A MODEL FOR PREDICTING TRAFFIC CONGESTION USING DEEP LEARNING ALGORITHM: CASE OF NAIROBI METROPOLITAN

BY

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MASTER OF SCIENCE IN DATA COMMUNICATIONS

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NOVEMBER, 2023

DECLARATION

I declare that dissertation is my original work, entirely unique and has not been published or applied for a degree anywhere. I also declare that this does not include any content authored or published by others, except for instances where appropriate citation is provided and the author is properly recognized.

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EZRA KIPCHIRCHIR CHERUIYOT

Student Name

I do herby confirm that this masters dissertation has been examined for

EZRA KIPCHIRCHIR CHERUIYOT

And have certified that all revisions that the dissertation panel and examiners recommended have been adequately addressed.

SIGN……………………………………..DATE……22/10/2023……..…………..

DR. STEPHEN NJENGA

Dissertation Supervisor

ABSTRACT

Traffic congestion is a widespread problem that plagues urban transportation systems, causing delays, increased fuel consumption, and environmental pollution. Addressing this issue requires accurate prediction of traffic congestion, enabling proactive management strategies and real-time information dissemination. Deep learning algorithms have emerged as powerful tools for traffic prediction, offering the potential to forecast congestion patterns effectively. The development of a model for predicting traffic congestion that is capable of accurately detecting and reducing the overall density of traffic in most urban areas frequented by motorists, such as offices, downtown, and establishments, has become one of the main challenges for engineers and designers in recent years. Traffic prediction models in use today are based on several modern technologies, including wireless sensor networks and surveillance cameras. In Kenya, the Nairobi Metropolitan Area has greatly felt the impacts of traffic congestion due to ever growing urban population. This is primarily because the number of vehicles has rapidly increased as compared to the infrastructure growth. This study presented a platform for addressing the traffic congestion through the establishment of Intelligent Traffic Management model using Deep Learning Algorithm. The study utilized observation checklist and questionnaire as the source of data for the study. An observation data collection sheet was used in collecting the data from the four main roads. To obtain data from the traffic officers, questionnaires was used. SPSS version 28 were used to analyze the data. Further from the correlation analysis, all the variables including High cost of travel/fares (r=.494), High vehicle maintenance (r=.206), Environmental pollution (r=.359), Staff fatigue (drivers and conductors) (r=.488), Accidents (r=.310), Poor road design (r=.308), Poor Traffic control system (r=.410), Road construction and maintenance works (r=.353),Vehicle break downs (r=.179), Roadside parking/obstruction (r=.452), High number of private cars (r=.233), High number of public transport vehicles (r=.071), Behavior of road usage (r=.228) Accidents (r=-.042), Poor road use (r=-.042) and Poor traffic management (r=-.209) had positive correlation with traffic congestion in Nairobi Metropolitan Area. Regression analysis further found that poor traffic management by traffic officers, a high number of public transport vehicles, poor road design, accidents, a high number of private cars, poor road use, poor traffic control systems, driver behavior, vehicle breakdowns, road construction and maintenance, and roadside parking explained up to 34.4% of the variation in travel time. In comparison, factors such as driver behavior, roundabout type, time of day, number of lanes, vehicle type, weather conditions, and travel rate explained 13.7% of the variation in road travel rates. Therefore, improved infrastructure, traffic management practices, and enhanced driver behavior are concluded to reduce travel time and improve transportation efficiency in the region. The study recommends that traffic engineering and urban planning practices should prioritize the optimization of road networks. The study recommends that local authorities and law enforcement agencies should collaborate to enforce traffic rules and regulations rigorously. The study also recommends that implementation of robust traffic management strategy by improving traffic signal synchronization, implementing intelligent traffic management systems, and investing in technology-driven solutions like real-time traffic monitoring and congestion alerts. Adequate and efficient traffic management by officers should also be ensured, as this factor has been found to play a substantial role in congestion mitigation. Additionally, policymakers should consider congestion pricing mechanisms during peak hours. This will incentivize drivers to use alternative routes or modes of transportation, thus reducing traffic congestion during high-demand periods. Revenues generated from congestion pricing can be reinvested in transportation infrastructure and improvements.

Key Words: Deep Learning Models, Traffic Congestion, Traffic Prediction Models

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ACRONYMS AND ABBREVIATIONS

ATC	:	Advanced Transportation Controller
ITMS	:	Intelligence Traffic Management System
NTCIP	:	National Transportation Communications for ITS Protocol
RCS	:	Rail Control System

TERMS AND DEFINITIONS

Deep Learning Models: Powerful models and intelligent tools capable of learning by using deep learning algorithms (Haq, 2020).

Road infrastructure is referred to as a kind of land transportation infrastructure that includes all elements of a road, as well as any auxiliary structures and tools used by traffic (Jammula et al., 2018).

Validity is the extent to which a data collection tool can collect and reflect the data it is intended to measure (Bridget and Lewin 2011).

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

The world population is increasing at an accelerating rate causing increase in number of vehicles on the road, traffic congestion and increased in cost of traffic congestion (Haq, 2020). Increase in vehicle traffic, transport infrastructure demand for better mobility systems has led to development of modern transportation accessible by all people. This increase in demand calls for better systematic transportation infrastructure that can carry a large mass of vehicles safely and ensures that it is environmentally friendly (Gregory, 2021). Numerous societies and companies around the globe strive to develop a model for predicting traffic congestion. The first establishment was set in 1991 by America, along with many prototypes proposed for implementation (Mallik, 2014).

Car to car communication, carriage to infrastructure interaction, and electronic charges are among the popular transportation models in operation globally. Even with adoption in information communication technology, adoption of intelligent models for traffic prediction remains low. In India for example, intelligent Traffic Management Model is at a primary phase in growth (Mallik, 2014). This is despite the fact that every nation in the world, including Kenya, requiring to implement intelligent technologies to ensure that the transportation system is safe, economical, and environmentally friendly.

Traffic congestion is a widespread problem that plagues urban transportation systems, causing delays, increased fuel consumption, and environmental pollution. Addressing this issue requires accurate prediction of traffic congestion, enabling proactive management strategies and real-time information dissemination.

1.1.1 Deep Learning Models

Deep learning algorithms have emerged as powerful tools for traffic prediction, offering the potential to forecast congestion patterns effectively (Haq, 2020). The development of a model for predicting traffic congestion that is capable of accurately detecting and reducing the overall density of traffic in most urban areas frequented by motorists, such as offices, downtown, and establishments, has become one of the main challenges for engineers and designers in recent years. Traffic prediction models in use today are based on several modern technologies, including wireless sensor networks (WSNs), surveillance cameras, and IoT (Gregory, 2021).

In Africa, in attempt to mitigate traffic congestions, countries have been investing heavily in expanding roads and interchange in urban areas. Whereas this has been an expensive affair, the traffic problem remains in many cities across Africa. There is also heavy reliance on time-based traffic lights at interchanges and police men come in to manage the inefficiencies of time-based traffic management models. In Kenya, even with advancement in technology, there remains to be no intelligent traffic management model. Most of the artificial intelligence models have also been relying on secondary data and offers no room for learning (Akhtar & Moridpour, 2021).

Several studies have explored the prediction of traffic congestion using deep learning algorithms. Zhang *et al.* (2016) introduced PredCNN, a convolutional neural network (CNN) model, for traffic flow prediction. They utilized historical traffic flow data along with time, day of the week, and weather conditions to forecast congestion. Their model outperformed traditional methods, exhibiting superior prediction accuracy. Ma *et al*. (2017) proposed DST-ResNet, a deep spatio-temporal residual network, for traffic flow prediction. Their model captured both spatial and temporal dependencies in traffic patterns by incorporating historical traffic flow data and other relevant information. Experimental results demonstrated the effectiveness of their approach in predicting traffic congestion. Liang *et al*. (2018) presented

ST-ResNet, a recurrent neural network (RNN) model, for short-term traffic flow prediction. The model leveraged spatio-temporal correlations and extracted long-term dependencies in traffic patterns. By incorporating historical traffic data and meteorological information, their model achieved accurate predictions of traffic congestion.

An Artificial Intelligence model for anticipating traffic congestion thus offers practical and efficient solutions to the management and decision-making issues associated with managing the flow of traffic, which helps to lower fuel consumption, lower greenhouse gas emissions, and raise the bar for sustainable living (Akhtar & Moridpour, 2021). A better, safer traveling experience will be made possible through the integration of ICT with the transportation infrastructure, as well as the transition to a traffic management model that focuses on four key principles: sustainability, integration, safety, and responsiveness (Tahifa, Boumhidi & Yahyaouy, 2018).

Lv *et al*. (2015) proposed a deep belief network (DBN) model for traffic flow prediction. While the research explored the potential of deep learning in predicting traffic congestion, a major limitation is the lack of comparison with other state-of-the-art deep learning models or traditional methods. Without such comparisons, it is challenging to determine the model's effectiveness and whether it outperforms existing approaches. Additionally, the study did not extensively discuss the interpretability of the DBN model, which is crucial for practical implementation and understanding the factors influencing traffic congestion.

Chen *et al*. (2018) presented a study on traffic flow prediction using a hybrid deep learning model that combined long short-term memory (LSTM) and convolutional neural network (CNN). While the research demonstrated improved prediction accuracy, one limitation lies in the absence of a comprehensive evaluation of the model's performance on different traffic conditions and road networks. Furthermore, the study did not thoroughly investigate the computational efficiency of the hybrid model, which could be essential for real-time deployment in large-scale traffic systems. Zheng *et al*. (2020) proposed a deep spatio-temporal graph convolutional neural network (STGCN) for traffic flow prediction. The model incorporated both spatial and temporal dependencies in traffic data through graph convolutions. While the research demonstrated promising results, one limitation is the lack of extensive analysis on the interpretability of the model. Additionally, a comparative evaluation against other deep learning models or traditional methods would further establish the model's performance and effectiveness.

Li *et al*. (2019) presented a study on traffic congestion prediction using a multi-view multi-task deep learning model. The model integrated information from various sources, such as traffic flow, road network, and meteorological data, to forecast congestion patterns. While the research addressed the need for incorporating multiple views, a limitation is the absence of a comprehensive evaluation on the impact of different data sources on the prediction accuracy. Analyzing the individual and combined contributions of each data view would help identify the most influential factors and guide future data collection efforts. Additionally, considering the scalability and computational efficiency of the multi-view model would be beneficial for real-world deployment. By building upon these works and further refining the models, the study aims to improve the accuracy and timeliness of traffic congestion predictions, leading to more efficient traffic management and reduced congestion-related issues. This research aimed to provide additional light on the platform utilized to access, gather, and interpret reliable data from the environment since it is crucial to the model's performance.

1.2 Problem Statement

Traffic congestion is a common problem for the infrastructure sector, especially in Nairobi, according to research by the Nairobi Metropolitan Area Transport Authority, which estimated that lost productivity from traffic jams may cost Kenya about $1 billion annually. This is a result of the absence of both a sophisticated non-motorized transportation network and a regularly scheduled public transportation system. In the Nairobi Metropolitan region, traffic congestion has become worse over a number of decades. Nairobi was recognized as the fourth-most crowded city in the world by the Narobi Metropolitan Area Transport Authority (Ombok, 2019). The motorization of society and the widespread use of the vehicle, which has raised the need for transportation infrastructure, are especially linked to congestion. But the availability of transportation infrastructure has often lagged behind the expansion of mobility.

Traffic congestion may be predicted using three different types of machine learning algorithms: supervised learning, unsupervised learning, and reinforcement learning (Tahifa *et al*., 2018). Traffic jams have a negative influence on vehicle motorization and dispersion, which raises the need for transportation infrastructure (Iqbal & Yukimatsu 2011). However, predicting traffic congestion using deep learning algorithms is a challenging problem with significant implications for urban transportation management. Through the use of historical traffic data, weather conditions, and other relevant factors, deep learning models can accurately forecast traffic congestion patterns. Previous studies, have demonstrated the effectiveness of deep learning algorithms in traffic prediction (Tahifa, Boumhidi & Yahyaouy, 2018; Lv *et al*., 2015; Zheng *et al*., 2020).

Particularly, an effort to ease traffic, the Nairobi Metropolitan Area Authority and the Nairobi County Government decongested bus terminals further from the city center, although this did not make the situation better. Reliance on time-based traffic lights and traffic police officers has also been faced with inefficiencies in reducing traffic congestion. There is no intelligent traffic prediction model in place. One of the most important stages in the operation of an Intelligent Transportation System (ITS) is the ability of practitioners to carry out route planning and traffic control. Large volumes of data may be used to analyze issues relating to traffic congestion utilizing machine learning and deep learning methods, which are currently being actively used in other industries. Despite these benefits, the use of such approaches in the area of traffic management is not in place necessitating the necessity for this research.

1.3 Main Objective

To propose a model for predicting traffic congestion within the Nairobi Metropolitan area using deep learning algorithm through deep neural network (DNN).

1.4 Specific Objectives

i. To investigate the critical factors affecting traffic congestion in Nairobi Metropolitan Area.

ii. To develop a model for predicting traffic congestion management within the Nairobi Metropolitan area using deep learning algorithm.

iii. To validate the traffic congestion management model designed for managing traffic within the Nairobi Metropolitan area.

1.5 Research questions

i. What are the critical factors affecting traffic congestion in Nairobi Metropolitan Area.

ii. What intelligent traffic model can be developed for traffic congestion management within the Nairobi Metropolitan area?

iii. How valid is the traffic congestion management model developed in managing traffic congestion management within the Nairobi Metropolitan area?

1.6 Significance of the Study

i. Improving the safety, convenience and productivity of personnel and the already available infrastructure.

ii. Reduction of congestion and enhancing mobility while minimizing environmental impacts resulting from harmful emissions.

iii. It will save on cost occasioned by fuel wastage and travel time thus spurring the economic growth.

1.7 Motivation of study

One of the most crucial factors affecting transportation and urban mobility is transit time. Any delays in moving people and things from one place to another have a cost associated with them, including lost production and increased fuel use. All stakeholders may make educated choices that result in increased efficiency, increased production, and a higher quality of life by receiving accurate trip time information. One of these problems is predicting travel times, which makes it the ideal use case for illustrating how machine learning may be used to solve issues. Statistical techniques are used in current traffic analysis techniques. However, since they are supposing a linear model, these statistical techniques do not take into account a range of influencing elements.

1.8 Scope of Study

The study focused on Nairobi, parts of Kiambu, Machakos and Kajiado counties that fall under the Nairobi Metropolitan Area. The data was collected using questionnaire surveys and analyzed using descriptive and inferential analysis.

1.9 Contribution of the Study

Traffic congestion in Nairobi Metropolitan area is a big problem to the county governments and national governments. A lot of resources go to waste every day from the traffic congestion in the metropolitan area. The government has also been investing massively in improving road designs in line with reducing traffic congestions. Large number of police officers must be deployed everyday morning and evening to assist in traffic control; a function that can be automated. This study will contribute to offering a solution and insights on resolution of this problem. In Kenya, technology has been accepted as possible solutions to the problems facing Kenyan although there lacks enough empirical literature on possible solution to the traffic menace. This study will contribute to existing literature and give clear direction to future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this chapter, a review of the past studies related to this topic will be presented. It will also cover the theoretical and empirical literature review that is to subject under study. The review will be based on the above listed research objectives. This study will identify specific zones in which all possible (or reasonable) traffic routes are located within the Nairobi Metropolitan Area.

2.2 Traffic Assignment Models

Traffic assignment is the process of assigning a collection of origin-destination pairs to an appropriate road network that already exists based on a set of criteria for traveler route selection. The least amount of trip impedance on the transportation network is required for a certain origin-destination pair. Therefore, the planner should concentrate on the optimum approach rather than the quickest path. The most efficient routes are those with the shortest travel distances or costs as well as the greatest levels of safety and dependability. The two major kinds of traffic assignment techniques are static traffic assignment methods and dynamic traffic assignment methods (Saw, *et al*., 2015).

2.2.1 Static Assignment Models

The element of the transportation planning process that determines the volume of traffic on the road network is called static traffic assignment. Static assignment models distribute OD (origin-destination) flows along routes in the network for an analysis period under the assumption that each connection has a volume-delay function. The cheapest route, which is determined by combining trip time and cost, is assumed to be used by the drivers. Static models used to depict travel time reveal a well-defined connection between volume (demand for trips over the road link) and travel time on the link (i.e., a separable volume-delay function). Travel time for a given demand is reliant on the volume on other connections and at the time before to the study period, making the existence of such a separable relationship in real-world scenarios with congestion improbable (Leeuwen, 2011).

As a consequence, it is deceptive to estimate transit time in these situations using separable volume-delay functions. The change in travel times due to changes in travel demand will typically be underestimated in a static model because the positive and non-linear (convex) relationships to other links and periods are not taken into account, even if the volume-delay functions and demand matrices can be calibrated to produce plausible traffic volumes and travel times in a baseline situation (Saw, *et al*., 2015). Static assignment continues to be the primary technique for strategic transportation planning because to its simplicity and computation efficiency even if the emphasis of traffic assignment research is turning to dynamic assignment. Additionally, it is quick and can manage extremely big networks (Michiel *et al*. 2013).

