International Journal of Computer (IJC)
ISSN 2307-4523 (Print & Online)
https://ijcjournal.org/index.php/InternationalJournalOfComputer/index

Implementation of Artificial Intelligence in Traffic Management in the United States

Olushola Adegoke*

Harrisburg University of Science and Technology, 326 Mkt St, Harrisburg PA 17101, United States
Email:Only.olushola@gmail.com

Abstract

This paper investigates the application and deployment of artificial intelligence (AI) in enhancing traffic management within the U.S., focusing mainly on predicting future traffic demand using machine learning and deep learning models. Utilizing datasets from the Tom-Tom Traffic Index and the Python programming language for data processing, the study aims to mitigate traffic congestion through accurate traffic prediction. The study specifically examines Baltimore, Maryland (used as a proxy for major U.S. cities) to assess the efficiency of AI technologies on traffic levels and provides a comparative analysis of machine learning and deep learning algorithms (decision tree, random forest, logistic regression, and deep learning neural network). The results revealed that decision tree models surpass other algorithms with an 85% accuracy rate in congestion prediction. The study contemplates the technical aspects of traffic management systems and addresses the practical implications for city planning and the overarching goals of reducing congestion and facilitating transportation logistics. The paper offers valuable insights to transportation planners, logistics managers, and academic researchers.

Keywords: artificial intelligence; machine learning; deep learning; traffic management; congestion prediction; GPS trajectory data; Tom-Tom Traffic Index; decision trees; Python.

1. Introduction

1.0.1 Traffic Congestion

Traffic congestion is a widespread issue in the United States, as in other developed countries, with a substantial adverse effect on individuals and the economy [1,2]. Also known as traffic jams, with characteristics such as slower vehicle speeds [2], longer vehicular queues [1], and extended trip durations [3], this problem upsets the daily routines of numerous American commuters [4].

Received: 10/4/2023
Accepted: 12/1/2023
Published: 12/10/2023

----

* Corresponding author.

In the transportation industry, the term "congestion" usually means overcrowding of vehicles on a specific stretch of road because of obstruction of "free flow" movement [3]. Congestion often results in traffic coming to a halt or moving at a stop-and-go pace. Congestion is caused by many factors, such as inadequate infrastructure, roadwork disruptions, ineffective traffic management, and unexpected incidents, such as accidents or breakdowns [5, 6].

Congestion levels fluctuate according to the day, with peak hours recording the most intense congestion [7]. Urban areas, in particular, face a compound challenge as the sheer volume of vehicles surpasses the capacity of their road networks [8]. However, the problem is not limited to cities, as suburban areas and even rural communities can experience congestion due to factors that lead to incidental population increases, such as tourism or seasonal events [1].

Traffic congestion has wide-ranging implications. It results in longer journey durations, higher fuel consumption, and elevated air pollution levels [8,9]. Moreover, it contributes to driver frustration, which can lead to aggressive driving behaviors, known as "road rage," and an increased risk of accidents [10].

As a result, effective management solutions to address these congestion challenges are urgently needed [5,8]. Congestion can be decreased by finding and assessing the severity of traffic bottlenecks [11], sharing current traffic information, and recommending alternative routes [12].

1.0.2 Traffic Collision

Traffic collisions, often due to congestion, malfunctioning traffic lights, and inefficient traffic management, have far-reaching consequences beyond vehicular damage to motorists, passengers, and pedestrians' safety [13]. The following are some consequences of traffic collisions:

Traffic collisions often result in delays, further exacerbating congestion issues and increasing fuel consumption and time wastage [14,16].

Traffic collisions can lead to severe injuries or even fatalities, with victims often needing immediate medical attention and, in some cases, long-term rehabilitation [17,19].

Traffic collisions have substantial economic implications. They lead to increased healthcare costs due to injury treatment and rehabilitation [19], loss of productivity from injured individuals unable to work [20], and property damage to vehicles and infrastructure [17].

Given these significant consequences, it is crucial to explore how advancements in artificial intelligence can help prevent traffic collisions and improve overall traffic management.

1.1 Definitions

Traffic management is a key branch within logistics, involving planning, controlling, and purchasing transport services needed to move vehicles and freight physically [21].

Artificial Intelligence (AI) is a broad field within computer science concerned with the development of systems capable of performing tasks that imitate human intelligence, including learning from experience, understanding natural language, recognizing patterns, and making decisions [22].

Machine Learning (ML), a subset of AI, involves the use of algorithms that improve their performance at tasks over time through experience [23]. In other words, ML systems learn from data, identifying patterns and making predictions without being explicitly programmed [24].

Algorithms are mathematical model mapping approaches utilized to learn or uncover underlying patterns entrenched in the data. It includes a group of computational algorithms that can do pattern recognition, classification, and forecast on data by learning from obtainable data referred to as a training set [24]-[25].

Deep Learning (DL), a subset of ML, involves using multiple-layer artificial neural networks (ANNs) to simulate human brain behavior in analyzing large datasets [26]. Although a neural network with a single layer can achieve rough predictions, additional hidden layers can help optimize the accuracy of these predictions [27].

1.2 Problem Statement

The escalating challenges of traffic congestion and collisions underscore the urgent need for effective traffic management solutions to reduce congestion, lower travel times, reduce pollution, make roads safer, and improve the overall efficiency of the transportation system [28,29].

Traditional traffic management systems are helpful but need help to address these issues because of their inability to adapt to real-time changes in traffic conditions [30,29]. Advanced traffic management systems aim to effectively control transportation resources in response to changing traffic circumstances [31]. Autonomous vehicles with more predictable behavior may help alleviate traffic congestion and pollution by allowing municipal management entities to minimize them, improving city traffic flow [32].

The advent of Artificial Intelligence (AI) presents an opportunity to revolutionize traffic management. It is possible to deploy this technology in forecasting future traffic circumstances by correctly evaluating traffic demand and using this knowledge to optimize car routes [33]. This involves optimizing traffic flow through better signal timing and route planning and predicting and managing incidents to minimize their impact on traffic.

There is limited research on the application of AI in the U.S. traffic management sector. As a result, this study aims to address this gap by exploring how AI technologies, like machine learning and deep learning, can predict traffic demand and improve traffic routes. The goal is to develop more proactive and dynamic traffic management strategies that can mitigate congestion, enhance road safety, and improve the efficiency of the U.S. transportation system.

1.3 Purpose Statement

The purpose of this quantitative study is to examine the relationship between the implementation of AI technologies - specifically, machine learning and deep learning algorithms used to predict traffic demand and optimize traffic routes - and changes in traffic congestion in Baltimore, Maryland. This study will compare the accuracy rates of the different algorithms to determine which is most effective for reducing traffic congestion.

1.4 Research Questions

1. What is the impact of implementing machine learning and deep learning algorithms on traffic congestion levels in Baltimore, Maryland (used as a proxy for major U.S. cities)?

2. How effective are different AI algorithms (decision tree, random forest, logistic regression, and deep learning neural network) in predicting traffic demand and optimizing routes to reduce traffic congestion in Baltimore, Maryland (used as a proxy for major U.S. cities)?

1.5 AI Use Cases in Traffic Management

In the context of traffic management, AI, and more specifically, ML and DL, can play a pivotal role. AI can revolutionize traffic management by analyzing data, detecting patterns, predicting future outcomes, adapting to changing conditions, and learning from error. These attributes make AI particularly useful in predicting traffic demand [34,35], optimizing signal timings [36,37], and managing incidents [38].

1.6 Significance of the study

The main objective of this research is to explore the use of artificial intelligence in fixing traffic congestion and collisions. The study looks at the practical application of AI in traffic management. By reducing congestion and facilitating logistics, AI can contribute to livable cities. This aligns with broader societal goals of enhancing quality of life and promoting sustainable development.

The study analyzes various machine and deep learning approaches and provides a detailed overview of the present state of AI in traffic management. The findings of this study could drive future research and technical improvements in this field.

The study's findings could have far-reaching implications for information systems and engineering management (ISEM), transportation planning, logistics, and academic research.

1.7 Delimitations of the Study

Several factors delimit the study:

1. Geographical Scope: The study focuses solely on traffic management in Baltimore, a city in the United States. While the findings may have ramifications for the rest of the U.S., the research is based on the specific environment, infrastructure, and traffic patterns in a single American urban center.

2. Data Availability: The study relies solely on data from the Tom-Tom Traffic Index. The availability and quality of these data sets limit the scope of the research.

3. Technology Constraints: The study investigates the use of AI in traffic management within the context of the existing technology landscape. Future advances in AI and related technologies may offer additional possibilities not addressed in this paper.

4. AI emphasis: The research focuses primarily on the application of AI technology in traffic management. This study does not explore other potentially effective solutions to traffic congestion and collisions, such as infrastructure expansion or regulatory reforms.

These delimitations must be considered when interpreting the study's findings and their relevance to diverse circumstances.

1.8 Limitations of Study

The study, while comprehensive, has several limitations:

1. Data Limitations: The study depends on publicly available Tom-Tom Traffic Index data. While this information is comprehensive, it may only cover some traffic patterns and congestion aspects. Furthermore, the accuracy of the AI models developed for this study depends on the data's quality and completeness.

2. Technological Limitations: The study is based on current AI technologies. Because artificial intelligence is a rapidly expanding field, the findings may become obsolete when new approaches and algorithms are created.

3. National Variations: The study, situated in Baltimore, Maryland, does not consider the variations in demographic factors and traffic density across different cities and regions in the United States. These factors can significantly influence traffic patterns and the effectiveness of AI in managing traffic.

4. Cost Implications: Implementing AI in traffic management systems, including the development of algorithmic models, data collection and processing, and system integration, incurs significant expenditures. These expenses may limit the practicability of the study's recommendations.

These limitations should be considered when interpreting the study's findings and assessing their implications for traffic control techniques.

1.9 Ethical Considerations

As with any other field, the use of Artificial Intelligence (AI) in traffic management raises several ethical concerns that must be addressed:

1. Data Privacy: Sensitive information such as vehicle locations and travel patterns are frequently included in traffic data used in AI models. This data must be anonymized and used to protect user privacy.

2. Transparency: The decision-making processes of AI systems are frequently opaque, resulting in the "black box" problem. Users need to understand how AI makes predictions and decisions, especially when these impact public services like traffic management.

3. Bias: AI systems learn from data; if this data is biased, the systems can become biased. Care must be taken to ensure that the data used to train AI models for traffic management is representative and free from bias.

4. Accountability: It must be clear who is responsible in the event of a system failure or error. This is especially important in traffic management, where AI decisions can have severe consequences in the real world.

5. Security: AI systems can be vulnerable to attacks, including data breaches and adversarial attacks designed to manipulate their output. Robust security measures must be in place to protect these systems.

2. Literature Review

This section reviews how previous studies have approached each research question under investigation in this study.

2.1 What is the impact of implementing machine learning and deep learning algorithms on traffic congestion levels in major U.S. cities?

