Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Hybrid Real-Time Traffic Management System with Time Series Analysis using Deep Learning Methods

G Senthil Velan[1], Dr. B. Shanthini[2], Dr. V. Cyril Raj[3]

[1]*Research Scholar, Computer Science and Engineering, St.Peter's Institute of Higher Education and Research, Tamilnadu, senthil2uin@gmail.com*
[2]*Professor and Head, Computer Science and Engineering, St.Peter's Institute of Higher Education and Research, Tamilnadu, csehod@spiher.ac.in*
[3]*Professor, Computer Science and Engineering, Dr MGR Educational and Research Institute, Tamilnadu. cyrilraj@hotmail.com*

Big city traffic is getting more and more backed up and wasting precious resources like time and fuel resulting into a great loss on GDP. Hence traffic congestion must be resolved immediately. In an intelligent transportation system, a lot of data from many different categories can be gathered and evaluated in order to predict and prevent traffic flow and road congestion. Dealing with this massive data is important but it is difficult. While most of the literature uses batch processing to handle large amounts of road data, real-time traffic prediction is not possible. In this research work, analyze huge streaming data, such as rainfall volume, traffic events, and road density, and employ Storm plus's spouts and bolts to create a real-time traffic forecast model. This paper outlines Storm plus's architecture as well as its distributed scale-out and fault-tolerance techniques. The real-time data set derived from storm plus was curated with RFE for eliminating irrelevant features. The execution of Storm Plus queries for traffic prediction is also covered in this paper. The proposed real-time urban traffic congestion prediction model was evaluated with SP-SVM and SP-CNN gathers. In our implementation SP-CNN has outperformed SP-SVM in the prediction accuracy. Finally Time series analysis helped us to regulate traffic flow from going out of hand as congestion.

Keywords: Traffic Prediction, Strom Plus, Time Series Analysis, Regressive feature Extraction.

1. Introduction

In cities, vehicle observation streaming mass data access is a hotspot for research. The frequency of data access is increasing exponentially with the number of vehicles in urban areas. If this information is used promptly and accurately to manage traffic congestion, it can assist drivers in making more informed decisions and reduce their carbon footprint. Real-time accurate road traffic prediction systems will meet these needs. Although the traffic authorities have access to a vast amount of real-time traffic data, data collection still plays a significant role in their operations.

In addition to decreasing social functioning efficiency, traffic congestion raises vehicle energy consumption. Solving traffic bottlenecks is an urgent need. An intelligent control system for traffic signals that combines big data, cloud computing, artificial intelligence, mobile communication, the Internet of things, and cloud computing can detect changes in real time, respond quickly, and make intelligent decisions. On streaming data, complex computations need to be handled in real time.

When there is a substantial increase in volume of data, the conventional data processing techniques are unable to handle it. In the same way rapid growth of such massive amounts of data also brings with it a host of problems like, incomplete and inconsistent data, scalability issues, timeliness issues, and security issues. There are significant analytical challenges associated with big data. The speed at which data analysis is being done is getting closer and closer to real time; i.e. big data analytics has increasing potential. Though highly challenging, big data analytics can be useful in identifying patterns and connections among large amounts of data. Big data is quickly becoming a catchphrase, but the abilities needed to analyze such vast volumes of data are insufficient. Advanced decision-making abilities are needed in conjunction with historical data. To manage traffic most of the Traffic engineering division of police and city administration need to know the nature of the current traffic scenario with the clear classification tag. Hence in our study vehicle movement in traffic situation is classified as follows: 1. Free flow of traffic 2. Sparse traffic congestion 3. Observable traffic congestion and 4. Huge traffic congestion. Once the current traffic scenario classification is obtained from the near matching classes of trained neural networks, it will be easy to analyze the progression of traffic congestion.

By referring the matching data and its transition will defiantly give scientific data to manage the traffic.

Intelligent Traffic Management System.

The classic traffic signal calculates the green phase delay, red and green time lengths, and other parameters using statistical analysis and the timing control method. Its operational efficiency is limited to the standard traffic scenario under particular circumstances, and it frequently lacks adaptability when circumstances change. To make informed decisions about traffic signals, a lot of traffic resources are required. These resources are divided into five categories: computer, detection, road, signal, and vehicle resources. Cloud computing, big data, artificial intelligence, and other modern technologies must be widely used in the development of a accurate traffic intelligent control system.

First, real-time traffic data is gathered by a vast number of IOT nodes equipped with edge computing capabilities. Secondly, adequate computing or storage resources that are potentially infinitely expandable and utilized whenever needed are provided by cloud platform technology. Third, there is storage for the enormous volume of data that IOT nodes gather. Fourth, feature information on particular themes is extracted through the use of big data mining. Ultimately, artificial intelligence technologies such as neural networks enable the realization of complicated decisions and control.

2. Literature Review

Traffic Forecasting Using Deep Learning

Deep learning algorithms have demonstrated superior ability to capture nonlinear spatiotemporal impacts in traffic forecasting. Numerous further NN-based models have been used to predict traffic conditions. It was suggested to do a preliminary study for vehicle trip time estimation using the feed-forward NN. Deep belief networks, generative adversarial networks, recurrent NN, convolution NN, auto-encoders, fuzzy NN and combinations of these models are some examples of these models [1]-[3]. Because recurrent neural networks (NNs) can capture temporal relationships, they are frequently employed in traffic forecasting models to anticipate vehicle speed, traffic flow and trip time. Examples of these models are LSTM and GRU. Further, a number of unique traffic forecasting models with deep learning have been presented recently by integrating pre-existing methodologies, adding auxiliary data, and altering the basic neural network model [4]-[6]. Numerous innovative, Long short-term memory model, such as deep LSTM, bidirectional LSTM, nested LSTM, and shared hidden LSTM, have been developed by reordering and merging single LSTMs [8],[9].

Long short-term memory models are utilized to comprehensively identify temporal dependencies in order to predict traffic. Furthermore, traffic state sequence forecasting has also made use of models based on sequence to-sequence (seq2seq) architecture [12]-[14].