Some of the traffic assignment models used in transportation planning and management are All or Nothing Assignment, Stochastic Traffic Assignment, Capacity Restrained Assignment, Incremental Assignment, User Equilibrium Assignment, and System Optimum Assignment. On the other hand, the assignment approach has a severe flaw in that the network is not well represented. While forbidden turning movements are not mentioned in the networks and inter-zonal trips are disregarded in the assignment, the end consequences emerge from the grouping of trip endpoints into zones represented by single centroids. Another presumption is that all network components have accurate cost data. Although it is fundamentally unrealistic, this is true of all models.

2.2.2 Dynamic Traffic Assignment Models

The transportation network's time-varying traffic flows are created using dynamic assignment techniques to demonstrate how congestion levels alter over time. They put both transportation planning and traffic management at the forefront. True dynamic traffic assignment (DTA) models, on the other hand, are able to represent the spatiotemporal dynamics of individual cars, bundles of vehicles, or vehicle flows. This corresponds to a spatial model resolution of vehicle lengths and a temporal model resolution of seconds. Traffic predictions from DTA are used to show the evolution of congestion levels and are crucial for managing and controlling traffic.

Advanced traveler information systems (ATIS), advanced traffic management systems (ATMS), telecommunications, computer science, and emergency planning have all seen significant growth in attention from DTA during the last 10 years (Ann *et al*. 2013). Dynamic traffic assignment (DTA) characteristics have significantly improved transportation planning and operations on a theoretical and computational level. These features are significantly influenced by the two DTA components, the traffic-flow component and the trip choice principle. The two kinds of DTA models that are accessible are analytical based models and simulation based models (Peeta and Zilaskopoulous, 2001).

Analytical-based models are those that are based on analytical formulations, such as mathematical programming, variational inequalities, and optimal control theory. The majority of analytical formulations are extensions of their counterparts, and they seem to have two fundamental flaws: they are rigid for networks of practical size, and they cannot accurately describe the reality of street networks owing to implications (Zilaskpoulous *et al*. 2004). The employment of link performance and/or link exist functions, as well as traffic holding-back at an intersection's minor approach in favor of the main approach, are problems with generic mathematical programming DTA formulations.

On the other hand, simulation offers a useful tool for simulating complex dynamic events, avoiding the difficulties associated with employing analytical mathematical formulations (Mitaskis *et al*., 2011). Traffic flow simulation modeling may be divided into three categories: microscopic, mecroscopic (which sits in between micro and macro), and macroscopic. In macroscopic simulation modeling, the deterministic correlations between the flow, speed, and density of the traffic stream are applied. In a macroscopic model, the traffic stream is taken into account section by section rather than taking into account or tracking individual automobiles. Initially, macroscopic simulation models were created to simulate traffic on a variety of transportation sub-networks, including freeways, corridors (which include freeways and parallel arterials), surface-street grid networks, and rural roads (Saw, *et al*., 2015).

Micro-scopic simulation models simulate the motion of individual cars based on car-following and lane-changing theories (Kerner, 2009). These models are helpful for assessing the system-level effects of proposed transportation upgrades that are beyond the scope of existing tools, complicated geometric designs, and highly crowded circumstances. On the other side, these models need a lot of time, money, and effort to calibrate. A microscopic model combines the characteristics of both microscopic and macroscopic simulation models. As a consequence, a mecroscopic model outperforms conventional planning analysis methods even if it lacks the realism of micro-simulation tools.

2.3 Traffic Congestion Prediction Model

The use of information technology in transportation planning is characterized as achieving more safety and mobility while reducing the environmental consequences of transportation. The model's primary goal is to establish a national multi-modal transportation infrastructure that can link the environment around all types of vehicles, the system, and employ passenger gadgets to advance the common good (Mallik, 2014). The method makes use of contemporary technologies to enhance mobility, road safety, and environmental concern.

Incorporation of new technologies caters for all forms of transportation and accounts for all components of the infrastructure, that is, the driver, client, car, mode of transportation, and connecting these facets dynamically. The function of the Traffic Congestion Prediction Model is to enhance decision-making in real time using the transport system (Mallik, 2014). Therefore, the definition of model incorporates a broad collection of methodologies and strategies accomplished through technological applications or improvements to further transportation strategies. Moreover, the model provides integration of different other models, and it is only through this collaboration the traffic congestion prediction model will operate to its potential.

Furthermore, model comprises a range of data depending on the necessity of the implementation approach and simultaneously combining these components to acquire an excellent information structure. It will also integrate environment data for traffic planning, control, and managing to boost the effectiveness of the transportation system (Iqbal & Yukimatsu, 2011). In essence, traffic congestion prediction model depends on various technologies and operations like connecting modes of communication with Bluetooth and the internet, geographical sites and data systems (Mallik, 2014). It also involves using modern applications such as camera systems, information acquisition and exchange, and digital mapping for detection and categorization.

According to Akhtar and Moridpour, (2021) traffic congestion model as illustrated in figure 2.1 has two basic steps of data collection and prediction model development. Every step of the methodology is important and may affect the results if not done correctly. After data collection, data processing plays a vital role to prepare the training and testing datasets. Case area differs for different research. After developing the model, it is validated with other base models and ground true results.

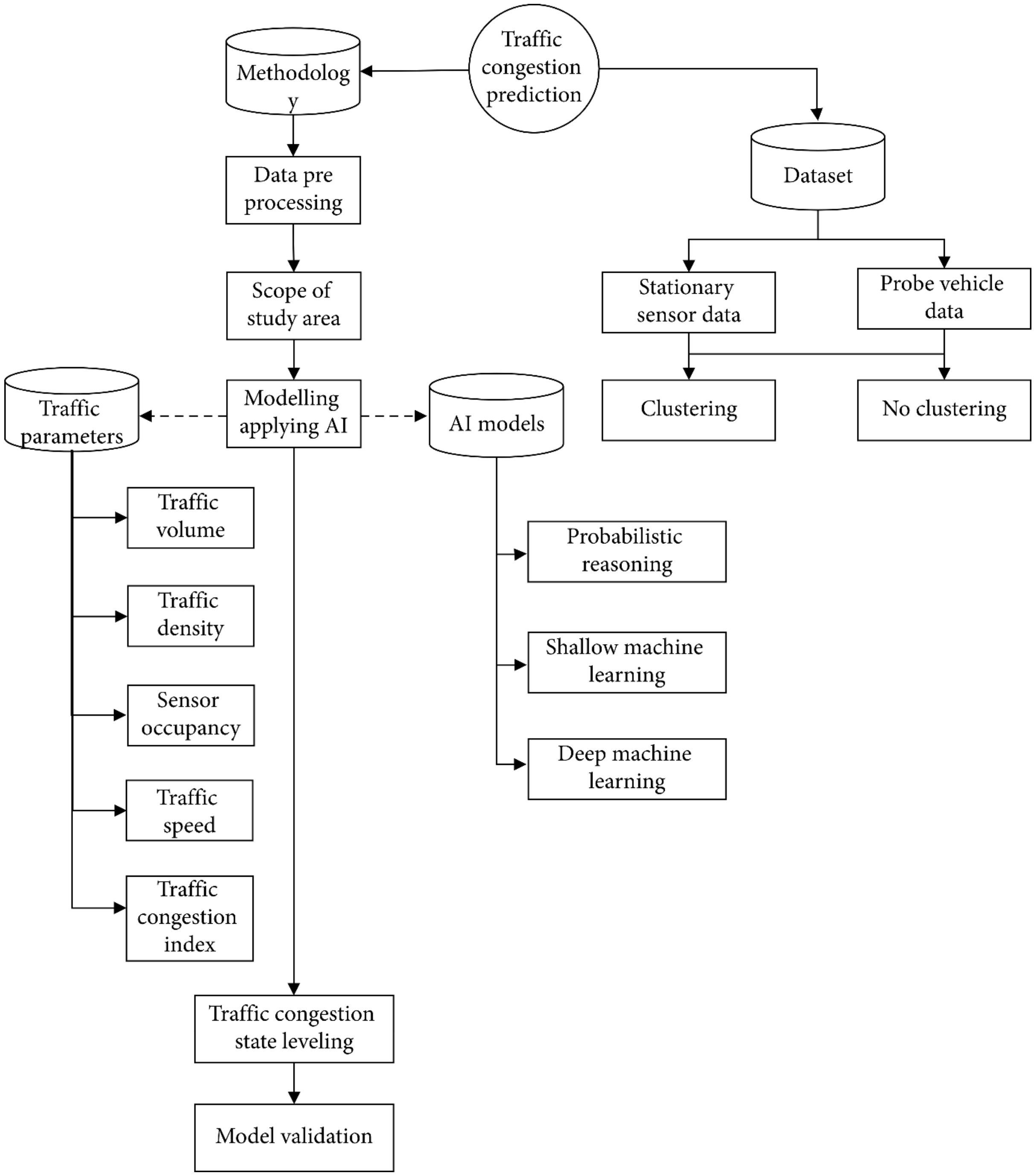

FIGURE 2. 1

Types of Sensors

Source: Akhtar and Moridpour, (2021)

2.3.1 Components of Traffic Congestion Prediction Model

The center of transportation administration is a traffic management center (TMC), where data is gathered, evaluated, and coupled with other operational and control ideas to manage the intricate transportation network. It serves as the main hub for informing the public and media about traffic issues, and it serves as a location for agencies to coordinate their reactions to traffic-related problems and conditions. Through a network of traffic operations centers, many agencies share management of the transportation infrastructure. In order to accomplish the objectives of traffic management, the centers typically employ alternative criteria and distribute data and information locally.

The following elements have a crucial role in how well the TMC functions and, therefore, how well the Traffic Congestion Prediction Model functions:

- Automated data collection and quick data transmission to traffic management facilities.
- Accurate data analysis at management centers.
- Reliable travel and public information.

Data Acquisition

Real-time monitoring and strategic planning depend on swift, thorough, and accurate data collecting and exchange. An effective data gathering, management, and communication system combines tried-and-true hardware with effective software that can gather trustworthy data on which to base subsequent Traffic Congestion Prediction Model operations. Sensors, cameras, automated vehicle IDs, GPS-based automatic vehicle locators (AVL), and servers with large data storage capacities are among the several types of hardware that are often utilized. The following are some of the crucial elements:

a. Sensors

The implementation of a wireless sensor network (WSN) in the streets leading up to a junction is a component of traffic congestion prediction models. These nodes are ground-based magnetic sensors placed at each junction of pathways. The employed sensor nodes are hybrid sensors (presence sensor+RFID readers), which allow for both the detection of cars' presence and the identification of such vehicles using the registration information contained in their RFID tags. The system alerts the parking attendant to input the registration number of the vehicle parked in the system if hybrid sensors detect the presence of a vehicle without an RFID tag.

These sensors come together to create a network architecture resembling a cluster, in which each node detects the presence of cars and transmits the information to the closest head cluster in order to reach the base station. Figure 2.3 illustrates how sensors may be divided into two groups depending on where they are: invasive and non-intrusive. The base station uses the WSN data to run an algorithm that determines the rate of traffic congestion in each lane and controls the traffic lights at the junction of the road dynamically.

Category	Sensor Type	Application and Use
Intrusive	Pneumatic road tube.	Used for keeping track of the number of vehicles, vehicle classification and vehicle count.
	Inductive Loop Detector (ILD).	Used for detection vehicle's movement, presence, count and occupancy. The signals generated are recorded in a device at the roadside.
	Magnetic sensors.	Used for detection of presence of vehicle, identifying stopped and moving vehicles.
	Piezoelectric.	Classification of vehicles, count vehicles and measuring vehicle's weight and speed.
Non-intrusive	Video cameras.	Detection of vehicles across several lanes and can classify vehicles by their length and report vehicle presence, flow rate, occupancy, and speed for each class.
	Radar sensors.	Vehicular volume and speed measurement, detection of direction of motion of vehicle and used by applications for managing traffic lights.
	Infrared.	Application for speed measurement, vehicle length, volume, and lane occupancy.
	Ultrasonic.	Tracking the number of vehicles, vehicle's presence, and occupancy.
	Acoustic array sensors	Used in the development of applications for measuring vehicle's passage, presence, and speed.

FIGURE 2. 2

Types of Sensors

b. Automatic Vehicle Identifies and Automatic Vehicle Locators

An automated vehicle locator (AVL) is a tool that uses the Global Positioning System (GPS) to let a company or government organization follow the whereabouts of its fleet of vehicles remotely through the Internet. These gadgets, which purport to enhance fleet management and customer service, combine GPS technology, cellular connectivity, street-level mapping, and an intuitive user interface. By accumulating a database of vehicle information, including consumer location in relation to established delivery routes, AVL systems can allow businesses to more effectively organize delivery routes.

A network of cars outfitted with a mobile radio receiver, a GPS receiver, a GPS modem, and a GPS antenna makes up an AVL system. A base radio with a PC computer station, a GPS receiver, and an interface links to this network. Instead than using static map pictures from the Web, GPS employs interactive maps. A company's dispatching process may be made more effective by AVL systems by making field staff more accountable. Figure 2.4 illustrates how dispatchers may connect with drivers directly and obtain a real-time view of how drivers are adhering to a route.

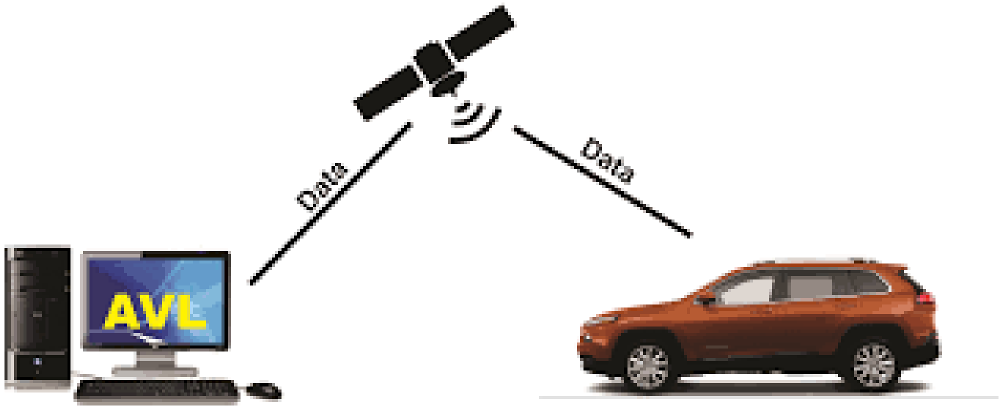

Figure 2. 3 Automatic Vehicle Locator

c. GPS

GPS is used to pinpoint both the actual locations of items and their times. It is used in many different industries for administration, monitoring, scientific research, and tracking. In all types of weather, it is utilized. Traffic management systems, like other applications, need precise and current data, which GPS provides. The use of GPS in traffic management allows for the data collection of vehicle speed and location at certain periods. As a result of the real-time geographical and temporal data it offers, it is increasingly used in various transportation research.

Communication Tools

The effectiveness of the Traffic Congestion Prediction Model depends not only on the gathering and analysis of data pertaining to traffic, but also on prompt and trustworthy communication of both data from the field to the TMC and information derived using the data and models from the TMC to the general public. This includes communication between data collecting centers and TMC as well as notifications about travel and traffic sent to cars through onboard equipment and to passengers via media like VMS, web sites, SMS, etc.

In select places, Dedicated Short-Range Communications (DSRC) provide communication between the car and the roadside. Road Side Units (RSUs) and On Board Units (OBUs) with transceivers and transponders are the main components of DSRC, which use radio frequencies in the Industrial Scientific and Medical (ISM) bands. Communications over Wireless Vehicles have network connection thanks to systems devoted to Intelligent Transport Systems, Road Transport, and Traffic Telematics. Permanent Air Interface A car and the roadside may communicate continuously over long and medium distances utilizing a number of communication channels, including as cellular, 5GHz, 63GHz, and infrared connections.

Data Analysis

Data cleansing, fusion, and analysis are all parts of data analysis. It is necessary to verify the data that is supplied to the TMC from the sensors and other data gathering devices. Clean data must be kept and inconsistent data must be eliminated. Additionally, data from several devices may need to be fused or integrated for additional analysis. To estimate and predict traffic states, the cleaned and fused data will be evaluated. To provide consumers the right information, several traffic status estimate techniques will be employed.

Traveler Information

The public watching is provided with traffic-related information via the use of travel advisory system services. These include: short messaging services, automated mobile phone messaging, variable message signs, television broadcasts, public radio announcements, the internet, short message signs, and other contemporary media technologies. These systems may provide real-time data on a variety of topics, including traffic conditions in construction zones, delays, accidents, and route closures and diversions.