The implementation of machine learning and deep learning algorithms has had a significant impact on traffic congestion levels in major U.S. cities. These algorithms have been applied to various aspects of traffic management, including traffic flow forecasting, congestion prediction, traffic state analysis, and traffic condition classification. Machine learning and deep learning algorithms have been utilized to overcome the challenges faced by congestion, such as the ability to capture complex patterns, automatic feature learning, and the prediction of traffic flow based on deep network structures [39]-[43]. Additionally, the use of deep learning models has shown improved predictive power compared to traditional machine learning techniques, leading to enhanced accuracy in traffic flow prediction and congestion identification [44,45].

Furthermore, the application of machine learning and deep learning algorithms has extended to traffic incident detection, road accident prediction, and traffic optimization in urban areas. These algorithms have been employed to detect the exact location of traffic lights, predict road accidents, and optimize road traffic in large cities [46, 48]. Moreover, the use of machine learning models has facilitated the classification of traffic conditions and the identification of recurrent congestion in heterogeneous urban traffic, contributing to a better understanding of various traffic phenomena [49, 50].

The integration of machine learning and deep learning algorithms has also enabled the efficient planning of journeys, the classification of mobile service traffic, and the prediction of traffic evolution in large-scale transportation networks. These algorithms have been instrumental in journey planning, mobile service traffic classification, and the prediction of transportation network congestion evolution based on GPS data [51, 54].

In conclusion, the implementation of machine learning and deep learning algorithms has significantly impacted traffic congestion levels in major U.S. cities by providing advanced capabilities in traffic flow forecasting, congestion prediction, incident detection, accident prediction, traffic optimization, and traffic condition classification. These algorithms have demonstrated their effectiveness in addressing the challenges associated with traffic congestion, thereby contributing to the development of more efficient and intelligent traffic management systems.

2.2 How effective are different AI algorithms (decision tree, random forest, logistic regression, and deep learning neural network) in predicting traffic demand and optimizing routes to reduce traffic congestion in major U.S. cities?

Based on the available references, it is evident that different AI algorithms have been extensively studied and applied in predicting traffic demand and optimizing routes to reduce traffic congestion in major U.S. cities. The effectiveness of various AI algorithms, including decision tree, random forest, logistic regression, and deep learning neural network, has been investigated in the context of traffic prediction and congestion reduction.

Random forest, a popular ensemble learning algorithm composed of decision trees, has been widely utilized in traffic behavior research, traffic identification, and traffic demand prediction [55]. Studies have reported promising results in predicting road-traffic severity using the random forest algorithm, demonstrating its effectiveness in addressing traffic-related challenges [56]. Additionally, the random forest algorithm has shown high prediction accuracy in traffic congestion prediction, further highlighting its potential in optimizing routes to reduce congestion [57].

Moreover, the application of deep learning neural networks, such as the deep forest algorithm, has gained attention for predicting traffic accident severity and congestion levels, indicating the effectiveness of deep learning approaches in addressing traffic-related issues [58]. Furthermore, the use of deep learning methodologies, including convolutional neural networks (CNN), long short-term memory (LSTM), and deep reinforcement learning, has been explored for traffic congestion prediction and route optimization, demonstrating their potential in improving traffic management systems [59,61].

While random forest and deep learning algorithms have shown promise in traffic prediction and congestion reduction, logistic regression and decision tree algorithms have also been considered in the context of traffic demand prediction and route optimization. Logistic regression has been utilized for crash severity predictive analysis, highlighting its relevance in assessing traffic-related risks and optimizing routes to enhance safety [62].

Additionally, decision tree learning has been explored for predicting trip cancellations and no-shows in paratransit operations, indicating its potential in route optimization and demand prediction [63].

In conclusion, the available references suggest that different AI algorithms, including random forest, deep learning neural networks, logistic regression, and decision tree, have been effectively applied in predicting traffic demand and optimizing routes to reduce traffic congestion in major U.S. cities. These algorithms have demonstrated their potential in addressing various traffic-related challenges and improving traffic management systems.

2.3 What are the impacts of implementing artificial intelligence (AI) technology in traffic management?

Implementing artificial intelligence (AI) in traffic management significantly improves decision-making, traffic flow prediction, congestion resolution, and overall transportation system efficiency. AI technologies such as machine learning, deep learning, and fuzzy modeling have been proposed to develop intelligent traffic management solutions [64]-[66]. These AI-based approaches aim to enhance the accuracy of traffic predictions, resolve congestion issues, and support intelligent transportation systems [67,69].

Furthermore, integrating AI algorithms in traffic management systems has shown promising success in behavior prediction of traffic actors for intelligent vehicles, leading to improved traffic control and decision-making [70, 71]. Moreover, the use of AI in traffic management extends to data visualization, urban traffic logistics, and traffic demand forecasting, where AI technologies such as machine learning and data mining play a crucial role in enhancing the accuracy of traffic flow prediction and developing intelligent traffic forecasting systems [72,74]. Additionally, AI-based traffic control approaches, including the use of artificial neural networks and fuzzy rule-based systems, have been proposed to optimize traffic flow, minimize congestion, and smoothen road traffic [75,77]. Furthermore, the application of AI in traffic management is not limited to prediction and control but also extends to the development of intelligent road traffic congestion control systems, delay estimation models, and intersection signal control using AI algorithms such as ant colony optimization and expert systems [78]. These AI-based systems aim to improve traffic flow, minimize delays, and enhance intersection signal control efficiency.

Overall, the integration of AI in traffic management can revolutionize transportation systems, leading to more efficient traffic control, improved decision-making, and enhanced overall system performance.

2.4 Theoretical Framework

Understanding human behavior through AI: The Machine Theory of Mind provides a theoretical framework for understanding human behavior through AI. The Machine Theory of Mind refers to the ability of an AI system to attribute mental states to others, like how humans understand and predict others' behavior based on their perceived beliefs, desires, and intentions. This concept is crucial in traffic management, where understanding human behavior can lead to more accurate predictions and more effective interventions. For instance, by understanding that drivers may slow down when they see a traffic officer, an AI system can predict a sudden decrease in speed in a particular area and adjust traffic signals or reroute traffic accordingly. Similarly, by attributing the intention of reaching a destination as quickly as possible to drivers, the AI system can predict potential routes a driver may take and manage traffic flow to minimize congestion.

The Machine Theory of Mind can also be applied to pedestrian behavior. By understanding that pedestrians may cross the road when they see a 'Walk' signal, the AI system can coordinate traffic signals to ensure pedestrian safety and smooth traffic flow.

Application in Robotics and AI Decision-Making: The Machine Theory of Mind provides a valuable framework for enhancing the capabilities of robotics and AI decision-making systems, leading to more effective and human-centered solutions. The Machine Theory of Mind has significant applications in robotics and AI decision-making.

In robotics, understanding and predicting human behavior is crucial for effective human-robot interaction. Robots equipped with a theory of mind can better anticipate human actions, leading to smoother interactions and more effective collaboration. For instance, a Machine Theory of Mind in autonomous vehicles can help predict the actions of other drivers, pedestrians, and cyclists, allowing the vehicle to navigate safely and efficiently. By attributing mental states to these road users, the autonomous vehicle can anticipate potential hazards and adjust its driving strategy accordingly.

In AI decision-making, a Machine Theory of Mind can enhance the system's ability to make decisions that align with human values and expectations. By understanding human beliefs, desires, and intentions, AI systems can make decisions that are technically optimal and socially and ethically acceptable. For example, an AI system with a theory of mind in traffic management could understand that drivers may prefer specific routes due to scenery or familiarity, even if these routes are not the most efficient. The system could incorporate these preferences into its traffic management strategy, increasing user satisfaction.

2.5 Review of Theories

Researchers claim that non-parametric approaches are better for problem learning when compared to parametric methods. This is because they are usually better at generalizing intricate data and can adapt to its patterns, such as predicting traffic data.

Parametric methods and tests assume fundamental statistical distributions in the data. Parametric approaches are usually the first option as the input and output traffic variables are noisy, and their correlation is non-linear and poorly understood. Pattern recognition-centered methods, a branch of the non-parametric methods, are more suitable as they are operative in recognizing similar traffic conditions required to create a prediction. Some of the data-driven models with non-parametric and parametric methods are discussed below.

2.6 Review of Methodologies

Several authors have contributed enough to the field of traffic flow management. A simple visualization method has been given to show traffic occurrences from the past data as map overlay in the shape of dynamic radial circles. Traffic origin circles are colored differently, each representing unlike road conditions, i.e., breakdowns, traffic, and congestion, which are plotted on the map. The traffic origins are the optical descriptors of where traffic incidents, breakdowns, and congestion are represented by their radius. Once that place has cleared, the circles retreat and eventually vanish at the source's central point. The traffic origin technique is said to determine better the impacts a cascaded mishap or restricted traffic flow could have on a particular road in a traffic network. From previous studies, traffic flow prediction can be categorized into different types. Parametric methods are based on statistical methods for time series prediction. Knowledge of data distribution is usually assumed in these approaches. These approaches mostly use traffic system simulations, road activities, and driver behavior constraints as part of the simulation process. The macroscopic traffic forecast approaches are based on vehicular traffic flow correlations (e.g., delay at traffic lights or mean time spent at bus stations) that can be utilized in the forecast process. A good understanding of the actual traffic conditions is achieved in places. However, the limitations of using many macroscopic forecast approaches are the intricate parameter estimations and an actual scuffle to produce close-to real-world simulation test conditions. The forecast is also highly impacted by the quality of the approximated traffic constraints. Both statistical Machine Learning and macroscopic methods are essential for developing an ideal traffic flow forecast model.

This study, however, focuses on the survey for the data-driven statistical to complex machine Learning methods for traffic management—the main difference between the ML and traditional analytical method-based model. While machine-learning approaches are intricate in improving learning, they are less intricate and computationally effective in calculating the ultimate forecast once trained. Constant training allows Machine Learning approaches to adapt to the varying behaviors witnessed in the data.

3. Techniques and Algorithms

3.1. Machine Learning for Congestion Management

Machine learning has shown significant potential in managing traffic congestion. The technology offers promising solutions for congestion management by providing agile control strategies and efficient learning techniques [79].

ML offers an agile and self-adaptive approach to congestion management [80]. One such concept is the Agile Net, an agile control strategy for congestion management. The model of Agile Net has three cores: it perceives the network environment using the concept of demand elasticity, possesses an online model-free learning technique for managing network externality such as congestion, and enables distributed system scalability.

Machine learning models and techniques have also been implemented in Vehicular Ad hoc Networks (VANET) for traffic management [81]. These systems need constant monitoring for proper functioning, which opens the doors to applying machine learning algorithms on the enormous data generated from different applications in VANET. Machine learning provides efficient supervised and unsupervised learning of these collected data, effectively implementing VANET’s objective.

3.2 Machine Learning Algorithms in Congestion Management

Machine learning has been helping in predicting road traffic and the detection of data. ML algorithms are formed centered on mathematical approaches and help create an intelligent traffic management system [82].

