National College of Business Administration & Economics Lahore

IoT BASED VEHICLE IDENTIFICATION USING MACHINE LEARNING TECHNIQUES

BY

UZAIR AHMAD

MASTER OF PHILOSOPHY
IN
COMPUTER SCIENCE

DECEMBER, 2022

NATIONAL COLLEGE OF BUSINESS ADMINISTRATION & ECONOMICS

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A dissertation submitted to
Faculty of Computer Sciences

In Partial Fulfillment oft he
Requirements for the Degree of

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بسم الله الرحمن الرحيم

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

NATIONAL COLLEGE OF BUSINESS ADMINISTRATION & ECONOMICS LAHORE

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Dissertation Committee:

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Chairman

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Member

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Member

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Director Research
National College of Business Administration and Economics

DECLARATION

It is to declare that this research work has not been submitted for obtaining similar degree from any other university/college.

UZAIR AHMAD
DECEMBER, 2022

Dedicated
To

My dearest Parents

Respected Teachers

&

Dear Friends

who always encouraged me

to work hard and led me

towards the right way

and destination.

ACKNOWLEDGEMENT

All praises to Allah Almighty, who is the most Gracious and Merciful, who created the universe and knows whatever is in it, hidden or evident. I have no words to express my thanks to ALLAH ALMIGHTY, who always blessed me a lot and give me light in every darkness and difficulty, billions of blessings and peace be upon the last Holy Prophet Hazrat Muhammad ﷺ.

I would like to pay my deep gratitude to my research supervisor "Dr. Muhammad Asif" for his guidance and rigorous appraisal not only improved the quality of this thesis, but also my overall understanding of the subject. Your advice on both research as well as on my career has been invaluable.

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This acknowledgement will remain incomplete if I do not say a few words about my parents I pay remarkable tribute to my Mother and Father as their love, care, devotion, dedication, encouragement, generous support, and

Hard work of life enabled me to achieve this goal. I would like to express my gratitude towards my family for the encouragement which helps me in completion of this thesis especially for my beloved sister. This thesis becomes a reality with the kind support and help of many individuals, my colleagues and friends. I would like to thank all of them. Special thanks to my senior Dr. Adnan Khan, Dr. Haris Mateen and friend Mr. Shan.

RESEARCH COMPLETION CERTIFICATE

Certified that the research work contained in this thesis entitled **“IoT Based Vehicle Identification using Machine Learning Techniques”** has been carried out and completed by **Uzair Ahmad** under my supervision during her **M.Phil. Computer Science** Programme.

(Dr. Muhammad Asif)
Supervisor

SUMMARY

Technology is growing fast, so a secure way of life and travel are in high demand among the community. A massive growth in traffic is caused by an excessively growing world population on hi-tech modern roads. There are more and more vehicles and trucks on the road. It is demand of time to identify vehicles and compute traffic jam on roads. For the control and monitoring systems, the identifying of vehicles is crucial. Number plates, which are a specific pairing of numbers and letters are used to identifying vehicles. However, physically identifying every single parked or moving car's license plate is a difficult and time-consuming task for anyone. Due to the daily tremendous growth of the vehicle industry, tracking individual vehicles has become a difficult undertaking. In the majority of applications involving the movement of vehicles, the identification and detection of a vehicle Number Plate (NP) are crucial techniques. In the field of image processing, it is also a hotly debated as well as ongoing research topic. For the purpose of discovering and identifying vehicle NPs, numerous techniques, methods, and algorithms have been created. You Only Look Once (YOLO) Algorithm is applied to detect as well as classify the vehicle NP. This proposed model shows more accuracy than the previous models.

In the first chapter, we discussed Introduction, information technology, internet of things, its history, its works, structure of IoT, applications of IoT, Vehicle identification, its techniques, machine learning, its scope, types of machine learning, its algorithms, deep learning, its positive aspects, deep learning algorithms, YOLO algorithm, its working, research gap, motivation, aims & objectives as well as research questions.

Second chapter, we discussed literature review and comparison table.

Third chapter, methodology, diagram and detail of diagram.

Fourth chapter results and comparison table.

Fifth chapter literature review

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Nowadays Life is busy and moving fast, everything which is related to or helps in serving life also growing fast. Technologies today play a significant role in all aspects of life to make things simpler by saving time and manpower. In Technology Machine learning is one of which is play a role as a backbone in modern-day life. One of the demanded artificial intelligence methods to handle the huge amount of data is Machine Learning (ML). The algorithm is self-learning. Improvised analysis and patterns are used to finish it [1]. In addition, deep learning, a subclass of ML, performs the ML process using a higher ranking level of neural networks [2–3]. The neuron nodes that are joined serve as the links in artificial neural networks, which simulate human brain function [4]. Deep learning is usually known as deep neural networking or learning [2]. Deep Learning is a subclass of ML techniques that were inspired by artificial neural networks, which contain structural and functional components. Artificial neural networks are used by the majority of deep learning models. The word deep in deep learning indicates how many layers are used to modify the data [5].

Day by day vehicles is an obligatory part of life. Vehicles are increased so it is a demand of time and also the huge demand between the people for a secure life as well as traveling and for maintaining the record and monitoring the Vehicles movements at road so, it is essential that Vehicles are monitor and detect. To perform the task manually detection of vehicles is very difficult and a lot of time is required which a lot of men is required but we cannot achieve the required results due to the massive vehicles on the roads. Both time and manpower required to manually identify automobiles will be wasted. Number plates, which are made up of a special alphabetic and numeric combination, can be used to identify cars. There are numerous machine learning algorithms available for reading plate numbers, but they all have some restrictions and real-time complexity issues, so we need a precise approach to read plate numbers in real-time. Although deep learning and machine learning methods for detecting vehicle number plates have made significant progress [6–7]. Through the use of You Only Look Once (YOLO)-inspired models, significant improvements in object detection were made [8, 9]. Based on the cutting-edge object detection system YOLO version 3, the number plate detection system for vehicles is presented in this study [10].

The numbering system, colors, and the languages used for the characters, fonts, and sizes, however, vary from one country to the next. Further research is required in this area in order to advance the efficiency of the detection in addition recognition process. Several existing systems work with very well controlled conditions, despite the fact that this field has been extensively studied by researchers. The YOLO algorithm and roadside security cameras are used in this study to develop an automated vehicle monitoring system for fast-moving cars. The major goal of our research is to build a robust number plate recognition model that operates in a variety of illumination and angles. There are four basic steps in the proposed work. Video footage is first turned into pictures, after which the YOLO algorithm begins to function and the image is separated into several grids known as Residual Blocks. The automobile is recognized from each frame, and each grid cell detects objects that appear within them. A bounding box is then an outline that draws attention to an object in a picture. The following stage is detecting a number plate from the identified auto. The Intersection Over Union (IOU) technique has been successful in the past. An IOU is applied by YOLO to create an output box that correctly encircles the items. In this step, the number plate characters reading are documented from the detected number plates. After detecting the vehicle number plate we connect our system with a database of different departments related to vehicles to check the vehicle's identification is it a stolen car or not, token paid or not, custom paid or non-custom etc. If the system finds any required identification of vehicle then, the system displays the identify vehicle status on screen.

1.2 INFORMATION TECHNOLOGY

Information technology (IT) is the technique of developing, producing, processing, storage, fortifying, in addition transporting all forms of electronic data using computers, storage, networking, as well as other physical devices, software, infrastructures, and processes.

An IT system is a general term for an information system, networking system, or, more precisely, a computer system that includes all peripheral devices, software, and hardware and is used by a limited percentage of IT users. Computer science, which is characterized as the comprehensive analysis of protocol, layout, and the processing of different types of data, includes information technology as one of its areas of study.

1.3 INTERNET OF THINGS

Internet of Things (IoT) is the network of physical objects or things that are integrated with hardware, programs, sensors, and networking capabilities. This system allowed these devices to collect data, collect information as well as exchange data.

Through the use of existing network infrastructure, IoT enables things to be detected and remotely operated. This more direct incorporation of the physical environment and computer-based platforms leads to increased effectiveness, accuracy, and financial gain. In the context of the IoT "things" can refer to a broad range of devices, including implants for heart monitoring, biochip transponders on farm animals, electric clams in coastal waters, cars through built-in sensors, DNA analysis strategies for environmental / food/ pathogen monitoring, or field process tools that benefit firefighters through search as well as rescue operations.

These devices cumulate useful data with the assist of multiple existing skills and then self-sufficiently flow the data between other devices.

1.3.1 History of IoT

Through the MIT Auto-ID Centre and associated market-analysis studies, the idea of the IoT first received attention in 1999. At that time, radio-frequency identification (RFID) was considered a requirement for the IoT. If every person and item in daily life had an identification, then computers could manage and keep a record of them. In addition to RFID, technologies including Bluetooth, near-field communication, barcodes, QR codes, in addition digital watermarking can also be used to label the objects.

1.3.2 How It Works

The IoT is not the outcome of a single innovative technological development; rather, a number of related modern technologies offer capabilities that, when combined, assisting in the integration of the physical and the virtual worlds.