To handle different feature types, deep learning models with multi-streaming have been studied and assessed for traffic forecasting issues. To increase the prediction performance, several deep learning based models additionally use additional traffic related data, such as weather, accident, and geographic attribute data for roads [15]-[17]. CNNs are used by many forecasting models to capture the spatial links present in traffic networks and to extract spatial features from 2D spatial-temporal traffic data [18],[19].

Expressing traffic structures are challenging problems with 2D spatial-temporal data, research have been done to translate traffic network topologies into images and train neural networks models to recognize spatial features. This noise in these processed images means that CNNs will inevitably identify false spatial correlations [26]-[28]. Other recent efforts have also attempted to convert traffic status data into three-dimensional (3D) matrices in order to use the 3D convolutional network to extract more useful features. However, traditional CNN-based methods are hampered by the traffic network's topological structure and physical attributes. Research has attempted to comprehend the traffic network as a graph in order to tackle this problem, and then use the graph-based convolution operator to extract features from the well-structured graph.

Deep neural network visualization and understanding

A portion of our understanding of how deep neural networks (DNNs) behave on language and picture tasks has improved. The instruments used to retrieve knowledge are quite similar to surgical experiments performed on human bodies. The most fundamental capability is the ability to view the activations of a trained DNN on each layer [22]. Perhaps a different kind of neural network. It is discovered that the DNN eventually produces a more invariant and abstract understanding of the inputs. Another method is to try to figure out the function that each individual neuron or all of its nodes calculates [23]. In a stacked RNN structure found that deeper layer neurons are more likely to maintain long-term memory [24]. Carried out some intriguing experiments using simulated data to activate the trained-DNN showed how a DNN can recognize as something distinct an image that has been altered yet is invisible to humans [25].

Investigating how the DNN operates on different datasets, such traffic flow and meteorological data, is an interesting endeavor. A result-centric approach (comparing the output of different approaches) is used to gain knowledge of prediction strategies when it comes to traffic flow prediction. This strategy is dependent on test data and model parameters. Our inadequate understanding of how and why prediction models work limits the development of improved models to haphazard is testing and parameter tinkering. Thus, studies must comprehend data-driven traffic flow prediction models [20],[21].

In summary, a multitude of traffic flow prediction algorithms that combine various methods from many fields have been developed in response to the growing need for real-time traffic flow information in Intelligent Transportation Systems (ITSs). Declaring that one strategy is unquestionably superior to another in every situation is difficult, though.

Time Series Analysis using ARIMA

An enhanced method for calculating the transient traffic stream depending on the ARIMA model was provided in Paper [7]. Suggests two combinational conjecture models depending on GM, ARIMA, and GRNN in an effort to increase the traffic stream's prediction accuracy. The Elman combinational estimate model is then built based on GM, ARIMA, and GRNN, achieving the coordination of these three, and it suggests using neural organizations to determine variable weight coefficients [10].

As reported in study [11], we find that ARIMA outperforms all other situations. However, the complex character of computation is negatively impacted by this accuracy.

3. Methodology

As stated in the Introduction, real-time analysis of traffic pattern is complex process where huge multidimensional data need to be handled and prepared as a dataset to apply in any machine learning techniques for predicting traffic congestions. In this research, the Strom Plus framework was used for handling real-time multi dimensional streaming data. In metropolitan city like Chennai, there are around 400 busy traffic junction and 35,000 semi traffic junctions are used to regulate traffic. Data derived from these junctions through vehicle detectors, video cameras, speed sensors, traffic light on/off timing is mounting as a huge dataset over a period of time. The dataset consist of so many attributes, it’s very important to identify the relevant attributes which will help for better classification. In this experimental study RFE was used to eliminate the irrelevant attributes. With the historical dataset using the supervised learning algorithms Strom Plus-Support Vector Machine (SP-SVM), Strom Plus-Convolutional neural network (SP-CNN) classification models are built and tested. Once trained, in the real-time scenario various unclassified instances of traffic data are generated and applied to the classification models to predict the traffic condition. Further, the Time series Analysis algorithm ARIMA is used to retrieve near matching history of traffic instance, so that relevant information can be retrieved for the traffic management like reducing the traffic density, regulating the traffic signals, speed of the vehicle and appropriate blocking of turns, etc.

Strom Plus

Apache Storm is a real-time, distributed, fault-tolerant streaming processing framework that can be used for a variety of data analytics, machine learning, and continuous computing applications.

Unlimited streams of data are reliably processed by Storm Plus. The stream, which is an infinite series of tuples, is a key idea in Storm Plus. With the help of two primitives that Storm offers, users can turn an existing stream into a new one: a spout and a bolt. Users must implement both of these interfaces in order to run their application-specific logic.

The open source distributed real-time computing system Storm Plus referred to foundation of the suggested cluster architecture. Nimbus and the Zookeeper user interface are included with the master node for data exchange. The worker and supervisor make up the slave node. Storm Plus topology framework implements the suggested congestion prediction method for real-time freeway traffic. It is made up of six parts, namely. i.e. traffic data bolt, social Interest data bolt, weather data bolt, data mapping bolt, and congestion prediction bolt, among others. Vehicle density on roads is computed by the traffic data bolt, which then transmits the computation results to the traffic data mapping module. The weather data bolt collects statistics on rainfall, analyzes, and transmits the information to the weather data mapping module.

