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Short-Term Road Traffic Forecast using LSTM-based Deep Learning Model

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***Abstract*—Real-time traffic predictions have now become a time-being need for efficient traffic management due to the exponentially increasing traffic congestion. This paper introduces a pragmatic traffic management system, especially for countries such as Sri Lanka where proper traffic database is absent. This system involves TFmini Plus light detection and ranging light detection and ranging (LiDAR) sensor for real-time traffic monitoring and vehicle count for next five minutes will be predicted by feeding consecutively collected data into the LSTM neural network. The sensor attains 89.7% accuracy, even in irregular traffic patterns in Sri Lanka. In the model training process, with a constant input data volume of 8,064 points, varying the window size to 6, 12, 24, 60, and 288 showed an improvement in prediction accuracy for 6, 12, and 24 window sizes, while it was declined for 60 and 288. The peak accuracy occurred with a window size of 24. Altering the input data volume from 2,016 to 8,064 points while keeping the window size at 24 resulted in a consistent accuracy increase with larger data volumes. 75.34% accuracy was experiments demonstrate that the proposed method for traffic flow prediction has superior performance. Moreover, accuracy results ensure that this system is capable to address Sri Lankan traffic conditions.**

Keywords—Real-time traffic monitoring, LSTM neural network, traffic predictions, LiDAR sensor traffic monitoring

I. Introduction

Road traffic has intensively escalated in recent years, causing widespread congestion, and emerging as a prominent issue. According to Victoria Transport Policy Institute's Congestion Costing Critique (CCC), published in 2021 [1], congestion cost is estimated to cost between $130 to $500 per capita annually, particularly compared to $2,000 in crash damages. Similarly, it estimates that by 2025, congestion cost will have risen to $200 billion [1]. According to the National Highway Traffic Safety Administration's statistics (NHTSA) [2], more than 2.3 million injuries and 32,719 deaths were recorded due to vehicular accidents, with traffic congestion identified as a major contributor [2, 3]. Additionally, congestion led to 5.5 billion lost hours, 2.9 billion gallons of fuel wasted, and approximately 31% of CO_2 emissions (56 billion pounds) annually [2, 4]. INRIX's 2021 indicates that global traffic strategies, including intelligent systems with adequate traffic sensing infrastructure, are effective but predominantly limited to developed countries [5].

This absence hinders effective traffic management, making it challenging to assess the progress of mitigation projects. In the inherently random nature of traffic, robust data and strategic sensor placement are vital for effective and intelligent traffic management systems (ITMS) [6].

The paper proceeds as follows: below Section II outlines the research problem in the context of Sri Lanka. Section III delves into the literature of real-time traffic monitoring and forecasting, addressing research gaps. Further, parts A and B of Section III provide an extensive evaluation of each method, including tables comparing their performances. Section IV expresses the methodology, while Section V presents results and validation. Section VI concludes by summarizing findings and introducing future work.

II. Research Problem Definition in the Context of Sri Lanka

Traffic congestion is a major issue in Sri Lanka [7]. Excessive fuel consumption due to prolonged travel time results in economic loss and frequent accelerations, leading to frequent repairs creating a significant loss to the national economy [8]. The congestion cost in Sri Lanka's western province exceeds Rs. 20,000 million per year, approximately 2% of regional GDP [9]. Moreover, Sri Lankan transport sector is responsible for 25% of greenhouse gas (GHG) and 47% of CO_2 emissions, compared to global averages [10]. Sri Lankan government initiatives to alleviate traffic jams in Sri Lanka include short-term measures such as building new transport infrastructures, roads, expressways, and expanding existing capacities [11]. In addition, long-term strategies involve revising vehicle ownership and public transport policies to align with road and transport capacities [9]. However, none of the above measures have been able to create a significantly effective impact on traffic management than implementing an ITMS. Therefore, the absence of an implemented ITMS in Sri Lanka appears to be the cause of the existing congestion.

