}_{i=1}^{k} \sim \Gamma(0.I)$;
  $\psi \leftarrow$ Adam ($\nabla_\varsigma \frac{1}{k} \sum_{i=1}^{k} D_\psi(x_g)$), $\varsigma, \alpha, \gamma_1, \gamma_2$);
end

CHAPTER 4

PROPOSED TEATMENT METHODLOGY

In this research work, an article was published by Zahid et al., 2023 to "**Treatment of chronic disease using Gold Nano Thermo Robot (GNTR) empowered with nanotechnologies approaches"** [1]. This research proposed a treatment of breast cancer using proposed GNTR based "**Heat Control System"** to control heat intensity has been maintained at 38 C^0 to 42 C^0 at different time of intervals used to specific targeted therapy saving surrounding healthy tissues to destroy. Due to worldly chronic disease, medical scientists, and researchers all over the world are investigating for save treatment techniques for this deadly disease. Recently, much hyperthermia based treatment approaches have been introduced but instead of better results, have many sad effects. This paper introduces a new approach to how to create heat, store heat and control heat and how to use it for safe treatment using the GNTR enabled with nanotechnologies techniques endowed in nanomedicine [1].

4.1 Design Methodology of Proposed "GNTRs"

The following is a step-by-step explanation of the proposed **"GNTRs"** approach.

4.1.1 Morphology of Proposed "GNTRs"

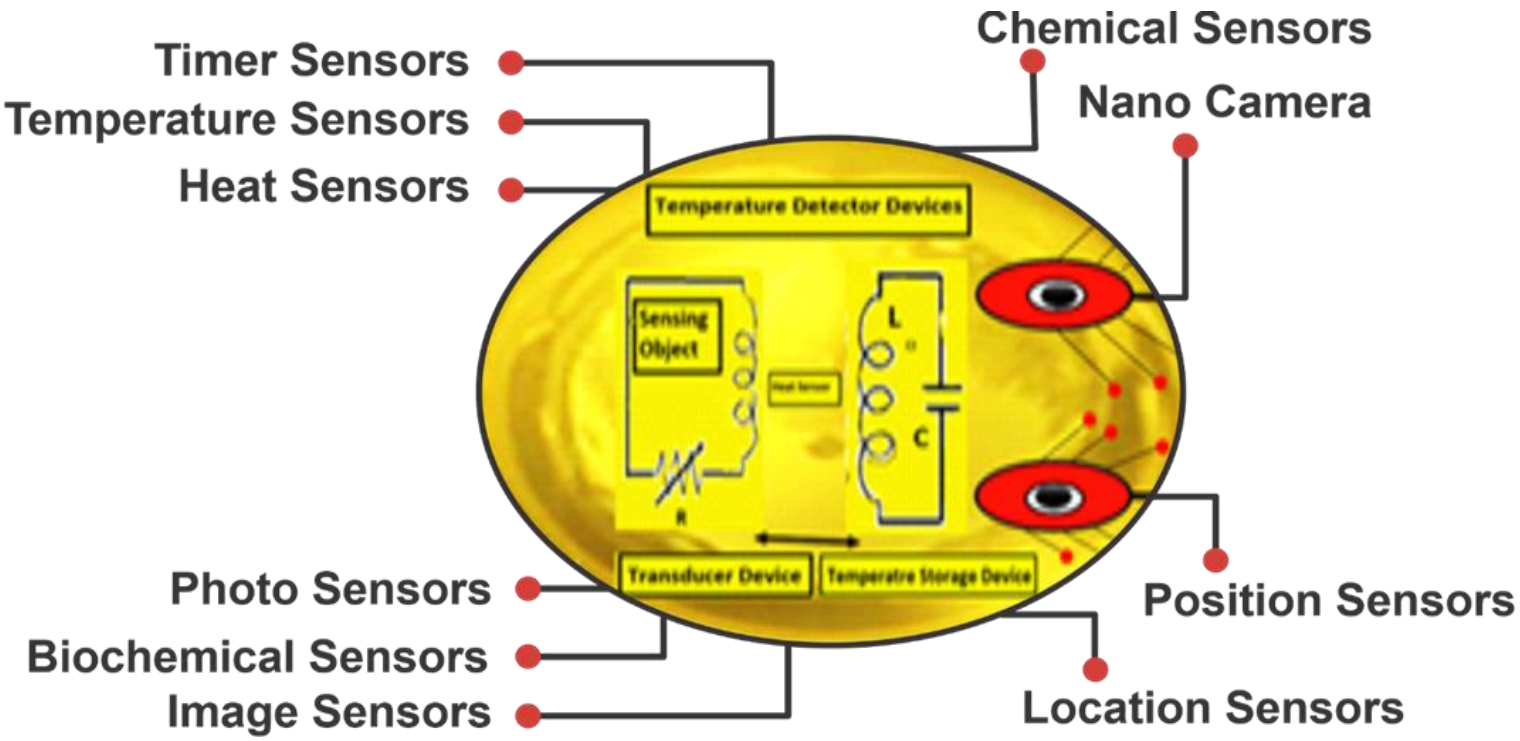


Figure 26: Proposed Design Methodology of GNTRs

The suggested **GNTRs** are crafted from gold, one of a crucial material for transmitting electrical signals throughout the body. Gold possesses the unique ability to absorb and release heat within a controlled approach. Moreover, gold compounds have garnered significant attention for their potential as anticancer agents. Gold nanoparticles (AuNPs) act a vigorous part in cancer research and treatment through reason of their exceptional amazing magical possessions, including surface enhanced "Raman spectroscopy", "controlled synthesis", "surface plasma resonance", "biological safety", constancy and "adaptable surface morphology", [1]. The design of these nano robots is inspired by the structures of unicellular biological organisms like Chlamydomonas. These structures enable these organisms to efficiently carry out their tasks. The incorporation of this structural inspiration is aimed at enhancing the performance of the nanorobots in their intended functions. The nanorobots are envisaged to exhibit prompt and controlled responses, resembling the efficiency seen in the biological organisms from which their design is derived. This integration of gold's unique properties and biomimetic design principles positions these nanorobots as promising tools, especially in the realms of cancer diagnosis and therapy.The use of nanomotors with a sophisticated sensor array to create a versatile and efficient system for targeted cancer therapy has been applied in this reseach.

4.1.2 Key Components of Proposed GNTR

The envisioned GNTRs introduces a dynamic control mechanism for nanomotors, revolutionizing cancer treatment by executing predetermined tasks. By utilizing nanomotors, this invention departs from the conventional lesion-targeting nanoplatforms and demonstrates improved capabilities for deep tumor penetration through their autonomous approach. By using their distinctive characteristics to facilitate more efficient infiltration into tissue from tumors, nano-motors provide a

contemporary attempt to malignant cells remedy that may improve the precision and efficacy of therapeutic interventions. Every nanorobot is tracked by a marine network implanted inside the patient's body, delivering accurate topographical information. A heat sensor, heat storing, photosensor, position sensor, chemical sensor, timer device, temperature transducer device, and heat storing device are just a few of the revolutionary Nano sensors included in the construction of this proposed nano theopoetic device. The precise position of the nanorobots inside the body is accurately determined by the nano camera. Actuators, sensors, power supplies, control systems, communication devices, other interfacial elements are all involved in the construction of nanorobots [77]. The novel features of the proposed GNTR model are shown in **Figure 6**.

4.1.3 Discrete Mesh Process of Proposed GNTR

Gold demonstrates outstanding heat conductivity owing to the arrangement of its atoms, facilitating the swift and effective transfer of thermal energy. Heat transfer manifests through three primary mechanisms: radiation, convection, and conduction. In our exploration, our specific emphasis has been on the conduction method. Conduction entails the movement of heat within a material through direct contact between atoms or nodes, as elucidated in **Figure 27.** The physical space is split up into a finite number of distinct points, or nodes, during the discretization technique. As shown in **Figure 27**, one such node symbolizes the gold rod within the **"GNTRs".** A system of equations defining correlations between the unknown temperature values at these discrete spots replaces the partial differential equation (PDE) controlling heat flow. These equations express the mathematical temperature differences between a location and its neighbor. They are referred to as different equations. The "Gold Nano Rod," which exhibits linear behavior, is the material domain for a one-dimensional heat equation. This line is broken down into a finite number of points, or nodes, in the discretization method. Every node is given a value as seen in **Figure 27**.

4.1.4 Composite Interior Discretize Mesh Procedure of Proposed GNTRs

If the interior structure of the envisioned "GNTR" is made up of several gold straight rods, then it might be considered a hierarchical arrangement of fundamental building components. To put it another way, each of these rods is further made up of small atoms known as mesh-discretized nanoparticles. This internal structure is created by discretizing nanoparticles or atoms utilizing a versatile and scalable technology that enables precise control as well as manipulation at the nanoscale.

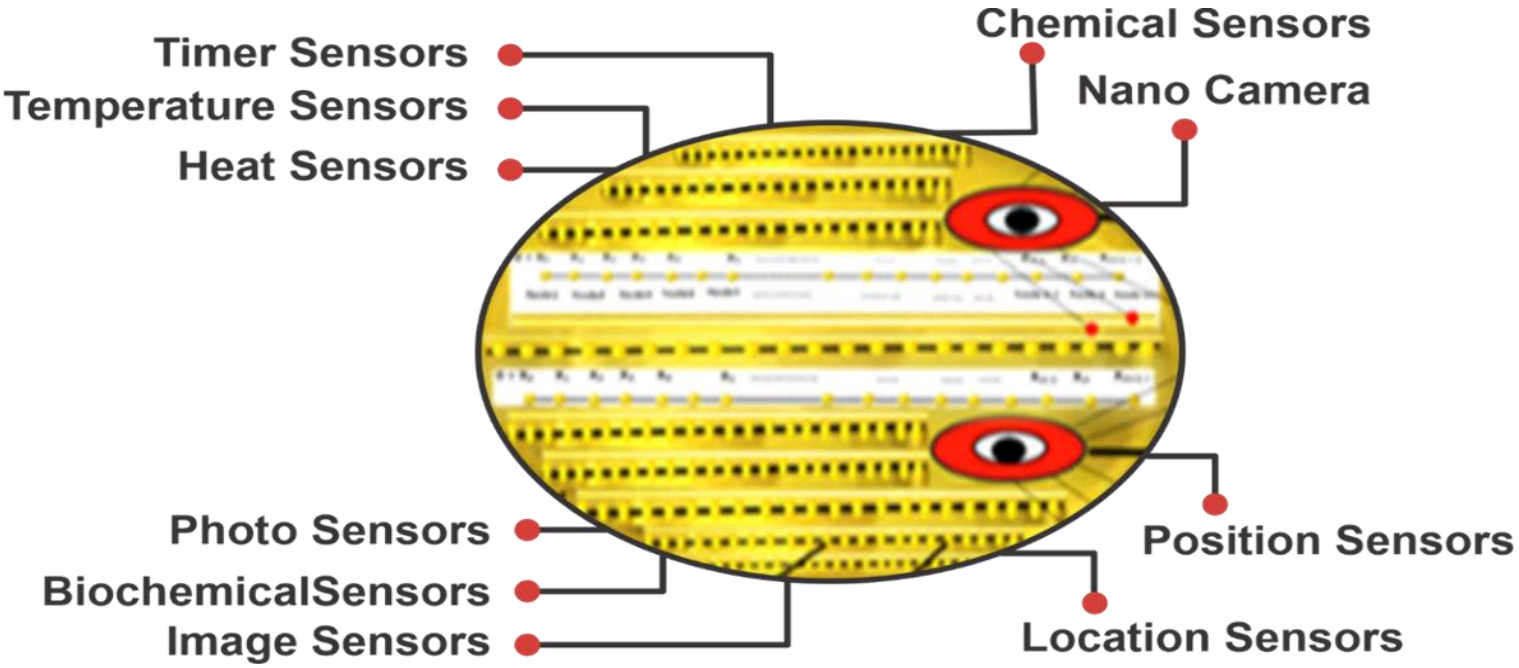


Figure27: Discretization mesh of proposed "Gold Nano Thermo Robot " (GNTR) [1].

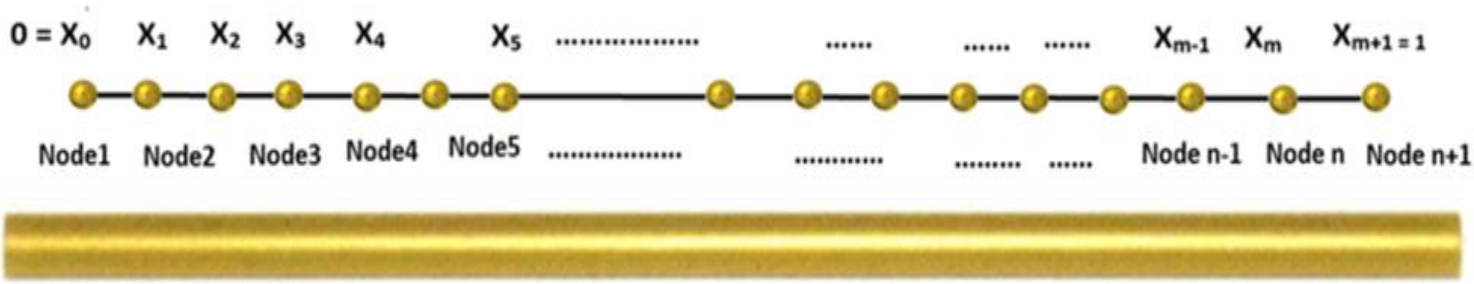


Figure28: Discretization mesh of Gold Rode of GNTR

According to the hypothesis, the "**GNTRs**" whole interior volume is split up into many uniform lengths of gold nano-rods. As seen in **Figure 27**, every single nano-rod is made up of an n+1 node building design. During the discretization manipulation, the actual physical area is split up into an infinite amount of distinct points, or nodes. Using one example gold rod, shown in **Figure 27**, the partial differential equation (PDE) controlling heat transmission is replaced by a set of equations that define correlations between the values of the unknown quantity at these particular locations.

4.1.5 Mechanism of action of Proposed GNTRs

Using modern technology, the novel "Gold Nano Thermo Robot" (GNTR) functions as a ground-breaking nanotherapeutic device. This device carefully collects inside data,

including biomarkers, temperature, and photos, by integrating nanosensors, heat sensors, and nanocameras. ECG and pulse oximetry nanosensors track blood oxygen levels and cardiac activity [1]. Heat intensity is controlled by a temperature storage mechanism between 38°C and 45°C. **Figure 29** demonstrates how a coulomb-explosion approach produces heat waves and microbullets in the treatment environment when a cluster of GNTRs with a radius of 10.0 nm is subjected to a 10.0 ns laser pulse. With a pulse length ranging from 10.0 to 40.0 ns, the heat intensity and nanobullet radius rise from 5.0 to 10.0 nm [1]. As demonstrated by the proposed GNTRs, the suggested nanotherapeutic device could regulate heat intensity between 33°C and 45°C, which is high enough to cause damage to malignant cells with a radius of 8.0 to 13.0 μm. While a temperature detection gadget keeps an eye on the temperature, a transducer device helps deliver heat to the tumor. Nano-sensors and nano-cameras use a revolutionary **"See and Treat"** approach to track vital signs and gather comprehensive health information from within the body. For real-time data flow, this data is sent via gateways and in-body networks. While exterior devices, for instance wearables strategies, facilitate user cooperation, implantable devices improve monitoring. Patients as well as physicians can easily use the user-friendly interface of digital mobile devices. By integrating internet technology, the GNTR may communicate with medical specialists and get treatment recommendations and diagnoses remotely. This integrated architecture revolutionizes nanomedicine and greatly improves access to medical knowledge by enabling accurate, real-time monitoring of healthcare. Through the use of digital devices, patients actively interact with their medical records, enabling remote medical help and accurate real-time diagnosis, which ultimately improves patient care and makes it easier for medical professionals to treat patients [99].

4.1.6 Inter Body Communication Network

The “IBCN” architecture, which was created for the treatment of breast malignant cells, represents an advanced paradigm in oncology. This innovative approach to treating breast cancer might lead to significant changes in patient outcomes, efficacy, and accuracy. This all-encompassing strategy requires the use of the synergy of state-of-the-art technology to provide highly customized, real-time services. This facilitates real-time monitoring of individuals, allows therapy to be adjusted depending on individual needs, and increases patient engagement [53]. Many different components are included in this modern system: implanted devices, digital mobile mobile phones and tablets, body-area-network (BAN) devices, gateways, in-body networks, nano-cameras, pulse-oximetry, nano-micro interfaces, and nano-sensors for ECG, blood pressure, and heat. Among these, nano-sensors are particularly important since they record the heart's electrical activity in high detail, providing crucial data on cardiovascular health. Blood pressure nanosensors are used to monitor vascular dynamics, which enables a comprehensive evaluation of the person's general well-being [54].

4.1.6 Ion MT's Function in the Nanotherapeutic System

Temperature sensors are incorporated into the design to function as watchful indications of any aberrant tissue activity or localized inflammation. When anomalies are found, nano-cameras are activated. These devices serve as potent imaging instruments that offer a thorough visual depiction of the impacted region in real-time. This all-inclusive method enables dynamic and responsive therapeutic approaches catered to the individual demands of each patient, in addition to enabling accurate monitoring of hyperthermia throughout breast-cancer therapy [78]. Treatment for breast cancer has advanced dramatically with the addition of a novel nanorobot device to the Ion MT construction. This device has a wide range of sensors, devices, and an accurate temperature control system. With its innovative technique, which combines precision, customization, and real-time reactivity, breast cancer may be effectively prevented by localized heat treatment. Error-free information flow is made possible by the nano_robot's integration with the body's network of sensors and cameras, which is made possible via nano_microscopic interfaces. This complex system uses cutting-edge digital signal processing to guarantee efficient data collecting and transmission. The raw data is subsequently sent to the gateways, the architectural centre of gravity, where it is conveyed via "IBCN" and acts as an information circulatory system.

In this framework, gateways are essential components that act as interfaces between "IBCN" and the outside environment. Before sending the data to external devices for example "BAN" devices, gateways aggregate, modify, and encrypt it to protect patients' data integrity and confidentiality. These gadgets function as extensions of the interbody network, enabling patients to communicate with their real time physical condition records using exterior interfaces like digital portable phones or tablets. They are frequently incorporated into wearable technology or smart clothing. This design uses the connection to reduce the gap involving patients and medical professionals in the era of widespread internet technology. Data is gathered by nanosensors and other devices and is readily transmitted over secure internet connections to data centers and remote medical professionals. This communication in real-time changes the methodology to breast tumor care has changed from a fixed, employment-based strategy to a dynamic, data-driven one by this real time communication, allowing for continuous assessment and surveillance.

The sensors for the measurement of pulse oximetry are incorporated to provide continuous oxygen saturation level monitoring, which is crucial for assessing respiratory health in general and especially helpful for patients receiving cancer therapy. Implanted devices provide information on how well a treatment works, allowing for quick adjustments and reducing side effects, particularly for patients undergoing chemotherapy [87]. Treatment for breast cancer is now patient-focused because of the cooperation of several technologies. Healthcare professionals and patients may easily exchange information through wearable body-area network devices.

Breast cancer therapy has become a dynamic, patient-centered process because of medical experts' ability to remotely monitor patients' progress, evaluate data trends, and make well-informed judgments. The Nano-camera is a crucial part of this suggested strategy as it is essential to the "**See-and-Treat"** method. The employment of nano-cameras in breast malignance treatment allows real-time monitoring of the absorption of nanorobots in malignance cells throughout thermal cure, improves the accurateness and exactness of cancer treatment, and directs processes. By shortening the interval between diagnosis and therapy, the **"See-and-Treat"** approach promotes prompt and effective treatments. **Figure 29** details the internet medical nano-things' whole operational mechanism.