These characteristics include:

- Communication and cooperation
- Addressability
- Identification
- Sensing
- Actuation
- Embedded information processing
- Localization
- User interfaces

1.3.3 Structure of IoT

The IoT may be thought of as a huge network made up of networks of gadgets as well as associated by a number of intervening technologies, many of which, including RFIDs and wireless connections, may serve as facilitators of this connectedness.

- **Labelling Things**: Addressable and real-time object detection using RFIDs.
- **Feeling Things**: The main tools for gathering environmental data are sensors.
- **Shrinking Things**: Miniaturization and nanotechnology have enabled micro objects to communicate and collaborate throughout objects and intelligent gadgets.
- **Thinking Things:** The network connection to the Internet has been built through sensors and embedded intelligence in equipment. It may enable things to recognize intelligent control.

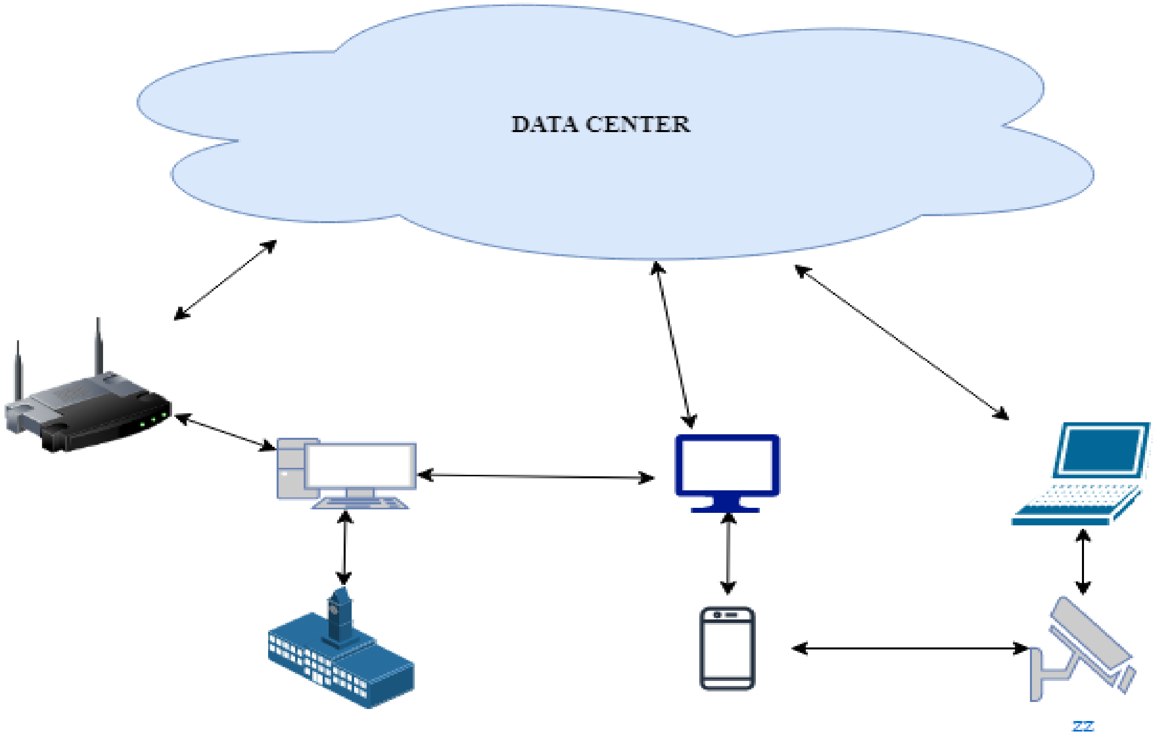

Figure 1: Structure of IoT

Figure 1 is showing that different devices connected with each other for communicate and share information between them and their all communication and data they share with each other is save in a data center. In this way different devices connected with each other and make a different structures of IoT.

1.3.4 Applications of IoT

- Transportation
- Environmental monitoring
- Building as well as Home automation
- Manufacturing
- Healthcare systems and Medical
- Media
- Infrastructure organization
- Energy organization
- Improved quality of life for old citizen

1.4 VEHICLE IDENTIFICATION

Detection of vehicles is a relatively new method of gathering transportation data and might serve as the backbone of an intelligent transportation system. It is currently being implemented in parts in the Europe, United States and some Arab nations, including the UAE, with Qatar and Saudi Arabia as future possible aims. The Global Positioning System (GPS tool) is helpful for tracking business trucks and for navigation. While technology like License Plate detection (LPD) and RFID labels are more commonly employed for detecting traffic infractions, congestion pricing, and road tolls.

The US road transportation authorities have conducted numerous studies evaluating various vehicle identification techniques. Most of that research came to the conclusion that RFID tag systems were significant due to their high reliability and favorable cost/benefit ratio. These studies have also addressed the several significant public and national welfares that can be obtained from using RFID label frameworks and have outlined the privacy concerns that prevent such widespread use [24, 25].

The use of engine-powered vehicles as an alternative method of moving people and products contributed to the development of motorized transportation systems at the beginning of the 19th century. To manage and regulate traffic flows, transportation planning and traffic engineering have become essential. Planning became important as time went on in order to predict the quality and variety of transportation frameworks that would be able to meet the travel petition of the expanding population and their escalating lifestyle activities. The quality of the various transportation researchers, their references, and plans will indisputably be squeezed by the accuracy of the data together, as social economic data, origin-destination surveys, traffic counts, and other statistical data are the fundamental and primary input for all transportation planning and evaluation studies. A review of the evolution of transportation systems and data collection techniques during the following stages is therefore worthwhile. [27]:

1.4.1 Medium Demand Stage/Low Tech

It was the greatest time of tenure and continued until the 1970s. The stage was widely considered to be one of moderate demand, and the only tools available were conventional data collection approaches. In general, transportation policies aim to expand capacity in accordance with predicted traffic growth.

1.4.2 High Demand Stage/Medium-Tech

It was the decade spanning the 1970s and 1990s. The stage was typically described as being in great demand and used basic standard data collection techniques that had been slightly updated. The use of public transportation has been encouraged through transportation policies.

1.4.3 Saturation Demand Stage/High-Tech

In order to address overall traffic overcrowding, infrastructure as well as transportation planning strategies were redirected to increase and uphold capacity, indorse public transport, in addition to enforce the reduction of car trip request through the use of fines. Camera systems, license plate scanners, RFID tag sensors, as well as GPS tools were added to transportation data organization systems in addition to the conventional techniques. In the majority of transportation studies, detailed modelling processes, micro simulation scenarios, as well as analysis have become standard practice and prerequisites. Road traffic data collection techniques are described in the part that follows [26]:

1.5 MACHINE LEARNING

The term ML pronounces a system's volume to gather and synthesis knowledge through extensive observation, as well as to progress in addition encompass itself by selection up new information rather than having it preprogrammed into it. Artificial intelligence is used in machine learning, which gives computers the capacity to learn and memorized automatically and get better over time without explicit programming.

ML is a specialization of AI that enables computers to learn independently over time from training data and develop without explicit programming. Machine learning algorithms can create their own predictions by identifying patterns in the data and learning from them.

1.5.1 Scope of Machine Learning

1. **Machine Learning in Search Engine**
   Search engine ranks page based on what you are most likely to click on. Search engine depends on ML to improve their services such

as voice recognition, image search and many more. In future many more interesting features will also come.

2. **Traffic Alert**

Google maps app is used to give assistance in direction and traffic also based on ML. Everyone who uses the maps app provides their position, average speed, and the route they are taking, which in turn helps Google accumulate a huge amount of traffic data that allows them to estimate incoming traffic and modify your route accordingly.

3. **Spam Detector**

In analyzing the emails and forwarding the spam emails to the spam folder, our mail operator, like Gmail, puts in a lot of labor on our behalf. Additionally, ML is used to do this.

1.5.2 Types of Machine Learning

Supervised Learning

Supervised learning is a subfield of artificial intelligence and machine learning. It stands out for the way it efficiently uses tagged datasets to train computers to perform classification or make predictions. The concept of an algorithm learning from a training dataset, which can be viewed as the instructor's rise to the phrase supervised learning.

With the use of training examples of inputs and their related outputs, supervised learning can predict the results of fresh inputs. In supervised learning, we train the computer using labels that accurately reflect the output of the data. Given that the dataset is tagged, the algorithm must specifically identify the characteristics before making a prediction or classifying data in accordance with them.

The objective is to create a mapping function that is efficient enough for the algorithm to predict the output from a new input. Every time the algorithm generates a projection, it is corrected or provided feedback, and this process is repeated until the algorithm performs at an appropriate standard.

Types of Supervised Learning Techniques

i) Classification

ii) Regression

Unsupervised Learning

Unsupervised learning, frequently referred to as "unsupervised ML," is the process by which ML algorithms analyses and categorize untagged datasets. These ML algorithms extract hidden information or data sets without the involvement of a human. In unsupervised ML, several unidentified patterns in the data are discovered. Using unsupervised approaches, you can discover traits that can be helpful for categorization.