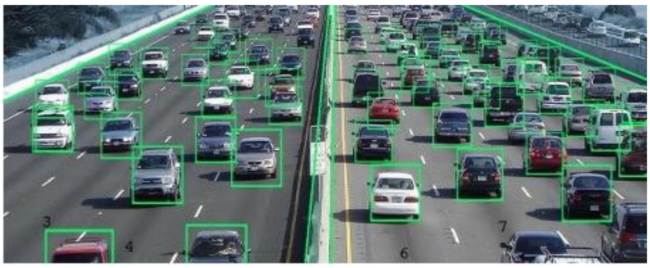

Fig. 1. Systematic traffic behaviour of other countries

Fig. 2. Traffic Behaviour of Sri Lanka

In contrast to countries with well-disciplined drivers, Sri Lankan vehicles often follow lack systematic lane adherence and adequate spacing. Fig. 1 and 2 depict Sri Lanka's traffic behavior compared to countries like Russia, Australia, and Europe. Fig. 1 shows vehicles maintaining proper spacing and moving in a single lane, while Fig. 2 illustrates Sri Lanka's traffic with vehicles closely positioned and disregarding lanes. This irregular behavior poses a significant challenge, impeding the effectiveness of image processing-based traffic monitoring systems. The unpredictable nature of traffic in Sri Lanka complicates the generation of accurate contours, particularly affecting vehicle identification.

Even though the color lights are there for alleviate congestion, their lack of intelligence and fixed programming is a hindrance. This often results in instances where the green light persists even in the absence of vehicles, causing traffic jams and restricting access for vehicles in other lanes [12]. Additionally, poor technical and digital literacy poses another obstacle. Even though many traffic surveys are conducted annually, there is a lack of a proper traffic database, and no automated system exists to retrieve past data for analysis to perform estimations, comparisons, or traffic predictions [13].

Nowadays Sri Lankan government is grappling with a large fiscal deficit, with the depreciation of the Sri Lankan rupee against major currencies and high debt. Since traffic congestion is a major factor affecting the country's economy, this real-time traffic management system has been developed to seamlessly align with the existing road conditions and technical constraints in Sri Lanka.

III. Literature Review

As early as the 1970s, an autoregressive integrated moving average (ARIMA) model for short-term highway traffic flow forecasting was introduced which has been recorded as the foremost approach under ITMS strategies [14]. Since then, a wide range of traffic forecasting models have been proposed along with traffic surveys to address this traffic issue with better traffic management. Hong Kong's road network, which is one of the busiest roads in the world, underwent a substantial improvement in traffic management through the implementation of an ITMS, effectively tracking its all major highways, roads, and tunnels [15].A low-cost sensor-based traffic monitoring network instrument was developed and tested to be used in a work zone [16]. Al-Holou et al. [17] developed a multi-dimensional model to estimate the influence of vehicles on the environment, traffic congestion, and traffic safety.

A. *Traffic Detection Methods*

Vehicle detection and surveillance play an integral role in both effective traffic management and ITMS. Since ITMS plays a critical role in national traffic management systems (TMS), the quality of provided data and the geographical arrangement of traffic sensors are also important factors for ITMS success [6].

Common vehicle detection technologies can be classified into three groups: intrusive, non-intrusive, and off- roadway sensors [18]. The inductive loops, magnetic detectors, piezoelectric sensors, weight-in-motion sensors and pneumatic road tubes are considered as invasive sensors. These are usually embedded in the road surface after saw-cutting the surface or adding roadway holes. The detection methods such as vision- based systems such as image processing traffic monitoring systems, infrared sensors, microwave radar and ultrasonic detectors are non-intrusive sensors which can be installed atop roadway or roadside surfaces or mounted overhead [18]. Remote sensing through airplanes or satellites and probe vehicles with GPS receivers are examples of off-roadway sensors [19], [20]. Consequently, these sensors are not suitable for large-scale integration, which are stationed in strategic areas and operate independently.

Video Image Processor is a very common traffic monitoring method since now Image processing has become a tendency and the most prominent traffic monitoring system in the world [6]. Video Image Processor (VIP) systems normally consist of a camera, a processor-based workstation for analyzing the images, and transforming them into data [6, 21]. Image processing systems provide live images of real-time traffic status, which covers multiple detection zones. So that it offers broad area detection [22]. In VIP systems, vehicular detection is performed using the contours drawn in the snapshots taken in constant time intervals [23]. It also offers occupancy, classification, and count of vehicles, as usual in most other sensors. Moreover, in the literature, several disadvantages of image processing have also been discussed. Being sensitive to weather conditions, vehicle shadows, and dust on the camera lens is notable. Additionally, camera mounting requirements such as height for better measurements, higher installation and maintenance costs are also significant drawbacks of these camera-based systems [22]. It also requires costly equipment for real-time video-image and data transfer, separate algorithms for day and night traffic detections [22].

