An Intelligent Transport System for Prediction of Urban Traffic Congestion Level

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***Abstract*—Developing a resilient infrastructure is crucial for nation-building by supporting innovations and promoting sustainable growth. The Kingdom of Saudi Arabia is striving to achieve the Sustainable Development Goals (SDGs) set by the United Nations. Industry, Innovation, and Infrastructure (I3) are some of the strategic objectives of the Kingdom's Vision 2030 par with the United Nations' SDGs. The objective is focused to develop trade and transport networks for international, regional, and local connectivity with an investment of billions of dollars to establish a robust transport network and improve the existing one for enhancing road safety to reduce the costs of deaths and serious injuries. For this, a control center for automatic monitoring could be established for 24x7 monitoring of traffic violators; the key project has been named the National Center for Transportation Safety, apart from launching the "Rental Contracts" facility with the Naql portal. Moreover, the growing urban population is causing more vehicles on the roads leading to more traffic congestion which has become severe during peak hours in the major cities causing several other issues such as environmental pollution, high greenhouse gases (GHGs) including CO_2 emissions, health risks to the citizen and residents, poor air quality, higher risks of road safety, more energy consumption, discomfort to the commuters, and wastage of time and other resources. Therefore, in this research, we propose an intelligent transport system (ITS) for predicting traffic congestion levels and assist commuters in taking alternative routes to avoid congestion. An intelligent model for predicting urban traffic congestion levels using XGBoost, Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) algorithms is developed. The comparative performance analysis of the techniques concerning the performance metrics: Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Error cost, Outlier sensitivity, and Model Complexity, demonstrate that the LSTM algorithm excels the other two algorithms.**

Keywords*—*Sustainable development goals; traffic congestion; traffic prediction; Gated Recurrent Unit; long short-term memory; intelligent transport system

I. Introduction

Millions of people visit the Kingdom of Saudi Arabia yearly to perform Hajj and Umrah. During the Hajj period, two Holy cities experience the peak of traffic. Due to the large number of expatriates, the other major cities also usually experience the peak. The Kingdom aims to reduce peak hour congestion levels in the major cities as an important element under the SDGs of Vision 2030. So, the priorities in the Kingdom's Vision 2030 include programs for self-driving vehicles [1]. An intelligent transport system for predicting the congestion level and traffic analysis will assist the self-driving vehicle program initiative.

Apart from the proper road design, the main focus of the Transport Ministry in the Kingdom of Saudi Arabia is on road safety mechanisms, like mounting proper traffic and guide signs, adequate water drainage, and highway fencing to avoid accidents due to animal entry [2]. The concerned committees on existing roads and improving safety policies are trying too hard to prevent fatalities due to accidents. The National Road Safety Center (NRSC) is one of the Kingdom's road safety initiatives to reduce traffic fatalities within the National Transformation Program 2020 [3]. The goal is to establish a center of technical excellence and strategic partner for road safety stakeholders to place the Kingdom among the top 20 countries in road safety by 2030 [3]. Therefore, one of the key initiatives of this research project is to apply Artificial Intelligence (AI) technologies to effectively forecast traffic congestion levels during peak traffic load periods to diversify road traffic efficiently.

So, our proposed system will offer effective management of the congestion level, thereby reducing the cost of accidental deaths, serious injuries, and travel time. Consequently, the quality of social life will improve.

Moreover, higher congestion leads to higher energy consumption and creates related challenges such as environmental pollution, high CO_2 emissions, health risks, etc. An ITS capable of predicting the congestion level will help minimize the traffic congestion levels and related challenges [4].

Novelty and Motivation of the Research Work

1) An intelligent transport model development: The research aims to develop an intelligent transport system model for forecasting traffic congestion levels using an amalgamation of ML and deep learning (DL) techniques.

2) Prediction of the traffic congestion levels: We investigate and exploit various learning techniques capable of effectively predicting the traffic congestion levels for developing an intelligent transport system.

3) Better traffic control and management: Controlling and managing traffic congestion during peak hours and in undesirable circumstances e.g., in an accident or any intentional road blockage is in line with the SDGs.