Unsupervised learning algorithms make an effort to utilize techniques on the input data in order to mine for rules, find patterns, summaries, and categories the data points, which aid in deriving relevant insight and better representing the data to users. Unlabeled data could consist of images, movies, audio files, etc. Each piece of unlabeled data is merely data with no interpretation; there is nothing else.

Types of Unsupervised Learning

i) Clustering

ii) Association

Semi-Supervised Learning

Semi-supervised learning is a technique of ML that, during training, merges a small quantity of tagged data with a large amount of untagged data. This method gives the advantages of both supervised and unsupervised learning without having to tackle the difficulties associated with detecting a large amount of tagged data. Therefore, you don't need to apply as much tagged training data when training a model to tag data.

Between the two is where semi-supervised learning falls. It handles classification issues, so you'll need a supervised learning algorithm for the project. Unsupervised machine learning approaches can enable you to train your model without labelling each and every training example, though if you want to.

Reinforcement Learning

In the field of ML known as reinforcement learning, behaviors that smart objects should perform in a given environment to maximize the concept of cumulative reward are considered. One of the three fundamental ML models, together with supervised learning and unsupervised learning, is reinforcement learning. A computer learns to execute a task through regular trial-and-error interactions with a dynamic environment. This is a sort of ML.

It varies between supervised and unsupervised ML techniques that demand sizable datasets for training. Reinforcement learning algorithms are created to constantly learn from experience as opposed to only data. An agent in deep learning will need to interact with the environment to determine the optimum outcome. The reinforcement learning method iteratively learns from the environment in a continuous manner until it has explored every possible state.

1.5.3 Machine Learning Algorithms

In a world when almost all manual operations are mechanized, the concept of manual is expanding. An algorithm set classified as a learning algorithm is employed in ML to enable a computer program to replicate how a human becomes more competent at identifying different varieties of data. As the programming is exposed to additional information, the mathematics and reasoning that underpin a learning algorithm could gradually update automatically (without operator interaction). ML algorithms can let machines do surgery, play chess, and become smarter and more human-like.

An ML method, which is a subset of AI, uses a variety of precise, probabilistic, and sophisticated techniques to enable computers to learn from their past experiences and discover challenging patterns from huge, noisy, or complicated information. Pattern recognition is a task performed by machine learning systems. Algorithms are fit to a dataset or learn from data.

The AI system performs its duty by using a ML algorithm, which generally estimates output values from given input data. Fast information processing and decision-making when it reaches the threshold require the use of machines.

There are numerous mentioned ML algorithms:

i) Linear regression.

ii) Logistic regression.

iii) Decision tree.

iv) SVM algorithm.

v) Naive Bayes algorithm.

vi) KNN algorithm.

vii) K-means.

viii) Random forest algorithm.

1.6 DEEP LEARNING

A neural network containing three or additional layers is a neural network, as well as Deep Learning (DL) is a branch of ML. Artificial neural networks (ANNs), which are used in DL, are self-learning algorithms that are modelled after the structure in addition operation of the brain.

ANNs will not get detailed commands on how to knob difficulties; instead, they are trained to learn models in addition patterns. These neural networks make an effort to mimic the function of the human brain, but they fall well short of matching its capacity for learning from massive amounts of information. More hidden layers could indeed help to refine and optimize for accuracy, even though a neural network with only one layer can still produce approximations.

DL networks learn by spotting intricate patterns in the data they analyses. By building computational models with various types of layers, the networks can develop various levels of abstraction to convey the information. In DL, training uses both and unstructured data. Virtual assistants, autonomous vehicle vision, money laundering, face recognition, as well as other applications are real-world examples of DL.

1.6.1 Positive Aspects of Deep Learning

i) Expandable.

ii) Generate feature automatically.

iii) Works well with Undefined Data.

iv) Better Self-Learning capabilities.

v) Supports Parallel as well as distributed Algorithms.

vi) Cost control.

vii) Advanced Analytics.

1.6.2 Deep Learning Algorithms

i) Convolutional Neural Networks (CNN)

ii) You look only once (YOLO)

iii) Multilayer Perceptrons (MLPs)

iv) Radial Basis Function Networks (RBFNs)

v) Recurrent Neural Networks (RNNs)

vi) Long Short-Term Memory Networks (LSTMs)

vii) Restricted Boltzmann Machines (RBMs)

viii) Self-Organizing Maps (SOMs)

ix) Generative Adversarial Networks (GANs)

x) Auto encoders

xi) Deep Belief Networks

1.7 YOLO ALGORITHM

"You Only Look Once" is referenced to as YOLO. This method immediately detects and recognizes various objects in an image based on real-time. The identification and verification practice in YOLO, which is carried out as a regression problematic, affords the class probabilities of the noticed images.

YOLO is a deep learning algorithm that works on real-time image classification with the help of neural networks, by which each object in an image is detected. This algorithm's popularity is a result of its accuracy and speed. It has been used in many different situations to distinguish between animals, people, car parks, and traffic signals. The major used of this algorithm is for detecting and identifying the different vehicles at same time.

Various methods are used for object recognition, including Retina-Net, rapid R-CNN, and Single-Shot Multi Box Detector (SSD). These approaches have addressed the problems of data shortage and modelling in object detection. However, they cannot find objects in a single algorithm run. Due to its superior performance to the above-mentioned object detection techniques, the YOLO algorithm has grown in popularity.

CNN are used in the YOLO method to quickly identify objects. As the name would suggest, the method only requires one additional replication through a neural network to detect objects. This shows that estimation is carried out across the entire image using a single algorithm run. CNN is used to predict both bounding boxes and multiclass classification probabilities. There are numerous variations of the YOLO algorithm. YOLO and YOLOv3 are a couple of the more popular ones.

YOLO algorithm is important because of the points given below:

- **Speed:** The real-time item prediction capability of this method increases the speed of detection.

- **High accuracy:** YOLO is a predictive method that yields precise findings with nothing in the way of background noise.

- **Learning capabilities:** The algorithm has exceptional learning potential that allow it to learn object characterization and use them in object detection.

YOLO algorithm works using the following **three procedure**:

- Residual blocks
- Bounding box regression
- Intersection Over Union (IOU)

1.7.1 Residual Blocks

The figure is initially divided into numerous grid blocks, or residual blocks. The following graphic shows the grids that were built using an input image.

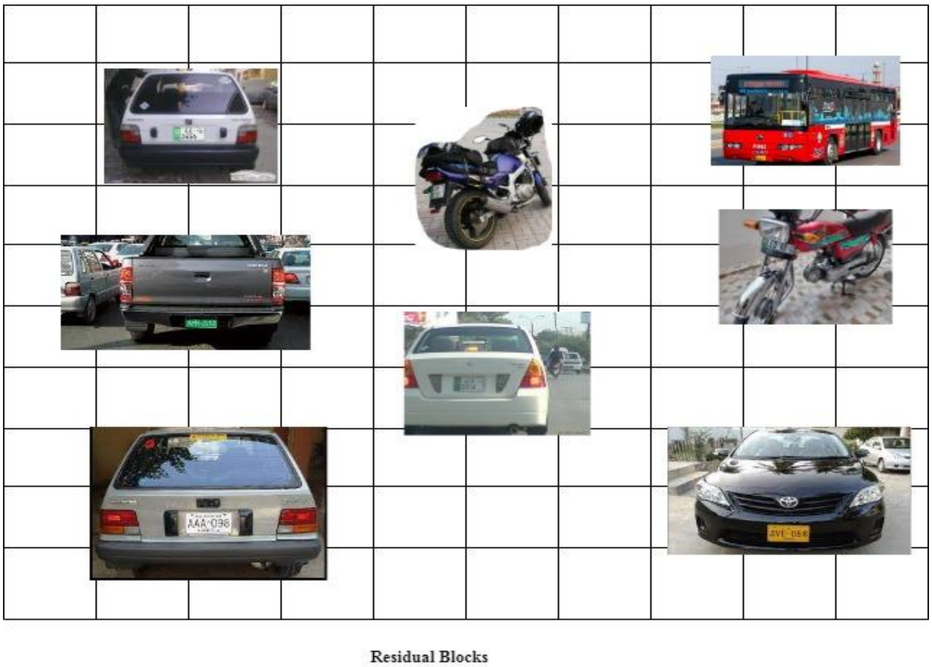

Figure 2: Residual Blocks

In Figure 2 the following graphic shows many grid blocks of uniform thickness. Vehicles that enter any grid block will be able to be detected. For examples, if an object's middle occurs inside a grid block, that block will be responsible for identifying the objects. To detect the vehicles in an image, residual blocks were used, by which each vehicle was detected and identified separately in a single image.