Light Detection and Ranging (LiDAR) technology is a novel technology in which research and investigations have been performed in recent years [24, 25]. LiDAR is a remote sensing method that uses light in the form of a pulsed laser to measure ranges of variable distances. The point cloud of LiDAR data is made up of thousands of points in X, Y, and Z coordinates [25]. Downsampling, noise reduction, object grouping, distant irrelevant object rejection, and ultimately vehicle recognition utilizing point cloud data are all part of this architecture [26, 27]. Geometric characteristics such as size, form, and height are retrieved for categorization in this method. Besides, there are a variety of other traffic monitoring technologies embedded with various electronic sensors. The strengths and weaknesses of each traffic monitoring technique are compared in Tab. 1 below.

TABLE I. COMPARISON OF TRAFFIC MONITORING TECHNIQUES

Type of the detector	Detector Methods Comparison		
	Working Mechanism	***Strengths***	***Weaknesses***
Inductive loop [28]	Detects vehicles by sensing the loop	• Flexible design to fullfil a great variety of applications. • Unresponsive to bad weather. • Offers accurate count data.	• Traffic disruptions may occur during installation and maintenance • Prone to damage by heavy vehicular movements
Microwave radar [28]	Transmits signals in recognition regions and captures the echoed signals	• Unresponsive to bad weather. • Speed is measured directly. • Multiple lane operation.	• Incapable of sensing immobile vehicles in outdoor applications
Acoustic [28]	Detect audible sounds produced by vehicular traffic. Using them vehicle presence and speed are measured[29]	• Applicable where loops are not likely. • Insensitive to bad weather. • Installation of some models does not require a pavement cut. • Less error prone than inductive loops.	• Installation needs a boring under the road. • Incapable of sensing immobile vehicle
Ultrasonic [28]	Sends ultrasonic waves to an object and captures the returning echoes.	• Monitors multiple lanes. • Proficient in detecting over-height vehicles.	• Environmental circumstances may affect. • Occupancy measurement may degrade with large pulse repetition periods.
VIP (Video image processor) [28]	This system normally consists of a camera, processor, and software	• Monitors multiple lanes. • Simple to add and change detection areas. • Offers broad-area detection	• Performance is sensitive to bad weather, vehicle shadows, and dust on the camera lens. • Requires specific camera mounting height for finest vehicle presence detection.
Light Detection and Ranging (LIDAR) [28]	This is a remote sensing method that uses a pulsed laser to measure ranges of variable distances	• Monitors multiple lanes. • Simple to add and change detection areas. • Insensitive to bad weather. • Offers broad-area detection	• Traffic disruptions while installation and maintenance.

B. Prediction Methods

Traffic flow is a real-time, totally non-linear, and high-dimensional random process [30]. Reviewing the literature emphasizes that vehicle forecasting is a common research topic [31, 32]. According to the reference [32], traffic forecasting is classified into two basic categories: long-term prediction and short-term prediction. The projection for the near future, spanning the next 5 to 10 minutes, is called short-term prediction, anticipating immediate changes due to factors like weather, events, or accidents [32].

There are comparative research articles which evaluate accuracy and efficiency of the prediction models. Among them [31, 32] and [33] references emphasize that both data-driven and experimental traffic flow prediction approaches can be classified as parametric, non-parametric, and hybrid, each having its own set of benefits and drawbacks. Linear regression, maximum likelihood (ML), Historical Mean Average, and exponential smoothing method are some of the parametric prediction approaches [32]. Parametric prediction methods are more accurate than the other two methods, yet its poor functionality amid the noise and other disturbances is an encountered major drawback [32, 33].

1) Non-Parametric Models: The number of parameters which assigned to a model is flexible. Therefore, the model structure and parameters are developed based on available data. These models have the benefit of allowing for the discovery of intricate non-linear correlations between traffic factors. In contrast, unanticipated events and outliers may effect when the model's structure is derived from the data [33]. The intricacy and their reliance on vast amounts of data are the other drawbacks. Neural networks, such as the multilayer perceptron (MLP), time-delay neural network (TDNN), and radial basis function (RBF) are the most popular and prominent non-parametric approaches. Besides these neural networks, Fuzzy [34], Bayesian networks k-nearest neighbor (KNN) [35], support vector machine, and wavelet are other non-parametric methods used for predictions [32].