4) Reduction in transportation time: The project's outcomes can be used in the concerned committee settings to

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reduce the overall transport time for the citizens and the residents.

5) Comparative analysis of multiple techniques: A comparative analysis of the proposed model's results with the existing traffic congestion prediction techniques strengthens its validity and viability.

This document is organized as follows. Section II describes the literature review. Section III discusses the Methodology; Section IV outlines the Proposed Work. Section V covers the Experimental Analysis. Section VI concludes the research.

II. Literature Review

The concept of an intelligent transport system is useful for overcoming the crisis of urban traffic congestion levels raised due to the migration of people to urban areas by efficiently predicting traffic congestion levels in urban areas [5-9]. The goal of such a system is to achieve traffic efficiency by minimizing the commuters' travel time, consumption of energy, and requirement of other resources and maximizing road safety and commuters' comfort level. These applications are deployed as strategic and sustainable development plans in techno-savvy countries to bring the concept of intelligent transport systems into reality.

Faster And Safer Travel Through Routing and Advanced Controls (FAST-TRAC) [9] is one of the earliest projects deployed in Oakland County, Michigan. The system receives and shares data and live video of traffic conditions with the Michigan Department of Transportation. It is one of the first suburban adaptive traffic control systems in the USA; also, the first to use video processing for an adaptive traffic control system in the world, and the first to launch a traffic website about real-time traffic information.

Sydney Coordinated Adaptive Traffic System (SCATS) [10] signal system uses eight phase signals to fit into the changing traffic patterns. This traffic control system optimizes traffic flow and implements intelligent algorithms to process real-time data to predict traffic patterns, reduce congestion and travel time, and enhance travel safety. It has reduced travel time by 28%, stops by 25%, fuel consumption by 12%, and emissions by 15%.

Some similar early systems to mention are Driver Information Radio using Experimental Communication Technologies (DIRECT), ADVANTAGE l-75, Suburban Mobility Authority for Regional Transportation (SMART), Cooperative Intersection Collision Avoidance System (CICAS), and Data Use Analysis and Processing (DUAP), etc.

Recent developments for automated and real-time processing of crowding information are the Google Maps transit service [11], Singapore LTA [12], and the Moovit travel app [13]. These systems are not cost-effective.

The paradigm of road safety has shifted from passive to active safety. Effective traffic congestion detection capability and effective analysis of real-time data are the keys to the efficiency of these systems [14].

The concept of intelligent traffic systems is incomplete without extracting useful and distinctive patterns from the collected data for real-time decision-making. A. Drabicki et al. [7] propose a framework for modeling an RTCI (real-time crowding information) system with an agent-based model with PT (public transport) simulations. This system is not validated as a reliable model and ceases to be an evidence-based analytical tool.

L. Li et al. [8] discuss the critical role of trajectory data focusing on traffic flow by revisiting traffic models at three levels (microscopic/mesoscopic/macroscopic). Their research is based on theoretical aspects of the field without practical implementation.

Authors in study [6] deal with the techniques of improved traffic flow and safety and less congestion including evaluating the performance of intelligent transport systems through a survey among the urban truck drivers. They do not implement a model for intelligent transport systems.

Authors in study [15] discuss sustainable traffic management issues focusing on IoT and intelligent information systems. Their research is based on theoretical aspects of the field without practical implementation.

Authors in study [16] propose a deep autoencoder neural networks model for traffic congestion prediction on the SATCS dataset. During the congestion level prediction in their work, there is a loss of information in representing the congestion levels in the proposed network. There is no clarity on information loss and what is the impact of information loss on prediction performance.

K. Zhang et al. [17] propose a data-driven model to predict traffic congestion flow in urban regions using the Convolutional Neural Network (CNN) LSTM network. The model depends on statistical analyses and employs a black box DL model for congestion prediction which lacks interpretable algorithms for traffic modeling.

Authors in study [18] described an intelligent traffic prediction approach using RFs and SVMs. However, they use simulations to validate the outcomes.