Congestion has proved to be a significant problem as the network traffic has increased faster than the available traffic infrastructure. This problem has been addressed using the Traffic Management System (TMS), which observes vehicles to reduce the time spent in traffic lights by suggesting alternative traffic routes. This method has worked because it uses machine learning. TMS works based on video sequence input collected from the convolutional neural network. The training process was instigated by using convolutional neural network topology made with the aid of the YOLO algorithm. This technique worked through the 3-D revealing of the object in the video frame. It has been considered the best data in most tracking algorithms. This system also uses machine learning to use a rectangular region of interest (ROI) and segment the objects [83]. Hence, it is evident that machine learning has been tried and is thriving.

3.3 Application of Deep Learning in Congestion Detection

AI and deep learning technologies are predicted to significantly control traffic by allocating and evaluating data from different sources. Comprehension from them can hasten traffic movements. In Pittsburgh, a company called Rapid-Flow launched an adaptive traffic control system made by researchers at the Robotics Institute. Since the rollout, the technology has reduced congestion by 40%. Traveling time has also fallen by 25%, and vehicle emissions have decreased by 20% [84]. This system uses machine learning to realize all the achievements mentioned.

3.4 Models for Predicting and Managing Traffic

Habtemichael and Cetin [33] suggested a non-parametric prediction model for short-term traffic flow rate prediction based on an upgraded k-nearest neighbors’ technique. They used and evaluated their model on 36 datasets (12 from the United Kingdom and 24 from the United States of America) acquired from various geographies. They discovered that their model outperformed the study’s other sophisticated parametric models. Additionally, Sharma and his colleagues. [85] emphasized the critical nature of precision in short-term traffic flow forecasts. They suggested a two-dimensional prediction approach for past traffic data based on Kalman filtering. They said their suggested technique outperformed the usual Kalman filtering strategy regarding accuracy. Sharma and his colleagues. [85] argued that while contemplating the future situation of ITS, interval prediction is more critical and complex than point prediction for traffic management. They developed a point and interval prediction forecasting model using fuzzy information granulation and ANN, SVM, and KNN algorithms using real-world traffic data acquired from American field transportation systems. Their findings indicated that when the time gap between predictions rose, the stability of prediction systems increased as well.

Convolutional Neural Networks (CNN): With the great success of deep convolutional neural networks (CNN) in object detection and recognition, CNN-centered methods benefit deep architectures to develop non-handcrafted features that accurately represent objects. This method is said to outperform conventional methods in both robustness and accuracy. The CNN-based semantic segmentation methods can be a neural way to track and detect objects. CNN-based techniques are suitable for analyzing real-time traffic congestion from data generated through UAVs [86]. Mask RCNN is the most current method of deep learning. After semantic segmentation on the acquired bounding boxes, it can identify the instances with a binary mask classifier.

Artificial Neural Networks (ANN): Kiran and Verma [87] examined mixed traffic flow while Asaithambi and his colleagues. [88] studied non-lane-based mixed traffic. In separate research, Sharma and his colleagues. (2018) investigated homogenous traffic flows and utilized an ANN model to construct a short-term traffic forecasting model using Istanbul traffic data. They said the day of the week, hour, and minute all had a part in predicting traffic flow. Sharma and his colleagues. [85] investigated the stability and effectiveness of neural networks for short-term traffic volume prediction under mixed Indian traffic flow circumstances on four-lane undivided roads. Sharma and his colleagues. [85] employed an ANN model to anticipate traffic flow, including traffic volume, speed, density, time, and any day of the week as input parameters. They claimed that the performance of the ANN remained constant even when the forecast time interval was adjusted from 5 to 15 minutes. Guo and his colleagues. [89] employed an adaptive Kalman filter technique to forecast short-term traffic flow rates and quantify uncertainty. They built a model for short-term traffic forecasting using real-world traffic data from four separate highway networks in the United Kingdom, Minnesota, Washington, and Maryland in the United States of America. They argued that adaptive Kalman filters are useful when traffic is highly variable.

Reinforced Learning Algorithms: Nama and his colleagues. [90] investigated the application of reinforcement learning in traffic management by forecasting the time automobiles waited at a junction using a neural network and using the Sarsa algorithm to determine the optimal control strategy [90]. Khamis & Gomaa [91], on the other hand, used reinforcement learning and evolutionary algorithms to produce a model for cooperative traffic light management. These solutions have a common theme: the idea known as the ‘dimension curse,’ which results from using a traffic-light value function. In this scenario, their success is limited due to the input structure’s restricted emphasis and use in cities with extensive road networks.

The reinforced learning paradigm has recently been successfully used in traffic management [92]. Its application is based on two primary variables: the agent and the environment. The agent variable’s objective is to learn about its surroundings and govern them optimally. However, when seen in a broader context, reinforced learning employs distinct principles of neural network activity and deploys a network across a specified time horizon [93]. To demonstrate the limitations of reinforced understanding in traffic management, recent research noted that only when the states are low-dimensional and built with linear value or policy functions does using function approximation in reinforcement learning produce significant results [94] and thus demonstrates the need of combining the approach with other features such as the artificial neural network (ANN), which is generally used as a functional approximator, and refer to potential issues with the reinforcement learning model [95].

3.5 Techniques for Traffic Flow Prediction

Historical Moving Average (HA): The historical moving average is a naïve and effective method in time series forecasting. This method is used as a primary performing model and considered a baseline in the set of experiments. Considering this method as a baseline performing approach, the error difference from it gives a general idea of the inherent temporal disparities in the data. For that reason, the moving average is always done using a window operation. Window-based moving average, usually called trailing moving average, utilizes past and future observations to determine averages and is slid along the entire time series. Window sizes 1, 2, and 3 are utilized in this experiment for short, medium, and long interval prediction, respectively [96].

For the univariate training data ($XXTT = xx1, xx2, \ldots . , xxtt$), with windows smmovingreater than zero (k >0), the kth ing average or HA at tt is given as $HHHH(tt) = yytt{-}kk{+}1 = mmmmmmmm\ (xxtt{-}kk{+}1 + xxtt{-}kk{+}2 + \cdots + xxtt\ )$

Deep Belief Networks (DBN): This type of neural network (DNN) has some hidden layers and many hidden units in each layer. The simplest DBN comprises stacks of Restricted Boltzmann Machine (RBM) methods, a neural layer at the top of the output layer. An archetypal DBN is trained using a layer-by-layer greedy algorithm for the supervised data [96].

4. Methodology and Results

4.1 Research Approach

The movement of vehicles on the road results from a complicated interplay between various cars. As a result, a simple and effective method for predicting traffic congestion may be traffic pattern prediction modeling. However, different AI models are used in various investigations based on the data's properties and quality. Deep and shallow learning algorithms are used in machine learning. As this text progressed, certain portions were broken down into more specific algorithms.

4.1.1 Research Worldview

The research worldview suitable for this research is post-positivism. This approach argues that the concept and even the actual identity of a researcher affects what they observe and, therefore, impacts their conclusions. The researcher chose this approach because it pursues objective answers by recognizing and working with such biases with theories and concepts that theorists develop. Moreover, this approach applies quantitative research design, experiments as research strategies, and descriptive and inferential analysis for data analysis.

4.1.2 Research Design

The construction and training of numerous deep convolutional neural network models that recognize and categorize specific items and partition traffic scenes into their constituent objects are at the heart of the proposed AI-enabled system. The data source for training these models was obtained from the TomTom Traffic Index, which comprises traffic information from several countries. However, only the data from the USA was considered for this study. The researcher applied data science techniques for data analysis, visualization, and data preprocessing and trained the processed data on some machine learning models.

4.1.3 Research Strategy

Before the data is ready for classical machine learning model training, several operations must be done. If there are duplicate cases in the dataset, it will bias machine learning algorithms. So, to prevent biasing, those duplicates need to be located and removed from the dataset.

In addition, the dataset can contain redundancy and irrelevancy. Therefore, data preprocessing is a necessary process that can be accomplished with many techniques and feature selection. Machine Learning Models with only numeric values will be best for this preprocessing.

Feature selection is an indispensable component of the machine learning process. The feature selection approach tries to pick a subset of features relevant to the target concept. They can be categorized into two based on their reliance on the inductive algorithm that will finally use the selected subset. This analysis will obtain features using the Recursive Feature Elimination (RFE) method. RFE is a wrapper method that recursively analyses alternative sets by running some induction algorithm on the training data.

Data clustering will be another part of this research where the selected features cluster the traffic according to their similar properties. Then, this data will be analyzed using machine learning models. The obtained data will be used for machine learning training and testing on classical machine learning models to get the desired results.

4.2 Data Collection

The dataset used for this project was obtained from the TomTom Traffic Index. TomTom Traffic Index shows how individuals move on the local and global levels, in real-time and over time. The dataset obtained consisted solely of traffic data and information from the USA.

TomTom is a unique community whose input is combined with knowledge harvested from local specialists. It combines conventional sources, including paper maps, surveys, satellite imagery, and aerial and mobile mapping vans. The output is a dynamic map filled with enhanced content ranging from points of concern to 3D city maps. The app uses road sensors, and real-time traffic scenarios are joined with anonymous GPS measurements of TomTom device users to develop a clear picture of traffic conditions as they evolve. This information is made accessible to the public and government markets.

4.2.1 Study Population

The United States has over 300 million people and 9,161,966 square kilometers, encompassing urban and rural regions. Every 10 seconds, GPS data is collected. As a reminder, each location has a unique latitude and longitude at a specific time. There are many samples for practically every vital highway and expressway in the region. Records that were found to be missing or erroneous have been purged. Vehicle occupancy in the timespace domain was calculated as a measure of congestion. This study divides congestion levels into severe congestion and moderate congestion.

4.2.2 Sample

The present research will execute all tests using the United States Cab GPS trajectory. Using the formula equations (1), (2), and (3), it is possible to acquire 11136 samples, which are 32*32 matrix and comprise two kinds of urban traffic flow data. The 32 × 32 matrix inflow statistics in the United States city area. The ratio value of two inflows on the same day in the US City region's residential and office areas. During the training of models over the past seven days, 7 * 48 samples were selected as testing data, and the remaining samples were utilized as training data. Following the prevalent practice, we utilize RMSE to assess all experiment methods.

4.3 Data Analysis

The collected data was treated through the data science processes of data visualization, preprocessing, and training the processed data on some machine learning models. Two algorithms, the classical machine learning model and deep learning, were used for this thesis, and the results were compared for better accuracy.

The data analysis used Python pandas, where the attribute was congested. The total number of entries was 26320. This data was collected between 30 December 2019 and 1 August 2020. After being analyzed, congestion had a mean of 10.888 with a standard deviation of 7.2075. The lower quartile was found to be 6.000; the median was 9.000. The higher quartile was 13.00.