Neural network is the most common traffic prediction method with its ability to model and simulate complicated non-linear relationships [33], [36]. There are different neural network types such as Feedforward neural networks, Convolutional Neural Network (CNN), Recurrent neural networks (RNN) and Long Short-Term Memory networks (LSTM) based on their training procedure, internal structure, methods of pre-processing input data and their models including spatial or temporal patterns [37]. Among them, LSTM is the most powerful model for sequential data [38]. The type of the neural network varies depending upon the application. As per mentioned in the research paper by Van Hinsbergen, Van Lint, et al., a typical neural network might deliver reliable findings in terms of extensions required for higher accuracy in traffic predictions [33].

2) Parametic Models: The model's structure and the number of parameters are fixed, and the model's parameters must be derived using data. These models excel in capturing unseen cases, requiring less data and sometimes offering higher accuracy with less computational work [33]. Hybrid models combine parametric and non-parametric prediction models, achieving higher prediction accuracy. Many hybrid models are combinations of neural networks and other parametric and non-parametric models such as ARIMA, MLP, and fuzzy. According to the reference [32], neural network-based MLP models are the most suitable prediction models for data-driven traffic forecasting systems with image processing compared to all other models.

Despite the facts that were included in literature review on these parametric, non-parametric and hybrid prediction models and the projects and research approaches evaluate the existing gaps subject to traffic predictions, there can be seen an outstanding tendency toward using Long Short-term Memory (LSTM) neural networks for traffic predictions, especially in recently published research articles. The reference [39] evaluates the growing adoption of LSTM algorithms for traffic prediction, highlighting their increasing prevalence. Another research carried out on LSTM [30], indicates that most prediction methods prioritize accuracy over immediacy.

LSTM neural networks, an advancement over RNNs, effectively tackle the vanishing gradient problem and long-term dependency issues [40, 41]. However, the reference [42] claims that even though most of the novel traffic management approaches used LSTM models, those existing projects and their models have failed to address the issue of massive traffic flow data being processed simultaneously with parallel to computing and distributed data storage [43], [44]. But it also emphasizes that the LSTM model is a better prediction model for more random and time-varying predictions such as traffic flow [45]. Also, there are few studies focusing on the time series for the Internet of Things (IoT) traffic forecast [46, 47]. Tab. 2 compares the strengths and weaknesses of each prediction model.

TABLE II. PREDICTION MODELS COMPARISON

Prediction Model	**Prediction Models Comparison**	
	Strengths	***Weaknesses***
Mean Average model[48]	• Low Prediction Error.	• Poor functionality in the presence of noise. • Average of all inputs are needed for the predictions. • Higher reliance on data.
Linear Regression method[48]	• Low Prediction Error. • Predicts the next variable online using real data	• Poor functionality amid the noise and other disturbances
Maximum Likelihood (ML)	• Low Prediction Error. • Robust for sensor failures and rapidly changing conditions.	• High dependency on recorded data.
Exponential Smoothing Method	• Low Prediction Error.	• Poor functionality amid the noise and other disturbances. • Difficulties to determine constant coverage.
ARIMA Model	• Low Prediction Error. • Simplicity. • More mathematical model Obtain the relationship between past and future data.	• Poor functionality amid the noise and other disturbances. • High dependency on recorded data.
MLP Model	• High Accuracy. • Predict traffic flow in proportion to road conditions.	• High dependency on recorded data.
Fuzzy Model	• Low Prediction Error. • Simplicity. • High Accuracy.	• Poor functionality • High dependency on recorded data.
KNN Model[46], [48]	• High Accuracy. • Predict traffic flow in proportionto road conditions.	• Poor functionality amid the noise and other disturbances. • High dependency on recorded data.
Bayesian Networks	• High Accuracy. • Relatively Low Errors	• High dependency on recorded data.
LSTM NN [46], [49]	• High Accuracy. • Better for time-based models. • Relatively Low Errors	• High dependency on recorded data.

