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Vehicular Movement Prediction Via Supervised Vector Machine

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ABSTRACT

In major urbanized cities, the increase in the number of vehicles on the road at certain periods creates traffic gridlocks. Most road users at these peak periods experience traffic congestion during these peak periods. This has resulted in the loss of hours of work, delays in travel time, accidents, and even loss of life Most special vehicles like ambulances and emergency vehicles are trapped in the grid lock. Hence, there is a need to have a better predictive model for vehicle movement. In this paper, a vehicle prediction system which was developed using Supervised Vector Machine in a python environment using road variables, such as road condition, type of vehicle, weather condition and time of day vehicle. The dataset was obtained from Kaggle online dataset. It was evaluated using the following evaluation metrics: Root Mean Square Error (RMSE 2.845), Sum of Square Error (SSE 809.6798875823043), R-Square (R2 -0.14387416306270362), and Adjusted R-Square (R2 -0.21767249616352324).

1. INTRODUCTION

The population increase globally has led to a surge in the number of vehicles on the highway. The development and improvement in infrastructural facilities in most developed nations have also resulted in growing populations and the increase of public conveyance automobiles. Thus, this has contributed to problems of traffic gridlock, such as traffic congestion, delays in logistics delivery times, higher rates of road accidents, and air pollution. Consequently, the need for intelligent traffic methods of handling these traffic issues (Jelínek et al. 2021).

The rising number of automobiles on roads globally has contributed to traffic congestion challenge. Several reasons contribute to these problems, such as inadequate infrastructure and the use of traditional traffic light methods with static time breaks. Such stationary switches manage to adjust to a vigorous real-time traffic dynamics system and are active simply once traffic densities are moderately steady (Meneguette et al., 2015)

Intelligent transportation schemes were introduced to solve transportation problems, which includes vehicular traffic movement and the organization of data for both automobiles and foot-travelers. The main goal of these results was to forecast

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upcoming traffic situations precisely and implement suitable methods to solve traffic flow issues on main roads and connections (Fusco et al., 2015).

An intelligent Traffic Application exploits Google Map API V2 to locate digital maps, to deliver guidelines, compute distances, decide the location of the Smart Traffic System, and evaluate traffic density. This application is developed for use by an infinite quantity of consumers (Google Developers 2015).

Volodymyr et al. (2014) designed an intelligent Traffic Light using Cognitive Traffic Management System (CTMS) built on the Internet of Things (IoT). The system was integrated with virtual models of physical traffic lights which generate switches through signals using various sensors and vehicle user data. The big-data approach was used to route and improve the existing traffic light controlling system.

2. RELATED LITERATURE

Anurag et al. (2014) suggested the use of live video surveillance at road connections to estimate real-time traffic density through image and video processing. The dataset was formerly used in adjusting traffic signal timing. The method was aimed to decrease power and petrol intake by efficiently determining light breaks and sequencing.

Machine learning, particularly artificial neural networks, has contributed significantly to various industries, including transportation. These networks possess remarkable analytical capabilities, adaptability, memory functions, and distributed processing abilities (Yang et al., 2016).

Different types of artificial neural networks, such as back-propagation neural networks, radial basis function neural networks, and fuzzy-neural networks, excel at approximating non-linear functions and perform exceptionally well depending on the dataset and application domain (Zhang et al. 2011).

In the past, transportation researchers relied on Kalman Filters, Hidden Markov Models, and ARIMA models for traffic prediction using geographical sensors. However, high sensor installation costs limited their use. The advent of the mobile internet, artificial intelligence, and portable devices has facilitated data collection and accessibility (Yin et al., 2016).

Convolutional Neural Networks (CNN) excel at capturing spatial features, while Recursive Neural Networks (RNN) are adept at capturing sequential patterns. These neural networks, along with their variations and hybrid models, find applications in traffic flow prediction. Recent times have witnessed the successful integration of artificial intelligence across various transportation domains, including service computing, edge computing, and social networks (Deng et al., 2016).

Intelligent Transport System (ITS) is a revolutionary tool which is a part of intelligent transportation. ITS assists in mitigating traffic problems, specifically, traffic jamming and, to enhance traffic flow. The establishment of transport network systems helps to assist the connectivity and mobility of commuters around a particular locality for better use of the road network. This also provides a group of cheaper, available travel options, observers crash and jamming, and offers the optimal value of provision to road users and commuters, (Hassn, et al., 2016 and Malaysian works, 2021)

Connected vehicles (CV) are an essential part of ITS application to assist commuters to reach their terminal carefully, in a costeffective way, and promptly, (Miglani and Kumar, 2019).