4.3.1 Data Preprocessing

```python
from mpl_toolkits.mplot3d import Axes3D
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from datetime import datetime, timedelta
import warnings
warnings.filterwarnings("ignore")
import seaborn as sns
import matplotlib.pyplot as plt
from pandas.plotting import register_matplotlib_converters
from pylab import rcParams
sns.set_style("darkgrid")
```

Figure1

The above figure shows how Python was used to explore the data from Tomtom index traffic.

	date	country	city	diffRatio	congestion
0	12/30/2019	United States of America	Akron	-0.181818	9
1	12/31/2019	United States of America	Akron	-0.166667	10
2	1/1/2020	United States of America	Akron	-0.769231	3
3	1/2/2020	United States of America	Akron	-0.333333	8
4	1/3/2020	United States of America	Akron	-0.083333	11
5	1/4/2020	United States of America	Akron	0.000000	7
6	1/5/2020	United States of America	Akron	-0.200000	4
7	1/6/2020	United States of America	Akron	-0.090909	10
8	1/7/2020	United States of America	Akron	-0.166667	10
9	1/8/2020	United States of America	Akron	0.076923	14

Figure 2

The figure above displays the first ten data instances after being extracted from the dataset.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26320 entries, 0 to 26319
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   date        26320 non-null  object
 1   country     26320 non-null  object
 2   city        26320 non-null  object
 3   diffRatio   25662 non-null  float64
 4   congestion  26320 non-null  int64
dtypes: float64(1), int64(1), object(3)
memory usage: 1.0+ MB
```

Figure 3

The figure above shows the comprehensive analysis of data.

4.3.2 Data Visualization

Graphs represent the data, and the results are below.

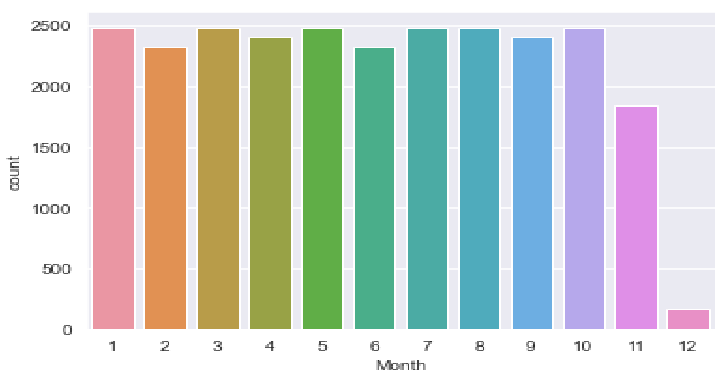

Figure 4: Congestion in the months of 2020

We can see from the figure above that most of the congestion is from January, March, May, July, August, and October, and very little data is from December.

Figure 4 represents the data of congestion in the 12 months of the year. December had the least congestion, below 500.

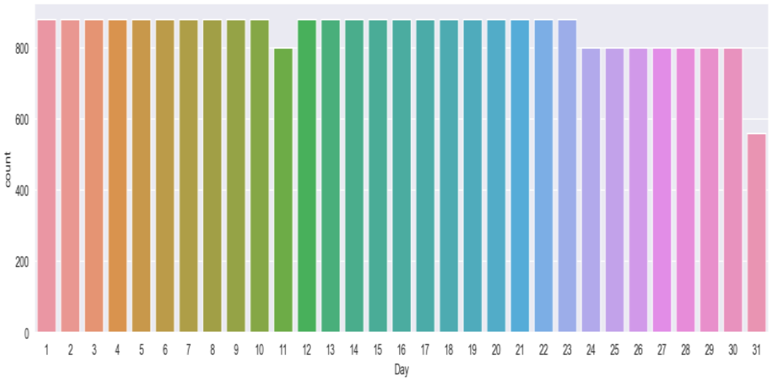

Figure 5: shows the data concerning the day of the month

Figure 5 represents the data of congestion on the days of the month. The data shows that congestion reduces on the 24th day and is least on the last day of the month.

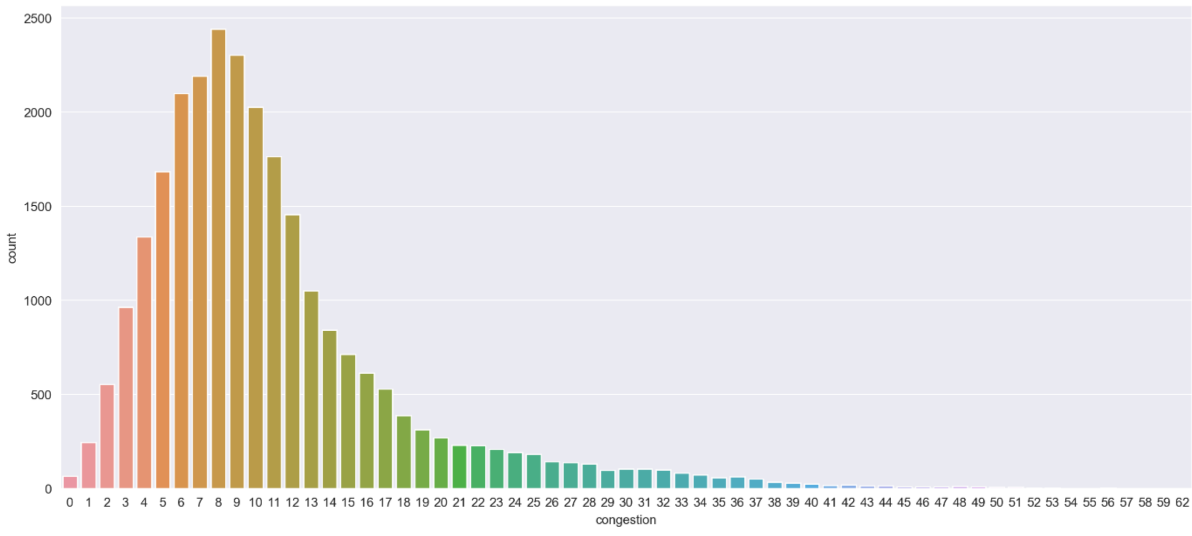

Figure 6: shows the data concerning traffic congestion

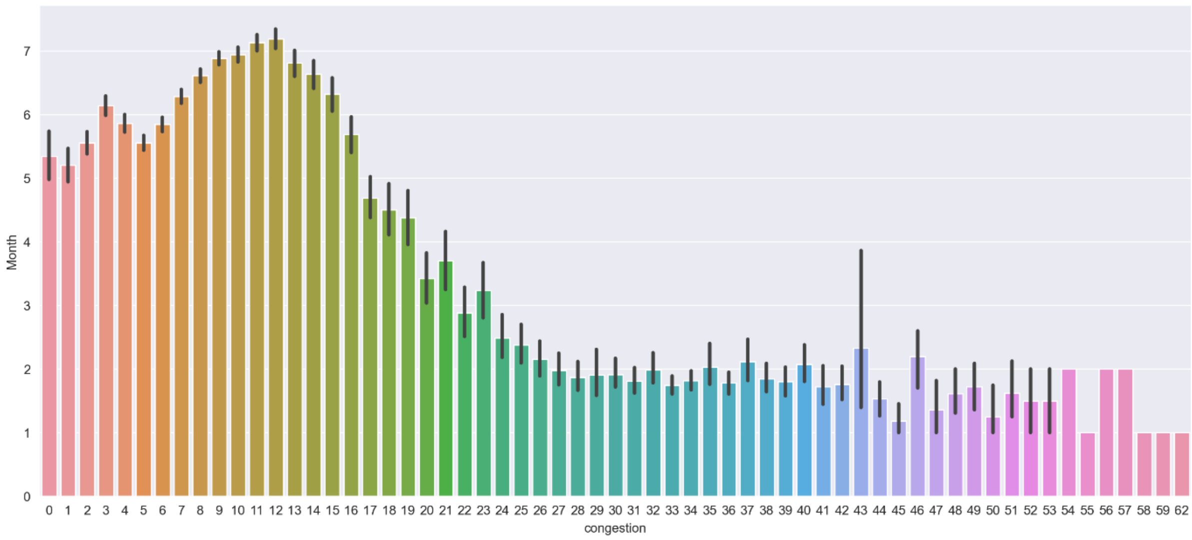

Figure 7: shows the traffic congestion during the month

Train and Test split

Processed data is divided into two parts training and testing data. Training data is 80% of the total data, and this training data is used to train four machine learning algorithms. Test data is 20% of the entire data and is used to evaluate the trained models.

4.3.3 Training of Processed Data on Machine Learning Models

Processed data is divided into two parts: training and testing data. Training data is 80% of the total data used to train four machine learning algorithms. Test data is 20% of the entire data and is used to evaluate the trained models.

Training of data was done using the following algorithms:

3. Decision tree
4. Random forest
5. Logistic Regression
6. Deep Learning

Decision Tree: Data is trained on a decision tree classifier with the default parameters of the algorithm. This is supervised machine learning, where it is explained what input is and what the corresponding output is in the training data. The data is constantly split according to parameters.

Random Forest: The random forest algorithm is a supervised machine learning algorithm applied widely in classification and regression challenges. This approach creates decision trees in different samples and takes their majority vote for analysis and average in case of regression.

Logistic Regression: Logistic regression is one of the statistical models used to model the probability of a particular class. We could have gotten a better result on this machine-learning algorithm to compare the accuracy with other models.

Deep Learning: Data is also trained using deep learning. Here is the model summary:

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 40)                3320

 dense_1 (Dense)             (None, 50)                2050

 dense_2 (Dense)             (None, 40)                2040

 dense_3 (Dense)             (None, 1)                 41

=================================================================
Total params: 7,451
Trainable params: 7,451
Non-trainable params: 0
_________________________________________________________________
```

Figure 8

The setting of hyperparameters of this model is as follows:

- Activation function = rel
- Optimizer = adam
- Learning rate = 0.05
- Epochs = 100
- Batch size = 10

4.4 Presentation of Results

The result achieved was 83.33% test accuracy on the decision tree model. Then, the test data was tested on a random forest, where the result was 79.44% accuracy, and then applied test data on a trained model on logistic regression, on which the result achieved 14.00% accuracy. The decision tree model in classical machine learning achieved the highest accuracy.

The following figure shows the performance compassion of different types of Machine learning models.

	n_neighbors	Score
0	Decision Tree	0.833587
1	Random Forest	0.794453
2	Logistic Regression	0.140008

Figure 9

Now, look at the results achieved on the deep learning model. With the setting mentioned above of the model's network, the model was trained using R^2, RMSE, and MAE. After this, the following results were achieved.

```
RMSE-train: 4.231574971454397
MAE-train: 3.005247627755791
R_2-train: 0.6521128978484891
```

Figure 10

As a result, an R-squared score of 65% test accuracy with deep learning was obtained. So, the highest accuracy on the decision three machine learning model was archived, which is 85%.

4.5 Brief Discussion of Results

Vehicle congestion is compared to months and days of the month. This was to help us train the machine learning models to predict traffic flow based on days and months. The data was also plotted against different U.S. cities. This was also important in training the models based on towns because every city had a different volume of congestion. Classical machine learning models and Deep learning were used to train the models. Decision trees were found to have high accuracy compared to other machine learning Algorithms and Deep Learning Algorithms.