IV. METHODOLOGY

The methodology is introduced by being split into two main sections: the traffic monitoring stage and the forecasting stage using neural networks emphasizing the main milestones of the project.

A. *Traffic Monitoring Stage*

Vehicle detection was achieved by installing a TFMini Plus LiDAR sensor beside the road to monitor vehicles on one side, as per illustrated in Fig. 4. TFMini Plus sensor's Time of Flight (ToF) principle is used to detect the presence of vehicles [50]. Sensor's periodically emitted modulation waves are used to detect and calculate the proximity to the object and its time-of-flight is estimated by measuring the round-trip phase difference of its reflection when it contacts an object [51]. These waves are directed towards the road and emitted at a frequency of 16.667 Hz with content intervals. Sensor's distance limitations are set between 800 to 1220 meters, considering white lines that separate traffic in the same direction, ensuring the sensor is triggered only by vehicles moving in the intended direction, and not by pedestrian movements or vehicles traveling in the opposite direction. Additionally, distance measurement must persist longer than 50 milliseconds and return back to the initial value to count it as a vehicle (refer Fig. 3). And total vehicle count after every 5 minutes intervals delivered to an IoT database. ESP8266 microcontroller was used enabling further improvements with IoT connecting several nodes.

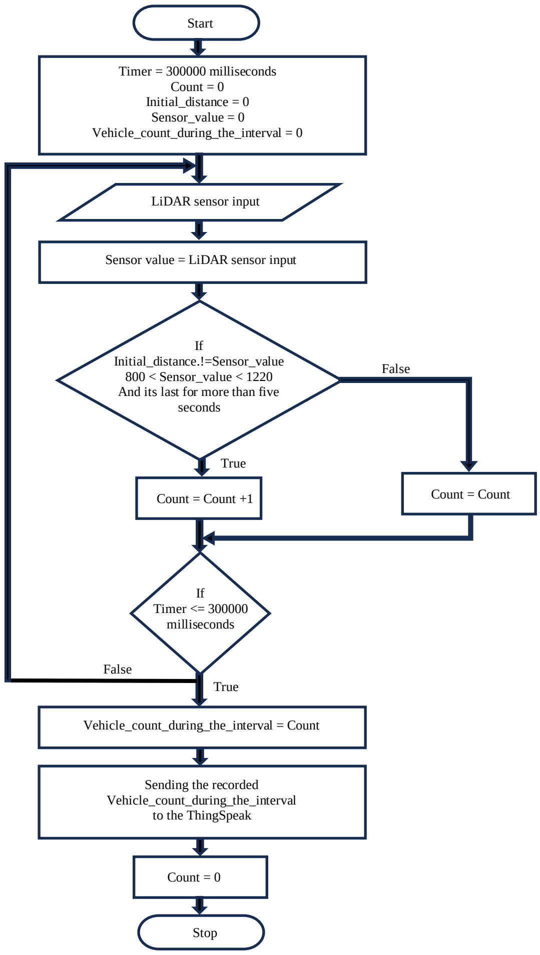

Fig. 3. Flow chart of the vehicle detection algorithm

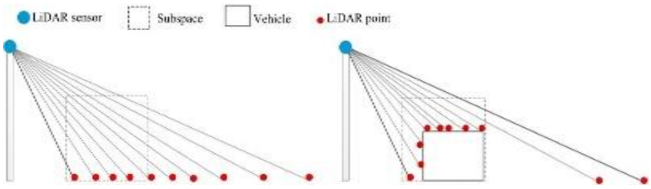

Fig. 4. An illustration of a subspace without (left) or with (right) a vehicle

B. *Neural Network Training and Forecasting Stage*

This stage involves training the LSTM neural network model, which includes data preparation and segmentation before initiating the training process. The data collected on ThingSpeak was exported as .csv files for LSTM model training. These modified .csv files were then input into the system in four segments, allowing for variations in the input data volume and window size to identify the optimal configuration for the prediction model.