1.7.2 Bounding Box Regression

Bounding box regression develops a border that highlights an identifying object in an image. The given attribute are present in each bounding box regression in the image which is detected by YOLO algorithm:

- Width
- Height
- Class (for example, Vehicle, bike, bus, traffic light, heavy motor, etc.).
- Center of Bounding box

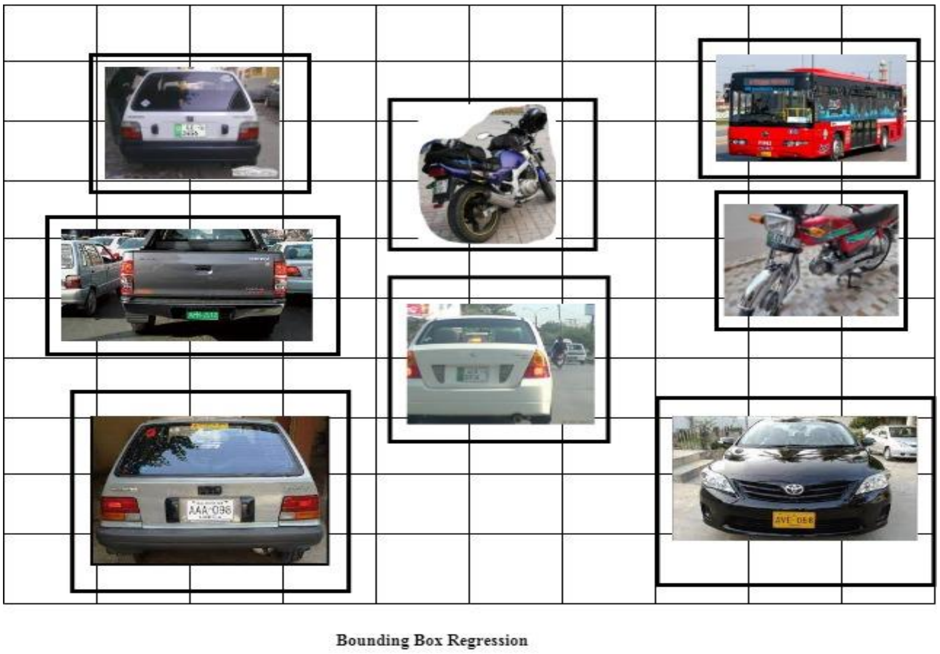

Figure 3: Highlight the Object with Bounding Box in Image

The following figure. 3 shows an example of a bounding box. Each bounding box indicated the objects separately within a single image, and they have been represented by a black outline.

To determine an object's width, center, height and class, YOLO utilize a single bounding box regression. The probability of an identification phase in the bounding box is indicated in the fig. 3.

1.7.3 Intersection Over Union (IOU)

The object detection phenomenon known as intersection over union (IOU) can be used to justify block overlapping. YOLO makes a bordered box that correctly encloses the vehicles using an IOU. Thus, every grid cell is accountable for forecasting the bounding box and ranking its efficiency. This approach removes bounding boxes that are not equivalent to the actual box.

The following figure offers a simple example of how to IOU works.

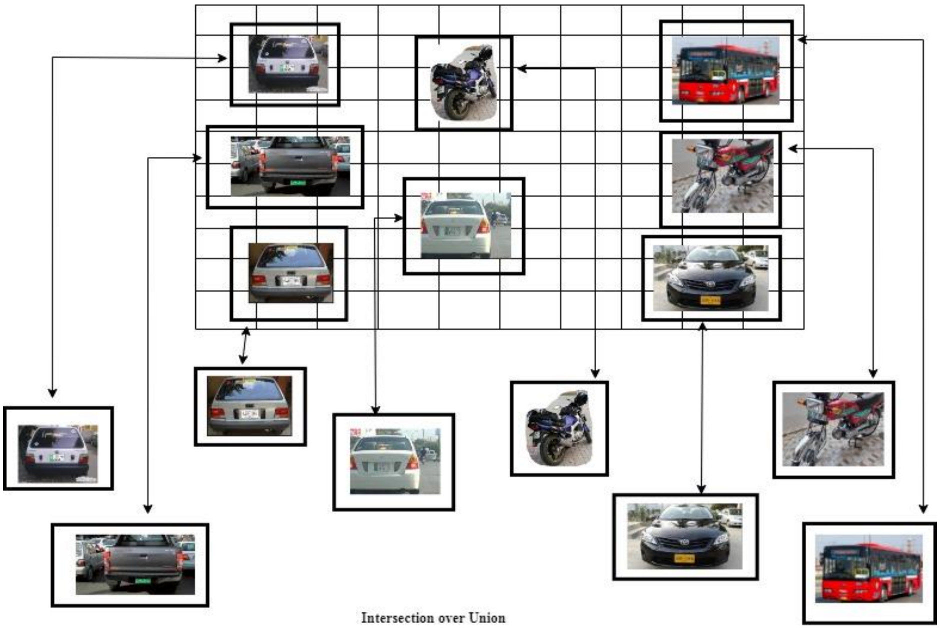

Figure 4: Intersection over Union

In Figure 4, we see that all vehicles that are in a single image are how marked or bordered after the residual blocks all at once and this procedure is known as IOU. In this way all the vehicles which are present in an image are detected and separated from each other.

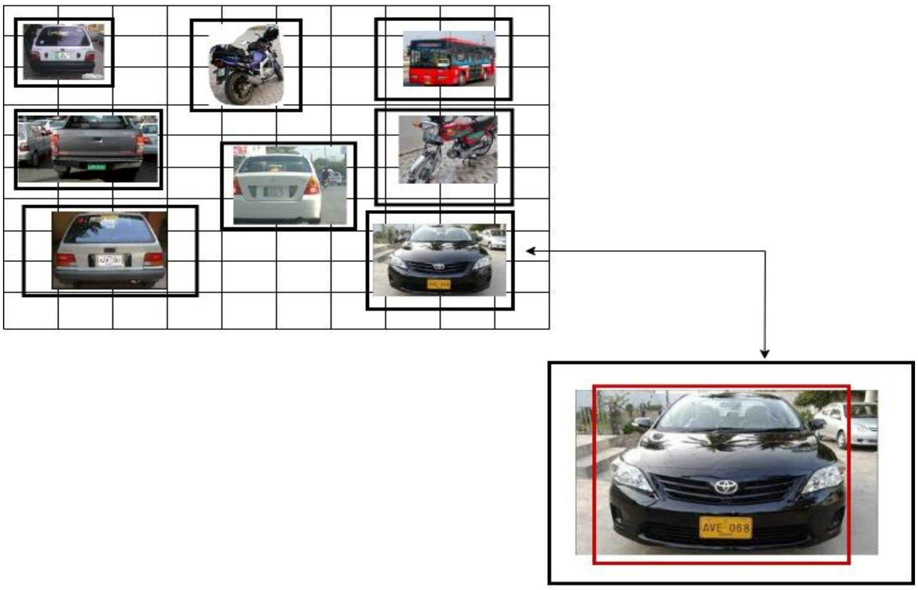

Figure 5: Show Working of Intersection Over Union

Figure 5 show the two different border for the same vehicle the outer border show the vehicle which are detected by residual blocks and the inner border show the working of IOU. The inner border detect and verified the vehicle within a border line.

Figure 6: Show working of IOU

There are two bounding boxes or bordered in the fig. 6, the outer one border in black and the other border in red. The black border is the actual box, while the red border is the anticipated box. The two bounding boxes are balanced.

Figure 7: Number Plate Detection

After detecting the vehicle with the help of the IOU, the next task is to identify the detected vehicle with the help of the vehicle registration number, which is a combination of different alphabets and digits that are embossed on the vehicle number plate. Each vehicle is distinguished by its registration number because each vehicle has a different combination of alphabets and digits in its registration number, by which every vehicle can be easily detected.

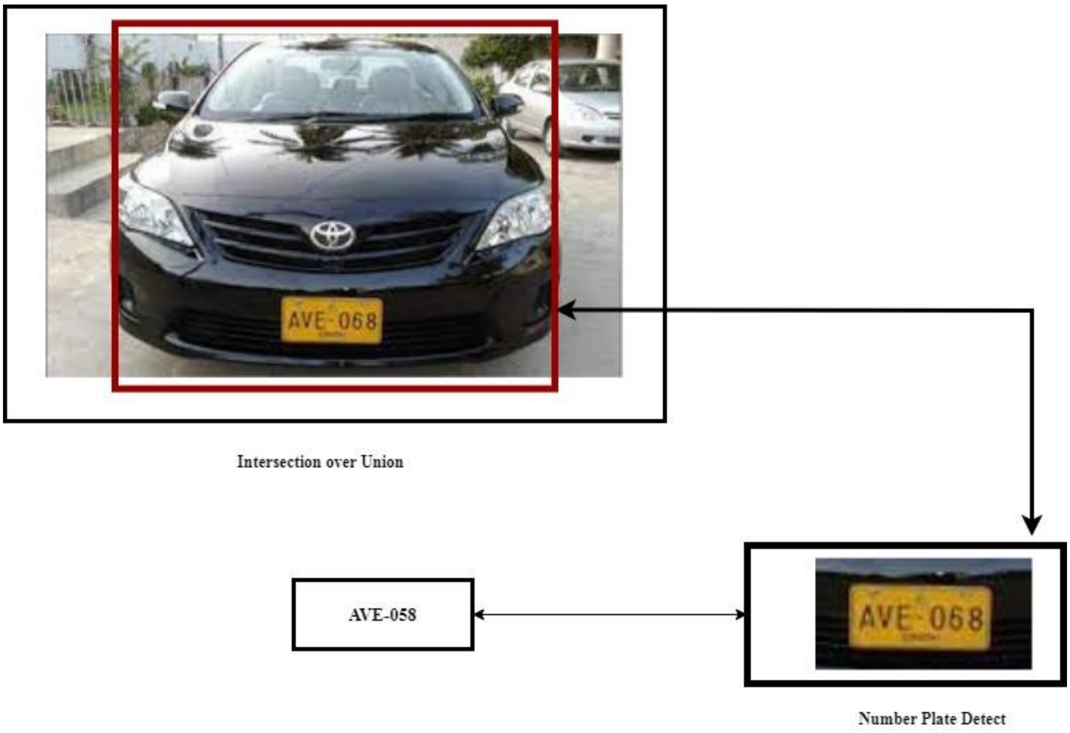

Figure 8: Number Plate Number Fetch

In figure 8 explain that after detection the vehicle number plate, all details about the vehicle and their owner find by the vehicle registration number for these purpose fetch the combination of alphabets and digits that are embossed on the vehicle number plate. For fetch the vehicle number first image of number plate is examined by algorithms to generate an alpha numeric transfer of the picture into a text format and finds the closest paired matching alphanumeric after analyzing the words from the given picture.