The dataset collected was helpful because it represented how people move in real-time and over time. Such data provided powerful insights into what driving patterns mean. Therefore, this data will help machine learning algorithms learn from the past, understand the present, and make informed decisions.

This study contributes to expanding research in traffic flow management using Machine Learning and Deep Learning techniques. However, there are gaps in the study, such as a need for computationally efficient methods and algorithms. Additionally, quality data for training could be improved. Since similar traffic flow data of traffic flow In the US was used, it led to the application of incomprehensive contents of data when training the models. These factors have been said to limit the improvement of traffic flow prediction using Machine learning and deep learning techniques. The gap is increased by failing to apply dynamically collected spatial and temporal relationships in deep learning due to intricate relationship features between road sections and bottleneck patterns in traffic zones or busy areas. These issues should be addressed to help us get reliable data to develop traffic management systems.

4.6 Brief Recommendation Based on Results

From the results obtained, it is evident that congestion increased in 2020 compared to 2019, which suggests that it has also increased from that time to now. That calls for an efficient method to help ease our roads' congestion. According to the study, machine learning algorithms and deep learning algorithms were used to train the models. From that, it was found that decision tree machine learning algorithms had an accuracy of 85% compared to 65% in deep learning. Therefore, decision tree machine learning algorithms are a practical approach to train models to ease congestion. This paper recommends that this approach be applied in developing traffic management systems in the US.

5. Discussion and Recommendations

5.1 Full Discussion of Findings

5.1.1 Effectiveness of Decision Trees in Traffic Management

Decision Trees (DT) are a machine learning algorithm with significant potential in traffic management [97]. They offer a simple and human-readable visual representation of the predictive model, making them an effective tool for classifying instances such as travel decisions and traffic areas.

One of the key advantages of decision trees is their ability to handle both categorical and numerical data [98]. This makes them particularly useful in traffic management, where data can include categorical variables (like road type or weather conditions) and numerical variables (like vehicle speed or number of vehicles).

In a study titled "Traffic Prediction Using Multifaceted Techniques: A Survey," the authors explored various machine learning techniques for traffic prediction, including decision trees [99]. The study confirmed that decision trees, along with other Computational Intelligence-Machine Learning (CI-ML) techniques and Deep Learning (DL) hybrid techniques, outperform other methods in the field of traffic prediction. Another study, "An Analysis of Network Traffic Identification based on Decision Tree," established a decision tree model based on C4.5 and random forest to compare the accuracy of the two decision tree algorithms in traffic classification [100]. The experimental results showed that these two methods can identify traffic effectively.

In conclusion, decision trees have proven effective in traffic management, particularly in congestion management and traffic prediction. Their ability to handle complex data and visually represent the predictive model makes them a valuable tool in this field.

5.1.2 Accuracy Comparisons with Deep Learning

Deep Learning (DL) has shown significant potential in traffic management, particularly in predicting and managing traffic congestion [101]-[102]. DL models, especially those considering spatiotemporal dependencies of transport phenomena, show better prediction accuracies than conventional machine learning models [102].

A study titled "Deep Learning in Transport Studies: A Meta-analysis on the Prediction Accuracy" conducted a comprehensive review of the literature and a meta-analysis on prediction accuracy [102]. The findings showed that, on average, the prediction accuracy is improved by 5.90% with 100 million additional data. In comparison, the accuracy is reduced by 5.28% with a 100 min increase in the prediction time horizon in traffic forecasting studies.

Another study titled "Deep learning and case-based reasoning for predictive and adaptive traffic emergency management" investigated the potential of using a convolution neural network (CNN) in detecting emergency cases and forecasting events that can interrupt the traffic flow [101]. The proposed system outperformed the benchmarking algorithms through experiments in various traffic scenarios.

In conclusion, deep learning models have proven effective in traffic management, particularly traffic management and prediction. Their ability to handle complex data and provide accurate predictions makes them a valuable tool in this field.

5.1.3 Congestion Trends Analysis

Traffic congestion has been a significant concern in traffic control mechanisms caused by an unbalanced demand-supply situation that directly affects the problem of a large amount of fuel consumption and greenhouse emissions [102]. The report "Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation" provides a snapshot of congestion in the United States by summarizing recent trends in congestion, highlighting the role of travel time reliability in the effects of congestion, and describing efforts to reduce the growth of congestion [3].

The report focuses on travel time reliability and strategies to improve reliability [3]. The variation in travel times is now understood as a separate component of the public's and business sector's frustration with congestion problems.

In their most recent annual report on congestion in America's cities, the Texas Transportation Institute noted that congestion has grown substantially over the past 20 years [3]. While the largest cities are the most congested, congestion occurs—and has grown—in cities of every size.

To decrease traffic congestion, there is a need for simulating and optimizing traffic control and improving traffic management [104]. Different ways to monitor and analyze traffic congestion exist, such as video monitoring and surveillance systems or static and dynamic sensors that allow real-time traffic management [105].

In conclusion, the analysis of congestion trends reveals a growing problem across cities of all sizes. However, with the advent of AI and machine learning, there is potential for more effective congestion management strategies that can mitigate this issue.

5.2 Full Recommendations Based on Findings

5.2.1 Efficient Traffic Management Practices

Based on the findings of this study, the following recommendations can be made for more efficient traffic management practices:

1. Leverage AI for Real-Time Traffic Management: AI and machine learning techniques should be leveraged for real-time traffic management. This includes using AI to predict traffic demand, optimize traffic routes, and manage incidents. Implementing these techniques can help reduce congestion, enhance road safety, and improve the overall efficiency of the transportation system.

2. Invest in Data Infrastructure: To fully harness the power of AI in traffic management, significant investment in data infrastructure is needed. This includes collecting comprehensive traffic data, ensuring the quality and accuracy of this data, and developing robust data processing capabilities.

3. Prioritize User Privacy: As AI systems rely on large volumes of data, it is crucial to prioritize user privacy. This includes anonymizing data, implementing robust data security measures, and being transparent about data use.

4. Promote Transparency and Accountability: The decision-making processes of AI systems should be transparent, and precise accountability mechanisms should be in place. This is particularly important in traffic management, where AI decisions can have significant real-world consequences.

5. Address Ethical Considerations: Ethical considerations, such as data privacy, transparency, bias, accountability, and security, should be at the forefront when developing and deploying AI for traffic management.

The future implications of these recommendations are vast. By harnessing the power of AI, we can transform our traffic management systems, making them more efficient, safe, and user-friendly. This can lead to significant cost savings, reduced environmental impact, and improved quality of life for all road users. The following sections will delve deeper into potential improvements and strategies for traffic management and future research directions in this field.

5.2.2 Potential Improvements and Strategies

The application of AI in traffic management opens a plethora of potential improvements and strategies:

1. Dynamic Traffic Signal Timing: AI can dynamically adjust traffic signal timings based on real-time traffic conditions. This can help reduce congestion and improve traffic flow.

2. Predictive Traffic Management: AI can predict future traffic conditions based on historical data and real-time inputs. This can help traffic management authorities proactively manage traffic and prevent congestion before it occurs.

3. Incident Detection and Management: AI can quickly detect accidents or road closures and reroute traffic in real time. This can help minimize traffic disruptions and improve road safety.

4. Personalized Route Recommendations: AI can provide drivers with personalized route recommendations based on their preferences and real-time traffic conditions. This can help reduce travel time and improve the driving experience.

5. Integrated Traffic Management Systems: AI can integrate different aspects of traffic management, such as traffic signals, incident management, and route planning, into a single, cohesive system. This can improve the efficiency and effectiveness of traffic management.

6. Data-Driven Infrastructure Planning: AI can analyze traffic data to identify infrastructure needs, such as where new roads or bridges are needed. This can help city planners make more informed decisions about infrastructure development.

These strategies, if implemented, could significantly improve traffic management practices, leading to reduced congestion, improved road safety, and a more efficient transportation system. The following sections will delve deeper into future research directions in this field.

5.3 Future Research Directions

5.3.1 Advancing AI Capabilities in Transportation

The field of AI in transportation is ripe for further research and development. Here are some potential directions for future research:

Development of More Advanced AI Models: While current AI models have shown significant potential in traffic management, there is scope for developing more advanced models that can handle more complex scenarios, make more accurate predictions, and adapt quickly to changing conditions.

Integration of AI with Other Technologies: Integrating AI with other emerging technologies, such as the Internet of Things (IoT) and 5G, could lead to more comprehensive and effective traffic management solutions.

For instance, IoT devices could provide real-time data for AI models, while 5G could enable faster and more reliable data transmission.

Exploration of New Use Cases for AI in Transportation: Beyond traffic management, there are many other potential use cases for AI in transportation, such as autonomous vehicles, smart parking, and predictive maintenance. Further research could explore these use cases in more detail.

Addressing Ethical and Regulatory Challenges: As AI becomes more prevalent in transportation, addressing the associated ethical and regulatory challenges will be necessary. This could include issues related to data privacy, algorithmic bias, and legal liability.

Evaluation of the Impact of AI on Transportation Jobs: As AI automates more tasks in transportation, it will be important to evaluate its impact on jobs in the sector. This could include studying the types of jobs that are most at risk and identifying new job opportunities that AI could create.

5.3.2 Extending Research on Urban Mobility

Urban mobility is a critical area of research that directly impacts the quality of life in cities. With the advent of AI and machine learning, there are numerous opportunities to extend research in this field:

Multimodal Transportation: Future research could explore how AI can optimize multimodal transportation systems, which involve multiple modes of transport, such as cars, buses, trains, bicycles, and walking. AI could help plan efficient routes that combine different modes of transport, improving accessibility and reducing travel time.

Shared Mobility: Shared mobility services like ride-sharing and bike-sharing are becoming increasingly popular in urban areas. AI can be crucial in managing these services, from matching riders and drivers to optimizing routes and pricing.

Smart Cities: As cities become more connected, a wealth of data can be leveraged for urban mobility research. AI can analyze this data to gain insights into mobility patterns, identify bottlenecks, and develop solutions to improve urban mobility.

Sustainable Transportation: With growing concerns about climate change, there is a need for more sustainable transportation solutions. AI can help design and manage transportation systems that minimize environmental impact, for example, by optimizing routes to reduce fuel consumption or integrating electric vehicles into the transportation network.

Accessibility: Ensuring that transportation systems are accessible to all, including people with disabilities, is a critical challenge in urban mobility. AI can help address this challenge, for example, by predicting the demand for accessible transportation services and optimizing their provision.

In conclusion, extending research on urban mobility presents a promising avenue for future research, significantly improving urban living and contributing to more sustainable and inclusive cities.

6. Conclusion

6.1 Summary of Study

The research paper provides a detailed examination of the potential for Artificial Intelligence (AI) in reshaping traffic management in the United States. It underscores how AI technologies, especially machine learning and deep learning, could be pivotal in addressing critical issues like traffic congestion and collisions. By utilizing AI to predict traffic demand and optimize routes, traffic management could become more proactive and dynamic.

