Deep Learning Based Smart Traffic Management System

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Deep Learning based Smart Traffic Management System

A project submitted

in partial fulfillment of the requirements for the degree of Bachelor of Technology in Computer Science and Engineering

by

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CERTIFICATE

This is to certify that the report entitled "**Deep Learning based Smart Traffic Management System**" submitted by "MD Massom (2019003930), Mohammed Salim (2019008306) and MD Anash (2019006476)" to Sharda University, towards the fulfillment of requirements of the degree of **"Bachelor of Technology"** is record of bonafide final year Project work carried out by them in the "Department of Computer Science & Engineering, Sharda School of Engineering and Technology, Sharda University".

The results/findings contained in this Project have not been submitted in part or full to any other University/Institute forward of any other Degree/Diploma.

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ABSTRACT

Artificial intelligence can be used to develop smart solution for traffic management that are effective decision-makers.The use of technology has profoundly changed the field of intelligent transport systems (ITS). Newer developments such as the internet of thing (IoT) based smart smoke detecting sensors or the surveillance camera feeds, and social media, along with increased demand for infrastructure, have opened up many possibilities. In response, STMS is taking advantage of artificial intelligence (AI) to create data-driven solutions that can help with traffic management decisions. Our proposed smart traffic management platform (STMP) AI techniques have certain limitations which this new AI technology aims to address, by making use of advanced machine learning techniques such as online incremental unsupervised based machine learning, and deep sequence based model learning. These techniques will help to improve predictive accuracy and automate decision-making processes, so that large data streams and traffic volatility can be better managed.The current artificial intelligence techniques used in isolation have limitations when it comes to developing a comprehensive platform for big data streams that are challenging due to their dynamicity, high frequency of unlabeled data from multiple sources, and the traffic condition's volatility over time. To address these limitations, we are trying to propose an expansive management system for traffic congestion based on the unsupervised time sequential learning and features based selective learning. As various streams of data flowed in from the IoT via smart sensors for smoke and weather and also from social media. Suddenly,The smart traffic system kicked in, analyzing the heterogeneous data and It also tracked the impact of these changes, ensuring the smooth flow of traffic in the city.

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INTRODUCTION

Artificial intelligence is constantly revolutionizing our lives through the development of intelligent agents, autonomous programs that can think, learn, and act independently. Traffic flow prediction involves predicting all movements of pedestrians vehicles on a highway or road network. Predictive models are used to calculate the likely future movements of vehicles on a road or highway system. The radical prediction of traffic flow is used to help the road travellers. The increasing number of vehicles in cities has caused a road congestion problem. To address this, solutions such as expanding the no. of lanes between the existing roads, or constructing a new road network, have been suggested. This smart system will help to make better travelling decisions in order to make traffic congestion less severe, reduce carbon emissions, and improve traffic operation efficiency. There are two ways to manage traffic: using the existing road network or using traffic control strategies. Traffic control strategies are more practical in reality because they don't require much expenditure. Traffic forecasting is an important tool for traffic control, and is often done through computational intelligence approaches. Deep learning is a popular technique in this area, as it can more accurately capture complex relationships in data than shallow learning techniques. Deep learning is also more efficient in dealing with high dimensional data, through its use of distributed calculation. As such, deep learning has become a popular approach for short period time traffic forecasting for the development of Smart Transportation Management Systems. Image-processing based models on cv2 and deep-learning-based approaches are aiding in the management of traffic and transportation systems. By being able to better handle the dynamic and drastic nature environments in which data generates more volatile, making it more difficult to make effective decisions. Also in this research we are using CNN and Sequence based models like RNN and LSTM to better evaluate the traffic monitoring and accident management through computer vision based techniques. CNNs are structures that work well in computer vision as they are made to take images as inputs. Additionally, improvements in GPU memory density technology have enabled deeper neural networks to be used, which has led to steadily better recognition performance.

Short-term traffic forecasts are using here the long-short term memory (LSTM) to improve the performance. Compared with those previously used simple RNNs, the LSTM network has become more capable in capturing these time series features within a longer time span. This greatly increase the performance by using LSTM. In our study, a new method for traffic forecasting is proposed using a cascading network based LSTM cell with multiple layers. This network captures the temporal spatial covariance in two dimensions, and uses an Ortho Diagonal Convex matrix as a parameter for full connection amongst layers and help in vector generation. This leads to newer time series generation within the LSTM network, which differs from the existing methods. To check the effectiveness and accuracy of the paper-proposed deep learning model, a comparative study was conducted.

Problem Statement

In metropolitan places, adding lanes to the existing roads can be expensive and frequently impractical. Road congestion is a problem brought on by the growing number of automobiles in cities, and the conventional solution of adding lanes to existing roadways is frequently impractical. The movement of traffic on a road or highway system can be predicted with the use of traffic flow modelling. Our job is to help road users make smarter travel decisions, alleviate traffic congestion, reduce carbon emissions, and improve traffic operation efficiency. Therefore, to accurately estimate traffic flow and relieve traffic congestion, an efficient traffic control system based on computational intelligence and deep learning technologies is required.

Project Overview

In metropolitan places, adding lanes to the existing roads can be expensive and frequently impractical. Road congestion is a problem brought on by the growing number of automobiles in cities, and the conventional solution of adding lanes to existing roadways is frequently impractical. In order to accurately estimate traffic flow and reduce traffic congestion in metropolitan areas, this research intends to build an efficient traffic control method that is based on computational intelligence and deep learning technologies. This initiative aims to increase traffic flow efficiency, assist road users in making better travel decisions, and lower carbon emissions. We will leverage existing data to train deep learning models and generate traffic flow predictions. In addition, we will assess these forecasts to provide a to develop a control strategy that can be used to reduce traffic congestion.

Existing data sets will be used in this research to train deep learning models and produce predictions. Following this analysis, we will create a control method to lessen traffic congestion. We will also employ computational intelligence methods to improve the control approach. Finally, we will use simulations to assess the effectiveness of the suggested control technique. A real-world traffic dataset will be used to test the suggested control strategy's efficacy in alleviating traffic congestion.

Expected Outcome

The expected outcome of this project is that we will have developed an effective traffic control strategy, based on computational intelligence and deep learning approaches, to accurately predict traffic flow and alleviate traffic congestion. This strategy will help road users make better travel decisions, alleviate traffic congestion, reduce carbon emissions, and improve traffic operation efficiency.