Therefore, in this project, we aim to design an effective intelligent model for traffic congestion prediction using an amalgamation of ML- and DL-based approaches which will improve the weaknesses of the previous work. This work will solve the urban traffic congestion of the Kingdom.

III. Methodology

An ITS consists of multiple components such as traffic management systems, electronic toll collection, vehicle-to-infrastructure communications, traffic flow forecasting, traveler information systems, etc. Traffic flow forecasting is an important component of ITS. Accurate traffic flow forecasting can improve an ITS in multiple ways such as improved traffic conditions by route optimization, improved travel efficiency by mitigating congestion, etc. Vehicle traffic flow is influenced by several factors that exhibit complex spatial-temporal dependencies. These complex spatial-temporal dependencies and non-linear relationships in the traffic data, make the forecasting task more challenging. Hence, different techniques of traffic flow forecasting face many challenges. This paper analyzes many AI techniques for forecasting effective and efficient traffic flow. Several machine-learning techniques have been utilized in forecasting and other complex real-world applications [19-26]. These techniques include LSTM networks for time series, GRU, Nonlinear Autoregressive with exogenous input (NARX), Random Forest (RF), and XGBoost. Each has been evaluated based on its strengths, weaknesses, and suitability for forecasting the inherent spatial-temporal dependencies within traffic data.

A. *Random Forest*

RF is a machine learning (ML) technique that can be utilized for classification and regression. However, the most common application of this technique is classification. It belongs to the category of ensemble ML approaches. The ensemble approach can be considered as a group of experts working together to find the solution to a problem. Ensemble techniques rely on multiple models (often base learners) working together to generate the final prediction by combining predictions of all the models. RF ensembles multiple decision trees [27, 28] as illustrated in Fig. 1.

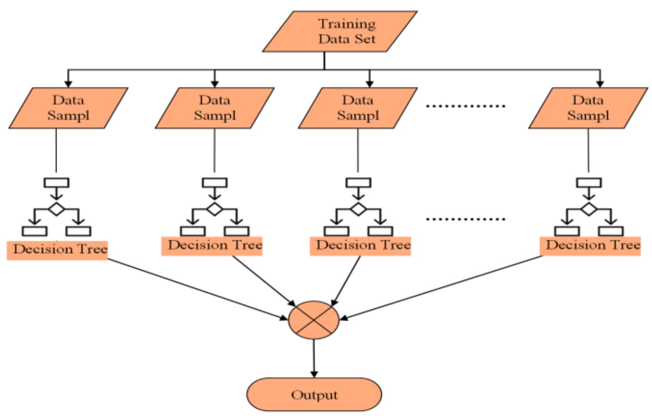

Fig. 1. Random forest.

Therefore, an RF builds an ensemble of multiple decision trees. The predictions of these trees are combined. Each subtree is built on a random subset (with replacement) of training data. This prediction aggregation process is also known as bagging or bootstrap aggregating. At each split in a tree, only a subset of features is considered. This process is known as random feature selection. Due to the randomness, caused by the random feature selection, overfitting is reduced. Each tree gets to vote for the final prediction. In the case of classification, the most likely outcome is the one with the majority of votes, and in the case of regression, the prediction is the averaged predicted value of all the trees [29]. This research predicts the number of vehicles and therefore, the RF regressor model has been utilized for the implementation. The traffic data of the time series has been categorized into four traffic categories for easier interpretation. Therefore, the predicted numbers are converted into high, low, normal, or heavy traffic category. Several research studies have analyzed the effectiveness of RF in forecasting road traffic [29-33]. An analysis by [30] compares the traffic prediction accuracy between the Bayesian network and RF. The study outlines that RF performs better than Bayesian networks in traffic prediction scenarios. Another study [33] analyzes multiple ML models and concludes that RF performs better than the other models.