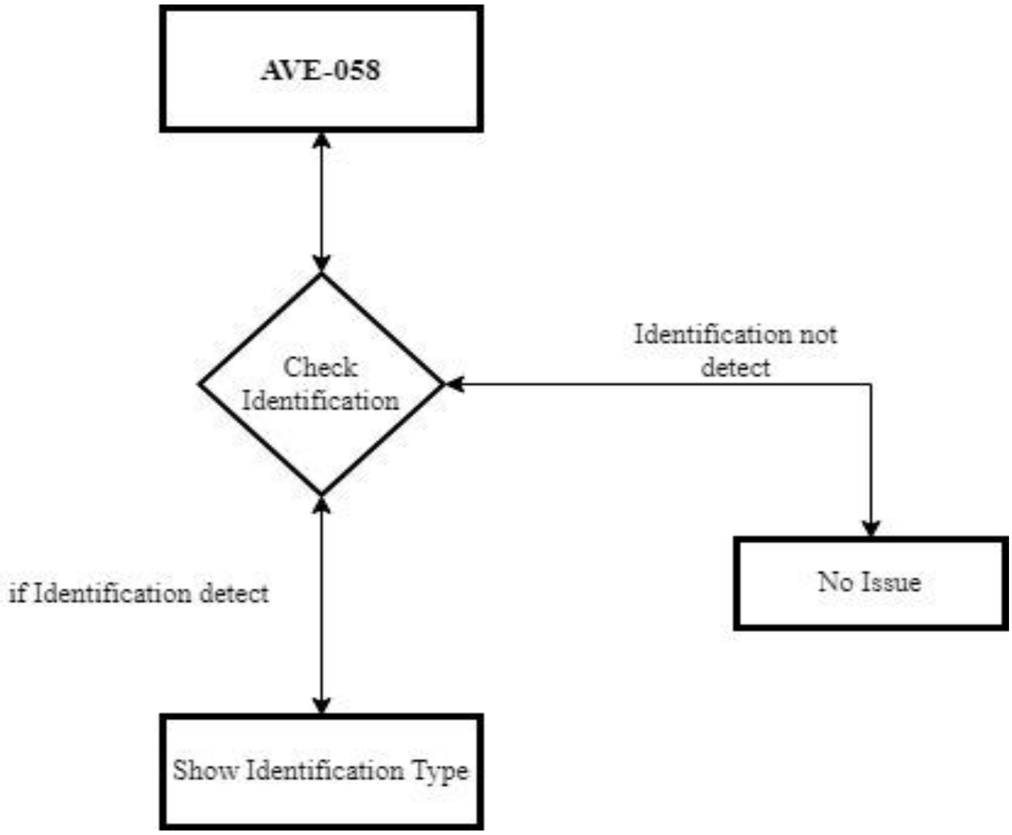

Figure 9: Vehicle Identification Flow

In Figure.9 show flow of vehicle identification procedure that how the identification of vehicle detect by vehicle number. First vehicle number move for check condition for detection the required identification, if required identification is detected then show the identification type that which type of identification was occur against the input vehicle number.

1.7.4 Combination of the Three Procedure of YOLO

The three procedures of YOLO algorithm is working combine for final detection of the vehicles. By which all the vehicles in a single image is detected and identified. So here we discuss the combination of these procedures.

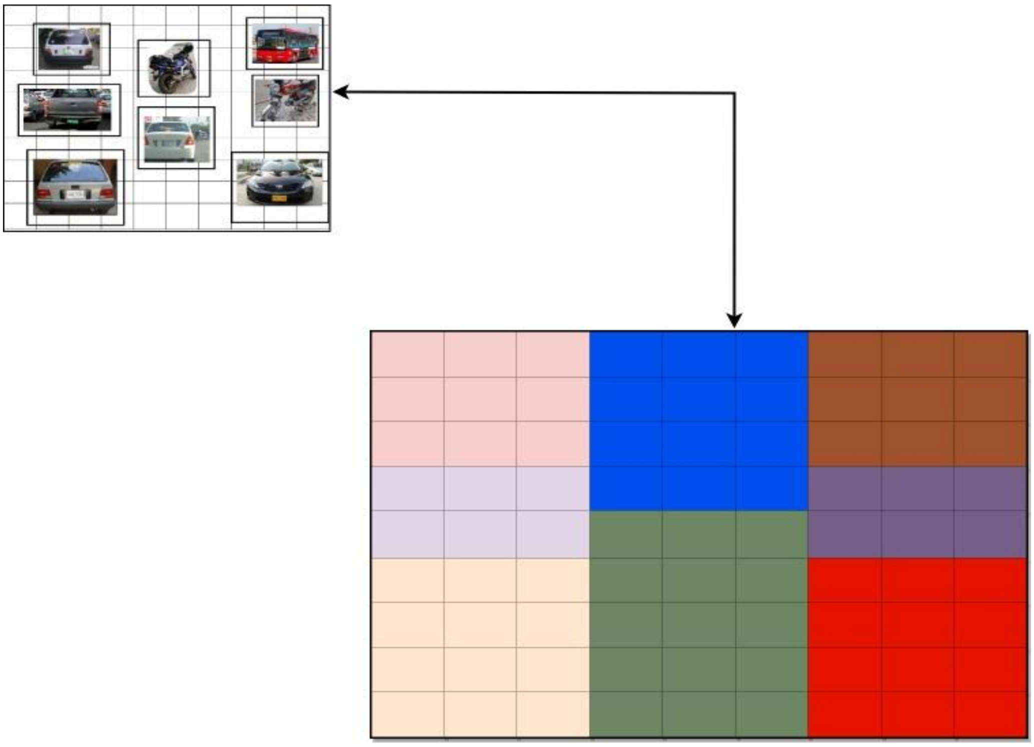

Figure 10: Class Probability Objects

In figure 10, we see that the Class probability objects which is the part of technique combinations of the image, which are taken from bounding box regression, also show the residual blocks' color, which is the same as the bordered color of all the vehicles marked in the image. This possibility was dependent on a grid cell containing an object inside it. No matter how many boxes are present, only one set of class probabilities is predicted by each grid cell. In this way, we get different-colored residual blocks, and each color detects only the single vehicle in an image. So, the whole image is converted in a different colors combinations which is known class probability objects and it's a part of techniques combinations.

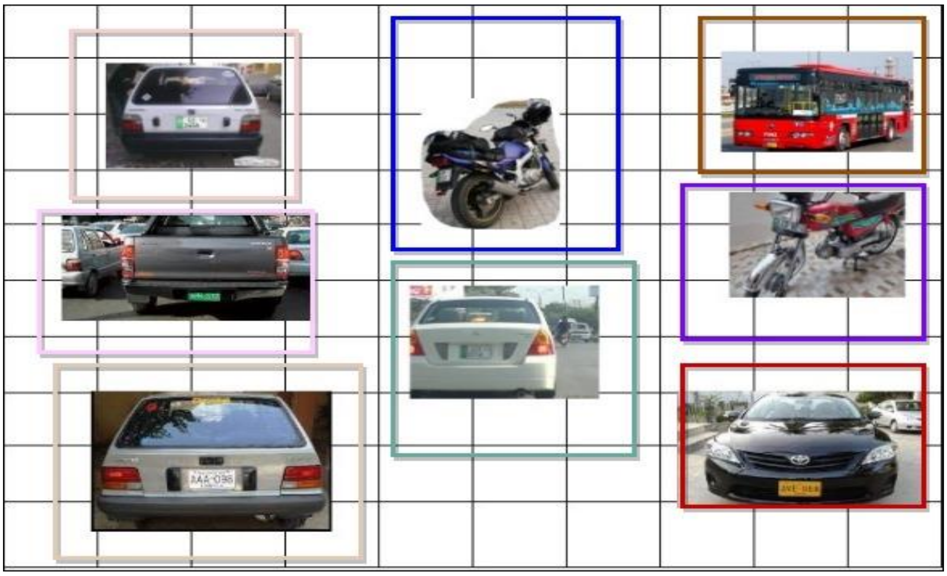

Figure 11: Detection

Figure. 11 indicate that each color detects only the single vehicle in an image which is the same as the bordered color of all the vehicles marked in the image. In this way between all vehicles in a single image distinguished them and detect in a same time. The specific color indicates which vehicle details are being discussed. For example, to discuss or detect the car from the image, the bordered color indicates which specific cars are discussed here.