The project will use a combination of traditional traffic control approaches, such as traffic signal optimization, and emerging techniques, such as deep learning and computational intelligence, to accurately predict traffic flow and congestion levels. We anticipate that the strategy will be able to provide near real-time feedback to road users and traffic operators, as well as provide guidance to traffic operators on when and where to adjust traffic signals to optimize traffic flow. Additionally, the strategy should be able to predict potential traffic flow patterns in advance and provide guidance on how to adjust traffic signals to prepare for potential congestion. We expect that the project will yield results that can be effectively implemented in a real-world environment. We anticipate that the strategy will be easily integrated into existing traffic control systems, and that it will improve the overall efficiency of traffic operations. We also anticipate that the strategy will be able to be easily adapted to different cities and regions, allowing for scalability and sustainability. Overall, we expect that this project will yield a comprehensive and effective traffic control strategy that can be implemented to improve traffic operations and provide a more efficient and sustainable way of managing traffic.

Hardware And Software Requirements

Hardware specifications

A graphics card from NVIDIA that supports CUDA Compute Capability versions 3.5 to 8.6.

CPU: CPUs that are newer than the Intel Core i7 7th Generation.

ASRock EPC612D8A motherboard is the device.

Processor: AMD Radeon, 10 cores, 2.2 GHz, with a top speed of 3.1 GHz.

A RAM size between 8GB and 16GB, preferably 16 GM.

1 to 2 TB of HDD capacity for storing deep learning projects' datasets

NVidia Titan X Pascal is the GPU (12 GB VRAM)

Intel Heatsink to regulate the temperature.

Software Requirements:

- ENVI 5.6.1 and the ENVI(Environment for Visualising Images) Deep Learning 1.2 module.

- · Operating System

- · Python

- · Jupyter Notebook/Google Collab

- · Tensorflow/Pytorch

Report Outline

This project aims to develop an effective traffic control strategy for urban areas, based on computational intelligence and deep learning approaches, to accurately predict traffic flow and alleviate traffic congestion. The project will involve the following steps:

1. Collect and analyze existing data sets to train deep learning models and generate traffic flow predictions.
2. Analyze the predictions to develop a control strategy that can be used to reduce traffic congestion.
3. Utilize computational intelligence techniques to optimize the proposed control strategy.
4. Simulate the performance of the proposed control strategy.
5. Test the proposed control strategy on a real-world traffic dataset to assess its effectiveness in reducing traffic congestion.

The expected outcome of this project is an effective control strategy that can be used to reduce traffic congestion in urban areas.

LITERATURE SURVEY

In general, deep learning models are able to learn complex patterns in data sets very well. In order to analyse large-scale transportation networks and predict traffic congestion evolution, here both deep restricted Boltzmann machine and RNN was used a combination. However, RNN was not suitable for long term time series prediction and analysis. This led to the implementation of Long Short Term Memory (LSTM) network as an enhanced approach, which was demonstrated in 2018 by Machial et alc., captured the nonlinear traffic dynamics in an efficient way.This showed that LSTM networks are a promising tool for analyzing large-scale transportation networks. A machine learning algorithm has been proposed that can be used to predict the avg speed of a vehicle on a roadway. The algorithm was used to predict the average speed of vehicles over a three-month period. The algorithm was successfully used to predict the avg speed and distance between vehicles over a small time interval (30 minutes), but was less successful when predicting the avg speed and distance between vehicles over a larger time interval (1 hour). The accuracy of the algorithm was high for small time intervals but lower for larger time intervals. Previously in the traffic reasearch, characteristics used features like volume and velocity of the vehicle with distance between two or more vehicles. However, lately, data-driven approaches have become more widespread, and researchers have proposed different forecasting models and algorithms that utilize parameters for making predictions. The latest advancements in artificial intelligence have enabled the development of more powerful techniques for processing large amounts of data and producing more accurate traffic forecasts.. These methods, known as “computational intelligence” or simply “intelligence,” are based on the use of algorithms that are able to analyze complex patterns and make deductions about the objects or information they are dealing with. One of the most common methods used in intelligence is Bayesian inference, which is a probabilistic method that is used to analyze data and make deductions about the objects or information they are dealing with. Bayesian inference is based on the idea that, given a set of observations, beliefs, and prior probabilities, an intelligent agent can derive new beliefs about the data based on the evidence that is available. Another type of intelligence that is becoming more common is neural networks. However, neural networks are more complex than Bayesian inference, and they are also able to learn more complex patterns. Another type of intelligence that is becoming more common is evolutionary computing. Evolutionary computing is a type of AI that is based on the idea that intelligent agents can evolve over time by using trial and error to solve problems. This approach is often used in Factory Automation, where it is used to create efficient and customized solutions. Autoencoders, a type of deep learning model, have been used to predict future behavior of a data set. Researchers have used this technique to predict traffic flow on weekdays, with an accuracy of up to

93%, using a support vector machine over a three-month period. Additionally, these convolution and long-short cell based neural networks have also been proposed as means to predict traffic congestion on highways. Traffic forcasting had used deep learning for achieving reasonable performance. Two notable studies in deep learning have used different approaches to process data. Huang cho. xo. developed a deep architecture network with multitask learning, while Lv et al. used a regression layer for unsupervised feature learning. Since the introduction of Recurrent Neural Networks (RNNs), many studies have been conducted to address this issue, with the most prominent being the work of Ma et al. There research team has developed a model that can predict traffic flow on highways. The model takes into account vehicles speed and classifies it into different categories, such as congestion, free flow, and jam flow. They have found that the model is able to predict crashes with high accuracy. The model used in this work could be improved by using a larger dataset and by employing exact values with smaller frames, which would provide a more accurate representation of the real situation on the roads. Furthermore, the accuracy of the model could be increased by making use of more precise data.