B. *XGBoost*

eXtreme Gradient Boosting (XGBoost) is one of the powerful ML techniques for prediction tasks like classification and regression [34]. XGBoost is an ensemble technique. It combines the capabilities of the decision trees and gradient boosting. The decision trees are ensembled sequentially. The prediction errors introduced by the previous tree are corrected by the next tree improving the final prediction. XGBoost incorporates Lasso (L1) and Ridge (L2) regularizations to prevent overfitting. Using regularization also helps in controlling the complexities of the trees. XGBoost allows custom-defined loss functions or uses commonly used loss functions such as MSE and log loss functions. Mean squared is used for regression tasks. As in this research, the model aims to predict the number of vehicles, therefore, the MSE loss function has been used. XGBoost utilizes parallel and distributed computing environments to speed up the training [35]. To improve the speed and optimization, XGBoost uses the computation by pruning the irrelevant branches in the early stage. The pruning process utilizes the sparse learning technique [36]. Several researchers have leveraged the capabilities of XGBoost for traffic predictions [37, 38]. As discussed, it utilizes regularization which helps in preventing overfitting. It can handle complex relationships and non-linearity present in the traffic data points.

C. *Neural Network Time Series Nonlinear Autoregressive*

Vehicle traffic data can often be subject to high variance and rapid transients. Therefore, time series forecasting models should be able to overcome the non-linearity of these changes. A research study [39] suggests that the following non-linear autoregressive model $\hat{y}(t) = h\big(y(t-1), y(t-2), \dots, y(t-d)\big) + \varepsilon(t)$ can be utilized to model such variance and transient time series data. This model equation has been explained in the next paragraph. The model analyzed past traffic data to predict future traffic volumes for vehicle traffic forecasting. However, as discussed earlier, traffic data is often non-linear, therefore, a non-linear autoregressive neural network has been utilized for traffic volume forecasting. The implemented neural network is a multilayer feedforward network with feedback connections [39, 40]. The general structure of the multilayer nonlinear autoregressive neural network has been illustrated in Fig. 2.

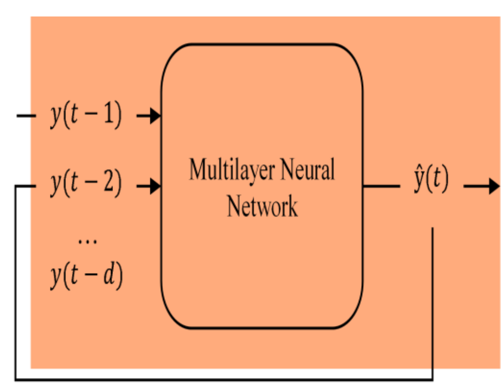

Fig. 2. Structure of the multilayer nonlinear autoregressive neural network.

The mathematical representation of the model can be stated using the following equation:

$$\hat{y}(t) = h\big(y(t-1), y(t-2), \dots, y(t-d)\big) + \varepsilon(t) \quad (1)$$

This equation states that the predicted value can be formulated into a function h of past time-series values. During the training process, weights and bias values are adjusted to approximate the function h. The term $\varepsilon(t)$ represents the error. It is a sequence of random independent variables. The sequence has a mean of zero and a finite variance. The neural network model trains on the past time series data using d feedback delays. The parameter d is the delay and can be tuned by the trial-and-error method for better accuracy. The proposed work has implemented different training algorithms- scaled conjugate gradient, Bayesian regularization (BR), and Levenberg-Marquardt (LM) with the dataset. Due to the features of each algorithm, they may perform differently with the same training data and network architecture. The scaled conjugate gradient algorithm used the gradient calculation method. It made it more memory efficient than the LM and BR training algorithms which utilize Jacobian calculations.

D. Long Short-Term Memory Networks

The LSTM neural network was proposed by Hochreiter and Schmidhuber [41]. These are a category of recurrent neural networks (RNNs) that are types of artificial neural networks. RNNs can identify the patterns in the data sequences or time series.

The vehicle traffic flow data used time series data in this research work. Time series forecasting may lead to sequence dependency issues on the input variable [42]. RNN maintains a memory of the previous inputs through the hidden states to learn from sequential or time-series data. However, RNNs can suffer from the vanishing gradient problem. A vanishing gradient problem where the gradients become very small as they are back-propagated through time. It leads to difficulties in learning long-term dependencies. LSTMs are specifically designed to address this problem. LSTMs utilize memory cells with gates. Gates control the information flow and allow the network to learn long-term temporal patterns. LSTM neural network is composed of multiple cells. The following Fig. 3 illustrates a typical cell of the LSTM neural network at the time t.