The paper stresses the tangible effects of traffic congestion on economic activity and everyday life while exploring AI's role in managing and solving these challenges. The adoption of AI in this context spans fields such as urban transportation planning, logistics, and sustainable city development. Various AI methodologies, including decision trees, have been identified as particularly effective in predicting traffic patterns and managing congestion.

Furthermore, the research argues for applying advanced AI models and integrating AI with technologies like IoT and 5G to augment traffic management systems. It suggests that stakeholders in traffic management should make concerted efforts to facilitate AI integration, which involves investing in technology, fostering collaborations, and ensuring ethical considerations, such as privacy and security, are duly addressed.

The paper concludes with recommendations for future research, emphasizing the development of new AI models, exploration of additional AI use cases in transportation, and the evaluation of AI's impact on jobs in the sector. It also calls for continued investigation into broader aspects of urban mobility, including smart cities and sustainable transport options.

6.2 Closing Thoughts on AI in Traffic Management

6.2.1 Promising Outlook for AI Applications

The application of Artificial Intelligence (AI) in traffic management presents a promising outlook. The ability of AI to analyze large volumes of data, identify patterns, make predictions, and adapt to changing conditions can significantly enhance traffic management practices.

AI can help predict future traffic conditions, optimize traffic routes, manage incidents, and provide drivers with real-time information about traffic conditions. These capabilities can lead to reduced congestion, enhanced road safety, improved transportation system efficiency, and a more pleasant driving experience.

Moreover, integrating AI with emerging technologies, such as the Internet of Things (IoT) and 5G, could lead to more comprehensive and effective traffic management solutions. For instance, IoT devices could provide real-time data for AI models, while 5G could enable faster and more reliable data transmission. In conclusion, the outlook for AI applications in traffic management is promising. With continued research and development, AI has the potential to revolutionize traffic management practices, contributing to more sustainable and livable cities.

6.2.2 Call to Action for Implementation

The promising outlook for AI applications in traffic management calls for immediate action towards implementation. Stakeholders, including city planners, traffic management authorities, and policymakers, should consider the following steps:

Invest in AI Technology: Allocate resources towards developing and integrating AI systems in traffic management. This includes investing in data infrastructure, AI model development, and system integration.

Collaborate with AI Experts: Establish partnerships with AI researchers and practitioners to leverage their expertise in developing and implementing AI solutions for traffic management.

Prioritize User Privacy and Security: Implement robust data privacy and security measures to protect user data. This includes anonymizing data, implementing robust data security measures, and being transparent about data use.

Develop Regulatory Frameworks: Develop regulatory frameworks to guide the use of AI in traffic management. This includes addressing issues related to data privacy, algorithmic bias, legal liability, and job impacts.

Educate the Public: Educate the public about the benefits of AI in traffic management and address any concerns they may have. This includes providing information about how AI systems work, how they make decisions, and how they can improve traffic conditions. By taking these steps, the power of AI can be harnessed to revolutionize traffic management practices, contributing to more sustainable and livable cities.

References

[1] A. Downs, "Traffic: Why It's Getting Worse, What Government Can Do," Jan. 2004. Accessed: Dec. 02, 2023. [Online]. Available: https://www.brookings.edu/articles/traffic-why-its-getting-worse-what-government-can-do

[2] J. MacDonald, "The Science of Traffic," *JSTOR Daily*, Dec. 2017, [Online]. Available: https://daily.jstor.org/the-science-of-traffic/

[3] Federal Highway Administration, "Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation," Mar. 2020. Accessed: Dec. 02, 2023. [Online]. Available: https://ops.fhwa.dot.gov/congestion_report/executive_summary.htm

[4] D. Schrank and B. Eisele, “Urban Mobility Report,” *Mobility Division - Texas a&M Transportation Institute*, 2021. https://mobility.tamu.edu/umr/ (accessed Dec. 02, 2023).

[5] E. M. Dogo, T. Makaba, O. J. Afolabi, and A. C. Ajibo, “Combating Road Traffic Congestion with Big Data: A Bibliometric Review and Analysis of Scientific Research,” in *EAI/Springer Innovations in Communication and Computing*, 2021, pp. 43–86. doi: 10.1007/978-3-030-66042-0_4.

[6] I. Thomson and A. Bull, “Urban Traffic Congestion: Its Economic and Social Causes and Consequences,” *CEPAL Review*, no. 76, pp. 105–116, Apr. 2002.

[7] M. Cogoni, “Estimating Peak-Hour Traffic Congestion Patterns For Interacting Agents On Urban Networks,” *arXiv.org*, Jul. 22, 2022. https://arxiv.org/abs/2207.11219

[8] H. Karimi, B. Ghadirifaraz, S. N. S. Boushehri, S.-M. Hosseininasab, and N. Rafiei, “Reducing traffic congestion and increasing sustainability in special urban areas through one-way traffic reconfiguration,” *Transportation*, vol. 49, no. 1, pp. 37–60, Jan. 2021, doi: 10.1007/s11116-020-10162-4.

[9] D. Q. Nguyen-Phuoc, W. Young, G. Currie, and C. De Gruyter, “Traffic congestion relief associated with public transport: state-of-the-art,” *Public Transport*, vol. 12, no. 2, pp. 455–481, Feb. 2020, doi: 10.1007/s12469-020-00231-3.

[10] American Psychological Association, “Road rage: What makes some people more prone to anger behind the wheel,” *American Psychological Association*, 2014. Accessed: Dec. 02, 2023. [Online]. Available: https://www.apa.org/topics/anger/road-rage

[11] Y. Chen, P. Yan, Z. Zheng, and D. Chen, “Identifying Traffic Bottleneck in Urban Road Networks via Causal Inference,” in *Lecture Notes in Computer Science*, 2021, pp. 372–383. doi: 10.1007/978-3-030-68884-4_31.

[12] G. P. R. Filho *et al.*, “Enhancing intelligence in traffic management systems to aid in vehicle traffic congestion problems in smart cities,” *Ad Hoc Networks*, vol. 107, p. 102265, Oct. 2020, doi: 10.1016/j.adhoc.2020.102265.

[13] A. Iqbal, Z. U. Rehman, S. Ali, K. Ullah, and U. Ghani, “Road traffic accident analysis and identification of black spot locations on highway,” *Civil Engineering Journal*, vol. 6, no. 12, pp. 2448–2456, Dec. 2020, doi: 10.28991/cej-2020-03091629.

[14] M. Al-Turki, A. Jamal, H. M. Al-Ahmadi, M. A. Al-Sughaiyer, and M. Zahid, “On the Potential Impacts of Smart Traffic Control for Delay, Fuel Energy Consumption, and Emissions: An NSGA-II-Based Optimization Case Study from Dhahran, Saudi Arabia,” *Sustainability*, vol. 12, no. 18, p. 7394, Sep. 2020, doi: 10.3390/su12187394.

[15] M. S. Kumar, K. Kumar, and P. Das, “Study on road traffic congestion: A review,” in *CRC Press eBooks*, 2021, pp. 230–240. doi: 10.1201/9781003193838-43.

[16] Y. J. Yasin, M. Grivna, and F. M. Abu-Zidan, “Global impact of COVID-19 pandemic on road traffic collisions,” *World Journal of Emergency Surgery*, vol. 16, no. 1, Sep. 2021, doi: 10.1186/s13017-021-00395-8.

[17] R. Fisa, M. Musukuma, M. Sampa, P. Musonda, and T. Young, “Effects of interventions for preventing road traffic crashes: an overview of systematic reviews,” *BMC Public Health*, vol. 22, no. 1, Mar. 2022, doi: 10.1186/s12889-021-12253-y.

[18] M. J. Giummarra, B. Beck, and B. Gabbe, “Classification of road traffic injury collision characteristics using text mining analysis: Implications for road injury prevention,” *PLOS ONE*, vol. 16, no. 1, p. e0245636, Jan. 2021, doi: 10.1371/journal.pone.0245636.

[19] K. K. C. Hung *et al.*, “Impacts of injury severity on long-term outcomes following motor vehicle crashes,” *BMC Public Health*, vol. 21, no. 1, Mar. 2021, doi: 10.1186/s12889-021-10638-7.

[20] C. Chantith, C. K. Permpoonwiwat, and B. Hamaide, “Measure of productivity loss due to road traffic accidents in Thailand,” *IATSS Research*, vol. 45, no. 1, pp. 131–136, Apr. 2021, doi: 10.1016/j.iatssr.2020.07.001.

[21] N. Drop and D. Garlińska, “Evaluation of intelligent transport systems used in urban agglomerations and intercity roads by professional truck drivers,” *Sustainability*, vol. 13, no. 5, p. 2935, Mar. 2021, doi: 10.3390/su13052935.

[22] D. West and J. Allen, “How artificial intelligence is transforming the world,” *Brookings*, Apr. 24, 2018. https://www.brookings.edu/articles/how-artificial-intelligence-is-transforming-the-world/ (accessed Dec. 02, 2023).

[23] C. Janiesch, P. Zschech, and K. Heinrich, “Machine learning and deep learning,” *Electronic Markets*, vol. 31, no. 3, pp. 685–695, Apr. 2021, doi: 10.1007/s12525-021-00475-2.

[24] B. Mahesh, “Machine Learning Algorithms -A Review,” *ResearchGate*, Jan. 2019, doi: 10.21275/ART20203995.

[25] I. H. Sarker, “Machine Learning: Algorithms, Real-World Applications and Research Directions,” *SN Computer Science*, vol. 2, no. 3, Mar. 2021, doi: 10.1007/s42979-021-00592-x.

[26] I. H. Sarker, “Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions,” *SN Computer Science*, vol. 2, no. 6, Aug. 2021, doi: 10.1007/s42979-021-00815-1.

[27] W. S. Gan, "Deep Learning and Artificial Neural Networks," in *Springer eBooks*, 2020, pp. 69–79. doi: 10.1007/978-981-10-5550-8_13.

[28] F. Dashdamirov, A. Aliyev, T. Verdiyev, and U. Javadli, "Improving Intersection Traffic Management Solutions by Means of Simulation: Case Study," in *Studies in fuzziness and soft computing*, 2023, pp. 279–286. doi: 10.1007/978-3-031-23476-7_25.

[29] A. Sukhadia, K. Upadhyay, M. Gundeti, S. Shah, and M. Shah, "Optimization of Smart Traffic Governance System Using Artificial Intelligence," *Augmented Human Research*, vol. 5, no. 1, Mar. 2020, doi: 10.1007/s41133-020-00035-x.

[30] Y. Modi, R. Teli, A. Mehta, K. Shah, and M. Shah, "A comprehensive review on intelligent traffic management using machine learning algorithms," *Innovative Infrastructure Solutions*, vol. 7, no. 1, Dec. 2021, doi: 10.1007/s41062-021-00718-3.

