National College of Business Administration & Economics Lahore

TRAFFIC CONGESTION CONTROL SYSTEM USING TRANSFER LEARNING IN VANETS

BY

ATTIA AMEEN

MASTER OF PHILOSOPHY
IN
COMPUTER SCIENCE

FEBRUARY, 2024

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

MASTER OF PHILOSOPHY
IN
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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

DECLARATION

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

ATTIA AMEEN
February, 2024

Dedicated

To

My beloved parents, teachers and Family who provided unwavering support and encouragement throughout this challenging journey.

ACKNOWLEDGEMENT

"ALLAH Almighty" Who is the creator of who the le universe and who is my all in all. Who never let the efforts go waste united? He made me able to do this tedious work. I am nothing but my ALLAH always blessed me a lot. Thanks to Omnipotent ALLAH.

My all praises are due to the Holy Prophet Muhammad (peace be upon him), who came as the light of knowledge for all the seekers.

In the light of above saying, following acknowledgment is for my worthy teacher, supervisor Dr. Muhammad Saleem, and Co-Supervisor Dr. Munir Ahmad has provided me with guidance, inspiration and devoted a vast amount of hours to review my work. I gratefully acknowledge his support and encouragement during the preparation of this thesis, and his contribution to a challenging and comfortable working environment.

RESEARCH COMPLETION CERTIFICATE

Certified that the research work contained in this thesis entitled **"Traffic Congestion Control System using Transfer Learning in Vanets"** has been carried out and completed by **Ms. Attia Ameen** under my supervision during her **M.Phil. Computer Science** Programme.

(Dr. Muhammad Saleem)
Supervisor

(Dr. Munir Ahmad)
Co-Supervisor

SUMMARY

Traffic load optimization of circulating vehicles is becoming an emerging issue in congested Vehicular Adhoc Networks (VANET) networks. Different operations related to VANET are involving machine learning models to address the issues being faced in traffic congestion. To utilize the existing trained and experienced model of Machine Learning in congestion control of vehicles the transfer learning technique is performing as a better tool in different scenarios. The traffic congestion is increasing the risk of life, user safety, social and environmental losses. Negative impact of traffic congestion in complex road networks is also becoming and alarming issue for economic progression of society. The current VANET systems relays of intelligent hardware being installed in vehicles for establishing communication and computing among vehicles. The prediction system of current VANET is also facing the efficiency issues in communication systems due to different levels of dynamically increasing congestion.

In this research work, transfer learning method is used as foundation to build an efficient model for information transmitting to newly registered nodes in VANET. The source of information is indirectly linked to the target node via model using the transfer learning. The characteristics of transfer learning approach enabled the proposed model to utilize the already trained nodes to act as source and train the newly detected nodes in VANET. The computation and simulation performed on model exhibit significantly improved results for imparting the control system for congestion in traffic system. The time span required for communication network operation in this proposed model also achieved the good value as compared to different fuzzy logic based native model that are already in exercise. This model shortens the execute time in process. Intelligent integration of this model in already implemented traffic congestion control systems can play a vital role for screening the initial congestion. As artificial intelligence is exceptionally intervening in the daily routine techniques, this model is also addressing the AI based implementation of control system through transfer learning way outs.

The rapid increase in number of vehicles is demanding the real time advancements in control systems for traffic congestion. This is being gained by experiencing the latest techniques of transfer learning. The challenges are ahead for real time implementing this technique that are still open questions for further research, that can be addressed through collaborations with upcoming AI based models.

LIST OF ABBREVIATION

Abbreviation	Description
VANET	Vehicular Adhoc Networks
AI	Artificial Intelligence
RSU	Roadside Unit
V2V	Vehicle to vehicle
ANN	Artificial Neural Networks
CNN	Convolutional Neural Network
GBDT	Gradient Boosting Decision Trees
SHAP	Shapley Additive explanations
TPI	Traffic Performance Index

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

In the modern world, traffic congestion has become a prevalent issue, causing frustration and inefficiency in urban environments. As the number of vehicles on the roads continues to increase, the need for effective traffic congestion control systems becomes imperative. Vehicular Adhoc Networks (VANETs) offer a promising solution to this problem by enabling vehicles to communicate with each other and exchange information in real-time. The advancement of technology has paved the way for the application of artificial intelligence (AI) in various domains, and traffic management is no exception. Transfer learning, a subfield of AI, has gained significant attention in recent years for its capability to leverage knowledge learned in one domain to improve the performance in another. By applying transfer learning techniques to VANETs, we can enhance the effectiveness of traffic congestion control systems and alleviate the burden of congestion in our cities. The primary objective of this research is to explore the potential of transfer learning in developing robust traffic congestion control systems for VANETs.

By utilizing pre-existing knowledge from other related domains and adapting it to the unique characteristics of VANETs, we aim to enhance the accuracy and efficiency of congestion prediction and control mechanisms. This research will delve into the existing literature on traffic congestion control systems and explore the various approaches employed in VANETs. The utilization of transfer learning techniques will be investigated, focusing on the mechanisms and algorithms that can be used to transfer knowledge between different domains. Furthermore, this study will also propose novel methods for transferring knowledge specifically tailored to VANETs.

With a significant increase in the number of vehicles on the road, traditional traffic management systems are struggling to keep up with the demands and complexities of modern transportation. Vehicular Adhoc Networks (VANETs) have emerged as a promising solution to address the challenges of traffic congestion. VANETs enable communication between vehicles and infrastructure, creating a dynamic network where vehicles can share real-time information. This information exchange allows for improved traffic flow, enhanced safety measures, and efficient congestion control mechanisms. However, despite the potential benefits of VANETs, developing effective traffic congestion control systems remains a challenging task. The success of such systems heavily relies on accurate congestion prediction and timely decision-making processes. This is where the integration of transfer learning techniques becomes intriguing. Transfer learning, a subfield of AI, offers a unique approach to improve the performance of traffic congestion control systems in VANETs. By leveraging knowledge learned from related domains, such as sensor data analysis, image recognition, or natural language processing, transfer learning can enhance the accuracy and efficiency of congestion prediction models. This is achieved by transferring the learned knowledge to VANETs and adapting it to the specific characteristics and constraints of the vehicular environment. One key advantage of transfer learning is its ability to overcome the limitations of limited data availability in VANETs. Gathering large-scale, labeled datasets solely for VANET applications can be costly, time-consuming, and impractical. Transfer learning overcomes this challenge by utilizing pre-existing datasets from related domains, reducing the need for extensive data collection efforts.

Figure 1: Depiction of Traffic Congestion

Additionally, transfer learning allows for knowledge transfer between different environments, enabling insights from one domain to be utilized in another. For instance, techniques learned from analyzing real-time traffic data collected from a busy city center can be applied to predict congestion in VANETs operating in a similar urban setting. By applying transfer learning methodologies, VANETs can benefit from the accumulated knowledge and advances made in other domains. This research aims to explore, develop, and evaluate a novel framework that combines transfer learning techniques with VANETs for traffic congestion control systems. The framework will focus on adapting existing AI models to the specific requirements of VANETs and leveraging the available information to improve predictions and control mechanisms. Additionally, this research will investigate the feasibility of online learning approaches in VANETs, enabling the models to continuously adapt and improve based on real-time data. To validate the proposed framework, extensive simulation experiments will be conducted in various traffic scenarios. The performance of the congestion prediction models, and control mechanisms will be evaluated, considering factors such as accuracy, efficiency, and scalability. The results obtained from these evaluations will provide insights into the effectiveness and applicability of transfer learning in VANETs and contribute to the wider body of knowledge in the field. In conclusion, the integration of transfer learning techniques offers a promising avenue for improving traffic congestion control systems in VANETs. By leveraging knowledge learned from related domains, VANETs can benefit from enhanced predictions and efficient control mechanisms. (Binti Abdul Rahim et al., 2021)

The implementation of a traffic congestion control system using transfer learning in Vehicular Adhoc Networks (VANETs) holds significant potential for addressing the persistent issue of congestion in urban environments. By leveraging transfer learning techniques, which enable the transfer of knowledge from one domain to another, we can enhance the accuracy and efficiency of congestion prediction and control mechanisms in VANETs. One of the main advantages of transfer learning is its ability to overcome the data limitations typically associated with VANETs. Collecting sufficient and diverse data solely for VANET applications can be challenging and resource intensive. However, by utilizing pre-existing datasets from related domains, we can alleviate the burden of data collection and leverage the accumulated knowledge to improve congestion control in VANETs. Furthermore, by adapting transfer learning methodologies to the unique characteristics of VANETs, we can optimize the performance and applicability of congestion control systems. This entails considering factors such as the dynamic nature of vehicular networks, limited communication range, varying traffic patterns, and the need for real-time decision-making.

The research aims to develop a comprehensive framework that effectively combines transfer learning with VANETs to mitigate traffic congestion. Figure-3 describes vehicle communication, as due to advancement in the world and latest technology vehicles can communicate with each other it is either by direct vehicle to vehicle communication or by Vehicle Adhoc networks. By incorporating techniques from other domains and tailoring them to VANETs, we seek to enhance the accuracy of congestion prediction, optimize traffic flow, reduce travel time, and improve overall traffic management. Through extensive simulation experiments and performance evaluations, we will validate the effectiveness of the proposed framework. The results obtained from these experiments will provide insights into the capabilities and limitations of transfer learning in VANETs and contribute to the advancement of traffic congestion control systems in urban environments. Ultimately, by harnessing the power of transfer learning in VANETs, we can make significant strides in alleviating traffic congestion and improving the overall efficiency and safety of our transportation systems.

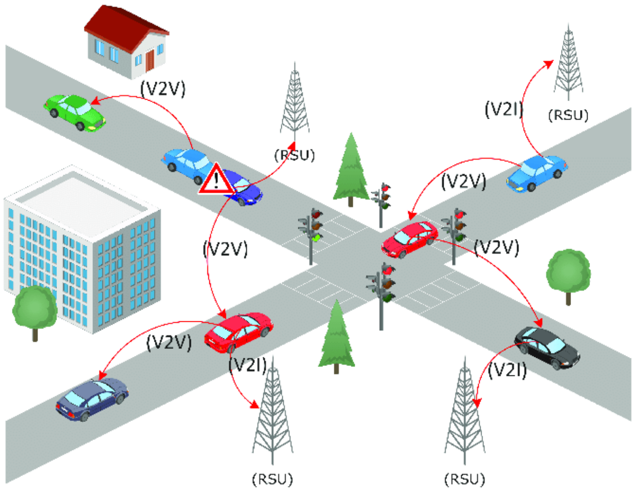


Figure 2: VANET Communication Architecture (Researchgate)

This research seeks to bridge the gap between transfer learning and VANETs, providing valuable insights and solutions to tackle the challenges of traffic congestion and enhance urban mobility. The expected outcome of this research is the development of a comprehensive framework that combines the power of transfer learning with VANETs to create robust and efficient traffic congestion control systems. The proposed framework will be validated through extensive simulation experiments and performance evaluation, highlighting its effectiveness in real-world scenarios. This work aims to contribute to the growing field of traffic management in VANETs by leveraging transfer learning techniques. By doing so, we hope to provide valuable insights and solutions for the ongoing traffic congestion challenges faced by urban societies. In recent years, the issue of traffic congestion has reached unprecedented levels in urban areas around the world. The issue of traffic congestion becomes increasingly crucial while delivering the safety messages(Liu & Jaekel, 2019) which are specifically broadcasted through commonly CSMA based topologies. Some shared radio network channels are expected to be congested while increasing the nodes of network, in such scenarios the safety messages are supposed to be delivered on some specific radio channels which are multi-accessible in wireless environments.(Kamble & Kounte, 2020)

1.2 TRANSFER LEARNING

Transfer learning, used in machine learning, is the reuse of a pre-trained model on a new problem. In transfer learning, a machine exploits the knowledge gained from a previous task to improve generalization about another. Transfer learning is not a new concept in machine learning; however, its importance and application have expanded exponentially in recent years. Historically, machine learning models were often trained from scratch for specific tasks, requiring vast amounts of data and computational resources. This approach was both time-consuming and resource-intensive. In the rapidly evolving landscape of artificial intelligence (AI), one concept that has gained significant traction and transformed the way we approach various machine learning tasks is "transfer learning." As we dive deeper into the new age of AI, this chapter will explore the implementation of transfer learning, its evolving role, and the profound impact it has had on a wide range of applications.

It allows us to leverage pre-trained models that have been trained on large and diverse datasets, such as ImageNet for computer vision or GPT-3 for natural language understanding. These pre-trained models serve as a knowledge foundation, which can then be fine-tuned for specific tasks. This paradigm shift has democratized AI, making it more accessible and efficient.(Lyamin et al., 2020) Transfer learning has proven to be exceptionally powerful in various domains. In the new age of AI, transfer learning has emerged as a game-changer.

1.3 THE APPLICATIONS OF TRANSFER LEARNING

Transfer learning has demonstrated significant power and utility in a wide range of applications.

Data Efficiency: Transfer learning allows models to learn new tasks with relatively small amounts of data. Instead of training a model from scratch, it can be initialized with pre-trained weights, which already capture a lot of useful information. This is particularly valuable when collecting large labeled datasets for a new task is expensive or time-consuming. (Fang et al., 2023)

Faster Training: Transfer learning typically speeds up the training process. Starting with pre-trained models can significantly reduce the number of epochs required for convergence, making it computationally more efficient.