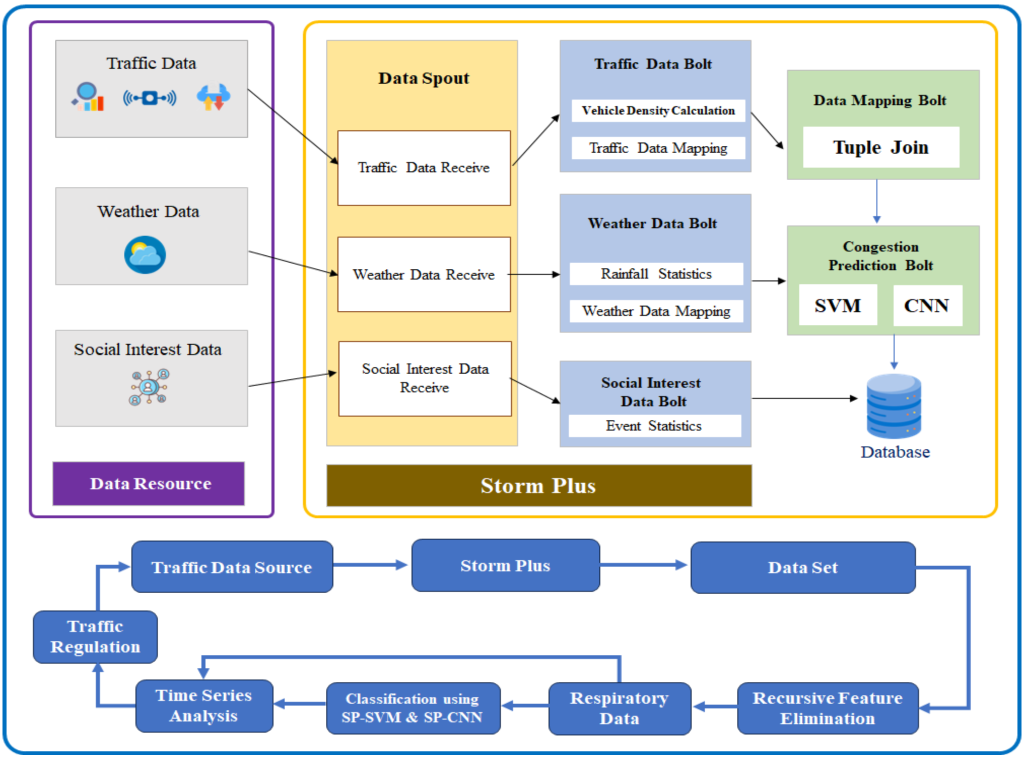

Fig. 1. StromPlus Data streaming Flow

The Storm Plus Spout gathers weather, traffic, and social Interest information. CNN and SVM are used in the Storm Bolt layer to forecast the lane traffic for the upcoming time period.

Dataset

Traffic flow datasets are compilations of information detailing the movement of vehicles on roads over specific time intervals. These datasets play a critical role in transportation planning, traffic engineering, and research fields such as urban mobility, congestion management, and the advancement of intelligent transportation systems.

Key components of traffic flow datasets include the following attributes:

Vehicle Counts: This metric quantifies the number of vehicles passing a particular point on the roadway within a defined time frame, offering insights into traffic volume.

Weather Conditions: Information about weather factors like temperature, precipitation, visibility, etc., is crucial for comprehending how weather impacts traffic flow.

Vehicle Classifications: This provides details about the types of vehicles (e.g., cars, trucks, motorcycles), which proves valuable in discerning traffic patterns.

Vehicle average speed, Vehicle Direction, Geographical Location, Traffic Density in each region, Queue Length at Congested Area and Road Condition, Social relevant occasions as such specious day, political rally, festivals long and short week ends, etc.

IITM-HeTra

There are around 85,000 CCTV cameras across various street and traffic junctions in Chennai. Appropriate processing of these videos with respective specific time will give lot of data about the traffic Indian Institute of Technology Madras has converted such videos into datasets for further analysis. It is a Heavy Traffic Dataset and widely used as traffic flow dataset for research purposes in computer vision, machine learning, and traffic analysis. It comprises high-resolution video footage of real-world traffic situations recorded at a bustling intersection in Chennai, India. This dataset is tailored for tasks such as vehicle detection, tracking, counting, and behavior analysis. It encompasses diverse lighting conditions, weather scenarios, and traffic densities, making it an invaluable resource for testing and benchmarking algorithms related to traffic management and analysis. This data set was also used in this proposed research work.

Recursive Feature Elimination

The paper contributes by determining the ideal feature count for achieving the best classification results in an actual dataset. In order to do this, we have chosen the optimum features set for the offline run using features selection techniques. Characteristics selection techniques, which are now an essential part of machine learning, aim to select a subset of characteristics that are pertinent to the goal notion. Feature selection has several advantages, including the ability to (i) overcome the curse of dimensionality and enhance learning algorithms' performance in terms of generalization ability and learning speed, as well as (ii) lowering storage requirements. In actuality, feature selection is a challenging process due to the large initial dataset, as well as the requirement to minimize the number of features and optimize learning capacity.

RFE for Multi_Class

Recursive Feature Elimination (RFE) can be applied to problems with multiple classes, often referred to as multi-class classification problems. In the context of feature selection for multi-class classification, RFE can be adapted to work with models that naturally support multiple classes.

4. Traffic Prediction Methods

Predicting traffic flow is a crucial component of the Intelligent Transportation System (ITS). This facilitates the safer and more intelligent use of transportation networks by traffic stakeholders. The technique of estimating the volume and density of traffic flow in order to control vehicle movement and relieve congestion is known as traffic forecasting. The problem of predicting traffic flow involves intricate non-linear connections between space and time as well as dependence on outside variables including weekends, public holidays, the weather, events, state of the roads, and more. In this case we are using supervisor algorithm SVM and CNN for predicting the Traffic condition.

Support Vector Machine

Support vector machines (SVMs) encompass a collection of akin supervised learning methodologies utilized for both regression and classification tasks. These methodologies belong to the broader family of generalized linear classification techniques. SVMs effectively optimize the geometric margin while simultaneously minimizing the empirical classification error. As a result of this optimization process, SVMs were aptly named Maximum Margin Classifiers. The underlying principle of SVMs is rooted in structural risk minimization. SVMs enable the direct derivation of decision functions from the training data, with the objective of maximizing the margin - the current spatial separation between decision boundaries - within a high-dimensional feature space. When confronted with a limited amount of input data, SVMs and alternative classification strategies exhibit notable differences in their classification capabilities. This classification approach effectively mitigates classification errors inherent to the training data and consequently achieves enhanced generalization prowess. The training and testing datasets with class labels are derived from Storm Plus and selected using RFE. We have chosen to use CNN to compare how accurate the predictions were.

