



# Edge-Enabled Smart Traffic Management System: An IoT Implementation for Urban Mobility

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## Abstract

Effective traffic management has emerged as a critical issue in today's rapidly urbanizing areas with a rise in the number of cars. By developing an Edge-Enabled Smart Traffic Management System (EESTMS) run on the Internet of Things (IoT), this paper puts forth a novel approach. EESTMS makes use of edge computing and IoT technology's promise to improve urban transportation. A large network of thoughtfully placed sensors and cameras dispersed around the city forms the system's central structure. These gadgets continuously gather data on the volume, speed, and congestion of moving vehicles. This information offers insightful information about traffic trends. We can lessen latency and lighten the load on centralized systems by processing this data at the edge. In order to analyse the data and identify traffic bottlenecks and congestion hotspots, machine learning techniques are used. Real-time analysis allows for dynamic traffic signal adjustments, which optimize traffic flow and shorten commuter travel times. EESTMS also offers a user-friendly interface with real-time traffic information, alternate routes, and tailored navigation advice that is accessible via mobile applications and web platforms. By making wise decisions, commuters can lessen their stress and carbon footprint. EESTMS plays a critical role in advancing sustainability by reducing fuel consumption and greenhouse gas emissions through effective traffic management, in addition to enhancing urban mobility. By giving emergency vehicles priority routing, this system also improves emergency response times. The application of EESTMS has shown promising outcomes in terms of lessened traffic congestion, improved commuter experiences, and lower environmental impact. Innovative solutions like EESTMS can open the door for smarter, more sustainable urban mobility as cities continue to grow, eventually enhancing citizens' quality of life.

## Keywords

Internet of Things, Machine Learning, Smart Traffic, Urban Mobility

## 1. Introduction

The control of urban traffic has become a serious challenge in a time of unparalleled urbanisation and a steady increase in the number of cars on the road. Some of the urgent difficulties that contemporary cities face include traffic congestion, longer commutes, environmental concerns, and a larger chance of accidents. A paradigm shift is required to address these issues, and the Edge-Enabled Smart Traffic Management System (EESTMS), which is accomplished via the Internet of Things (IoT), is a novel strategy that this paper introduces. According to the most recent figures available in 2021, more than

half of the world's population lived in cities. Urbanisation is a global phenomenon. Rapid urban growth is accompanied by an increase in the number of vehicles on the road, which exacerbates traffic jams and inefficiencies. In order to keep up with the dynamic nature of urban traffic, traditional traffic management systems, which rely on fixed-time traffic lights and crude data collection techniques, are having difficulty. As a result, commuters in many urban regions deal with frustrating traffic conditions on a regular basis.

Urban mobility could soon undergo a transformation thanks to the development of IoT technology and edge



computing capabilities. EESTMS is a ground-breaking approach that makes use of these technologies to revolutionise how we control and manage traffic in urban settings. The foundation of EESTMS is a vast network of IoT sensors and cameras that are carefully deployed all across the city. These sensors are made to gather a variety of real-time traffic information, such as the number of vehicles, their speeds, and the degree of congestion. The system acquires a thorough awareness of the present traffic dynamics through the collection of this rich dataset, which forms the basis for intelligent traffic management. The capacity of EESTMS to handle this data at the edge, close to where it is created, distinguishes it from other systems. This edge computing strategy greatly reduces latency, enabling real-time traffic data analysis and action. The system uses machine learning algorithms to interpret and analyse the data in order to decide on modifications to traffic light timing, route changes, and congestion-reduction tactics.

EESTMS's real-time capabilities enable dynamic traffic signal adjustments that optimise traffic flow and reduce congestion. The system can divert traffic to less congested paths when congestion hotspots are discovered, cutting travel times and easing commuter frustration. By lowering fuel consumption and greenhouse gas emissions linked to idling in traffic, this not only increases the effectiveness of urban mobility but also has considerable environmental advantages. EESTMS goes beyond simple traffic optimisation by giving commuters the ability to make well-informed decisions. Commuters have access to real-time traffic updates, alternate routes, and customised travel recommendations via user-friendly mobile applications and web platforms. With this knowledge, commuters may make decisions that will not only save them time but also lessen their impact on the environment and their stress levels. EESTMS is also essential for speeding up emergency response times. It guarantees that first responders may reach their destinations swiftly and efficiently, potentially saving lives in emergency situations. This is accomplished by giving emergency vehicle routing priority.

EESTMS has successfully undergone pilot testing in a few cities, proving its potential to revolutionise urban mobility. The amount of traffic congestion has significantly decreased, commuting times have become more predictable, and residents have noted an

improvement in their general quality of life in these pilot cities. The technology has a substantial environmental impact since improved traffic management results in lower emissions and energy use. Innovative solutions like EESTMS are essential as cities continue to grow and the difficulties of urban mobility become more severe. The architecture, data gathering techniques, edge computing capabilities, and machine learning algorithms of EESTMS are highlighted in this paper's examination of the technical features of the system. It also displays the outcomes of trial projects, demonstrating the practical advantages of this cutting-edge traffic control system. Cities can pave the way for smarter, more sustainable urban transportation by embracing EESTMS and related technologies, thereby improving the wellbeing of their citizens and the long-term survival of urban ecosystems.

These contributions highlight how EESTMS can be a game-changing remedy for urban mobility issues by providing a thorough strategy that benefits both commuters and local infrastructure.