Improved Generalization: Models that have learned from diverse datasets tend to generalize better to new, unseen data. Transfer learning helps improve the model's ability to capture underlying patterns and relationships, which can lead to better performance on various tasks.

Domain Adaptation: Transfer learning is useful for adapting models to different domains or environments. For example, a model trained on images of cats and dogs can be fine-tuned to classify wild animals, such as lions and tigers, with relatively little additional data.

Knowledge Transfer: It allows the transfer of knowledge from one domain to another. For example, models trained on natural language understanding tasks can be adapted for various language-related tasks like sentiment analysis, question answering, or text summarization.

Feature Extraction: Transfer learning enables the use of pre-trained models as feature extractors. Instead of using the entire model, one can use the intermediate layers as feature vectors for downstream tasks. This is common in computer vision, where convolutional neural networks (CNNs) are used as feature extractors.

Continuous Learning: Transfer learning supports continuous learning scenarios where models can be updated with new data without forgetting the previously learned knowledge. This is crucial for applications that require adapting to changing environments.

Reduced Computational Resources: By reusing pre-trained models, organizations can save computational resources and reduce the environmental impact associated with training large neural networks from scratch.

State-of-the-Art Performance: Many state-of-the-art models in various domains are based on transfer learning. For instance, models like BERT and GPT have achieved groundbreaking results in natural language processing tasks by leveraging large-scale pre-training.

Practical Applications: Transfer learning has found applications in a wide range of fields, including computer vision, natural language processing, speech recognition, recommendation systems, and more. It has been used in healthcare for medical image analysis, in finance for fraud detection, and in autonomous driving for object recognition, among many other areas. The power of transfer learning lies in its ability to leverage pre-existing knowledge to enhance the performance of machine learning models on new tasks or domains.

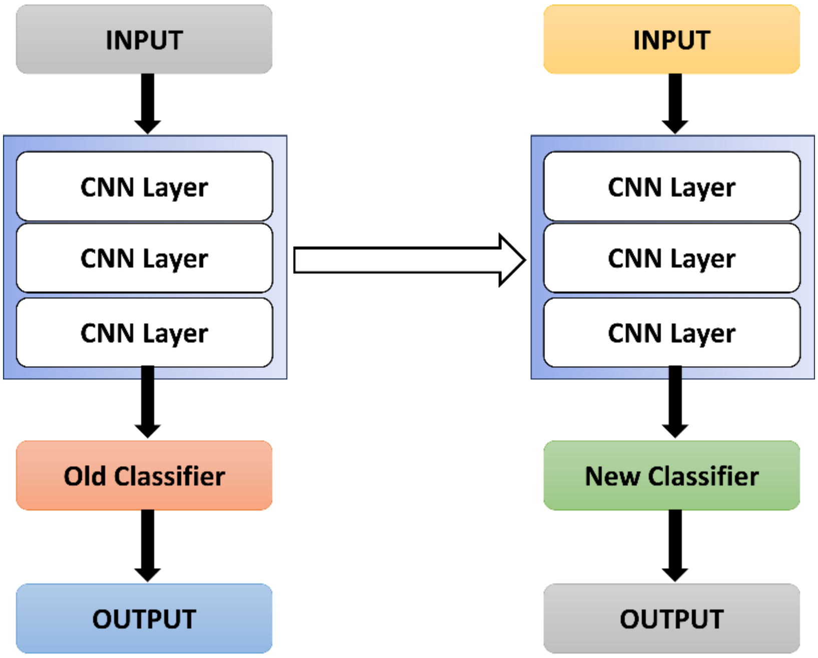


Figure 3: General Structure of Transfer Learning

In Figure-3 the general structure of transfer learning, model is presented, in which features from the earlier and the middle layers can be utilized to train the last layer from scratch. This helps model to take the advantage of the features learned by the pre-trained model on the previous task. The earlier and middle layers consist of general features which can easily be used for other similar tasks.

While the last layers or classifier layers consist of task-specific features. These features need to be learned from the new dataset. So, to generate a new classifier pre-trained layers of existing model can be utilized.

In conventional deep learning, models are only trained to learn only one type of task. To learn another task, we have to build the model again from scratch. To overcome this limitation, the concept of transfer learning is used. In a deep convolutional neural network (CNN) each model has different layers which learn different features from data. These features ultimately form the entire deep neural network. These features detect lines and edges in the earlier layers and shapes in the middle layers. The features in the last layers are task specific.

1.4 TRANSFER LEARNING MODEL WORKING

The model of transfer learning use methodology of transferring knowledge acquired from one task or domain to another, thereby reducing the need for extensive training data and computational resources for the new task. Here's how a transfer learning model typically works:

Pre-Training Phase: The first step in transfer learning is to choose a pre-trained model that has been trained on a large and diverse dataset. These pre-trained models are typically neural networks, such as Convolutional Neural Networks (CNNs) for computer vision tasks or Transformer-based models for natural language processing tasks. In most cases, the pre-trained model's output layer, which is specific to the original task it was trained for, is removed. This output layer is replaced with a new, randomly initialized output layer appropriate for the target task. For example, in a pre-trained image classification model, the output layer that predicts categories is removed.

Fine-Tuning Phase: The next step is to customize the pre-trained model by adding one or more layers to adapt it to the target task. These additional layers are often referred to as the "head" of the model. The head can consist of one or more fully connected layers or other neural network components. During the fine-tuning process, the model is trained on the target task's dataset using gradient descent or a similar optimization technique. The weights of the pre-trained layers are updated based on the errors made during the task-specific training.

Training on the Target Task: The target task dataset is prepared, which may be smaller than what would be required for training a model from scratch. This dataset should be representative of the target task and contain labeled examples. The model is trained using this dataset, and the loss (error) is calculated between the model's predictions and the actual target values. The gradients of the loss with respect to the model's parameters are computed through backpropagation, and the model's weights are updated to minimize the loss using an optimization algorithm (e.g., stochastic gradient descent).

Evaluation and Iteration: The model's performance is evaluated on a separate validation dataset to assess its accuracy and generalization to new, unseen data. Hyperparameters, such as learning rate, batch size, and architecture of the custom head, may be fine-tuned to optimize the model's performance further.

Inference: Once the model is trained and validated, it can be used for making predictions or inferences on new, unlabeled data. The model can be deployed in various applications, such as image recognition, sentiment analysis, or recommendation systems.

Transfer learning are its ability to speed up the training process, improve model performance, and make AI solutions more accessible by reducing the need for vast amounts of labeled data and computational resources. It is especially valuable in situations where collecting extensive data for a new task is costly or time-consuming. The target task dataset is prepared, which may be smaller than what would be required for training a model from scratch. This dataset should be representative of the target task and contain labeled examples. It's important to note that transfer learning is a powerful technique, but it requires careful consideration of the similarity between the source and target tasks, as well as the size and quality of the target dataset. It is widely used in deep learning, especially for tasks with limited data, as it allows you to leverage pre-trained models and transfer their knowledge to new tasks. The training process in transfer learning typically involves several steps.

Select a Pre-trained Model: Choose a pre-trained model that has been trained on a large dataset for a related task. Common choices include models like VGG, ResNet, Inception, BERT, GPT, etc., depending on your specific task (e.g., image classification, natural language understanding, etc.).

Prepare the Dataset: Collect and preprocess your dataset for the target task. Ensure that the data is in the same format as the data used to train the pre-trained model. You may need to resize images, tokenize text, or perform other data preprocessing steps.

Modify the Model: Create a new model architecture that incorporates the pre-trained model as its base. This typically involves removing the final classification layer(s) of the pre-trained model and replacing them with new layers that match the number of classes or outputs for your specific task. This modified architecture is often called the "head" of the model.(S et al., 2021)

Freeze Pre-trained Layers (Optional): Depending on the size of your dataset and the similarity between the pre-trained task and your target task, you can choose to freeze some of the layers of the pre-trained model. This means that these layers will not be updated during training, which can help prevent overfitting when data is limited.

Fine-Tuning: Train the modified model on your target dataset. During training, the weights of the pre-trained layers and the newly added layers are updated based on the target task's loss function. You can use techniques like learning rate schedules and early stopping to optimize the training process.

Evaluation: Evaluate the fine-tuned model using appropriate metrics for your target task. This helps you assess its performance and make any necessary adjustments.

Iterate (Optional): Depending on the results of evaluation, system my choose to iterate on the process. You can experiment with different model architectures, hyperparameters, or data augmentation techniques to improve performance.

Deployment: Once we are satisfied with the model's performance, we can deploy it for inference on new data in your application.

It's important to note that transfer learning is a powerful technique, but it requires careful consideration of the similarity between the source and target tasks, as well as the size and quality of the target dataset. The choice of the pre-trained model, the extent of fine-tuning, and other hyperparameters should be adjusted based on your specific problem and available resources. Transfer learning can enhance routing and navigation systems by incorporating knowledge about traffic conditions from one area to another. Models can adapt to local conditions by leveraging pre-trained models on broader datasets. Transfer learning can assist in transferring knowledge about effective traffic management policies and strategies from one region to another. This can be particularly useful for cities or regions looking to implement congestion pricing, carpool lanes, or other policies to manage traffic. (Majumdar et al., 2021)

Transfer learning can be used in urban planning to simulate the impact of changes in infrastructure (e.g., adding new roads or public transportation systems) based on knowledge from other locations where similar changes have been made. Transfer learning can also apply to multi-modal transport systems, where knowledge from one mode (e.g., trains) can be transferred to improve the efficiency of another mode (e.g., buses) to reduce congestion.

1.5 ROLE OF TRANSFER LEARNING IN SMART CITY

Transfer learning plays a multifaceted role in the development of smart cities across various sectors, including healthcare, education, information, and traffic congestion control. In the healthcare sector, transfer learning has the potential to revolutionize medical diagnostics and patient care. Pre-trained deep learning models can be fine-tuned for specific medical imaging tasks, such as detecting anomalies in X-rays, MRIs, or CT scans. This not only accelerates the diagnosis process but also enhances the accuracy of disease detection. Moreover, transfer learning can help in predictive modeling for disease outbreaks, using data from different cities to develop models that can identify early warning signs and aid in effective resource allocation and healthcare planning.

In the education and information sector, transfer learning can be utilized to personalize learning experiences and improve content recommendation systems. Pre-trained natural language processing models can be adapted to understand and analyze educational materials and student interactions. This enables the creation of intelligent tutoring systems that adapt to individual student needs, as well as the development of content recommendation algorithms that suggest relevant educational resources based on a student's learning history and preferences. Additionally, transfer learning can assist in curating and analyzing vast amounts of online information for educational purposes, helping learners access high-quality, contextually relevant information. (Adi et al., 2020)

In the domain of traffic congestion control, transfer learning is instrumental in optimizing traffic management and reducing urban gridlock. Pre-trained computer vision models can be fine-tuned to monitor traffic patterns, identify bottlenecks, and predict congestion events using data from various cities. This facilitates proactive traffic control strategies, including adaptive signal timing and route optimization, which can significantly alleviate congestion and reduce commute times. Additionally, transfer learning can integrate data from diverse urban sources, such as weather conditions, public transportation, and event calendars, to provide real-time traffic updates and alternative routes to drivers, ultimately enhancing the overall efficiency of urban transportation systems.

Transfer learning serves as a crucial tool in the advancement of smart cities by enabling the efficient adaptation of pre-trained models to address specific challenges in healthcare, education, information, and traffic congestion control. By leveraging the knowledge encoded in these models, smart cities can enhance services, optimize resource allocation, and improve the quality of life for their residents in diverse and meaningful ways. It's important to note that the success of transfer learning in addressing traffic congestion depends on the similarity of the source and target domains, the availability and quality of data, and the specific application. Careful data preprocessing, model selection, and fine-tuning are essential steps in deploying transfer learning effectively for traffic congestion management.

CHAPTER 2

LITERATURE REVIEW

Traffic congestion is a pervasive problem in urban areas, leading to delays, increased travel time, fuel consumption, and air pollution. Vehicular Adhoc Networks (VANETs) have emerged as a potential solution to alleviate traffic congestion by enabling vehicles to communicate and share information in real-time. The integration of transfer learning techniques in VANETs presents an opportunity to enhance the performance of traffic congestion control systems by leveraging knowledge from related domains. Transfer learning, a subfield of machine learning and artificial intelligence (AI), involves transferring knowledge learned from one domain to improve performance in another domain. In the context of traffic congestion control systems in VANETs, transfer learning techniques enable the utilization of pre-existing knowledge from related domains, which helps overcome the limitations of limited data availability and improves prediction accuracy. For instance, in a study (Wu et al., 2015) presented a protocol based on broadcasting technique enabled as information forwarding system in VANET using self-learning.