The interconnecting with other vehicles is part of the benefit of using CV technology. Technology allows connectivity with highway infrastructures; it provides crucial cautionary information.

A major concern of researchers is to find solutions to CV growth and development of traffic congestion issues. The forecast of traffic movement and congestion has remained a major research area of different works and scholars. Even if the process of information distribution in congested areas is of serious concern, the development of CVs has made it considerably easier to disseminate information, (Kamble and Kounte, 2020).

The usage of Artificial Intelligence (AI) technologies, mainly Machine Learning (ML), creates and generates traffic flow predictions in an innovative manner. It brings an additional precise method of creating and generating traffic movement predictions (Bhavsar et al., 2017).

Deep learning (DL) is subdivided into machine learning (ML) models that are mainly connected to others in AI systems. This has completely resulted in the exploration of traffic movement prediction for linked vehicles via machine learning; this has helped in conducting several studies in traffic congestion management studies. The execution of CV assists in the use of ML techniques to improve the ability of technology by generating massive amounts of information in an improved and more precise analysis of data that might not be achieved by traditional approaches. A major area of the applications of ML in CV is for traffic movement forecasts (Ekler et al., 2015).

Traditionally, manual traffic control systems require a substantial workforce to manage intersections. These systems suffered from inefficiencies in traffic regulation and personnel allocation, particularly in densely populated urban areas.

Currently, the Internet of Vehicles technology has greatly gained widespread attention and is presently a new method of solving traffic problems in the future. Several new technologies and applications, such as the Internet of Things (IoT), 5G technology, and eco-friendly views (Manias and Shami, 2021).

The IoV represents another application area of the Internet of Things (IoT) in the field of transportation. It utilizes different electronic devices in a vehicle, and uses the most recent communication technology to create data of service networks, in order to achieve inter-connection between automobiles and all equipment (like automobiles, individuals and road infrastructures, etc.) (Qureshi et al., 2021).

Traffic congestion can greatly reduce accidents on the road if they are properly managed, and also help in increasing the road capacity, road systems for commuters, and making sure that individuals safely travel. There have been different causes of traffic congestion in recent times. The use of cutting-edge technologies, like the use of Internet of Vehicles (IoV), would help to forecast the pattern of traffic movement variations that is likely to occur in the future. The huge of data information in the IoV provides robust data provision for research related to traffic movement forecasts (Zhang et al., 2020).

The IoV location consists of traffic flow information. This could help in traffic prediction and could also be relevant for traffic control units to understand the traffic position on time, convey appropriate traffic flow control strategies, and drastically manage traffic movement, in other ways to advance traffic resources and enhance traffic situations. Alternatively, it could create a suitable travel route on time, for other commuters to avoid congested roads, thereby saving travel time. Furthermore, the growth and the demand for intelligent transportation is so paramount, traffic movement figures in the IoV setting are fast becoming a key subject in computer vision (Zhao et al., 2020).

The advancement in models related to deep learning, several deep neural networks are used in areas, such as convolutional neural network (CNN) (Park and Oh, 2021), recurrent neural network (RNN) (Lalapura and Satheesh, 2021) and several enhanced structural networks. These different areas of application have realized exceptional results in traffic movement forecast studies.

Jie et al. (2022) recommended a state space neural network. The model utilizes the spatial dimension features for traffic movement prediction data and the method could predict a better result.

Kouziokas (2020) developed a long short-term memory (LSTM)-based system for traffic movement data forecasts. This system uses the complete benefit of the characteristics of LSTM to improve and abstract the historical features of traffic flow data, and then achieve better prediction of traffic movement data.

Li et al. (2021), developed an improved neural network by merging CNN and LSTM with their model and using it for traffic movement forecasts. Boukerche and Wang (2020), designed a road network traffic movement prediction architecture method that was developed with stacked RNN units.