Convolutional Neural Network (CNN)

The CNN method's primary objective is to handle 2D data, like pictures. An input layer, an output layer, and numerous hidden layers—convolution layers, fully linked layers, and pooling, for instance—make up the model. A convolution layer uses filters to modify the input value in a defined way in order to save features. The clustering result from the previous stage is combined with the minimum or maximum matrix in the subsequent level to create a separate section. By using a pooling layer, abstract level data can be educated while reducing dimensionality to support the entire model.

The three main layers of a CNN are the fully connected, pooled, and convolutional layers. A crucial component of the CNN is the convolutional layer. This layer is responsible for feature extraction from input feature maps or images. To obtain multiple feature maps, a convolution kernel can be present in each convolutional layer. Here's how to calculate the convolution layer:

$$x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} * k_{ij}^l + b_j^l\right)$$

where f(.) is the activation function, x_j^I is the output of the i^{th} channel of the j^{th} convolution layer, and x_j^{I-1} is the characteristic map of the output of the preceding layer. In this case, b_j^I is the matching offset, $k_{ij}^I$is a convolution kernel, and M_j is a subset of the input feature maps used to compute u_j^I. Here also dataset obtained from storm plus architecture is used but with RFE to eliminate the irrelevant features.

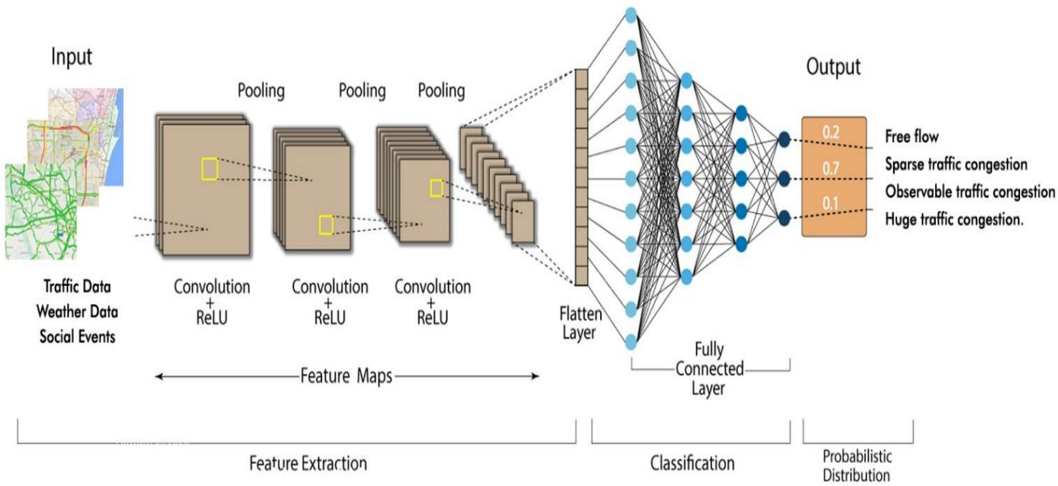

Fig. 2. CNN Model for Traffic Prediction

Time series analysis

Time-ordered data points are analyzed and predictions are based on time series algorithms. Time series data are observations or measurements that are gathered over an extended period of time, usually on a regular basis.

Autoregressive Integrated Moving Average (ARIMA):

For time series analysis and forecasting, the ARIMA model is a popular and effective method. It works well for capturing seasonality, noise, and trends, among other elements of time series data. The AutoRegression (AR), Integration (I), and Moving Average (MA) components comprise the ARIMA model.

These three elements are combined into a single model by the ARIMA model, which uses it to describe the time series data as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_p Y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - ... - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

Where

- The time series value at time t is denoted by yt.
- The term "c" is constant.
- The autoregressive parameters are denoted by ϕ.
- The moving average parameters are denoted by θ.
- The error terms are ε.

ARIMA models can provide valuable insights into temporal patterns and trends for traffic flow regulation, especially in complex urban environments with dynamic factors. An exact match of this historical data can help the traffic planners to take appropriate decisions like removal or blocking of certain number of vehicles in individual regions so that reoccurrence of such situations can handled or prevented.

The significance of the generated forecasts determines how long the time series should be done. It is possible to forecast vehicle counts with reasonable accuracy for each hour of the day; however, it is more difficult to use this hourly information when a signal adjustment algorithm is making decisions. When maximizing the number of vehicles in each location, a brief duration of fifteen minutes might be employed as the foundation unit of time extension. After using SP CNN and SP SVM classifiers to anticipate traffic conditions, we need to know the past data set reflecting vehicle density, weather, socially significant events, and vehicle classification, all of which have contributed to the progressive development of traffic congestion as classified by the following categories. 1. Free flow, 2. Sparse traffic congestion, 3. Observable traffic congestion and 4. Huge traffic congestion.

5. Experiments and Results

For the experimental purpose Chennai Metropolitan traffic are used as dataset. The study site is divided into twenty five regions (5X5), each region measuring approximately two kilometers in length and width. The dataset includes traffic in Chennai from 6.00 AM to 10.00 PM. The snapshots of the traffic details are taken once in 15 minutes during the above period. Unpredicted events like accident, protest, road repair works, rain, auspicious day and short and long weekend’s traffic conditions are also included in the dataset. Each instance of dataset is classified as 1. Free flow 2. Sparse traffic congestion 3. Observable traffic congestion 4. Huge traffic congestion.