[31] M. Gregurić, M. Vujić, C. Alexopoulos, and M. Miletić, "Application of Deep Reinforcement Learning in Traffic Signal Control: An Overview and Impact of Open Traffic Data," *Applied Sciences*, vol. 10, no. 11, p. 4011, Jun. 2020, doi: 10.3390/app10114011.

[32] S. Saha, "A TRAFFIC MANAGEMENT SYSTEM APPROACH WITH THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE ALGORITHMS," *International Journal of Engineering Applied Sciences and Technology*, vol. 4, no. 6, pp. 1–6, Oct. 2019.

[33] F. Habtemichael and M. Cetin, "Short-term traffic flow rate forecasting based on identifying similar traffic patterns," *Transportation Research Part C: Emerging Technologies*, vol. 66, pp. 61–78, May 2016, doi: 10.1016/j.trc.2015.08.017.

[34] X. Fan *et al.*, "Deep learning for intelligent traffic sensing and prediction: recent advances and future challenges," *CCF Transactions on Pervasive Computing and Interaction*, vol. 2, no. 4, pp. 240–260, Sep. 2020, doi: 10.1007/s42486-020-00039-x.

[35] N. A. M. Razali, N. Shamsaimon, K. K. Ishak, S. Ramli, M. F. M. Amran, and S. Sukardi, "Gap, techniques and evaluation: traffic flow prediction using machine learning and deep learning," *Journal of Big Data*, vol. 8, no. 1, Dec. 2021, doi: 10.1186/s40537-021-00542-7.

[36] H. K. An *et al.*, "Optimized Intersection Signal Timing: An Intelligent Approach-Based Study for Sustainable Models," *Sustainability*, vol. 14, no. 18, p. 11422, Sep. 2022, doi: 10.3390/su141811422.

[37] Z. Ma, T. Cui, W. J. Deng, F. Jiang, and L. Zhang, "Adaptive Optimization of Traffic Signal Timing via Deep Reinforcement Learning," *Journal of Advanced Transportation*, vol. 2021, pp. 1–14, Nov. 2021, doi: 10.1155/2021/6616702.

[38] Y. Modi, R. Teli, A. Mehta, K. Shah, and M. Shah, “A comprehensive review on intelligent traffic management using machine learning algorithms,” *Innovative Infrastructure Solutions*, vol. 7, no. 1, Dec. 2021, doi: 10.1007/s41062-021-00718-3.

[39] Y. Feng, J. Fang, B. Chen, and Y. Shao, “An incremental learning based convolutional neural network model for Large-Scale and Short-Term traffic flow,” *International Journal of Machine Learning and Computing*, vol. 11, no. 2, pp. 143–151, Mar. 2021, doi: 10.18178/ijmlc.2021.11.2.1027.

[40] A. S. Iliyasu, I. Abba, B. S. Iliyasu, and A. S. Muhammad, “A review of deep learning techniques for encrypted traffic Classification,” *Computational Intelligence and Machine Learning*, vol. 3, no. 2, pp. 15–21, Oct. 2022, doi: 10.36647/ciml/03.02.a003.

[41] F. Kong, J. Li, B. Jiang, T. Zhang, and H. Song, “Big data-driven machine learning-enabled traffic flow prediction,” *Transactions on Emerging Telecommunications Technologies*, vol. 30, no. 9, Jul. 2018, doi: 10.1002/ett.3482.

[42] X. Ma, H. Yu, Y. Wang, and Y. Wang, “Large-Scale transportation network congestion evolution prediction using deep learning theory,” *PLOS ONE*, vol. 10, no. 3, p. e0119044, Mar. 2015, doi: 10.1371/journal.pone.0119044.

[43] S. Rajagopal, S. A. Angayarkanni, R. R. Y V., and A. S. Sadiq, “Traffic flow forecasting using natural selection based hybrid Bald Eagle Search—Grey Wolf optimization algorithm,” *PLOS ONE*, vol. 17, no. 9, p. e0275104, Sep. 2022, doi: 10.1371/journal.pone.0275104.

[44] F. U. Islam, G. Liu, W. Liu, and Q. M. U. Haq, “A deep learning-based framework to identify and characterise heterogeneous secure network traffic,” *Iet Information Security*, vol. 17, no. 2, pp. 294–308, Oct. 2022, doi: 10.1049/ise2.12095.

[45] İ. Kılıç and G. Aydın, “Traffic Lights Detection and Recognition with New Benchmark Datasets Using Deep Learning and TensorFlow Object Detection API,” *Traitement Du Signal*, vol. 39, no. 5, pp. 1673–1683, Nov. 2022, doi: 10.18280/ts.390525.

[46] A. A. Alkhatib, K. A. Maria, S. AlZu’bi, and E. A. Maria, “Novel system for road traffic optimisation in large cities,” *IET Smart Cities*, vol. 4, no. 2, pp. 143–155, Jun. 2022, doi: 10.1049/smc2.12032.

[47] Y. Fang, Q. Yang, L. Zheng, X. Zhou, and B. Peng, “A Deep Cycle limit Learning Machine method for urban Expressway traffic incident detection,” *Mathematical Problems in Engineering*, vol. 2020, pp. 1–11, Jul. 2020, doi: 10.1155/2020/5965089.

[48] F. A. Shakil, S. M. Hossain, R. Hossain, and S. Momen, “Prediction of road accidents using data mining techniques,” in *Algorithms for intelligent systems*, 2021, pp. 25–35. doi: 10.1007/978-981-16-4103-9_3.

[49] R. M. AlZoman and M. J. F. Alenazi, “A comparative study of traffic classification techniques for smart city networks,” *Sensors*, vol. 21, no. 14, p. 4677, Jul. 2021, doi: 10.3390/s21144677.

[50] L. Peng, Q. Wang, S.-Q. Zhou, and Z. Tian, “Research on the evolution law of incidental traffic congestion based on CTM,” *Journal of Physics*, vol. 2277, no. 1, p. 012007, Jun. 2022, doi: 10.1088/1742-6596/2277/1/012007.

[51] N. M. Balamurugan, M. Adimoolam, M. H. Alsharif, and P. Uthansakul, “A novel method for improved network traffic prediction using enhanced deep reinforcement learning algorithm,” *Sensors*, vol. 22, no. 13, p. 5006, Jul. 2022, doi: 10.3390/s22135006.

[52] C. Li, C. Dong, K. Niu, and Z. Zhang, “Mobile service traffic classification based on joint deep learning with attention mechanism,” *IEEE Access*, vol. 9, pp. 74729–74738, Jan. 2021, doi: 10.1109/access.2021.3081504.

[53] F. Liu, X. Ma, X. An, and G. Liang, “Urban Traffic Flow Prediction Model with CPSO/SSVM Algorithm under the Edge Computing Framework,” *Wireless Communications and Mobile Computing*, vol. 2020, pp. 1–11, Sep. 2020, doi: 10.1155/2020/8871998.

[54] M. S. B. Othman, S. L. Keoh, and G. Tan, “Efficient journey planning and congestion prediction through deep learning,” *IEEE Xplore*, Nov. 2017, doi: 10.1109/isc2.2017.8090805.

[55] Y. Shi, Z. G. Wang, and Y. Zhong, “Research on Dwell Point Strategy of Compact Intelligent Parking System under Dynamic Demand,” *Journal of Physics*, vol. 2583, no. 1, p. 012005, Sep. 2023, doi: 10.1088/1742-6596/2583/1/012005.

[56] W. Sirikul, N. Buawangpong, R. Sapbamrer, and P. Siviroj, “Mortality-Risk Prediction Model from Road-Traffic Injury in Drunk Drivers: Machine Learning Approach,” *International Journal of Environmental Research and Public Health*, vol. 18, no. 19, p. 10540, Oct. 2021, doi: 10.3390/ijerph181910540.

[57] N. Zafar and I. U. Haq, “Traffic congestion prediction based on Estimated Time of Arrival,” *PLOS ONE*, vol. 15, no. 12, p. e0238200, Dec. 2020, doi: 10.1371/journal.pone.0238200.

[58] J. Gan, L. Li, D. Zhang, Z. Yi, and Q. Xiang, “An alternative method for traffic accident severity prediction: using deep forests algorithm,” *Journal of Advanced Transportation*, vol. 2020, pp. 1–13, Dec. 2020, doi: 10.1155/2020/1257627.

[59] A. H. A. Hussain *et al.*, “Urban Traffic Flow Estimation System based on Gated Recurrent Unit Deep learning Methodology for Internet of Vehicles,” *IEEE Access*, vol. 11, pp. 58516–58531, Jan. 2023, doi: 10.1109/access.2023.3270395.

[60] A. Paul and S. Mitra, “Deep reinforcement learning based cooperative control of traffic signal for multi-intersection network in intelligent transportation system using edge computing,” *Transactions on Emerging Telecommunications Technologies*, vol. 33, no. 11, Jul. 2022, doi: 10.1002/ett.4588.

[61] S. Zhang, Y. Yao, J. Hu, Y. Zhao, S. Li, and J. Hu, “Deep autoencoder neural networks for Short-Term Traffic Congestion prediction of transportation networks,” *Sensors*, vol. 19, no. 10, p. 2229, May 2019, doi: 10.3390/s19102229.

[62] A. Jamal, M. T. Rahman, H. M. Al-Ahmadi, and U. Mansoor, “The dilemma of road safety in the eastern province of Saudi Arabia: Consequences and prevention strategies,” *International Journal of Environmental Research and Public Health*, vol. 17, no. 1, p. 157, Dec. 2019, doi: 10.3390/ijerph17010157.

[63] F. Pérez, G. E. R. Ortiz, E. R. Muñiz, F. J. O. Sacarello, J. E. Kang, and D. Rodríguez-Román, “Predicting trip cancellations and No-Shows in paratransit operations,” *Transportation Research Record*, vol. 2674, no. 8, pp. 774–784, Jun. 2020, doi: 10.1177/0361198120924661.

[64] T. Bandaragoda *et al.*, “Artificial intelligence based commuter behaviour profiling framework using Internet of things for real-time decision-making,” *Neural Computing and Applications*, vol. 32, no. 20, pp. 16057–16071, Feb. 2020, doi: 10.1007/s00521-020-04736-7.

[65] D. Nallaperuma *et al.*, “Online Incremental Machine Learning platform for Big Data-Driven smart traffic management,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 12, pp. 4679–4690, Dec. 2019, doi: 10.1109/tits.2019.2924883.

[66] A. Stathopoulos, L. Dimitriou, and T. Tsekeris, “Fuzzy modeling approach for combined forecasting of urban traffic flow,” *Computer-Aided Civil and Infrastructure Engineering*, vol. 23, no. 7, pp. 521–535, Aug. 2008, doi: 10.1111/j.1467-8667.2008.00558.x.

[67] A. Boukerche, Y. Tao, and P. Sun, “Artificial intelligence-based vehicular traffic flow prediction methods for supporting intelligent transportation systems,” *Computer Networks*, vol. 182, p. 107484, Dec. 2020, doi: 10.1016/j.comnet.2020.107484.