The three procedures are applied to create the final detection of vehicle, as seen in the accompanying figure.

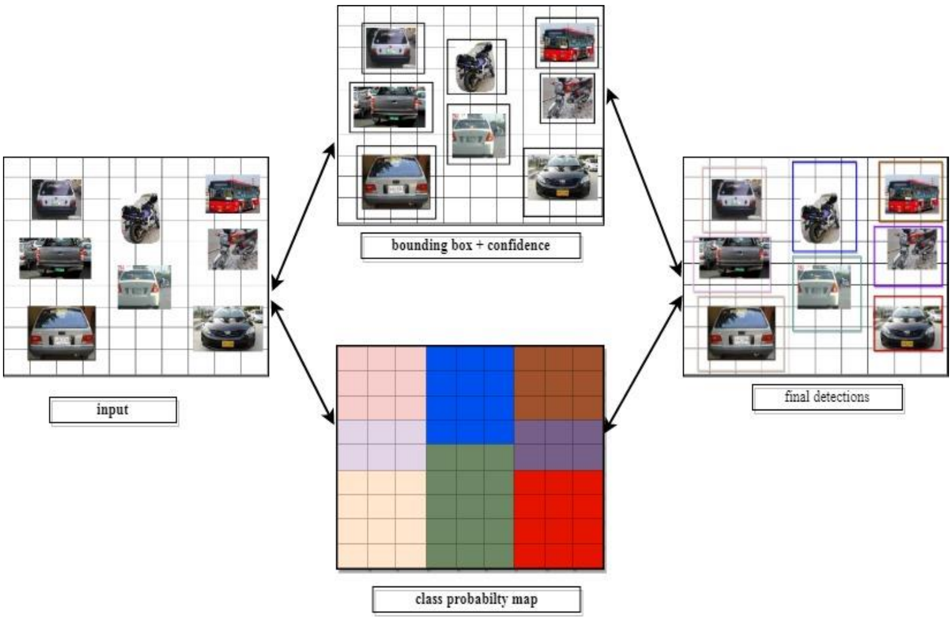

Figure 12: Techniques Combinations

In figure. 12 grid blocks are initially used to partition up the image. So every grid block predicts bounding boxes and provides reliability values. The blocks apply the class probability to identify each object's class.

The bus is bordered by the brown bounding box, but the heavy bike is bordered by the blue bounding box. The vehicle has been marked using the red bounded box.

For example, a heavy bike, a bus, and a car are examples of at least three different categories of vehicles. All of the consecutive predictions are made by a single convolutional neural network. With the assist of IOU, the projected bounding boxes are equivalent to the actual boxes of the detected vehicles. Bounding boxes that are basically unnecessary or don't meet the characteristics of the components are eliminated by this phenomena (like height and width). The final detection will comprise of unique bounding boxes that are specially customized to the vehicles.

1.7.5 Fields were YOLO Algorithm can be Applied

Autonomous Driving: The YOLO method can be utilized by autonomous vehicles to detect nearby items, including other cars, people, and parking signals. Since there is no human driver operating the automobile, item detection is performed in autonomous vehicles to prevent collisions.

Wildlife: This method is used to find different kinds of wildlife in forests. Journalists and wildlife rangers both utilize this form of detection to locate animals in still photos and films, both recorded and live. Camels, elephants, and bears are a few of the creatures that can be spotted.

Security: YOLO can also be employed in security systems in order to impose security on a location. Assume that a particular place has security restrictions prohibiting individuals from entering there. The YOLO algorithm will identify anyone who enters the restricted area, prompting the security staff to take additional action.

1.8 CONCLUSION

The YOLO method and its application to object detection have been discussed in general in this article. In comparison to Fast R-CNN, Retina-Net, and other object detection methods, this method yields better detection results.

1.9 RESEARCH GAP

- The Accuracy of the proposed model will be greater than the previously proposed approaches.
- In Previous research works, only vehicle numbers are detected, but do not identification the vehicle required condition.
- Differentiate between common or the same words like 0 and O.
- If the weather is not clear like foggy, cloudy, and heavy rain then it's difficult for cameras to detect the vehicle number plate.

1.10 MOTIVATION

My car is stolen from the outside of the house at the day time. When I look outside of the house, my car is not parked. I quickly report to the police, but they cannot track my car at present. After a week I received a call from the police station to check the safe city camera video. In the video my car was detected, but now it's too late because the thief cross the province week ago. So, from there I got the idea that if the smart city camera also identifies the defaulter condition of the vehicle with number detection so it's easy to track the car within a time.

1.11 AIMS & OBJECTIVES

- Detection of the vehicle number plate by using the YOLO algorithm.
- Identification the required condition of the vehicle with the help of the YOLO algorithm.
- Display the vehicle required identification message on the screen.

1.12 RESEARCH QUESTIONS

- Which algorithm gives more accurate results for vehicle number detection?
- How to read a vehicle number plate to get the vehicle's number?
- What kind of identification do you detect in a vehicle?
- How to identification the required condition of the vehicle?

CHAPTER 2

LITERATURE REVIEW

An extensive overview of earlier studies on vehicle number plate detection is provided in this section. There have been numerous investigations and research projects conducted in the past. In the Research area most researchers are used machine learning algorithms are included in which are given here:

Wen et al. [2011] investigated a solution for picture disturbance caused by uneven lighting and several environmental factors such as shade and exposure, which are typically difficult to analyze well utilizing classic binary methods and use support vector machines (SVM), by which they get 93.54% accuracy for license plate recognition [11].

Anagnostopoulos et al. [2006] proposed an algorithm for number plate position and character segmentation, based on a novel adaptive image segmentation technique (SCWs), and connected component analysis is used. Probabilistic neural networks (PNNs) are used to identify alphanumeric characters which have recently been segregated from the candidate's domain [12].

Giannoukos et al. [2010], introduces operator context scanning, a novel scanning method that uses pixel operators in the form of sliding windows to identify a pixel and its environment. The method's overall success rate is 88.1% [13], with a probability of referring to the objects it is looking for as high as possible.

Jiao et al. [2009] used Artificial Neural Networks (ANN) to work on recognizing number plate patterns, and this publication introduces new concepts and methodologies that include a thorough categorization and analysis of multiple license plate styles [14].

According to Llorens et al. (2005), there are two distinct issues with car license plate recognition. The Hidden Markov model (HMM) is used as the fundamental model for engine Car License Plates detection and Extraction [15]. It involves 1) locating the portion of the image that corresponds to the plate, 2) identifying the character in the plate, and 3) evaluating a solution.

Gong et al. [2019] proposed multi-label classification and the object detection task performed for both as a multi task framework of objects [16].

Shindeet al. [2018] developed real-time video data which is collected from a surveillance camera to detect all the objects from a single frame [17].

Zhang et al. [2018] proposed vehicle counting framework by passing through video by object detecting process [19].

Redmon and Farhadi (2020) proposed (YOLO) a real-time object detection algorithm. A single neural network is enough to detect the object from the whole image [20].

Patel et al. [2013] introduced an automatic vehicle number plate detection system using a machine learning approach is developed [21].

Sr	**Authors**	**Title Paper**	**NP Detection**	**Vehicle Status**	**Method**	**Accuracy**
1	Yuan Yuan, et al. 2017 [22]	An Incremental Framework for Recognizing, Tracking, and Detecting Traffic Signs in Videos	YES	NO	CNN	94%
2	Naren Babu R., et al. 2019 [23]	Using deep learning, identify Indian vehicle licence plates	YES	NO	YOLO V3	91%
3	Tayara, H., et al. 2017 [3]	Utilizing Convolutional Regression Neural Networks for Vehicle Detection and Counting in High-Resolution Aerial Images	YES	NO	CNN	93.2%
4	Chen, R. C. (2019) [4]	Automatic License Plate Recognition via sliding-window darknet-YOLO deep learning	YES	NO	Darknet -Yolo	78%
5	Masood, S. et al. (2017) [7]	Deeply learnt convolutional neural networks are used for license plate detection and recognition.	YES	NO	CNNs	90%

Punyavathi et al. [2021] discussed the modern techniques that are used for vehicle detecting and tracking for different scenarios by using IoT to reduce road accidents. They used two methods for this purpose. One is traditional and the second is the modern method. In traditional methods, they work on statistic method for vehicle detection. Then they used development of algorithm techniques which use blob detection, its outcome efficient then statistics methods. But they work on another method which is based on deep learning is YOLOv3, which gives more accurate and fastest results in a minimum duration [28].