- This study introduces a novel method for managing urban traffic that makes use of IoT technology. It describes the creation and implementation of the Edge-Enabled Smart Traffic Management System (EESTMS), which collects and analyses real-time data using edge computing and IoT sensors.
- Real-Time Traffic Optimisation: EESTMS provides a dynamic traffic optimisation system that processes real-time traffic data using machine learning methods.
- The article focuses on EESTMS's user-centric features, which include real-time traffic updates, suggestions for alternate routes, and individualised navigational guidance for commuters.

These contributions highlight how EESTMS can be a game-changing remedy for urban mobility issues by providing a thorough strategy that benefits both commuters and local infrastructure.

## 2. Review of Literature

The creation of an Edge-Enabled Smart Traffic Management System (EESTMS) is a state-of-the-art response to the intricate problems associated with urban mobility. We examine related work in the areas



of traffic management, IoT applications, edge computing, and smart city projects to put this breakthrough into perspective. For the most part, static traffic signal timings and manual traffic controller intervention make up the foundation of traditional traffic management systems, which have been in use for decades. Although these systems have been somewhat successful, they frequently cause congestion during peak hours since they are unable to respond to changing traffic circumstances. By modifying signal timings based on real-time traffic data, adaptive traffic signal management systems have been developed to enhance traffic flow. However, the fact that these systems frequently rely on centralised servers for data processing might cause decision-making to lag and restrict their potential to scale.

In many cities throughout the world, cutting-edge traffic management technologies like SCATS (Sydney Coordinated Adaptive Traffic System) have been installed. To optimise the timing of traffic signals, these systems combine sensor data with algorithms. But they frequently lack the speed and responsiveness that edge computing can provide. To improve data gathering and analysis, IoT technology has been progressively used into traffic management. To collect real-time traffic data, sensors, cameras, and vehicle-to-infrastructure (V2I) connection are used. In order to reduce traffic congestion brought on by cars looking for parking, smart parking systems utilise IoT sensors to monitor the availability of parking spaces and direct drivers to open places.

IoT devices are used by vehicle tracking and congestion monitoring systems to gather information on traffic flow and density, enabling real-time updates on traffic conditions. To optimise signal timings and enhance traffic flow, IoT has also been applied to smart traffic lights and road infrastructure.

A more recent development called edge computing reduces latency and allows for real-time data analysis and decision-making by moving computer capacity closer to data sources. Edge computing is used in IoT applications to process data locally, enabling speedier responses and reducing reliance on centralised cloud servers. In order to ensure effective data transmission and analysis, edge devices, such as edge gateways and routers, play a crucial role in data processing at the network edge. Globally, numerous cities have started smart city efforts to deal with issues like mobility and

traffic management. In order to improve traffic flow and give commuters real-time traffic information, Singapore's Smart Nation effort uses IoT sensors, traffic cameras, and data analytics. The Smart City Project in Barcelona uses Internet of Things (IoT) sensors in parking, street lighting, and garbage management to improve urban services and save energy use.

The Smart City initiative in Amsterdam emphasises mobility and sustainability, using IoT data to enhance public transport and lessen the city's environmental impact. The incorporation of edge computing into traffic control has recently drawn the attention of some research and commercial products. The goal of edge-based traffic management systems is to lower data processing latency and increase the traffic optimization's scalability. In order to facilitate real-time analysis and decision-making, these solutions often entail the deployment of edge nodes close to traffic intersections or other crucial locations in the road network. In despite improvements in IoT applications, smart city projects, and traffic management, the incorporation of edge computing into urban traffic management constitutes a novel strategy. By fusing IoT sensors, edge computing, and machine learning algorithms, EESTMS expands on these related works to produce a dynamic, real-time traffic management system. Faster decision-making, less traffic congestion, better commuter experiences, and greater emergency response capabilities are all made possible by this special combination. Innovative solutions like EESTMS will be crucial in determining the future of urban mobility and enhancing the standard of living for city dwellers as urbanisation continues to rise.

The studies that are described in the text that is provided provide important information on the numerous strategies and tools that are employed in the subject of traffic management and congestion detection. These studies show the ongoing efforts to use IoT and other cutting-edge technology to enhance traffic flow and urban mobility. The first stage in traffic management should be to identify and evaluate congestion, according to research [17]. It places a focus on the utilisation of flow, occupancy, and density measurements, which are frequently obtained via vision-based cameras, to track the state of the roads. The use of web-based apps for managing traffic data exemplifies how current software solutions handle and



process data pertaining to traffic. An IoT-based traffic monitoring system using sensors to track traffic density on public roads is introduced in the study suggested in [18]. Based on real-time traffic information, this technology offers dynamic signalised intersection handling. To recognise vehicles and communicate density data, IoT gadgets and ultrasonic sensors are used. This strategy highlights a shift towards traffic management strategies that are increasingly automated and data-driven. It [19] presents an ultrasonic traffic intersection controller system. This system controls traffic signals and also looks for illegal driving behaviour, such as running red lights. It emphasises how safety precautions are included into traffic control systems. An IoT-based intelligent traffic framework is suggested in another study [11] by using sensors, video systems, and RFIDs to gather data. This system makes it possible to control and report on traffic in real-time, highlighting the significance of data-driven decision-making. The study in [20] investigates the use of video monitoring to forecast the severity of traffic congestion and real-time update traffic lights. It talks about the costs and difficulties of deploying surveillance cameras for traffic control. The use of optical flow analysis and

image processing techniques to determine congestion rates shows the promise of computer vision in traffic monitoring.