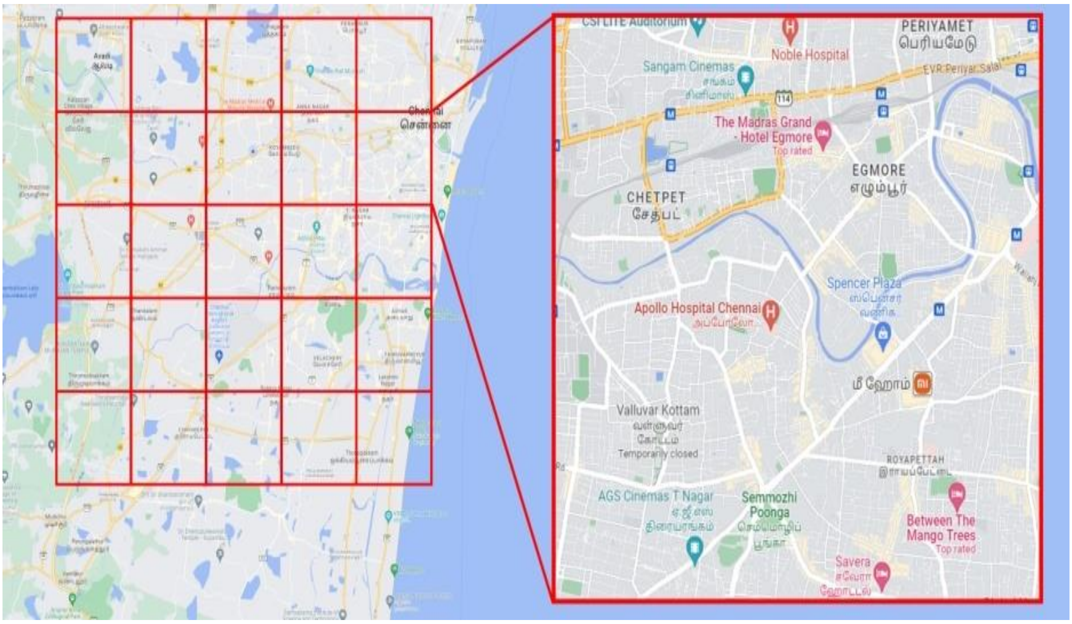

Fig. 3. The 5X5 Traffic study Region in Chennai

This Highly complex dataset is accumulated for 3 years which has resulted into a huge dataset several million instances with approximately 300 attributes per data instance. Multiclass Regressive Feature Elimination method is used for reducing the dimensionality of the data. Using SP-SVM and SP-CNN algorithm supervised learning are performed and tested with 30% of Dataset. Since our aim is to predict traffic pattern in live scenario. Strom plus framework was used to create a test dataset where the data from multiple sources are integrated in the framework. Since hybrid prediction model was used with SP-SVM and SP-CNN followed by the output from time series analysis, which has helped to find the nearest transition of attributes in the reverse order to manage the traffic. Several case studies are done to study the impact of traffic management. With the prediction where the nearest match can help to manage the traffic pattern from getting into huge traffic congestion such as restricting vehicular movement in certain Region based on the prediction from time series analysis. Most relevant instances are retrieved from the dataset and used to regulate the traffic pattern.

Experiment 1:

As per the figure 4 it is observed that in a normal day, the average speed of the vehicle across the all region is 35Km per hour upto 100 thousand vehicle. When the vehicle density increases, there are notable variation in the average speed but its only +/- 5 Km per hour.

On an Auspicious day, the average speed of the vehicle starts at 34 to 32 KM hour upto 60 thousand vehicles, after that there is a gradual reduction in vehicle speed up to 125 thousand vehicles. From then onwards there is a sharp reduction and average speed and finally emerging as huge traffic congestion beyond 180 thousand vehicles.

On a rainy day, the average speed of the vehicle starts at 20 km per hour for 40 thousand vehicles. Beyond that upto 100 thousand vehicle the average speed gradually decreases upto 10 km per hour and emerging us huge traffic congestion.

After classifying the real time instances of traffic patterns on normal day, auspicious day and Rainy day, Time series Analysis was done to maintain consistency on various similar occasions. Matches obtained such as average traffic density, speed, traffic restrictions and traffic signaling time are used to regulate traffic density. Time serious analysis helped as to identify the exact match of transition with respect to vehicle density from free flow to sparse traffic congestion, from sparse traffic congestion to observable traffic congestion and finally from observable to huge traffic congestion which has given scenario in the previous instance and if applied in reverse order can deregulate the congestion. In some cases average speed of the vehicle was maintained for further increasing vehicle density. As per the Fig. 5, its observe that there is no change in average speed in a normal day. In case of auspicious day the average speed was maintain from 34 km hour to 25 km per hour without going for congestion. In case of rainy day average speed maintain between 20 km to 10 km per hour with observable traffic congestion.

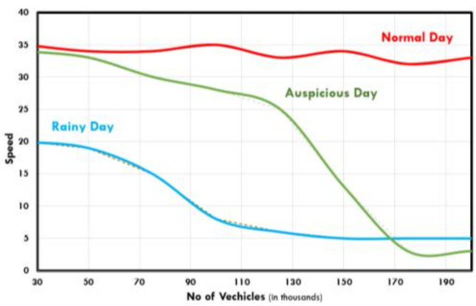

Fig. 4. 40% of the Region huge Traffic Flow

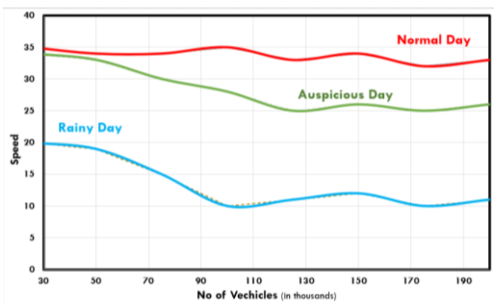

Fig. 5. Trained with historical data Proposed model has enabled the controlling of the traffic moment by modeling the traffic light signals (limiting the crossing of road- left and right turn

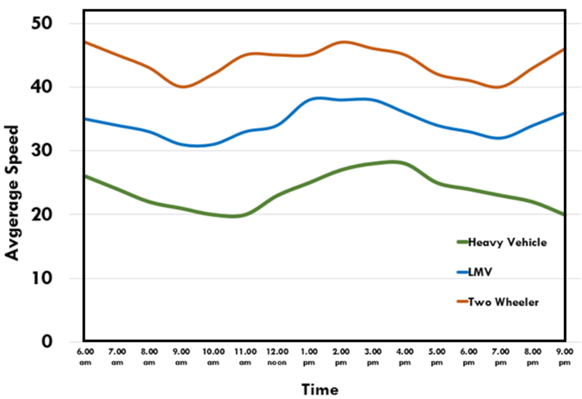

Fig. 6. Average speed of various vehicles during the peak hours of Normal day- Real Time traffic pattern.