Avatefipour, & Sadry, [2018] covered several IoT-related intelligent traffic management systems, as well as the many ways to collect raw information, including triangulation, automobile re-identification, GPS-based approaches, and smartphone-based tracking. The "vehicle re-identification" technique proved to be quite effective at gathering relevant data. Traffic monitoring systems, green wave systems, RFID tags, wireless technology, worldwide structure for smartphones, and infrared sensors are among the efficiency methods for managing traffic signals that are being compared. When comparing several approaches, "dynamic cycle TLS" comes out on top as having the maximum performance ratings. [29].

The suggested passive technique of verification discussed by Riener and Ferscha [30] Biometrics-based methods have been used in early investigations on driver verification. The information gathered from pressure patterns on the seats of a vehicle in general and from the seated positions of drivers in particular.

The driver recognition method is suggested based on pressure mapping systems by Chen et al. [31]. In their investigations, they used the arrangements of hand grips on the steering wheel to identify drivers. These biometrics technique likewise others such as voice identification [32], face detection [33], or finger-vein pattern investigation [34] suffer from a number of disadvantages, such as being customized for particular activities to take place and being inappropriate for ongoing accurate situations.

To overcome some of the above-mentioned disadvantages, the driving behavior analysis using multiple types of information is advantageous in certain other driver identification techniques that have been discussed. Rahim et al. [35] used the identified zero-to-stable objects from GPS data to recognize drivers. Zero-to-stable was identified as an order of time sampled driving data subsets starting with a zero sample where its speed is constant and omitting the subsets for the duration the vehicle is jam-packed in congested traffic.

To identify imposters for public transportation drivers, Virojboonkiate et al. [36] suggested a method based on accelerometer data. Their methods might achieve an F1 score of approximately 85% by applying KNN algorithm. In another proposal, Jafarnejad et al. [37] describe benefits of a variety of data, including that gathered by automobiles' Controller Area Networks (CAN-VAN). Results for 35 drivers were obtained using five different traditional ML techniques, including Random Forest and SVM. It has been demonstrated that the combination of the gas pedal and steering wheel angles can increase performance by more than 20%. Recent frameworks for driver recognition have recommended using deep learning algorithms because they have been verified to perform better than traditional machine learning methods. [38].

Based on the gathered mobile and automobile sensing datasets, Mekki et al. [39] presented a novel model to differentiate between the drivers. Long short-term memory and convolutional neural networks are the core of the model. Furthermore, the effectiveness of the model was evaluated in the presence of data irregularity. With a 50% rate, an efficiency of roughly 57% was reached. Convolutional neural networks are applied in another research by Xun et al. [40] to retrieve hidden driving attributes from CAN-bus data, combining information from the steering wheel, accelerator, and gas pedal, among other sources. One convolution layer precedes a max pooling layer, a fully connected layer, and a softmax layer for the output in their model development.

There are only a few research that address driver identification using the triplet loss and unsupervised learning approaches. Triplet loss has received a lot of attention recently in a number of fields, especially face recognition and natural language processing [41]. However, in a more recent work by Sanchez et al. [42], for the supervised objective of driver identification, the researchers applied Siamese neural networks with triplet loss. They generated an F1 score of 74.09% using accelerometer data that is gathered from cellphones. To minimize the demand on the computer's processing capabilities for driver identification, Tanprasert et al. [43] used an unsupervised anomaly detection method. This strategy was used by the researchers to ensure that the identification procedure would only start if the driver's driving style was deemed unusual.

CHAPTER 3

METHODOLOGY

Technology is growing fast, there is a tremendous desire among people for safe living and travel. The number of vehicles on the road has increased due to the excessively increasing worldwide population, which has resulted in an increase in traffic on hi-tech modern roadways. Vehicle monitoring is an significant topic in smart transportation networks. Vehicle license plate recognition and vehicle identification can be used to identify the vehicles in the video recordings. In order to implement proper detection and identification of a vehicle Number Plate (NP).

The initial stage in locating and identifying the vehicle NP is to locate and collect data for each road bound. To detect and recognize vehicle NPs, numerous strategies, methodologies, and algorithms develop. To accomplish this objective, we can successfully assist using the YOLO method. A database can be used to record all the information on the cars that are capture by security cameras, in addition to their categories and priority. The first step is successfully complete following the transfer of these data, which were gathered from security cameras position along the road. In the following steps, this technique offers a situation where this current information can be used for traffic monitoring. This model can be a big assistance to us in figuring out how to handle the issue of the direction of stolen vehicles. They can be put in place ahead of every intersection with a traffic signal so that the direction of a stolen car can be quickly identify.

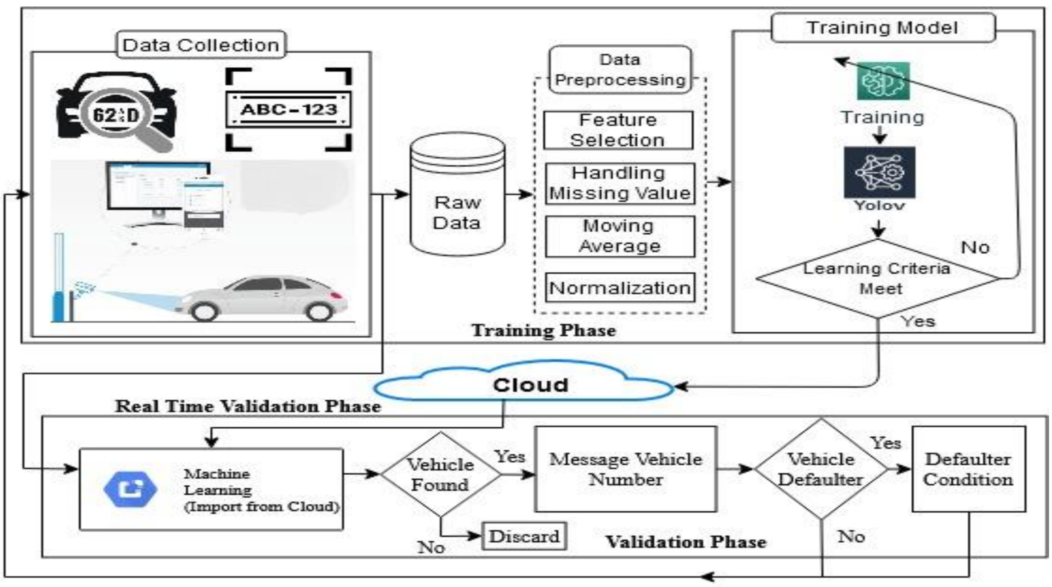

Figure 13: IoT Based Vehicle Identification System Using Machine Learning Techniques

Figure 13 is showing that the proposed system is dependent on the training and validation phase.

First Training phase is divided into three processes.

In the training phase firstly, data is collected with the help of different sensors from input parameters will be stored in a database known as raw data. The next process is to preprocess the data to minimize the noisy data. After preparing the preprocessed data will be forwarded for training the data while using Yolo Algorithm.

The target detection task's loss function is divided into two parts: classification loss as well as bounding box regression loss. IoU and its enhanced algorithm are the furthermost frequently utilised bounding box regression losses. The intersection in addition union ratio is the full name of the IoU algorithm, which is acquired by manipulative the ratio of the connection as well as union of the predicted bounding box as well as the ground-truth bounding box, that is, IoU(I, J) = (I ∩ J) / (I U J), where I is the expected bounding box as well as J is the ground- truth bounding box. IoU can be utilized as a distance; formerly, $Loss_{IoU}$ = 1-IoU. The benefit of IoU is that it can represent the sensing effect of both the forecast as well as ground-truth frames. In addition, IoU has the features of no negativity, scale invariance, individuality, regularity, and triangle disparity. IoU has these two difficulties:

- Once the prediction as well as ground-truth bounding boxes do not intertwine, as well as IoU(I,J) = 0, the distance among I and J cannot be imitated. The loss function is not thrust vectoring at this time, and IoU loss cannot optimise the scenario where the relevant parts boxes do not intersect.
- Presuming that the sizes of the prognostication bounding box as well as the ground-truth bounding box are unwavering, the IoU value cannot reflect how the two bundles intersect as long as the crossing value of the two cartons is ascertained plus their IoU values are the similar.

EIoU

$$EIoU(I,J) = IoU(I,J) - \frac{|K| - |IUJ|}{|K|} \quad (1)$$

$$Loss_{EIoU} = 1 - EIoU(I,J) = 1 - IoU(I,J) + \frac{|K| - |IUJ|}{|K|} \quad (2)$$

where K is the minimum box covering I then J. EIoU overwhelms the disjoint state of I in addition J in IoU as well as has the similar scale-invariance possessions as IoU. EIoU can be measured the lower certain of IoU, which is less than or equivalent to IoU. EIoU considers not only the intersecting area nevertheless likewise other non-overlapping areas that can better reproduce the level of crossover amid both the two. When the two containers have no meeting area, EIoU is a amount that differs in the range of [-1, 0], in addition there is a incline, so optimization can be achieved. The optimization course progressively contracts the distance among the two boxes.