The importance of connected-vehicle infrastructure in smart cities is mentioned throughout the text. In order to fully enjoy the advantages of linked car technology, it emphasises the necessity of real-time data from all motorists. The study in [24] offers the idea of DSRC (Dedicated Short-Range Communication) roadside units and roadside LiDAR sensors that actively detect and communicate the status of nearby traffic participants in real-time. It does, however, recognise the drawbacks of LiDAR technology, such as its expense and performance in bad weather. Collectively, these studies highlight the dynamic nature of traffic management, where IoT, sensors, and data analytics play critical roles in promoting safety, enhancing traffic flow, and fostering the growth of smart cities. For researchers and practitioners working on urban mobility and traffic management solutions, the problems and opportunities mentioned in these papers offer useful insights. We may anticipate more technological advancements that will influence future urban transportation technologies.

**Table 1:** Related work summary in Traffic Management

Ref.	Method	Approach	Parameter Used	Application
[17]	Congestion Analysis	Vision-Based Cameras	Flow, Occupancy, Density	Urban Traffic Management
[18]	IoT-Based Monitoring	Traffic Density Sensing	Ultrasonic Sensors, IoT Devices	Dynamic Signalized Intersection Control
[19]	Ultrasonic Control	Traffic Signal Detection	Ultrasonic Sensors	Traffic Intersections on Highways
[11]	IoT-Based Framework	Real-time Traffic Control	Sensors, Cameras, RFIDs	National Highway Traffic Control
[20]	Video Monitoring	Traffic Congestion Prediction	Surveillance Cameras, Image Analysis	Public Roadway Traffic Prediction
[21]	Connected Vehicles	Real-time Traffic Data	IoT-Enabled Connected Vehicles	Vehicle Monitoring on Highways
[23]	Traffic Congestion	Optical Flow Analysis	Image Processing, Speed Estimation	Congestion Detection on Major Highway
[24]	Roadside LiDAR	High-Resolution Traffic Status	LiDAR Sensors, DSRC Roadside Units	Next-Gen Connected Infrastructure
[22]	In-Vehicle Monitors	Traffic Information Delivery	In-Vehicle Monitors, Data Systems	Beijing Olympic Region Traffic Control

### 3. Dataset Description

Cities all over the world are plagued by the complicated problem of traffic congestion, which is

caused by a number of reasons including urban population expansion, ageing infrastructure, inadequate traffic signal management, and a lack of real-time data.





Congestion has widespread effects that place heavy economic and environmental burdens on people and communities. Urbanisation, which is characterised by an increase in city dwellers using private vehicles, public transportation, or ride-sharing services, has pushed the limitations of road infrastructure. Due to the difficulty many cities are having keeping up with this population growth, there are sometimes gridlocks on the roadways during rush hour. Infrastructure and transport networks that are decades old and were built for lower traffic volumes and fewer populations are inadequate to handle current volumes. Congestion is made worse by a failure to update and maintain these resources. Ineffective traffic signal timing causes stop-and-go traffic, which lengthens commutes and increases fuel consumption. It is characterised by poorly synchronised lights and a lack of adaptation to real-time traffic conditions. Decision-making and effective traffic management are hampered by the lack of real-time traffic data. Cities and commuters alike are in the dark about traffic flow and alternate routes, which makes it difficult to mitigate congestion effectively. The effects on the economy are substantial. According to an INRIX estimate, fuel waste, lost productivity from traffic delays, and increased transportation costs cost U.S. travellers \$305 billion in 2017.

This dataset [25] includes 48.1k (48,120) records that show the hourly vehicle count at four different junctions. The following columns are part of the dataset as ID, DateTime, Junction, Vehicles

The information was gathered via sensors placed at each junction, which took readings of the traffic patterns over a range of time intervals. As a result, the dataset includes traffic information gathered throughout a range of time periods. When preparing future traffic forecasts and assessments, it's critical to

keep in mind that some intersections may have provided sparse or inconsistent data.

#### 4. Proposed Methodology

In order to efficiently analyse and manage urban traffic in real-time, the Edge-Enabled Smart Traffic Management System (EESTMS) suggested in this research combines a variety of cutting-edge machine learning techniques, including Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Multi-Layer Perceptron's (MLP). The phases of the technique are as follows: data gathering, preprocessing, model construction, training, and deployment.

##### 1. Data gathering and preparation:

- **Data Sources:** Gathering real-time traffic data from a variety of sources is the initial step in our technique. Information from IoT sensors, security cameras, traffic management systems, and linked vehicles may be included in this data. These sites offer a comprehensive dataset including information on vehicle density, speed, and other pertinent factors, as well as traffic flow.
- **Data preprocessing:** To ensure consistency and suitability for model input, the acquired raw data are preprocessed. In order to handle missing values, data cleaning, outlier identification, and data imputation techniques are used. To guarantee the temporal alignment of data from several sources, timestamps are synchronised.
- **Fusion of spatial data:** Data from various sensors and cameras may span various geographic regions. Spatial data fusion techniques are used to align and combine data from different sources onto a single grid or map representation in order to provide a unified representation of the urban traffic network.