Figure 29: Proposed Inter Body Communication Network Architecture

Coulomb-Explosion Method

This part presents a coulomb-explosion approach intended to generate hotness for molecular and nano-atomic targeted heat treatment against malignant cancerous cells. This model makes use of the elliptic structure of the GNTRs and the remarkable characteristics of gold to deliver powerful and brief heat pulses via the Coulomb-explosion phenomena [87]. The suggested GNTRs absorb laser energy and cause a quick temperature to rise when exposed to brief laser pulses. When the laser energy interacts with the nano-robots, it transforms

into heat energy, a mechanism called photothermal heating [88]. The length, concentration, and inclusion properties of the laser pulse, among other things, affect how quickly the high temperature of the nano machines rises. Nonlinear effects appear at a certain temperature threshold, which causes micro-bubbles to grow on the surface of the nano-robots. Due to the high pressure and temperature, these bubbles enlarge quickly before bursting, generating audible waves that may be heard by ultrasonic monitoring [70]. The complex physical processes entailing bubble formation, high energy shockwaves, and the production of significant temperature for thermotherapy are schematically depicted in **Figure 30.**

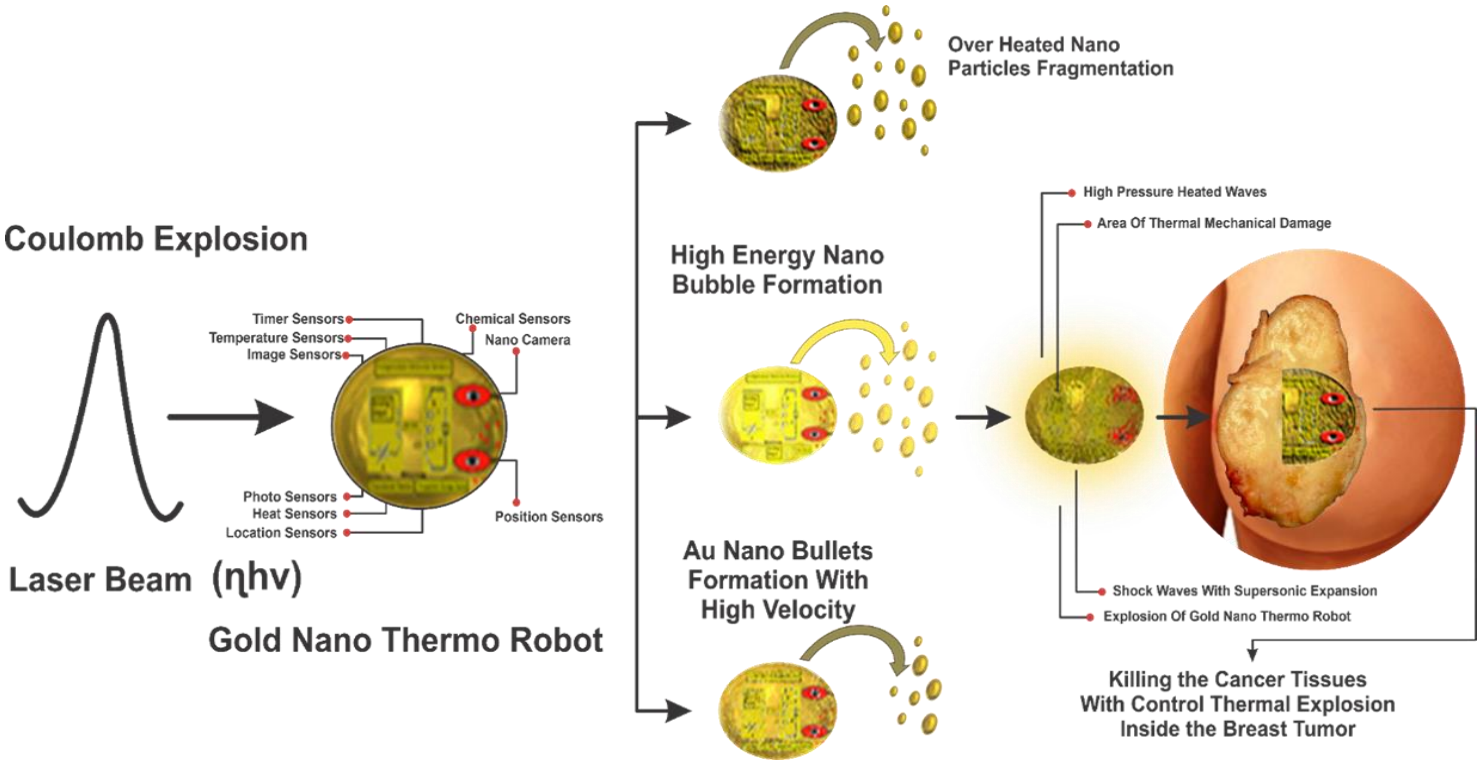


Figure 30: Schematic coulomb explosion procedure flowchart

By carefully adjusting the heat therapy's strength, this elevated temperature may be used to harm cancer cells and cause them to die. To specifically kill cancer cells, this treatment strategy involves heating malignant tissue between 38°C and 45°C. The "**GNTRs**" absorbs radiation energy in the thermal expansion mode, which causes a localized material expansion and a sharp rise in surface temperature. Heat transmission within the nanorobot is influenced by this transitory variation of its thermal conductivity. "**GNTRs**" are excited to higher electronic states by short laser pulses that lie within the Surface Plasmon Resonance spectral band. This is achieved by the absorption of multiple photons. The efficient transformation of grasped photon energy into heat energy via electron-phonon coupling is necessary for the quick relaxation of "**GNTRs**" atoms to their ground state. This process is carefully

regulated by a “heat control system” [1], to preserve the necessary target temperature limit. The flow diagram shown in **Figure 31** illustrates the full Coulomb explosion process. Different effects can happen depending on the “**GNTRs”** temperature, Z. These include the 'classic' photoacoustic (PA) phenomenon, which produces linear acoustic waves because of the growth of a single **“GNTRs”** and the thin fluid layer around it. Z_GNR, or the “**GNTRs”** melting point, is ~ 1063 C^0, and Z_LV≤ -Z< Z_GNR. Another result is the development, expansion, and collapse of bubbles, together with the sound and shockwaves that are produced. The Gold-Nano-Robot reaches its boiling point at greater temperatures, which causes liquid gold droplets to encircle vaporized gold. The melting point is at 1063 °C, while the boiling point is roughly 2719 °C [88].

4.1.6.1 Time Scale Calculations

Determining the value of the threshold laser energy concentration (Exp ρ) necessary to attain the thermal expansion state is the goal of the theoretical modelling. This technique minimizes the effect of heat diffusion by quickly overheating a heavily absorbing object during a brief laser pulse [80]. First, let us evaluate the thermal relaxation timeframe due to heat diffusion from the nanorobot surface. For an elliptical GNTR, the thermal relaxation time may be calculated as e_T = R^2/6.75k, where k is the thermal-diffusivity, in the vicinity of the **“GNTRs”** (GNR) with - $GNR \leq 5R$, here R is the nano machine's radius [87]. An approximation of 2.6, 10, and 41 ns is given for R = 50, 100, and 200 nm. We may disregard heat losses from the GNTR surface resulting from heat diffusion into the surrounding medium for laser pulse durations e_P < e_T, as heat is created within the **GNTR**s more quickly than it can be diffused away. It is legitimate to use picosecond as well as femtosecond laser pulses with smaller **“GNTRs”**. Here, however, we will focus on nanosecond pulse durations because most experimental results both ours and others'—have been obtained using lasers typically used in the biomedical field (e_P ~ 5–12 ns), which are less costly and less damaging to normal tissue than picosecond and femtosecond lasers while still meeting the requirement that e_P ≤ e_T for relatively large gold nano robots. Determining the laser-induced thermal explosion threshold energy during the Coulomb explosion is a crucial step in this process. This information plays a major role in determining the laser settings required to provide the desired temperature impact without unnecessarily injuring the surrounding healthy tissue. With precise control over the laser's intensity, physicians can guarantee that the energy of the beam is enough to cause thermal damage to the tumor without triggering a complete Coulomb-explosion, which might have detrimental consequences [69].

4.1.6.2 Threshold Intensity for Laser Induced Thermal-Explosion

Suppose that a specified region, such as a cancerous breast tumor, is selectively exposed to laser irradiation at the intensity I, employing a nanoparticle, namely a **"GNTRs".** Given the absorption cross-section of the **"GNTRs"**, abs, we can find the strength of the absorbed electromagnetic field (P) as follows: =abs P=σabs I [70]. A thermal explosion of the **"GNTRs"** may happen at specific values of the threshold laser intensity exp Expo ρ, if abs is big enough. This threshold intensity is lower than the optical plasma generation threshold in the surrounding medium. Au 1ρqV = -NAuq1V is the amount of energy needed for the entire thermal explosion of "GNTRs," whereas expel = / expel = R / us is the energy that the gold nanoparticles of -GNTRs absorb throughout the inertial retention period in a vapour condition. This energy is more than what might be needed if the "GNTRs" were completely abandoned.. The variables in this case are volume (V), density (ρ), number of Au atoms per unit volume (AuNAu), sound velocity in Au vapor at critical temperature cr ≈ GNRBU cr ≈ UGNRB (us), and nanogold nodes (q and 1q1) of the proposed "Gold Nano Robot". Compared to expel=expel=R/us (~1 ps for ≈10R≈10 nm), where expel is the explosive evaporation period, the laser pulse duration eL (~1 ns) is significantly longer. Using absorption efficiency abs=abs / (2) E abs = σ abs/ (πR2), the energy balance equation abs exp l ≈ σ abs I exp l R/us ≈ ρ q v is used to compute Eexp ρ. Figure 31 shows the laser energy threshold strength required to cause the thermal explosion of the rod-shaped gold nanoparticle. The **"GNTRs"** transforms into a gas (vapor) with a radius of about R, containing high-temperature ≈ GNRBU ≈ UGNRB and high pressure ≫∞P≫P∞, where ∞P∞ is the ambient pressure, in a moderately powerful laser field with intensity > exp l I ≥ I exp l during the brief time expel≈/expel ≈ R/us. The underlying premise of this analysis is that the thermal explosion of a "GNTRs" results from the production of shockwaves with ultrasonic velocity =/expel = expel / (4Δ) ≈ -105 cm / sus = R / expel = Expel / (4ΔH) ≈ 105 cm / s, where Δ = Δ -300 − vap + Δ vap ΔH = ΔH 300 − vap + ΔH vap, and Δ300−vapΔH300−vap is the enthalpy change per unit volume for heating the **"GNTRs"** from ambient high temperature to the -vaporization high-temperature, and Δ vap ΔH vap is the vaporization enthalpy per unit volume. Around the explosion's core, the shockwaves may be waves with strong acoustics that travel farther. **Figure 31,** depicts the full Coulomb explosion process, including the formation of conservative bubbles and shock waves during the laser stimulated thermal development of the elliptic constructed "GNTRs".

4.1.7 Heat Control System Methodology

The procedure of understanding and using the principles of heat transfer to sustain a exact temperature for a predefined period of time is necessary to develop a mathematical pattern for the heat controller mechanism applied in thermal rehabilitation for breast malignance. The recommended approach controls heat intenseness at 42°C for 30.0 minutes using the heat conductivity calculation, a version of the heat calculation that expresses how warmth circulates across a medium

over time. The nanotherapeutic system must be applied with the appropriate boundary and commencement conditions in order to keep the temperature at 42°C for the full 30.0 minute period. Temperature border line conditions surrounding the perimeter of the body area being treated must be stated, depending on the specific treatment arrangement. The system would normally adjust the temperature to 42°C at the outer edges of the zone of focus. The temperature distribution at the start of the therapy is represented by the starting condition. The system must identify the initial distribution of temperatures in the treatment zone as well as the treatment's time course. One of the numerical methods the system uses to gradually solve the 2D heat equation is the finite difference approach. This approach changes the ambient temperature values at all grid points periodically and discretizes the spatial and chronological variations in the calculation [70]. The total layout of the heat-management system is illustrated in Figure 36, providing a visual representation of the whole strategy utilized to regulate temperature during thermal therapy for breast cancer.

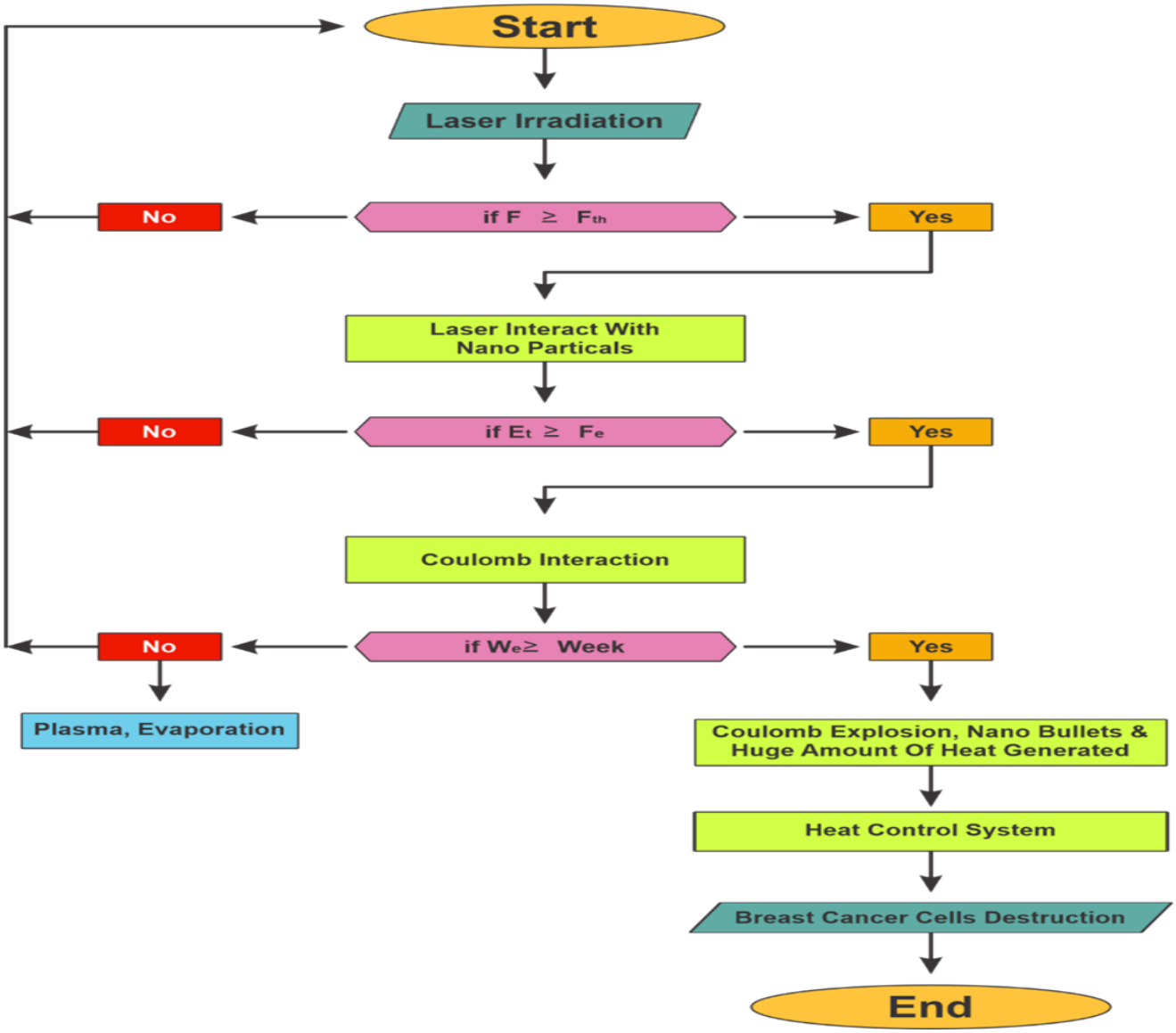


Figure 31: Procedure of Coulomb Explosion

4.1.8 Mathematical Model

With two variables that are independent along with a dependent variable, the general second-order linear equation with partial differential equation (PDE) may be formulated as follows:

$$\kappa \frac{(\partial^2 Z)}{\partial x^2 Z} + l \frac{(\partial^2 Z)}{\partial x \partial Z} + m \frac{(\partial^2 Z)}{\partial y^2 Z} + \delta = 0 \qquad (1)$$

Here, we used k,l,m as a functions of independent variable and the derivative of $\frac{\partial Z}{\partial x}$ and $\frac{\partial Z}{\partial y}$ are used. If l^2- 4km = 0, Equation (1) is used as refers of parabolic-partial-differential equation. As illustrated in Figure 36, For the heat conductivity equation, we employed a gold metallic bar from the suggested GNTR's construction as a model. The following illustrates one dimension of the heat formula.

$$k\frac{(\partial^2 Z)}{\partial x^2 Z} = \frac{\partial Z}{\partial t},\ 0.0 \leq x \leq 1.0, t \geq 0.0 \qquad (2)$$

Temperature, position, and time are considered as functions of Z, where Z (x, t), t The measurement of the thermal diffusion coefficient is expressed as l β/ρC, where β is the coefficient of thermal conductivity of the gold metal and ρ is the density of the gold bar. Equation (1) represents a model of the thermal equilibrium of a gold bar with a thickness of L. An endlessly long duration, semi-infinite width strip is the domain of solution. The correct answer in a practical computation is only obtained for a certain period, t/max.

Equation (1) may be solved by defining beginning conditions at t = 0 and boundary conditions at x = 0.0 and x = L. Z (0.0, t) = Z_0.0, Z (L, t) and Z, Z (x, 0.0) = f_0 (x) are the simple boundary and beginning conditions. To determine the total amount of heat Z in x, y, and t as time passes, the steps for all variation in x, y, and t are as well as in that order, i, j, and k. Using the following formula, we can get Z's solution:

Z (x, y, t) = $Z_{i,j}^K$,

$$l\left(\frac{\partial^2 Z}{\partial x^2} + \frac{\partial^2 Z}{\partial y^2}\right) = \frac{\partial Z}{\partial t} \qquad (3)$$

The superscript β represents the Z time step. A finite technique such as this one might be used to write a two-dimensional heat equation:

$$\left(\frac{Z_{i,}^{\beta+1} - Z_{i,}^{\beta}}{\Delta t}\right) = l\left\langle\frac{Z_{i+1,j}^{\beta} - 2Z_{i,j+}^{\beta} Z_{i-1,j}^{\beta}}{\Delta x^2} + \frac{Z_{i,j+1}^{\beta} - 2Z_{i,j}^{\beta} + Z_{i,j-1}^{\beta}}{\Delta y^2}\right\rangle = 0 \qquad (4)$$

If arrange the above equation by taking $\Delta x = \Delta y$ get this equation as:

$$Z_{i,j}^{\beta+1} = \gamma\left\{Z_{i+1,j}^{\beta} + Z_{i-1,j}^{\beta} + Z_{i,j+1}^{\beta} + Z_{i,j-1}^{\beta} - 4Z_{i,j}^{\beta}\right\} \qquad (5)$$

R is equal to L ($\frac{\Delta t}{\Delta x^2}$) . The heat equation may be calculated by explicit method, which will provide numerical constant at any point in time.

$$\Delta t \leq \left\{\frac{\Delta x^2}{4l}\right\},$$

4.1.8.1 Finite Difference Method

The finite-difference approach [105] is applied to solve the heat equation by calculating temperatures at various locations over a period of time within a specific area. Using this method, the domain of the gold bar is divided into a lattice of points, as discribed in **Figure 32.** The second-order partial derivatives related to temperature

are subsequently estimated using finite difference methods [105]. The discretization procedure for a one-dimensional heat equation is as follows: Equation 4 demonstrates how to divide the space of the gold-rod into a sequence of points that are uniformly spaced along the x-axis [1].If we represent Z(x, t) as the temperature at a specific point x and time t, we can approximate the second derivative of ‚Z' with respect to x using the following finite difference approximation:

$$\frac{[Z(x+h,t)-2Z(x,t)+Z(x-h,t)]}{h^2} \qquad (6)$$

Here, $\hbar$ indicates the distance among nearby points on the grid. The heat equation is then modified to include this approximate solution, turning it into a collection of ordinary-differential equations at every lattice point. Numerical methods like Euler's method and Runge-Kutta method are capable of helping solve these outcome ODEs [105]. At every time step, the outcome is revised iteratively, predicting the ambient temperature at every point on the grid by utilizing the values of nearby sites along the gold nanorod [1].

A multifaceted heat equation is discretized by splitting the domain into an x-y planar lattice of points [1]. The proposed system may estimate the two subsequent partial derivatives of temperature concerning x as well as y by employing finite-difference approximations, as follows:

$$\frac{[Z(x+h,y,t)-2Z(x,y,t)+Z(x-h,y,t)]}{h^2} \qquad (7) \quad \text{(Used for x direction)}$$

$$\frac{[Z(x,y+h,t)-2Z(x,y,t)+Z(x,y-h,t)]}{h^2} \qquad (8) \quad \text{(Used for y direction)}$$

4.1.8.2 Forward Time Central Space (FTCS) Scheme

FTCS is an explicit scheme [101], as the island in **Figure. 33**, which means $\{Z_i^{K+1}\}$ can be explicit if the values of Z at the proceeding-interval level n are identified. Therefore, the FTCS scheme has been used to solve our problem as described in the equation- (9)

$$.\frac{Z_i^{\beta+1}-Z_i^{\beta}}{\Delta t} = \frac{\alpha}{\Delta x^2}\ (Z_{i+1}^{\beta} - 2Z_i^{\beta} + Z_{i-1}^{\beta}) \qquad (9)$$

Since $\left\{\mathrm{R} = \frac{\alpha\Delta t}{\Delta x^2}\right\}$, R is counted as mesh Fourier quantity.

4.1.8.3 Backward Time Central Space (BTCS) Scheme

As shown in **Figure 33**, BTCS is an implicit scheme [34], meaning that each time step's temperature has been calculated by an iterative set of linear equations. The BTCS method has been designed for this purpose, as stated in Equations 11 and 12.

$$(Zt)_i^{\beta+\frac{1}{2}} = l\,(Z_{xx})_i^{n+\frac{1}{2}} = \frac{l}{2}\left[(Z_{xx})_i^{\beta} + (Z_{xx})_i^{\beta+1}\right] \tag{10}$$

Z_{xx} is now applied to the system at the $(\frac{\beta+1}{2})$ time level by summing the data from the previous and current times utilizing m and m+1, correspondingly. Equation (14) describes an elementary second sequence central difference computation of the space-derivatives and the time imitative at the $(\frac{\beta+1}{2})$ time rank.

$$\frac{Z_i^{\beta+1}-Z_i^{\beta}}{\Delta t} = \frac{\alpha}{2}\left[\frac{Z_{i+1}^{\beta} - 2Z_i^{\beta}+U_{i-1}^{\beta}}{\Delta x^2} + \frac{Z_{i+1}^{\beta+1} - 2Z_i^{\beta+1}+Z_{i-1}^{\beta+1}}{\Delta x^2}\right] \tag{11}$$

$$Z_i^{\beta+1} = Z_i^{\beta} + \frac{r}{2}\left[\left(Z_{i+1}^{\beta+1}\, 2Z_i^{\beta+1} Z_{i-1}^{\beta+1}\right)\right]\frac{1}{\alpha}\left[\frac{Z_i^{\beta+1}-Z_i^{\beta}}{\Delta t}\right] =$$

$$n\left[\frac{Z_{i+1}^{\beta}-2Z_i^{\beta}+Z_{i-1}^{\beta}}{(\Delta x)^2}\right] + (1-n)\left[\frac{Z_{i+1}^{\beta+1}-2Z_i^{\beta+1}+Z_{i-1}^{\beta+1}}{(\Delta x)^2}\right] \tag{12}$$

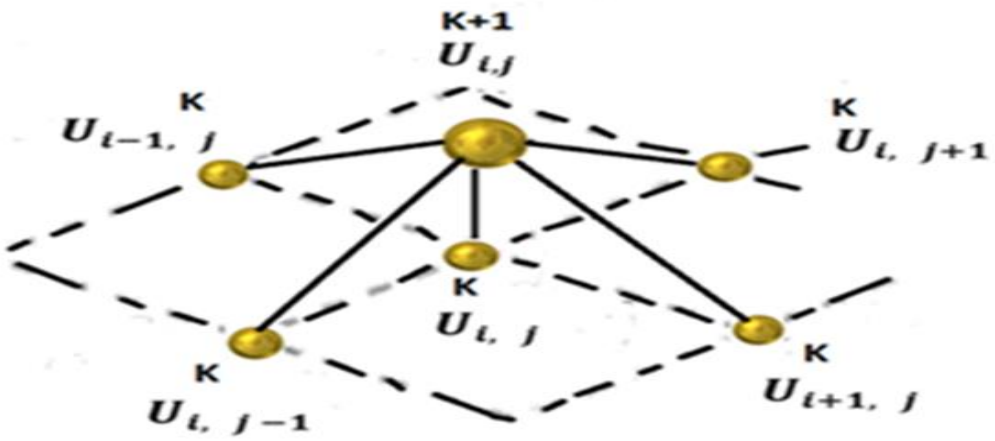


Figure 32: Explicit Method Stencil

Now, when n = 1 is entered into Eq. 17, the system will revert to the explicit structure [101], as seen in Figure 35, and will switch to the implicit structure [102], as indicated in Equations 4 and 5 above, when n = 0 is entered.