They used information from the preceding three months to anticipate flow on weekdays. This study reported support vector machine-based traffic forecast accuracy of up to 93%. The authors have proposed a method for predicting traffic flow using convolution neural networks (CNN) and long short-term memory (LSTM). They've used it to predict traffic on the roads. They approximated the flow over periods of 30 minutes using data from PeMS. The outcomes of this study have been analysed using RMSE. These produced forecasts based on event data as well, and they were rather accurate. The entire dataset was nevertheless not that big because they only used data from two months. utilising deep learning applied to the traffic forecast, with acceptable results

Huang et al. suggested a deep architecture network with multitask learning, and Lv et al. applied a regression layer for unsupervised feature learning. Although these two representative research used deep learning, the temporal-spatial link is not immediately apparent. Since the RNN was first proposed, numerous works have been produced using RNN versions, with Ma et al. conducting a sample research. The research team has created a model that can forecast highway traffic flow. The model considers vehicle speed

Proposed System

1. Data Preprocessing

The input dataset contains a list of input parameters. So our main challenge revolves around extracting useful information from data involves parsing it and extracting the necessary information, which can be done manually or through a machine learning algorithm. Data parsing is the process of extracting useful information from a dataset. In this research, we have processed some of the dataset's attributes to extract other useful information. We had processed the "timestamp" attribute to takeout the values such as minute(m), hours(h), day_names, days(d), month(m) and year(y). In order to create a balanced dataset, we analyzed the attributes of the dataset and found that they had different effects on the training process. We then changed the input parameters of our deep model to see how they would affect the predictions. By doing this, we were able to create a dataset that was as balanced as possible. After analyzing the input data, we determined that some of the features were not beneficial to our deep learning based model, so we used new input attributes extracted from the "timestamp" attribute to improve its accuracy. We distributed the dataset into three subsets: 80% for train_set, 10% for validation_set and 10% for output_set. The train_set was used to train our deep learning model, the testing set was employed to evaluate its performance, and the remaining set was used to make predictions. First, we remove all null values from the input data. Next, we use a predefined criteria to find all non-null values in the dataset. Finally, we normalize the data and divide it into the training, testing, and prediction subsets. The occupancy data that was used to train the model was small and decimals were used as labels. We investigated different model configurations and input datasets to try to improvized the current accuracy of the fine-tuned model in distinguishing and predicting occupancy values.

2. Data Transformation Layer

For this study, we are only working through a limited amt of data related to road traffic, event data, severity score, distance in miles, airport code, planned public events, and road construction activities. The preprocessed data transform layer received a selected features from big data streams for evaluation. Here we have collected out the main features which should be passed into the data transformation pipeline where we filter out the month and day column. We are creating some features from the existing features like the time_taken by taking the difference between the EndTime and StartTime. also distance(meters) which are being extracted from the distance in miles. The scope of this study is limited to specific pre-processed and transformed data sources, which are integrated into a format suitable for ingestion by the deep traffic congestion system layer (L2).

3. Exploratory Analysis

A. Correlation between Traffic Features

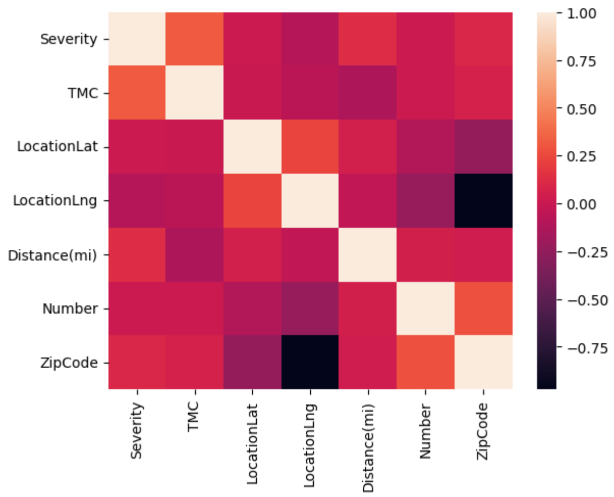

Fig 5. Correlation Heatmap for Traffic Features

In the above figure, the values that have a range closer to 1 are brighter in color and these values are showing more positive correlation amongst themselves which response to if one feature is increase the other feature will also increase. While those values with the dark contrasting color are showing negative correlation which means they work opposite to other feature.

Here TMC or traffic volume is showing +ve correlation with the Severity feature. While the other features like the Locationlng is showing negative correlation with the Zip code.

B. Traffic Volume over week days

We see a sharp rise in traffic volume over week starting days sunday and monday. This rush in traffic keep decreasing till friday which itself shows a minor increase in traffic. But sudden dip in volume can visualize in the bar plot on saturdays due to weekend holiday. This Week day traffic data was taken by grouping the dataframe startdate with “day”.

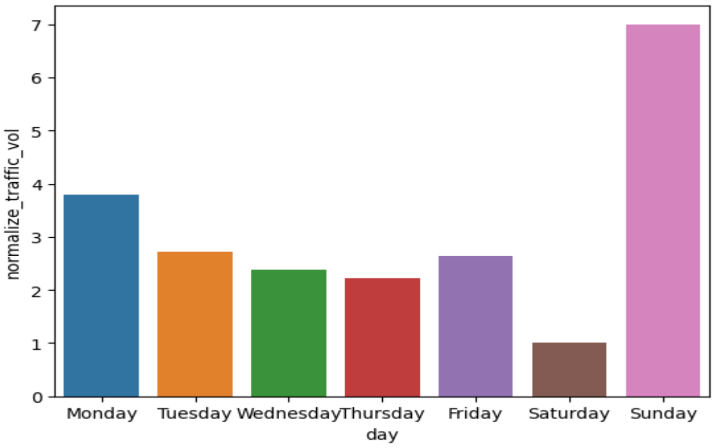

Fig 6. Normalize Traffic Volume over Weekdays

C. Traffic Volume over months

On grouping the traffic dataframe with the month values. These values are then passed for normalization due to large internal differences between the value. So we normalize the value between 1 to 7. Hence we can visualize a bar plot for every month where it clearly shows an increase in traffic volume from feb to jul, followed by a dip in the traffic on aug month which continues till the january, while showing little variations.