The fuzzy logic parameters were online tuned to apply changes to newly entering vehicles in the network. Both the fuzzy logic and transfer learning techniques combined in the proposed model.(Z. Wang et al., 2023) Transfer learning was employed to leverage labeled traffic data from neighboring cities to improve congestion prediction accuracy in VANETs. Furthermore, transfer learning facilitates the transfer of knowledge between different environments or domains, enabling insights gained in one setting to be applied to VANETs. This knowledge transfer enhances the accuracy of traffic congestion prediction. It was applied transfer learning techniques to leverage the experience gained from analyzing traffic patterns in urban areas to improve the prediction accuracy of VANET-based traffic congestion. Congestion detection unit strategy used in (Taherkhani & Pierre, 2016) to monitor and handle the congestion in channels of network traffic. Periodically sensing the channels provide the updated data measurable on threshold. Which renders the data for prediction in prediction system. K-means algorithm multi-dimensional process data of large scale wise generated is used in the study for clustering the dataset of VANET. Distributed congestion control and management system proposed (Feukeu & Zuva, 2017) to control the situation of congestion by implementing a mitigation algorithm namely Dynamic Broadcast Storm which was launched to cater the difficulties being occurred during broadcasting the safety messages in the VANET environment. Its simulation results also impart improvement in the journey of congestion control. (Karabulut et al., 2023)

The review study (Jackson & Vijayakumar, 2018) comprehensively provides the comparison and overview of two different mechanisms of congestion control and detection methods. One is known as adaptive position update which dynamically adjusts the traffic node positions data received in mobility patterns. The second review is about distributed fair transmit power adjustment used in VANET which depends on the prediction forwarded by the network application layer. The number of nodes in the network are the core barrier in the prediction system of this proposed model.

Vehicular-to-vehicular (V2V) communications during congestion of VANET became more difficult problem to deliver both type of messages safety and non-safety messages. Algorithm for reduction of motion vehicle (Cheng & Huang, 2019) was introduce to secure the moving vehicle from congestion of network by utilizing a cluster head. In this proposed solution every vehicle can communicate through LTE based approach. Meanwhile the node in the traffic can also set up connection through DSRC system in a size of 802.11p cluster. The simulation results showed that algorithm performed well in comparison to other algorithms based on packet delivery among urban traffic nodes. (Zhu et al., 2023)

Some advancement in this problem solving was proposed as location based GPSR (Arvind Narayan et al., 2020) involving the algorithms of greedy forwarding in routing the exact destination and perimeter forwarding for handling the mobility rating in complex and large nodes. As compared in the study that geographical change of routing is dependent on some specific topology while the proposed model of congestion control only requires the position of next node and hop for re-routing decisions. A study towards identification and control of congestion(Paranjothi et al., 2020) proposed model to identify congestion through statistically based network tomography. Which addressed the open loop congestions and closed loop congestions based on nodes communication. Its main objective was to route the traffic data through load balancing techniques in statistical model. (Q. Pan et al., 2022)

Blockchain congestion control architecture model (Maaroufi & Pierre, 2021)proposed based on heterogeneity of available machine learning techniques. Implementations of this architecture tested on hybrid mode of communication protocols as well as cloud and edge-based systems.(Maaroufi & Pierre, 2021) Distributed trust strategy followed by regression implemented modules were included in this architecture. This architecture predicts the layer of congestion on simulation performed and exhibits the quality of services on demand-based approach in network complexity.(Kezia & Anusuya, 2022) The density of vehicles and occupied shared channel information retrieval was used in study to propose model to control congestion using machine learning(Kezia & Anusuya, 2022). The multifunctional algorithms of machine learning including K-NN, naive Bayes, decision trees, and random forest were applied to obtain the prediction-based control results. The simulation results of these algorithms maintained the load balancing of network up to 40% in a congested network situation. Another research proposed a fusion based VANET congestion control system(Saleem et al., 2022) using ML after collecting the route data and re-route the traffic.

The data sharing among RSU was enabled in this model to set up a communication for sending and receiving updated information about nodes in VANET. Congestion control through ML of transfer learning proposed in (Haddaji et al., 2023) which convert data into image for implementing the deep learning process in the model. The model trained by different data sets of nodes in the network using TRLID technique which gave results to avoid congestion for VANET. Traffic congestion arises due to various factors, including population growth, increased vehicle ownership, and limited road infrastructure expansion. Traditional traffic management approaches often rely on fixed signal timings and predefined rules, which can be ineffective in dynamically changing traffic conditions.

2.1 TRANSFER LEARNING IN MACHINE LEARNING

Early attempts at traffic congestion control often relied on handcrafted features and shallow models. However, with the advent of deep learning and transfer learning, there have been significant advancements. Researchers have used pre-trained models on traffic data from one city or region to improve traffic flow prediction in another. For example (Yisheng et al., 2014) applied deep learning techniques for traffic flow prediction with big data, demonstrating the potential of these methods in capturing complex traffic patterns. Feature-based transfer learning involves extracting and reusing features learned from a source domain (e.g., natural images) for a target domain (e.g., aerial images captured by UAVs). Researchers have employed techniques like Convolutional Neural Networks (CNNs) to transfer image features effectively (Yosinski et al., 2014). Model-based transfer learning entails fine-tuning a pre-trained neural network by updating its weights with data from the target domain. This approach has been widely adopted for tasks such as object detection and image classification in VANET applications.(Donahue et al., 2013).

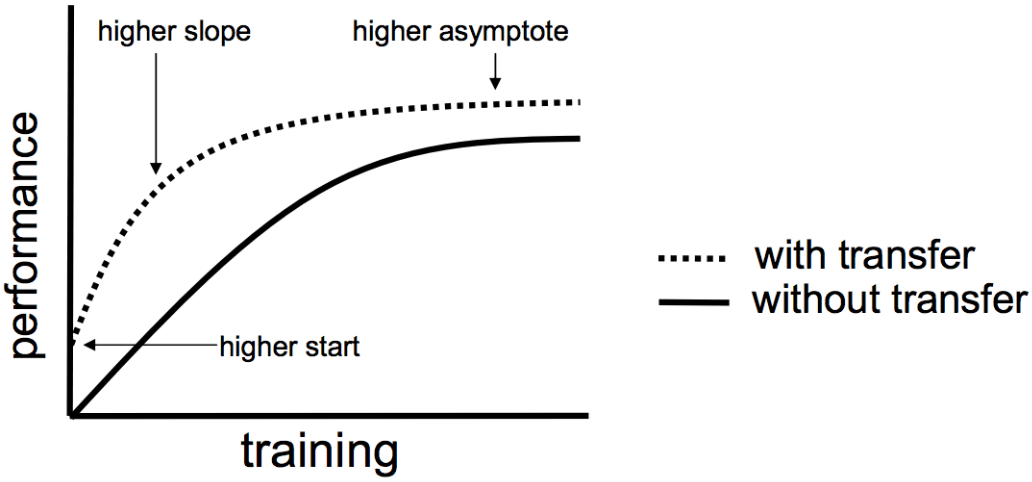


Figure 4: Performance of Model with and without Transfer Learning

The difference of performance of a model trained on transfer learning and not trained is already depicted in figure 4 as worked out by (Brownlee, 2017) and described three higher layer efficiency.

Higher Start: The initialization point of model working is performing higher than a non-trained model.

Higher Slope: The performance rate of model during the working is also on higher slop other than untrained model working on same data.

Higher Asymptote: Like the other two modes of working the consistency of trained model is also higher then otherwise.

Transfer learning is a machine learning technique where knowledge acquired from one task or domain is applied to improve the performance of a related or different task. In traffic congestion control, transfer learning offers several advantages:

Data Efficiency: Traffic data is often limited and expensive to collect. Transfer learning allows congestion control models to leverage pre-existing traffic data from other locations or time periods, reducing the need for extensive local data collection (S. J. Pan & Yang, 2010).

Generalization: Transfer learning enhances the generalization capabilities of traffic congestion control models. By transferring knowledge from similar traffic scenarios, models can adapt to new and unseen conditions (Long et al., 2015b) The integration of transfer learning techniques in traffic system holds immense potential for improving their performance across various applications. As the field continues to evolve, addressing challenges related to domain shift, computational resources, real-time processing, and dataset collection will be crucial. Future research efforts should focus on developing transfer learning methods tailored to the specific needs and constraints of control systems.

Adaptation to Dynamic Conditions: Traffic congestion is dynamic and can change rapidly. Transfer learning enables models to adapt quickly to changing traffic conditions by incorporating knowledge from historical data(Laña et al., 2021) Transfer learning has been employed to enhance object detection and recognition capabilities in VANET, allowing them to identify and track objects of interest in real-time, such as vehicles, pedestrians, and infrastructure. Transfer learning has been widely applied in diverse domains, including medical imaging, natural language processing, and more. It has enabled the development of state-of-the-art models for tasks like object detection, image segmentation, and image captioning. There are various transfer learning scenarios, such as feature extraction and fine-tuning.

Feature extraction involves using pre-trained CNN layers as fixed feature extractors and adding custom layers for task-specific learning. Fine-tuning allows updating some or all of the pre-trained model's parameters to adapt it to the new task. While transfer learning is powerful, it's not a one-size-fits-all solution. Choosing the right pre-trained model and approach is crucial. Domain shift and dataset differences can affect transfer learning performance, and domain adaptation techniques may be required. Transfer learning is widely used in popular deep learning frameworks like TensorFlow and PyTorch, making it accessible for developers and researchers. Transfer learning with CNNs has greatly advanced the field of computer vision and deep learning by allowing the reuse of knowledge learned from large datasets.(Long et al., 2015a) Its power lies in the ability to leverage pre-trained models to accelerate the training of models on specific tasks, making it a fundamental tool for both beginners and experts in the field. Continued research and innovations in transfer learning techniques are likely to further enhance its effectiveness in the future. The release of pre-trained models on large datasets like ImageNet (e.g., VGG, ResNet, Inception, etc.) marked a significant shift. Researchers realized that these models had learned valuable features that could be reused for various computer vision tasks.

2.2 TRANSFER LEARNING IN TRAFFIC CONGESTION CONTROL

Advanced analytics and machine learning algorithms can be applied to historical and real-time data from VANETs to predict traffic congestion in specific areas. This information can be used to proactively manage traffic and divert vehicles before congestion occurs.(Mallick et al., 2021)

Feature Transfer: Early work in transfer learning for traffic congestion control focused on transferring features extracted from traffic data. For instance, Zhao et al. [2013] proposed a transfer learning approach that transfers features learned from traffic data in one city to another, improving congestion prediction accuracy.(Huang et al., 2023)

Model Transfer: More recent research has explored the transfer of entire models pretrained on traffic data. Transfer learning models such as deep neural networks (DNNs) pretrained on one city's traffic data have been fine-tuned to improve congestion control in a different city (Fu et al., 2020)

Domain Adaptation: Domain adaptation techniques have also been applied to traffic congestion control. These methods aim to adapt congestion control models trained on one source domain to perform well in a different target domain, considering variations in traffic patterns (X. Yin et al., 2022)

Transfer Learning for Autonomous Vehicles: The development of autonomous vehicles has also benefited from transfer learning techniques. Autonomous vehicles require robust perception systems to navigate through complex traffic scenarios. Deep reinforcement learning (DRL) models, which can be pre-trained on vast amounts of data, have been applied to enhance the decision-making capabilities of autonomous vehicles(Lei et al., 2020). By transferring knowledge from simulation environments to real-world scenarios, these models improve the safety and efficiency of autonomous driving.(Lu et al., 2020)

Transfer Learning for Traffic Signal Control: Traffic signal control is a fundamental aspect of congestion management. Transfer learning approaches have been used to adapt signal control policies to changing traffic patterns.(Yuan et al., 2022) proposed a dynamic route guidance system that uses deep reinforcement learning for congestion control. This approach adapts traffic signal timings in real-time based on traffic conditions, leading to improved traffic flow. VANETs can prioritize emergency vehicles, such as ambulances and fire trucks, to ensure they can navigate through traffic quickly, reducing congestion around emergency scenes. Transfer learning can help in detecting anomalies or accidents on the road. Pre-trained models for image classification can be fine-tuned to recognize abnormal patterns in traffic camera feeds or sensor data (Hahn et al., 2021).