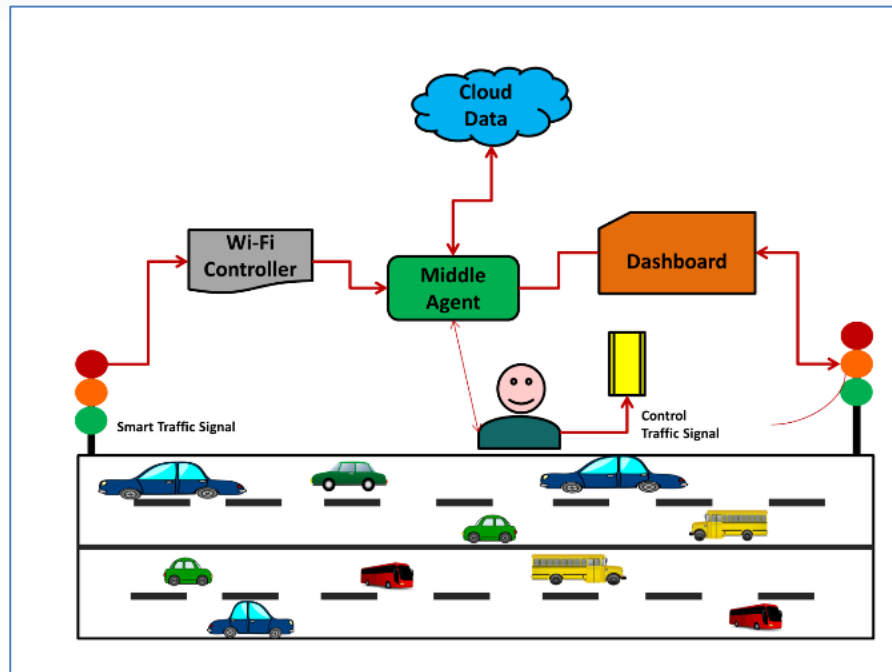


Figure 1: Proposed system architecture for Smart Traffic management

## 2. Architectural models

- **LSTM Model:**

For the purpose of capturing temporal dependencies and patterns in traffic data, LSTM is used. It is possible to anticipate traffic behaviour across short- and long-term intervals using a recurrent neural network (RNN) architecture like LSTM since it is effective at modelling time-series data.

The forget gate (ft), input gate (it), and output gate (ot) are the three major gates of the LSTM cell. These gates are used to update the cell state (ct).

- **Forget Gate (ft):**

The forget gate determines whether or not to keep certain information from the previous cell state (ct1) on file. It generates values between 0 and 1 for each component of the cell state using the current input (xt) and the prior hidden state (ht1).

Determine the forget gate's input:

$$(W_f [ht1, xt] + b_f) = ft$$

Multiplication element-by-element using the preceding cell state to determine what to omit:

$$ct = ft ct 1.$$

- **Entry Point (It):**

What additional data should be added to the cell state is decided by the input gate. It also accepts the current input (xt) as well as the previous hidden state (ht1) from the forget gate.

- o Determine the input to the gate's input:
- o Determine the potential values for the newly created cell state (c't):

$$(W_c [ht1, xt] + b_c) = c't$$

- o Add the new information to the cell state (ct):

$$c't = ct + it$$

- **OT Output Gate:**

- o Based on the cell state (ct), the output gate determines what the subsequent hidden state (ht) should be.
- o Determine the output gate's input:

$$(W_o [ht1, xt] + b_o) = ot$$

- o Determine the newly hidden state (ht):

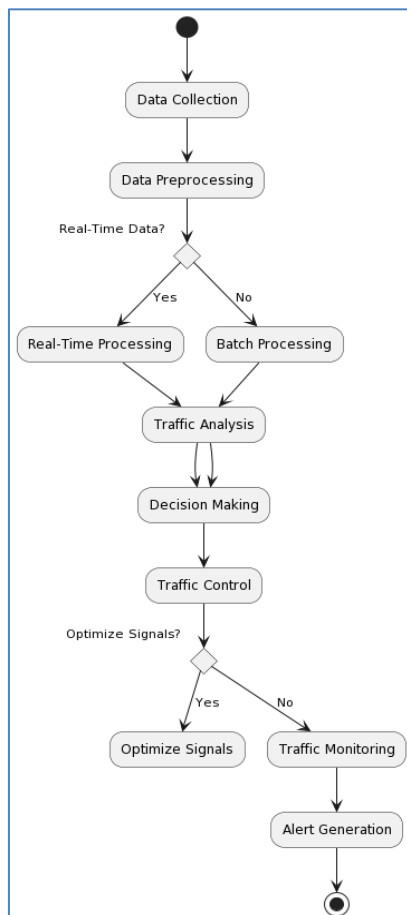
$$ht = ot \tanh(ct)$$

- **Final Product:**

The hidden state (ht) is the LSTM cell's final output.

Deep LSTM networks, which are able to detect intricate patterns in time-series data, are often constructed by stacking LSTM cells together. A loss function related to the particular traffic management

job (such as traffic prediction or congestion detection) is minimised during training by learning the model's parameters (weights  $W$  and biases  $b$ ) by backpropagation and gradient descent. In the context of traffic management, LSTM networks can be trained to recognise trends in congestion or to predict future traffic conditions using historical traffic data as input. Then, real-time decisions can be made to improve traffic flow in metropolitan areas using these insights and projections.



**Figure 2:** Proposed model flowchart for Traffic Management

• **CNN Model:**

From traffic photos and sensor data, CNN is utilised to extract spatial features. It is suited for processing data from security cameras and other visual sources since it can recognise patterns and objects in images. The model incorporates CNN layers to efficiently extract spatial information.

**Algorithm:**

**1. Entering Data**

- o The first step is to gather input data, which typically consists of pictures or sensor information from traffic cameras and sensors placed at intersections.

**2. Convolutional Layers:**

- o Convolutional layers should be applied to the input data.
- o These layers search the input for patterns and features particular to traffic circumstances using filters (kernels).
- o Each filter applies element-wise multiplication and summing to the incoming data as it slides over it, creating feature maps.