Since the vehicle count is taken in five minutes intervals,

In one hour: 12 data points

In one day: 12 × 24 = 288 data points

In a week: 12 × 24 × 7 = 2016 data points

In a month: 12 × 24 × 30 = 8640 data points

Data collected over a five-week period, monitoring vehicular traffic, was utilized to build this forecasting models. This entire data collection was divided into two sets: a training set and a testing set. The training dataset consisted of 8,064 data points, collected over a month, while the remaining 2,016 data points, gathered over a week, served as the test dataset for model testing. The entire training dataset was further divided into four segments representing weeks 1, 2, 3, and 4 and the data patterns over a day and month were observed to identify the traffic behavior patterns. Subsequently, ten distinct models were trained to determine the most effective and accurate model.

Initially, the first set of models was created with a window size of 12, varying the input data volume from 2,016 data points to 8,064 data points. In the second model set, based on the results of the first four models, the input data volume was fixed at 8,064 data points, while the window size was varied to 6, 12, 24, 60, and 288. Here window size 6 means 6 data points (data gathered over 30-minute intervals) is fed to the system at a time. Likewise, four other models were trained for 1, 2, 5 and 24-hours data. Based on the results of those five models, the optimal window size was determined as 24. The third model set was trained setting window size to 24, while ranging the input data volume from 2,016 data points to 8,064 data points.

Then these trained model sets were critically assessed for accuracy to determine the most suitable prediction method. All accuracy-related computations in this project, including sensor accuracy and prediction model accuracy, were performed using the following two equations adhering IEEE standards [51]. Below (1) used to determine the error rate.

$$Error\ Rate = \frac{|\text{Observed Value} - \text{Actual Value}|}{\text{Actual Value}} \times 100\% \qquad (1)$$

Once the error rate is calculated, accuracy was determined using below (2).

$$Accuracy = 100\% - Error\ Rate \qquad (2)$$

V. Results and Validarion

A. *Results of the Sensor Accuracy Test*

First of all, the sensor accuracy was tested considering the data gathered during a random day. Taking actual vehicle counts from counting, and the sensor-detected vehicle counts from sensor records, actual vehicle count vs sensor-detected vehicle count plot was created. The accuracy of the sensor has been tested considering 200 data points which resulted = 89.86% accuracy. Fig. 5 illustrates the actual vehicle count vs sensor-detected vehicle count, highlighting that sensor detected vehicle count is almost closer actual vehicle count. This sensor accuracy plot also provides insights into the daily traffic behavior from 0:00 hours to 23:59 hours. It indicates that the traffic behavior during the day exhibits a normal distribution pattern, with higher values concentrated in the middle of the range, and a symmetrical tapering off towards both extremes.

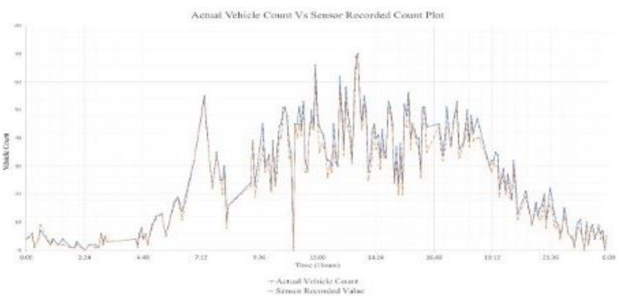

Fig. 5. Actual vehicle count vs sensor-recorded vehicle count

B. *Traffic Behavior Analysis*

After observing the traffic behavior of a day, the traffic behavior of over a week was also plotted. In this case, each day's traffic behavior exhibited a normal distribution pattern. Weekly traffic behavior appeared as a combination of seven normal distributions. Additionally, the traffic behavior of each week was also plotted to identify whether the traffic flow remains the same following a pattern every week or shows significant fluctuations. Below Fig. 6 represents the overall traffic behavior of the entire month. These plots were the only source to identify the traffic patterns and to decide the window size to train the model.

C. *Prediction Results*

There can be seen significant deviations in traffic flow after intervals of 60 minutes (during an hour). Therefore, first it was identified it is better to take 12 data points at a time to train the prediction model. Then the desired window size was kept to 12 and using data gathered over a month the very first LSTM neural network model was trained. Below Fig. 7 illustrates the resulted predicted traffic behavior vs test data plot and Fig. 8 illustrates the entire plot of the trained data, test data and resulted predicted traffic data. Finding the best traffic prediction model is one major research objective of this project. Therefore, more than ten LSTM neural network models were created and evaluated in terms of accuracy to identify the most suitable forecasting model. Here all the result accuracies were more than 70%. And no model exhibits large deviations in predicted traffic behavior vs test data plot.