The cells of the LSTM network are very similar to those of the RNN neural network and utilize the previous timestep as shown in Fig. 1.

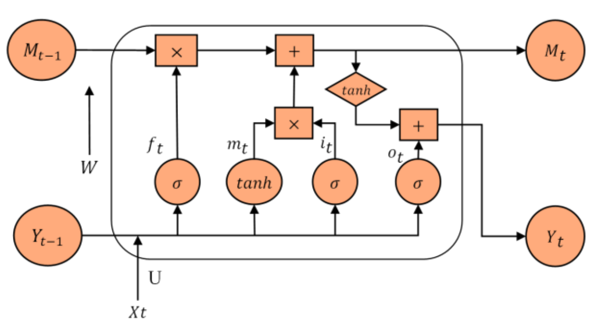

Fig. 3. LSTM neural network cell at the time t.

In LSTM, each cell is composed of an input gate (i_t), an output gate (o_t), a forget gate (f_t) and memory (m_t). The additional component in the LSTM neural network is the memory unit. These cells are the elementary units for the layers of the neural network. The memory of the LSTM neural network comes from the cells of the hidden units. The cell memorizes the values of the unit for an arbitrary period. The forget gate and input gate apply the sigmoid activation function (represented as σ) and the activation function for memory is $tanh$. M_{t-1} represents the memory from the previous cell and M_t represents the memory of the current cell. Similarly, the Y_{t-1} is the output from the previous cell and Y_t represents the output of the current cell. The symbol '×' illustrates the elementwise multiplication and the symbol '+' represents the elementwise addition. X_t is the t^{th} timestep input to the cell. U and W are the weight vectors. The output of these gates is the vectors computed by applying the weights and corresponding activation functions on the input for every timestep. Each cell generates a memory and an output. The memory can either be utilized or forgotten by the next cell depending on the values from the activation function of the forget gate as depicted in Fig. 1.

E. Gated Recurrent Units

The GRUs were introduced by [43], one of the powerful architectures based on RNN. Similar to LSTM, they use a gating mechanism to manage information flow. However, they have simpler architectures with fewer parameters than LSTM, making them faster to train than LSTM [43]. The vanishing gradient issue is where the information from old data sequences does not propagate properly through the network. The GRUs mitigate this issue by capturing long-term dependencies. Research studies [44, 45] have implemented GRUs for traffic prediction with promising results. We discuss the functions of each component of GRUs in the below paragraph.

A GRU unit consists of two main gating mechanisms known as update gate (z_t) and reset gate (r_t). The output hidden state (h_{to}) at time t is determined by the candidate's hidden state (h_t), update gate (z_t) and reset gate (r_t). The update gate is represented mathematically as:

$$z_t = \sigma\,(W_z[h_{t-1},\ x_t] +\ b_z) \quad (2)$$

The values close to 0 disregard the past state and values close to 1 indicate the higher influence of the past states. The update gate controls the information flow from the previous hidden state (h_{t-1}). The reset gate (r_t) controls the influence of the past states. That is, how much or to what extent, the processing of the current state (x_t) of the network relies on the past hidden states. The reset gate is represented mathematically as:

$$r_t = \sigma\,(W_r[h_{t-1},\ x_t] +\ b_r) \quad (3)$$

The values close to 1 indicate that the network can utilize the past state and the values close to zero indicate that the network should focus on the current input. The information flow is managed using the activation functions such as sigmoid (σ) or hyperbolic tangent ($tanh$). The candidate's hidden state is calculated using the current input and the selective information from the previous hidden state. It is represented mathematically as:

$$h_t = tanh\,(W_h[r_t * h_{t-1},\ x_t] + b_h) \quad (4)$$

The output hidden state (h_{to}) is computed by using the previous hidden state, candidate hidden state, and update gate as:

$$h_{to} = (1 - z_t) * h_{t-1} + z_t * h_t \quad (5)$$

In the above equations, W and b are parameter metrics and vectors.