$$\frac{1}{\alpha}\left[\frac{Z_i^{t+1}-U_i^t}{\Delta t}\right]=\left[\frac{Z_{i+1}^t-2Z_i^t+Z_{i-1}^t}{(\Delta x)^2}\right] \quad (13)$$

$$\frac{1}{\alpha}\left[\frac{Z_i^{t+1}-Z_i^t}{\Delta t}\right]=\left[\frac{Z_{i+1}^{t+1}-2Z_i^{t+1}+Z_{i-1}^{t+1}}{(\Delta x)^2}\right] \quad (14)$$

Let select n = 0.5 in our problematic in among 0.0 and 1.0

$$=\frac{1.0}{\alpha}\left[\frac{Z_i^{t+1}-Z_i^t}{\Delta t}\right]\ 0.5\left[\frac{Z_{i+1}^t-2Z_i^t+Z_{i-1}^t}{(\Delta x)^2}\right]0.5\ \frac{Z_{i+1}^{t+1}-2Z_i^{t+1}+Z_{i-1}^{t+1}}{\Delta x} \quad (15)$$

Each of the nodes in the chosen **"Gold Nano Rod**" will have these equations applied to them, resulting in a approach with a tri-diagonal coefficient of given matrix. The mean is the Crank Nicolson- Method, [1].

$$0.5\left[\frac{l\Delta t}{(\Delta x)^2}\right]Z_{i-1}^{\beta+1}+\left[1+2\frac{l\Delta t}{(\Delta x)^2}\right]Z_i^{\beta+1}-0.5\left[\frac{l\Delta t}{(\Delta x)^2}\right]Z_{i+1}^{\beta+1}=0.5\left[\frac{l\Delta t}{(\Delta x)^2}\right]Z_{i-1}^{\beta}+\left[1-2\frac{l\Delta t}{(\Delta x)^2}\right]Z_i^{\beta}-\left[\frac{l\Delta t}{(\Delta x)^2}\right]U_{i+1}^{Z} \quad (16)$$

The statement $\left\{\frac{lt\Delta}{(\Delta x)^2}\right\}$ is referred to as the diffusion integer, and it is represented by K, i.e., K = $\frac{l\Delta t}{(\Delta x)^2}$ then Eq. 16. becomes as below:

$$-0.5KZ_{i-1}^{\beta+1}+(1+2K)\,Z_i^{\beta+1}-0.5Z_{i+1}^{\beta+1}\,0.5Z_{i-1}^{\beta}+(1-2K)Z_i^{\beta}+KZ_{i+1}^{\beta}\ \therefore \mathrm{K}\left[Z_{i-1}^{\beta+1}+Z_{i+1}^{\beta+1}\right]+\ 2(1+K)Z_i^{\beta+1}\ =K\left[Z_{i-1}^{\beta}+U_{i+1}^{k}\right]+2[(1-K)]\,Z_i^{\beta} \quad (17)$$

Equation 17., sometimes referred to as the "Crank-Nicolson scheme", is connected to boundary and beginning conditions and is described in Figure 33. Suppose that the x interval is partitioned into h equal intervals for each row duration $0 \leq x \geq 1$. The set of (h-1) linear equations for the (h-1) might then be used to identify (h-1) interior lattice points per row for k = 1.0 and, i = 1,2,3,4….h-1 [1].

$$\mathrm{TU}\ =\ \mathrm{tr} \quad (18)$$

Where the unknown U = U^{K+1} is the known concentrat

$$\begin{bmatrix} \mathbf{2(1+a)} & \mathbf{-a} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{-a} & \mathbf{2(1+a)} & \mathbf{-a} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{-a} & \mathbf{2(1+a)} & \mathbf{-a} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ : & : & \mathbf{-a} & \mathbf{2(1+a)} & \mathbf{-a} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ : & : & : & \mathbf{-a} & \mathbf{2(1+a)} & \mathbf{-a} & \mathbf{0} & \mathbf{0} \\ : & : & : & : & \mathbf{-a} & \mathbf{2(1+a)} & \mathbf{-a} & \mathbf{0} \\ : & : & : & : & : & \mathbf{-a} & \mathbf{2(1+a)} & \mathbf{-a} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{-a} & \mathbf{2(1+a)} \end{bmatrix} \begin{bmatrix} \mathbf{Z_1^{\beta+1}} \\ \mathbf{Z_2^{\beta+1}} \\ \mathbf{Z_3^{\beta+1}} \\ \mathbf{Z_4^{\beta+1}} \\ : \\ : \\ : \\ \mathbf{Z_{N-1}^{\beta+1}} \end{bmatrix}$$

(19)

$$\begin{bmatrix} \mathbf{2(1-a)} & \mathbf{a} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{a} & \mathbf{2(1-a)} & \mathbf{q} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{a} & \mathbf{2(1-a)} & \mathbf{a} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ : & : & \mathbf{a} & \mathbf{2(1-a)} & \mathbf{a} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ : & : & : & \mathbf{a} & \mathbf{2(1-a)} & \mathbf{a} & \mathbf{0} & \mathbf{0} \\ : & : & : & : & \mathbf{a} & \mathbf{2(1-a)} & \mathbf{a} & \mathbf{0} \\ : & : & : & : & : & \mathbf{a} & \mathbf{2(1-a)} & \mathbf{a} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{a} & \mathbf{2(1-a)} \end{bmatrix} \begin{bmatrix} \mathbf{Z_1^{\beta}} \\ \mathbf{Z_2^{\beta}} \\ \mathbf{Z_3^{\beta}} \\ \mathbf{Z_4^{\beta}} \\ : \\ : \\ : \\ \mathbf{Z_{N-1}^{\beta}} \end{bmatrix}$$

(20)

By convergence, it's the condition now became as

a = $\frac{l\Delta t}{(\Delta x)^2} \leq 0.5$ or a= $\frac{l\Delta t}{(\Delta x)^2} \leq \frac{1}{2}$

(21)

a = $\frac{l\Delta t}{(\Delta x)^2}$ (22)

There are issues with the condition given in equation (22). Selecting a tiny Δx is necessary to achieve sufficient accuracy, and this calls for a very small Δt for equation (22). This results in unnecessarily long calculations, which means that more time will be needed to finish the job. The Crank-Nicolson technique, which is seen in Figure 33, has been employed as a solution to these problems.

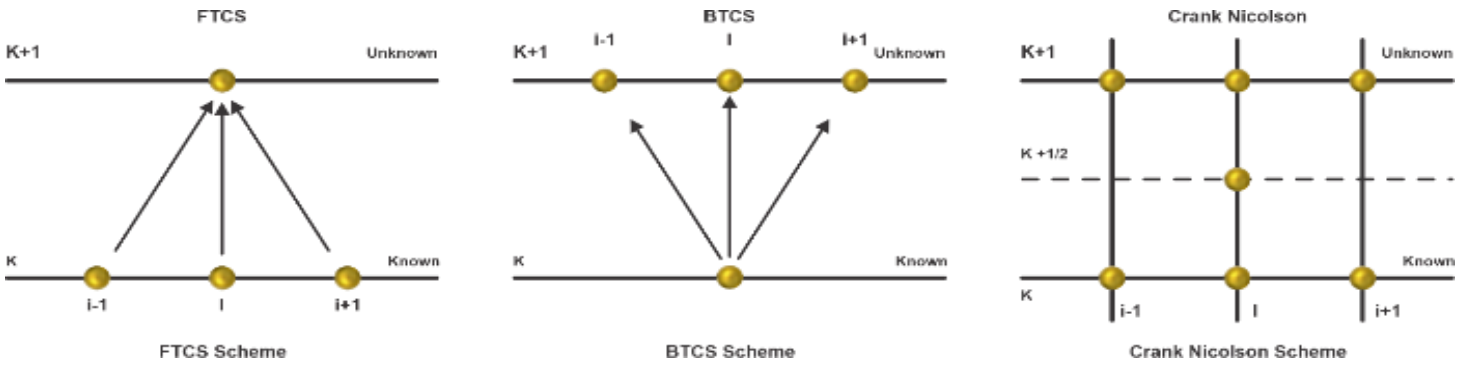


Figure 21: a). FTCS scheme, b). BTCS scheme, c). Crank Nicolson

4.1.8.3 The stability of Crank Nicolson Scheme

By applying equation (9), the result is provided below:

$$a\left[Z_{i-1}^{\beta+1} + Z_{i+1}^{\beta+1} + 2(1+q)Z_i^{\beta+1}\right] = a\left[Z_{i-1}^{\beta} + Z_{i+1}^{\beta}\right] + 2[1-m]Z_i^{\beta} \qquad (23)$$

Putting eq. (23) into Eq. (9), the worst-case result is offered below:

$$ap^{(\beta+1)}[-1.0]^{i-1}[-1.0]^{i-1} + [-1.0]^{i+1} + 2(1.0+q)p^{\beta+1}[(1.0)]^{i} = a \qquad (24)$$

$p^{\beta}[1.0]^{i}[1.0]^{(i+1)} + [1.0]^{(i+1)} + 2(1.0+a)\ p^{\beta}[(-1.0)]^{i}$ p(-a) (-1.0)-1.0+2(1.0+a)-r (-1.0) +1.0] =a(-1.0)-1.0+2(1.0-a) +a (5)

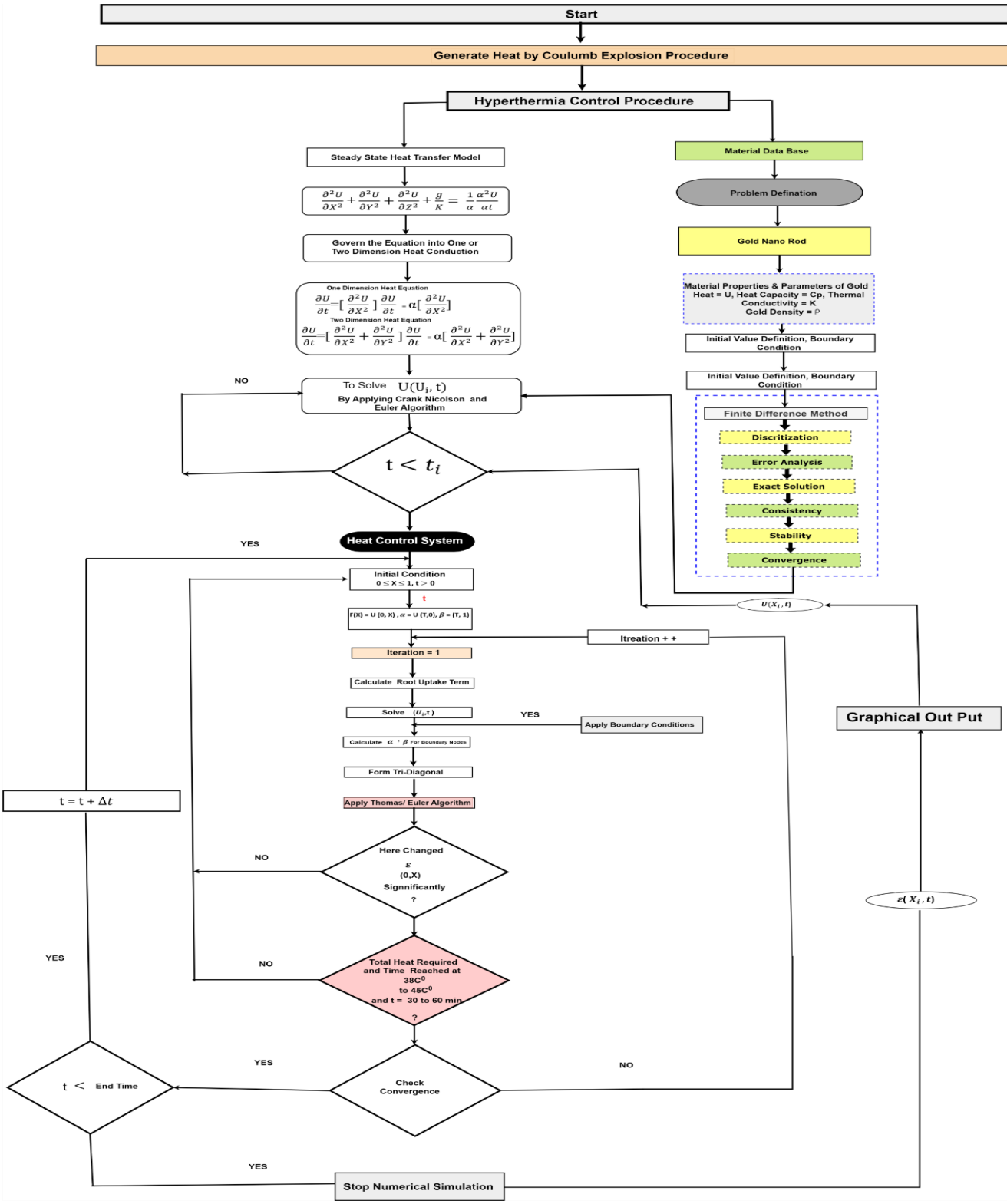


Figure 34: Flowchart of Heat Control System

4.1.9 Pseudo Code

The pseudocode for applying the finite difference approach to resolving the multifaceted thermal calculation is provided below:

1. *Write the following problematic constraints for instance the thermal diffusivity δ, the length L_X and width W_Y domain, the length of time T, the integer of lattice facts in X and Y path are N_X and N_Y and the time stride dimension Δt. Put the preliminary heat sharing U (X, Y,0.0) for each lattice point.*

2. *Calculate the lattice layout's* $\Delta X = \frac{L_X}{(N_X-1)}$ *plus* $\Delta Y = \frac{L_Y}{(N_X-1)}$*).*

3. *Put the edge surroundings intended for the problematic, for example u (X, 0.0, t), U (X, Ly, T), moreover U (0.0, Y, T),*

4. *Explain a background also a trajectory for the scheme of rectilinear calculations to be always resolved phase.*

5. *Put the diagonal entrances of pattern to* $1 + 2\alpha \frac{\Delta T}{\Delta X^2} + 2\alpha \frac{\Delta T}{\Delta Y^2}$ *also the off sloping.*

6. *Attempts to* δ, $2\delta \frac{\Delta T}{\Delta X^2}$ *and* $-\delta . 2\delta \frac{\Delta T}{\Delta Y^2}$

7. *Applied instead of the initially time phase* ($T = \Delta T$), *resolve the approach of linear calculations to acquire the temperature giving out by* $T = \Delta T$.

8. *In place of the succeeding time phases* ($T = 2\Delta T, 3\Delta T, ..., T$), *inform the vector b established on the preceding temperature spreading and resolve the approach of linear equations to attain the original temperature circulation.*

9. *Yield the ultimate temperature circulation U (X, Y, T) at the end of the replication.*

CHAPTER 5

SIMULATION RESULTS AND DISCUSSION

The research has been divided into two stages. Diagnosis of chronic diseases has been conducted by using soft computing approaches in the first stage and in second stage treatment methodology has been applied to find out safe treatment by using nanotechnologies approaches. The results of the two stages have been given below one by one.

5.1 Results And Discussion of Diagnostic Stage

The proposed "**GNTR"** [1], has been provided with its diagnostic results using deep learning algorithms, GANs "Generative Adversarial Networks", "SVM", and "image segmentation". The proposed "**GNTR"** uses deep learning algorithms, such as "convolutional neural networks" (CNNs), for image analysis and pattern recognition. These algorithms have been trained on a dataset of images related to the GNTR to learn complex features and relationships within the data. The nano-diagnostic device, which consists of a discriminator and a generator that is taught concurrently through adversarial training, employs GAN algorithms to diagnose chronic illnesses. Below are the suggested **"GNTRs"**[1], outcomes.

5.1.1 5.1.1 Performance Evaluation

The accuracy, sensitivity, specificity, and receiver operating characteristics (ROC) curve, which is, and precision-recall (PR) curve were computed to thoroughly assess the performance of the test dataset. Here is how to methodically calculate the accuracy, sensitivity, and specificity score as fellows:

$$\textbf{Accuracy} = \left\{\frac{TP+TN}{TP+TN+FN+FP}\right\}$$

$$\textbf{Sensitivity} = \left\{\frac{TP}{TP+FN}\right\}$$

$$\textbf{Specificity} = \left\{\frac{TN}{TN+FP}\right\}$$

The values TP and FP represent the number of images that were predicted properly and inaccurately, respectively, while TN and FN stand for the number of images that were correctly predicted. In this study, the area under the ROC

curve (AUC) was also computed. Two widely accepted assessment criteria for segmentation approaches, the dice score and intersection over union (IOU), are derived for our segmentation network. The score is defined as follows:

Dice Coefficient = $\left\{\frac{2TP}{2TP+FN+FP}\right\}$

And IOU is calculated by:

IOU = $\{TP/(TP + FN + FP)\}$

Where TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

Segmentation Result

5.1.1 Breast Cancer Dataset / Kaggle

The Breast-Cancer Segmentation Dataset, illustrated in Table-I, currently includes only one dataset specifically designed for mammogram data, known as the Breast-Cancer Mammogram-Segmentation dataset. This dataset comprises 100 axial mammogram images sourced from various Breast-Cancer patients. The data collection was conducted by the Italian-Society of Medical and Interventional-Radiology and is accessible at [98]. A radiologist meticulously segmented the mammogram-images, assigning different labels to identify breast-infections. Despite being the initial open-access breast-cancer dataset for infection segmentation, it is limited by a small sample size, featuring only 100 labeled images.

To overcome this limitation, our work introduces a semi-supervised Breast-Cancer infection segmentation dataset, labeled as Breast-Cancer-Semi_Seg [126]. The objective is to leverage a substantial number of unlabeled Breast-Cancer images to enhance the training-dataset. For the labeled data (D Labeled), we utilize the Breast Cancer Mammogram Segmentation dataset, randomly selecting 45 mammogram images for training, allocating 5 images for validation, and reserving the remaining 50 images for testing. The unlabeled mammogram-images are obtained from the Breast-Cancer Mammogram Collection-dataset, which includes 20 mammogram volumes from diverse Breast Cancer patients. From these 3D volumes, we extract 1,600 2D mammogram axial slices. Non-breast regions are then removed to create an unlabeled training-dataset (D Unlabeled) tailored for effective semi_supervised-segmentation [29].

5.1.2 Experimental Settings

In the experiments related to infection regions and multi class labeling, we compare our model with two leading models acknowledged in the computer

vision community . Support Vector Machine (SVM) and a multiclass GAN [25]. To evaluate the performance, we utilize several established metrics consistent with prior research [127]. These selected metrics encompass the Dice similarity coefficient, Sensitivity (Sen.), Specificity (Spec.), and Precision (Prec.), which are widely embraced in the literature. Furthermore, we introduce three metrics commonly employed in the field of object detection.

5.1.3 Structure Measure S_α

Enhance-alignment Measure and Mean Absolute Error. Following the approach outlined in [], [105], our evaluation focuses on employing S3 with the Sigmoid function as the final prediction. In this context, we gauge the similarity or dissimilarity between the final prediction map and the ground truth object level segmentation (denoted as G).

$$S_\alpha = (1-\alpha) * S_0\ (S_{P,}G) + \alpha * S_r\ (S_P\ _,G)$$

Where α is a balance factor between object aware-similarity $S_o$and region aware similarity S_r. We report S_α using the default setting ($\alpha = 0.5$) suggested in the original paper [40].

5.1.3.1 Enhanced alignment Measure (E_φ^{mean})

A new metric for assessing the global as well as local resemblance of two binary maps has been presented. The expression as E_φ is as described below:

$$= \frac{1}{w \times h} \sum_x^w \sum_y^h \varphi(S_P\ (x, y), \text{G (x, y)}),$$

where (x, y) denotes the coordinates of each pixel in G, and w and h stand for the ground truth of G's width and height, respectively. The increased alignment matrix is represented by the symbol φ. By applying a threshold ranging from 0 to 255, we convert the prediction S_(P) into a binary mask and get a set of E_φ. We describe the meaning of E_δ calculated for every threshold during the experiment [41].

5.1.3.2 Mean Absolute Error (MAE):

This calculates the pixel wise fault concerning S_P and G, which is explained below as:

MAE = $\frac{1}{w \times h} \sum_x^w \sum_y^h \varphi(S_P\ (x, y)$ - G (x, y)),

5.1.3.3 Segmented Results

The purpose of this comparison is to evaluate the achievement based on the designated measures. The objective of the suggested method is to measure how similar a prediction map is to the ground truth mask structurally. The goal of this measure is to match the human visual system as nearly as possible. The parameter α functions as a balancing factor in this formulation, weighing both the region-aware similarity (S_r) and the object-aware similarity (S_o). As suggested in the original study [24], the default option of α = 0.5 is used to construct the reported measure Sα.

5.23.3.1 Quantitative Results:

To assess infection segmentation performance, we compare U-Net and GAN, two cutting-edge models. The table displays the quantitative findings. Interestingly, the suggested GAN shows a considerable improvement over both GAN and U_Net in terms of Dice, S_∝, E_φ^mean, and MAE [31]. We credit this improvement to our new approach of combining explicit edge attention modeling with implicit reverse attention, which strengthens feature representation. Moreover, a 5.9% improvement in Dice is obtained by including a semi-supervised learning technique in our architecture. Our model attempts to provide comprehensive information about the affected region as a diagnostic aid. For multi-class labelling, namely GGO and consolidation segmentation, we therefore enhance the model. The quantitative assessment of our Breast Cancer Semi Seg dataset is shown in the table, with SVM and GAN denoting combinations of our SVM and GAN. We show competitive performance in GGO segmentation across several evaluation measures with our SVM and GAN pipeline. Our suggested process provides the greatest outcomes for the more difficult consolidation segmentation. For instance, our approach achieves segmentation results that are on average 13% better than the state-of-the-art model Multiclass U_Net [34] when it comes to Dice. Overall, especially in terms of Dice and S_∝, our suggested pipeline outperforms current state-of-the-art models in multi-class labelling for consolidated segmentation and average segmentation outcomes.