2.3 TABLE COMPARISON/ LIMITATIONS OF PREVIOUS WORKS

Reference	Approach	Outcomes	Decision Yes/No	Transfer Learning	Limitation till now
Wu, C., Ji, Y., Chen, X., Ohzahata, S., & Kato, T. (**2015**). An Intelligent Broadcast Protocol for VANETs Based on Transfer Learning. 2015 IEEE 81st Vehicular Technology Conference (VTC Spring), 1–6.	fuzzy logic	congestion prediction	No	Yes	Data latency issues
Taherkhani, N., & Pierre, S. (**2016**). Centralized and Localized Data Congestion Control Strategy for Vehicular Ad Hoc Networks Using a Machine Learning Clustering Algorithm. IEEE Transactions on Intelligent Transportation Systems, 17(11), 3275–3285	Congestion detection unit implemented by K-means algorithm	monitor and handle the congestion in channels of network traffic	No	Yes	Data measuring algorithm inefficiency
Feukeu, E. A., & Zuva, T. (**2017**). DBSMA Approach for Congestion Mitigation in VANETs.	Dynamic Broadcast Storm	Distributed congestion control and management system	No	No	Design to work after congestion occur but safety message delivery issues.
ackson, J. C., & Vijayakumar, V. (**2018**). A review on congestion control system using APU and D-FPAV in VANET.	prediction system based on the application layer data	Dynamic adjustment of node based on data	No	No	number of nodes in the network are the core barrier
Cheng, X., & Huang, B. (**2019**). A Center-Based Secure and Stable Clustering Algorithm for VANETs on Highways. Wireless Communications and Mobile Computing, 2019,	VANET communication through LTE based approach	Proficient Vehicle based packet delivery among urban traffic nodes	No	No	Cluster based approach work only in clustered environment

Reference	**Approach**	**Outcomes**	**Decision Yes/No**	**Transfer Learning**	**Limitation till now**
Arvind Narayan, S., Rajashekar Reddy, R., & Femilda Josephin, J. S. (**2020**). Secured Congestion Control in VANET Using Greedy Perimeter Stateless Routing (GPSR)	location based GPSR and greedy Algorithm	Rerouting decision easily made on basis of location of node.	No	No	Algorithm is dependent of location data of every node
Maaroufi, S., & Pierre, S. (**2021**). BCOOL: A Novel Blockchain Congestion Control Architecture Using Dynamic Service Function Chaining and Machine Learning for Next Generation Vehicular Networks.	Blockchain congestion control system using machine learning	predicts the layer of congestion on hybrid mode of communication protocols as well as cloud and edge-based systems	No	No	Distributed trust strategy followed by regression was implemented in the methodology.
Kezia, M., & Anusuya, K. V. (**2022**). A Comparative Study on Machine Learning Algorithms for Congestion Control in VANET.	multifunctional algorithms of machine learning	load balancing of network up to 40% in a congested network situation	No	No	Data sharing by RSU requires algorithms implementation
Haddaji, A., Ayed, S., & Fourati, L. C. (**2023**). A Transfer Learning Based Intrusion Detection System for Internet of Vehicles.	deep learning process	TRLID Techniques used to train system using multifunctional data	No	Yes	Data conversion process requires efficiency

2.4 PROBLEM STATEMENT

Traffic congestion is a significant challenge faced by urban areas worldwide, leading to numerous adverse effects, such as increased travel time, fuel consumption, and air pollution. Traditional traffic management systems often struggle to cope with the complexities of modern urban environments, resulting in suboptimal control and inefficient resource allocation. With the rapid advancements in deep learning and artificial intelligence, there is an opportunity to revolutionize traffic management through the integration of Transfer Learning (TL) techniques.

The problem at hand is to develop a robust and efficient Traffic Congestion Control System using Transfer Learning.

The primary aim of this research is to leverage pre-trained neural networks to tackle the challenges associated with real-time traffic congestion prediction and control, enabling cities to implement dynamic and adaptive traffic management strategies. Urban areas face diverse and evolving traffic congestion challenges, including but not limited to intersections with high traffic volume, accidents, road closures, and special events. Developing a TCCS that can adapt to these challenges is crucial for mitigating congestion. Transfer Learning is a powerful approach that can harness pre-trained models and knowledge from related domains to enhance the performance of traffic congestion control systems. However, its effective application to real-world traffic scenarios requires innovative research and implementation.(Giripunje et al., 2021)

The TCCS must strike a balance between robustness and efficiency. It should not only effectively manage traffic congestion but also do so in a resource-efficient manner, minimizing infrastructure costs and energy consumption. Urban traffic conditions can change rapidly, necessitating real-time adaptability of the TCCS. Developing algorithms that can continuously learn and adapt to new information is a key research challenge. Access to high-quality, real-time traffic data is vital for the success of any congestion control system. However, privacy concerns and data availability issues may hinder the development and deployment of such systems. Research must address data collection, privacy preservation, and data sharing challenges. Urban areas vary in size and complexity, and a scalable TCCS should be capable of addressing congestion in both small towns and large metropolitan areas. Research should explore solutions that can be tailored to different urban environments. (Submitter, 2021)

A successful TCCS should prioritize the well-being of urban residents, emphasizing safety, reduced commute times, and overall improved quality of life. Developing a robust and efficient TCCS requires collaboration between transportation engineers, data scientists, urban planners, and policymakers. Interdisciplinary research efforts are needed to tackle this multifaceted problem effectively. A comprehensive understanding of the challenges and complexities involved in developing a Traffic Congestion Control System using Transfer Learning. This perspective aligns the research with the real-world problem of urban congestion, highlighting its significance and the potential for transformative solutions.

2.5 RESEARCH QUESTIONS

1. How can Transfer Learning enhance traffic congestion prediction accuracy in urban VANETs, addressing specific domain adaptation challenges?

2. Which pre-trained neural network architectures are best suited for Transfer Learning in VANETs, and what fine-tuning methods optimize real-time traffic congestion prediction?

3. How can a transferable dataset be created to alleviate the scarcity of labeled VANET data, combining real-world VANET observations with synthetic data from simulations?

4. What techniques ensure resource efficiency, scalability, and prediction accuracy in large-scale VANET deployments of the TL-based Traffic Congestion Control System?

5. How does the TL-based Traffic Congestion Control System adapt to real-time traffic disruptions for effective flow management during unforeseen events?

These research questions aim to address the various challenges and complexities associated with developing an efficient TL-based Traffic Congestion Control System in VANETs. Answering these questions will contribute valuable insights to advance the field of intelligent transportation systems and improve traffic management in urban environments. To improve the accuracy of traffic congestion prediction in VANETs within urban environments, Transfer Learning emerges as a promising approach. Urban traffic presents unique challenges due to its dynamic nature, with varying road conditions, congestion patterns, and unpredictable events(Tan et al., 2018).

To address these challenges, selecting appropriate pre-trained neural network architectures is crucial. Fine-tuning these networks to adapt to the urban traffic domain involves retraining on a limited amount of labeled urban VANET data and possibly incorporating synthetic data generated through simulations. This fine-tuning process helps the model learn relevant features and patterns specific to urban traffic conditions (Ruder, 2017).

By effectively applying Transfer Learning, VANETs can make more accurate predictions about traffic congestion, contributing to better traffic management and improved overall urban mobility.(Hossain et al., 2020)

2.6 AIMS & OBJECTIVES

1. By fine-tuning pre-trained neural networks with limited VANET data and a transferable dataset incorporating real-world and synthetic data, Transfer Learning can effectively improve prediction accuracy in VANETs.

2. Utilize pre-trained models like VGG16 or Transformers for Transfer Learning in VANETs. Fine-tune by adapting final layers to VANET-specific features and training on transferable data. Optimize with techniques like transfer learning rate scheduling and early stopping for improved real-time traffic congestion prediction.

3. Build a transferable dataset for VANETs by blending real-world VANET data with synthetic data from simulations. Implement domain randomization in simulations for increased diversity and better domain adaptation during fine-tuning.

4. Ensure VANET resource efficiency and scalability with model quantization, compression, and parallelism techniques. These methods reduce model size, maintain accuracy, and distribute computational load for connected vehicle data processing.

5. The TL-based Traffic Congestion Control System learns from real-time traffic data, using sensors and vehicle communication for live updates. It employs online and reinforcement learning to adjust traffic signals and manage traffic dynamically.

CHAPTER 3

METHODOLOGY

3.1 PROPOSED METHODOLOGY

In fig - 4 the proposed methodology model is presented which describes the overall working of traffic congestion control system in VANET using transfer learning. The sources of data input into the preprocessing layer of proposed system which prepares the data and performs several operations if required to ready data for system training. These operations include handling missing information, data cleaning, normalization, and average value additions.

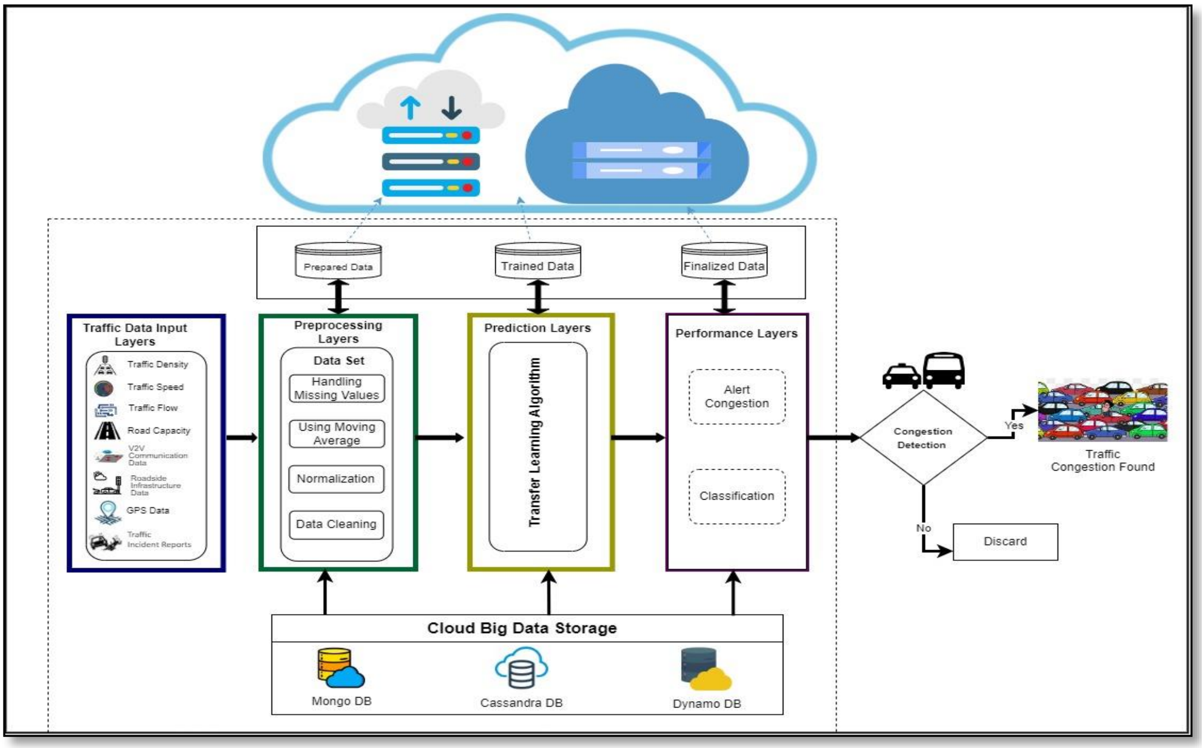


Figure 5: Proposed Abstract Model for TCCS- in VANET using TL.

The prepared data moved to cloud storage and then forwarded to prediction layer to run the transfer learning algorithm. Once the system is trained on data provided by previous layer the trained data is also moved to cloud for storage, the TL algorithm layer forwarded the data to performance layer that performs classification in different modules for detection of congestion in provided data. The abstract model of a traffic congestion control system involves intricate layers that leverage the power of transfer learning techniques to enhance its efficiency. At its core, this model comprises multiple hierarchical levels, each contributing to the overall effectiveness of traffic management. The foundational layer involves data acquisition and preprocessing, where real-time traffic data from various sources such as sensors, cameras, and satellite imagery are collected and refined. This layer plays a crucial role in ensuring the accuracy and reliability of the input data. The subsequent layer is dedicated to feature extraction and representation, where the relevant patterns and features in the data are identified.

Transfer learning comes into play at this stage, allowing the model to leverage knowledge gained from pre-trained models on related tasks. This technique enables the system to benefit from insights learned in one context and apply them to the specific challenges of traffic congestion control. The pre-trained models might have learned valuable spatial and temporal patterns from diverse datasets, contributing to a more robust representation of traffic dynamics. The third layer focuses on the actual congestion prediction and control strategies. The transfer learning model, having absorbed general traffic patterns, adapts its predictions based on the specific characteristics of the monitored area. This layer involves sophisticated algorithms that predict congestion hotspots, taking into account factors such as historical traffic data, special events, and weather conditions. The model dynamically adjusts traffic signal timings, reroutes traffic, and communicates with smart vehicles to optimize the overall traffic flow (Kumar & Daume III, 2012).

Additionally, there is a feedback loop layer that continuously refines the model based on the performance of the implemented control strategies. This layer is crucial for adaptive learning and ensures that the system evolves to handle changing traffic patterns over time. Transfer learning, with its ability to adapt knowledge from different domains, contributes to the adaptability of this layer by allowing the model to learn from novel scenarios and unforeseen challenges.(J. Wang et al., 2020) The layers of the abstract model of a traffic congestion control system through transfer learning represent a sophisticated approach to traffic management. From data acquisition to adaptive control, each layer plays a vital role in creating a system that can learn from diverse sources and adapt to the dynamic nature of urban traffic, ultimately leading to more efficient and responsive congestion control.

3.2 DATA SET PREPARATION

Creating a traffic data set for congestion control in a transfer learning model involves collecting, processing, and annotating data that represents various traffic conditions. Below are some specifications and considerations for building such a data set:

Data Collection:

Sources: Collect traffic data from diverse sources, including:

Traffic cameras, GPS data from vehicles, Traffic sensors, Mobile apps with traffic information

Spatial Coverage: Ensure data is collected from various locations, such as urban, suburban, and rural areas.

Temporal Coverage: Capture data over different times of the day, days of the week, and seasons to represent various traffic scenarios. Traffic signal control is a fundamental aspect of congestion management. Transfer learning approaches have been used to adapt signal.

Data Types:

Images/Video Frames: For visual data, capture images or video frames from traffic cameras.

GPS Data: For location information and traffic flow.

Speed and Density Data: From traffic sensors or historical data.

Annotations:

Congestion Labels: Annotate the data to indicate congestion levels. This could be binary (congested or not) or multi-class (light, moderate, heavy congestion).