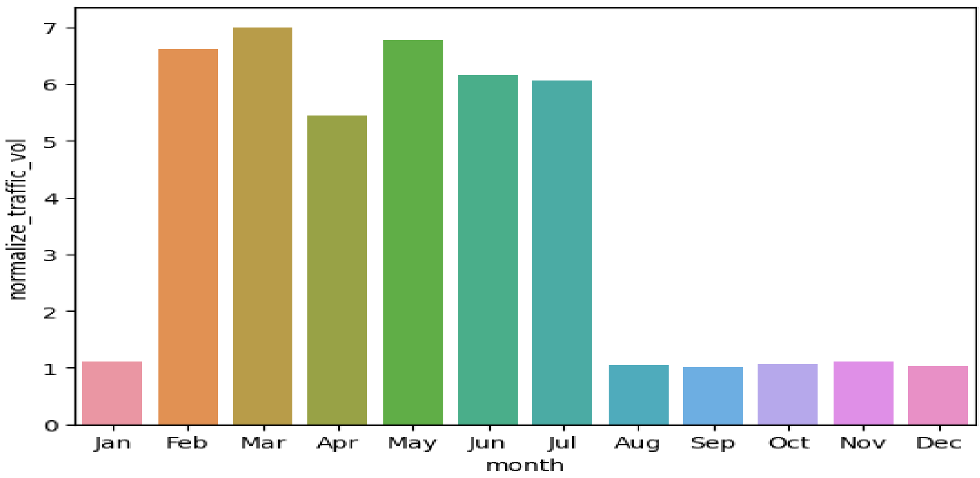

Fig 7. Normalize Traffic Volume over Months

D. Scatter plot for distance over time

When plotting a scatter plot over the distance (miles) and the time_taken variable. We tend to see the regressive cluster in the first two block of both values. As the time period increases distance start to decreasing trend meaning congestion or accidents which further lead to more time taken to cross distance. While the increase in distance only show cluster till 60 miles with the time ranging from 0-400 minutes.

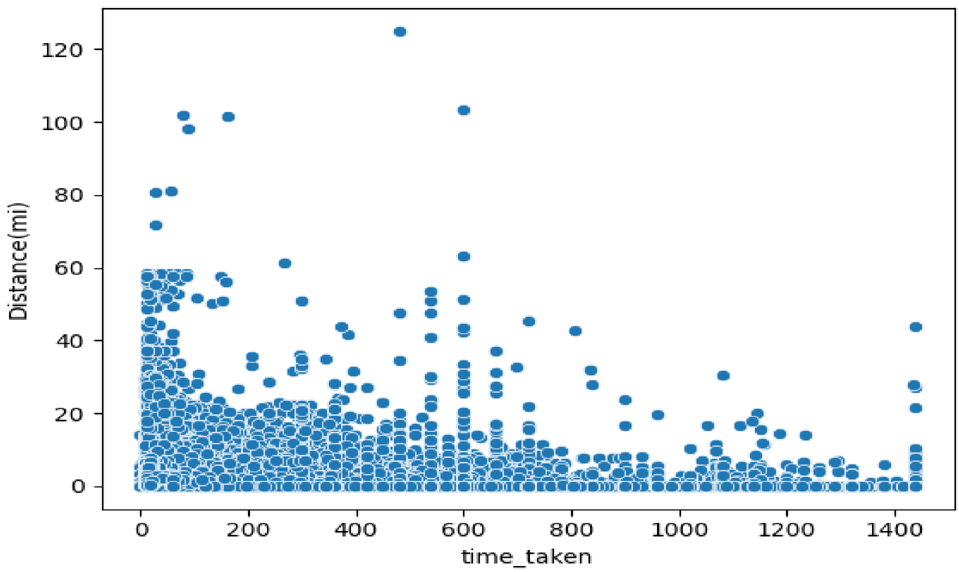

Fig 8. Normalize Traffic Volume over Months

E. Bar plot for different timezone over no. pedestrian for event

In this barplot, US/Eastern tends to show a rising pattern over the traffic volume, where congestion tend to be a major problem while US/Central shows a quite opposite look where these traffic volume shows a decreasing trend in the accidents, constructions and congestions. This is due to technological advancement in traffic management sector in these areas.

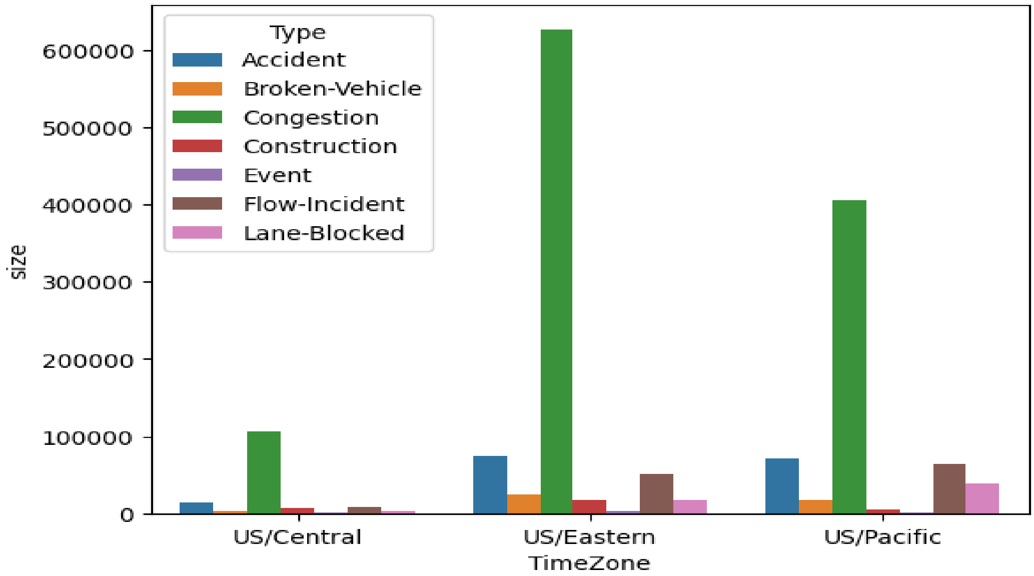

Fig 9. Normalize Traffic Volume over Months

4. Deep Learning Model

In the traffic modeling section, a deep model is used that has multiple input parameters and a single output parameter. The diagram illustrates the model having four hidden layers, but this number may vary depending on the training strategy. The model is composed of a neural based network, where neuros are connected in such a system which output single neuron that is employed as an input for another neuron. This allows the neural network to learn patterns or relationships from the data.