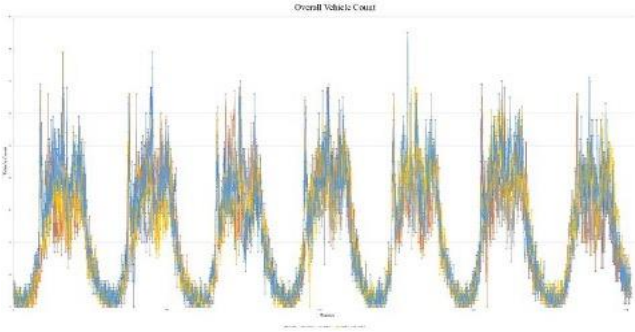

Fig. 6. Overall traffic behavior of each week

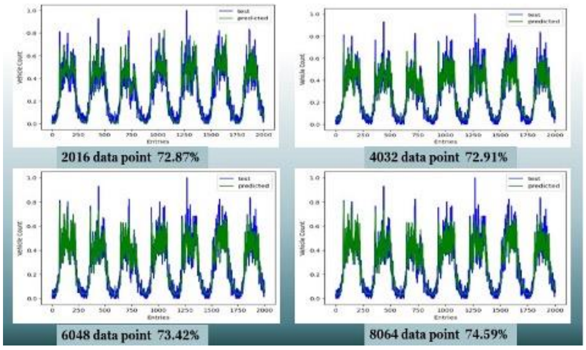

Fig. 7. Predicted traffic behavior vs test data plots

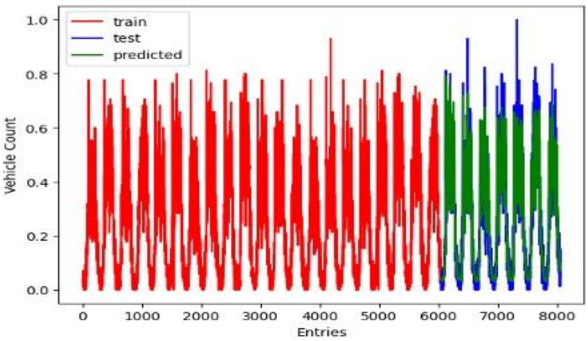

Fig. 8. Predictions results of the most precise forecasting model

TABLE III. ACCURACY TABLE OF MODEL SET_1

Volume of Input (Data Points)	*Window Size*	*Accuracy %*
2016	12	72.87
4032	12	72.91
6048	12	73.42
8064	12	74.59

TABLE IV. ACCURACY TABLE OF MODEL SET_2

Volume of Input (Data Points)	*Window Size (Data Points)*	*Accuracy %*
8064	6	74.49
8064	12	74.59
8064	24	75.34
8064	60	73.58
8064	288	72.07

TABLE V. ACCURACY TABLE OF MODEL SET_3

Volume of Input (Data Points)	*Window Size*	*Accuracy %*
2016	24	74.20
4032	24	73.78
6048	24	73.96
8064	24	75.34