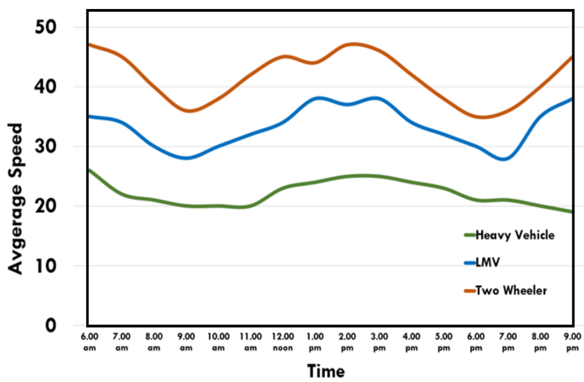

Fig. 7. Average speed of various vehicles during the peak hours of Normal day- Real Time traffic pattern with prediction.

Experiment 2:

In order to understand the impact of vehicle types and its average speed pattern over a period of 16 hours in a normal working day, starting from 6.00 AM to 10.00PM where observable peak hour delays are inevitable. The proposed model was used to predict such condition and further with time series appropriate traffic regulations which had resulted in maintaining the steady flow of traffic in previous such cases where used to main the average speed.

As per the Fig. 6, it is observed that the average speed of the two wheelers during the non peak hours was around 40 Km per hour. During the peak hours it comes down to 33 km per hour. In case of Light Motor Vehicle the average speed was around 35 Km per hour during the non peak hour and 25 Km per hour during the Peak hour. Where in, average speed of the heavy vehicle during the non peak hour 24 km per hour and it comes down to 10 km per hour during the peak hour. With the time series Analysis the previous nearest traffic regulations insistences are obtain from the dataset and implemented to regulate the traffic pattern during the peak hour and was found that the average speed of all the above three types of vehicles had not come across with traffic congestion rather maintaining average speed as shown in the fig.7:

Comparisons of SP-SVM and SP-CNN

Case 1: Classification in a regular day

In the process of Traffic decongestion during peak hours in a normal day, it is necessary to first classify the real time instance with SP-SVM classifier or SP-CNN classifier. The proposed model was evaluated with 75% of training data and 25% of testing data from the dataset. Traffic prediction accuracy in a regular day was calculated both with SP-SVM and SP-CNN classifier. Accuracy of proposed model is initially better in a normal day, when traffic density increases, accuracy has slightly decreased. Comparing to SP-SVM and SP-CNN model prediction accuracy is better as per the Fig.8 graph.

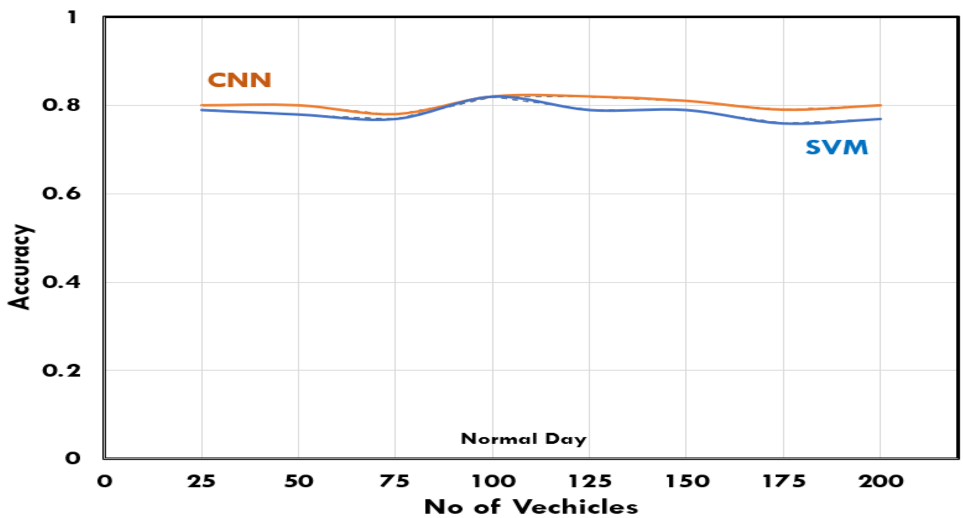

Fig. 8. Performance of accuracy in Normal day

Case 2: Classification of traffic in a rainy day

In a raining day the real-time traffic flow data are obtained and compare with the predicted datasets and found the following observation. In rainy day the prediction accuracy stand at 75% upon increasing the traffic density, the accuracy is becoming unstable. This may be due to insufficient attributes from various observation posts. When traffic density was less SP-CNN has outperformance then SP-SVM but with increase in traffic density, accuracy changes without following a study state.

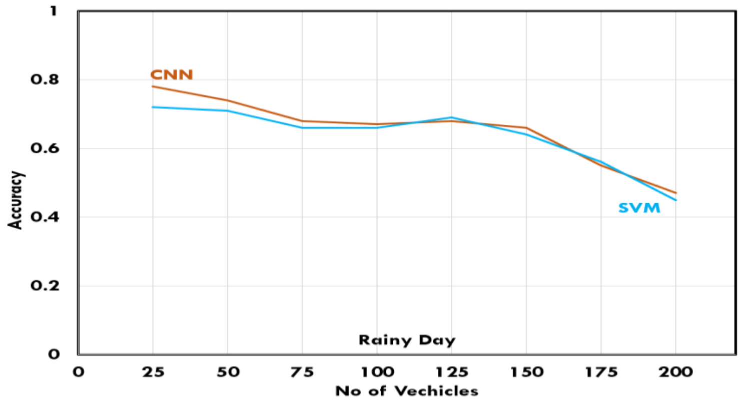

Fig. 9. Performance of accuracy in Rainy day

Case 3: Classification of traffic in social relevant auspicious day.