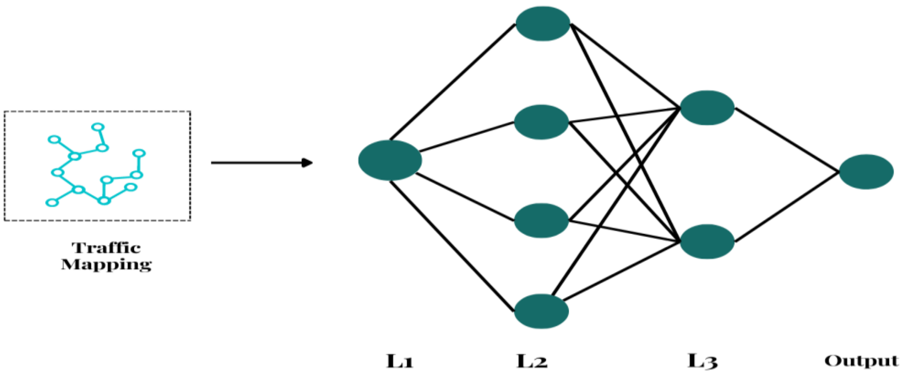

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Fig.1 Neural Network for Traffic Mapping

A deep layered model learn these collection of mathematical equations that describe the relation in input data and the output. It contains an data preprocesssing layer and an predicting layer, where the no. of neurons in processing layer corresponds to the no. of input parameters in our input dataset, and the output layer produces a single neuron, which is the predicted occupancy value. In order to create a model that can accurately predict outcomes, a certain number of mathematical equations must be included. In our example, the number of equations used in our model was 3. This means that the model is made up of three layers. The first layer is composed of input data that is fed into the second layer, which is responsible for training the model. The third layer is used to output results. Each layer in a deep learning model is responsible for a specific task. The input layer is responsible for gathering data from the environment. The second layer is responsible for transforming this data into a format that the model can understand. The third layer is responsible for outputting the results of the model. In general, a deep learning model typically has a large no. of hidden layers . The number of hidden layers can be different for different configurations of the model. The number of hidden layers can change the f1-score of the model.

5. Impact Propagation Estimation

The L2 thick layer captures the idea drift brought on by traffic incidents as they continue to happen on the highways. In an effort to lessen the effects of these occurrences, this information is utilised to design and modify traffic routes almost immediately. based on previous vehicle trajectory data, a data-driven approach is provided to forecast event impact spreading along the network of arterial roads. The strategy is grounded on the impact propagation theory, which claims that impact events spread through a system following the path of least resistance.

The data used in the approach is collected from public road networks in the United States. The results of the approach are used to improve the understanding of impact propagation and to develop strategies for mitigating the effects of incidents on the arterial road network

$$P_t(t, S_i \to s) = \frac{T(t, S_i \to s)}{\sum_{j=1}^{n} \mathrm{j}\, T(t, S_j \to s)}$$

The impact of an occurrence at location Si at while T will be proportional to the traffic flow from Si to s at time t, or T (t, Si s). It is assumed that any incident at s will impede or slow down traffic flowing via Si s, which will have an effect on traffic on Si. It should be emphasised that, given the availability of earlier vehicle trajectory data, the relative influence of traffic at point Si on traffic at point s is defined by the traffic flow at Si relative to the traffic flow at S at time t. A key issue for transportation planners is estimating how a road stretch would affect nearby highways. Road sections may be a significant impact on the traffic flow on surrounding roadways, and the propagation of that impact can be difficult to predict. Frequently, impact predictions are carried out using mathematical models, which may be suboptimal due to the differences between actual traffic situations and the expectations made in the models. Impact propagation models are learned using a data-driven supervised learning approach using incident data from historical incident reports and road occupancy data from induction loop networks.

SYSTEM DESIGN

1. Project Perspective

The following characteristics would be present in the suggested traffic control system:

• A deep learning model that was trained on historical traffic data to precisely forecast how traffic will behave in cities.

• A review of the forecasts to create an efficient traffic-congestion control strategy.

• Methods of computational intelligence to enhance the control approach.

• Simulations to assess how well the suggested control technique performs.

• A dataset of actual traffic to evaluate how well the suggested control approach reduces congestion.

2. Performance Requirements

This project demands a control approach that can reliably forecast urban traffic flow and lessen congestion. The control strategy must be built on deep learning and computational intelligence principles, and it must make use of current data to create models and make predictions.

Additionally, computational intelligence approaches must be used to optimise the control strategy. Finally, simulations and a dataset of actual traffic must be used to assess the performance of the suggested control approach. This initiative aims to lessen urban traffic congestion, increase the effectiveness of traffic operations, and cut carbon emissions. These objectives ought to be accomplished by the control approach successfully

3. System Features

The suggested traffic control system will have a number of parts. It will initially train deep learning models on current data sets and produce predictions. To build a control strategy to lessen traffic congestion, these projections will be used.

In order to optimise the control approach, the system will second use computational intelligence techniques. This will guarantee that the suggested plan can effectively lessen traffic congestion. A simulation module will also be incorporated into the system to evaluate and assess the suggested control technique. This will enable us to evaluate how well the suggested plan works to lessen traffic congestion.

The system will also include a real-world traffic dataset that can be used to evaluate how well the suggested control approach performs in practise..

4. Methodology

A. Internet Of Vehicles

IOVs (Intelligent Vehicle Networks) is a vast information network that collects data about vehicles, such as their location, speed, and route. This data is gathered through a combination of GPS, RFID devices, sensors, cameras, and the internet. This allows us to get real-time updates on traffic conditions. A traffic sensor is a device that measures traffic flow on a roadway. Traffic sensors can be installed along the side of the road, on the median, or even in the middle of the street. By measuring the traffic flow, the traffic sensor can generate a traffic report. Traffic reports can be used to generate traffic forecasts. Traffic forecasts can help drivers know when to expect heavy traffic and when to plan for an alternate route. Traffic forecasts can also help transportation planners make decisions about how to best allocate road resources.