RIoU

$$RIoU = IoU - \frac{f^2(l, l^{gt})}{m^2} \quad (3)$$

$$Loss_{RIoU} = 1 - RIoU = 1 - IoU + \frac{f^2\left(l, l^{gt}\right)}{m^2} \quad (4)$$

where l in addition l^{gt} characterize the center points of forecast Box J as well as ground-truth box J^{gt}, individually, m characterizes the square of the oblique length of the minimum bounding Box K, as well as f characterizes the control of the Euclidean distance amongst the two center points. RIoU converges far faster than EIoU because it can directly minimize the distance among the two target boxes. The RIoU loss can end up making the regression very fast in the case of two boxes in the vertical and vertical commands, whereas the EIoU loss almost devolves to the IoU loss.

TIoU

$$IoU = IoU - \left(\frac{f^2(l, l^{gt})}{m^2} + \beta n \right) \tag{5}$$

$$Loss_{TIoU} = 1 - IoU + \frac{f^2\left(l, l^{gt}\right)}{m^2} + \beta n \tag{6}$$

where β the weight parameter is also n is used to measure the resemblance of the aspect ratio.

$$n = \frac{4}{\pi^2} \left(\arctan \frac{o^{gt}}{\pi^{gt}} - \arctan \frac{o}{s} \right)^2 \tag{7}$$

$$\beta = \frac{n}{(1 - IoU + n)} \tag{8}$$

It can be understood from the meaning of β that the loss function will be additional motivated to enhance in the direction of cumulative meeting areas, particularly when the IoU is zero.

After predicting it will check the condition that learning criteria will be met or not. If the criteria will be met, the output move to the cloud if, the criteria will not be meet the training process will be again updated with the data.

In the validation phase the real time data will be collected from input and trained values will be imported from the cloud for prediction purposes. Then it will be checked the condition of the required condition fulfill and vehicle number plate detected then display the vehicle number on screen if not found the vehicle number then the system discard. After detect the vehicle number the proposed model check the condition of defaulter vehicle, if model detect defaulter condition indicate the vehicle and return to system and if model not detect any default in vehicle then proposed model direct return at the start point of the system.

CHAPTER 4

RESULTS

In this proposed IoT based Vehicle identification using Machine Learning techniques (YOLO) are employed on a dataset. The total data is 433 samples which is separated commonly into 70% training (303 samples) in addition 30% validation (130 samples). The proposed model intentional the output by means of manifold statistical measures, as defined in Equations 01-09.

$$Sensitivity = \frac{\sum True\ Positive}{\sum Condition\ Positive} \tag{1}$$

$$Specificity = \frac{\sum True\ Negative}{\sum Condition\ Negative} \tag{2}$$

$$Accuracy = \frac{\sum True\ Positive + \sum True\ Negative}{\sum Total\ Population} \tag{3}$$

$$Miss - Rate = 1 - Accuracy \tag{4}$$

$$Fallout = \frac{\sum False\ Positive}{\sum Condition\ Negative} \tag{5}$$

$$Likelihood\ Positive\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \tag{6}$$

$$Likelihood\ Negative\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \tag{7}$$

$$Positive\ Predictive\ Value = \frac{\sum True\ Positive}{\sum\ Predicted\ Condition\ Positive} \tag{8}$$

$$Negative\ Predictive\ Value = \frac{\sum True\ Negative}{\sum\ Predicted\ Condition\ Negative} \tag{9}$$

Tables 1-2 depict the training and validation of ML approaches (YOLO). In addition to comparisons, the numerous statistical measures utilized for performance are measured from various metrics.

Table 1
Training of proposed IoT based Vehicle Identification using Machine Learning Techniques (YOLO)

Proposed Model Training			
Input	**Total Samples (303)**	**Output**	
	Expected output	**Predicted Positive**	**Predicted Negative**
	160 Positive	True Positive (TP)	False-Negative (FN)
		153	7
	143 Negative	False Positive (FP)	True Negative (TN)
		11	132

Table 1 is showing the proposed IoT based Vehicle identification using Machine Learning techniques inside the training phase w.r.t YOLO. A total of 303 samples are applied within the training phase alienated into 160 and 143 positives as well as negative samples, correspondingly. It is determined that 153 samples are properly predicted as positive, showing there is traffic routing, but 7 samples are incorrectly predicted as negative, that means there is no traffic routing. Correspondingly, a total of 143 samples are composed, where negative specifies no traffic routing, in which 132 samples are properly predicted as negative, means there is no traffic routing, and 11 records are imprecisely predicted as positive, showing traffic routing.

Table 2
Validation of proposed IoT based Vehicle Identification using Machine Learning Techniques (YOLO)

Proposed Model Validation			
Input	**Total Samples (130)**	**Output**	
	Expected output	**Predicted Positive**	**Predicted Negative**
	79 Positive	True Positive (TP)	False-Negative (FN)
		76	3
	51 Negative	False Positive (FP)	True Negative (TN)
		7	44

Table 2 is showing the proposed IoT based Vehicle identification using Machine Learning techniques within the validation phase w.r.t SVM. A total of 130 samples are applied within the training phase divided into 79 and 51 positive as well as negative samples, correspondingly. It is determined that 76 samples are properly predicted as positive, showing there is traffic routing, but 3 samples are imperfectly predicted as negative, that means no traffic routing.

Correspondingly, a total of 51 samples are composed, where negative showing no traffic routing, in which 44 samples are correctly predicted as negative, means there is no traffic routing, and 7 records are imprecisely predicted as positive, which means traffic routing.

Table 3
Performance Evaluation of Proposed IoT based Vehicle Identification using Machine Learning Techniques (YOLO) in Training and Validation using Diverse Statistical Measures

		Accuracy (%)	**Sensitivity TPR (%)**	**Specificity TNR (%)**	**Miss-Rate FNR (%)**	**Fall-out FPR**	**LR +ve**	**LR -ve**	**PPV (Precision) (%)**	**NPV (%)**
YOLO	Training	94.05	95.6	92.3	4.37	0.076	12.43	0.047	93.2	94.9
	Validation	92.30	96.2	86.2	3.79	0.13	7.01	0.043	91.5	93.6

Table 3 is showing the performance of the IoT based Vehicle identification using Machine Learning techniques in the training and validation phases w.r.t. YOLO correspondingly. This specifies that the proposed model using the YOLO approach provides 94.05%, 95.6%, 92.3%, 4.37%, and 93.2% within the training, and provides 92.30%, 96.2%, 86.2%, 3.79%, and 91.5% within the validation, in terms of accuracy, True Positive Rate (TPR) expressed as sensitivity, True Negative Rate (TNR) expressed as specificity, False Negative Rate (FNR) expressed as miss rate, and Positive Predictive Value (PPV) expressed as precision, respectively. In addition, more statistical measures of the proposed model are providing 0.076, 12.43, 0.047, and 94.9% within the training, and 0.13, 7.01, 0.043, and 93.6% within the validation in terms of False Positive Rate (FPR) expressed as fall-out, Likelihood Positive Ratio (LR+ve), Likelihood Negative Ratio (LR-ve), and Negative Predictive Value (NPV), respectively.

CHAPTER 5

CONCLUSION

Due to the daily tremendous growth of the vehicle industry, tracking individual vehicles has become a difficult undertaking. In the majority of applications involving the movement of vehicles, the identification and detection of a vehicle Number Plate (NP) are crucial techniques. In the field of image processing, it is also a hotly debated as well as ongoing research topic. For the purpose of discovering and identifying vehicle NPs, numerous techniques, methods, and algorithms have been created. In this research, we present an IoT based vehicle identification with the help of YOLO algorithm is proposed. The proposed model use YOLO algorithm for vehicle identification.

Firstly the vehicle is detecting and then verified by vehicle registration number with the help of YOLO algorithm after that we identified the vehicle and achieved the 94.05 % accuracy in training phase and 92.30 % accuracy in validation phase.

In the future, we will upgraded the proposed model for get more accurate results, minimize the drawbacks and merged with multiple departments database for track the specific vehicle in a real time for control the crime rate and rapid action against the complains.

Comparison Table

Sr	Authors	Title Paper	NP Detection	Vehicle Status	Method	Accuracy
1	Yuan Yuan, et al. 2017 [22]	An Incremental Framework for Video-Based Traffic Sign Detection, Tracking, and Recognition.	YES	NO	CNN	94%
2	Naren Babu R., et al. 2019 [23]	Indian Car Number Plate Recognition using Deep Learning.	YES	NO	YOLO V3	91%
3	Tayara, H., et al. 2017 [3]	Vehicle Detection and Counting in High-Resolution Aerial Images Using Convolutional Regression Neural Network.	YES	NO	CNN	93.2%
4	Chen, R. C. (2019) [4]	Automatic License Plate Recognition via sliding-window darknet-YOLO deep learning.	YES	NO	Darknet -Yolo	78%
5	Masood, S. et al. (2017) [7]	License plate detection and recognition using deeply learned convolutional neural networks.	YES	NO	CNNs	90%
6	Proposed	IoT Based Vehicle Identification System Using Machine Learning Techniques.	YES	NO	YOLO	< 94%

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