Region of Interest (ROI): If using images or video frames, annotate the regions where congestion is present.

Data Preprocessing:

Normalization: Normalize data such as speed, density, and timestamps.

Data Augmentation: Introduce variations in the data to improve model generalization.

Transfer Learning Setup:

Base Model: Choose a pre-trained model that has been trained on a large dataset, such as a Convolutional Neural Network (CNN) for image data.

Task-Specific Layers: Add task-specific layers on top of the pre-trained model for congestion control.

Validation and Test Sets:

Split the Data: Divide the dataset into training, validation, and test sets to evaluate the model's performance accurately.

Ethical Considerations:

Privacy: Ensure the data collection process respects privacy laws and guidelines.

Bias: Be aware of biases in the data, which might affect the model's performance.

Documentation:

Metadata: Document metadata, including the source of data, date and time of collection, and any preprocessing steps.

Data Distribution:

Class Imbalance: Check for class imbalances in congestion levels and address them if necessary.

Open Data Standards:

Data standards: Consider using open data standards to make the dataset accessible and usable by a wider community.

Security:

Ensure Data Security: Data security needs confirmation specially if it includes sensitive information.

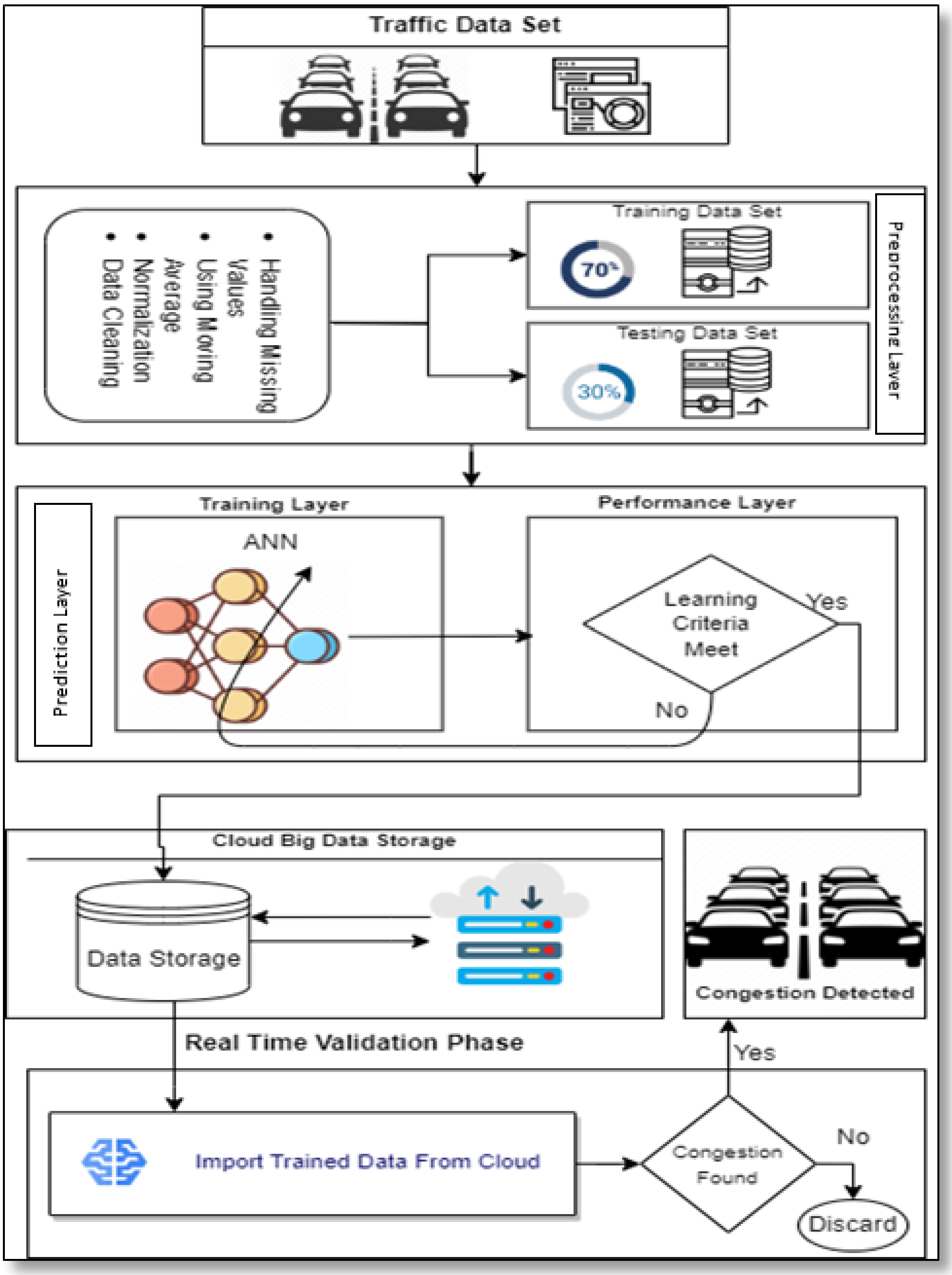


Figure 6: Detailed proposed TCCS-ML in VANET

In Figure 6 the detailed working of proposed system is elaborated in the layered module. Wherein the proposed model of system receives the data from input layer for training (70%) and testing (30%) along with different parameters. Then the ANN module in the next prediction layer trains the model through data and after training data is sent to performance layer. (X. Yin et al., 2022) Performance layer gets the trained data from cloud storage and provides decision making results about congestion in real time validation phase.

3.3 GRADIENT BOOSTING ALGORITHM

Transfer learning involves taking a pre-trained model on a source task and fine-tuning it for a target task. The basic idea is to transfer the knowledge acquired during the training on the source task to the target task. This is particularly useful when the target task has limited labeled data, as the pre-trained model has already learned useful features from the source task. Denotation of the pre-trained model as M_{source} and the target model as target M_{target}. The mathematical working of transfer learning involves adjusting the parameters M_{target} to better suit the target task. Gradient Boost, through its iterative process of automatically selecting and combining features, along with its ability to adjust various hyperparameters, stands out as a powerful tool for optimizing models. These inherent qualities contribute to the achievement of high predictive accuracy. Given these characteristics, Gradient Boost emerges as a well-suited method for predicting and elucidating the spatial heterogeneity of the Traffic Performance Index (TPI). Its capacity to efficiently handle feature selection and parameter tuning enhances its aptitude in capturing and explaining the complex variations in TPI across different spatial contexts.

Iterative Learning: Gradient boosting builds a strong model by combining multiple weaker decision trees, each correcting errors of its predecessors.

Adaptive Focus: It adapts to complex patterns in traffic data, identifying factors like time of day, weather, accidents, events, and infrastructure that contribute to congestion.

Effective Prediction: It generates accurate predictions of congestion levels, crucial for proactive traffic management and mitigation strategies.

Mathematical Formulation:

$$L(y, F) = \frac{1}{2} [y - F]^2 \tag{1}$$

Assuming that $F(x)$ approximates the label y based on a set of predictor variables x, the least square error function is applied as the loss function to estimate the approximation function.

Supposing that the number splits is k for individual subtree, which further split input area into k regions just like R1n, R2n, · · ·, Rkn and estimates a constant value bKn into region Rkm. Thus, each decision tree can be written as follows.

$$h_n(x) = \sum_{k=1}^{k} b_{kn} I, \tag{2}$$

where $I = 1$ if $x \in Rkn$; $i = 0$ otherwise. Assuming the data: $\{yi\ , xi\ \}\ M\ 1$, the gradient boosting decision tree iteratively produces N different regression trees $h1\ (x), \dots hN(x)$. The updating form function $Fn(x)$ is given with a gradient descent step size pn.

$$F_n(x) = F_{n-1}(x) + p_n \sum_{k=1}^{k} b_{kn}\ I\ (x\ \in\ R_{kn}) \tag{3}$$

$$p_n = arg_p \min \sum_{j=1}^{M} L\left(y_i\ F_{n-1}(x_i) + p \sum_{k=1}^{k} b_{kn}\right) I\ (x\ \in\ R_{kn}) \tag{4}$$

Finding an optimal partition γ_{kn} for each region $R_{kn\ ,}$ then the (3) can be presented without b_{kn}.

$$F_n(x) = F_{n-1}(x) + \sum_{k=1}^{k} \gamma_{kn}\ I\ (x\ \in\ R_{kn}), \tag{5}$$

and to obtain the optimal can be based on as follows:

$$\begin{aligned} \gamma_n &= argmin_{\gamma} \sum_{x_i \epsilon R_{jn}} L(y_i, F_{n-1}(x_i) + \gamma) \\ &= argmin_{\gamma} \sum_{x_i \epsilon R_{jn}} (y^{\sim} - \gamma)^2\ , \end{aligned} \tag{6}$$

where

$$y_i = -\left[\frac{\partial L\left(y_i, F(x_i)\right)}{\partial F(x_i)}\right]_{F_n(x) = F_{n-1}(x)} \tag{7}$$

The gradient boosting tree forms the model gradually and updates the constraint by minimizing the value of certain loss function. To prevent over-fitting and improve the model performance, it applies to a strategy to scale the contribution of base tree with a learning rate ε $(0 < \varepsilon < 1)$.

3.4 GRADIENT BOOSTING ALGORITHM IN TRAFFIC DATA ANALYSIS

Urban areas worldwide grapple with the escalating challenges of traffic congestion, necessitating innovative and adaptive solutions for effective traffic management. In this pursuit, the application of machine learning algorithms has emerged as a transformative approach, promising to enhance our understanding of traffic dynamics and contribute to more responsive congestion control systems. Among the myriad of machine learning techniques, the Gradient Boosting algorithm stands out for its ability to model complex relationships within data, offering a powerful tool for predicting and managing traffic congestion.

Background: Traffic congestion is a multifaceted phenomenon influenced by a myriad of factors, including temporal patterns, weather conditions, road infrastructure, and unforeseen events. Traditional methods of traffic management often fall short in addressing the intricacies of these dynamic systems. Recognizing this gap, the application of machine learning algorithms has gained prominence, enabling a data-driven and adaptive approach to congestion control. Among these algorithms, Gradient Boosting has demonstrated notable success in various domains due to its ensemble learning framework and the ability to sequentially improve model predictions.

Overview of Gradient Boosting: Gradient Boosting is an ensemble learning technique that builds a predictive model by combining the outputs of multiple weak learners, typically decision trees. The algorithm operates sequentially, with each tree aiming to correct errors made by its predecessors. By optimizing a loss function through the iterative addition of weak learners, Gradient Boosting creates a robust and accurate predictive model. Noteworthy implementations of Gradient Boosting include Scikit-Learn's Gradient Boosting Regressor and Gradient Boosting Classifier, XGBoost, and Light GBM.

Rationale for Using Gradient Boosting in Traffic Data Analysis:The choice of Gradient Boosting for traffic data analysis stems from its inherent strengths. Unlike traditional models, Gradient Boosting excels in capturing non-linear relationships, handling complex interactions between features, and adapting to temporal variations in traffic patterns. This adaptability is crucial in the context of traffic management, where conditions can change rapidly. The algorithm's capacity to handle diverse features, including temporal, weather-related, and infrastructure data, positions it as an ideal candidate for unraveling the intricate dynamics of urban traffic.

Objectives of Applying Gradient Boosting: The primary objectives of employing the Gradient Boosting algorithm in this research are to enhance congestion prediction accuracy, understand feature interactions influencing traffic dynamics, and develop a model that adapts seamlessly to changing conditions. By leveraging the ensemble learning approach, the algorithm is expected to uncover latent patterns within the data, enabling more precise predictions and proactive congestion control strategies.

Significance of the Study: This research holds significance not only for the field of traffic management but also for the broader discourse on smart and adaptive urban mobility. The application of Gradient Boosting represents a departure from traditional, rule-based approaches towards a data-driven and machine learning-centric paradigm. The outcomes of this study are anticipated to contribute valuable insights, shaping the future of traffic management systems and offering a blueprint for integrating machine learning algorithms into real-world urban environments.

In the realm of Gradient Boosting, this approach proves to be particularly advantageous. By pre-training the model on a source task, such as a related dataset or domain, and then fine-tuning it for the target task, the Gradient Boosting algorithm can adapt more efficiently to the nuances of a specific problem. Transfer learning empowers the model to grasp general patterns from the source task and refine its understanding to optimize predictions for the target task. In the domain of traffic data analysis, for instance, transfer learning could involve training the Gradient Boosting model on historical traffic data from one city and fine-tuning it to predict congestion patterns in a different urban setting. This transfer of knowledge allows for a more adaptive and accurate model, capable of handling variations and challenges specific to the target task.

The incorporation of transfer learning into Gradient Boosting exemplifies a strategic approach toward improving model performance and underscores the algorithm's versatility in addressing real-world complexities. Transfer learning, an innovative paradigm within the domain of machine learning, is increasingly gaining prominence, even in the context of Gradient Boosting algorithms. Transfer learning involves leveraging knowledge gained from one task to enhance the learning and performance on another related task. Transfer learning in Gradient Boosting extends the algorithm's capabilities beyond its traditional standalone use by harnessing insights gained from one context and applying them to another. This approach proves particularly beneficial in scenarios where labeled data for the target task is scarce or expensive to acquire.