2.4 Empirical Review

The study will begin by reviewing case studies from other countries that focuses on Intelligent Traffic Management Systems. Our case studies will focus on United and States of America and Switzerland Intelligent Traffic Management systems. These countries were fortunate to have several early success stories which provided excellent opportunities to promote the virtues in the Intelligent Traffic Management System. Quick mobility has become a need in cities across the aforementioned nations, and people employ a variety of modes of transportation, including bicycles, cars, and subways. However, many communities choose to employ automobiles as their primary mode of transportation because of their convenience and usefulness. Traffic congestion became a serious problem as a result of cities throughout the US and Switzerland seeing a quicker rise in automobiles than there was transit capacity to accommodate. Due to a surge in traffic accidents, high levels of greenhouse gas emissions, and negative economic effects, traffic congestion has raised various issues for the environment and society.

2.4.1 Traffic Management in the US

In the latter half of the 20th century, American cities suffered significant problems with traffic congestion, and some still struggle to control the problem. Three major causes of traffic jams throughout the nation have been identified by the US Department of Transportation. The first concern relates to things that affect traffic, such construction zones, accidents, inclement weather, etc. The following variable has to do with traffic demand, which includes changes in regular traffic and noteworthy occurrences (Afrin & Yodo, 2022). The transportation infrastructure, which consists of physical bottlenecks and traffic-control systems, is the last and most important source. Traffic incidents, such as car accidents, account for 25% of the total traffic congestion, while construction zones, poor traffic signal timing, and special events each contribute for 5%. Bottlenecks account for 40% of the total traffic congestion (Rafi, 2021).

In this manner, traffic management systems (TMSs), which are designed to lessen traffic congestion and other difficulties related with traffic, are heavily relied upon by big cities that concentrate on avoiding traffic congestions and enhancing overall traffic efficiency. TMSs are composed of a number of management tools and applications that combine communication, sensor, and processing technology. The systems gather information on traffic from a variety of sources, including traffic signals, moving cars, and in-road and wayside sensors (Afrin & Yodo, 2022). Several traffic hazards can be identified in real-time and consequently mitigated, increasing the overall traffic efficiency and enhancing the smooth flow of traffic. This can be done by aggregating and utilizing the collected data among vehicles or in a traffic management center (TMC) concentrated in a data center or a cloud. We will look at the traffic management systems of Santa Ana in the state of California and New York Metropolis, the most populated city in the US, to get an idea of the scale of the traffic management systems used in the nation.

2.4.2 New York City

As the most populated city in the country (with a population of over 8 million), New York City faces the difficulty of traffic congestion. For years, areas like Manhattan, the center of residential and economic activity in New York, have struggled with traffic, particularly during rush hours. The goal of minimizing traffic congestion in New York has been pursued by a number of governments, some of which have implemented laws that encourage using public transportation, riding bicycles, or even walking to work or other destinations (Afrin & Yodo, 2022). The problem of traffic congestion requires immediate attention notwithstanding the efforts of different governments to promote public transportation. The New York administration developed a new, technologically-based traffic management system to reduce traffic congestion. This system allowed the city's traffic engineers to monitor and react to traffic conditions in Midtown Manhattan in real time, which helped to improve traffic flow on the city's most congested streets.

The city's new program, known as Midtown in Motion, used a number of different technologies to accomplish its stated objectives. To assess traffic volumes, congestion, and record vehicle travel times in the roughly 110-square-block region bounded by Second to Sixth Avenues and 42nd to 57th Streets, the new system comprised 100 microwave sensors, 32 traffic video cameras, and E-Z Pass readers at 23 junctions. Wireless transmission of the combined sources' data allows engineers at the city's traffic control center in Long Island City to instantly detect congestion choke spots as they arise and, in reaction, remotely change the Midtown traffic light patterns to alleviate traffic bottlenecks (Gregory, 2021).

Engineers from the New York Department of Transportation are employing recently upgraded traffic signal control systems to modify the traffic lights. Additionally, drivers and app developers will have access to real-time traffic flow information with the use of PDAs and mobile phones. The wireless transmission is made feasible via the usage of the New York City Wireless Network (NYCWiN), a wireless network created and managed by the Department of Information Technology and Telecommunications.

Older traffic signal generations could be efficiently programmed to adapt to predetermined signal patterns depending on the time of day, leaving little capacity to react to collisions, construction projects, special events like the UN General Assembly, and times when network congestion overwhelms the network and creates delays that obstruct roads and crosswalks. Depending on the traffic situation, traffic lights are changed to provide a more even distribution of traffic entering Midtown so that already crowded areas do not become overloaded or the clearing of isolated backups caused by breakdowns, fender-benders, or double-parked vehicles can be given priority (Gregory, 2021). Engineers can more easily convert between a simultaneous signal pattern on the avenues, where all of the signals turn green or red at once, and a traffic signal progression that allows cars traveling at the speed limit to experience green lights as they move along a corridor. The tool aids engineers in selecting the best layout based on estimated traffic conditions.

As part of the Midtown in Motion program, turn lanes were built at 53 intersections so that cars could turn into avenues from cross-town streets without blocking the entire through-traffic path. Turn signals were also installed at 23 of these intersections so that cars could turn more easily without obstructing pedestrians (De Souza, etc. 2017). Beginning last summer, planning and construction of the Midtown in Motion components took place alongside ongoing infrastructure upgrades to the city's traffic light system.

2.4.3 Santa Ana

Santa Ana, a largely constructed area, considered the cost of adding traffic lanes and new roads prohibitive. With the need to both decrease delays and to replace an aging transport system, the city decided to replace the current system with an automated traffic control system that would be run from a traffic management center (TMC). The big transportation issue facing Orange County and Southern California is traffic congestion along the Santa Ana Freeway (I-5), State Route 22, State Route 57, and connecting arterial streets in and around Anaheim's Commercial Recreation Area. The integrated traffic management system (TMS) of the City of Anaheim is a holistic approach to traffic management in one of the most populous regions of America.

The main aim of the TMS is to control traffic strategically in order to alleviate congestion, minimize travel time and, in turn, reduce annoyance for the millions of people in Southern California who live, work or visit. The TMS works with the Orange County Transportation Board, local governments, and the Transportation Department of California (Caltrans). It incorporates data from current information systems, including the Anaheim Convention Center, Anaheim Stadium, the Computer-Aided Dispatch System of the Police

Department, and the Freeway Surveillance System of Caltrans. Via controlling signal timing from a centralized traffic management center (TMC), announcing traffic information on a 'AM' radio channel, and displaying detailed route information using overhead changeable message signs, the assessment of this data is then used to establish a traffic circulation management plan.

The Traffic Management Center, staffed by two traffic engineers, who track, plan and control traffic, is the heart, or command center, of this system. The TMC is staffed by engineers, traffic police supervisory officers, and the City's Special Events Transportation Coordinator during special events. The TMC collects information from a number of outlets, including closed-circuit television cameras monitoring important intersections and major freeways and the Computer-Aided Dispatch Center of the Police Department. Together, this information helps TMC operators to analyze local and regional traffic congestion and proactively control it.

Operators use a sophisticated traffic signal computer system to control 180 traffic signals based on data collected by the TMC, with plans to control timing at 350 signals eventually. The device utilizes high-resolution color graphic displays with large-screen projection, using a modified version of the Federal UTCS Enhanced program, to allow operators and decision-makers to envision conditions as they occur. In times of heavy traffic, the use of 12 electronic changeable message signs can provide route direction information to vehicles unfamiliar with the region and alternate route information. Signs will be managed by the central computer and signing plans will be synchronized with special event signal plans or in response to a particular incident. Finally, the TMC broadcasts on a low-band highway advisory radio channel, using an AM frequency, to ensure motorists receive real-time traffic and parking information.

2.4.4 Switzerland

The global champions in rail travel are the Swiss. Every day, almost 10,000 trains travel the more over 3,000 kilometers of track owned and maintained by SBB, transporting 1.21 million passengers. Additionally, SBB moves 205,000 tonnes of freight daily on its rails (Acherman, 2021). These amazing figures have no equal elsewhere in the world. Managing such enormous numbers on a daily basis is no simple task. An increase in traffic density is being caused by the continued growth of rail services and the increased demand for freight transportation services.

In order to regulate rail traffic safely, timely, and effectively, SBB has created its own Rail Control System (RCS) for train dispatching and monitoring. RCS is highly equipped to handle present and future difficulties since it can be integrated to a range of applications. The top dispatching app in Switzerland is called RCS-Dispo. It is used by BLS, SOB, and SBB in addition to SBB. Infrabel, a Belgian supplier of rail systems, transitioned successfully to RCS-Dispo in late 2016.

Learning that Switzerland is the world champion in rail travel might make one wonder whether they have learned and mastered traffic control for other forms of public transport as they have mastered controlling traffic on their railway lines. Just like many other regions of the world, Switzerland is experiencing an increasing number of vehicles and traffic and as such there is need to an intelligent traffic management system as well as additional requirements for areas such as safety, environment and regulations (Petersen, 2021). Using manual paper processes and large teams, has been the norm in carrying out many administrative and monitoring activities today. This takes a lot of time and makes it hard to ensure the information is always reliable, consistent and up-to-date. Therefore, government agencies are not only looking for ways of optimizing their processes and structures. To assist them in the substantial transition to a digital workplace, they are also searching for partners with the requisite business and technological know-how.

Borrowing a leaf from the success of their railway operations, Switzerland set out to acquire a traffic management system that would manage various aspects of road traffic and transportation. With the aim of increasing safety, protecting the environment, to streamline and optimize processes, the Swiss set out to attain a traffic management system whose functionalities would include;

Analysis of accidents: In order to identify patterns, enhance protection at black spots and provide data, all relevant information is recorded and analyzed. The solution is based on a GIS interface that is very efficient and intuitive.

Special transportations management: From request to the actual road, very large trucks are handled via an online system. All the parties involved (police, security companies, etc.) have either direct access to the device or a communication and data sharing interface.

Supervision of national roads: A multi-screen traffic control program, including real-time GIS (Geographical Information System) traffic information, video stream display, road work management, data sharing with other incident control systems, weather forecasting, truck management, etc.

Heavy traffic control: Switzerland must, through a collection of EU criteria, regulate trucks on the route. The solution enables people with an online and an offline device to do this function for the police. Information and statistics are given to the parties concerned (countries and cantons).

Issuance of cards for digital tachigraphs: Management of licenses for drivers and vehicle ownership firms, controller cards and configurator cards. The solution has interfaces with a variety of Swiss and European frameworks to verify whether applications are legitimate or not.

Zürcher Verkehrsverbund

The Zurich Transportation Council (ZVV) is in charge of overseeing passenger transportation in the Canton of Zurich. The 171 Communities of the Canton and the Cantonal Government jointly control ZVV. The Cantonal Government is in charge of setting the basic rules controlling development, services and tariffs, worldwide appropriations, and the budget. The Communities must participate in timetabling, and they must be consulted on rates. Roles at ZVV include strategic marketing, planning, and finance for transportation (Rafi, 2021). ZVV has contracts with companies that provide transportation services. The automated fare and ticket system is now under ZVV's control.

With 8 "Business Responsible Transport Firms," ZVV has agreements. Seven of these transportation firms are in charge of providing passenger transportation services in certain Canton of Zurich geographic regions (Peterson, 2021). In collaboration with these businesses, S-Bahn, the regional division of the Swiss national railway corporation, offers train services across the Canton.

VBZ is an integrated multi-modal transport operator that is owned by the City of Zurich. VBZ direct runs tram, trolleybus, bus, and funicular services in Zurich and its surroundings. The S-Bahn runs rail services throughout the city (SBB). In collaboration with VBZ, other operators conduct a few bus routes inside the coverage region. The employment of ITS by VBZ dates back to 1971. At this time, ITS has been fully included into VBZ's operational procedures and business operations.

The deployment of ITS by Switzerland would serve as a model for other governments to adopt in order to relieve bottlenecks in their transportation networks, reduce traffic, and reduce carbon emissions from moving cars. However, the new traffic control system incorporates real-time traffic data into the ZVV traffic management software operating at the

VBZ through field sensors, RFID readers, and cameras (Peterson, 2021). For different times of the day, modern traffic management systems employ pre-programmed signal sequences. Engineers can swiftly address the issues that generate traffic backlog due to congestion, construction, special events, motorcades, or accidents thanks to this full perspective of the current traffic patterns.

Switzerland uses cutting-edge solid state traffic controllers (ASTC) and a modern traffic controller located at signalized junctions that is remotely managed by ZVV. The wireless system is powered by a high-speed, citywide infrastructure devoted to public safety and public service applications (Rafi, 2021). The Advanced Transportation Controller (ATC) standard, the traffic control NEMA TS2 standards, and the National Transportation Communications for ITS Protocol (NTCIP) specifications are all used in the framework. Additionally, ZVV assisted with the creation, acquisition, and testing of the specifications for traffic controllers as well as the acquisition of wireless routers. With the help of their technology, the US and Switzerland have been able to continue writing their success stories in terms of both driving their economies and being able to regulate some of the forces that do so.

2.5 Conceptual Framework

In this section, the independent variables affect travel duration whereas dependent variable is the travel traffic as per Figure 2.4.

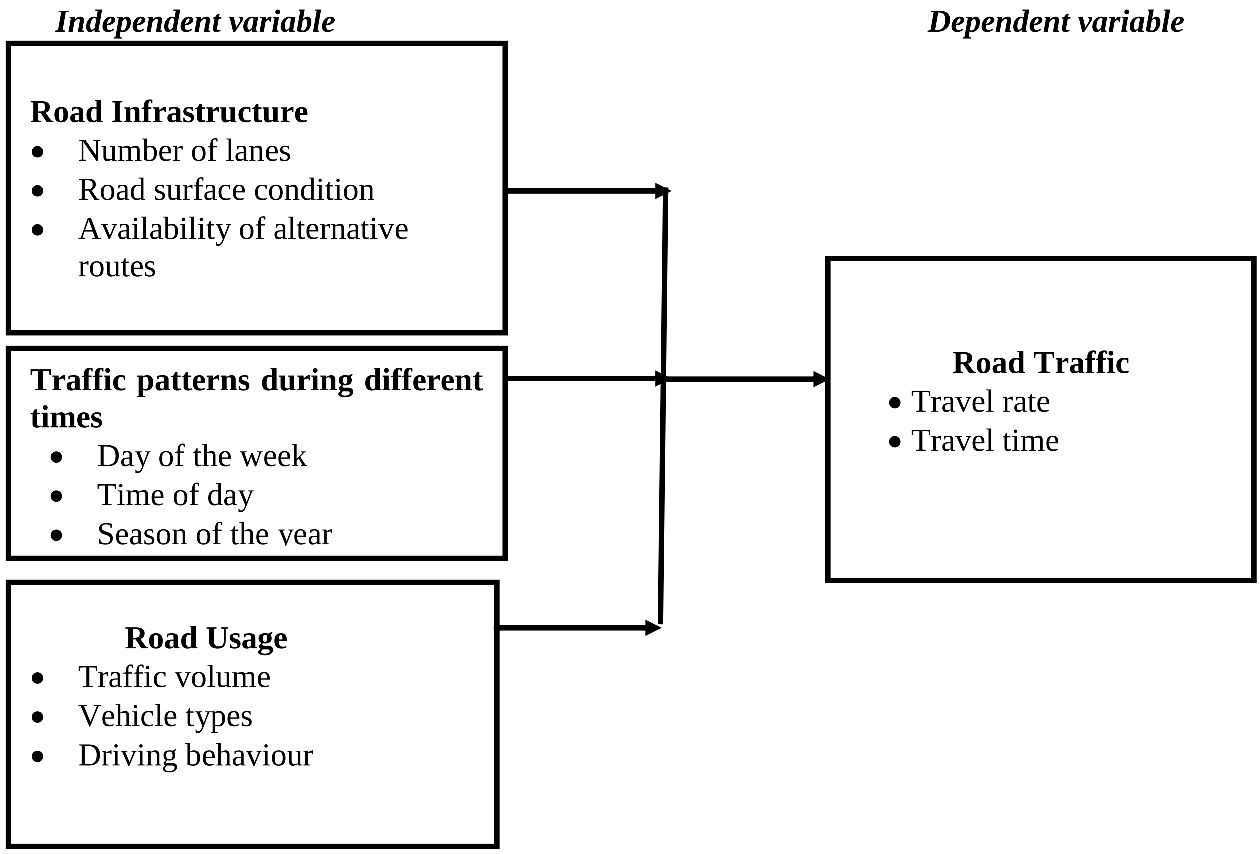

FIGURE 2. 4

Conceptual Framework

Traffic jams have a negative influence on vehicle motorization and dispersion, which raises the need for transportation infrastructure. Predicting traffic congestion using deep learning algorithms is a challenging problem with significant implications for urban transportation management. Through the use of historical traffic data, weather conditions, and other relevant factors, deep learning models can accurately forecast traffic congestion patterns. Previous studies, have demonstrated the effectiveness of deep learning algorithms in traffic prediction. Lv *et al*. (2015) proposed a deep belief network (DBN) model for traffic flow prediction. While the research explored the potential of deep learning in predicting traffic congestion, a major limitation is the lack of comparison with other state-of-the-art deep learning models or traditional methods. Without such comparisons, it is challenging to determine the model's effectiveness and whether it outperforms existing approaches. Additionally, the study did not extensively discuss the interpretability of the DBN model, which is crucial for practical implementation and understanding the factors influencing traffic congestion.