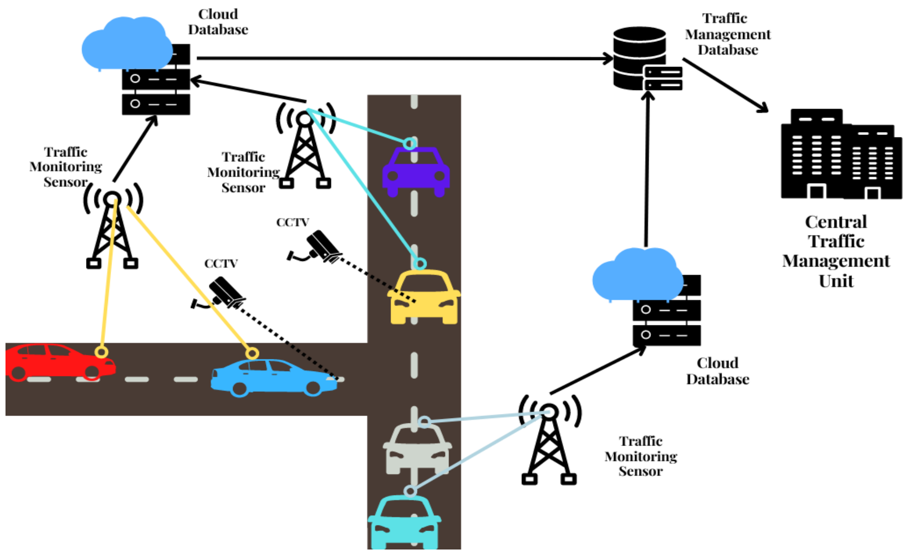

Fig.2 Smart Traffic Management System

Moreover, the precision of these sensory items had suddenly improved in past few years, which get to contribute in short-term traffic forecasts.

B. Dataset

We have taken the LSTW dataset which consists of Large Scale Traffic and Events in the United states. In terms of events there are many types including accidents, congestion, and construction . This dataset was continuously being collected from August 2016 till today. This dataset contains about more than 15 million data points. These contain features like starttime, endtime, timezone, location, city and latitude. Here most of the locations are written in latitudes and longitudes which are unique for every location in the United States. The first step we need to do is to split this dataset into two parts. The first part of the data is the training set, that is used in creating the model. While the second-most part is the testing set, which is employed to validate the base model. The testing set is us to make sure that the model can accurately predict the outcomes of the testing set. After validating the base model, the testing set can be used to evaluate the accuracy of the model.

C. Deep Learning Techniques

RNN

Before these reccurent based deep learning cell the before conventional neural networks do not have connections between nodes in the same layer. This type of architecture may not be suitable for tasks that involve recognizing patterns over time or space, as there are no connections to help the network "remember" the previous state.An RNN is a type of neural network that is composed of a dict of input nodes and a set of hidden nodes. The input nodes are in the form of a sequence of inputs, while the hidden nodes are in the form of a sequence of weights. The RNN is able to learn by receiving feedback from the previous hidden layer to the current layer.

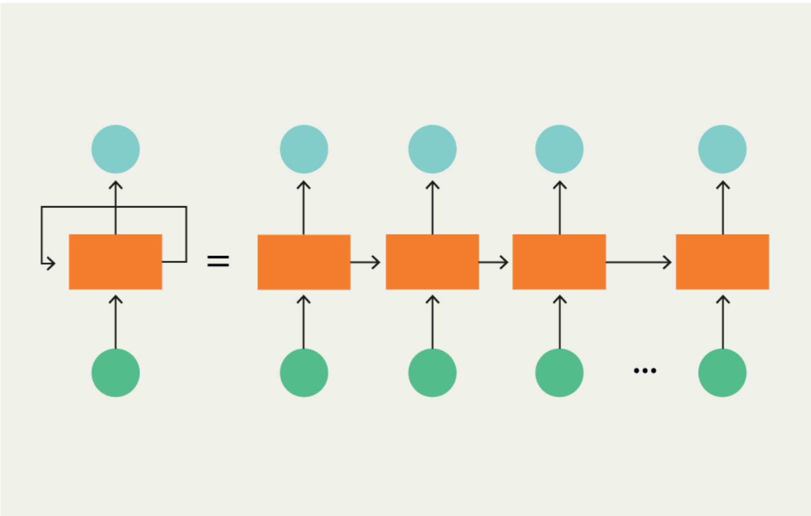

Fig. 4 Unfolding of RNN

RNNs are an advanced type of neural network architecture that can process a sequence of input data. Unlike normal neural networks that take in a set number of input vectors, RNNs can take in input data one at a time and use all of the available information up to the present. This allows the user to customize the depth of the RNN based on their specific needs. RNNs are useful for simulating the correlation between data points that occur in succession, but they are not as accurate over a longer period of time.

LSTM

Long Short Term Memory (LSTM) networks are special types of recurrent neural networks that are able to learn from time series data and account for both short and long term correlations. This memory cell structure consists of three main gates - Gate for input , forget and output for any given data - which determine which values from the input, memory cell, and output are used. Inputs to the network are the known data and outputs are the forecast results. This proposed model uses an ODC matrix to identify temporal and spatial correlations of traffic patterns. It further divides long-term traffic forecasting into multiple short-term forecasting processes. A LSTM cells is employed to produce short-term traffic patterns, resulting in more accurate and dynamic forecasts of traffic flows in the near future. The network is composed of two main layers: input neuron layer, which receive observations in the time domain, and output or predicted neuron layer

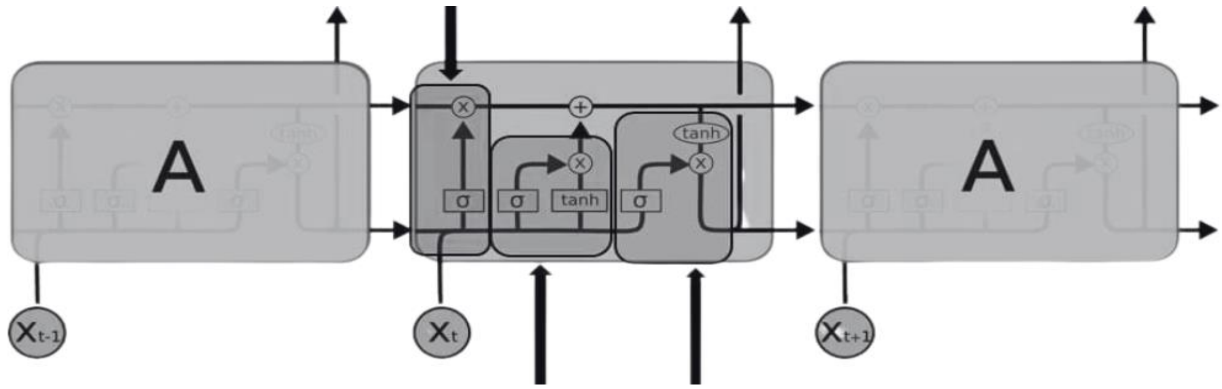

Fig.3 Long Short Term Memory (LSTM) Architecture Design

A 2D long short-term memory (LSTM) cell is used to predict future traffic congestion in a specific area by taking into account the special temporal unit that produces covariance between the traffic data sets. The network is trained by initializing it with a historical traffic data set and then comparing the predictions with the actual traffic data set, with the results being used to improve the performance. The neurons responsible for producing the predictions in the time domain have their indexes in ascending order, from bottom to top.