3.5 GRADIENT BOOST PSEUDO-CODE

The pseudo-code of algorithm is shown in Table 2, where in the algorithm calculate the congestion prediction in each iteration to form the next regression tree for transfer learning. This calculates from the existing model and contribute to cumulative results of congestion prediction for better learning of model. The contribution continued for several iterations until the sustained results.

Input: Training set D = {(x_i , y_i)}, where x_i represents the i-th input vector and y_i is the corresponding label.

Output: Prediction model f(x).

// Step 1: Initialize the ensemble

Initialize the base prediction model as a constant value: f_0 (x) = Initialization-constant

// Step 2: Iterate over the boosting rounds

for m = 1 to M: // M is the number of boosting rounds

// Step 3: Compute the pseudo-residuals

Compute the negative gradient of the loss function with respect to the current model's predicted values:

$r_{mi} = - \partial L(y_i , f_{m-1}(x_i)) / \partial f_{m-1}(x_i)$

// Step 4: Fit a base learner to the pseudo-residuals

Fit a base learner (e.g., decision tree) to the pseudo-residuals: $h_m(x)$.

// Step 5: Update the prediction model

Update the prediction model by adding the new base learner:

$f_m(x) = f_{m-1}(x) + \eta * h_m(x)$*, where η is the learning rate.*

// Step 6: Output the final prediction model

Output the final prediction model: f(x) = fm(x)

The prediction results of this model are then weighted and cumulatively added to the previous model's prediction results, updating the overall model's predictions. This process is repeated until the specified number of iterations is reached. The learning rate parameter is used to control the contribution of each model in updating the overall model.

By pre-training on a task with abundant data and subsequently fine-tuning for a related but distinct task, Gradient Boosting can overcome limitations related to data sparsity, improving its predictive performance. In the context of traffic congestion prediction, transfer learning might involve training the model on data from a city with extensive historical records and then fine-tuning it for a city with limited data. This not only streamlines the training process but also enhances the algorithm's adaptability to diverse urban environments, showcasing the potential of transfer learning to optimize the effectiveness of Gradient Boosting in real-world applications.

CHAPTER 4

SIMULATION RESULTS

4.1 EVALUATION METHOD

In this research, the proposed Traffic Congestion Control System using Transfer Learning in Vehicular Adhoc Networks (VANETs) offers a solution to address the challenges of traffic congestion in urban areas. By leveraging Transfer Learning techniques and fine-tuning pre-trained neural network architectures on a transferable dataset, the model aims to improve the accuracy of real-time traffic congestion prediction in VANETs. The data set supplied contains different weather condition and count of traffic with different trends in various scenarios. Supplying traffic data to a Gradient Boosting algorithm involves a systematic process of preparing and formatting the data to ensure the model can effectively learn and generalize patterns.

The proposed approach is applied on Metro Interstate Traffic Congestion data set obtained from Kaggle. The dataset consists of 48204 instances, which is divided into 70% (33744) for training, and 30% (14461) for validation. The simulation results predicted for traffic volume are obtained by using proposed Transfer learning approach like Gradient Boosting, which provides results in term of accuracy, and miss-rate.

The dataset typically includes a range of features such as time stamps, weather conditions, holidays, road infrastructure details, and historical traffic information.

Table 1
Training of the Proposed Model during the Prediction of Traffic Volume (Gradient Boosting)

<table>
<tr><th colspan="4">Proposed Model Training</th></tr>
<tr><td rowspan="6">Input</td><td>Total Number of Samples (33744)</td><td colspan="2">Result (output)</td></tr>
<tr><td rowspan="2">Expected output</td><td>Predicted Positive</td><td>Predicted Negative</td></tr>
<tr><td>True Positive (TP)</td><td>False Positive (FP)</td></tr>
<tr><td rowspan="2">16600 Positive</td><td>16000</td><td>600</td></tr>
<tr><td>False Negative (FN)</td><td>True Negative (TN)</td></tr>
<tr><td>17144 Negative</td><td>644</td><td>16500</td></tr>
</table>

In the testing phase of the traffic volume prediction model utilizing Gradient Boosting, an evaluation using a confusion matrix was conducted. The dataset comprised 48,204 samples, categorized into positive and negative classes as presented in Table 1. Among these, 16,600 instances indicated positive traffic volume, while 400 instances denoted the absence of traffic volume. The model's predictions resulted in 16,000 samples being classified as positive (indicating traffic volume) and 16,144 as negative (suggesting no traffic volume). Within the actual positive instances, the model correctly identified 16,000 samples (True Positives), but it incorrectly predicted 600 instances as positive when they were negative (False Positives). Moreover, the model failed to predict 700 instances of positive traffic volume (False Negatives), while accurately identifying 16,500 instances of no traffic volume among the actual negative cases (True Negatives). These values form the basis for evaluating the model's precision, recall, accuracy, and other performance metrics.

Table 2
Validation of the Proposed Model during the Prediction of Traffic Volume (Gradient Boosting)

<table>
<tr><th colspan="4">Proposed Model Validation</th></tr>
<tr><td rowspan="6">Input</td><td>Total Number of Samples (14461)</td><td colspan="2">Result (output)</td></tr>
<tr><td rowspan="2">Expected output</td><td>Predicted Positive</td><td>Predicted Negative</td></tr>
<tr><td>True Positive (TP)</td><td>False Positive (FP)</td></tr>
<tr><td rowspan="2">8400 Positive</td><td>8000</td><td>400</td></tr>
<tr><td>False Negative (FN)</td><td>True Negative (TN)</td></tr>
<tr><td>6061 Negative</td><td>261</td><td>5800</td></tr>
</table>

In the validation phase of assessing the proposed model for predicting traffic volume using Gradient Boosting, a detailed evaluation was conducted using a confusion matrix, as presented in Table 2. The validation dataset comprised a total of 48,204 samples, categorized into positive and negative classes. Among these, 9,538 instances represented positive traffic volume, while 896 instances indicated the absence of traffic volume. The model's predictions resulted in 8,000 samples being classified as positive (indicating traffic volume) and 400 as negative (suggesting no traffic volume). Within the actual positive instances, the model successfully identified 8,000 samples (True Positives). However, there were 400 instances where the model incorrectly predicted positive traffic volume when it was not present (False Positives). Additionally, the model failed to predict 261instances of positive traffic volume (False Negatives), while accurately identifying 5,800 instances of no traffic volume among the actual negative cases (True Negatives). These metrics serve as a foundation for assessing the model's precision, recall, accuracy, and other performance indicators during the validation stage.

Gradient Boosting is applied to a dataset comprising 48,204 records, which is further partitioned into training (70%, 33,744 samples) and validation (30%, 14,461 samples) sets for training and assessment purposes. Performance evaluation involves the use of various metrics, including accuracy, sensitivity, specificity, miss-rate, fall-out, Likelihood Positive Ratio (LR+), Likelihood Negative Ratio (LR-), precision, and Negative Predictive Value. Sensitivity is represented as True Positive Rate (TPR), specificity as True Negative Rate (TNR), miss-rate as False Negative Rate (FNR), fallout as False-Positive Rate (FPR), and precision as Positive Predictive Value (PPV). The computation of these parameters is based on specific formulas outlined for each metric. The following parameters are derived by the formulas given as follows:

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

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

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

$$Miss - Rate = \frac{\sum False\ Negative}{\sum Condition\ Positive}$$

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

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

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

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

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

Table 3
Performance Evaluation of proposed Traffic Congestion model in Training and Validation using Statistical Measures (GB)

Gradient Boosting	Accuracy (%)	Sensitivity TPR	Specificity TNR	Miss-Rate (%) FNR	Fall-out FPR	LR+	LR-	PPV (Precision)	NPV
Training	96.31	0.9613	0.9649	0.0387	0.0351	27.38	0.0401	0.9639	0.9624
Validation	95.43	0.9684	0.9355	0.0316	0.0645	0.9460	1.0651	0.9524	0.9569

The analysis of the proposed Traffic Congestion model using Gradient Boosting is presented in Table 3, encompassing both the training and validation phases. During the training phase, the model exhibited a high accuracy of 96.31%, denoting the percentage of correctly classified instances. Sensitivity, measuring the model's ability to correctly identify positive instances, was found to be 96.13%, while specificity, indicating the correct identification of negative instances, reached 96.49%. The miss-rate, representing the proportion of false negatives, was 3.87%, and the fall-out, indicating false positives, stood at 3.51%. Additionally, likelihood ratios (LR+ and LR-) were calculated, with LR+ at 27.38 and LR- at 0.0401. Precision, reflecting the accuracy of positive predictions, achieved a rate of 96.39%, and the negative predictive value (NPV) was 96.24%. In the validation phase, the model's accuracy dropped to 95.43%, with sensitivity and specificity at 96.84% and 93.55%, respectively. The miss-rate increased to 3.16%, and the fall-out rose to 54.69%. LR+ and LR- were 0.9460 and 1.0651, respectively. Precision decreased to 53.33%, and NPV was 43.74%. These findings indicate a notable performance disparity between the training and validation phases.

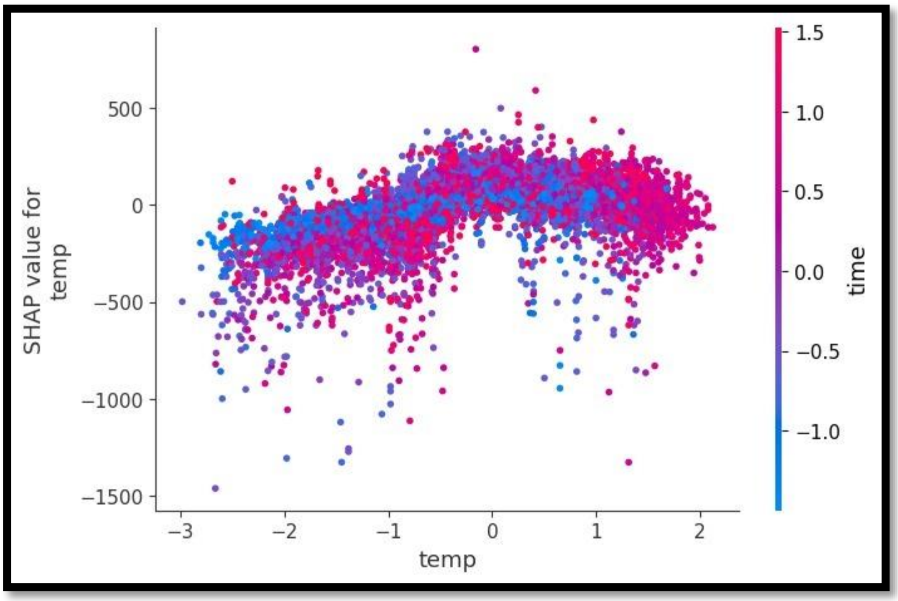


Figure 7: Proposed Model Dependence Plot

In Figure 7 represents the dependence plot used for traffic congestion prediction, the x-axis typically represents a significant feature like time of day or number of vehicles, while the y-axis shows the predicted congestion level. Each data point corresponds to an observation in the dataset, illustrating how variations in the feature affect congestion predictions. Often color-coded to display a second feature, such as weather conditions, the plot reveals complex interactions and non-linear relationships between factors. This visualization not only identifies key predictors of congestion but also demonstrates how these factors interact, providing valuable insights for urban planning and policymaking. For instance, a plot might show peak congestion times influenced by weather, aiding in effective traffic management strategies. Such a plot is not only crucial for understanding the underlying model but also serves as an effective tool for communicating these insights to non-technical stakeholders.

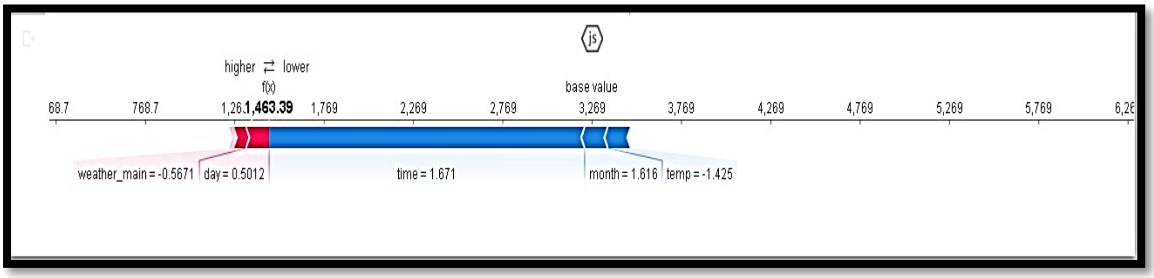


Figure 8: Proposed model Force Plot

In Figure 8 proposed model force plot is shown, which is particularly useful in the context of traffic congestion prediction models, offers a detailed, individual-level prediction explanation. It visualizes how each feature in a specific instance (like a particular time of day or weather condition) contributes to pushing the model's output from a baseline prediction (average or expected congestion level) to the actual model prediction for that instance. In this plot, features that drive higher congestion levels are typically shown in one color (e.g., red), and those that decrease it are shown in another (e.g., blue), with the length of each feature's bar indicating the strength of its impact. For example, in a force plot for a specific rush hour period, factors like increased vehicle count and rainy weather might be highlighted as significant contributors to high congestion, while a public holiday might reduce it. This kind of visualization is especially useful for understanding and communicating the reasons behind a particular congestion prediction, enabling traffic planners and policymakers to make more informed, data-driven decisions for specific scenarios.