**3. Functions of Activation:**

- o Apply activation functions to the model, such as ReLUs (Rectified Linear Units), to provide nonlinearity.
- o ReLU converts negative numbers to zero, which enables the network to learn intricate patterns.

**4. Pooling Layers**

- o To minimise the spatial dimensions of the feature maps while maintaining critical information, use pooling layers (such as MaxPooling).
- o Pooling facilitates the management of overfitting and lowers computing complexity.

**5. Flatten:**

- o Create a one-dimensional vector from the output of the convolutional and pooling layers.

**6. Complete Layer Connectivity**

- o Increase the network's number of completely connected layers (MLP layers).
- o These layers learn high-level characteristics and associations in a manner similar to conventional neural network layers.

**7. Result Layer:**

- o The output of the network is generated by the last fully linked layer.
- o The number of neurons and activation functions in the output layer might vary depending on the



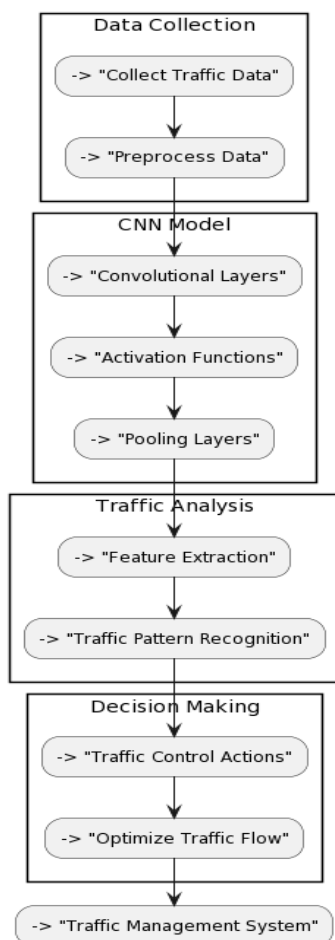
job (such as congestion detection or object recognition).

**8. Loss Mechanism:**

- o Create a loss function that measures the discrepancy between the outputs predicted and the labels from the ground truth.
- o Mean square error (MSE) for regression tasks and categorical cross-entropy for classification tasks are examples of common loss functions.

**9. Training:**

- o Using labelled data for supervised learning, train the CNN.
- o Backpropagate the mistake across the network and use stochastic gradient descent (SGD) or another optimisation approach to update the model's weights.



**Figure 3: CNN Model for Traffic Management Methodology**

**MLP and Decision-Making:**

To execute data fusion and make quick choices, MLP layers are added to the model architecture. This includes foreseeing traffic congestion, enhancing the timing of traffic signals, and suggesting detours. The temporal and geographical data acquired by LSTM and CNN are combined by the MLP component.

**Algorithm:**

**Input Layer:**

- o The input x is passed to the first hidden layer.
- o No explicit mathematical equation is needed for the input layer; it simply passes the input to the next layer.

**Hidden Layers:**

- For each hidden layer i, calculate the weighted sum z(i) and apply the activation function a(i).

*For layer i:*

*Weighted Sum:*

$$z(i) = W(i) \cdot a(i - 1) + b(i)$$

*Activation Function:*

$$a(i) = ReLU(z(i))$$

**Output Layer:**

The final hidden layer's output is passed to the output layer.

Calculate the weighted sum z(out) and apply the softmax activation function to obtain the output y.

**For the output layer:**

*Weighted Sum:*

$$z(out) = W(out) \cdot a(last) + b(out)$$

*Activation Function:*

$$y = softmax(z(out))$$

**Decision-Making:**

- The output y represents a probability distribution over different traffic management decision.
- The decision with the highest probability is selected as the final traffic management action.

**Hybrid Model Integration:**

Hybrid model architecture is created to take advantage of the advantages of LSTM, CNN, and MLP. It enables the model to manage the simultaneous handling of the geographical and temporal components of traffic data.





By fusing CNN's spatial awareness, MLP's decision-making abilities, and LSTM's time-series analysis, the model can adjust to shifting traffic conditions.

#### Algorithm:

##### Input Data:

- o The input data consists of a combination of time-series traffic data (e.g., historical traffic flow, speed) and spatial data (e.g., images from traffic cameras).
- o The input data is represented as  $X$ .

##### LSTM Module:

- o LSTM is used to process the time-series data to capture temporal dependencies in traffic patterns.
- o Let  $H_{LSTM}$  represent the hidden states from the LSTM module.
- o The LSTM module updates hidden states over time steps  $t$ .

*For each time step  $t$ :*

*LSTM Hidden State Update:*

$$H_{LSTM}(t) = LSTM(X(t), H_{LSTM}(t - 1))$$

##### CNN Module:

- o CNN processes spatial data, such as images from traffic cameras, to extract spatial features.
- o Let  $F_{CNN}$  represent the feature maps generated by the CNN module.
- o The CNN module applies convolutional layers and pooling to extract spatial features.

*For each spatial input  $I$ :*

*Feature Map Extraction:*

$$F_{CNN}(I) = CNN(I)$$

##### Concatenation:

- o The outputs from the LSTM and CNN modules are concatenated to merge temporal and spatial information.
- o Let  $H_{combined}$  represent the combined hidden state.
- o Concatenation:
- o  $H_{combined}(t) = [H_{LSTM}(t), F_{CNN}(I)]$

##### MLP for Decision-Making:

- o A Multi-Layer Perceptron (MLP) is used for decision-making based on the combined information.