In auspicious day both SP-CNN and SP-SVM accuracy start with 67% and 85% for a traffic density of 25K vehicles which is also resembling like a normal day. Both the models accuracy slightly decreases upto 100K vehicles. Behind 100K vehicles the accuracy is fluctuating it may be due to erratic traffic condition, which was not captured properly through appropriate attributes in the dataset during the training and testing case. Even in the case also SP-CNN case is better than SP-SVM classification accuracy.

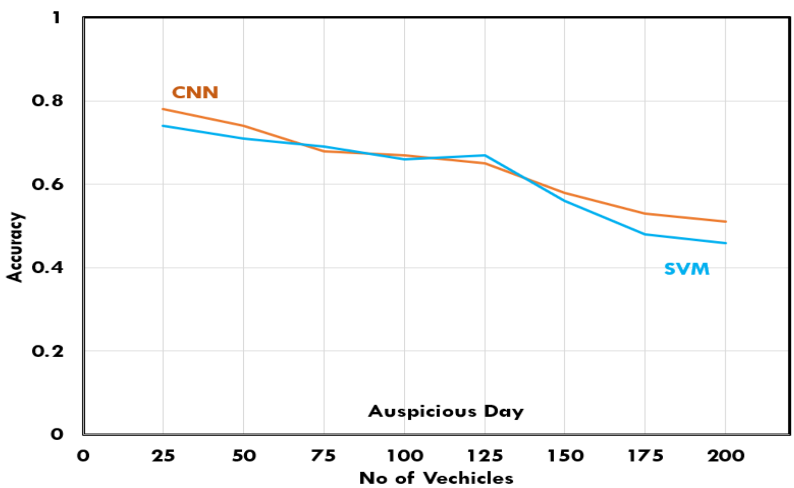

Fig. 10. Performance of accuracy in Auspicious day

6. Conclusion and Future work

Understanding the materialistic wastage, environmental pollution and cumulative loss of man power due to traffic congestion is becoming a common problem across the globe which needs an efficient solution. In this research work we have made a maiden attempt to address the complication of traffic regulation from its initial stage of capturing hundreds of attributes which are directly or in-directly affecting the movement of vehicle in a Metropolitan city like Chennai. Continuing to that handling of such huge real-time data possesses a challenge which was addressed in this research by the implementation of Strom Plus framework. Since so many attributes are there REF has helped us to eliminate irrelevant features, which has resulted in a handleable dataset over a period of time with observed classification. In SP-SVM and SP-CNN models the above datasets are trained and tested. During the real-time implementation the present unclassified dataset was given as input to the trained model and prediction accuracy was compared among SP-SVM and SP-CNN. The result shows that SP-CNN is giving consistence accuracy over a specific traffic density. The success of the work lies in the management of the Traffic such that it should not progress into huge congestion. Hence a Time Series Analysis ARIMA was done on the generated historical dataset to find several matches of transition of traffic from one stage to next worst stage, so that pre-transition instances can help the authorities to regulate the traffic.

In the future work, the reasons for inconsistence in the accuracy over increasing traffic density need to be identified. If attributes which are specific to increase traffic density and adverse weather condition and unexpected social events are considered in the dataset, it may help to augment the prediction accuracy of the model. In order to enhance traffic flow and reduce congestion, Adaptive Traffic Management Algorithms that incorporate AI and Reinforcement Learning will help to modify traffic signal timings based on current traffic circumstances.

References

1. W. Huang, G. Song, H. Hong, and K. Xie, "Deep architecture for traffic flow prediction: Deep Belief networks with multitask learning," IEEE Trans. Intell. Transp. Syst., vol. 15, no. 5, pp. 2191–2201, Oct. 2014.
2. J. Park, D. Li, Y. L. Murphey, J. Kristinsson, R. McGee, M. Kuang, and T. Phillips, ''Real time vehicle speed prediction using a neural network traffic model,'' in Proc. Int. Joint Conf. Neural Netw., San Jose, CA, USA, Jul. 2011, pp. 2991–2996.
3. M.-C. Tan, S. C. Wong, J.-M. Xu, Z.-R. Guan, and P. Zhang, ''An aggregation approach to short-term traffic flow prediction,'' IEEE Trans. Intell. Transp. Syst., vol. 10, no. 1, pp. 60–69, Mar. 2009.
4. M. Preetha, Raja Rao Budaraju, Jackulin. C, P. S. G. Aruna Sri, T. Padmapriya "Deep Learning-Driven Real-Time Multimodal Healthcare Data Synthesis", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), ISSN:2147-6799, Vol.12, Issue 5, page No:360-369, 2024.
5. Apache Storm Rationale Version 1.1.0. [Online]. Available: http://storm.apache.org/releases/current/Rationale.html