The Nairobi Metropolitan Area Authority and the Nairobi County Government decongested bus terminals further from the city center, although this did not make the situation better. Reliance on time-based traffic lights and traffic police officers has also been faced with inefficiencies in reducing traffic congestion. There is no intelligent traffic prediction model in place. One of the most important stages in the operation of an Intelligent Transportation System (ITS) is the ability of practitioners to carry out route planning and traffic control. Large volumes of data may be used to analyze issues relating to traffic congestion utilizing machine learning and deep learning methods, which are currently being actively used in other industries.

2.5.1 Road Infrastructure

Road infrastructure is referred to as a kind of land transportation infrastructure that includes all elements of a road, as well as any auxiliary structures and tools used by traffic. The construction of roads must adhere to safety and security criteria in order to provide a secure road infrastructure. Road engineering requirements for security, as well as concerns about the geometry and condition of the road's surface (Jammula *et al.*, 2018). Technical compliance with road geometry, pavement structures, complementing building structures, usage of road components, traffic engineering, and road equipment is required for roads to be practical to run. Traffic results when guidelines are not followed. The quality and capacity of road infrastructure play a crucial role in predicting traffic congestion. Factors such as the number of lanes, road surface condition, presence of bottlenecks or chokepoints, and availability of alternative routes can impact traffic flow. High-capacity roads with efficient lane configurations and well-maintained surfaces generally experience less congestion compared to narrow or deteriorated roads. Analyzing the characteristics and limitations of the road infrastructure can provide insights into potential congestion points.

2.5.2 Timing

Day of the week, hour of the day, and season of the year are all known to have a significant impact on the volume of traffic on the roads. Peak hour, often known as rush hour, is the period of the day when there is the most traffic for vehicles. On weekdays, this often occurs twice a day, once in the morning and once in the evening. Travel times are often greater during peak hours than during non-peak hours because free flow conditions are at their worst (International Labour Office, 2004; Mosoti & Moronge, 2015). Weekdays often see greater traffic than weekends (Liu, Gong, Gong, & Liu, 2015; Mosoti & Moronge, 2015). Empirical research has demonstrated that during school breaks, there is often less traffic on the roadways than while classes are in session, which leads to shorter travel times (Cools, Moons, & Wets, 2008; Otieno, 2016; uddin & Noor, 2018).

Additionally, inclement weather, such as persistent rain, snow, or high winds throughout various seasons, tends to have a detrimental effect on traffic and, therefore, travel time (Cools, Moons, & Wets, 2009; Juga & Vajda, 2012; Mosoti & Moronge, 2015; Stern, Shah, Goodwin, & Pisano, 2003). Roads become slick from heavy rain or snow, slowing down travel. Roadways may sometimes become inaccessible because to water or snowfall. Strong winds have the potential to uproot trees and move utility poles, obstructing roadways with debris. Analyzing historical data on traffic patterns during different times of the day, days of the week, and seasons can reveal recurring congestion patterns. Factors such as rush hour periods, peak travel times, and special events can significantly impact traffic flow and contribute to congestion. By considering the temporal aspect and incorporating time-related features into predictive models, it becomes possible to anticipate congestion during specific periods and plan mitigation strategies accordingly.

2.5.3 Road Usage

In the fundamental economic categorization, public highways are categorized as common resource products. Since it is difficult to bar anybody from using such products, they are competitor goods, eaten by a single consumer at a time (Otieno, 2016). When there is competition for space and the cost of the road is cheap because of tax-funded construction, there is traffic congestion. The cheapest way to go around communities is by using various public transportation options. Understanding how roads are utilized by different types of vehicles and the behavior of road users is essential for predicting traffic congestion. Factors such as traffic volume, vehicle types (e.g., private cars, buses, trucks), and driving behavior (e.g., aggressive driving, lane changing) influence traffic flow and congestion. Collecting data on traffic counts, vehicle types, and observing driving patterns through surveillance systems or traffic cameras can provide valuable insights into road usage. Integrating this information into predictive models allows for a more accurate assessment of congestion risk.

2.5.4 Road Traffic

One of the biggest issues in metropolitan areas is traffic. A supply and demand mismatch results in traffic congestion when there are more automobiles on the road than there is room for them. Demand for the route may rise up to and beyond the saturation threshold depending on the time of day, the density of the local workforce and population, the state of the road and its junctions, and other factors. High costs, delays, and fuel usage are all results of traffic congestion, which also has detrimental social and environmental effects. Using travel rate, trip time, and cost of travel/fare, this research will quantify the amount of traffic on the roads.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the researcher's research strategy. It helps with effective study session planning. The research design that will act as the study's guide is thoroughly explained in this chapter. Additionally, it covers the research population, the selection process for the study sample, data collecting methods, and the analysis and presentation of the results.

3.2 Research Design

Research design is the methodical organization of the methods employed in the studied area. It alludes to a theoretical investigation of the methods and ideas used in a certain subject of research (Creswell & Creswell, 2017). The study used descriptive research design in seeking to determine the factors that affect traffic flow and proposing a prediction an Intelligent Traffic Management System. The detailed steps of the research method to be used following this research design is shown by Figure 3.1.

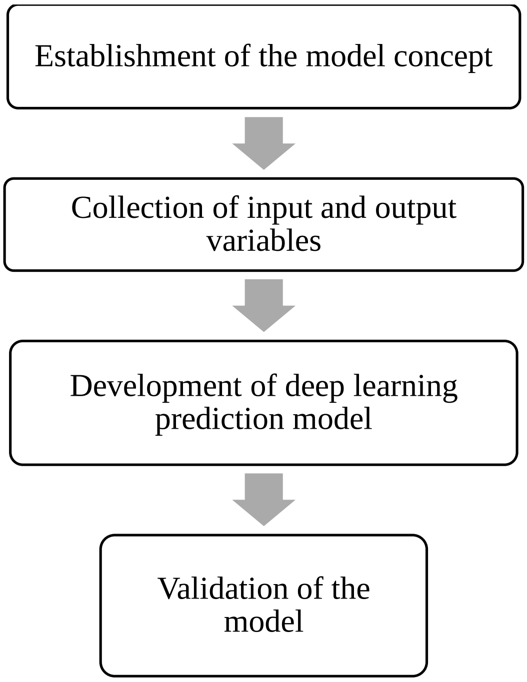

FIGURE 3. 1

Methodology

The study first objective was to investigate the critical factors affecting traffic congestion in Nairobi Metropolitan Area. To achieve this objective, based on past studies, critical factors affecting traffic congestion were determined and data relating to the factors obtained from observation data collection processes. The factors' data were correlated to traffic to determine which factors are responsible for traffic congestion in Nairobi. Google based traffic data relating to traffic on various roads in Nairobi metropolitan area was also obtained for period of three months and analyzed using correlation and regression methods to determine how the identified factors will be influencing the travel time. The significant factors formed the model to be used for predicting traffic in Nairobi metropolitan area.

The study's second objective was to develop a model for predicting traffic congestion management within the Nairobi Metropolitan area using deep learning algorithm. To achieve this, a model was developed from indicators and used in road traffic prediction. Significant factors affecting travel time were collected as input and output will be the travel time. In this study, the inputs will be the factors affecting travel duration namely road infrastructure, timing and road usage. The dependent variable on the other hand was road traffic measured using travel time. IBM Statistical Package for the Social Sciences (SPSS) V28 was used to determine the significant factors that were the input for the deep learning model. The statistics model and the deep learning model were both created. The model had data capture, analysis and comparison with actual traffic for model learning.

The third objective of the project was to validate the traffic congestion management model created to control traffic inside the Nairobi Metropolitan region. To achieve this objective, the prediction results were compared to actual traffic data to determine how the predicted traffic compares with actual data. Root mean squared error (RMSE) and mean absolute error (MAE) performance validation metrics were used to assess whether prediction results are statistically different from actual results. The model was adjusted accordingly to ensure high accuracy levels. The identified inputs were also compared to data collected using primary data sources. This offered a chance to compare the findings as per secondary data with expert opinion on causes of traffic congestion.

3.3 Population of the Study

This study targeted traffic within the Nairobi Metropolitan Area which cover the whole of Nairobi County. Major roads and round abouts were studied for a period of 30 days. Five major roads feeding to six roundabouts leading to Nairobi that were studied are presented in Table 3.1. Each lane was assigned an observer who will record the data every 30 minutes for eight hours a day, for 10 days. This resulted to 3,520 data set which was considered adequate in developing deep learning model. Additionally, data collected using questionnaires provided validity to the results of data collection. Secondary data from CCTVs could not be used since it was not available.

TABLE 3. 1

Road to be Studied

Road	**Number Lanes**	**Daily Number of Vehicles**	**Number of Observers**
Thika Road (Globe Roundabout)	8	60,000	8
Mombasa Road (Haille Sellasie and Nyoyo stadium roundabout)	6	31,000	6
Ngong Road (Kenyatta Avenue-Uhuru highway Roundabout)	4	25,000	4
Waiyaki way (university way roundabout)	4	28,000	4
Total	**22**	**144,000**	**22**

To validate the results of traffic officers in Nairobi County were presented with the results and their views considered. To achieve this, the study targeted for the target 100 traffic police officers and officials in Nairobi CBD.

Data collection assistants were deployed to the roundabouts for 30 days capturing data for vehicles inbound to town. Each event recorded was town inbound traffic clearing from the roundabout. This formed the unit of analysis. A total of 3520 events were analyzed to develop a model for predicting traffic.

3.4 Sampling

This study employed Nassiuma's (2009) formula to calculate the size of the sample as shown below. The respondents were selected through stratified random sampling method which was preferred because it gives all the respondents an equal chance to be selected to participate in the research as shown by Table 3.2.

The formula is:

$$n = \frac{N}{1 + N(e^2)}$$

Where, n= sample size, N=population size e=sampling error.

A sample error of 5% was used, N is 100. The sample size for the study was:

$$n = \frac{100}{1 + 100(0.05^2)}$$

= 80

TABLE 3. 2

Sample Frame

Category	**Number**	**Sample**
Traffic Police Officers and officials	100	80
Total	**100**	**80**

3.5 Research Instruments

The study utilized observation checklist and questionnaire as the source of data for the study. A observation data collection sheet was used in collecting the data from the four main roads. To obtain data from the traffic officers, questionnaires were used. A structured form with both closed-ended and open-ended questions were sent to respondents along with instructions on how to complete it, and the researcher then waited for their replies. The benefits of employing a questionnaire for data collection are variety, speed, and affordability. According to appendix II, the questionnaire was split into parts depending on the objectives of the research. Using a Likert scale, the respondents' responses were scored. The researcher left the questionnaires with the respondents under a drop-and-pick administration method.

3.6 Reliability and Validity of Research Instruments

3.6.1 Reliability of Research Instruments

The consistency with which data is measured is referred to as reliability. The results from the pilot test were evaluated for reliability using Cronbach's alpha. In order to investigate and improve the reliability of variables created by summated scales, Cronbach's alpha was used to evaluate the normal correlation or internal consistency of the research instrument's components. The Cronbach's alpha coefficient, with values ranging from 0 to 1, were used to assess dependability in order to ensure that the findings were more than 0.7. (Mugenda, 2008).

3.6.2 Validity of Research Instruments

Validity is the extent to which a data collection tool can collect and reflect the data it is intended to measure (Bridget and Lewin 2011). Data validity was ensured by the use of content validity, which is the degree to which the data obtained reflect a certain phenomenon. It was used to consult with the research supervisor, colleagues working on related topics, and others who have completed their study satisfactorily.

3.7 Data Analysis

The completed questionnaires were tagged, tabulated, and reviewed for completeness after being returned. While coding enables the transmission of data to the computer, this guaranteed the completeness, consistency, and readability of the data. The data was organized in an orderly fashion by tabulation. Descriptive statistics were used to examine the central tendency and dispersion of how respondents answered the questionnaire's questions. Visual representations of the data, including frequency tables, frequency distributions, scatter plots, and a correlation matrix, were used to explain the data.

3.8 Deep Learning Algorithm Model Development

In this study, a design process for deriving optimal input variables and parameters were constructed to develop a deep learning-based traffic congestion prediction model. This study concentrated on the creation of a model utilizing deep learning techniques. The predictive model design process to be used is shown in Figure 3.2.

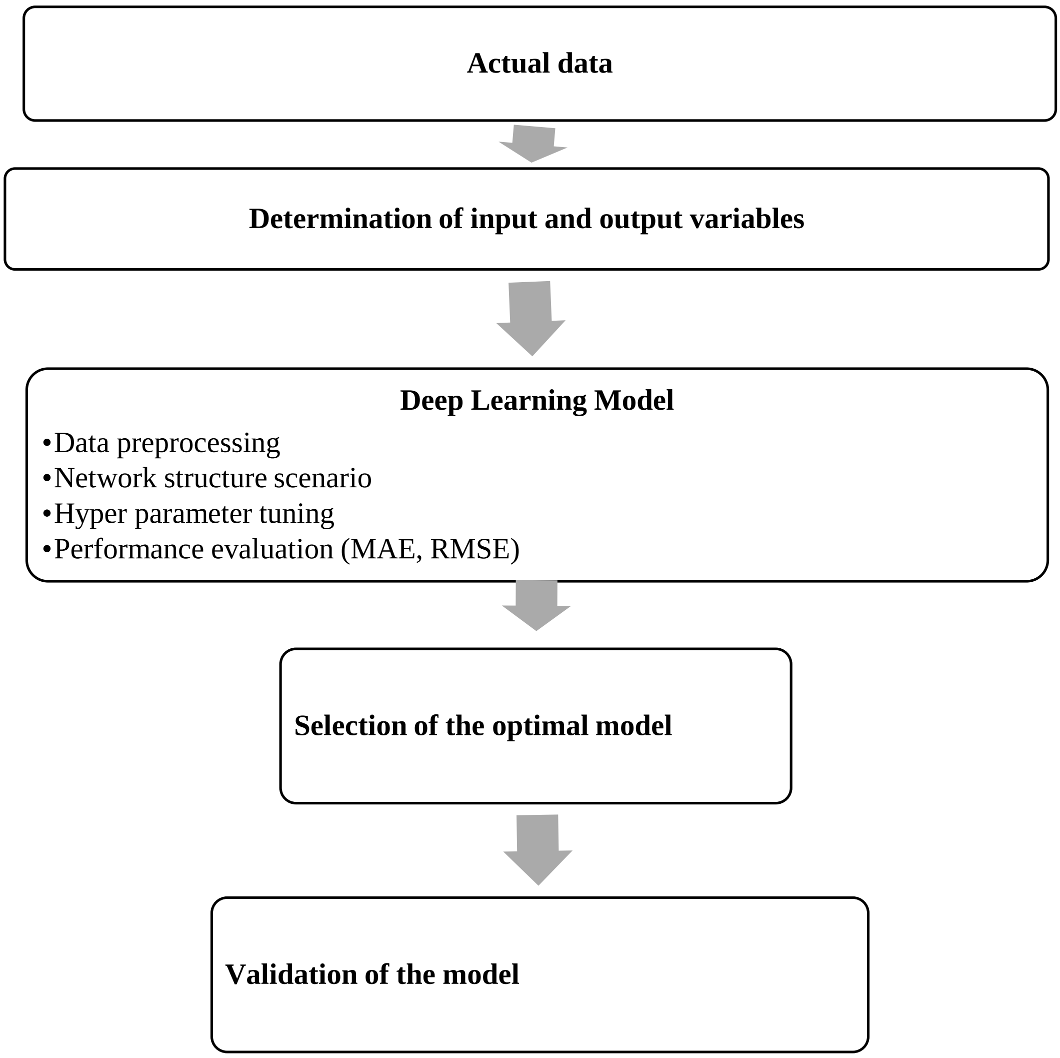

Figure 3. 2

Deep Learning algorithm Model Development

A deep learning model based on the deep neural network was proposed after the input variable derivation process and the optimum parameter derivation process are finished, as illustrated in Figure 3.2. The final created model's efficacy was next verified and assessed. As the first phase in the process of obtaining ideal input variables, significant variables from the actual data were selected using prior research and expert knowledge.

Deep learning uses a variety of models, including the deep neural network (DNN), convolutional neural network (CNN), recurrent neural network (RNN), autoencoder (AE), and generative adversarial network, depending on the processing technique and structure (GAN). DNNs are generally neural networks with depth enhancement. There are hidden layers in between the input and output layers, and the quantity of hidden layers affects the degree of the neural network. A neural network is called deep if the credit assignment route depth exceeds 2, however there is no specific threshold. DNNs are taught to depict complex nonlinear interactions since each of the many layers is intended to identify a certain function. Like a traditional artificial neural network, DNNs have the benefit of being able to simulate a variety of things. However, they do have the drawback of being prone to overfitting. They are thus often used for classification and prediction across a range of areas.