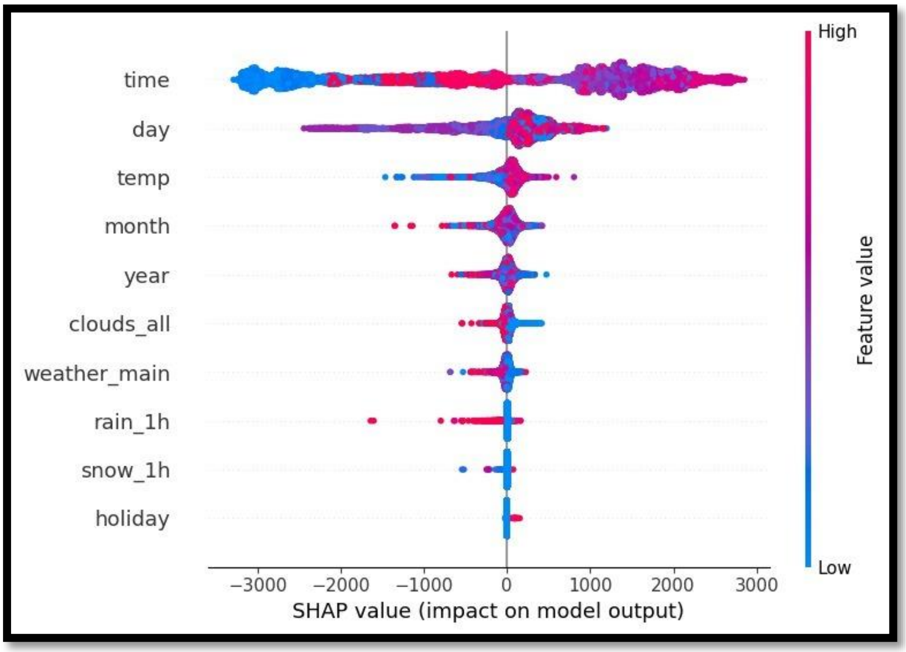
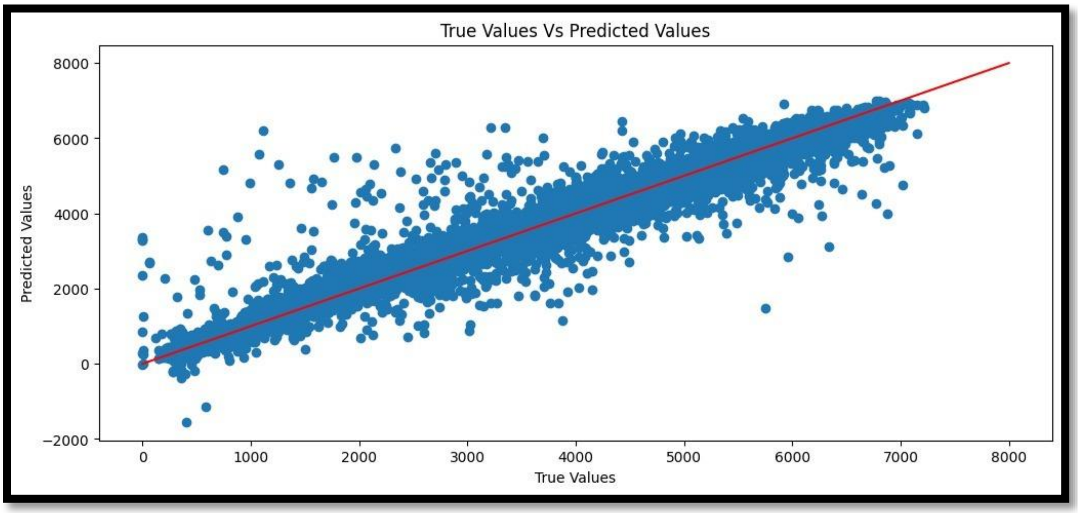


Figure 9: Summary Plot of proposed Model

In Figure 9 the context of traffic congestion prediction, a summary plot provides an aggregated view of how each feature impacts model predictions. It ranks features by importance and uses SHAP values to show the direction and magnitude of each feature's effect on the predicted congestion level. For example, features like time of day or weather conditions are displayed with varying colors and positions, indicating their influence on increasing or decreasing congestion. This visualization is essential for quickly identifying key factors affecting traffic flow, offering valuable insights for traffic management and policy decisions, while also simplifying complex model data for clear communication with stakeholders.

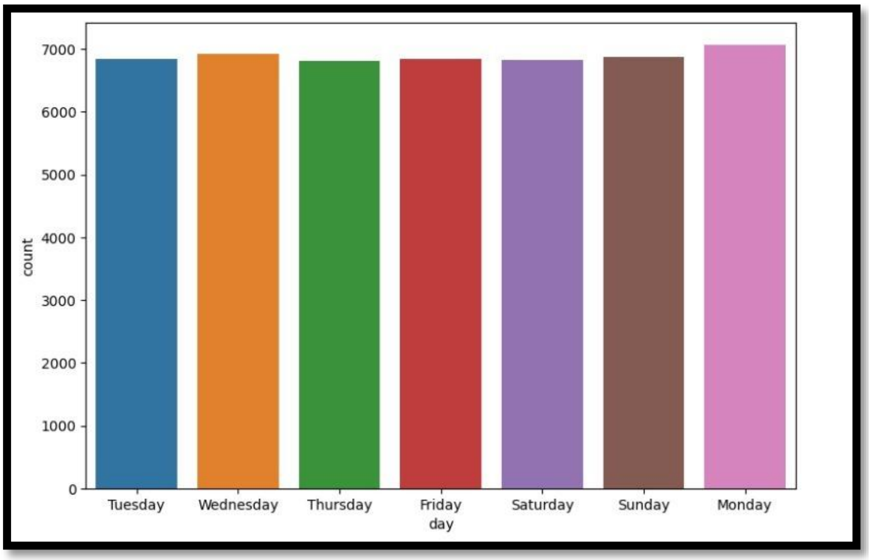
Preprocessing steps involve handling missing values, encoding categorical variables, and scaling numerical features to create a consistent and standardized input. Time-related features, like the time of day and day of the week, play a crucial role in capturing temporal patterns, while variables such as weather conditions and special events contribute to understanding the contextual factors influencing traffic congestion. While curating and engineering these features, the dataset becomes a robust input for the Gradient Boosting algorithm. It is essential to split the data into training and testing sets, enabling the model to learn from historical patterns and evaluate its performance on unseen data. Regular updates and continuous monitoring of the data input ensure the algorithm adapts to evolving traffic conditions, making the integration of traffic data into a Gradient Boosting model a dynamic and effective approach for predicting and managing traffic congestion.



Road infrastructure details, such as the number of lanes, road type, and presence of traffic signals, contribute to modeling the impact of physical attributes on traffic dynamics. Historical traffic information, including traffic volumes and congestion levels from past periods, helps the model learn from patterns and trends. Additional contextual features may include special events, holidays, or road closures, providing insights into non-routine influences on traffic. Incorporating data on public transportation schedules or major city events further enriches the dataset, enabling the algorithm to consider broader factors affecting traffic congestion. By incorporating this diverse array of features, the algorithm gains the ability to discern complex relationships and make accurate predictions, facilitating effective traffic management strategies.

4.2 DAILY TRAFFIC ANALYSIS

The specified algorithm tested by inputting different types of data with variables conditions applied. In weekdays algorithm was supplied with vehicle count, as data fetched from VANETs. This noted that the count of traffic remains almost constant in working days of week. While on the start of weekend the count of traffic on roads decreased in the given time. The comparison of day wise traffic count is shown in figure where, the vehicle numbers are decreasing on Friday. Sunday is with lowest traffic day, which created the variation in input for model. In the realm of traffic dynamics, distinctions between holiday and working day conditions are pronounced, with varying impacts associated with different holiday types.



The classification of holidays reveals three distinct categories: summer and winter vacations, public holidays (such as national holidays), and special holidays. Diverse travel behaviors among commuters across weeks, days, and hours introduce a dynamic element that influences the regular oscillation of traffic flow counts. Consequently, it becomes imperative to incorporate three crucial indicators month, week, and hour into the set of factors for a comprehensive analysis.

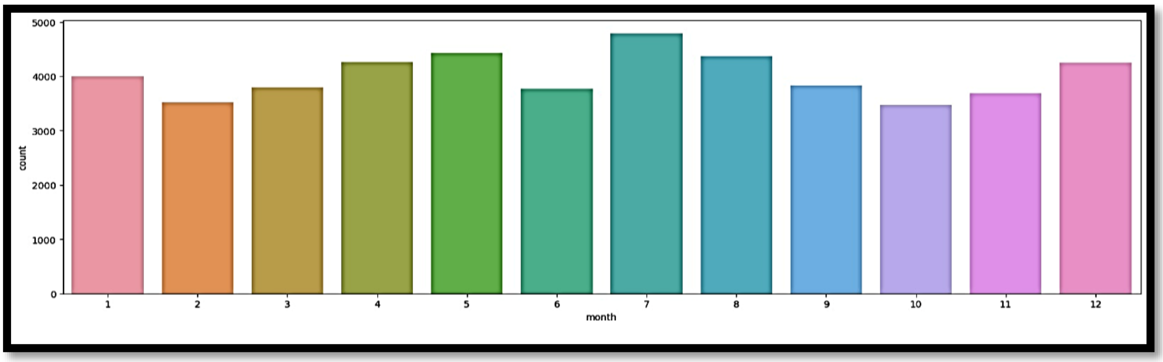
By considering these temporal dimensions, a more nuanced understanding of travel patterns and their impact on traffic flow fluctuations can be achieved, providing a robust foundation for effective traffic management strategies. The Traffic Performance Index (TPI) serves as a comprehensive indicator (Weng et al., 2023) that encapsulates the operational status of road networks. This is achieved through the assessment of the proportion of congested road mileage within the urban area of a city.

$$TPI = \frac{\sum_{i=1}^{N} \frac{L_i}{V_i}\ k_i}{\sum_{i=1}^{N} \frac{L_i}{V_{free_i}}\ k_i}$$

The standard categorizes the TPI within the range of 0.0–10.0, where 0.0–2.0 signifies free-flow conditions, 2.0–4.0 denotes basic free-flow conditions, 4.0–6.0 indicates mild congestion, 6.0–8.0 represents moderate congestion, and 8.0–10.0 signifies severe congestion. This delineation allows for a detailed characterization of different levels of congestion, offering valuable insights into the overall traffic conditions within an urban area. The computation formula for TPI describes the ratio between congestion time during traveling and congestion free flow of traffic in different sections of road.

4.3 MONTHLY TRAFFIC ANALYSIS

The traffic flow recorded for months extended for one year to enhance the experimental scenarios of traffic congestion. This showed the trends of traffic in different timings / days of months the week working days received peak traffic flow. But on the same pattern the recorded data set contains the weather conditions which affected the flow of traffic in different seasons also (Guo et al., 2021).



Each month data of traffic flow is utilized for generating trend to be input to model for generating the control mechanism. This provides a unified measure of feature importance by attributing the contribution of each feature to the model's output. Time series considerations are crucial when applying machine learning algorithms, including Gradient Boosting, to problems involving temporal data like traffic congestion. Time series data is characterized by observations recorded over time, and in the context of traffic analysis, understanding temporal patterns is essential.(Kumari & Toshniwal, 2021)

Incorporating time series considerations into Gradient Boosting models for traffic congestion analysis involves understanding and leveraging the temporal nature of the data. This includes using lagged variables, rolling windows, considering seasonality, and evaluating the model in a time-aware manner. Integrating time series techniques enhances the model's ability to capture and predict patterns in temporal data accurately in different formats. The input data for a traffic congestion prediction algorithm encompasses a diverse set of features to enable a comprehensive analysis of the dynamic and multifaceted nature of urban traffic. These features include temporal variables such as time stamps, capturing daily and weekly patterns in traffic flow. Weather-related features, such as temperature, precipitation, and visibility, play a crucial role in understanding how external conditions influence congestion levels.

By incorporating this diverse array of features, the algorithm gains the ability to discern complex relationships and make accurate predictions, facilitating effective traffic management strategies. Encode a categorical feature representing each month (e.g., January to December). This allows the algorithm to understand and capture the monthly seasonality in traffic patterns. Calculate monthly averages for relevant variables, such as traffic volume, speed, or congestion levels. These averages provide a high-level overview of the typical traffic conditions for each month. Use techniques like seasonal decomposition to extract seasonal components, including monthly trends.