[68] S. S. Kolekar, S. Gite, B. Pradhan, and K. Kotecha, “Behavior Prediction of traffic actors for intelligent vehicle using Artificial Intelligence Techniques: a review,” *IEEE Access*, vol. 9, pp. 135034–135058, Jan. 2021, doi: 10.1109/access.2021.3116303.

[69] I. O. Olayode, L. K. Tartibu, M. O. Okwu, and A. Severino, “Comparative traffic flow prediction of a heuristic ANN model and a hybrid ANN-PSO model in the traffic flow modelling of vehicles at a Four-Way signalized road intersection,” *Sustainability*, vol. 13, no. 19, p. 10704, Sep. 2021, doi: 10.3390/su131910704.

[70] S. C. S. Chen, H. W. S. Chen, and J. W. H. Wen, “Artificial intelligence based traffic control for edge computing assisted vehicle networks,” *Journal of Internet Technology*, vol. 23, no. 5, pp. 989–996, Sep. 2022, doi: 10.53106/160792642022092305007.

[71] X. Yang, Z. Pu, and L. Zhang, “Designing data visualization using artificial intelligence for urban intelligent transportation scenarios,” *Mobile Information Systems*, vol. 2022, pp. 1–11, Aug. 2022, doi: 10.1155/2022/3967267.

[72] A. Ata, M. A. Khan, S. Abbas, G. Ahmad, and A. Fatima, “MODELLING SMART ROAD TRAFFIC CONGESTION CONTROL SYSTEM USING MACHINE LEARNING TECHNIQUES,” *Neural Network World*, vol. 29, no. 2, pp. 99–110, Jan. 2019, doi: 10.14311/nnw.2019.29.008.

[73] Z. Li and D. Li, “Data visualization and interaction of Urban Traffic Logistics Management System using WebGIS,” *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–12, Jun. 2022, doi: 10.1155/2022/9347247.

[74] A. Srivastava, Aryan, and M. Khurana, “A survey paper on traffic Prediction using Machine learning,” *International Journal for Research in Applied Science and Engineering Technology*, vol. 11, no. 5, pp. 44–48, May 2023, doi: 10.22214/ijraset.2023.51390.

[75] M. E. C. Bağdatlı and A. Ş. Dokuz, “Vehicle delay estimation at signalized intersections using machine learning algorithms,” *Transportation Research Record*, vol. 2675, no. 9, pp. 110–126, Aug. 2021, doi: 10.1177/03611981211036874.

[76] P. M. Kumar, U. D. G, G. Manogaran, R. Sundarasekar, N. Chilamkurti, and R. Varatharajan, “Ant colony optimization algorithm with Internet of Vehicles for intelligent traffic control system,” *Computer Networks*, vol. 144, pp. 154–162, Oct. 2018, doi: 10.1016/j.comnet.2018.07.001.

[77] A. Stathopoulos, M. G. Karlaftis, and L. Dimitriou, “Fuzzy Rule-Based System approach to combining traffic count forecasts,” *Transportation Research Record*, vol. 2183, no. 1, pp. 120–128, Jan. 2010, doi: 10.3141/2183-13.

[78] W. Xu, Z. Dong, S. Wu, and N. Hao, “A Control Method of Traffic flow Based on Region Coordination,” *Advances in Intelligent Systems Research*, Jan. 2015, doi: 10.2991/meici-15.2015.257.

[79] P. Chhatpar, N. Doolani, S. Shahani, and Priya, “Machine Learning Solutions to Vehicular Traffic Congestion,” *IEEE Xplore*, Nov. 2018, doi: 10.1109/ICSCET.2018.8537260.

[80] M. Babar, M. H. Roos, and P. H. Nguyen, “Machine Learning for Agile and Self-Adaptive Congestion Management in Active Distribution Networks,” *IEEE Xplore*, Aug. 2019, doi: 10.1109/eeeic.2019.8783624.

[81] S. Khatri *et al.*, “Machine learning models and techniques for VANET based traffic management: Implementation issues and challenges,” *Peer-to-Peer Networking and Applications*, vol. 14, no. 3, pp. 1778–1805, Sep. 2020, doi: 10.1007/s12083-020-00993-4.

[82] E. Mangortey, M.-H. Bleu-Laine, T. G. Puranik, O. Fischer, and D. N. Mavris, “Machine learning approach to the analysis of traffic management initiatives,” *Journal of Air Transportation*, vol. 29, no. 2, pp. 56–68, Apr. 2021, doi: 10.2514/1.d0212.

[83] S. J. Kamble and M. R. Kounte, “Machine Learning Approach on Traffic Congestion Monitoring System in Internet of Vehicles,” *Procedia Computer Science*, vol. 171, pp. 2235–2241, Jan. 2020, doi: 10.1016/j.procs.2020.04.241.

[84] F. Baker, “The technology that could end traffic jams,” *BBC Future*, Dec. 12, 2018. Accessed: Dec. 02, 2023. [Online]. Available: https://www.bbc.com/future/article/20181212-can-artificial-intelligence-end-traffic-jams

[85] B. R. Sharma, S. Kumar, P. Tiwari, P. Yadav, and M. I. Nezhurina, “ANN based short-term traffic flow forecasting in undivided two lane highway,” *Journal of Big Data*, vol. 5, no. 1, Dec. 2018, doi: 10.1186/s40537-018-0157-0.

[86] E. I. Vlahogianni, J. Del Ser, K. Κεπαπτσόγλου, and I. Laña, “Model Free Identification of Traffic Conditions Using Unmanned Aerial Vehicles and Deep Learning,” *Journal of Big Data Analytics in Transportation*, vol. 3, no. 1, pp. 1–13, Mar. 2021, doi: 10.1007/s42421-021-00038-z.

[87] M. Kiran and A. Verma, “Review of Studies on Mixed Traffic Flow: Perspective of Developing Economies,” *Transportation in Developing Economies*, vol. 2, no. 1, Feb. 2016, doi: 10.1007/s40890-016-0010-0.

[88] G. Asaithambi, V. Kanagaraj, and T. Toledo, “Driving Behaviors: Models and Challenges for Non-Lane Based Mixed Traffic,” *Transportation in Developing Economies*, vol. 2, no. 2, Aug. 2016, doi: 10.1007/s40890-016-0025-6.

[89] J. Guo, W. Huang, and B. M. Williams, “Adaptive Kalman filter approach for stochastic short-term traffic flow rate prediction and uncertainty quantification,” *Transportation Research Part C: Emerging Technologies*, vol. 43, pp. 50–64, Jun. 2014, doi: 10.1016/j.trc.2014.02.006.

[90] M. Nama *et al.*, “Machine learning-based traffic scheduling techniques for intelligent transportation system: Opportunities and challenges,” *International Journal of Communication Systems*, vol. 34, no. 9, Apr. 2021, doi: 10.1002/dac.4814.

[91] M. A. Khamis and W. Gomaa, “Adaptive multi-objective reinforcement learning with hybrid exploration for traffic signal control based on cooperative multi-agent framework,” *Engineering*

Applications of Artificial Intelligence, vol. 29, pp. 134–151, Mar. 2014, doi: 10.1016/j.engappai.2014.01.007.

[92] A. E. Sallab, M. Abdou, E. Pérot, and S. Yogamani, "Deep Reinforcement Learning framework for Autonomous Driving," *IS&T International Symposium on Electronic Imaging Science and Technology*, vol. 29, no. 19, pp. 70–76, Jan. 2017, doi: 10.2352/issn.2470-1173.2017.19.avm-023.

[93] R. Boutaba *et al.*, "A comprehensive survey on machine learning for networking: evolution, applications and research opportunities," *Journal of Internet Services and Applications*, vol. 9, no. 1, Jun. 2018, doi: 10.1186/s13174-018-0087-2.

[94] S. Madjiheurem and L. Toni, "Representation Learning on Graphs: A Reinforcement Learning Application," *Proceedings of Machine Learning Research (PMLR)*, 2019. https://proceedings.mlr.press/v89/madjiheurem19a.html (accessed Dec. 02, 2023).

[95] Z. Li, C. Xu, and G. Zhang, "A Deep Reinforcement Learning Approach for Traffic Signal Control Optimization," *arXiv.org*, Jul. 13, 2021. https://arxiv.org/abs/2107.06115 (accessed Dec. 02, 2023).

[96] A. A. Rahi, "Machine Learning Approaches for Traffic Flow Forecasting," Oct. 23, 2019. https://uhra.herts.ac.uk/handle/2299/22590

[97] W. Alajali, W. Zhou, S. Wen, and Y. Wang, "Intersection Traffic Prediction Using Decision Tree Models," *Symmetry*, vol. 10, no. 9, p. 386, Sep. 2018, doi: 10.3390/sym10090386.

[98] O. Günlük, J. Kalagnanam, M. Li, M. Menickelly, and K. Scheinberg, "Optimal decision trees for categorical data via integer programming," *Journal of Global Optimization*, vol. 81, no. 1, pp. 233–260, Mar. 2021, doi: 10.1007/s10898-021-01009-y.

[99] S. George and A. K. Santra, "Traffic Prediction Using Multifaceted Techniques: A Survey," *Wireless Personal Communications*, vol. 115, no. 2, pp. 1047–1106, Jul. 2020, doi: 10.1007/s11277-020-07612-8.

[100] J. Dai, Y. Chen, Y. Chen, and A. Meng, "An analysis of Network Traffic Identification based on Decision Tree," *IEEE Conference Publication | IEEE Xplore*, Sep. 02, 2021. https://ieeexplore.ieee.org/document/9525567 (accessed Dec. 03, 2023).

[101] A. Louati, H. Louati, and Z. Li, "Deep learning and case-based reasoning for predictive and adaptive traffic emergency management," *The Journal of Supercomputing*, vol. 77, no. 5, pp. 4389–4418, Oct. 2020, doi: 10.1007/s11227-020-03435-3.

[102] V. Varghese, M. Chikaraishi, and J. Urata, "Deep Learning in Transport Studies: A Meta-analysis on the Prediction Accuracy," *Journal of Big Data Analytics in Transportation*, vol. 2, no. 3, pp. 199–220,

Dec. 2020, doi: 10.1007/s42421-020-00030-z.

[103] U. Jilani, M. Asif, M. Y. I. Zia, M. Rashid, S. Shams, and P. Otero, “A Systematic Review on Urban Road Traffic Congestion,” *Wireless Personal Communications*, Aug. 2023, doi: 10.1007/s11277-023-10700-0.

[104] S. P. Singh, A. A. Khan, R. Souissi, and S. A. Yusuf, “Leveraging Neo4j and deep learning for traffic congestion simulation & optimization,” *arXiv (Cornell University)*, Mar. 2023, doi: 10.48550/arxiv.2304.00192.

[105] N. Petrovska, A. Stevanovic, and B. Furht, “Innovative Web Applications for Analyzing Traffic Operations,” *SpringerLink*, 2016, doi: 10.1007/978-3-319-33319-9.