The input and output data formats, as well as other modeling options, were taken into consideration while developing a traffic congestion prediction model using DNN in this research. DNN was used to obtain the best parameters. The parameter range was decided when the actual data has been divided into learning and verification data. To find the best settings for the DNN model, the number of inputs, hidden layers, hidden layer nodes, dropout, activation function, optimizer, batch, epochs, and other parameters should be specified directly.

Validating the model was the last stage. Without iterating, the input variables, training weights, and learned biases used to immediately construct the model output variables during validation.

Mean Absolute Error (MAE) and Root Mean Square Error will be used to verify the produced model's prediction ability (RMSE). Model validation metrics like MAE and RMSE are often used in machine learning and deep learning. The MAE and RMSE, which gauge the discrepancy between expected and actual values, are indicators of how well-predictive a model is. The anticipated performance will then be compared to the current method, Multiple Regression Analysis, after choosing the best DNN model (MRA).

CHAPTER FOUR

RESEARCH FINDINGS AND DISCUSSIONS

4.1 Introduction

The study sought to obtain information for predicting traffic congestion within the Nairobi Metropolitan area using deep learning algorithm. This chapter presents the research findings by based on the specific objectives of the study. It also describes the descriptive and inferential analysis. Out of a target of 80 respondents, 77 responses were obtained from the respondents which translate to a response rate of 96%. This response rate is considered to be more than sufficient enough in generalization of the results of the study (Mugenda, 2008).

4.2 Background Information

4.2.1 Gender of the respondents

The findings obtained by the study as shown by Figure 4.1 indicated that 55% were female while 45% were male. This shows that there was representation of both genders in the responses hence no biasness.

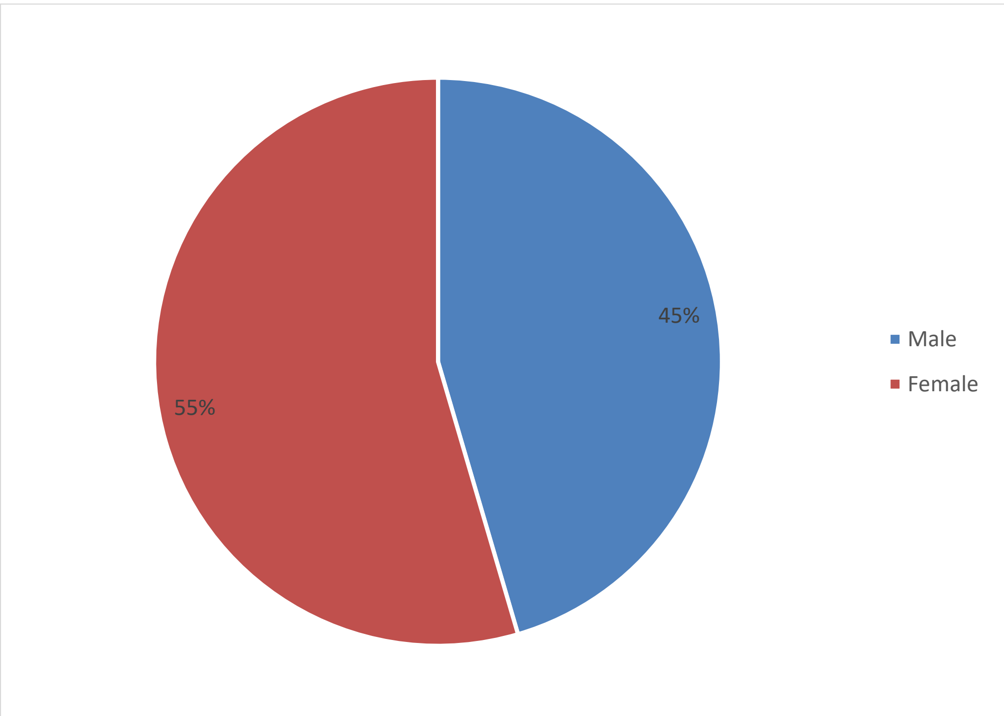

FIGURE 4. 1

Gender of the Respondents

4.2.2 Duration Resided within Nairobi Metropolitan area

The study also sought to examine the duration the respondents had resided within Nairobi Metropolitan area. As per Figure 4.2, majority of the respondents (71%) had resided within Nairobi Metropolitan area with only 19% and 9% having resided in the region for durations of less than a year and 6-10 years respectively. This implies that majority of the respondents had resided for a considerable period hence well conversant with the aspects of traffic congestion in the region.

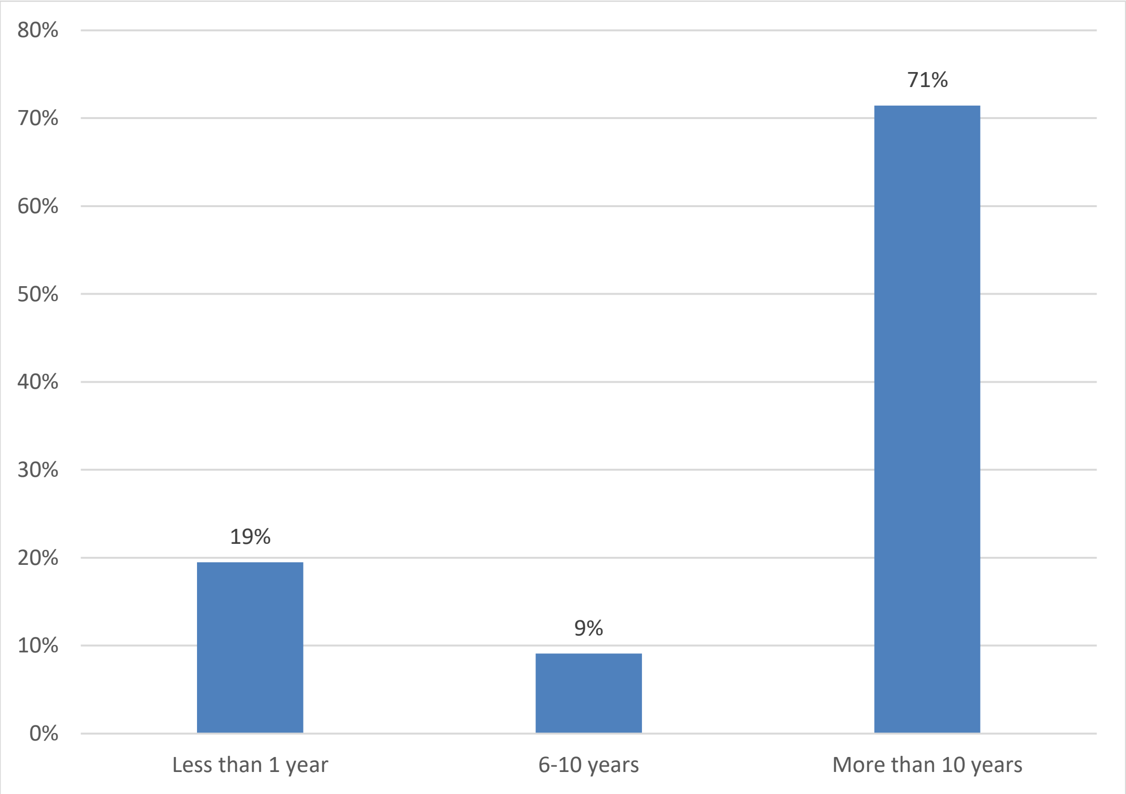

FIGURE 4. 2

Duration Resided within Nairobi Metropolitan area

4.2.3 Preferred Mode of Transport

On the preferred mode of transport, majority of the respondents (79%) preferred private means of transport while only 21% preferred public means of transport as shown by Figure 4.3.

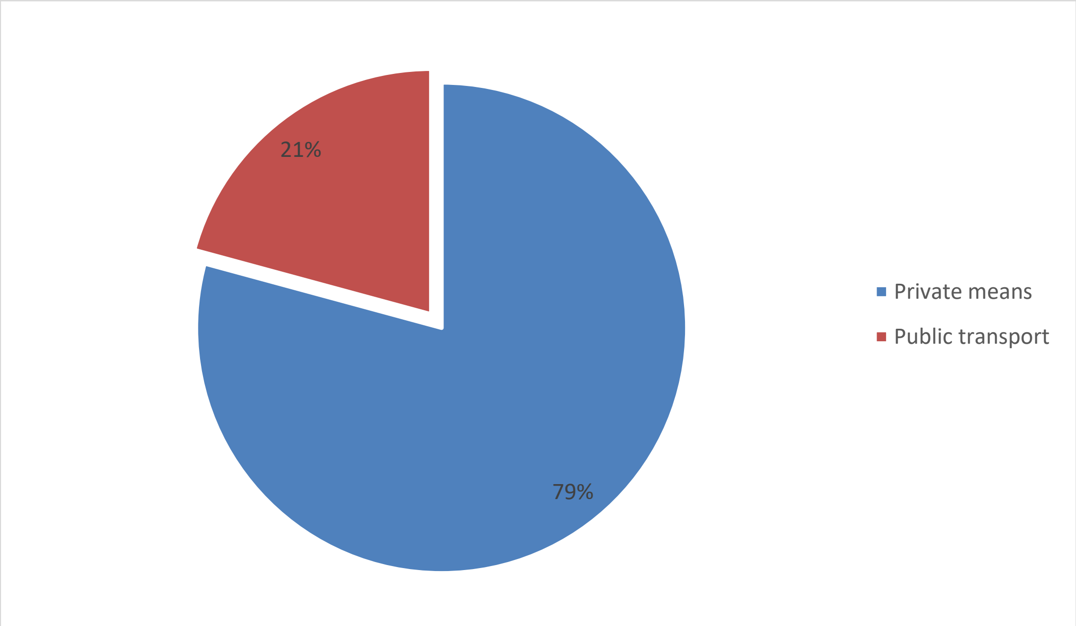

FIGURE 4. 3

Preferred Mode of Transport

4.3 Descriptive statistics

This section presents the descriptive statistics of the dependent and independent variables of the study.

4.3.1 Critical Factors Affecting Traffic Congestion in Nairobi Metropolitan Area

The study sought to determine the critical factors affecting traffic congestion in Nairobi Metropolitan Area. To achieve this, a Likert Scale (5-point) was used in rating the responses. The results are shown below.

TABLE 4. 1

Critical Factors Affecting Traffic Congestion in Nairobi Metropolitan Area

Statement	Mean	Std. Dev
Poor road design	3.58	1.331
Poor Traffic control system	3.45	1.372
Road construction and maintenance works	3.58	1.445
Vehicle break downs	4.01	1.323
Accidents	3.38	1.308
Poor road use	3.40	1.680
Roadside parking/obstruction	3.84	1.257
High number of private cars	3.84	0.988
High number of public transport vehicles including matatus, buses and motorbikes	4.01	1.219
Behaviour of road usage	4.12	1.203
Poor traffic management by traffic officers	3.68	1.381
Average Mean Score	**3.72**	**1.319**

As shown by Table 4.1, a very large extent was noted on vehicle break downs, high number of public transport vehicles including matatus, buses and motorbikes and behaviour of road usage affecting traffic congestion in Nairobi Metropolitan Area with respective means of 4.01, 4.01

and 4.12 respectively. A large extent of effect was also indicated on poor road design, road construction and maintenance works, roadside parking/obstruction, high number of private cars and poor traffic management by traffic officers with means of 3.58, 3.58, 3.84, 3.84 and 3.68 respectively. However, on Accidents and Poor road use a moderate extent was stated with respective means of 3.38 and 3.40. This therefore implies that the respondent were in agreement on these critical factors affecting traffic congestion in Nairobi Metropolitan Area with an average mean score of 3.72 and standard deviation of 1.319.

4.3.2 Effects of Traffic Congestion in Nairobi Metropolitan Area

The study aimed to examined the effects of traffic congestion in Nairobi Metropolitan Area. To achieve this, a Likert Scale (5-point) was used in rating the responses. The results are shown below.

TABLE 4. 2

Effects of Traffic Congestion in Nairobi Metropolitan Area

Statement	Mean	Std. Dev
Long travel times	4.12	1.051
High cost of travel/fares	3.56	1.824
High vehicle maintenance	3.82	1.439
Environmental pollution	4.14	1.211
Staff fatigue (drivers and conductors)	3.96	1.240
Accidents	3.90	1.209
Average Mean Score	**3.92**	**1.329**

The results obtained showed that the respondents agreed to a very large extent on the effects of traffic congestion on long travel times and environmental pollution with means of 4.12 and 4.14 respectively. A large extent was also stated on traffic congestion affecting high cost of travel/fares, high vehicle maintenance, staff fatigue (drivers and conductors) and accidents with means of 3.56, 3.82, 3.96 and 3.90 respectively. Based on these responses, the respondents were in agreement that the effects of traffic congestion in Nairobi Metropolitan Area with an average mean of 3.92 and standard deviation of 1.329.

4.3.3 Traffic Congestion Management Measures in Nairobi Metropolitan Area

The study also established the traffic congestion management measures in Nairobi Metropolitan Area. To achieve this, a Likert Scale (5-point) was used in rating the responses. The results are shown below.

TABLE 4. 3

Traffic Congestion Management Measures in Nairobi Metropolitan Area

Statement	**Mean**	**Std. Dev**
Build new roads	3.47	1.643
Re-design and expand existing roads	3.56	1.241
Control private car use	3.53	1.721
Control matatus access to CBD	3.96	1.152
Better traffic control system	3.99	1.352
Prosecute Roadside parking and obstruction	4.12	1.051
Enforce Traffic rules	3.56	1.824

Statement	Mean	Std. Dev
High number of private cars	4.12	1.051
Schedule Road works for night times	3.56	1.824
Integration of traffic congestion prediction models	4.14	0.928
Average Mean Score	**3.80**	**1.379**

The results as per Table 4.3, showed that the respondents agreed to a very large extent there being prosecute roadside parking and obstruction, high number of private cars and integration of traffic congestion prediction models having means of 4.12, 4.12 and 4.14 respectively. A large extent was also stated on re-design and expand existing roads, control private car use, control matatus access to CBD, better traffic control system, enforce traffic rules and schedule road works for night times with respective means of 3.56, 3.53, 3.96, 3.99, 3.56 and 3.56. However, on building roads, a moderate extent was noted with a mean of 3.47. This affirms that these traffic congestion management measures have been adopted in Nairobi Metropolitan Area as an average meanscore of 3.80 was obtained.

4.4 Observation Checklist Analysis

A observation data collection sheet was further used in collecting the data from the four main roads in Nairobi Metropolitan Area. The results are shown below.

TABLE 4. 4

Observation Checklist Analysis

Statement	Frequency (n)	Percent (%)
Time of day		

Statement	Frequency (n)	Percent (%)
Early morning	54	2%
Mid morning	106	3%
Mid day	524	15%
Afternoon	1333	38%
Late afternoon	1282	36%
Evening	221	6%
Weather condition		
Rainy	1170	33%
Sunny	1024	29%
Foggy	1326	38%
Type of vehicles		
Saloon cars	2040	58%
Buses	1200	34%
Trucks	280	8%
Number of vehicles		
<1000	2058	58%

Statement	**Frequency (n)**	**Percent (%)**
1001-5000	1011	29%
5000-1000	451	13%
Number of lanes		
1	592	17%
2	734	21%
3	244	7%
4	1182	34%
5	768	22%
Nature of roundabout		
Traffic lights	2058	58%
Traffic officers	1011	29%
No traffic lights, no traffic officers	451	13%
Behaviour of road users		
Motorists not observing lane discipline	1360	39%
Pedestrian crossing	734	21%
Pedestrian not observing the road rules	244	7%

Statement	Frequency (n)	Percent (%)
Motorists not observing road rules	1182	34%
Time taken to get to pass the intersection in seconds		
Less than 1 minute	18	1%
1min-5 min	192	5%
5-10 minutes	189	5%
10-15min	1597	45%
Over 15 min	1524	43%
Total	**3520**	**100%**

As shown, the roads were busier during the afternoon and late afternoon with 38% and 36% of traffic being observed during these times. Pertaining the weather conditions, weather condition 33% was during rainy season, 20% during sunny season and 38% during foggy season. On the type of vehicles, 58% were saloon cars, 34% were buses and only 8% were trucks. On the number of vehicles during a particular time 58% were less than 1000, 29% between 1001 to 5000 ne 13% between 5000-1000. The study also observed the number of lanes whereby most of the roads had 4 lanes (34%), 5 lanes (22%) and 2 lanes (21%). It was also observed that most of the roundabouts were traffic lights (58%), most of the motorists not observing lane discipline (39%) or observing road rules (34%). In addition, regarding the time taken to get to pass the intersection in seconds, most took 10-15 minutes (45%) and over 15 minutes (43%).

4.5 Inferential Analysis

4.5.1 Correlation Analysis

Various factors were identified to be the causes of traffic congestion in Nairobi. These were correlated with the amount of time motorists take at the roundabout. The studied causes of traffic included poor road design, poor traffic control system, road construction and maintenance works, vehicle break downs, accidents, poor road use, roadside parking/obstruction, high number of private cars, high number of public transport vehicles including matatus, buses and motorbikes, behavior of road usage and poor traffic management by traffic officers.