5.23.3.2 Qualitative indicates:

Segmentation outcomes for breast infections and our GAN's outstanding improvement over the baseline techniques are demonstrated in **Figure 23.** Interestingly, our GAN yields segmentation results that closely match the ground truth, with far fewer cases of incorrectly segmented tissue. Initially, the dataset is classified by the SVM into normal and abnormal pictures [30], which leads to the appearance of huge, segmented tissues. These outcomes are improved by using the Generative Adversarial Network Algorithm. We may credit our course-to-fine-segmentation approach for the GAN's performance. In this case, breast cancer infection zones are first roughly localized using a parallel partial decoder, and then the regions are finely segmented using multiple edge attention modules. This approach shows promising results since it mimics how actual physicians divide breast infection locations from mammography images. In addition, Figure 8 clearly illustrates the effectiveness of our semi-supervised learning approach. In contrast, segmentation results with more accurate boundaries are generated using GAN. We show the multi-class infection labelling findings in Figure 16, where our GAN consistently beats all other approaches. Notably, GAN correctly classifies consolidation diseases as well as GGO infections, highlighting our model's benefits. On the other hand, baseline techniques, such as Deep Lab V3+ with various strides and FCNs, produce inadequate findings and are unable to precisely segregate consolidation infections or GGO.

5.23.3.3 Evolution on Real Mammograms Volumes

We are describing a method for infection segmentation in mammogram volumes, particularly focusing on breast cancer infections. Our proposed method is designed for infection segmentation in mammogram volumes, with a focus on breast cancer infections. The evaluation on a real-world dataset demonstrates the effectiveness of the proposed approach, and the semi-supervised learning strategy is employed to leverage both labeled and unlabeled data for model training. Additionally, the flexibility of the framework for handling different types of infections is highlighted. Here's a breakdown of the information provided:

5.23.3.4 Dataset for Real Mammogram Volume Validation:

Utilized the recently released Breast Cancer infection segmentation dataset, consisting of 638 slices. The dataset includes slices from 9 mammogram volumes of real breast cancer patients. There are 285 non-infected slices and 353 infected slices in the dataset. This data set serves as a test set to evaluate the performance of the proposed method.

5.23.3.5 Performance Evaluation:

Results are presented in Table V, and despite the presence of non-infected slices, your method performs the best. Two datasets are employed for semi-supervised learning. The labeled dataset contains 100 infected slices, divided into 50 for training and 50 for testing. The unlabeled dataset consists of 1600 mammogram slices from real volumes. The unlabeled data includes a significant number of non infected slices to ensure the model can effectively handle them.

5.23.3.6 Generalization to Other Infections:

Emphasizes the versatility of the proposed method by stating that it is a general infection segmentation framework. Indicates that the framework can be easily implemented for other types of infections, extending its applicability beyond breast cancer.

Table 1: Results for Breast Muscle Segmentation

	Table II	
Category	No. of Images	Percentage (%)
Good	312	96.89
Acceptable	8	2.48
Unacceptable	2	0.62

Table 3: Results for Removal of Pectoral Muscle

Table III		
Category	No. of Images	Percentage (%)
Successful	150	93
Unsucessful	12	7

Table 2: Results Comparison of Breast Muscle Segmentation

Table IV				
Features	Testing - Training	Sensitivity (%)	Specificity (%)	Accuracy (%)
GLCM	87-191	96.97	96.29	93

Table5: Results Comparison of Pectoral Muscle Removal

Table V		
Researchers	Acceptable (%)	Unacceptable (%)
Chandrasekar et al. [43]	94	96.89
Raba et al. [50]	98	2
Proposed	99.42	0.62

Table 4: Results comparison of Breast Cancer Detection

Table VII		
Researchers	Training -Testing examples (%)	Unacceptable (%)
Al Qoud et al. [52]	70.30	98.72
Proposed	200-90	97.55

Table7: Results Comparison of Breast Cancer Detection

Table VI		
Researchers	Acceptable (%)	Unacceptable (%)
Sreedevi et al. [30]	90.06	9.94
Ojo et al. [42]	96.27	3.73
Proposed	95	8

Table8: Diagnostic Results of Breast Cancer

Diagnostic Results	Parameters													
	Accuracy	Processing Time	Mean	RMS	Variance	Kurtosis	SD	Contrast	Entropy	IDM	Correlation	Skewness	Smoothness	Homogeneity
MALIGANT	80%	0.114157 Sec.	0.00368496	0.0898027	0.0080607	5.71328	0.0897392	0.2298012	3.43664	0.570978	0.122324	0.399837	0.9320123	0.92591324
BENIGN	90%	0.10336 Sec.	0.00265643	0.0898027	0.00806254	20.7734	0.0897755	0.315629	2.60342	0.204445	0.16203301	1.8842601	0.9077921	0.94513342
BENIGN	90%	0.0866756 Sec.	0.0047292	0.789026	0.0070279	19.0604	0.0897371	0.323418	2.72101	0.767328	0.130495	0.932842	0.944559	1.29491
BENIGN	80%	0.111302 Sec.	0.002222301	0.0898027	0.0080266	5.43108	0.0897872	0.218576	3.56088	1.0147	0.07292	0.440132	0.89212	0.930223
BENIGN	90%	0.07229878 Sec.	0.00198503	0.0898027	0.0084159	5.04311	0.0897928	0.2297	3.60331	0.354314	0.06626	0.404932	0.88073	0.925241

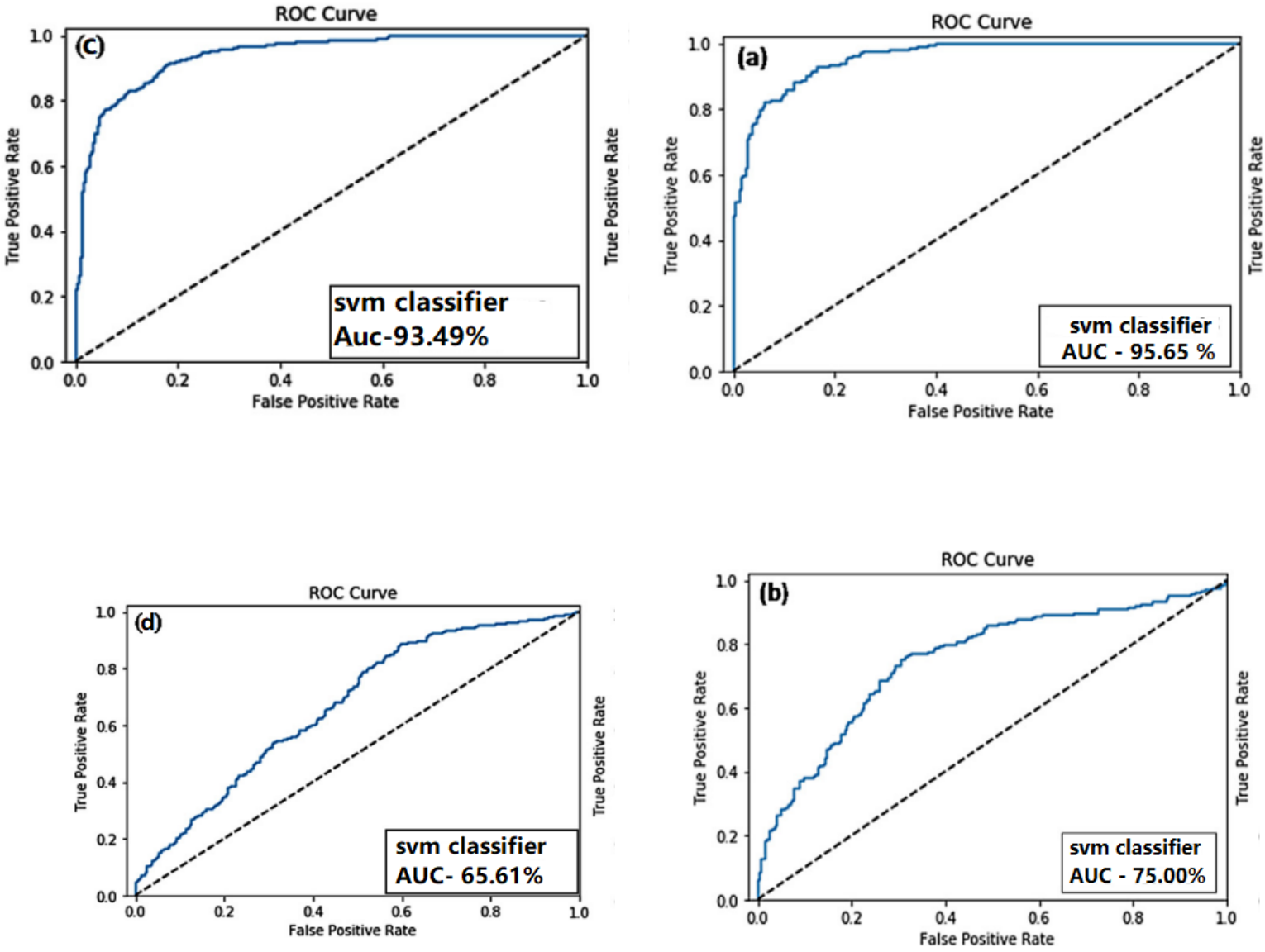


Figure 35: SVM classifier curve, ROC calculation for the breast cancer classifier with 80%, 20% testing set and training set partitioning in (a) SVM classifier AUC 95.65%, (b) SVM classifier AUC 75.00%, (c) SVM classifier AUC 93.49%, SVM classifier AUC 93.49%.

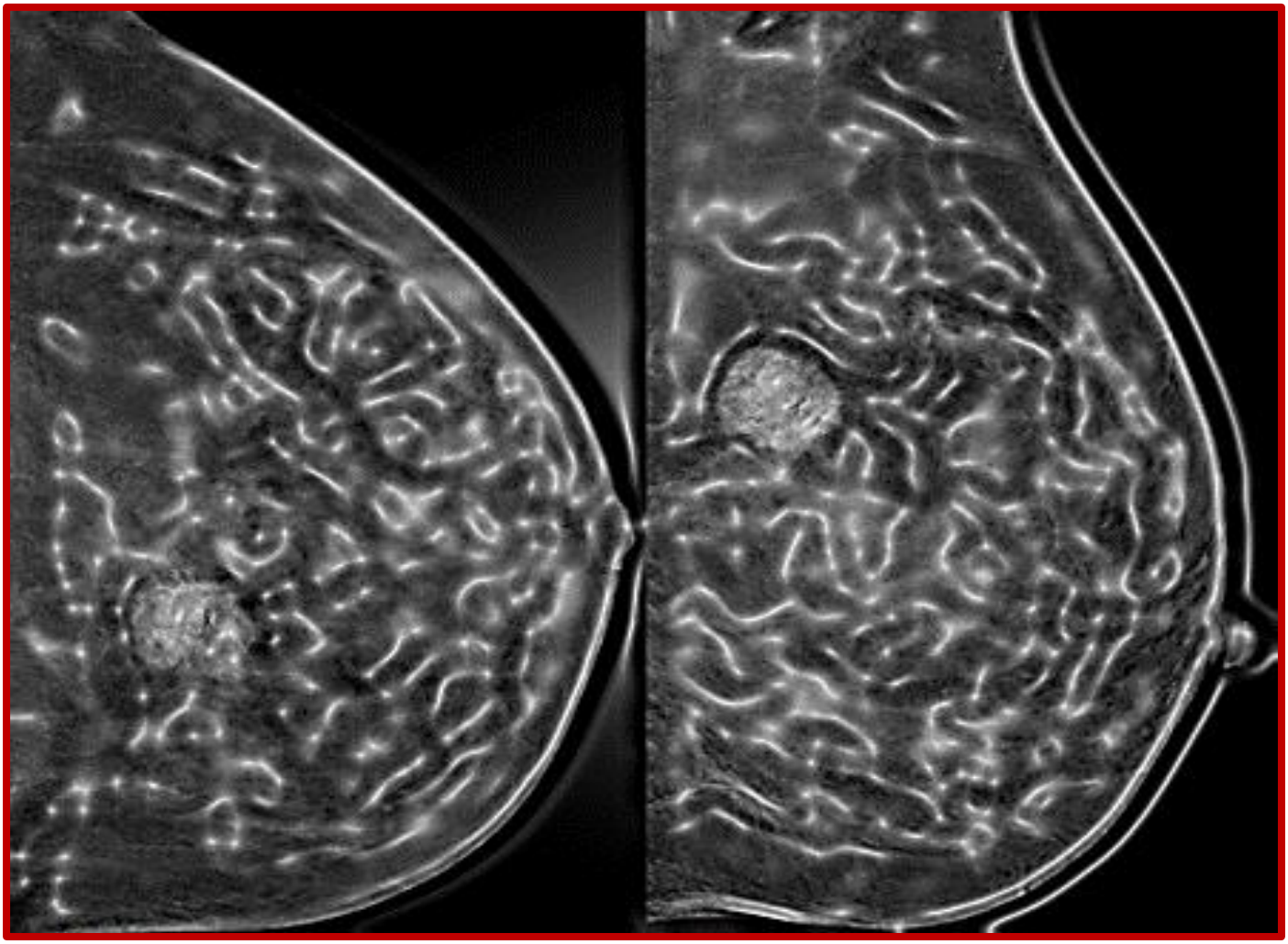


Figure 36: Visual Inflection Regions on Our Breast Cancer Seg Datasets

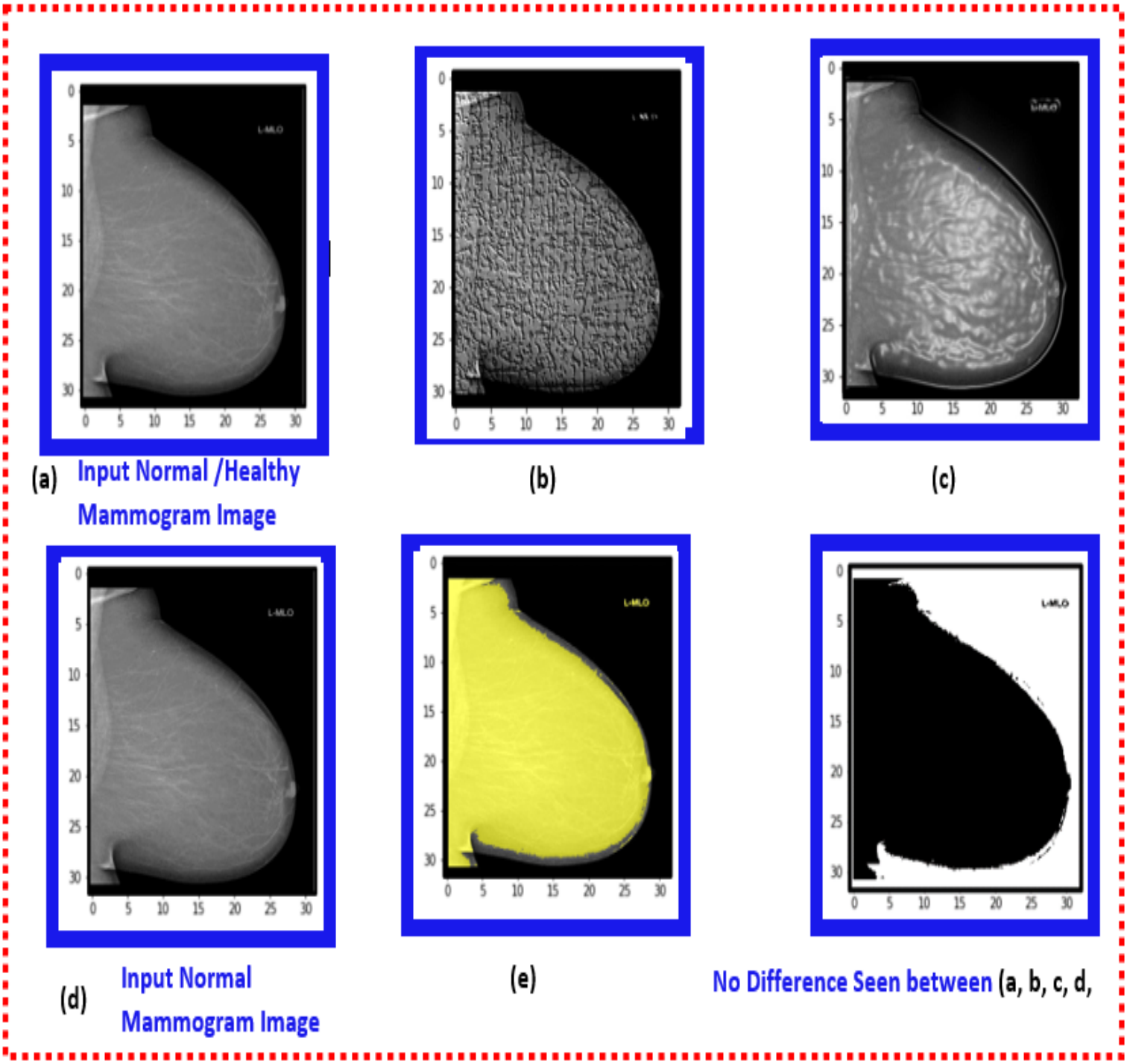


Figure37:(a): Input Normal mammogram images, (b): Filtering process, (c): Segmentation, (d): Input Normal Images (e): Filtering process, (f) Comparison Net Results. No Difference Seen in (a, b, c, d, e).

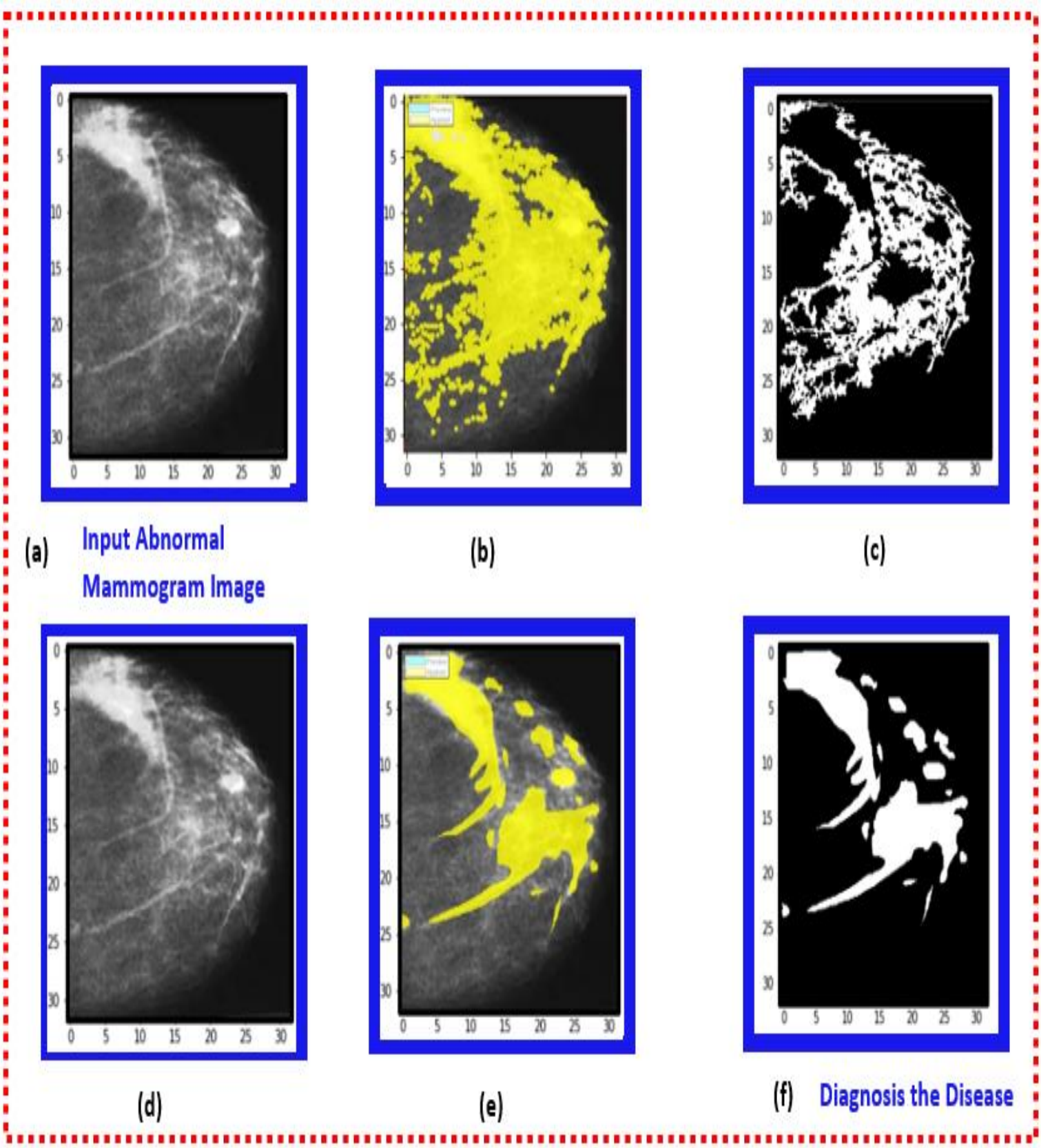
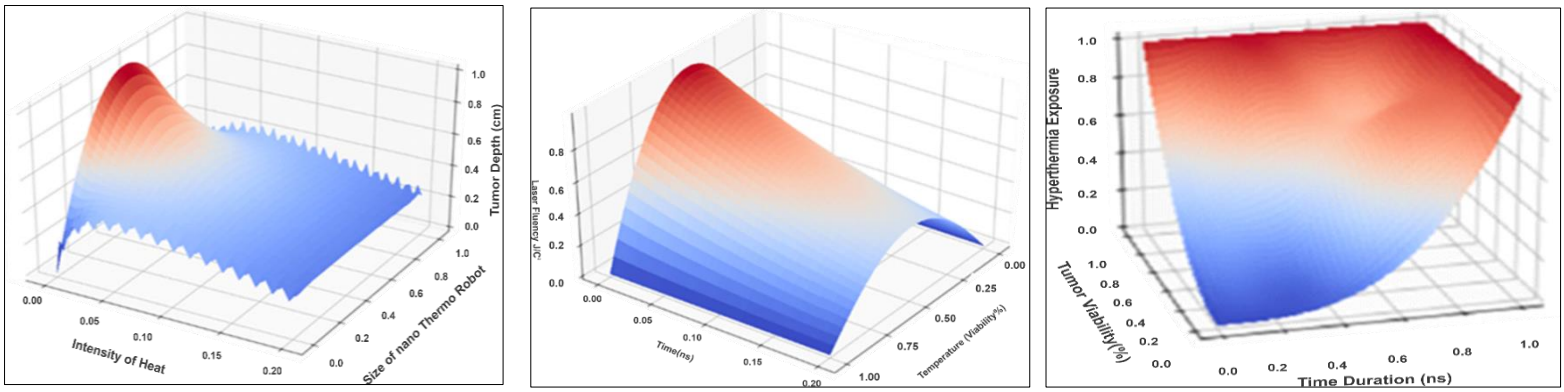


Figure38: (a): Input abnormal mammogram images, (b): Filtering process, (c): Segmentation, (d): Input abnormal Images (e): Filtering process, (f) Comparison Net Results. Difference Seen in (a, b, c, d, e) and diagnosis the disease.