Jamiya and Rani (2021) and Ali et al. (2021), in their literature, examined the use of deep neural networks (including gated recurrent unit (GRU), LSTM, and RNN) and outdated machine learning methods (support vector machine (SVM), autoregressive integrated moving average (ARIMA), Sparse Auto-encoder (SAE), radial basis function (RBF) in traffic movement forecast, separately, and equated their forecast performance of the different model represented in the investigation.

Ern et al. (2021) combined the benefits of LSTM and RNN models in traffic movement prediction and developed a spatio-temporal recurrent convolutional neural network system. Meanwhile, prompt and efficient traffic movement figures can help to solve traffic congestion challenges and lessen the likelihood of traffic accidents, thereby decreasing the density of metropolitan traffic. Hence, developing a consistent, capable and precise traffic movement forecast model is crucial for improving the traffic of the IoV route system.

The of data in traffic flow prediction research is often very large. The advantage of deep learning technology is basically crucial, as it can mine valuable data from s of data. This helps to understand the changes in traffic rules rapidly and accurately and significantly improves the effectiveness and precision of traffic movement forecasts. Thus, it is important to study and develop a road network based traffic optimization using deep learning in an IoV setting. This is not the same as traditional machine learning techniques. Deep learning approaches depend on data for illustration learning. This helps in directly training the models using a large of original dataset. This helps remove abstract and complex feature symbols (Montieri et al., 2021).

3. METHODOLOGY

In this study, traffic data variables used are road conditions, number of vehicles on the road, classes of vehicles and weather conditions. And the traffic dataset was obtained from kaggle online dataset. The Python environment and its libraries were used to establish the SVM model based on principal component analysis for the SVM classification, according to the SVM models predict jams at road intersections. The SVM algorithm was simulated in the Python environment to achieve the core content in the application of the optimization toolbox. Implementation of the support vector machine algorithm was based on characteristics of the traffic variables, which was simple, convenient and quick code transplantation, reliable performance, easy to control the program runs. It specifically provides a simple, quick support for vector machine algorithm research and application of technology platforms to non-computer scientists. Through comparison and analysis of function types and the related parameters of the software package, to find the best experimental model, it finally achieves the ideal prediction. Principal component analysis (PCA), is an unsupervised learning technique for reducing the dimensionality of the dataset. It increases its interpretability time, and minimizes information loss. By finding the most significant features and making it easy for plotting.

The equations of the evaluation metrics are given in equation 1,2,3, and 4 respectively.

The Root Mean Square Error is given as:

$$RMSE = \sqrt{MSE} = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}} \qquad (1)$$

where, yˆ_i denotes the forecast value, y_isignifies the experimental value, n is the entire number of noted or data points, and Σ shows that a summation is performed over all values of i or location.

Formula for R-squared:

$$R^2 = 1 - \frac{RSS}{TSS}, \qquad (2)$$

where RSS is the residual sum of squares and TSS is the total sum of squares. R2, R-squared (R2) is use to measure the percentage of the inconsistency in the response adjustable that could be explain by the analyst variable in a regression model.

Adjusted R^2 is given by:

$$Adjusted\ R^2 = 1 - \frac{(1-R^2)(N-1)}{N-P-1} \qquad (3)$$

where R^2 is sample R-squared, N is the total sample size and P is the number of independent variables utilized in the design.

Sum of Squares Error (SSE) is given by:

$$SSE = \sum_{i=0}^{n} (y_i - f(x_i))^2 \qquad (4)$$

where y_i is the ith value of the predicted variable, f(x_i) is the forecast value, and x_iis the ith value of the descriptive variable. The summation of squares in statistics is an instrument that could be used to appraise the dispersal of a dataset.