Road infrastructure is referred to as a kind of land transportation infrastructure that includes all elements of a road, as well as any auxiliary structures and tools used by traffic. The construction of roads must adhere to safety and security criteria in order to provide a secure road infrastructure. Road engineering requirements for security, as well as concerns about the geometry and condition of the road's surface. Technical compliance with road geometry, pavement structures, complementing building structures, usage of road components, traffic engineering, and road equipment is required for roads to be practical to run. Traffic results when guidelines are not followed. The quality and capacity of road infrastructure play a crucial role in predicting traffic congestion. Factors such as the number of lanes, road surface condition, presence of bottlenecks or chokepoints, and availability of alternative routes can impact traffic flow. High-capacity roads with efficient lane configurations and well-maintained surfaces generally experience less congestion compared to narrow or deteriorated roads. Analyzing the characteristics and limitations of the road infrastructure can provide insights into potential congestion points. Day of the week, hour of the day, and season of the year are all known to have a significant impact on the volume of traffic on the roads. Peak hour, often known as rush hour, is the period of the day when there is the most traffic for vehicles. On weekdays, this often occurs twice a day, once in the morning and once in the evening. Travel times are often greater during peak hours than during non-peak hours because free flow conditions are at their worst. Weekdays often see greater traffic than weekends. Empirical research has demonstrated that during school breaks, there is often less traffic on the roadways than while classes are in session, which leads to shorter travel times.

Traffic congestion was hypothesized to lead to long travel times, high cost of travel/fares, high vehicle maintenance, environmental pollution, staff fatigue (drivers and conductors) and accidents. Solution to these were tested to include building new roads, re-design and expand existing roads, control private car use, control matatus access to central business district, better traffic control system, prosecute roadside parking and obstruction, enforce traffic rules, high number of private cars, schedule road works for night times and integration of traffic congestion prediction models.

To establish the relationship that existed between the research variables, Karl Pearson's coefficient of correlation was employed by the study and the results obtained are as per Table 4.5.

TABLE 4. 5

CORRELATION ANALYSIS

		Y	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
Y	Pearson Correlation	1.000										
	Sig. (2-tailed)	0.000										
X1	Pearson Correlation	.494**	1.000									
	Sig. (2-tailed)	0.000										
X2	Pearson Correlation	0.206	.375**	1.000								
	Sig. (2-tailed)	0.073	0.001									
X3	Pearson Correlation	.359**	0.112	.234*	1.000							
	Sig. (2-tailed)	0.001	0.331	0.040								
X4	Pearson Correlation	.488**	.504**	0.166	.381**	1.000						
	Sig. (2-tailed)	0.000	0.000	0.150	0.001							
X5	Pearson Correlation	.310**	0.045	0.110	.855**	0.208	1.000					
	Sig. (2-tailed)	0.006	0.701	0.341	0.000	0.070						
X6	Pearson Correlation	.308**	.319**	.468**	.568**	0.086	.496**	1.000				
	Sig. (2-tailed)	0.006	0.005	0.000	0.000	0.459	0.000					
X7	Pearson Correlation	.410**	.465**	.249*	.333**	.629**	0.132	.299**	1.000			
	Sig. (2-tailed)	0.000	0.000	0.029	0.003	0.000	0.253	0.008				
X8	Pearson Correlation	.353**	.319**	0.001	0.207	.299**	0.201	.559**	.342**	1.000		
	Sig. (2-tailed)	0.002	0.005	0.992	0.070	0.008	0.080	0.000	0.002			
X9	Pearson Correlation	0.179**	0.188	.450**	-0.042	0.169	-0.164	0.048	.330**	0.058	1.000	
	Sig. (2-tailed)	0.000	0.102	0.000	0.715	0.142	0.155	0.679	0.003	0.617		
X10	Pearson Correlation	0.042**	.269*	.302**	.314**	0.204	0.208	0.212	.277*	-0.034	.294**	1.000
	Sig. (2-tailed)	0.000	0.018	0.008	0.005	0.075	0.069	0.064	0.015	0.766	0.010	
X11	Pearson Correlation	0.042**	0.175	.461**	0.088	0.153	-0.057	.264*	0.205	0.064	.311**	0.188
	Sig. (2-tailed)	0.000	0.129	0.000	0.448	0.184	0.623	0.020	0.074	0.578	0.006	0.102
X12	Pearson Correlation	.452**	.308**	.566**	.490**	.486**	.370**	.527**	.331**	.304**	.270*	0.164
	Sig. (2-tailed)	0.000	0.006	0.000	0.000	0.000	0.001	0.000	0.003	0.007	0.017	0.154
X13	Pearson Correlation	.233*	0.158	0.202	0.217	.392**	0.163	-0.030	0.199	-0.203	0.032	0.015
	Sig. (2-tailed)	0.041	0.169	0.078	0.058	0.000	0.158	0.796	0.083	0.077	0.784	0.894
X14	Pearson Correlation	0.071**	.405**	.286*	-.278*	0.166	-.410**	0.093	.248*	0.220	.522**	0.104

		Y	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
	Sig. (2-tailed)	0.000	0.000	0.012	0.015	0.150	0.000	0.423	0.030	0.055	0.000	0.367
X15	Pearson Correlation	.228*	.288*	.225*	.232*	0.153	0.135	.310**	0.199	.240*	.338**	0.064
	Sig. (2-tailed)	0.046	0.011	0.049	0.042	0.184	0.241	0.006	0.083	0.035	0.003	0.582
X16	Pearson Correlation	0.209**	-0.105	-0.189	-.365**	-.353**	-0.210	-0.117	-.282*	-0.082	-.264*	-0.150
	Sig. (2-tailed)	0.000	0.365	0.100	0.001	0.002	0.067	0.310	0.013	0.480	0.020	0.193
	N	77	77	77	77	77	77	77	77	77	77	77

***. Correlation is significant at the 0.01 level (2-tailed).*

Key: Y=Traffic congestion, X1=High cost of travel/fares, X2=High vehicle maintenance, X3=Environmental pollution, X4=Staff fatigue (drivers and conductors), X5=Accidents, X6=Poor road design, X7=Poor Traffic control system, X8=Road construction and maintenance works,X9=Vehicle break downs, X10=Accidents, X11=Poor road use, X12=Roadside parking/obstruction, X13=High number of private cars, X14=High number of public transport vehicles including matatus, buses and motorbikes, X15=Behaviour of road usage, X16=Poor traffic management by traffic officers

As shown, all the variables including High cost of travel/fares (r=.494), High vehicle maintenance (r=.206), Environmental pollution (r=.359), Staff fatigue (drivers and conductors) (r=.488), Accidents (r=.310), Poor road design (r=.308), Poor Traffic control system (r=.410), Road construction and maintenance works (r=.353),Vehicle break downs (r=.179), Roadside parking/obstruction (r=.452), High number of private cars (r=.233), High number of public transport vehicles (r=.071), Behavior of road usage (r=.228) Accidents (r=-.042), Poor road use (r=-.042) and Poor traffic management (r=-.209) had positive correlation with traffic congestion in Nairobi Metropolitan Area. Based on this, a unit increase in these variables will lead to a unit increase in the traffic congestion in Nairobi Metropolitan Area. The p-value<0.01 of all the variables indicated that the effect was significant at 95% confidence level. This implies that these variables can effectively predict the changes in the traffic congestion in Nairobi Metropolitan Area.

These findings agree with empirical evidence obtained by the study. Afrin & Yodo (2022) found that causes of traffic included transportation infrastructure, which consists of physical bottlenecks and traffic-control systems, incidents, such as car accidents, account for 25% of the total traffic congestion, while construction zones, poor traffic signal timing, and special events each contribute for 5%. Similarly, Rafi (2021) found that bottlenecks accounted for 40% of the total traffic congestion in most parts of the world. This the reason why traffic management systems, which are designed to lessen traffic congestion and other difficulties related with traffic, are heavily relied upon by big cities that concentrate on avoiding traffic congestions and enhancing overall traffic efficiency. TMSs are composed of a number of management tools and applications that combine communication, sensor, and processing technology. The systems gather information on traffic from a variety of sources, including traffic signals, moving cars, and in-road and wayside sensors (Afrin & Yodo, 2022). Several traffic hazards can be identified in real-time and consequently mitigated, increasing the overall traffic efficiency and enhancing the smooth flow of traffic. This can be done by aggregating and utilizing the collected data among vehicles or in a traffic management center (TMC) concentrated in a data center or a cloud. We will look at the traffic management systems of Santa Ana in the state of California and New York Metropolis, the most populated city in the US, to get an idea of the scale of the traffic management systems used in the nation.

Additionally, inclement weather, such as persistent rain, snow, or high winds throughout various seasons, tends to have a detrimental effect on traffic and, therefore, travel time (Cools, Moons, & Wets, 2009; Juga & Vajda, 2012; Mosoti & Moronge, 2015; Stern, Shah, Goodwin, & Pisano, 2003). Roads become slick from heavy rain or snow, slowing down travel. Roadways may sometimes become inaccessible because to water or snowfall. Strong winds have the potential to uproot trees and move utility poles, obstructing roadways with debris. Analyzing historical data on traffic patterns during different times of the day, days of the week, and seasons can reveal recurring congestion patterns. Factors such as rush hour periods, peak travel times, and special events can significantly impact traffic flow and contribute to congestion. By considering the temporal aspect and incorporating time-related features into predictive models, it becomes possible to anticipate congestion during specific periods and plan mitigation strategies accordingly.

In the fundamental economic categorization, public highways are categorized as common resource products. Since it is difficult to bar anybody from using such products, they are competitor goods, eaten by a single consumer at a time (Otieno, 2016). When there is competition for space and the cost of the road is cheap because of tax-funded construction, there is traffic congestion. The cheapest way to go around communities is by using various public transportation options. Understanding how roads are utilized by different types of vehicles and the behavior of road users is essential for predicting traffic congestion. Factors such as traffic volume, vehicle types (e.g., private cars, buses, trucks), and driving behavior (e.g., aggressive driving, lane changing) influence traffic flow and congestion. Collecting data on traffic counts, vehicle types, and observing driving patterns through surveillance systems or traffic cameras can provide valuable insights into road usage. Integrating this information into predictive models allows for a more accurate assessment of congestion risk.

One of the biggest issues in metropolitan areas is traffic. A supply and demand mismatch results in traffic congestion when there are more automobiles on the road than there is room for them. Demand for the route may rise up to and beyond the saturation threshold depending on the time of day, the density of the local workforce and population, the state of the road and its junctions, and other factors. High costs, delays, and fuel usage are all results of traffic congestion, which also has detrimental social and environmental effects. Using travel rate, trip time, and cost of travel/fare, this research will quantify the amount of traffic on the roads.

4.5.2 Multiple Regression Analysis (Travel time as dependent variable)

The study sought to establish the effect of causative factors of road traffic (predictor variables) on traffic congestion as measured by travel time taken (dependent variable). The Regression model summary is presented in Table 4.6.

TABLE 4. 6

Model Summary (Travel time as dependent variable)

R	R Square	Adjusted R Square	Std. Error of the Estimate
.663a	0.439	0.344	0.85124

a. Predictors: (Constant), Poor traffic management by traffic officers, High number of public transport vehicles including matatus, buses and motorbikes, Poor road design, *Accidents, High number of private cars, Poor road use, Poor Traffic control system , Behaviour of road usage , Vehicle break downs, Road construction and maintenance works, Roadside parking/obstruction*

From Table 4.6, the coefficient of determination (Adjusted R^2) was 0.344 implying that that the regression could explain up to 34.4 percent of the variation in the travel time taken in Nairobi Metropolitan Area. The remaining 65.6 percent of the variation could be due to other predictors not in the model. The model test of fitness results are presented below indicating the reliability of the model.

TABLE 4. 7

ANOVA Travel time as dependent variable

	Sum of Squares	Df	Mean Square	F	Sig.
Regression	36.849	11	3.350	4.623	.000[b]
Residual	47.100	65	0.725		
Total	83.948	76			

The model result of model fitness indicates an F-statistic of 4.623>3.350 and a p-value of 0.000<0.05. F statistic of 4.623 which is higher than the critical f meaning that the model is statistically significant. This indicates that the model is fit for prediction at 95 percent confidence level. The multiple regression model coefficients obtained which could be used for prediction are presented below.

TABLE 4. 8

Model Coefficients (Travel time as dependent variable)

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	T	Sig.
(Constant)	1.574	0.978		1.609	0.112
Poor road design	0.021	0.108	0.027	0.196	0.845
Poor Traffic control system	0.196	0.088	0.256	2.233	0.029
Road construction and maintenance works	0.094	0.094	0.129	1.001	0.320
Vehicle break downs	0.060	0.100	0.076	0.605	0.548
Accidents	-0.121	0.085	-0.151	-1.424	0.159
Poor road use	-0.222	0.075	-0.355	-2.951	0.004
Roadside parking/obstruction	0.368	0.116	0.440	3.180	0.002

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	T	Sig.
High number of private cars	0.132	0.127	0.124	1.032	0.306
High number of public transport vehicles including matatus, buses and motorbikes	0.031	0.108	0.036	0.283	0.778
Behaviour of road usage	0.069	0.101	0.079	0.684	0.496
Poor traffic management by traffic officers	0.012	0.084	0.016	0.144	0.886

0a. *Dependent Variable: Travel time*

As per Table 4.10, the model coefficients showed that all the independent variables except accidents and poor road use had a positive significant effect on the road traffic in Nairobi Metropolitan Area. However, all the variables except poor traffic control system, poor road use and roadside parking/obstruction have no significant effect as the p values are more than 5% ($P > 0.05$) meaning that they are not able to effectively explain changes in the road traffic in Nairobi Metropolitan Area. The predictive model below is thus developed

$Y_t = 1.574 + 0.021\, X_1 + 0.196X_2 + 0.094X_3 + 0.060X_4 - 0.121X_5 - 0.222X_6 + 0.368X_7 + 0.132X_8 + 0.031X_9 + 0.069X_{10} + 0.012X_{11}$

Whereby; Y= Travel time, X1=Poor road design, X2=Poor Traffic control system, X3=Road construction and maintenance works, X4=Vehicle break downs, X5=Accidents, X6=Poor road use, X7=Roadside parking/obstruction, X8=High number of private cars, X9=High number of public transport vehicles including matatus, buses and motorbikes, X10=Behaviour of road usage and X11=Poor traffic management by traffic officers

4.5.3 Multiple Regression Analysis (Travel Rate as dependent variable)

The study sought to establish the effect of road traffic attributes (predictor variables) on road traffic as measured by travel rate in terms of time taken to get to pass the intersection (dependent variable). The Regression model summary is presented in Table 4.9.

TABLE 4. 9

Model Summary (Travel Rate as dependent variable)

R	R Square	Adjusted R Square	Std. Error of the Estimate
.371a	0.138	0.137	0.752

a. Predictors: (Constant), Behaviour of road users, Nature of roundabout, Time of day, Number of lanes, Type of vehicles, Weather condition

From Table 4.9, the coefficient of determination (Adjusted R^2) was 0.137 implying that that the regression could explain up to 13.7 percent of the variation in the road travel rates in Nairobi Metropolitan Area. The remaining 86.3 percent of the variation could be due to other predictors not in the model. The model test of fitness results are presented below indicating the reliability of the model.

TABLE 4. 10

ANOVA (Travel Rate as dependent variable)

	Sum of Squares	Df	Mean Square	F	Sig.
Regression	333.194	6	55.532	93.736	.000[b]
Residual	2081.224	3513	0.592		
Total	2414.418	3519			

The model result of model fitness indicates an F-statistic of 93.736>55.532 and a p-value of 0.000<0.05. F statistic of 93.736 which is higher than the critical f meaning that the model is statistically significant. This indicates that the model is fit for prediction at 95 percent confidence level. The multiple regression model coefficients obtained which could be used for prediction are presented in table 4.11.