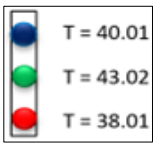
Results and Discussion of Treatment Stage

The outcomes of the suggested GNTRs, which represent the most advanced level of action and technical advancement now achievable, are completely confirmed and provided in this section [1]. These results are highly verified and will be important considerations for any future nanomedicine initiative aimed at treating breast cancer. A detailed description of the suggested findings may be provided below.



(a) **(b)** **(c)**

Figure 39: The first subsection (a) explained the association among the dimension of the GNTR, tumor sustainability, and overheating; the second subsection (b) explained the association between the temperature availability and laser proficiency over duration; and the third section (c) explained the interactions between the exposure to heat exhaustion, tumor their viability, and specific time interval.



This implicit approach maintains continuous stability, according to the stability analysis. This feature is justified numerically stepwise in the heat manage system diagram shown in Figure 36. GNTRs with elliptical forms and varied scale intensities provide the necessary hyperthermia exposure for laser irradiation. Tumor depths are chosen as functions, and tumor depth viability percentages are tracked over nanoseconds. The three sections of Figure 41 (subsections 18a, 18b, plus 18c) show the standard size of GNTRs for irradiation. Figure 41, sections 18a, 18b, and 18c, details the findings of the medical heat cure study and how the variables of malignant tumor depth, needed heat concentration, GNTR dimensions, laser facility, and time duration length interact. The heat treatment approach is employed by the suggested

nanotherapeutic system to treat superficial cutaneous metastases, including melanomas and breast cancer. After thorough validation, the suggested approach produces noteworthy therapeutic results and provides fresh perspectives on the workings of heat therapy in single-modal treatments for cancer, especially for breast cancer. The suggested GNTRs can modulate heat intensity by utilizing a heat control system to minimize or maximize it based on requirements, as shown in **Figure 42.** The temperature differences between the various nodes of the suggested GNTRs are depicted by the radish, bluish, and greenish color rings. The size of the suggested GNTRs in nanometers is shown in the noticeable 2D square shape block schematic in **Figure 43**. The 3D cubic block diagrams that are displayed show varying radii and percentages of temperature variations at different periods. The diagram's blue, green, and red points correspond to control temperatures of 42.01°C, 40.02°C, and 31.01°C, respectively, at which time the temperature stabilizes at 1800 seconds. A steady state temperature is reached in 2520 seconds, as shown in Figure 43, which also describes the length and breadth of GNTRs in nanometers. Figure 42 shows that the control temperatures are shown by the red, green, and blue circles, respectively, at 42.01°C, 40.62°C, and 38.19°C. In **Figure 43**, a steady state temperature at 2700 seconds is displayed together with the GNTR's dimensions in nanometers (length and breadth) based on the measurements of the targeted breast malignant tumor. In **Figure 44**, the control high temperature of 42.01 C^0, 43.02 C^0, and 38.01C^0, respectively are represented by reddish, greenish, and blueish rings in the shape of graph.

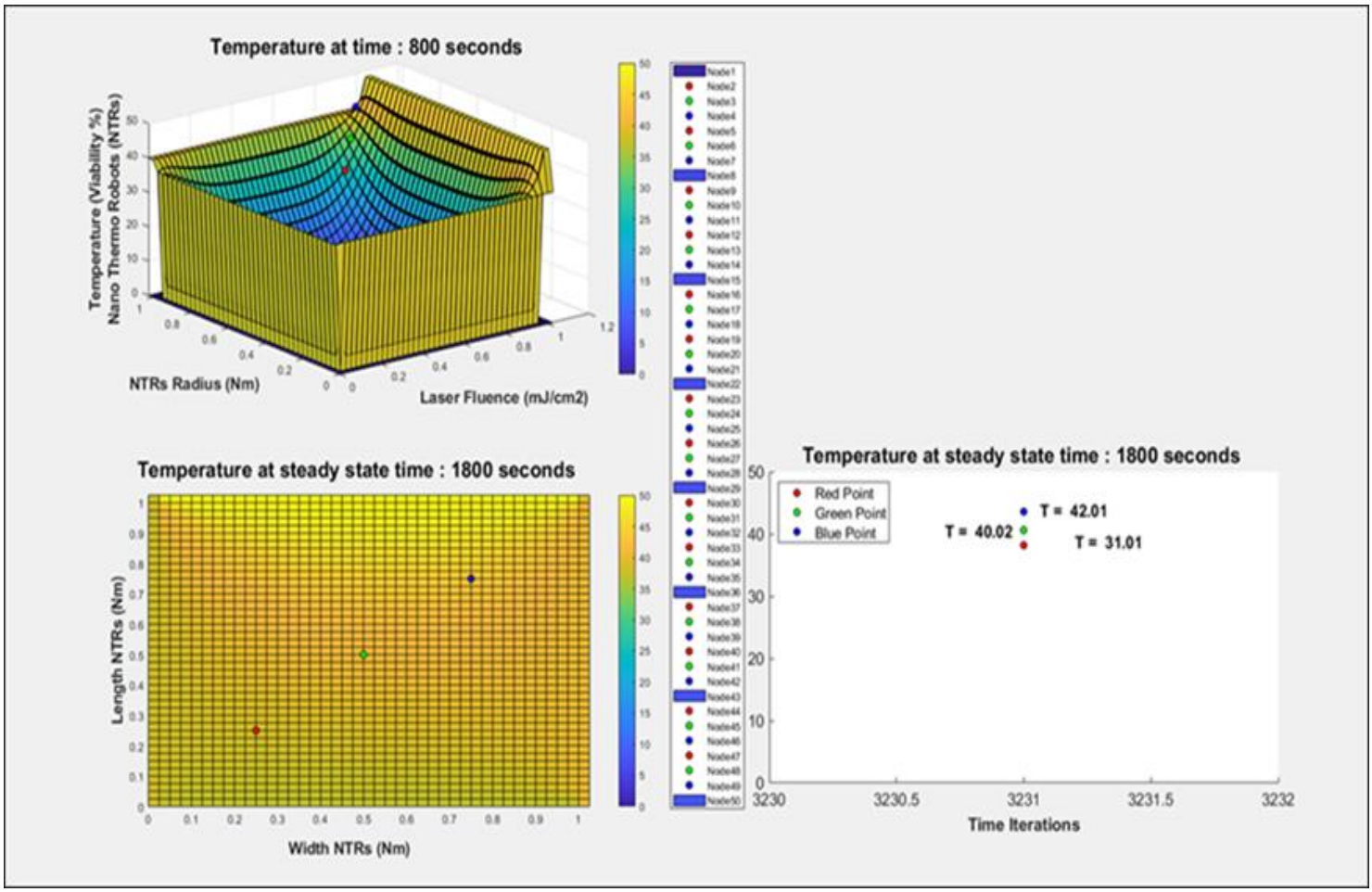


Figure 22: Regulate Temperature Reactions Among GNTR Nodes at Steady State Time 1800s.

Temperatures in brick in deg. C =

0.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
0.0	49.7	69.2	78.2	83.0	85.8	87.6	88.7	89.4	89.8	89.9	89.8	89.4	88.7	87.6	85.8	83.0	78.2
0.0	29.7	48.9	60.7	68.0	72.7	75.8	77.8	79.1	79.9	80.1	79.9	79.1	77.8	75.8	72.7	68.0	60.7
0.0	20.1	36.0	47.5	55.6	61.2	65.1	67.7	69.4	70.4	70.7	70.4	69.4	67.7	65.1	61.2	55.6	47.5
0.0	14.8	27.6	37.8	45.6	51.4	55.6	58.5	60.5	61.6	62.0	61.6	60.5	58.5	55.6	51.4	45.6	37.8
0.0	11.4	21.8	30.6	37.7	43.2	47.3	50.4	52.4	53.6	54.0	53.6	52.4	50.4	47.3	43.2	37.7	30.6
0.0	9.1	17.6	25.0	31.3	36.3	40.2	43.2	45.2	46.3	46.7	46.3	45.2	43.2	40.2	36.3	31.3	25.0
0.0	7.4	14.4	20.7	26.1	30.6	34.2	36.9	38.8	39.9	40.2	39.9	38.8	36.9	34.2	30.6	26.1	20.7
0.0	6.1	11.9	17.2	21.8	25.8	28.9	31.4	33.1	34.2	34.5	34.2	33.1	31.4	28.9	25.8	21.8	17.2
0.0	5.0	9.8	14.3	18.3	21.7	24.5	26.7	28.2	29.1	29.4	29.1	28.2	26.7	24.5	21.7	18.3	14.3
0.0	4.2	8.2	11.9	15.3	18.2	20.6	22.5	23.9	24.7	25.0	24.7	23.9	22.5	20.6	18.2	15.3	11.9
0.0	3.5	6.8	9.9	12.8	15.3	17.3	19.0	20.1	20.8	21.1	20.8	20.1	19.0	17.3	15.3	12.8	9.9
0.0	2.9	5.6	8.2	10.6	12.7	14.5	15.8	16.8	17.4	17.6	17.4	16.8	15.8	14.5	12.7	10.6	8.2
0.0	2.4	4.6	6.8	8.8	10.5	11.9	13.1	13.9	14.5	14.6	14.5	13.9	13.1	11.9	10.5	8.8	6.8
0.0	1.9	3.8	5.5	7.1	8.5	9.7	10.7	11.4	11.8	11.9	11.8	11.4	10.7	9.7	8.5	7.1	5.5
0.0	1.5	3.0	4.4	5.7	6.8	7.8	8.5	9.1	9.4	9.5	9.4	9.1	8.5	7.8	6.8	5.7	4.4
0.0	1.2	2.3	3.4	4.4	5.2	6.0	6.6	7.0	7.3	7.4	7.3	7.0	6.6	6.0	5.2	4.4	3.4
0.0	0.9	1.7	2.5	3.2	3.8	4.4	4.8	5.1	5.3	5.4	5.3	5.1	4.8	4.4	3.8	3.2	2.5
0.0	0.6	1.1	1.6	2.1	2.5	2.9	3.1	3.3	3.5	3.5	3.5	3.3	3.1	2.9	2.5	2.1	1.6
0.0	0.3	0.5	0.8	1.0	1.2	1.4	1.5	1.7	1.7	1.7	1.7	1.7	1.5	1.4	1.2	1.0	0.8
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Figure 42: Using Mat Lab software, regulate the temperature behavior among each node of the gold nano rode of the GNTR.

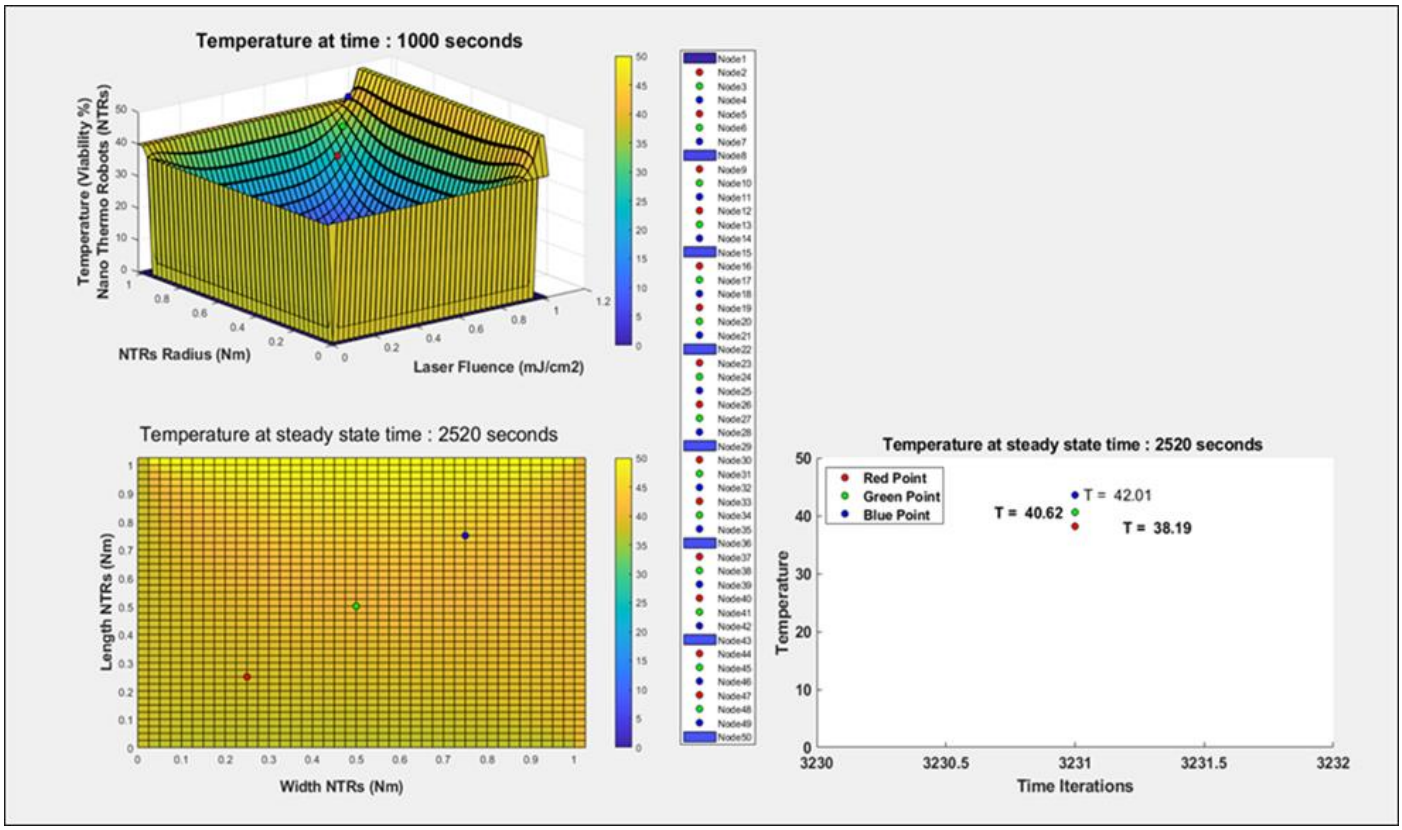


Figure 23: Regulate Temperature Reactions Among GNTR Nodes at Stable State in Time 2520.0 s.

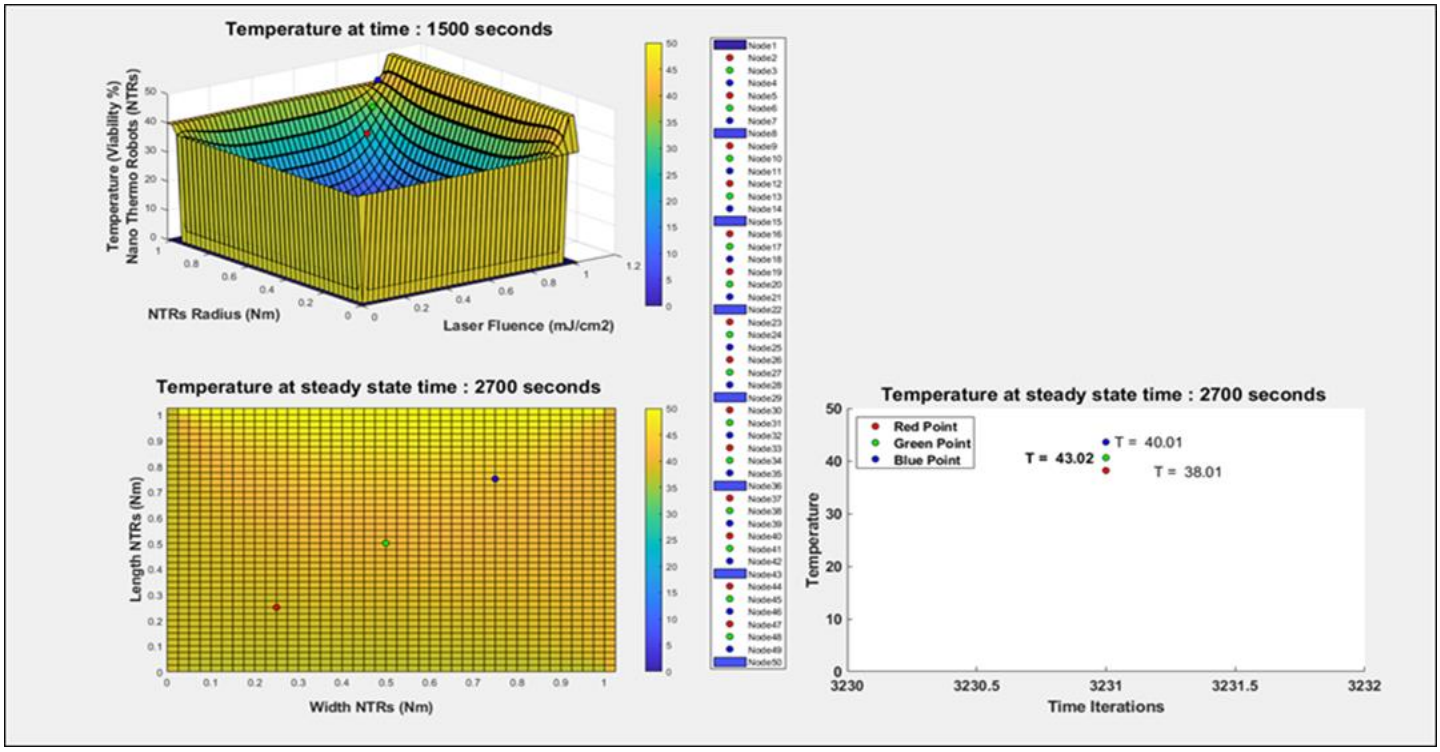


Figure 42: Regulate Temperature Reactions Among GNTR Nodes at Stable State in Time 2700.0 s.

5.23 The Multifaceted Impact of the Coulomb-Explosion Procedure on the Surface of GNTR

The Coulomb explosion procedure exerts a profound and complex impact on the surface of GNTRs, involving structural alterations, color transitions, temperature-induced disintegration, nano bullet generation, local expansion, and photoacoustic effects. The interplay of these effects highlights the intricate nature of the Coulomb-explosion process and its potential implications for various applications. The surface of GNTR encompasses intricate and dynamic changes that significantly influence their physical and chemical properties. This procedure involves the rapid and explosive expansion of charged particles within GNTRs, driven by the repulsive forces arising from their charged nature. The coulomb explosion process on the surface of **"GNTRs"**, unfolds in a series of nine distinct stages and effects. These stages expose the cycle of changes in the state and performance of GNTRs as they undergo fluctuations in temperature and duration. Each contributing to the intricate and dynamic transformation and showcasing the complex and dynamic nature of this phenomenon on the physical state of the GNTRs and explanation of each effect is given below and shown in **Figure 22**.

5.3.1.1 FIRST STAGE: "Moderate Temperature, 33°C for Duration of 30.0 Minutes"

In the firstly stage, the proposed GNTRs acts as reasonably modest temperature in the range of 33 C^0 for thirty minutes duration. The GNTRs experience the initiation of structural changes. The original golden color begins to transition to a darker shade, indicating alterations in atomic structure. Disruption caused by the temperature leads to the initial breakdown of GNTRs' integrity.

5.3.1.2 SECOND STAGE:"Nano Bullet Formation and Elevated Temperature, 35 °C for Duration of 40 Minutes"

In the second stage, with an increase in temperature, now at 35°C, the transformation accelerates. Nano gunshots, tiny extreme speed particles, emerge from the GNTRs, scattering randomly. The GNTRs undergo further disintegration under the heightened thermal stress, contributing to the generation of these nano bullets.

5.3.1.3 THERID STAGE:"Accelerated Nano Bullet Generation at Temperature 38 °C for Duration of 42 Minutes"

In the third step, the production of nanoparticles or bullets is accelerated due to a combination of longer exposure times and higher temperatures. These particles accelerate further when the GNTRs break apart, adding to the dynamic development of the GNTRs' surface properties.

5.3.1.4 FOURTH STAGE:" Local Expansion due to Radiation Absorption at Temperature 39 °C for Duration of 32 Minutes"

In the fourth stage, as GNTRs absorb radiation energy, the material state expands locally. As a result of the intensive heating, the surface temperature rises quickly to 39°C in only 32 minutes, forcing the GNTRs to physically expand and change. This initiates the Coulomb explosion process at a critical point.

5.3.1.5 FIFTH STAGE:"Impact of Short Laser Pulses and Photoacoustic Effect at Temperature 42 °C for duration of 30 Minutes"

In the fifth stage, it is investigated the effect of short laser pulses in the spectrum region of GNTR outward plasmon resonance. GNTRs attract several photons in response, which causes them to transition into higher electronic states. This stimulation causes GNTRs' transient thermal conductivity to be modulated, which affects heat transport inside the nanoparticles and nanobubbles. The 'classic' photoacoustic (PA) effect is a phenomenon that results from the growth of an individual GNTR and the thin liquid layer that surrounds it. After thirty minutes, the temperature reaches 42°C, considered a high level of heating.

5.3.1.6 SIXTH STAGE "Effective Electron-Phonon Conversion and Nano Bullet

In the sixth stage, The GNTRs reach a step when effective electron-phonon conversion, which converts engrossed photon energy into heat energy, occurs, leading to the deterioration of GNTR particles to their basic state. At this step, shock and acoustic waves are produced together with the production, development, and breakdown of nano bullets. The GNTRs' physical condition deteriorates significantly, as shown by the change in color from golden to dark. In just 25 minutes, they can achieve 43°C in surface temperature, make a heated stream, unleash hot, dispersed ion particles, and produce Nano bullets.

5.3.1.7 SEVENTH STAGE: "Continued Disintegration at Temperature 40°C for duration 45 minutes"

During the seventh stage, the GNTRs continued to break down while being heated to 40°C for 45 minutes. The development of nano bullets and their material change are ongoing processes. The GNTRs' golden color is getting darker, and its outer surface temperature is still high.

5.3.1.8 EIGHTH STAGE: "Escalation of Effects at Temperature 45 °C for 55.0 Minutes"

The realizes intensify in the eighth stage when the GNTRs are heated to a constant 45°C temperature for 5.0 minutes. The coulomb explosion activity escalates, causing the GNTRs to disintegrate more dramatically. The creation of hot streams,

hot dispersed ion particles, and nano bullets is further enhanced by the temperature increase.