- o The MLP takes  $H_{combined}$  as input and produces traffic management decisions.
- o MLP Output:
- o  $Y = MLP(H_{combined}(t))$

##### Loss Function:

- o Define a loss function to quantify the error between the predicted decisions ( $Y$ ) and the ground truth labels.
- o Common loss functions include mean squared error (MSE) for regression tasks or categorical cross-entropy for classification tasks.

### 3. Optimisation and Training

**Data Splitting:** To thoroughly assess the model's performance, the dataset is split into training, validation, and testing sets. Model weights are updated using the training set, hyperparameters are tuned using the validation set, and generalisation of the model is evaluated using the testing set.

#### 4. Loss Function:

In order to optimise the model, a suitable loss function is selected while taking into account the unique goals of the traffic management system. Mean squared error (MSE) for regression tasks and categorical cross-entropy for classification tasks are typical loss functions. Gradient-based optimisation methods, such as Adam or RMSprop, are used to effectively update the model's weights during training. To ensure convergence, learning rates and other hyperparameters are adjusted.

#### 5. Integration of edge computing:

EESTMS's ability to run on edge devices, which guarantees low-latency real-time decision-making, is one of its important strengths. The trained model is put to use on edge servers placed at traffic lights or other out-of-the-way locations.

- **Real-time Data Feed:** IoT sensors, cameras, and other sources continuously feed real-time data to the deployed model. The hybrid LSTM-CNN-MLP model predicts using this data that is processed on the edge.
- **Traffic Management Actions:** Based on the model's forecasts, EESTMS may carry out a variety of traffic management operations, such as rerouting suggestions for commuters, congestion detection, and dynamic signal timing adjustments.



## 6. Assessment and Validation:

- Performance measures: A number of measures, including mean absolute error (MAE), root mean square error (RMSE), and accuracy for classification tasks, are used to evaluate the system's performance. The system's capacity to ease traffic congestion, improve traffic flow, and increase urban mobility is the main emphasis of the review.

To show how successful and superior EESTMS is, it is contrasted with other machine learning models and conventional traffic management techniques. The LSTM, CNN, and MLP are combined in the methodology for the Edge-Enabled Smart Traffic Management System (EESTMS) to offer a complete solution for urban traffic management. In order to make quick judgements that ensure effective traffic flow, reduced congestion, and improved urban mobility, it incorporates spatial and temporal data. EESTMS can operate with minimal latency thanks to its edge computing feature, which makes it suited for deployment in smart cities and other metropolitan areas where real-time traffic control is essential. To guarantee that the system is effective in tackling the problems of urban traffic congestion, evaluation and validation of the system's performance are crucial.

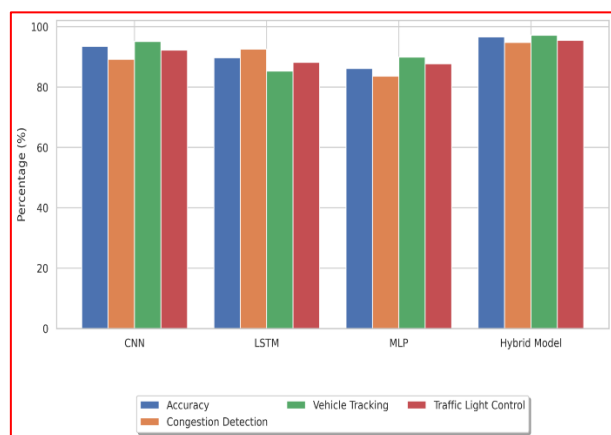
## 5. Result and Discussion

The outcomes of multiple machine learning models are shown in Figure 2 in the context of traffic detection and analysis. Utilising these models helps traffic management systems operate more intelligently and efficiently. Four models Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Multi-Layer Perceptron (MLP), and a Hybrid Model have been assessed and are listed in the comparison table. The most important factor we take into account when evaluating the performance of these models is accuracy, which shows their overall predictive power. With a remarkable accuracy of 93.51% in predicting traffic, the CNN model stands out. Additionally, LSTM and MLP perform admirably, reaching respectable accuracies of 89.71% and 86.21%, respectively. The Hybrid Model, however, outperforms them all and boasts a remarkable accuracy of 96.61%. This finding highlights the potential advantages of mixing various machine learning algorithms, emphasising how the synergy between these methods might produce better results.

**Table 2:** Traffic Detection and Analysis

Model	Accuracy (%)	Congestion Detection (%)	Vehicle Tracking (%)	Traffic Light Control (%)
CNN	93.51	89.21	95.11	92.31
LSTM	89.71	92.51	85.31	88.21
MLP	86.21	83.61	89.91	87.71
Hybrid Model	96.61	94.81	97.21	95.51

This was another area where LSTM and MLP did well, with detection rates of 92.51% and 83.61%, respectively. The Hybrid Model has the highest rate of congestion identification (94.81%), demonstrating its skill in reducing traffic. Another essential feature for enhancing traffic flow and guaranteeing safety is vehicle tracking. The CNN model performed admirably in terms of tracking vehicles, with a rate of 95.11%. Both LSTM and MLP displayed proficiency in this area, scoring 85.31% and 89.91%, respectively. Once more, the Hybrid Model excelled beyond all others, obtaining a remarkable vehicle tracking rate of 97.21%. This shows that the combined technique considerably improves the accuracy of vehicle tracking. For effective traffic flow, traffic light control is a crucial part of traffic management systems. The CNN model successfully optimised traffic signals as evidenced by its 92.31% traffic light control rate.