TABLE 4. 11

Model Coefficients (Travel Rate as dependent variable)

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	T	Sig.
(Constant)	2.833	0.082		34.350	0.000
Time of day	0.254	0.012	0.302	21.575	0.000

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	T	Sig.
Weather condition	0.041	0.015	0.042	2.709	0.007
Type of vehicles	-0.108	0.019	-0.083	-5.603	0.000
Number of vehicles	0.458	0.015	0.460	30.581	0.000
Number of lanes	-0.041	0.009	-0.070	-4.739	0.000
Nature of roundabout	-0.255	0.019	-0.219	-13.454	0.000
Behaviour of road users	-0.017	0.010	-0.026	-1.724	0.085

a. *Dependent Variable: Travel rate*

As per Table 4.11, the model coefficients showed that all the independent variables except type of vehicles, number of lanes, nature of roundabout and behavior of road users had a positive significant effect on the road traffic congestion in Nairobi Metropolitan Area as measured by travel rates. All the variables except behavior of road users have a significant effect as the p values are less than 5% ($P < 0.05$) meaning that they are able to effectively explain changes in the time spent at the intersections in Nairobi Metropolitan Area.

$$Y_t = 2.833 + 0.254\,X_1 + 0.041X_2 - 0.108X_3 + 0.458X_4 - 0.041X_5 - 0.255X_6 - 0.017X_7$$

Whereby; Y= Travel rate at particular time, X1=Time of day, X2=Weather condition, X3=Type of vehicles, X4=Number of vehicles, X5=Number of lanes, X6=Nature of roundabout and X7=Behaviour of road users

Several studies have explored the prediction of traffic congestion using deep learning algorithms.Zhang *et al*. (2016) introduced PredCNN, a convolutional neural network (CNN) model, for traffic flow prediction. They utilized historical traffic flow data along with time, day of the week, and weather conditions to forecast congestion. Their model outperformed traditional methods, exhibiting superior prediction accuracy. Ma *et al*. (2017) proposed DST-ResNet, a deep spatio-temporal residual network, for traffic flow prediction. Their model captured both spatial and temporal dependencies in traffic patterns by incorporating historical traffic flow data and other relevant information. Experimental results demonstrated the effectiveness of their approach in predicting traffic congestion. Liang *et al*. (2018) presented ST-ResNet, a recurrent neural network (RNN) model, for short-term traffic flow prediction. The model leveraged spatio-temporal correlations and extracted long-term dependencies in traffic patterns. By incorporating historical traffic data and meteorological information, their model achieved accurate predictions of traffic congestion.

An Artificial Intelligence model for anticipating traffic congestion thus offers practical and efficient solutions to the management and decision-making issues associated with managing the flow of traffic, which helps to lower fuel consumption, lower greenhouse gas emissions, and raise the bar for sustainable living (Akhtar & Moridpour, 2021). A better, safer traveling experience will be made possible through the integration of ICT with the transportation infrastructure, as well as the transition to a traffic management model that focuses on four key principles: sustainability, integration, safety, and responsiveness (Tahifa, Boumhidi & Yahyaouy, 2018). This research aimed to provide additional light on the platform utilized to access, gather, and interpret reliable data from the environment since it is crucial to the model's performance.

Traffic jams have a negative influence on vehicle motorization and dispersion, which raises the need for transportation infrastructure (Iqbal & Yukimatsu 2011). However, predicting traffic congestion using deep learning algorithms is a challenging problem with significant implications for urban transportation management. Through the use of historical traffic data, weather conditions, and other relevant factors, deep learning models can accurately forecast traffic congestion patterns. Previous studies have demonstrated the effectiveness of deep learning algorithms in traffic prediction. Lv *et al*. (2015) proposed a deep belief network (DBN) model for traffic flow prediction. While the research explored the potential of deep learning in predicting traffic congestion, a major limitation is the lack of comparison with other state-of-the-art deep learning models or traditional methods. Without such comparisons, it is challenging to determine the model's effectiveness and whether it outperforms existing approaches. Additionally, the study did not extensively discuss the interpretability of the DBN model, which is crucial for practical implementation and understanding the factors influencing traffic congestion.

Chen *et al*. (2018) presented a study on traffic flow prediction using a hybrid deep learning model that combined long short-term memory (LSTM) and convolutional neural network (CNN). While the research demonstrated improved prediction accuracy, one limitation lies in the absence of a comprehensive evaluation of the model's performance on different traffic conditions and road networks. Furthermore, the study did not thoroughly investigate the computational efficiency of the hybrid model, which could be essential for real-time deployment in large-scale traffic systems. Zheng *et al*. (2020) proposed a deep spatio-temporal graph convolutional neural network (STGCN) for traffic flow prediction. The model incorporated both spatial and temporal dependencies in traffic data through graph convolutions.

While the research demonstrated promising results, one limitation is the lack of extensive analysis on the interpretability of the model. Additionally, a comparative evaluation against other deep learning models or traditional methods would further establish the model's performance and effectiveness.

Li *et al*. (2019) presented a study on traffic congestion prediction using a multi-view multi-task deep learning model. The model integrated information from various sources, such as traffic flow, road network, and meteorological data, to forecast congestion patterns. While the research addressed the need for incorporating multiple views, a limitation is the absence of a comprehensive evaluation on the impact of different data sources on the prediction accuracy. Analyzing the individual and combined contributions of each data view would help identify the most influential factors and guide future data collection efforts. Additionally, considering the scalability and computational efficiency of the multi-view model would be beneficial for real-world deployment. By building upon these works and further refining the models, the study aims to improve the accuracy and timeliness of traffic congestion predictions, leading to more efficient traffic management and reduced congestion-related issues.

4.5.4 Model Validity

As per Table 4.10, the model coefficients showed that all the independent variables except accidents and poor road use had a positive significant effect on the road traffic in Nairobi Metropolitan Area. However, all the variables except poor traffic control system, poor road use and roadside parking/obstruction have no significant effect as the p values are more than 5% ($P > 0.05$) meaning that they are not able to effectively explain changes in the road traffic in Nairobi Metropolitan Area. The predictive model below is thus developed;

$$Y_t = 1.574 + 0.021\,X_1 + 0.196X_2 + 0.094X_3 + 0.060X_4 - 0.121X_5 - 0.222X_6 + 0.368X_7 + 0.132X_8 + 0.031X_9 + 0.069X_{10} + 0.012X_{11}$$

Whereby; Y= Travel time, X1=Poor road design, X2=Poor Traffic control system, X3=Road construction and maintenance works, X4=Vehicle break downs, X5=Accidents, X6=Poor road use, X7=Roadside parking/obstruction, X8=High number of private cars, X9=High number of public transport vehicles including matatus, buses and motorbikes, X10=Behaviour of road usage and X11=Poor traffic management by traffic officers.

Further, the study used one-way analysis using Analysis of Variance (ANOVA) was used to determine the validity of the predictive model adopted.

TABLE 4. 12

Model Validity

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	296.727	4	74.182	551.246	0.000
Within Groups	473.016	3515	0.135		
Total	769.743	3519			

As shown by Table 4.12, the model was established to be valid ($p<0.05$). Deep learning model will improve the accuracy as more data is fed. From Table 4.6, the coefficient of determination (Adjusted R^2) was 0.344 implying that that the regression could explain up to 34.4 percent of the variation in the travel time taken in Nairobi Metropolitan Area. The remaining 65.6 percent of the variation could be due to other predictors not in the model. The model test of fitness results are presented below indicating the reliability of the model. This meant that the initial model is 34.6 percent accurate. Subsequently, through deep learning and more data is gathered, the model accuracy would be expected to continue to increase.

CHAPTER FIVE

DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter gives discussions of the collected data with reference to the objectives of the study. The study sought to develop a model for predicting traffic congestion within the Nairobi Metropolitan area using deep learning algorithm through deep neural network. Specifically, the study sought to investigate the critical factors affecting traffic congestion in Nairobi Metropolitan Area, to develop a model for predicting traffic congestion management within the Nairobi Metropolitan area using deep learning algorithm, to validate the traffic congestion management model designed for managing traffic within the Nairobi Metropolitan area and to evaluate the traffic congestion management model designed for managing traffic within the Nairobi Metropolitan area. The conclusion of the findings related to research questions and recommendations derived from the conclusion are also presented.

5.2 Discussion of Findings

The study sought to determine the critical factors affecting traffic congestion in Nairobi Metropolitan Area. The world population is increasing at an accelerating rate causing increase in number of vehicles on the road, traffic congestion and increased in cost of traffic congestion. Increase in vehicle traffic, transport infrastructure demand for better mobility systems has led to development of modern transportation accessible by all people. This increase in demand calls for better systematic transportation infrastructure that can carry a large mass of vehicles safely and ensures that it is environmentally friendly. Numerous societies and companies around the globe strive to develop a model for predicting traffic congestion. The first establishment was set in 1991 by America, along with many prototypes proposed for implementation. Car to car communication, carriage to infrastructure interaction, and electronic charges are among the popular transportation models in operation globally. Even with adoption in information communication technology, adoption of intelligent models for traffic prediction remains low. In India for example, intelligent Traffic Management Model is at a primary phase in growth. This is despite the fact that every nation in the world, including Kenya, requiring to implement intelligent technologies to ensure that the transportation system is safe, economical, and environmentally friendly.

Traffic congestion is a widespread problem that plagues urban transportation systems, causing delays, increased fuel consumption, and environmental pollution. Addressing this issue requires accurate prediction of traffic congestion, enabling proactive management strategies and real-time information dissemination. Deep learning algorithms have emerged as powerful tools for traffic prediction, offering the potential to forecast congestion patterns effectively. The development of a model for predicting traffic congestion that is capable of accurately detecting and reducing the overall density of traffic in most urban areas frequented by motorists, such as offices, downtown, and establishments, has become one of the main challenges for engineers and designers in recent years. Traffic prediction models in use today are based on several modern technologies, including wireless sensor networks (WSNs), surveillance cameras, and IoT.

The findings revealed that vehicle breakdowns, a high number of public transport vehicles such as matatus, buses, and motorbikes, and driver behavior contribute to traffic congestion in the area, with respective mean scores of 4.01, 4.01, and 4.12. This suggests that these factors have a substantial impact on the traffic congestion problem in Nairobi. Moreover, poor road design, road construction and maintenance, roadside parking and obstruction, a high number of private cars, and inadequate traffic management by officers also had a notable impact, with mean scores ranging from 3.58 to 3.84. This implies that issues related to infrastructure, road maintenance, and traffic control practices play significant roles in exacerbating traffic congestion. In contrast, accidents and poor road use had a moderately significant effect, with mean scores of 3.38 and 3.40, respectively. While these factors are not as prominent as others, they still contribute to traffic congestion to some degree. The respondents generally agreed on these critical factors, with an average mean score of 3.72 and a standard deviation of 1.319, indicating a consensus among the participants regarding the factors affecting traffic congestion.

The study aimed to examine the effects of traffic congestion in the Nairobi Metropolitan Area. Respondents strongly agreed that traffic congestion leads to longer travel times and environmental pollution, with mean scores of 4.12 and 4.14, respectively. This highlights the negative impacts of congestion on daily life and the environment in the region. They also recognized its impact on higher travel costs, increased vehicle maintenance expenses, driver and conductor fatigue, and accidents, with mean scores ranging from 3.56 to 3.96. These findings suggest that traffic congestion has wide-ranging adverse effects on both individuals and transportation services in the area. Observational data further revealed that traffic was busiest during the afternoon and late afternoon, with 38% and 36% of traffic occurring during these periods, respectively. This indicates that traffic congestion is particularly pronounced during these times, likely due to factors such as rush hour and commuters returning home from work.

Further from the correlation analysis, all the variables including High cost of travel/fares (r=.494), High vehicle maintenance (r=.206), Environmental pollution (r=.359), Staff fatigue (drivers and conductors) (r=.488), Accidents (r=.310), Poor road design (r=.308), Poor Traffic control system (r=.410), Road construction and maintenance works (r=.353),Vehicle break downs (r=.179), Roadside parking/obstruction (r=.452), High number of private cars (r=.233), High number of public transport vehicles (r=.071), Behavior of road usage (r=.228) Accidents (r=-.042), Poor road use (r=-.042) and Poor traffic management (r=-

.209) had positive correlation with traffic congestion in Nairobi Metropolitan Area. Based on this, a unit increase in these variables will lead to a unit increase in the traffic congestion in Nairobi Metropolitan Area. The p-value<0.01 of all the variables indicated that the effect was significant at 95% confidence level. This implies that these variables can effectively predict the changes in the traffic congestion in Nairobi Metropolitan Area.

Regression analysis was further undertaken in developing predictive models for road traffic in Nairobi Metropolitan Area. Using travel time taken and travel rate (time taken to get to pass the intersection) as dependent variables. The study established that poor traffic management by traffic officers, high number of public transport vehicles including matatus, buses and motorbikes, poor road design, accidents, high number of private cars, poor road use, poor traffic control system , behaviour of road usage , vehicle break downs, road construction and maintenance works and roadside parking/obstruction explained up to 34.4 percent of the variation in the travel time taken in Nairobi Metropolitan Area (R^2=0.344). Comperatively, Behaviour of road users, Nature of roundabout, Time of day, Number of lanes, Type of vehicles, Weather condition were established to explain 13.7 percent of the variation in the road travel rates in Nairobi Metropolitan Area (R^2=0.137).

Based on the model coefficients, the following models are predicted;

$$Y_t = 1.574 + 0.021\,X_1 + 0.196X_2 + 0.094X_3 + 0.060X_4 - 0.121X_5 - 0.222X_6 + 0.368X_7 + 0.132X_8 + 0.031X_9 + 0.069X_{10} + 0.012X_{11} \quad \text{(Model 1)}$$

Whereby; Y= Travel time, X1=Poor road design, X2=Poor Traffic control system, X3=Road construction and maintenance works, X4=Vehicle break downs, X5=Accidents, X6=Poor road use, X7=Roadside parking/obstruction, X8=High number of private cars, X9=High number of public transport vehicles including matatus, buses and motorbikes, X10=Behaviour of road usage and X11=Poor traffic management by traffic officers.

$$Y_t = 2.833 + 0.254\,X_1 + 0.041X_2 - 0.108X_3 + 0.458X_4 - 0.041X_5 - 0.255X_6 - 0.017X_7$$

(Model 2)

Whereby; Y= Travel rate at particular time, X1=Time of day, X2=Weather condition, X3=Type of vehicles, X4=Number of vehicles, X5=Number of lanes, X6=Nature of roundabout and X7=Behaviour of road user

The findings compare well with empirical literature from the rest of the world. Petersen (2021) found that Just like many other regions of the world, Switzerland was experiencing an increasing number of vehicles and traffic and as such there was need to an intelligent traffic management system as well as additional requirements for areas such as safety, environment, and regulations. Additionally, empirical literature confirms that factors responsible for traffic that need to be fed to the model. These include, weather conditions such as persistent rain, snow, or high winds throughout various seasons, tends to have a detrimental effect on traffic and, therefore, travel time (Cools, Moons, & Wets, 2009; Juga & Vajda, 2012; Mosoti & Moronge, 2015; Stern, Shah, Goodwin, & Pisano, 2003).

Several studies have explored the prediction of traffic congestion using deep learning algorithms. Zhang *et al.* (2016) introduced PredCNN, a convolutional neural network (CNN) model, for traffic flow prediction. They utilized historical traffic flow data along with time, day of the week, and weather conditions to forecast congestion. Their model outperformed traditional methods, exhibiting superior prediction accuracy. Ma *et al*. (2017) proposed DST-ResNet, a deep spatio-temporal residual network, for traffic flow prediction. Their model captured both spatial and temporal dependencies in traffic patterns by incorporating historical traffic flow data and other relevant information. Experimental results demonstrated the effectiveness of their approach in predicting traffic congestion. Liang *et al*. (2018) presented ST-ResNet, a recurrent neural network (RNN) model, for short-term traffic flow prediction. The model leveraged spatio-temporal correlations and extracted long-term dependencies in traffic patterns. By incorporating historical traffic data and meteorological information, their model achieved accurate predictions of traffic congestion.

An Artificial Intelligence model for anticipating traffic congestion thus offers practical and efficient solutions to the management and decision-making issues associated with managing the flow of traffic, which helps to lower fuel consumption, lower greenhouse gas emissions, and raise the bar for sustainable living (Akhtar & Moridpour, 2021). A better, safer traveling experience will be made possible through the integration of ICT with the transportation infrastructure, as well as the transition to a traffic management model that focuses on four key principles: sustainability, integration, safety, and responsiveness (Tahifa, Boumhidi & Yahyaouy, 2018). This research aimed to provide additional light on the platform utilized to access, gather, and interpret reliable data from the environment since it is crucial to the model's performance.

Traffic jams have a negative influence on vehicle motorization and dispersion, which raises the need for transportation infrastructure (Iqbal & Yukimatsu 2011). Iqbal & Yukimatsu (2011) found that deep learning models could accurately forecast traffic congestion patterns. Further previous studies have demonstrated the effectiveness of deep learning algorithms in traffic prediction. Lv *et al*. (2015) proposed a deep belief network (DBN) model for traffic flow prediction. While the research explored the potential of deep learning in predicting traffic congestion, a major limitation is the lack of comparison with other state-of-the-art deep learning models or traditional methods. Without such comparisons, it is challenging to determine the model's effectiveness and whether it outperforms existing approaches. Additionally, the study did not extensively discuss the interpretability of the DBN model, which is crucial for practical implementation and understanding the factors influencing traffic congestion.

Chen *et al.* (2018) the study did not thoroughly investigate the computational efficiency of the hybrid model, which could be essential for real-time deployment in large-scale traffic systems. Zheng *et al*. (2020) proposed a deep spatio-temporal graph convolutional neural network (STGCN) for traffic flow prediction. While the research demonstrated promising results, one limitation is the lack of extensive analysis on the interpretability of the model. Additionally, a comparative evaluation against other deep learning models or traditional methods would further establish the model's performance and effectiveness. Li *et al*. (2019) presented a study on traffic congestion prediction using a multi-view multi-task deep learning model. The study achieved a similar conclusion to this study that considering the scalability and computational efficiency of the multi-view model would be beneficial for real-world deployment.