5.3.1.9 NINTH STAGE: "Extreme Conditions at 60°C Temperature for Duration of 60 Minutes"

The GNTRs in the last stage experienced the worst circumstances, with a constant 60°C temperature for a whole hour. This is the highest point of the coulomb explosion impact. The GNTRs understand maximum collapse, which causes a significant change in their physical condition. There is a notable increase in surface temperature, and the GNTRs probably turn nearly completely black in color. When the explosive effect reaches its peak intensity, a significant amount of ion particles and Nano bullets are released.

5.1.4 Relationship Among Tumor Dimension and Minimum Needed GNTRs Diameter.

To investigate the relationship amongst tumor dimension and the length of the suggested "**Gold Nano Thermo Robots**" [1], we performed a comparison investigation. Our research aimed to clarify the complex connection between the depth of tumor penetration and the necessary GNTR radius. Evaluating how distinct GNTR sizes coincide or deviate from the objective of successfully treating malignancies at varied tissue depths was the aim. We divided the scenarios into four categories,"best-suitable," "better-suitable," "good-suitable," and "not-suitable." [1]. **Table 2** shows the correlation between the volumes of tumor penetration depths {1.1130 cm, 1.1540 cm, 1.1880 cm, 1.2100 cm, and 1.220 cm} and the required radii of GNTRs {10.0 nm, 20.0 nm, 30.0 nm, 40.0 nm, and 50.0 nm} [1].

5.1.5 BEST SUITABLE SETUP

When it pertains to GNTRs and tumor entrance, a "best setup" situation arises as the tumor's depth and the GNTR's radius line up perfectly. For instance, GNTRs with a smaller radius, like 10.0 nm, would be the best setup for a somewhat thin malignant tumor with a deepness of 1.1130 cm. Smaller GNTRs can more easily go through the tissue matrix and enter this lesser tumor depth. Conversely, bigger GNTRs, such as those with a radius of 50.0 nm, could be the greatest suit for a deeper tumor with a entrance deepness of 1.220 cm. The deeper tumor may be more effectively reached by these bigger GNTRs, resulting in efficient treatment administration. The "best setup " situation increases the chances of both tumor diffusion and cure success.

5.4.2 BETTER SUITABLE SETUP

A situation classified as a "better setup" occurs when the selected GNTR radius shows fair efficacy but does not match the tumor depth exactly. With a tumor deepness of 1.1540 cm, for instance, GNTRs with a area of 20 nm would not be the "best setup," but they might be a "better setup." Even while they might not pierce as well as 10.0 nm GNTRs, they can nevertheless make their way finished the tissue and get to the tumor. Likewise, GNTRs with a 30.0 nm radius at 1.1880 cm depth can be regarded as a "better setup." They might not be the best option for deeper tumors, but they can yet have a significant healing impact. In "better setup" situations, the GNTR dimensions could not match.

5.4.3 GOOD SUITABLE SETUP

The chosen GNTR size in a situation categorized as a "good- setup" might not be the best setup designed for the malignant tumor depth, but it yet has certain chance of being therapeutically beneficial. For instance, neither lower GNTRs (e.g., 10 nm or 20 nm) nor bigger ones (e.g., 40 nm or 50 nm) are excellent setup when considering a tumor deepness of 1.210 cm. GNTRs with a 30 nm radius, however, could be a "good setup." They can only partially reach the tumor, providing targeted therapy, even if they might not be able to effectively penetrate the full tumor depth. The GNTR dimension may not coordinate the tumor deepness precisely in "good setup" situations, but it can still be helpful in therapy, especially when paired with other therapeutic approaches.

5.4.4 NOT SUITABLE SETUP

Whenever the chosen GNTR dimension is essentially conflicting with the tumor deepness, therapy is not feasible, and the case is classified as "not setup." In the case of 1.22 cm tumor depth, GNTRs with a area of 10 nm or 20 nm, for instance, would probably be labelled as "not setup." Their tiny size makes effective penetration into the tumor at such a depth extremely difficult. To solve the restrictions resulting from the size-depth mismatch, alternate treatment procedures or GNTR design adjustments are required in "not setup" instances.

5.1.6 EFFECTIVE MEDICATION REACTION

The effectiveness of medication in the field of thermal therapy is dependent upon the dynamic interaction of two essential factors: the therapy time and the temperature threshold. We have investigated a wide range of thermal-therapy times, from 25.0 to 60.0 minutes, as well as hotness restrictions, from 33.0 to 60.0 degrees Celsius.

Determining the many facets of therapy response within this complex interaction is the goal. The arrangement of therapeutic results into discrete levels—normal, medium, satisfactory, best, and worst is the fundamental component of this research. These grades are useful indicators for evaluating the efficacy of thermal treatment concerning chosen temperature thresholds and treatment times. In thermal therapy, choosing the right temperature threshold and length of rehabilitation is crucial and requires careful evaluation of the specific features of the tumor, the patient's general fitness, and the goals of the healing [85]. It is crucial to strike a compare involving protecting healthy tissues and applying enough heat energy to terminate malignance cells. Tumor location, size, and heat sensitivity are among the factors that need to be taken into account.Thermal therapy's comparative study of treatment response highlights the complex interaction between temperature limit and therapy time [104], highlighting the necessity for a customized strategy based on the condition and treatment objectives of each patient, as shown in **Table 2.** The objective is to attain the "best response," but the range of responses from "normal" to "worst" highlights the difficulties and intricacies of thermal treatment in clinical settings. The efficiency and safety of thermal treatments for a range of medical problems, including cancer, are continuously improved by ongoing research and technology developments that help us optimize treatment parameters [107].

5.5.1 NORMAL REACTION

Once the chose temperature threshold and treatment time are within a scope that produces the intended therapeutic benefits deprived of inadvertently harming healthy tissues, a "normal reaction" occurs in thermal therapy. For example, if a therapy successfully targets and kills malignant cells although protecting the nearby healthy tissue, it may result in a normal reaction when administered for 25 minutes at a temperature limit of 33°C [57]. A well-balanced therapeutic regimen that effectively achieves cure goals devoid of unfavorable side influences is reflected in normal reactions.

5.5.2 AVERAGE REATION

An "average reaction" is a therapy outcome when some therapeutic effect is still obtained despite the parameters not being perfect. Usually, this response is in the middle range, providing some tumor suppression but not the maximum effectiveness. An average response, for example, may be obtained from a 30.0-minute therapy session with a high temperature restriction of 38.0°C. This would result in a partial

tumor response, but not as successfully as a treatment falling into the "normal reaction" class [57].

5.5.3 SATISFACTORY REACTION

While not in the best way possible, a "satisfactory reaction" suggests the therapy has succeeded in achieving the wanted treatment objectives. It suggests that the chosen temperature threshold and treatment time successfully target the tumor, resulting in a substantial therapeutic benefit, albeit more improvement may be possible. A temperature threshold of 39°C for 30.0 minutes, for instance, would produce a good reaction involving significant tumor removal and tolerable adverse effects [33].

5.5.4 BEST REACTION

The phrase "best reaction" refers to the ideal course of treatment, wherein the temperature limit and length of therapy are selected to optimize therapeutic outcomes and minimize side effects. This situation embodies the peak of therapy effectiveness. A treatment session lasting 30 minutes at a temperature threshold of 42°C, for example, may provide the optimum result, almost eliminating the tumor while causing the least amount of damage to healthy tissues.

5.5.5 WORST REACTION

The phrase "worst reaction" describes a therapy outcome where the selected parameters are unable to provide the intended therapeutic effects and may potentially exacerbate the illness or damage healthy tissues. This reaction highlights the important necessity to carefully tune temperature and time in the process of thermal treatment and serves as a warning example. As an example, using a high temperature threshold of 60°C, for 60 minutes could cause significant tissue harm and represent the worst-case situation [133].

5.2 DISCUSSION

In this subsection, we engage in an in-depth study of the results and performing of the suggested "**GNTRs"**. Hailed as a miracle of contemporary medicine, these GNTRs are implanted nanotherapeutic devices that have been painstakingly engineered to completely alter the breast cancer treatment environment. This section provides a thorough rundown of their operational processes and their resulting products. The

implanted nanotherapeutic device is placed close to the breast tumor position to begin the therapy process. 1) Sensors of Heat, 2) Nano Devices of Heat Storage 3) Sensors of ECG, 4) INBNW, 5) Gateways, 6) Nano Devices of BP 6) BAN Devices and 7) Nano Cameras are just a few of the components that make up this device. Using a **"See and Treat"** method for treating localized hyperthermia, the gadget plays a crucial role in this novel treatment strategy. Once inserted into the body, the GNTRs follow the path of intelligent nano-sensors to target certain cancer cells close to the location of the breast tumor. The nanorobot technology uses nano-cameras to see the tumor and provides high-resolution photos that help map the malignant tissue exactly. The basis for starting hyperthermia treatment, which involves applying controlled heat directly to the tumor site for 30 minutes at a temperature of 42°C, is the precise identification of the tumor location. This specifically designed heat treatment eliminates cancer cells while causing the least amount of damage to surrounding healthy tissue, guaranteeing an extraordinary degree of accuracy and customization throughout the process. In addition, the suggested nanotherapeutic system includes wearable nanosensors that can gather patient data in real-time. Upon outline into the body, the GNTRs, guided by intelligent nano sensors, navigate towards specific cancer cells proximate to the breast cancer tumor site. Leveraging nano cameras, the nano robot device visualizes the tumor, providing high-resolution images that create a precise map of the cancerous tissue. This accurate identification of the tumor site serves as the foundation for initiating hyperthermia therapy, wherein controlled heat is delivered directly to the tumor site, targeting a temperature of 42°C for an interval of 30.0 minutes. This meticulously targeted heat therapy effectively impairs cancer cells while reducing harm to surrounding healthy tissue, ensuring a remarkable level of correctness and personalization throughout the procedure. Furthermore, the proposed nanotherapeutic system incorporates wearable nano sensors capable of collecting real ime data from patients. The collected data is sent over the in-body network with ease, serving as a communication system inside the body of the patient. To get data from the therapeutic Nano-system's interconnected devices, the gateway is essential.

To enhance the effectiveness of GNTRs, a targeted attachment to breast tumors is enabled, which is then exposed to brief laser pulses. Through a variety of complex physical processes, this process causes a coulomb explosion on the GNTRs' surface, which produces heat. To combat erratic, asymmetrical, unstructured, and uncontrollably generated heat, an advanced heat control system has been implemented. With the integrity of healthy tissue preserved, this approach guarantees the targeted destruction of cancerous cells.

As an additional and alternative approach to treating breast cancer, controlled hyperthermia treatment is used in the suggested nanotherapeutic device. This implantable nanorobot targets the tumor precisely by navigating through the patient's body under remote supervision. The nanorobot's integrated heat-generating components cause tumor cells to become hyperthermic, which leads to their demise. With its non-invasive and highly focused approach, this innovative strategy offers significant prospects for the treatment of breast cancer. It can reach difficult locations that are inaccessible by standard means. When combined with the "**See and Treat"** method, Ion MT framework, and regulated heat generation, implantable nanorobots could carry out essential tasks [122].

This novel solution integrates a complex network of technologies, such as 1) nano cameras, 2) nano pulse oximetry body area network devices, 3) nanosensors for blood pressure, 4) an IBCN, and 5) ECG sensors. When these components operate together, nanorobots working in conjunction with Ion MT technology and an in-body communication network can provide targeted hyperthermia treatment. The nanorobotic system is empowered by this thorough integration, which has great potential for treating breast cancer [125]. Throughout the course of therapy, the therapeutic nanomedicine device is guided by the suggested approach. Its capacity to prioritize patient safety and comfort while accurately identifying, visualizing, and treating malignant tissue is a significant leap [131]. This raises the bar in the battle against breast cancer and improves treatment results as well [127]. Affixed to the implanted GNTR, nano cameras offer high-resolution imaging of the tumor location in real-time, facilitating precise identification of malignant tissue. Ensuring a steady heart speed and pulse is important for patient care throughout hyperthermia healing, and implanted ECG sensors continually examine the patient's cardiac movement during the process [135]. Blood pressure nanosensors are an essential part of the patient's monitoring system because they can quickly identify changes in blood pressure during treatment and take appropriate action to keep the circulatory system stable. Throughout the treatment, respiratory health is maintained for the patient thanks to the use of nano pulse oximetry sensors, which monitor blood oxygen saturation levels [100]. All of these parts are connected via an in-body network, which makes it easier for the nanorobot device, sensors, and cameras to communicate and share data. Real-time data gathering and analysis are based on this network [90]. By serving as a link connecting the IBN and other techniques, such as cloud-created resources, gateways effectively gather and prepare data for additional examination and action [123]. Real-time alerts for any deviations from the norm are enabled by the continuous monitoring of vital signs by nano pulse oximetry devices, blood pressure nanosensors, and ECG sensors. This allows for prompt intervention if necessary. Temperature detector- gadgets carefully monitor and manage the temperature during

therapy, a critical factor for its success. Devices known as transducers are essential for transforming one type of energy into another. For example, they help transform electrical information into thermal energy. The regulated heat output necessary to cause hyperthermia depends on this contribution [56]. To put it briefly, the incorporation of these innovative methods into the nanorobotic system illustrates a thorough and complex strategy to raise the accuracy and effectiveness of breast cancer treatment. The nanorobot apparatus is furnished with position and location sensors, which provide accurate navigation within the body and guarantee exact targeting of the tumor site for therapeutic purposes [79]. Furthermore, by identifying chemical and molecular markers linked to cancer, chemical, light, imaging, and biochemical sensors offer a thorough perspective of the tumor location. While heat sensors keep an eye on the tumor site's temperature to make sure the therapy doesn't get too hot, photo and image sensors take high-resolution pictures. With the use of timer sensors, the 30-minute treatment period is precisely controlled during the course of the therapy. The integrated system performs with painstaking accuracy and customization throughout the process [128]. With controlled nano-sensors and functionalization of the surface, the GNTRs enhanced with Ion-MT demonstrate effective localization to the target region. After placement, the device activates a heat-control mechanism that precisely raises the tumor-site temperature to 42°C, the therapeutic threshold [70]. For the whole thirty minutes that are recommended, this focused hyperthermia therapy is continued [106]. Figure 22 presents nine temperature panels with time intervals for validation, displaying noteworthy results. As an example of nanomedicine, the GNTRs are carefully investigated at different temperatures (33°C to 60°C) and times in order to understand their changes in physical condition. Changes in temperature have an effect on their hue, which reflects changes in their physical characteristics. Lower temperatures (33°C as well as 35°C) preserve the GNTRs' stability, but higher temperatures (38°C as well as higher up) lead to notable variations in color and composition, suggesting variations in physical states. However, limiting collateral harm to healthy cells and achieving maximum therapy efficacy need careful balancing. These Gold-Nano Thermo-Robots may be remotely controlled thanks to the integration of Ion MT, which allows for real-time temperature modifications for the best possible therapeutic results [128]. The novel method uses the **"See and Treat"** strategy to carefully adjust the temperature at different levels and times to destroy breast cancer tumors while protecting surrounding healthy cells. The dynamic interaction between temperature fluctuations and the physical states of GNTRs is revealed by the simulation findings. GNTRs retain their solid-state composition and gold color after 25 minutes at 33°C. Subtle variations appear when temperature rises, suggesting that GNTRs are able to adjust to changing environmental conditions. Greater heat causes more noticeable transitions into semi-solid, gel-like, and liquid-like forms, each of which intensifies the beneficial effect of therapy. The deadly

temperature of 60°C for 60 minutes, resulting in an exceedingly viscous liquid condition and significant cellular death within the tumor microenvironment, is how the research terminates. Physicians may monitor patients in real time using tablets and smartphones due to the suggested inter-body communication network planning, which is shown in **Figure 28.** This eliminates the need for frequent hospital visits. The principal aim is to attain regulated hyperthermia via a coulomb explosion, whereby the size of the suggested **"GNTRs"**, is modified in accordance with the tumor's volume and depth. The objective has been achieved by keeping the temperature at 42°C for 30 minutes in order to regulate the thermotherapy threshold level. This particular temperature and duration are thought to be essential for the breast therapy environment's ability to effectively kill abnormal cells. The "best reaction" would ideally be the goal of treatment planning, which would carefully adjust temperature and time to optimize therapeutic efficacy while minimizing adverse effects. But in therapeutic settings, trade-offs are frequently necessary due to practical concerns, which might result in responses that range from **"normal"** to **"worst"**. The optimization of treatment responses during thermal therapy is greatly dependent on developments in real-time monitoring and control. By providing constant feedback on the distribution of temperature in the target region and the surrounding tissues, therapeutic settings may be changed throughout the surgical procedure, potentially leading to better results and a lower chance for adverse reactions. A hotness restriction of 42°C administered for 30.0 minutes has always been recognized by the literature as the ideal response to achieve therapeutic effectiveness. This method preserves the integrity of surrounding healthy tissues while triggering targeted cell death to optimize therapy effectiveness. On the other hand, insufficient treatment settings, such as a temperature restriction of 33°C for a 25-minute therapy session, may cause the worst results. These combinations frequently have a minimal therapeutic effect, highlighting the significance of careful parameter selection for successful results. In comparison to surgical procedures or radiation cure, thermal ablation is a less invasive method that is safe and effective for treating breast disease. It also carries a lower risk of consequences. The treatment is quite brief, allowing patients to return house on the same calendar day The **"Heat Control System"** [1], results, which are derived using MATLAB software and the Crank Nicolson numerical approach as demonstrated in **Figure 45**, are diagnostic biomarkers for the successful outcome of breast cancer treatment.

Table 5: Comparison of treatment reaction among temperature limit and duration of thermal treatment (in seconds)

Thermal Therapy Duration	Temperature Limit								
	$33\ C^0$	$35\ C^0$	$38\ C^0$	$39\ C^0$	$40\ C^0$	$42\ C^0$	$43\ C^0$	$45\ C^0$	$60\ C^0$
25.0 mint / 1500.0 s	Ordinary Reaction	Ordinary Reaction	Regular Reaction	Regular Reaction	Regular Reaction	Regular Reaction	Regular Reaction	Nastiest Reaction	Nastiest Reaction
30.0 mint / 1800.0 s	Ordinary Reaction	Ordinary Reaction	Regular Reaction	Regula Reaction	Finest Reaction	Finest Reaction	Finest Reaction	Nastiest Reaction	Nastiest Reaction
32.0 mint/ 1920.0 s	Average Reaction	Average Reaction	Regular Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction
40.0 mint/ 2400.0 s	Average Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction
42.0 mint/ 2520.0 s	Average Reaction	Average Reaction	Regular Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction
45.0 mint/ 2700.0 s	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction
55.0 mint/ 3300.0 s	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction
60.0 mint/ 3600.0 s	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction	Nastiest Reaction

By using thermal therapy approaches, the suggested nanotherapeutic system keeps temperatures between 38°C and 45°C for 30-to 32-minute intervals. With the help of the suggested GNTRs, this targeted heating focuses on the patient's infected area as opposed

to using whole-body hyperthermia. The data show that controlled heat within the designated temperature range significantly and efficiently reduces tumor development.

An adverse relationship between the diameter of **"GNTRs"** and tumor depth can be observed by comparing the needed GNTR diameter and tumor thickness during penetration, illustrated in **Table 9**. When the tumor depth is deeper and the diameter is smaller, the best match is shown. On the other hand, as Table 9 illustrates, matching performance declines with a constant radius as the tumor grows deeper.

The study analyzes various situations by retaining the radius of the Nano system at varied values {"10 nm, 20 nm, 30 nm, 40 nm, and 50 nm"}[1], while modifying the tumor depth. The findings show the average, better, and best fits for reducing tumor depth. On the other hand, the fitting result is not good when the tumor depth is at its highest (1.22 cm) and the radius is at its maximum (50 nm). As shown in **Table 9**, the best-response mode is obtained by keeping a temperature range of 38°C to 43°C and a thermotherapy duration of 1800 s in order to establish the optimal match between the diameter of GNTRs and tumor thickness. Based on various heat intensities and time durations, the suggested GNTRs provide normal, average, and **worst reactions**; the temperature of 42°C for 30 minutes yields noticeably better results. Following a thorough review of the literature on thermal-treatment data, involving both comparative and non-comparative studies, the suggested GNTRs show outstanding removal of cancerous tissues.

Table 6: Evaluating the relative occurs necessary to determine the depth of the tumor and the GNTRS during entrance.

Obligatory tumor deepness (in cm) for entrance	**Obligatory Diameter (in nm) of Suggested GNTRs Throughout Entrance**				
	10.0 nm	**20.0 nm**	**30.0 nm**	**40.0 nm**	**50.0 nm**
1.1130 cm.	Greatest Setup	Well Setup	Standard Setup	Standard Setup	Standard Setup
1.1540 cm.	Greatest Setup	Well Setup	Standard Setup	Non-Setup	Standard Setup
1.1880 cm.	Well Setup	Nice Setup	Standard Setup	Not Setup	Non Setup
1.2100 cm.	Nice Setup	Standard Setup	Non Setup	Non-Setup	Non-Setup
1.220cm.	Average Setup	Average Setup	Not Setup	Not Setup	Not Setup

The GNTRs perform exceptionally well, demonstrating a definite relationship between the treatment response and survival without disease. Patients showed good drug tolerance, and no significant side effects were noted. After experimenting with different temperature and thermotherapy time combinations, it was shown that the poorest reaction occurs when temperatures are kept at 43°C or above for 45 minutes, or 2700 seconds. On the other hand, an average reaction is obtained by keeping the temperature at 33°C, 40°C, 41°C, and 42°C for 25 minutes (or 1500 s) and 30 minutes (or 1800 s). The most detrimental effects occur at 42°C, 45°C, and 55°C, with treatment durations of 42 minutes (or 2520 s), 45 minutes (or 2700 s), and 55 minutes (or 3300 s), respectively. There is a chance that these temperatures will burn immune system cells. During 2700 s, or 45 minutes, the worst reaction occurs. Conversely, keeping the temperature constant for 25 minutes (or 1500 seconds) and 30 minutes at 33, 40, 41, and 42 degrees Celsius.