Encoder-Decoder Model

The encoder-decoder deep learning architecture is a neural network architecture used for encoding and decoding text. The encoder is responsible for transforming a sentence into a sequence of symbols, while the decoder is responsible for decoding a sequence of symbols into a sentence. MT (Machine Translation) is an active field of research in NLP that aims to develop efficient, automated programs to translate a source language text into a target language. Despite its usefulness, there are certain issues, such as the difference in context between the input and output, which can cause problems. However, this can also lead to opportunities, such as in video captioning and question and answer.

Seq -2- Seq Model

The sequence-2-sequence deep learning architecture is a two-layer deep neural network with a sequence input unit and a sequence output unit. The first layer encodes the input data and feed it in sequence of datapoints using a dense layer, while the second layer utilizes the encoded tokens to generate the output sequence. The second layer in the sequence-2-sequence deep learning architecture is a sparse layer that is designed to map the tokens from the dense layer into a sequence of outputs. Autoencoders are recurrent neural network which are utilized to accomplish complex tasks for language like the language translation, zero shot classification. They are deep learning models that learn representations of data by encoding it into a lower-dimensional representation. The autoencoder is then able to reconstruct the original data representation from the encoded representation.

D. Traffic States Features

Traffic states are influenced by both long-term and short-term traffic factors. Long-term features are influenced by societal behaviours, such as the increase in morning and evening traffic. Short-term features that are impacted by severe weather, car accidents, and other irregular events can cause uncertainty in the traffic flow. To successfully estimate traffic, a lot of data must be promptly analysed. A traffic flow model is influenced by both long-term and short-term factors. While short-term features are brought about by unfavourable weather, car accidents, and other sporadic events, long-term features are the outcome of societal activities. There are a lot of automobiles, buses, and motorcycles on the city streets. The cars' movements are coordinated by the traffic signals to keep the roadways safe.The deep learning methods are better suited to handle the complex traffic signals and the interrelated traffic states.

RESULTS

The proposed model was tested in virtual environment inside a desktop computer with an Intel i7 f-34 3.4GHZ CPU, 16GB memory and GPU employed is NVIDIA GTX750 to determine its effectiveness in predicting traffic flow on roads with varying levels of traffic load. The results indicated that the model was successful in accurately predicting the traffic flow on roads with huge, normal and lower loads of traffic, as verified by comparison with the observed traffic flow. Traffic flow over state is non-uniformly distributed due to different conditions in the state wise resource distribution also due to the technological advancement in the traffic management system .

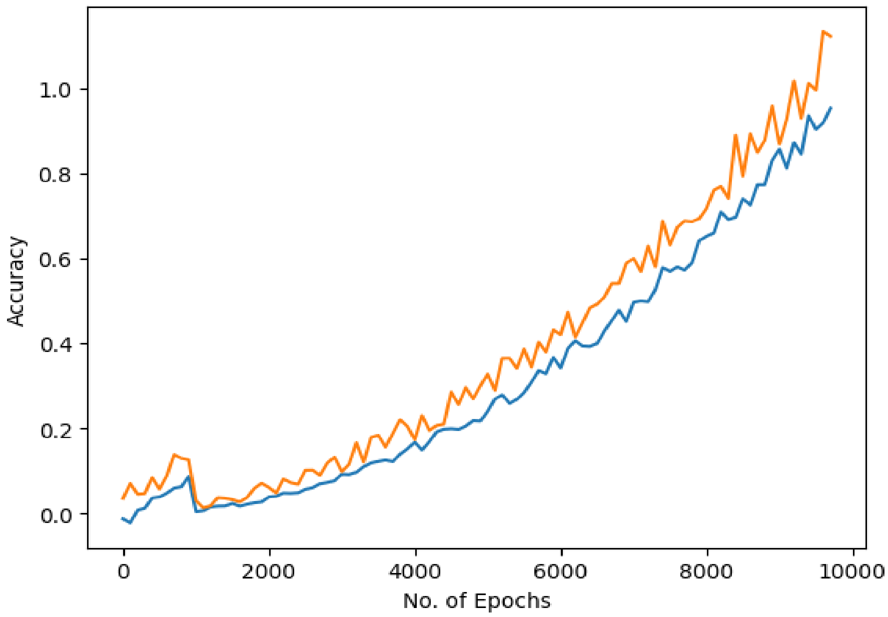

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Fig. 6 Predictions on Low Traffic Flow

The comparison of observed and predicted traffic flow rate shows that the relative error is higher for lower traffic flow rate. This is due to even shorter differences seen on the observed and model predicted flow can lead to huge relative error. Hence, the proposed method of traffic flow prediction can be considered successful, particularly for huge and normal level of traffic conditions. To prove them, three observated posts near the north second and fifth ring roads, with different traffic volumes, have been used to distinguish the predicted data point and the original traffic data point.