5.3 Conclusions

Traffic congestion is a big problem in Nairobi. To mitigate traffic congestions, countries have been investing heavily in expanding roads and interchange in urban areas. Whereas this has been an expensive affair, the traffic problem remains in many cities across Africa. There is also heavy reliance on time-based traffic lights at interchanges and policemen come in to manage the inefficiencies of time-based traffic management models.

The study sought to investigate the critical factors affecting traffic congestion in Nairobi Metropolitan Area. In line with this objective, the study concludes that factors contributing to traffic congestion in the Nairobi Metropolitan Area are several. The study concludes that poor road design, ineffective traffic control systems, road construction and maintenance issues, vehicle breakdowns, accidents, poor road use, roadside parking or obstruction, a high number of private cars, a high number of public transport vehicles, and the quality of traffic management by officers have a significant influence on how long it takes for vehicles to travel through the Nairobi Metropolitan Area. Therefore, improved infrastructure, traffic management practices, and enhanced driver behaviour is concluded to reduce travel time and improve transportation efficiency in the region. Further, the study concludes that time of day, weather conditions, vehicle type, the number of vehicles on the road, the number of lanes, roundabout types, and driver behavior affect how external factors and driver behavior impact the overall flow of traffic in the area.

The study also sought to develop a model for predicting traffic congestion management within the Nairobi Metropolitan area using deep learning algorithm. The study concludes that implementation of deep learning model to predict and manage traffic within Nairobi Metropolitan area is achievable solution to traffic issues. In Kenya, even with advancement in technology, there remains to be no intelligent traffic management model. Most of the artificial intelligence models have also been relying on secondary data and offers no room for learning. Particularly, an effort to ease traffic, the Nairobi Metropolitan Area Authority and the Nairobi County Government decongested bus terminals further from the city center, although this did not make the situation better.

Reliance on time-based traffic lights and traffic police officers has also been faced with inefficiencies in reducing traffic congestion. There is no intelligent traffic prediction model in place. One of the most important stages in the operation of an Intelligent Transportation System is the ability of practitioners to carry out route planning and traffic control. Large volumes of data may be used to analyze issues relating to traffic congestion utilizing machine learning and deep learning methods, which are currently being actively used in other industries. Despite these benefits, the use of such approaches around traffic management is not in place necessitating the necessity for this research. Manual management of traffic takes a lot of time and makes it hard to ensure the information is always reliable, consistent and up to date. Therefore, government agencies are not only looking for ways of optimizing their processes and structures. To assist them in the substantial transition to a digital workplace, they are also searching for partners with the requisite business and technological know-how.

The study further sought to validate the traffic congestion management model designed for managing traffic within the Nairobi Metropolitan area. The study also concludes that the initial model developed results may be different from actual results but with deep learning, the model accuracy will keep improving. The identified issues in road design, traffic control, driver behavior, and considering external factors, efforts can be directed towards improving transportation efficiency and ultimately alleviating traffic congestion in the Nairobi Metropolitan Area. By enhancing road design, traffic control and change in driver behaviour, there will be alleviated traffic congestion in the Nairobi Metropolitan Area. These models provide a data-driven foundation for improving transportation efficiency and alleviating traffic congestion in the Nairobi Metropolitan Area.

5.4 Recommendations

5.4.1 Recommendations for practice

Road design has been found by the study to be cause of traffic in Nairobi. The study recommends that traffic engineering and urban planning practices should prioritize the optimization of road networks. This includes conducting thorough traffic impact assessments for new developments and ensuring that road expansion and construction projects adhere to best practices in road design and capacity management. Public transportation services should also be improved to incentivize their use. This involves investing in modern and well-maintained public transit infrastructure, increasing the frequency and reliability of services, and implementing cashless payment systems to enhance convenience for passengers. Creating dedicated bus lanes and transit corridors can also expedite public transport, reducing congestion.

The study recommends that local authorities and law enforcement agencies should collaborate to enforce traffic rules and regulations rigorously. This includes addressing issues like illegal roadside parking and obstruction, reckless driving, and ensuring that motorists adhere to lane discipline. Regular traffic patrols and visible law enforcement can serve as deterrents to violations. Urban planners and architects are also recommended to design cities and communities with a focus on reducing the need for long commutes. This can be achieved through mixed-use zoning, where residential, commercial, and recreational areas are integrated, reducing the need for extensive travel. Collaboration between public and private sectors is further encouraged to develop innovative solutions.

The study further recommends that a deep learning model should be developed and deployed at all the roundabouts to manage traffic flow. There should be no fixed time lights but instead an intelligent deep learning based model that will asses the number of vehicles at the specif roads and considering multiple other factors decide to increase the time allocated to each road. There should be no manual inturreptions in managing roundabouts.

5.4.2 Recommendations for policy

The study recommends that policymakers should prioritize infrastructure improvements. This includes expanding the number of lanes, optimizing traffic flow through improved intersection design, and enhancing road maintenance practices. The study also recommends that implementation of robust traffic management strategy by improving traffic signal synchronization, implementing intelligent traffic management systems, and investing in technology-driven solutions like real-time traffic monitoring and congestion alerts. Adequate and efficient traffic management by officers should also be ensured, as this factor has been found to play a substantial role in congestion mitigation.

The study also recommends that policy measures should encourage the use of public transportation. Given that a high number of public transport vehicles contribute to congestion, promoting the use of efficient and reliable public transit systems can help reduce the reliance on private cars. This includes investing in a well-connected and well-maintained public transport network, ensuring affordability, and improving the quality of service. Additionally, policymakers should consider congestion pricing mechanisms during peak hours. This will incentivize drivers to use alternative routes or modes of transportation, thus reducing traffic congestion during high-demand periods. Revenues generated from congestion pricing can be reinvested in transportation infrastructure and improvements.

5.5.3 Recommendations for further studies

The study suggests future studies into the dynamics of public transportation systems, including the optimization of routes, schedules, and the integration of various modes of public transit. Investigating the impact of new technologies like ride-sharing and on-demand services on public transport can also be valuable. Future studies can also employ behavioral economics and psychology to better understand why drivers make certain choices and how their behavior can be influenced positively. Given the changing landscape of work in response to global events like the COVID-19 pandemic, future studies should investigate the long-term effects of telecommuting and remote work on traffic congestion. Analyzing the sustainability of flexible work arrangements and their implications for urban planning is crucial. The study further suggests conducting longitudinal studies that track changes in traffic patterns and congestion levels over time can provide insights into the effectiveness of implemented policies and initiatives. Long-term data collection and analysis will help refine strategies for congestion management.

REFERENCES

Acherman, D. (2021). The Swiss way to capacity optimization for traffic management. Retrieved 15 February 2021, from https://www.globalrailwayreview.com/webinar/60339/the-swiss-way-to-capacity-optimization-for-traffic-management/

Afrin, T. & Yodo, N., (2020). A Survey of Road Traffic Congestion Measures towards a Sustainable and Resilient Transportation System. *Sustainability*, 12(11), p.4660.

Akhtar, M & Moridpour, S., (2021). Machine Learning Applications in Transportation Engineering. *Journal of Advanced Transportation*, vol. 2021, Article ID 8878011, 18 pages, 2021. https://doi.org/10.1155/2021/8878011

Awad, M., & Khanna, R. (2015). Support vector regression. In *Efficient learning machines* (pp. 67-80). Apress, Berkeley, CA.

Chen, X., Ma, Z., Wang, Y., Wang, H., & Tian, Q. (2018). A hybrid deep learning model for traffic flow prediction. IEEE Access, 6, 16667-16675.

De Souza, A., Brennand, C., Yokoyama, R., Donato, E., Madeira, E. & Villas, L., (2017. Traffic management systems: A classification, review, challenges, and future perspectives. *International Journal of Distributed Sensor Networks*, 13(4), p.155014771668361.

Gregory, W., (2021). *New York unveils 'Midtown in Motion' traffic management system*. [online] ITS International. Available at: <https://www.itsinternational.com/its9/news/new-york-unveils-midtown-motion-traffic-management-system> [Accessed 15 February 2021].

Haq, I. (2020). Traffic congestion prediction based on Estimated Time of Arrival. *PLoS ONE*. 15. 1-19. 10.1371/journal.pone.0238200.

Iqbal, R., & Yukimatsu, K. (2011). Intelligent transportation systems using short-range wireless technologies. *Journal of Transportation Technologies*, *1*(4), 132-137.

Kerner, B. S. (2009). Traffic congestion, modeling approaches to. *In Encyclopedia of Complexity and Systems Science*. Springer.

Leeuwen, A. S. (2011). *Static traffic assignment with queuing.* Unpublished Master Thesis Applied Mathematics, University of Tewente

Li, X., Wang, Y., Gao, L., Wang, D., & Hu, Z. (2019). Multi-view multi-task deep learning for traffic congestion prediction. IEEE Transactions on Intelligent Transportation Systems, 21(9), 3650-3661.

Liang, X., Hu, S., Hsieh, H. P., & Xing, X. (2018). Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. Proceedings of the 32nd AAAI Conference on Artificial Intelligence, 7234-7241.

Lv, Y., Duan, L., Kang, W., & Zhang, B. (2015). Traffic flow prediction with big data: A deep learning approach. IEEE Transactions on Intelligent Transportation Systems, 16(2), 865-873.

Ma, X., Dai, Z., He, Z., Ma, J., & Wang, Y. (2017). Learning traffic as images: A deep convolutional neural network for large-scale transportation network speed prediction. Sensors, 17(4), 818.

Mallik, S. (2014). The intelligent transportation system. *International Journal of Civil Engineering Research*, *5*(4), 367-372.

Ombok E. (2019). Traffic Jams in Kenya's capital bleed $1 Billion from Economy: https://www.bloomberg.com/news/articles/2019-09-24/traffic-jams-in-kenya-s-capital-bleed-1-billion-from-economy

Petersen, G. (2021). New Organisation of Traffic Information and Traffic Management Services in Switzerland Gerhard Petersen, Federal Roads Office, Switzerland. Retrieved 15 February 2021, from https://trid.trb.org/view/843486

Rafi, A., 2021. *Integrated Road Management Systems (IRMS)*. [online] Citeseerx.ist.psu.edu.

Saw, K., Katti, B. K., & Joshi, G. (2015). Literature review of traffic assignment: static and dynamic. *International Journal of Transportation Engineering*, 2(4), 339-347.

Tahifa, M., Boumhidi, J., & Yahyaouy, A. (2018). Multi-agent reinforcement learning-based approach for controlling signals through adaptation. *International Journal of Autonomous and Adaptive Communications Systems*, *11*(2), 129-143.

Wairimu A. (2019, September 25). *Nairobi ranked world's 4th most congested city.* Retrieved from Kenya Wallstreet: https://www.kenyanwallstreet.com/nairobi-ranked-worlds-4th-most-congested-city/

Zeynoddin, M., Bonakdari, H., Azari, A., Ebtehaj, I., Gharabaghi, B., & Madavar, H. R. (2018). Novel hybrid linear stochastic with non-linear extreme learning machine methods for forecasting monthly rainfall a tropical climate. *Journal of environmental management*, *222*, 190-206.

Zhang, J., Zheng, Y., & Qi, D. (2016). Deep learning for traffic prediction from large-scale transportation data. Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, 1-10.

Zheng, Y., Zhang, J., & Ma, Z. (2020). Deep spatio-temporal graph convolutional neural network for traffic flow prediction. IEEE Transactions on Intelligent Transportation Systems, 21(9), 3838-3848.

Ziliaskopoulos, A. K., Waller, S. T., Li, Y., & Byram, M. (2004). Large-scale dynamic traffic assignment: Implementation issues and computational analysis. *Journal of Transportation Engineering*, 130(5), 585-593.

APPENDICES

Appendix I: Introduction Letter

KCA University,
P.O Box 56808 – 00200

Nairobi, Kenya

Dear Respondent,

RE: DATA COLLECTION FOR ACADEMIC RESEARCH

I am masters student at the KCA University, pursuing a Degree in MSC Data Communications. In partial fulfillment of the requirements of the Masters degree, I am required to submit a project. In response to this, I am therefore conducting research on ***"A MODEL FOR PREDICTING TRAFFIC CONGESTION USING DEEP LEARNING ALGORITHM: CASE OF NAIROBI METROPOLITAN"***

It is in this light that I hereby request for your assistance by filling the attached questionnaire with the most appropriate responses for all the questions as much as you can. The information you provide will be used for purely academic purpose and held and treated confidentially and thus will not be disclosed without prior permission from you. Codes shall be used instead of your names.

Thank you in advance as I look forward to your cooperation and assistance.

Yours sincerely,

Ezra Kipchirchir Cheruiyot
19/03909

Appendix II: Research Questionnaire

The purpose of this research is to obtain information for predicting traffic congestion within the Nairobi Metropolitan area using deep learning algorithm. Please offer information as openly and truthfully as possible. All given information will be kept strictly private and used exclusively for academic reasons.

Kindly answer by checking or writing in the appropriate spaces.

PART A: BACKGROUND INFORMATION

1. Please indicate your gender

Male [ ] Female [ ]

2. Please indicate your age (years) ……………………………

3. For how long have you resided within the Nairobi Metropolitan area?

Less than 1 year [ ] 2-5 years [ ] 6-10 years [ ] More than 10 years [ ]

4. Please indicate your category in terms of road usage ………………………………….

5. Please indicate your preferred mode of transport?

Private means [ ] Public transport [ ] Other, specify……………………………

PART B: CRITICAL FACTORS AFFECTING TRAFFIC CONGESTION IN NAIROBI METROPOLITAN AREA

6. Please rate the extent to which the following factors affect traffic congestion in Nairobi Metropolitan Area. Use a scale of 1 to 5 where 1 is very small extent, 2 is small extent, 3 is moderate extent, 4 is large extent and 5 is to a very large extent in the following sections.

Factor	**1**	**2**	**3**	**4**	**5**
Poor road design					
Poor Traffic control system					

Road construction and maintenance works					
Vehicle break downs					
Accidents					
Poor road use					
Roadside parking/obstruction					
High number of private cars					
High number of public transport vehicles including matatus, buses and motorbikes					
Behaviour of road usage					
Poor traffic management by traffic officers					
Other, specify…………………………………….					

PART C: EFFECTS OF TRAFFIC CONGESTION IN NAIROBI METROPOLITAN AREA

7. Please rate the extent of effect of traffic congestion in Nairobi Metropolitan Area on the following. Use a scale of 1 to 5 where 1 is very small extent, 2 is small extent, 3 is moderate extent, 4 is large extent and 5 is to a very large extent in the following sections.

Effect	**1**	**2**	**3**	**4**	**5**
Long travel times					
High cost of travel/fares					
High vehicle maintenance					
Environmental pollution					
Staff fatigue (drivers and conductors)					
Accidents					
Other, specify…………………………………….					

PART D: TRAFFIC CONGESTION MANAGEMENT MEASURES IN NAIROBI METROPOLITAN AREA

8. Please rate the extent to which the following measures ought to be adopted in order to reduce traffic congestion in Nairobi Metropolitan Area. Use a scale of 1 to 5 where 1 is very small extent, 2 is small extent, 3 is moderate extent, 4 is large extent and 5 is to a very large extent in the following sections.

Measure	**1**	**2**	**3**	**4**	**5**
Build new roads					
Re-design and expand existing roads					
Control private car use					
Control matatus access to CBD					
Better traffic control system					
Prosecute Roadside parking and obstruction					
Enforce Traffic rules					
High number of private cars					
Schedule Road works for night times					
Integration of traffic congestion prediction models					
Other, specify…………………………………….					

End

Thank you for your time

Appendix III: Observation Checklist

Type of variable	Measure	Construct	Data
Inputs	Time of day	Early morning	
		Mid morning	
		Mid day	
		Afternoon	
		Late afternoon	
		Evening	
	Weather condition	Rainy	
		Sunny	
		Foggy	
	Type of vehicles	Saloon cars	
		Buses	
		Trucks	
	Number of vehicles	Saloon cars	
		Buses	
		Trucks	
	Number of lanes		
	Nature of roundabout	Traffic lights	
		Traffic officers	
		No traffic lights, no traffic officers	
	Behaviour of road users	Motorists not observing lane discipline	

		Pedestrian crossing	
		Pedestrian not observing the road rules	
		Motorists not observing road rules	
Output	Time taken to get to pass the intersection in seconds		

Appendix IV: Work Plan

Activity	Jan-Sep 2022	Dec-Jan 2023	Feb-Mar 2023	Apr-May 2023	Jun-23	Aug-23
Concept development						
Project preparation						
Project defence						
Corrections						
Data collection						
Data analysis						
Report writing						
Submission of final report						

Appendix V: Budget

Item Description	**Cost- KShs**
Stationery	10,000
Photocopying Services	5,000
Printing & binding	5,000
Travel Charges	10,000
Internet Expenses	5,000
Data collection	30,000
Data analysis	20,000
Publishing	40,000
Contingency	12,500
Total	**137,500**