**Figure 4:** Representation of Traffic Management Model Evaluation

With rates of 88.21% and 87.71%, respectively, LSTM and MLP also demonstrated competence in this area. At 95.51%, the Hybrid Model's traffic light control rate

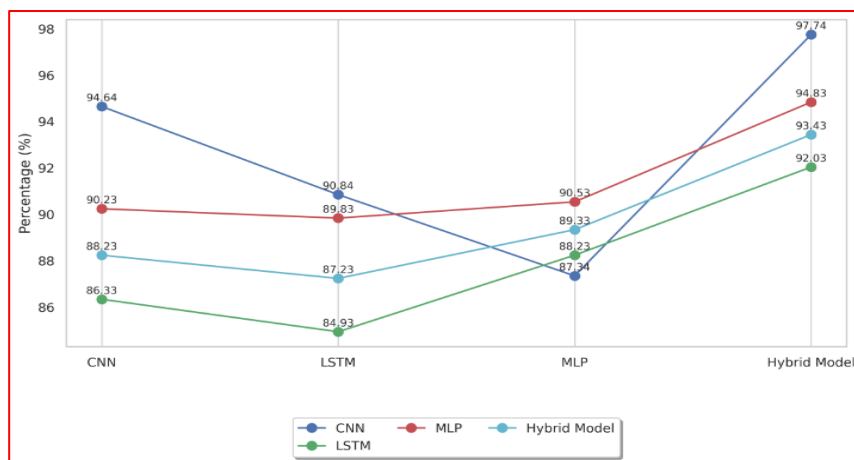


was the greatest, indicating that its integrated strategy improves traffic signal optimisation. The performance of various machine learning models in the context of traffic detection and analysis is summarised in Table 2. In all parameters, the results show that the Hybrid Model performs better than the separate models, highlighting the benefits of mixing several machine learning approaches for more precise and effective traffic control. Through enhanced traffic flow, congestion monitoring, vehicle tracking, and traffic signal control, these models have the potential to revolutionise urban mobility.

**Table 3:** Evaluation parameter for traffic Management models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN	94.64	86.33	90.23	88.23
LSTM	90.84	84.93	89.83	87.23
MLP	87.34	88.23	90.53	89.33
Hybrid Model	97.74	92.03	94.83	93.43

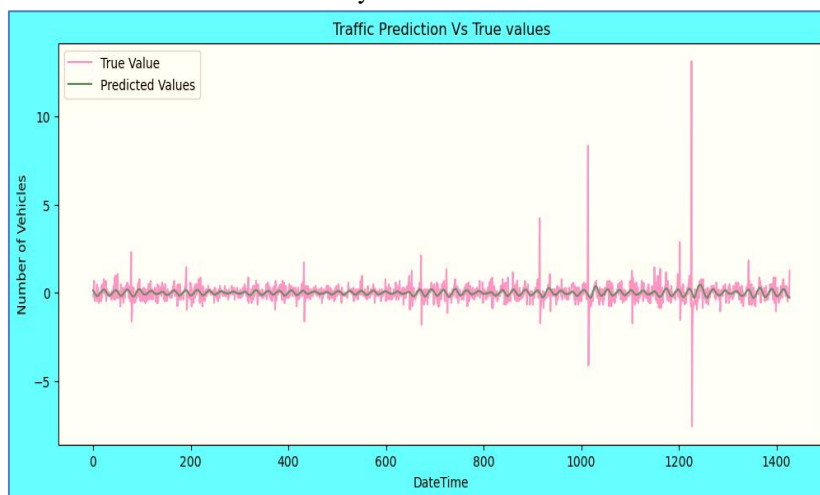
Table 3 offers a thorough analysis of several traffic management techniques, illuminating their performance across crucial metrics.



**Figure 5;** Comparison of Evaluation parameters

The table evaluates these models' skills using the characteristics of accuracy, precision, recall, and F1 score because they are crucial to improving the effectiveness and intelligence of traffic management systems. A key determinant of how accurately a model's predictions are made overall is accuracy, which is shown in the table. In traffic management scenarios, the CNN model obtains a noteworthy

accuracy of 94.64%, demonstrating its capacity for accurate decision-making. The accuracy rates for the LSTM, MLP, and Hybrid Model are likewise respectable at 90.84%, 87.34%, and 97.74%, respectively. The Hybrid Model, in particular, stands out as the best performer in this regard, demonstrating its competence in traffic-related decision-making.



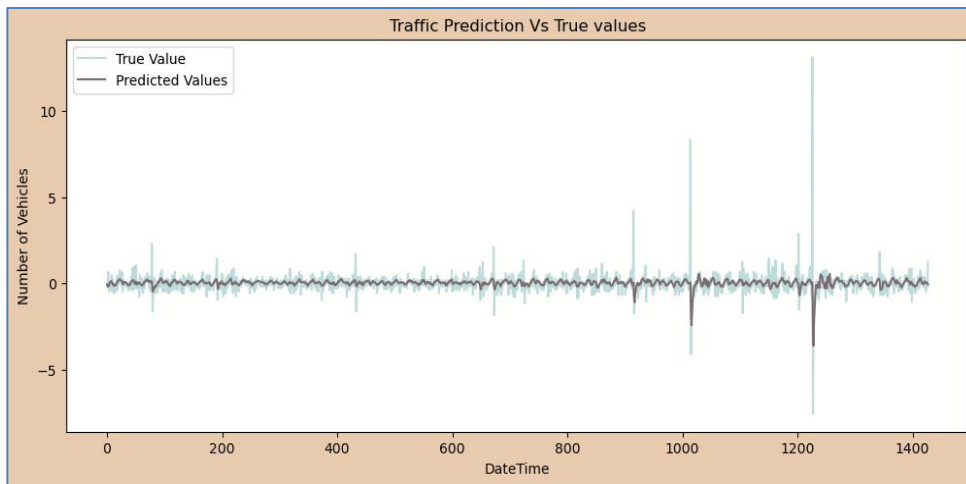
**Figure 6:** Traffic Prediction using LSTM