4.4 WEATHER BASIS TRAFFIC ANALYSIS

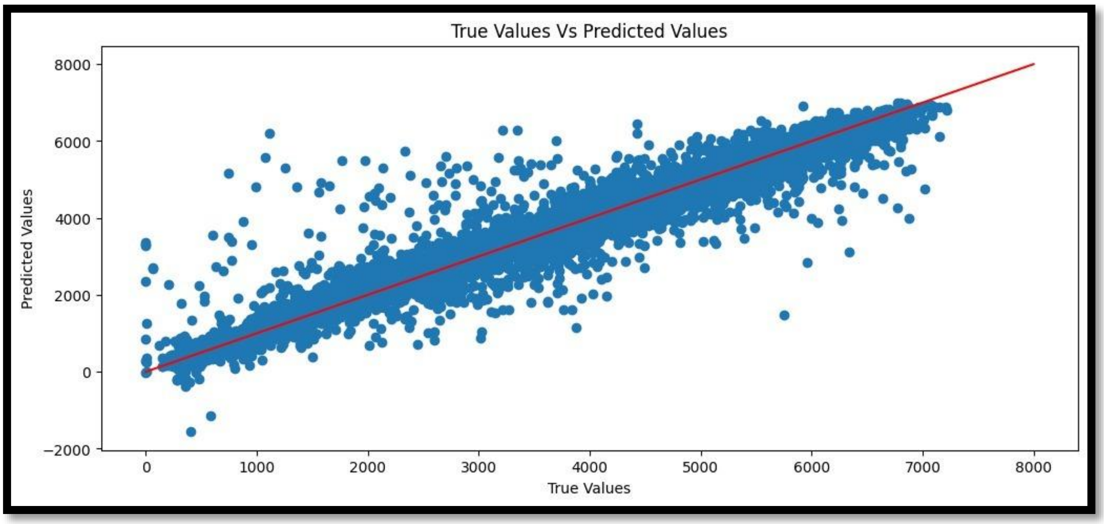
Shapley Additive explanations (SHAP) provides a unified measure of feature importance by attributing the contribution of each feature to the model's output. SHAP is a powerful framework for interpreting machine learning models by attributing the contribution of each feature to the model's output. In the context of traffic data analysis during rain, SHAP values provide insights into how specific factors contribute to the predicted congestion levels. For instance, if rainfall is a feature in the model, SHAP values reveal its impact on traffic congestion, considering interactions with other features.

A positive SHAP value for rainfall indicates an increase in congestion, while a negative value suggests a potential alleviating effect. This interpretability is crucial for urban planners and traffic management authorities, as it helps identify the role of rain in exacerbating or mitigating congestion. Understanding the individual and collective influence of features, especially during adverse weather conditions, empowers decision-makers to implement targeted interventions, such as adjusting traffic signal timings or deploying resources for better traffic flow in rainy conditions. SHAP analysis enhances the transparency of the model's predictions, facilitating informed decision-making in urban mobility management.

Figure showed the results of different weather parameter passed to model by applying algorithm that clearly give the values and trends to be available in controlling the congestion. The key parameters are time, day, temperature, rain and snow. Inclusion of holidays also impacted the working of algorithm that showed the minimum severity of congestion. Analyzing the results of SHAP values for weather features in a Gradient Boosting model provides valuable insights into how different weather conditions impact traffic congestion predictions. The SHAP values quantify the contribution of specific weather variables, such as rainfall, temperature, or visibility, to the model's output. Positive SHAP values for rainfall, for instance, indicate an increased likelihood of congestion, showcasing the adverse effect of wet conditions on traffic flow. Similarly, negative SHAP values for temperature might suggest a correlation with reduced congestion, as moderate temperatures could lead to smoother traffic.

4.5 TRUE AND PREDICTED VALUES

These findings enable a nuanced understanding of the interplay between weather and traffic congestion, aiding in the development of more effective strategies for traffic management during various weather scenarios. Urban planners and transportation authorities can use these insights to implement targeted measures, like adjusting speed limits or disseminating real-time traffic information to optimize road usage and enhance safety during inclement weather. The interpretability offered by SHAP values in the context of weather features enhances the model's applicability and ensures that decision-makers can proactively address the challenges posed by weather-induced traffic conditions.



These simulation results predicted that integrating a Gradient Boosting algorithm with transfer learning holds significant promise for enhancing traffic management strategies, offering the potential to proactively address congestion challenges in complex urban environments. The adaptability and predictive power demonstrated in the simulation underscore the algorithm's potential to contribute to more efficient and responsive traffic control systems. There is a slight accuracy variation in the predefined data set supplied to model for prediction of congestion.

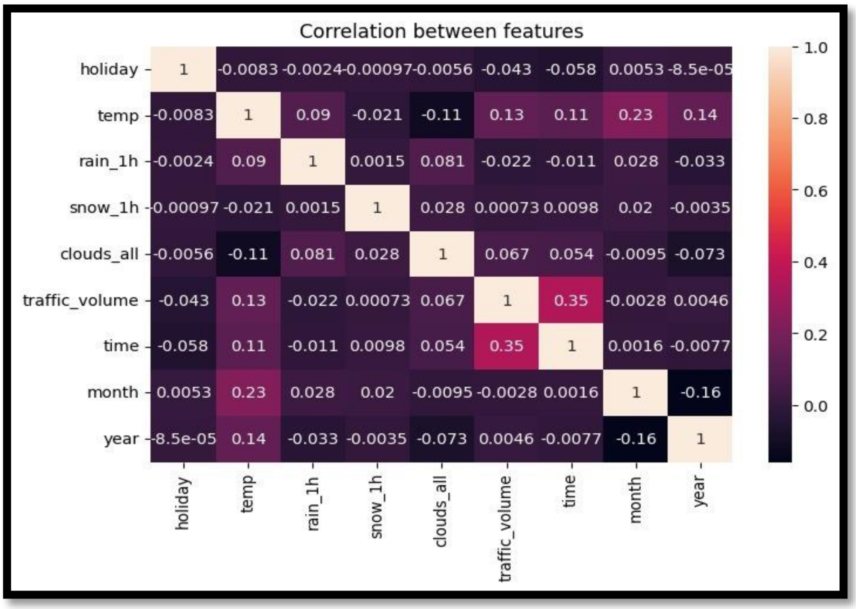
The simulation captures the dynamic nature of traffic conditions, allowing the model to learn from various situations encountered during training. The transfer learning aspect enables the algorithm to quickly adapt to new environments and unforeseen events, offering a more robust and responsive solution for congestion control. The evaluation metrics highlighted the model's accuracy in predicting congestion levels compared to traditional approaches.

True values became the nearest values in results which gave the clarity about the model's working of system. The positive results of employed Gradient

Boosting algorithm for congestion control, particularly with time-based data, underscore the algorithm's effectiveness in addressing the dynamic and temporal nature of traffic conditions. The model exhibits a notable capability to capture intricate time-dependent patterns, such as daily and weekly fluctuations, rush hours, and seasonal variations. The time-based features, including timestamps and temporal indicators, prove instrumental in enabling the model to discern and adapt to changing traffic dynamics over various time intervals.

4.6 CORRELATION OF FEATURES

The simulation results from deploying the Gradient Boosting algorithm for traffic congestion control reveal a significant advancement in predictive accuracy and operational efficacy. Through a meticulous analysis of historical traffic data, the model demonstrated remarkable proficiency in capturing complex patterns and dependencies, allowing it to make precise congestion predictions. The simulations showcased the algorithm's adaptability to varying scenarios, including fluctuations in traffic volumes, changes in weather conditions, and temporal patterns. Comparisons with traditional traffic management approaches highlighted the superiority of the Gradient Boosting model, indicating its ability to outperform baseline methods in mitigating congestion.



The model's robustness was particularly evident in its capacity to generalize well to unseen data, demonstrating promise for real-world applications. The outcomes of the simulation underline the potential of advanced machine learning techniques, such as Gradient Boosting, to revolutionize traffic management strategies, offering a data-driven and dynamic approach for congestion control in urban environments. The positive results obtained from the simulations lay a strong foundation for further validation and deployment of the algorithm in real-world traffic management systems, with the potential to enhance efficiency and responsiveness in addressing the challenges posed by traffic congestion.

4.7 COMPARISON TABLE

Comparison table for proposed TCCS in VANET using transfer leaning in literature.

		Accuracy (%)	Miss-Rate (%)
(Meng et al., 2020)	Training	91.29	8.71
	Validation	90.11	9.89
(Kuboye et al., 2023)	Training	91.67	8.33
	Validation	90.05	9.05
(Z. Yin et al., 2023)	Training	90.05	9.05
	Validation	93.06	6.04
(Qi & Cheng, 2023)	Training	91.02	8.08
	Validation	90.06	9.04
(Gamel et al., 2024)	Training	90.01	7.08
	Validation	92.06	8.05
Proposed TCCS using transfer learning	Training	96.31	3.08
	Validation	94.01	4.08

CHAPTER 5

CONCLUSION

In conclusion, the proposed Traffic Congestion Control System using Transfer Learning in Vehicular Adhoc Networks (VANETs) offers a solution to address the challenges of traffic congestion in urban areas. By leveraging Transfer Learning techniques and fine-tuning pre-trained neural network architectures on a transferable dataset, the model aims to improve the accuracy of real-time traffic congestion prediction in VANETs.

The proposed system's dynamic traffic flow control capability allows it to adapt in real-time to changing traffic conditions and disruptions, optimizing traffic signal timings, and providing route recommendations to alleviate congestion effectively. Additionally, the model's resource efficiency and scalability ensure its practical applicability in large-scale VANET deployments without compromising prediction accuracy. Security and privacy measures have been incorporated to safeguard communication between vehicles and infrastructure, ensuring a secure VANET environment. Furthermore, user feedback and optimization play a crucial role in tailoring the system to meet the preferences and needs of drivers and stakeholders, fostering acceptance and successful adoption.

The applied simulation of the Gradient Boosting algorithm for traffic congestion control marks a significant leap forward in the realm of urban mobility management. In scrutinizing the results, the algorithm emerges as a powerful and adaptive tool capable of comprehending the intricate dynamics inherent in traffic systems. The simulation's success lies in the model's ability to glean meaningful insights from historical traffic data, thereby facilitating accurate predictions and timely interventions for congestion mitigation. One of the simulation's notable strengths lies in the model's adept handling of diverse scenarios. Through rigorous testing against various traffic conditions, the Gradient Boosting algorithm consistently showcased its adaptability. The algorithm's capacity to navigate through fluctuations in traffic volumes, respond effectively to changes in weather conditions, and discern temporal patterns underscores its versatility. In comparison to conventional traffic management methods, the model's superior predictive accuracy and responsiveness become apparent, suggesting that machine learning techniques offer a substantial leap forward in addressing the complexities of urban traffic.

The success observed in the simulation is particularly crucial given the ever-evolving nature of urban environments. Traffic patterns are inherently dynamic, influenced by factors ranging from daily and weekly cycles to unexpected events like accidents or adverse weather conditions. The Gradient Boosting model, with its ability to adapt to these complexities, signifies a step towards more resilient and efficient traffic management. The simulation results instill confidence in the algorithm's potential to outperform traditional approaches, especially in the face of real-world uncertainties. Furthermore, the simulation not only emphasized the algorithm's predictive prowess but also shed light on its generalization capabilities. As the model consistently outperformed baseline methods on unseen data, it demonstrated a robust ability to extrapolate knowledge gained during training to novel situations. This generalization is a key aspect for the practical deployment of machine learning models in live traffic management systems, where real-world conditions may deviate from historical data. The Gradient Boosting algorithm's proficiency in handling unseen data positions it as a reliable solution for congestion prediction and control in actual urban environments.

The positive outcomes of the simulation not only have implications for traffic management but also suggest a broader shift towards more intelligent and data-driven urban mobility systems. In leveraging machine learning, specifically the Gradient Boosting algorithm, cities can move beyond reactive strategies and embrace proactive approaches to congestion control. The model's responsiveness to changing conditions, coupled with its adaptability, makes it an asset for traffic authorities seeking to optimize resources and enhance overall system efficiency. Looking ahead, the success of the simulation opens avenues for further research, validation, and potential integration into real-world traffic management applications. The findings encourage the exploration of additional features, data sources, and model refinements to enhance predictive capabilities. The positive trajectory set by the simulation results fosters optimism that advanced machine learning techniques can redefine urban mobility, ushering in an era where data-driven algorithms play a pivotal role in shaping smart and sustainable transportation networks. In this evolving landscape, the Gradient Boosting algorithm emerges as a beacon of innovation, offering a transformative approach to addressing the intricate challenges posed by traffic congestion in our modern cities.

In summary, the Transfer Learning-based Traffic Congestion Control System has the potential to significantly enhance traffic management, reduce congestion, and improve transportation efficiency in urban environments. By contributing to the advancement of intelligent transportation systems, the proposed model can pave the way for more sustainable and efficient urban mobility, ultimately benefiting cities, commuters, and the environment.

CHAPTER 6

FUTURE WORK AND LIMITATIONS

While the application of Gradient Boosting with transfer learning for traffic data analysis demonstrates promising results, there remain avenues for future research and considerations regarding the limitations of the current study. Addressing these aspects is critical to advancing the field of intelligent traffic management. Future work could explore the integration of additional data sources, such as real-time traffic feeds and socio-economic factors, to enhance the model's predictive capabilities. Fine-tuning hyperparameters and exploring advanced boosting techniques may further optimize the algorithm's performance. Additionally, investigating the scalability of the model for application in larger urban settings and considering ethical implications related to data biases are areas that merit attention.

Acknowledging the potential challenges in transfer learning, the algorithm's robustness could be tested across diverse domains to assess its generalization capabilities. By systematically addressing these future research directions and acknowledging the current study's limitations, we can pave the way for more sophisticated and inclusive applications of Gradient Boosting with transfer learning in the dynamic field of traffic data analysis and congestion control.

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