3.1 FLOW CHART OF THE SUPERVISED VECTOR MACHINE

The flowchart of the supervised vector machine is shown in figure 1

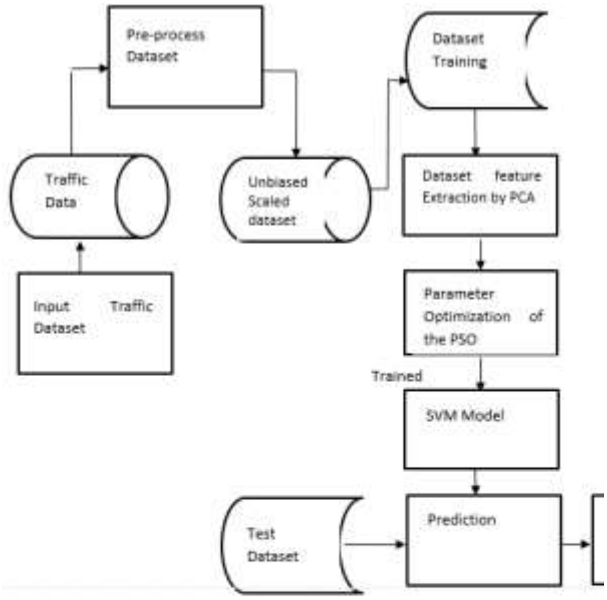

Figure 1: Flowchart of SVM

Algorithm for SVM
1. Input dataset
2. Divide training dataset and test dataset
3. Unbiased Scaled dataset
4. SVM training (Dataset feature Extraction by PCA
5. Parameter Optimization of the PSO
6. Trained the model
7. Test the model
8. prediction
9. Output: the best fitness curve using the different evaluation metrics

4. RESULTS AND DISCUSSION

4.1 Traffic Training Process

Five hundred (500) road traffic datasets were used for the (SVM). It is shallow neural network architecture. Five hundred databases were used for both training and testing validation. The traffic data was divided into 90 % for training and 10% appropriately for testing and validation of the model, respectively. Figure 1 shows the flow diagram of the implementation; Table 1 shows the result of training was adjudged to be the SVM optimal performance evaluation metrics of the different models. Figure 2 and figure 3 show the loss function of prediction and actual results of the training, testing and validation results of the train, while figure 3 shows numbers of vehicles at certain periods. The overall optimal validation performance of the SVM is shown in table 1; predictions of traffic congestion and traffic flow prediction. These results clearly show that the traffic data's inputs and outputs are well correlated. Table 1, presents the overview graph of the gradient epoch and validation performance of the SVM model and the results obtained from the analysis of the traffic performance evaluation of the parameters for training, testing and validation of the SVM using various architectures.

Table 1: Validation performance of the SVM

1	Root Mean Square Error (RMSE)	2.845
2	Sum of Squared Errors (SSE)	809.6798875823043
3	R-squared (R^2)	- 0.14387416306270362
4	Adjusted R-squared (Adj. R^2)	-0.21767249616352324

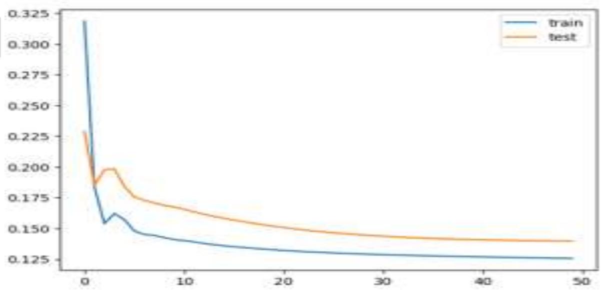

Figure 2: SVM Model Train Test loss

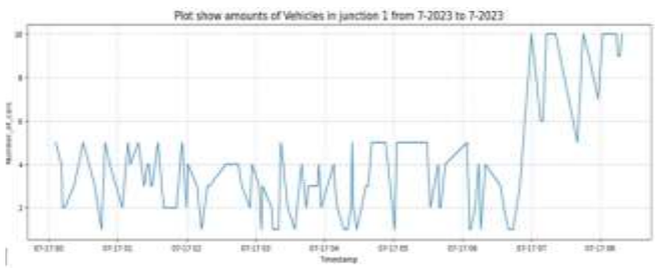

Figure 3: vehicle at junctions at certain periods

4.0 CONCLUSION

Traffic congestion is a major challenge in most urban cities. This is due to the increase in the population and the number of cars on the road. This has resulted in an accident which may lead to loss of lives. Traffic congestion can also cause air pollution, due to emissions from cars. This SVM model will help in reducing traffic congestion by predicting traffic congestion at intersections during the peak period in the morning and the close of business. This will also help to prevent accidents at densely concentrated intersections. This will be achieved using cameras, videos and online datasets from a kaggle model using the support vector machine (SVM). Conclusively, the vehicular traffic flow has shown that having an insight into the traffic flow of vehicles at a particular intersection, it is imperative to have a fundamental understanding of the traffic and density and the period of the day. This will help in managing the traffic congestion and understanding how to travel in these cities to avoid traffic congestion on the road.

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