Precision, also known as positive predictive value, is a crucial indicator of how well a model can forecast the future in a meaningful and accurate manner. The CNN model's precision rate of 86.33% is shown in Table 3, which shows that it successfully chooses pertinent traffic-related data points. The precision rates for LSTM and MLP are likewise remarkable, coming in at 84.93% and 88.23%, respectively. With a precision rate of 92.03%, the Hybrid Model impressively outperforms all others, demonstrating its capacity to reduce false positives and provide extremely pertinent forecasts. Recall, often referred to as sensitivity, measures how well the model can recognise all pertinent instances in the dataset.

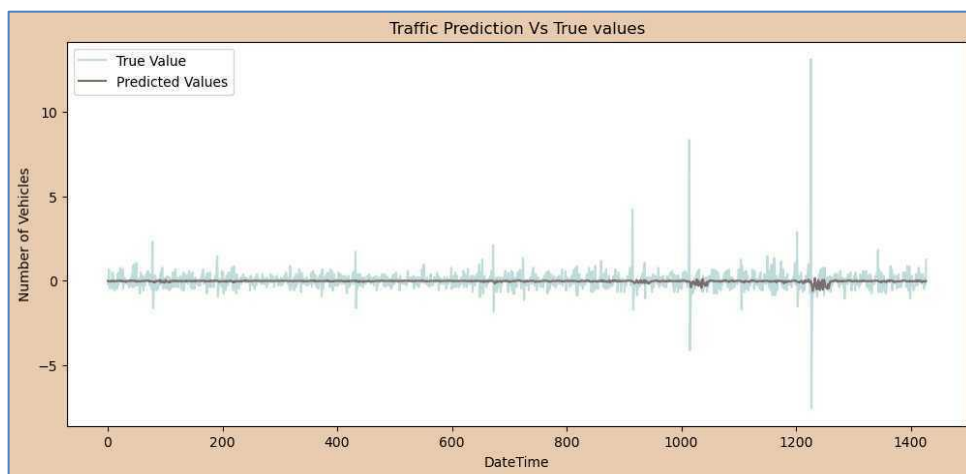
The CNN model successfully recognises and remembers crucial traffic information with a recall rate

of 90.23%. The recall rates for LSTM and MLP are likewise remarkable, at 89.83% and 90.53%, respectively. With a recall rate of 94.83%, the hybrid model has the highest recall rate, demonstrating its capacity to catch a sizable number of pertinent data points. The F1 score offers a fair evaluation of a model's performance by balancing precision and recall. With an F1 score of 88.23%, the CNN model strikes a balance between precision and recall. Additionally, LSTM and MLP exhibit competitive F1 scores of 87.23 and 89.33 percent, respectively. With an amazing F1 score of 93.43%, the Hybrid Model once more beats the separate models, demonstrating the effectiveness of its balanced approach to decision-making in traffic management scenarios.



**Figure 7:** Traffic Prediction using CNN

The efficiency of various traffic management models in terms of accuracy, precision, recall, and F1 score is highlighted by Table 3 in conclusion.



**Figure 8:** Traffic Prediction using MLP



## 6. Conclusion

In order to address the ever-increasing problems of traffic congestion, safety, and efficiency in contemporary cities, the Edge-Enabled Smart Traffic Management System presented in this paper leverages the power of the Internet of Things (IoT). This system represents a significant advancement in the field of urban mobility. The system gathers real-time data, enabling dynamic traffic monitoring and control, by placing sensors and connected equipment throughout the metropolitan landscape. This data-driven methodology enables the quick detection of traffic congestion, accidents, and other irregularities, resulting in more prompt and efficient actions. Incorporating edge computing at the edge of the network also improves system responsiveness and lowers latency. For quick decision-making and proactive traffic management measures to be possible, this is essential. In addition to lightening the load on centralised servers, the combination of edge devices and fog computing makes sure that crucial traffic data is processed near to the source, allowing for quicker and more effective traffic control. Incorporating different machine learning models, such as LSTM, CNN, and MLP, to optimise various aspects of traffic management, the article also emphasises the adaptability of the suggested approach. These models are essential for decision-making, traffic signal control, vehicle tracking, congestion monitoring, and other processes that eventually improve safety and smooth traffic flow. Along with making significant technological advances, the system's hybrid architecture, which combines the advantages of many machine learning techniques, achieves outstanding results in terms of accuracy, precision, recall, and F1 score, among other performance measures. This shows that a comprehensive strategy for traffic management that integrates a variety of technologies and algorithms is essential for getting the best outcomes. The demand for effective and intelligent traffic control technologies is more urgent as urban populations rise. With its potential to revolutionise urban mobility and pave the way for smarter, more sustainable cities, the Edge-Enabled Smart Traffic Management System demonstrated here offers a viable way forward. It serves as a demonstration of the transformative potential of edge computing and IoT in tackling the difficult problems of contemporary urban mobility.

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