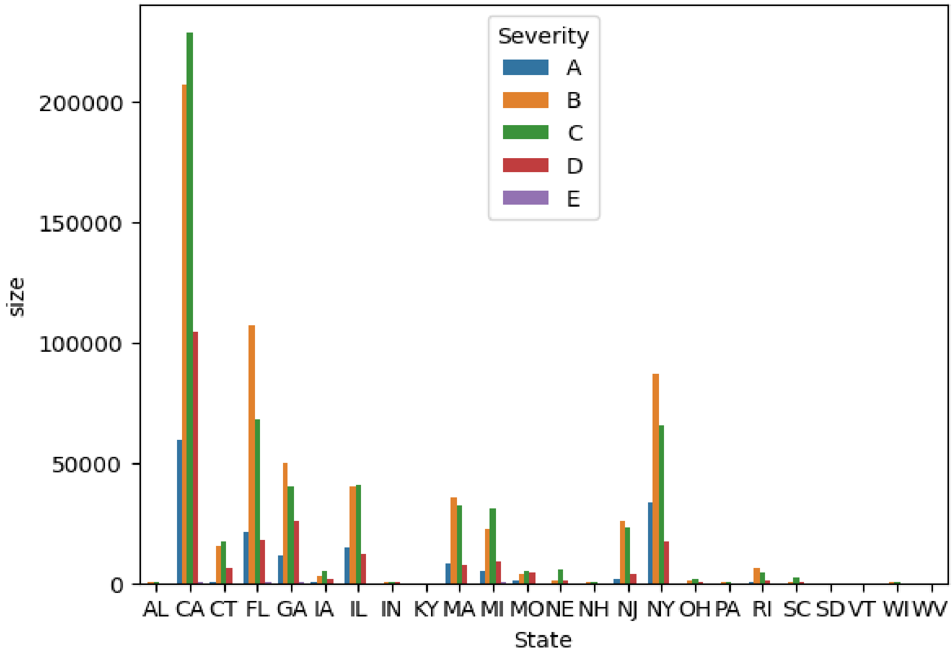

Fig 11. State-wise Traffic Distribution

In the above graph, some countries like the california, florida, georgia and new york is showing heavy severity in their bar graph. While on the other hand some countries like alaska, pennsylvania are showing decreased severity and some are even not severe at all. Previous research has demonstrated that those model simulated traffic flow datapoints show some similar followup patterns for the observed traffic flow datapoints while still that model is performing best in both heavy and normal traffic conditions. Nevertheless, these produced method did not correct the accuracy problem in traffic flow estimation for the low traffic conditions, which is still been a common challenge for current traffic prediction models.

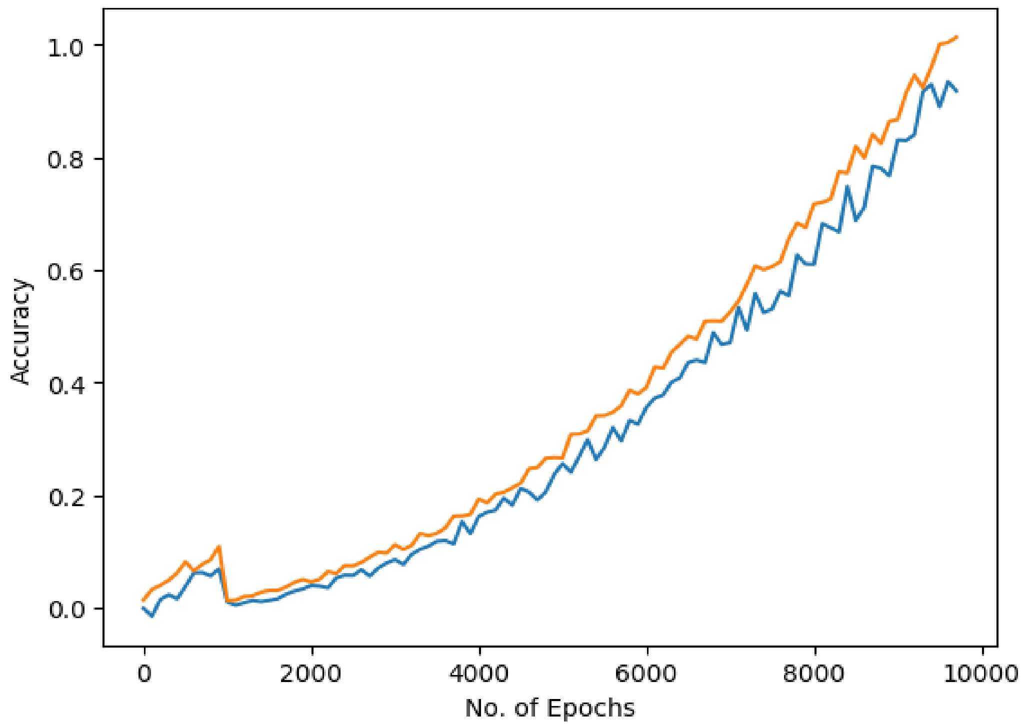

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Fig. 7 Predictions on High Traffic Flow

The model produced results predicted that these traffic volume at observation point A would be high, while the traffic volume at observation point B would be medium. The traffic volume at observation point C would be low. The produced model is tested by three common main metrics to test its performance. The fine tuned model of traffic forecasting was tested and validated for accuracy by comparing its output to the observed traffic flow. Mean absolute error (MAE), mean square error (MSE) and mean relative error (MRE) were employed to test these fine-tuned model's performance. The predictions showed that the fine tuned method was reliable and effective in predicting traffic patterns, as the forecast traffic patterns were close to the observed traffic patterns. This was confirmed by the Mean Relative Error (MRE) scores, which were 6.41%, 6.05%, and 6.21%. In this paper, a recurrent neural net and LSTM is proposed to test the traffic flow in a test time section. The proposed model is compared to some conventional methods, and the results show that it usually has the minimum mean relative error. Thus, this fine tuned model is more efficient than other previous models based on the previous results of traffic observations in A, B, and C.

CONCLUSION

Here in this current paper we try to implement a smart traffic management model that uses artificial intelligence to analyze traffic data and make predictions about how the flow of traffic will change in the future. This allows the platform to adjust traffic signals or routes in real-time in order to keep traffic moving smoothly and efficiently. A system utilizing computer technology is able to accurately distinguish between repeated and one-off events from a variety of intermediary sensor network information and social media content. This platform is able to do this in a timely manner and with minimal user input. The latest computerized platform is able to surpass the restrictions posed by current algorithms and technologies that are dependent on restricted labeled data and specific data and traffic patterns. Traffic flow estimation is a unique and important method for the management of traffic, aiming to anticipate the traffic at a future point in time, based on present traffic conditions. Deep reinforcement learning is one approach to accomplish this, which involves modeling the traffic flow as a neural network. The network is then trained using a set of data samples. This is important because it means that the traffic signal control can be improved in response to changing conditions. Deep reinforcing learning based system was tested in a simulation of a large-scale traffic network to ascertain its efficacy in improving traffic control decisions based on a variety of real-time data streams. The results showed that it was able to learn and make better decisions. This is important because it means that the traffic signal control could be improved while responding to those evolving conditions.

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