6. Xueyan Yin, Genze Wu, Jinze Wei, Yanming Shen, Heng Qi, and BaocaiYin,"Deep Learning on Traffic Prediction: Methods, Analysis and Future Directions", IEEE Transactions on Intelligent Transportation Systems, 2021
7. Preetha. M, D. S. Wankhede, R. Kumar, G. Ezhilarasan, S. Khurana and G. S. Sahoo, "Leveraging AI-Driven Systems to Advance Data Science Automation," 2023 International Conference on Emerging Research in Computational Science (ICERCS), Coimbatore, India, 2023, pp. 1-7, doi: 10.1109/ICERCS57948.2023.10434009.
8. Aisha Aamir, MinijaTamosiunaite and Florentin Wörgötter ,"Caffe2Unity: Immersive Visualization and Interpretation of Deep Neural Networks" , https://doi.org/10.3390/electronics11010083, 2022
9. G. Omkar and S. V. Kumar, "Time series decomposition model for traffic flow forecasting in urban midblock sections," 2017 International Conference On Smart Technologies For Smart Nation (SmartTechCon), 2017.
10. Dr.M.Preetha, K.Elavarasi, K.Ramyadevi, Dr.S.Veena. "Detecting Malicious Android Applications through Machine-Learning Techniques", Journal of Advance Research in Dynamical & Control Systems,Vol.10,14-Special Issue, Pg.No-1095-1099, November 2018. ISSN 1943-023X.
11. Z. Yu, T. Sun, H. Sun, and F. Yang, "Research on Combinational Forecast Models for the Traffic Flow," Mathematical Problems in Engineering, vol. 2015, pp. 1–10, 2015.
12. M. Preetha, Archana A B, K. Ragavan, T. Kalaichelvi, M. Venkatesan "A Preliminary Analysis by using FCGA for Developing Low Power Neural Network Controller Autonomous Mobile Robot Navigation", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), ISSN:2147-6799. Vol:12, issue 9s, Page No:39-42, 2024
13. K Siva Kumar, T.Mayavan, S. Sambath, A. Kadirvel, T.S.Frank Gladson, S. Senthilkumar "Artificial Neural Networks to the Analysis of AISI 304 steel sheets through limiting Drawing Ratio test" Journal of Electrical Systems, https://doi.org/10.52783/jes.3463 ISSN 1112-5209 2024, Vol: 20, 4s, 2282-2291.
14. V. R. Ghule, A. K. Agrawal, J. R. R. Kumar, D. Mondal, S. Hemelatha and Preetha M, "An Evaluation of the Impact of AI on Data Access Optimization Performance," 2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/SMARTGENCON60755.2023.10442704
15. R. K. Yadav and M. Balakrishnan, "Comparative evaluation of ARIMA and ANFIS for modeling of wireless network traffic time series," EURASIP Journal on Wireless Communications and Networking, vol. 2014, no. 1, 2014.
16. A. Jaya Mabel Rani, A Sumalatha, S Annie Angeline Preethi, R Indhu, M. Jayaprakash, M. Preetha, " Innovations in Robotic Technology: A Smart Robotic Design for Effortless Wall Painting using Artificial Intelligence," 2024 International Conference on Automation and Computation (AUTOCOM), , doi: 10.1109/AUTOCOM60220.2024.10486126.
17. M. Sughasiny, K.K.Thyagarajan, A. Karthikeyan, K. Sangeetha, K Sivakumar, "A Comparative Analysis of GOA (Grasshopper Optimization Algorithm) Adversarial Deep Belief Neural Network for Renal Cell Carcinoma: Kidney Cancer Detection & Classification," International Journal of Intelligent Systems and Applications In Engineering, ISSN: 2147-6799, 2024, 12(9s), 43–48.
18. Srinivasan, S, Hema, D. D, Singaram, B, Praveena, D, Mohan, K. B. K, & Preetha, M. (2024), "Decision Support System based on Industry 5.0 in Artificial Intelligence", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), ISSN:2147-6799, Vol.12, Issue 15, page No-172-178.
19. K Sivakumar, J.V Sai Prasanna Kumar, K Loganathan, V Mugendiran, T Maridurai, K Suresh "Machining characteristics of silane-treated wheat husk biosilica in deionized water dielectric

on EDM drilling of Ti-6Al-4 V alloy," Biomass Conversion and Biorefinery Published online: 1 February 2022 https://doi.org/10.1007/s13399-022-02308-4. ISSN 2190-6823

20. M. Mohammed Thaha, M. Preetha, K Sivakumar, Rajendrakumar Ramadass " An Investigative Analysis using 'Prior' Knowledge of Physical Interaction to Learn State Representation in Robotics ," International Journal on Recent and Innovation Trends in Computing and Communication https://doi.org/10.17762/ijritcc.v11i3.8907 ISSN: 2321-8169 Volume: 11 Issue: 3 ,February 2023.
21. A. Nithya, M. Raja, D. Latha, M. Preetha, M. Karthikeyan and G. S. Uthayakumar, "Artificial Intelligence on Mobile Multimedia Networks for Call Admission Control Systems," 2023 4th International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2023, pp. 1678-1683, doi: 10.1109/ICOSEC58147.2023.10275999.
22. Jason Yosinski, Jeff Clune, Anh Nguyen, Thomas Fuchs, Hod Lipson," Understanding Neural Networks Through Deep Visualization", https://doi.org/10.48550/arXiv.1506.06579
23. K.Sivakumar, R. Ramesh, "Optimization and Experimental Analysis of Drilling Process Parameters In Radial Drilling Machine for Glass Fiber / Nano Granite Particle Reinforced Epoxy Composites", IOP Conf. Series: Materials Science and Engineering Volume 62, Part 2, 2022, Pages 835-840, IOP Publishing https://doi.org/10.1016/j.matpr.2022.04.042.
24. Andrej Karpathy, Li Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", https://doi.org/10.48550/arXiv.1412.2306.
25. Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich, "Going Deeper with Convolutions", https://doi.org/10.48550/arXiv.1409.4842.
26. Xueping Hu, Jingya Wang, Liuliu Wang and KemingYu,"K-Nearest Neighbor Estimation of Functional Nonparametric Regression Model under NA Samples", https://doi.org/10.3390/axioms11030102,2022
27. S. L. Dhingra, P. P. Mujumdar, and R. H. Gajjar, "Application of time series techniques for forecasting truck traffic attracted by the Bombay metropolitan region," Journal of Advanced Transportation, vol. 27, no. 3, pp. 227–249, 1993.
28. Luisa M Zintgraf, Taco S Cohen, Tameem Adel, Max Welling, "Visualizing Deep Neural Network Decisions: Prediction Difference Analysis", https://doi.org/10.48550/arXiv.1702.04595.