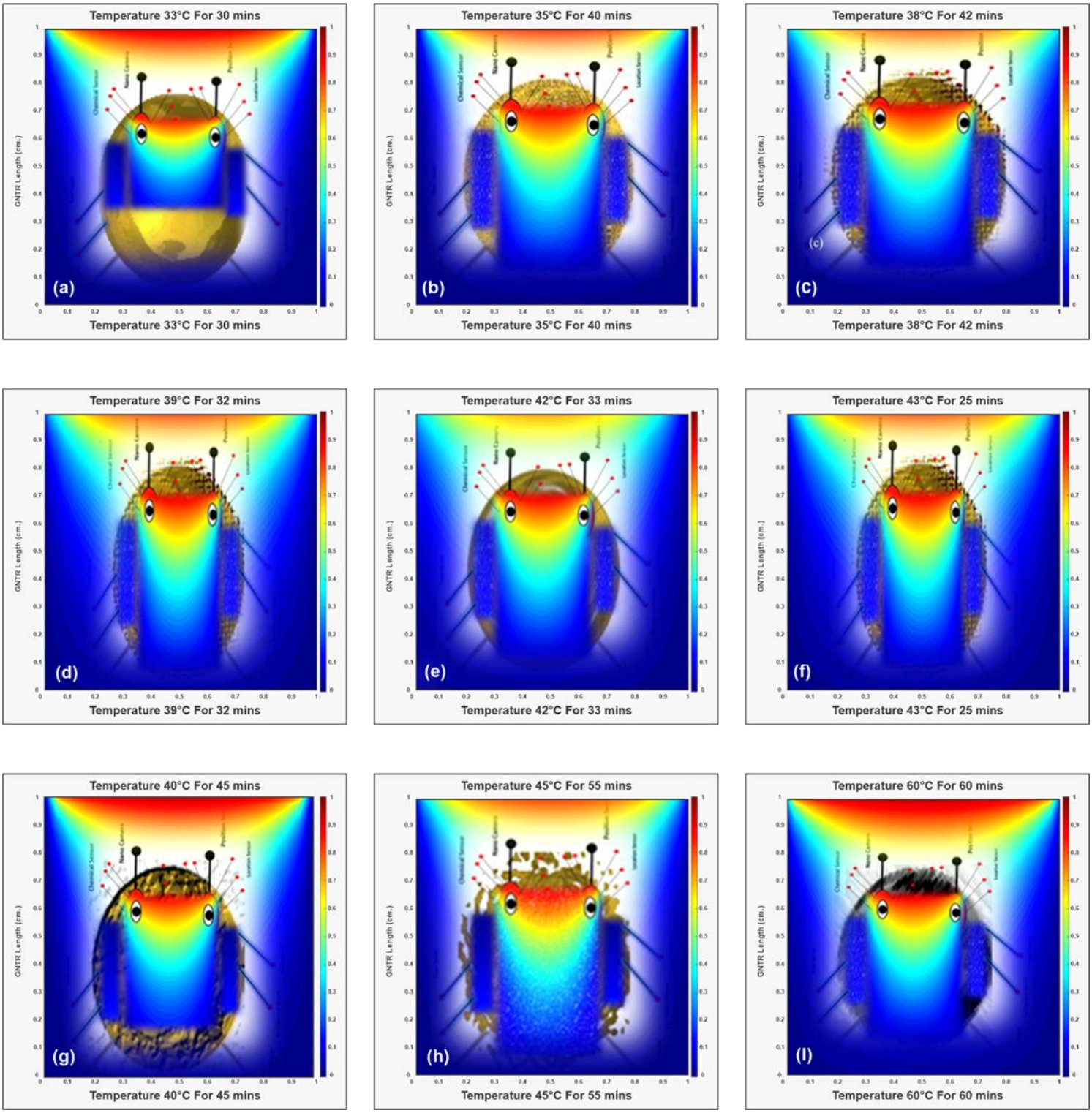


Figure 43: Various Temperature Actions with Varying Periods for Breast Tumor Therapy

provides an average response (about 1800 s). The lowest temperatures 42°C, 45°C, and 55°C along with the longest treatment times 42 minutes (or 2520 s), 45 minutes (or 2700 s), and 55 minutes (or 3300 s), respectively as well as the highest risk of burning immune cells, are achieved. Table 3 illustrates the efficacy of the suggested thermal ablation

strategy for treating breast cancer. This technique involves thermotherapy at 42°C or 45°C for 30 minutes (or 1800 s). Exact targeting for efficacious therapy is ensured by the suggested approach, which discusses the relationship between pulse length and penetration depth into the tumor. Because of their higher density per unit volume, the study suggests that GNTRs with bigger radii penetrate tumors more deeply. The relationship between GNTR size and penetration depth is explained in detail, showing that smaller GNTRs, because of their high density, penetrate deeper into the tumor. Effective thermal treatment is demonstrated by the suggested GNTRs, especially those with a radius of 10 nm, within the given temperature range. The study highlights the limits of hyperthermia as a single therapy method by acknowledging symptoms of skin-burning wounds or lesions following the trial, despite favourable outcomes. In the future, it may be possible to combine systemic chemotherapy and specifically targeted heat treatment for improved results.

CHAPTER 6:

CONCLUSION

Breast cancer, a complex and widespread disease among females globally, prompted the introduction of a groundbreaking nanodevice known as Gold Nano Thermo Robots (GNTRs). This innovative approach aims to selectively eliminate abnormal cells through the laser thermal explosion of GNTRs, utilizing a technique called Nano Medicine, particularly coulomb explosion. Heat therapy, a novel method in cancer treatment, has the potential to enhance cytotoxic effects within the tumour volume without causing harm to normal tissues.

In this research, we introduce a groundbreaking technique of diagnosis and treatment of chronic diseases by using soft computing and nanotechnologies approaches. We divided our research methodology in to two stages. **In First Stage** we introduced the new method of diagnosis of chronic diseases such as breast cancer, for infection segmentation network for breast cancer mammograms, we used termed Inf-GAN. This network incorporates implicit reverse attention and explicit edge attention mechanisms to enhance the accurate identification of infected regions. Additionally, we present a semi-supervised solution, Semi-Inf GAN, addressing the challenge of limited high-quality labelled data. Through extensive experiments conducted on our Breast Cancer-Semi Seg dataset and real mammogram volumes, our proposed Inf-GAN and Semi-SVM models outperform state of the art segmentation models, demonstrating advancements in performance. The system exhibits promising applications in breast cancer diagnosis, including tasks such as quantifying infected regions, monitoring longitudinal disease changes, and facilitating mass screening processes. **In Second Stage** we introduced novel method of treatment of chronic diseases by using control hyperthermia. To achieve these goals, we developed the Heat-Control-System, which allows focused treatment while protecting nearby healthy body cells. Using a controlled-heat treatment strategy, the current study aimed to investigate the effects of temperature and heat-shock duration on the survivability of human normal tissues and breast cancer cell lines. Specifically, heat intensity was regulated between 38 and 42 degrees Celsius. The analysis, simulation results, and discussions that follow highlight the tremendous potential of GNTRs that are outfitted with nanotechnologies, Intra-Body Nanomedical Technology (Ion MT), and accurate temperature control for the use of **SEE and TREAT** techniques in the treatment of breast cancer. The combination of nanotechnology and medicine is bringing forth more effective, less intrusive, and better tolerated treatments for cancer, which gives hope for the disease's future. The nonlinear processes that accompany the thermal explosion of GNTRs are responsible for the success in killing breast cancer cells, highlighting the significance of specific treatment options for breast tumors in future oncology approaches. The development of such procedures appears promising when it comes to the synthesis of nanomedicine with consistent size and shape, especially in cases when yield is

impoverished. Of the various nanomedicines, GNTRs stand out as one of the most promising choices in oncology, offering a variety of uses in heat therapy based strategies catered to specific types of cancer. Future developments that combine a heat control system with a certain dosage of chemotherapy (CT) may produce even better results.

It's noteworthy that our model excels at detecting objects with low-intensity contrast between infections and normal tissues, a scenario commonly encountered in natural camouflage objects. Looking ahead, we aim to extend the application of Inf-GAN to other pertinent tasks, such as polyp segmentation, product defects detection, and the identification of camouflaged animals [98].

CHAPTER 7:

LIMITATIONS & FUTURE WORK

The proposed Gold Nano Thermo Robot (GNTR) technology presents a promising avenue for revolutionizing the landscape of chronic disease treatment and diagnosis. While acknowledging the current limitations, there is substantial potential for advancements in addressing these challenges and steering the technology towards impactful clinical applications. Further research and development can refine the targeting capabilities of GNTRs, enabling them to identify and treat specific types of chronic diseases with a high degree of precision. This may involve advancements in nanomaterial design, enhanced sensing technologies, and improved navigation within the human body. The proposed GNTRs offer a unique approach to targeted treatment through localized hyperthermia therapy, aiming to selectively eliminate abnormal cells without causing extensive damage to healthy tissues. Future research should focus on optimizing the safety profile of GNTRs [1]. This involves exploring biocompatible materials, conducting extensive pre-clinical trials with diverse models, and developing strategies to minimize potential side effects. The scalability of GNTR technology for widespread clinical use is a current challenge. Manufacturing, mass production, and cost-effectiveness need careful consideration. The integration of soft computing techniques, such as Support Vector Machines (SVM) and Generative Adversarial Networks (GAN), introduces computational complexities. Advancements in soft computing algorithms should be pursued to enhance the efficiency of medical image segmentation and disease diagnosis. Optimizing these algorithms for real-time processing and integration with GNTRs can contribute to more accurate and timely clinical interventions. The invasive nature of the proposed GNTR technology for hyperthermia therapy is a limitation that may not be suitable for all patients. Exploring non-invasive alternatives for delivering hyperthermia therapy, such as focused ultrasound or magnetic hyperthermia, can broaden the applicability of GNTRs. The integration of soft computing techniques, such as Support Vector Machines (SVM) and Generative Adversarial Networks (GAN), poses technical challenges. Implementing these complex algorithms within the nanorobot system may demand advanced computational resources and optimized algorithms for real-time processing [44]. This may improve patient acceptance and minimize potential complications associated with invasive procedures. the GNTR technology holds significant promise for revolutionizing chronic disease treatment and diagnosis. By addressing the outlined limitations and pursuing these future research directions, the field can advance towards safer, more effective, and ethically sound applications, ultimately improving patient outcomes in the realm of chronic disease management.

REFERENCES

1. Hasan, Z., Fatima, A., Shahzad, T., Abbas, S., Ghazal, T. M., Al-Sakhnini, M. M., ... & Ahmed, A. (2023). Nanomedicine: Treatment of Chronic Disease Using Gold Nano Thermo Robot (GNTR) Empowered with Nanotechnology Approaches. IEEE Access.

2. Bromma, K., & Chithrani, D. B. (2020). Advances in gold nanoparticle-based combined cancer therapy. Nanomaterials, 10(9), 1671.

3. Okuyucu, C. E., Kalaycioglu, G. D., Kacaroglu, D., Ozden, A. K., & Aydogan, N. (2023). Trojan-like doxorubicin and gold nanoparticle entrapped smart nanostructured lipid carriers for breast cancer synergistic chemo/photothermal therapy. Colloids and Surfaces A: Physicochemical and Engineering Aspects, 131763.

4. Ashiq, M. G. B., Saeed, M. A., Tahir, B. A., Ibrahim, N., & Nadeem, M. (2013). Breast cancer therapy by laser-induced Coulomb explosion of gold nanoparticles. Chinese Journal of Cancer Research, 25(6), 756.

5. Soto, F., Wang, J., Ahmed, R., & Demirci, U. (2020). Medical micro/nanorobots in precision medicine. Advanced Science, 7(21), 2002203.

6. Fraguas-Sánchez, A. I., Martín-Sabroso, C., Fernández-Carballido, A., & Torres-Suárez, A. I. (2019). Status of nanomedicine in the chemotherapy of breast cancer. Cancer chemotherapy and pharmacology, 84, 689-706.

7. Assi, H., Yang, C., Shaswary, E., Tam, M., Tavakkoli, J., Kolios, M., ... & Kumaradas, C. (2020). Real-time control of nanoparticle-mediated thermal therapy using photoacoustic imaging. IEEE Transactions on Biomedical Engineering, 68(7), 2188-2194.

8. Bakker, A., van der Zee, J., van Tienhoven, G., Kok, H. P., Rasch, C. R., & Crezee, H. (2019). Temperature and thermal dose during radiotherapy and hyperthermia for recurrent breast cancer are related to clinical outcome and thermal toxicity: A systematic review. International Journal of Hyperthermia, 36(1), 1023-1038.

9. Banerjee, A., Chakraborty, C., & Rathi Sr, M. (2020). Medical imaging, artificial intelligence, internet of things, wearable devices in terahertz healthcare technologies. In Terahertz biomedical and healthcare technologies (pp. 145-165). Elsevier.

10. Bellizzi, G. G., Paulides, M. M., Drizdal, T., van Rhoon, G. C., Crocco, L., & Isernia, T. (2019). Selecting the optimal subset of antennas in hyperthermia treatment planning. IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology, 3(4), 240-246.

11. Bellizzi, G. G., Paulides, M. M., Drizdal, T., van Rhoon, G. C., Crocco, L., & Isernia, T. (2019). Selecting the optimal subset of antennas in hyperthermia treatment planning. IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology, 3(4), 240-246.

12. Boix-Montesinos, P., Soriano-Teruel, P. M., Arminan, A., Orzaez, M., & Vicent, M. J. (2021). The past, present, and future of breast cancer models for nanomedicine development. Advanced drug delivery reviews, 173, 306-330.

13. Cappiello, G., Paulides, M. M., Drizdal, T., O'Loughlin, D., O'Halloran, M., Glavin, M., ... & Jones, E. (2019). Robustness of time-multiplexed hyperthermia to temperature dependent thermal tissue properties. IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology, 4(2), 126-132.

14. Deenen, D. A., Maljaars, B., Sebeke, L. C., de Jager, B., Heijman, E., Grüll, H., & Heemels, W. M. H. (2020). Offset-free model predictive temperature control for ultrasound-based hyperthermia cancer treatments. IEEE Transactions on Control Systems Technology, 29(6), 2351-2365.

15. Dementieva, O. V., & Kartseva, M. E. (2023). Noble Metal Nanoparticles in Biomedical Thermoplasmonics. Colloid Journal, 85(4), 500-519.

16. Dolev, S., Narayanan, R. P., & Rosenblit, M. (2019). Design of nanorobots for exposing cancer cells. Nanotechnology, 30(31), 315501.

17. Gote, V., Nookala, A. R., Bolla, P. K., & Pal, D. (2021). Drug resistance in metastatic breast cancer: tumor targeted nanomedicine to the rescue. International Journal of Molecular Sciences, 22(9), 4673.

18. Elengoe, A., & Hamdan, S. (2013). Heat sensitivity between human normal liver (WRL-68) and breast cancer (MCF-7) cell lines. J. Biotechnol. Lett, 4, 45-50.

19. Kermany, D. S., Goldbaum, M., Cai, W., Valentim, C. C., Liang, H., Baxter, S. L., ... & Zhang, K. (2018). Identifying medical diagnoses and treatable diseases by image-based deep learning. cell, 172(5), 1122-1131.

20. Gokhman, R., & Sutton, O. Detecting Diabetic Retinopathy Using Convolutional Neural Networks for Image Classification.

21. Zhou, K., Gao, S., Cheng, J., Gu, Z., Fu, H., Tu, Z., ... & Liu, J. (2020, April). Sparse-gan: Sparsity-constrained generative adversarial network for anomaly detection in retinal oct image. In 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI) (pp. 1227-1231). IEEE.

22. Zhou, X., Niu, S., Li, X., Zhao, H., Gao, X., Liu, T., & Dong, J. (2023). Spatial–contextual variational autoencoder with attention correction for anomaly detection in retinal OCT images. Computers in Biology and Medicine, 152, 106328.

23. Tao, Y., Ma, X., Zhang, Y., Huang, K., Ji, Z., Fan, W., ... & Chen, Q. (2023). LAGAN: Lesion-Aware Generative Adversarial Networks for Edema Area Segmentation in SD-OCT Images. IEEE Journal of Biomedical and Health Informatics.

24. Bao, J., Sun, H., Deng, H., He, Y., Zhang, Z., & Li, X. (2023). BMAD: Benchmarks for Medical Anomaly Detection. arXiv preprint arXiv:2306.11876.

25. Agarwal, S., & Bhat, A. (2023). A survey on recent developments in diabetic retinopathy detection through integration of deep learning. Multimedia Tools and Applications, 82(11), 17321-17351.

26. Wang, M., Lin, T., Peng, Y., Zhu, W., Zhou, Y., Shi, F., ... & Chen, X. (2023). Self-Guided Optimization Semi-Supervised Method for Joint Segmentation of Macular Hole and Cystoid Macular Edema in Retinal OCT Images. IEEE Transactions on Biomedical Engineering.

27. Elbasi, E., & Zreikat, A. I. (2021, May). Efficient early prediction and diagnosis of diseases using machine learning algorithms for IoMT data. In 2021 IEEE World AI IoT Congress (AIIoT) (pp. 0155-0159). IEEE.

28. Tang, Z. Y., Lin, Y. C., & Shen, C. C. (2022, October). Dual-Path Convolutional Neural Network for Chronic Kidney Disease Classification in Ultrasound Echography. In 2022 IEEE International Ultrasonics Symposium (IUS) (pp. 1-4). IEEE.

29. Begum, S. H., & Vidyullatha, P. (2022, November). A Study of Deep Learning Models in Diagnosis and Prediction of Chronic Diseases. In 2022 3rd International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT) (pp. 1-6). IEEE.

30. Ogunleye, A., & Wang, Q. G. (2019). XGBoost model for chronic kidney disease diagnosis. IEEE/ACM transactions on computational biology and bioinformatics, 17(6), 2131-2140.

31. Kaur, S., Singla, J., Nkenyereye, L., Jha, S., Prashar, D., Joshi, G. P., ... & Islam, S. R. (2020). Medical diagnostic systems using artificial intelligence (ai) algorithms: Principles and perspectives. IEEE Access, 8, 228049-228069.

32. Tsai, A. C., Zhou, Z. G., Ou, Y. Y., & Wang, I. J. F. (2022, November). Tuberculosis Detection Based on Multiple Model Ensemble in Chest X-ray Image. In 2022 10th International Conference on Orange Technology (ICOT) (pp. 1-4). IEEE.

33. Kumar, R. R., Polepaka, S., Likithasree, D., & Keerthika, S. (2023, January). An Investigation on CNN-based Lung Cancer Prediction Method. In 2023 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1-5). IEEE.

34. Tsai, A. C., Zhou, Z. G., Ou, Y. Y., & Wang, I. J. F. (2022, November). Tuberculosis Detection Based on Multiple Model Ensemble in Chest X-ray Image. In 2022 10th International Conference on Orange Technology (ICOT) (pp. 1-4). IEEE.

35. Kumar, R. R., Polepaka, S., Likithasree, D., & Keerthika, S. (2023, January). An Investigation on CNN-based Lung Cancer Prediction Method. In 2023 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1-5). IEEE.

36. Sawhney, R., Malik, A., Sharma, S., & Narayan, V. (2023). A comparative assessment of artificial intelligence models used for early prediction and evaluation of chronic kidney disease. Decision Analytics Journal, 6, 100169.

37. Yu, H., Nnamdi, N. P., Seo, A., Park, J., & Son, Y. (2023). Motility Analysis of Diaphragm in Patients with Chronic Pulmonary Lung Disease Based on Computed Tomography Technique. IEEE Access.

38. Yu, H., Nnamdi, N. P., Seo, A., Park, J., & Son, Y. (2023). Motility Analysis of Diaphragm in Patients with Chronic Pulmonary Lung Disease Based on Computed Tomography Technique. IEEE Access.

39. Yu, H., Nnamdi, N. P., Seo, A., Park, J., & Son, Y. (2023). Motility Analysis of Diaphragm in Patients with Chronic Pulmonary Lung Disease Based on Computed Tomography Technique. IEEE Access.

40. Choy, Y. P., Hu, G., & Chen, J. (2021). Detection and classification of human stool using deep convolutional neural networks. IEEE Access, 9, 160485-160496.

41. Xu, T., & Yuan, Z. (2022). Convolution neural network with coordinate attention for the automatic detection of pulmonary tuberculosis images on chest x-rays. IEEE Access, 10, 86710-86717.

42. Zhou, Y., Huang, W., Dong, P., Xia, Y., & Wang, S. (2019). D-UNet: a dimension-fusion U shape network for chronic stroke lesion segmentation. IEEE/ACM transactions on computational biology and bioinformatics, 18(3), 940-950.

43. Mondal, S., Sadhu, A. K., & Dutta, P. K. (2021). Adaptive local ternary pattern on parameter optimized-faster region convolutional neural network for pulmonary emphysema diagnosis. IEEE Access, 9, 114135-114152.

44. Abd El-atty, S. M., Arafa, N. A., Abouelazm, A., Alfarraj, O., Lizos, K. A., & Shawki, F. (2022). Performance Analysis of an Artificial Intelligence Nano system with Biological Internet of Nano Things. CMES-Computer Modeling in Engineering & Sciences, 133(1), 111-131.

45. Abd El-Atty, S. M., Lizos, K. A., Alfarraj, O., & Shawki, F. (2023). Internet of Bio Nano Things-based FRET nano communications for eHealth. Mathematical Biosciences and Engineering, 20(5), 9246-9267.

46. Ademaj, A., Puric, E., Timm, O., Kurti, D., Marder, D., Kern, T., ... & Riesterer, O. (2023). Real World Analysis of Quality of Life and Toxicity in Cancer Patients Treated with Hyperthermia Combined with Radio (chemo) therapy. Cancers, 15(4), 1241.

47. Afzal, M., Alharbi, K. S., Alruwaili, N. K., Al-Abassi, F. A., Al-Malki, A. A. L., Kazmi, I., ... & Anwar, F. (2021, February). Nanomedicine in treatment of breast cancer–A challenge to conventional therapy. In Seminars in cancer biology (Vol. 69, pp. 279-292). Academic Press.

48. Aggarwal, M., & Kumar, S. (2022). The use of nanorobotics in the treatment therapy of cancer and its future aspects: a review. Cureus, 14(9).

49. Loukanov, A., Nikolova, S., Filipov, C., & Nakabayashi, S. (2019). Nanomaterials for cancer medication: from individual nanoparticles toward nanomachines and nanorobots. Pharmacia, 66(3), 147-156.

50. Ammar, H. O., Tadros, M. I., Salama, N. M., & Ghoneim, A. M. (2019). Therapeutic strategies for erectile dysfunction with emphasis on recent approaches in nanomedicine. IEEE Transactions on NanoBioscience, 19(1), 11-24.

51. Ammar, H. O., Tadros, M. I., Salama, N. M., & Ghoneim, A. M. (2019). Therapeutic strategies for erectile dysfunction with emphasis on recent approaches in nanomedicine. IEEE Transactions on Nano Bioscience, 19(1), 11-24.

52. Anzar, N., Yadav, N., & Narang, J. (2023). Nanorobots for improved theragnostic applications. In Advanced Nano formulations (pp. 579-603). Academic Press.