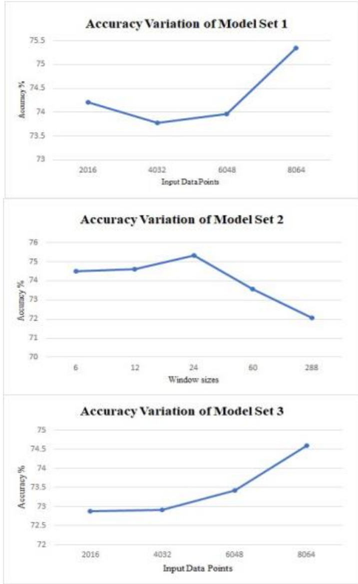

Fig. 9. Accuracy variations of the prediction model sets

Further, the prediction accuracy results of these test models which are presented above shown in Tab. III, IV, and Tab. V emphasize that both window size and the volume of the input data creates a significant impact on the prediction accuracy of the prediction models. The accuracy test results of all the 3 model sets show that all of them were above 70%. Above Tab. 3 represents the training model set 1 created by setting the window size to 12 while changing the input data volume from 2016 data points to 8064 data points. In model set 1, a noticeable improvement in accuracy was observed as the input data volume increased. In the second model set (as shown in Tab. 4), the input data volume was kept constant at 8,064 data points, while the window size was varied to 6, 12, 24, 60, and 288. Although the accuracy improved in the first three models, a noticeable decline in accuracy was observed with larger window sizes. This suggests that the most appropriate window size is 24. In the third model set, presented in Tab. 5, the window size was set to 24, and the input data volume was again adjusted, ranging from 2,016 data points to 8,064 data points. There also can be seen a consistent increase in accuracy with larger input data volumes. Fig. 9 displays multiple plots comparing predicted traffic behavior to test data. These plots are remarkably similar, with closely aligned predicted and actual traffic behaviors. Fig. 10 provides a graphical representation of the data from Tab. 3, 4, and 5. It offers a visual comparison of the accuracy results obtained from each model set. Meanwhile, it indicates that increasing the input data volume leads to a gradual improvement in accuracy. However, it also implies that the window size should be kept within a certain range, as excessive increases in the window size can lead to reduced accuracy beyond a certain point.

Based on the results, the best prediction accuracy is achieved with a 24-window size for training, in which the data gathered for two hours will be fed into the system at a time and increasing the input data volume to the greatest extent possible. Similarly, resulted accuracies indicate that highest precision can be achieved when the model is trained using 80% data and tested using 20% data.

VI. Conclusion

Results from sensor accuracy tests and prediction models emphasize the successful achievement of the main objectives and the effective contributions of utilized strategies in reducing traffic congestion, particularly in Sri Lanka. Furthermore, several benefits are evident in this project. The cost-effectiveness, easy implementation, and adaptability to various traffic behaviors stand out as notable advantages of this system, surpassing other ITMS in the literature.

Monitoring vehicular movement in Sri Lanka, is challenging with its erratic traffic patterns. However, this traffic monitoring method, using TFmini plus LiDAR sensor, provides accurate readings, achieving 89.86% accuracy even under the that unsystematic traffic conditions. Hence, the sensor proves its adaptability to diverse traffic environments, addressing Sri Lanka's traffic issues effectively. Unlike video-based systems requiring advanced technology and significant capital, this system is more suitable for Sri Lanka's technical capabilities and traffic infrastructure due to its affordability and compatibility. Its resistance to dust and rain also makes it well-suited for placement in such environments. Many traffic forecasting models rely on extensive traffic databases to train their prediction models. Image processing models also require prior data to identify vehicles. However, in Sri Lanka, traffic database collected over extended period unavailable. Therefore, the prediction model introduced in this project is better suited for countries like Sri Lanka as it doesn't necessitate a large dataset for training. The achieved prediction accuracy results indicate that this model can deliver predictions with 74.20% accuracy even it is trained using data gathered over just one week. Thus, the absence of a substantial traffic database no longer poses a hurdle to implementing traffic prediction models with this system.

However, the biggest challenge is the sensor needs to run 24x7. The loss of a few hours of data can substantially affect predictions. Maintaining a high level of reliability, preferably close to 100%, becomes imperative. Despite the increased difficulty, ensuring the consistent performance of the sensor is a necessary and critical aspect. Besides that, the road infrastructure in Sri Lanka differs from many other countries. Unlike the typical one-directional roads in most nations, Sri Lankan roads often accommodate vehicles moving in both directions, demarcated by white lines in the middle. Since here the sensor is situated on one side of the road, to track vehicles in one direction, sometimes there may be unavoidable miscounting of vehicles if a vehicle overtakes another vehicle by crossing the lane. Similarly, most of the vehicles in Sri Lanka do not move adhering strictly to lanes which may occasionally impact the accuracy of sensor readings. Therefore, this system is a more practical approach for addressing traffic congestion, particularly in Sri Lanka, where the traffic behavior databases are scarce, and the traffic behaviour is messy and complex. Moreover, resulted prediction accuracy values demonstrate that increasing input data volume substantially enhances prediction model accuracy. Thus, this system can be initiated with a short one-month data collection period at the initial stage, with potential for further development and improved forecasting accuracy through continuous training data integration. Additionally, the system could incorporate mechanisms to prevent miscounting of vehicles when overtaking vehicles.

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