53. Asorey-Cacheda, R., Correia, L. M., Garcia-Pardo, C., Wojcik, K., Turbic, K., & Kulakowski, P. (2022). Bridging Nano and Body Area Networks: A Full Architecture for Cardiovascular Health Applications. IEEE Internet of Things Journal, 10(5), 4307-4323.

54. Asorey-Cacheda, R., Correia, L. M., Garcia-Pardo, C., Wojcik, K., Turbic, K., & Kulakowski, P. (2022). Bridging Nano and Body Area Networks: A Full Architecture

for Cardiovascular Health Applications. IEEE Internet of Things Journal, 10(5), 4307-4323.

55. Eversole, D., Subramanian, K., Harrison, R. K., Bourgeois, F., Yuksel, A., & Ben-Yakar, A. (2020). Femtosecond Plasmonic Laser Nano surgery (fs-PLN) mediated by molecularly targeted gold nanospheres at ultra-low pulse fluences. Scientific Reports, 10(1), 12387.

56. Faid, A. H., Shouman, S. A., Thabet, N. A., Badr, Y. A., & Sliem, M. A. (2023). Laser enhanced combinatorial chemo-photothermal therapy of green synthesis gold nanoparticles loaded with 6mercaptopurine on breast cancer model. Journal of Pharmaceutical Innovation, 18(1), 144-148.

57. Gamal, H., Tawfik, W., Fahmy, H. M., & El-Sayyad, H. H. (2021, April). Breakthroughs of using photodynamic therapy and gold nanoparticles in cancer treatment. In 2021 IEEE International Conference on Nanoelectronics, Nano photonics, Nanomaterials, Nano bioscience & Nanotechnology (5NANO) (pp. 1-4). IEEE.

58. Gani, C., Lamprecht, U., Ziegler, A., Moll, M., Geller Mann, J., Heinrich, V., ... & Zips, D. (2021). Deep regional hyperthermia with preoperative radio chemotherapy in locally advanced rectal cancer, a prospective phase II trial. Radiotherapy and Oncology, 159, 155-160.

59. Gote, V., Nookala, A. R., Bolla, P. K., & Pal, D. (2021). Drug resistance in metastatic breast cancer: tumor targeted nanomedicine to the rescue. International Journal of Molecular Sciences, 22(9), 4673.

60. Gu, Y., Piñol, R., Moreno-Loshuertos, R., Brites, C. D., Zeler, J., Martínez, A., ... & Millán, A. (2023). Local Temperature Increments and Induced Cell Death in Intracellular Magnetic Hyperthermia. ACS nano, 17(7), 6822-6832.

61. Hamdi, M., & Ferreira, A. (2013). Guidelines for the design of magnetic nanorobots to cross the blood–brain barrier. IEEE Transactions on Robotics, 30(1), 81-92.

62. Henson, J. C., Brickell, A., Kim, J. W., Jensen, H., Mehta, J. L., & Jensen, M. (2022). PEGylated gold nanoparticle toxicity in cardiomyocytes: assessment of size, concentration, and time dependency. IEEE Transactions on Nano Bioscience, 21(3), 387-394.

63. Huang, L., Chen, F., Lai, Y., Xu, Z., & Yu, H. (2021). Engineering nanorobots for tumor-targeting drug delivery: from dynamic control to stimuli-responsive strategy. ChemBioChem, 22(24), 3369-3380.

64. Kim, J. Y., Zschaeck, S., Debus, J., & Weykamp, F. (2023). Combined Hyperthermia and Re-Irradiation in Non-Breast Cancer Patients: A Systematic Review. Cancers, 15(3), 742.

65. Johnson, A. (2023). Investigation of network models finite difference method. Eurasian Journal of Chemical, Medicinal and Petroleum Research, 2(1), 1-9.

66. Kaur, M., Nagpal, M., & Aggarwal, G. (2023). Nanotechnology for Targeted Drug Delivery to Treat Osteoporosis. Current Drug Targets, 24(1), 2-12.

67. Kher, C., & Kumar, S. (2022). The application of nanotechnology and nanomaterials in cancer diagnosis and treatment: A review. Cureus, 14(9).

68.]Kim, J. Y., Zschaeck, S., Debus, J., & Weykamp, F. (2023). Combined Hyperthermia and Re-Irradiation in Non-Breast Cancer Patients: A Systematic Review. Cancers, 15(3), 742.

69. Kristensen, H. H., Kranabetter, L., Schouder, C. A., Arlt, J., Jensen, F., & Stapelfeldt, H. (2023). Laser-induced Coulomb explosion imaging of alkali-metal dimers on helium nanodroplets. Physical Review A, 107(2), 023104.

70. Kuo, L. W., Chiu, L. C., Lin, W. L., Chen, J. J., Dong, G. C., Chen, S. F., & Chen, G. S. (2018). Development of an MRI-compatible high-intensity focused ultrasound phased array transducer dedicated for breast tumor treatment. IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, 65(8), 1423-1432.

71. Kuo, L. W., Dong, G. C., Pan, C. C., Chen, S. F., & Chen, G. S. (2020). An MRI-guided ring high-intensity focused ultrasound system for noninvasive breast ablation. IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, 67(9), 1839-1847.

72. Bromma, K., & Chithrani, D. B. (2020). Advances in gold nanoparticle-based combined cancer therapy. Nanomaterials, 10(9), 1671.

73. Li, D., Zhao, P., Feng, J., Xing, L., Chen, B., & Liao, D. (2022). Theoretical and experimental investigations on the photo-thermal effect of gold nanorods irradiated by femtosecond and nanosecond laser. Thermal Science, 26(4 Part A), 3133-3142.

74. Li, J., Dekanovsky, L., Khezri, B., Wu, B., Zhou, H., & Sofer, Z. (2022). Biohybrid micro-and nanorobots for intelligent drug delivery. Cyborg and Bionic Systems.

75. Li, J., Wang, B., Zhang, D., Li, C., Zhu, Y., Zou, Y., ... & Wang, X. (2021). A preclinical system prototype for focused microwave breast hyperthermia guided by compressive thermoacoustic tomography. IEEE Transactions on Biomedical Engineering, 68(7), 2289-2300.

76. Li, M., Xi, N., Wang, Y., & Liu, L. (2018). Atomic force microscopy in probing tumor physics for nanomedicine. IEEE Transactions on Nanotechnology, 18, 83-113.

77. Li, M., Xi, N., Wang, Y., & Liu, L. (2020). Progress in nanorobotics for advancing biomedicine. IEEE Transactions on Biomedical Engineering, 68(1), 130-147.

78. Liao, L. D., Wang, Y., Tsao, Y. C., Wang, I. J., Jhang, D. F., Chu, T. S., ... & Ger, T. R. (2019). Design and validation of a multifunctional android-based smart home control and monitoring system. IEEE Access, 7, 163313-163322.

79. Li, M., Xi, N., Wang, Y., & Liu, L. (2018). Atomic force microscopy in probing tumor physics for nanomedicine. IEEE Transactions on Nanotechnology, 18, 83-113.

80. Löke, D. R., Kok, H. P., Helderman, R. F., Franken, N. A., Oei, A. L., Tuynman, J. B., ... & Crezee, J. (2023). Validation of thermal dynamics during Hyperthermic Intraperitoneal Chemotherapy simulations using a 3D-printed phantom. Frontiers in Oncology, 13, 1102242.

81. Loscrí, V., Matekovits, L., Peter, I., & Vegni, A. M. (2016). In-body network biomedical applications: From modeling to experimentation. IEEE Transactions on Nano bioscience, 15(1), 53-61.

82. Loscrí, V., & Vegni, A. M. (2015). An acoustic communication technique of nanorobot swarms for nanomedicine applications. IEEE transactions on nano bioscience, 14(6), 598-607.

83. Loscrí, V., Matekovits, L., Peter, I., & Vegni, A. M. (2016). In-body network biomedical applications: From modeling to experimentation. IEEE Transactions on Nano bioscience, 15(1), 53-61.

84. Lukyanov, A., Nikolova, S., Filipov, C., & Nakabayashi, S. (2019). Nanomaterials for cancer medication: from individual nanoparticles toward nanomachines and nanorobots. Pharmacia, 66(3), 147-156.

85. Manickam, P., Vashist, A., Sadasivam, M., Shinde, R., & Kanagavel, V. (2023). Mobile nanorobotics for biomedical applications. In Engineered Nanostructures for Therapeutics and Biomedical Applications (pp. 297-311). Woodhead Publishing.

86. Manickam, P., Mariappan, S. A., Murugesan, S. M., Hansda, S., Kaushik, A., Shinde, R., & Thipperudraswamy, S. P. (2022). Artificial intelligence (AI) and internet of medical things (IoMT) assisted biomedical systems for intelligent healthcare. Biosensors, 12(8), 562.

87. Mazhukin, V. I., Shapranov, A. V., Demin, M. M., Koroleva, O. N., & Mazhukin, A. V. Visualization Analysis of the Results of Continuum-Atomistic Modeling of a Coulomb Explosion in Metals Under the Influence of Ultrashort (fs, ps) Laser Action.

88. McNabb, E., Sharma, D., Sannachi, L., Giles, A., Yang, W., & Czarnota, G. J. (2023). MR-guided ultrasound-stimulated microbubble therapy enhances radiation-induced tumor response. Scientific Reports, 13(1), 4487.

89. Merten, R., Ott, O., Haderlein, M., Bertz, S., Hartmann, A., Wullich, B., ... & Fietkau, R. (2019). Long-term experience of chemoradiotherapy combined with deep regional hyperthermia for organ preservation in high-risk bladder cancer (Ta, Tis, T1, T2). The oncologist, 24(12), e1341-e1350.

90. Afzal, M., Alharbi, K. S., Alruwaili, N. K., Al-Abassi, F. A., Al-Malki, A. A. L., Kazmi, I., ... & Anwar, F. (2021, February). Nanomedicine in treatment of breast cancer–A challenge to conventional therapy. In Seminars in cancer biology (Vol. 69, pp. 279-292). Academic Press.

91. Muhumed, A. M., Solihin, M. I., Teh, B. H., & Ng, W. K. (2023). A Mini Review on Nanorobots in the Medical Field: Applications and Challenges. MEKATRONIKA, 5(1), 13-17.

92. Muhumed, A. M., Solihin, M. I., Teh, B. H., & Ng, W. K. (2023). A Mini Review on Nanorobots in the Medical Field: Applications and Challenges. MEKATRONIKA, 5(1), 13-17.

93. Nakhla, S., Rahawy, A., Abd El Salam, M., Shalaby, T., Zaghloul, M., & El-Abd, E. (2020). Radio sensitizing and phototherapeutic effects of AuNPs are mediated by differential Noxa and Bim gene expression in MCF-7 breast cancer cell line. IEEE Transactions on Nano Bioscience, 20(1), 20-27.

94. Nakhla, S., Rahawy, A., Abd El Salam, M., Shalaby, T., Zaghloul, M., & El-Abd, E. (2020). Radio sensitizing and phototherapeutic effects of AuNPs are mediated by differential Noxa and Bim gene expression in MCF-7 breast cancer cell line. IEEE Transactions on Nano Bioscience, 20(1), 20-27.

95. Jabbari, N., Akbari Azar, E., Feqhhi, M., Rahbar ghazi, R., & Rezaie, J. (2020). Breast cancer-derived exosomes: tumor progression and therapeutic agents. Journal of cellular physiology, 235(10), 6345-6356.

96. Ning, Z., Lian, Y., Jiang, L., Sun, J., Wu, S., & Wang, F. (2022). Femtosecond Laser-Induced Anisotropic Structure and Nonlinear Optical Response of Yttria-Stabilized Zirconia Single Crystals with Different Planes. ACS Applied Materials & Interfaces, 14(34), 39591-39600.

97. Odion, R., Liu, Y., & Vo-Dinh, T. (2021). Plasmonic gold nano star-mediated photothermal immunotherapy. IEEE Journal of Selected Topics in Quantum Electronics, 27(5), 1-9.

98. Adir, O., Poley, M., Chen, G., Froim, S., Krinsky, N., Shklover, J., ... & Schroeder, A. (2020). Integrating artificial intelligence and nanotechnology for precision cancer medicine. Advanced Materials, 32(13), 1901989.

99. Onal, H., Yilmaz, T., & Akinci, M. N. (2023). A BIM-Based Algorithm for Quantitative Monitoring of Temperature Distribution during Breast Hyperthermia Treatments. IEEE Access.

100. Ott, O. J., Gani, C., Lindner, L. H., Schmidt, M., Lamprecht, U., Abdel-Rahman, S., ... & Fietkau, R. (2021). Neoadjuvant chemoradiation combined with regional hyperthermia in locally advanced or recurrent rectal cancer. Cancers, 13(6), 1279.

101. Boix-Montesinos, P., Soriano-Teruel, P. M., Arminan, A., Orzaez, M., & Vicent, M. J. (2021). The past, present, and future of breast cancer models for nanomedicine development. Advanced drug delivery reviews, 173, 306-330.

102. Pramanik, P. K. D., Solanki, A., Debnath, A., Nayyar, A., El-Sappagh, S., & Kwak, K. S. (2020). Advancing modern healthcare with nanotechnology, nano biosensors, and internet of nano things: Taxonomies, applications, architecture, and challenges. IEEE Access, 8, 65230-65266.

103. Pramanik, P. K. D., Solanki, A., Debnath, A., Nayyar, A., El-Sappagh, S., & Kwak, K. S. (2020). Advancing modern healthcare with nanotechnology, nano biosensors, and internet of nano things: Taxonomies, applications, architecture, and challenges. IEEE Access, 8, 65230-65266.

104. Nakhla, S., Rahawy, A., Abd El Salam, M., Shalaby, T., Zaghloul, M., & El-Abd, E. (2020). Radio sensitizing and phototherapeutic effects of AuNPs are mediated by differential Noxa and Bim gene expression in MCF-7 breast cancer cell line. IEEE Transactions on Nano Bioscience, 20(1), 20-27.

105. Rao, X. (2023). An upwind generalized finite difference method (GFDM) for meshless analysis of heat and mass transfer in porous media. Computational Particle Mechanics, 10(3), 533-554.

106. KM, R., & MMF, A. H. (2020). Silver: Gold Nanoparticles Medicating for Phototherapy against Breast Cancer Cell Line (MCF7). Indian Journal of Public Health Research & Development, 11(4).

107. Sadeghi-Goughari, M., Jeon, S., & Kwon, H. J. (2019). Enhancing thermal effect of focused ultrasound therapy using gold nanoparticles. IEEE Transactions on Nano Bioscience, 18(4), 661-668.

108. Santhakumar, H., Nair, R. V., Govindachar, D. M., Periyasamy, G., & Jayasree, R. S. (2023). Engineering of Tripeptide-Stabilized Gold Nanoclusters with Inherent

Photosensitizing Property for Bioimaging and Photodynamic Therapy. ACS Sustainable Chemistry & Engineering, 11(6), 2102-2114.

109. Shen, X., Ouyang, Q., Tan, H., Ouyang, J., & Na, N. (2023). Computation-Assisted Design of ssDNA Framework Nanorobots for Cancer Logical Recognition, Toehold Disintegration, Visual Dual-Diagnosis, and Synergistic Therapy. Analytical Chemistry, 95(14), 5903-5910.

110. Sogomonyan, A. S., Deyev, S. M., & Shipunova, V. O. (2023). Internalization-Responsive Poly (lactic-co-glycolic acid) Nanoparticles for Image-Guided Photodynamic Therapy against HER2-Positive Breast Cancer. ACS Applied Nano Materials.

111. Soto, F., Wang, J., Ahmed, R., & Demirci, U. (2020). Medical micro/nanorobots in precision medicine. Advanced Science, 7(21), 2002203.

112. Srivastava, M., Mandal, R. K., & Prasad, N. K. (2022). AC Magnetic Field Dependent Hyperthermia for Controlled Heating Near Therapeutic Temperature. IEEE Transactions on Magnetics, 58(10), 1-6.

113. Venmathi, A. R., & Vanitha, L. (2021). Performance Evaluation of Nanorobot Drug Delivery Mechanism for Breast Cancer. In Next Generation of Internet of Things: Proceedings of ICNGIoT 2021 (pp. 233-242). Springer Singapore.

114. Voss, J. M., Olshin, P. K., Charbonnier, R., Drabbels, M., & Lorenz, U. J. (2019). In situ observation of coulomb fission of individual plasmonic nanoparticles. ACS nano, 13(11), 12445-12451.

115. Zhao, H., Zhan, W., Yuhui, Z., Zhang, T., Li, H., & Rao, X. (2023). A connection element method: Both a new computational method and a physical data-driven framework—-Take subsurface two-phase flow as an example. Engineering Analysis with Boundary Elements, 151, 473-489.

116. Lukyanov, A., Nikolova, S., Filipov, C., & Nakabayashi, S. (2019). Nanomaterials for cancer medication: from individual nanoparticles toward nanomachines and nanorobots. Pharmacia, 66(3), 147-156.

117. R Kamal, I., M Abd El-Atty, S., El-Zoghdy, S. F., & F Soliman, R. (2023). A Multi Compartmental model for Targeted Drug Delivery Based on Internet of Biological Nano Things. Menoufia Journal of Electronic Engineering Research, 32(1), 15-23.

118. Dheyab, M. A., Aziz, A. A., Khaniabadi, P. M., Jameel, M. S., Oladzadabbasabadi, N., Rahman, A. A., ... & Mehrdel, B. (2023). Gold nanoparticles-

based photothermal therapy for breast cancer. Photo diagnosis and photodynamic therapy, 103312.

119. Kaur, I., Tieu, T., Deepagan, V. G., Ali, M. A., Alsunaydih, F., Rudd, D., ... & Voelcker, N. H. (2023). Combination of Chemotherapy and Mild Hyperthermia Using Targeted Nanoparticles: A Potential Treatment Modality for Breast Cancer. Pharmaceutics, 15(5), 1389.

120. Akter, Z., Khan, F. Z., & Khan, M. A. (2023). Gold nanoparticles in triple-negative breast cancer therapeutics. Current Medicinal Chemistry, 30(3), 316-334.

121. Abed, A. S., Khalaf, Y. H., & Mohammed, A. M. (2023). Green synthesis of gold nanoparticles as an effective opportunity for cancer treatment. Results in Chemistry, 5, 100848.

122. Faid, A. H., Shouman, S. A., Thabet, N. A., Badr, Y. A., & Sliem, M. A. (2023). Laser enhanced combinatorial chemo-photothermal therapy of green synthesis gold nanoparticles loaded with 6mercaptopurine on breast cancer model. Journal of Pharmaceutical Innovation, 18(1), 144-148.

123. Kalyane, D., Polaka, S., Vasdev, N., & Tekade, R. K. (2023). Cancer Cell-Specific and Laser-Activatable NanoSeeds for Targeted Photothermal Ablation of Triple-Negative Breast Cancer. Photochemistry and Photobiology, 99(4), 1157-1171.

124. Nori, Z. Z., Bahadori, M., Moghadam, M., Tangestaninejad, S., Mirkhani, V., Mohammadpoor-Baltork, I., ... & Alem, H. (2023). Synthesis and characterization of a new gold-coated magnetic nanoparticle decorated with a thiol-containing dendrimer for targeted drug delivery, hyperthermia treatment and enhancement of MRI contrast agent. Journal of Drug Delivery Science and Technology, 81, 104216.

125. Shabani, L., Kasaee, S. R., Chelliapan, S., Abbasi, M., Khajehzadeh, H., Dehghani, F. S., ... & Kamyab, H. (2023). An investigation into green synthesis of Ru template gold nanoparticles and the in vitro photothermal effect on the MCF-7 human breast cancer cell line. Applied Physics A, 129(8), 564.

126. Dongsar, T. T., Dongsar, T. S., Abourehab, M. A., Gupta, N., & Kesharwani, P. (2023). Emerging application of magnetic nanoparticles for breast cancer therapy. European Polymer Journal, 111898.

127. Nosrati, H., Salehiabar, M., Charmi, J., Yaray, K., Ghaffarlou, M., Balcioglu, E., & Ertas, Y. N. (2023). Enhanced in vivo radiotherapy of breast cancer using gadolinium oxide and gold hybrid nanoparticles. ACS Applied Biomaterials, 6(2), 784-792.

128. Shojaedini, S. V., Abedini, M., & Monajemi, M. (2023). Generative adversarial network: a statistical-based deep learning paradigm to improve detecting breast cancer in thermograms. Medical & Biological Engineering & Computing, 1-11.

129. Yao, Z., Luo, T., Dong, Y., Jia, X., Deng, Y., Wu, G., ... & Zhou, J. (2023). Virtual elastography ultrasound via generative adversarial network for breast cancer diagnosis. Nature Communications, 14(1), 788.

130. Haq, D. Z., & Fatichah, C. (2023). Ultrasound Image Synthetic Generating Using Deep Convolution Generative Adversarial Network for Breast Cancer Identification. IPTEK The Journal for Technology and Science, 34(1), 12.

131. Ghose, S., Cho, S., Ginty, F., McDonough, E., Davis, C., Zhang, Z., ... & Badve, S. S. (2023). Predicting Breast Cancer Events in Ductal Carcinoma In Situ (DCIS) Using Generative Adversarial Network Augmented Deep Learning Model. Cancers, 15(7), 1922.

132. Anwar, S., Ali, S., Abdulla, D., Omekara, S. D., Mendiola, S., Wright, K., & Muhammed, S. A. (2023, May). Breast Cancer Radio genomics Data Generation Using Combined Generative Adversarial Networks GANs. In International Conference on Intelligent Systems and Pattern Recognition (pp. 106-119). Cham: Springer Nature Switzerland.

133. Park, S., Lee, K. H., Ko, B., & Kim, N. (2023). Unsupervised anomaly detection with generative adversarial networks in mammography. Scientific Reports, 13(1), 2925.

134. Inan, M. S. K., Hossain, S., & Uddin, M. N. (2023). Data augmentation guided breast cancer diagnosis and prognosis using an integrated deep-generative framework based on breast tumor's morphological information. Informatics in Medicine Unlocked, 37, 101171.

135. Suresh, T., Brijet, Z., & Subha, T. D. (2023). Imbalanced medical disease dataset classification using enhanced generative adversarial network. Computer Methods in Biomechanics and Biomedical Engineering, 26(14), 1702-1718.

136. Nasser, M., & Yusof, U. K. (2023). Deep Learning Based Methods for Breast Cancer Diagnosis: A Systematic Review and Future Direction. Diagnostics, 13(1), 161.