GRUs offer compelling performance with simple architecture which is computationally lighter to train than LSTM.

The predictive ability of the combined method was evaluated by four indices, namely, the MAE, the MSE, the RMSE, and the MAPE:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t|$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{y_t - \hat{y}_t}{y_t} \times 100\% \quad (6)$$

IV. Proposed Work

Fig. 4 represents the proposed system's general architecture. This project will investigate and exploit several prediction techniques using three algorithms, XGBoost, GRUs, and LSTMs. These methods will be compared based on the performance of prediction accuracy. After evaluating the implemented techniques, the model that performs the best among these alternatives will be selected for forecasting the congestion level and presented as a model for deployment.

A. Dataset Description and Analysis

Actual urban traffic scenarios are complex. Traffic is dynamic over the days of the week and hours of the day. Therefore, proper data analysis depends on the actual traffic scenario. During the weekdays there are very high volumes of traffic usually called rush hours often from 6 am to 8 am and from 4 pm to 6 pm when most people are either going to or coming from work. This period heavily impacts traffic congestion levels. Fridays show unique deviation from anticipated as typical weekday traffic patterns; despite being considered part of weekdays. Congestion is not experienced during normal working hours but there is still increased road usage though not as much as on other days of the week perhaps due to leisure activities and social gatherings. Monday is the only day commuters commute consistently, most likely because it is the first day after taking a weekend off. Therefore, temporal factors should be considered when designing effective management systems since they offer better insights into the potential intensity of bottlenecks at specific times if nothing is done to mitigate them.

The dataset used in the research work is publicly available at Kaggle [46]. Table I summarizes the features of the dataset. The detailed dataset description is available in Table II.

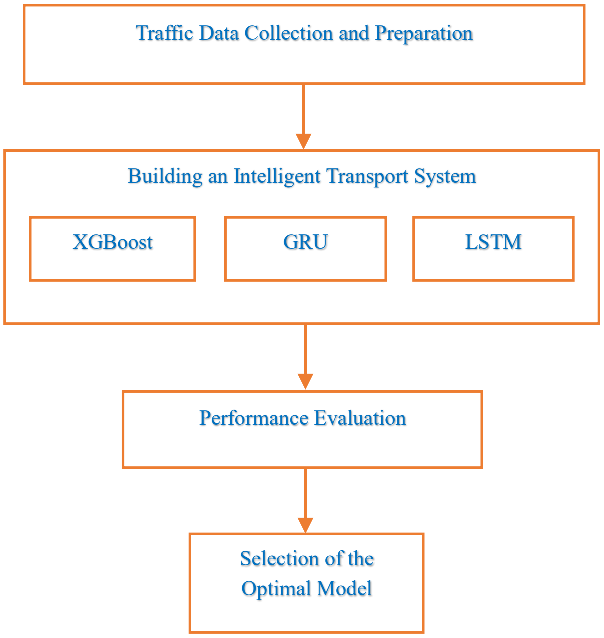

Fig. 4. The proposed ITS architecture.

TABLE I. DATASET SUMMARY

Total Records	5952
No. of Attributes	9
Attributes	Time, Date, Day of the week, CarCount, BikeCount, BusCount, TruckCount, Total, Traffic Situation

TABLE II. SUMMARY OF TEMPORAL TRAFFIC DATASET

Day	**Period**	**Traffic Volume**	**Key Observations**
Weekdays	06:00 - 08:00	High	Morning rush hour due to work commutes
	16:00 - 18:00	High	Evening rush hour due to work commutes
Friday	06:00 - 08:00	Lower	Reduced morning congestion compared to other weekdays
	16:00 - 18:00	Moderate	Evening traffic due to social and recreational activities
Weekends	Various	Variable	Much lesser uniformed traffic patterns contrast to weekdays

The quantiles and distributions of the four vehicle types are illustrated in Fig. 5 with box plots and histograms respectively.

The research considers four categories of traffic situations namely low, normal, high, and heavy to analyze the traffic congestion situations. The number of average total transportation for each category of traffic situations has been depicted in Fig. 6.

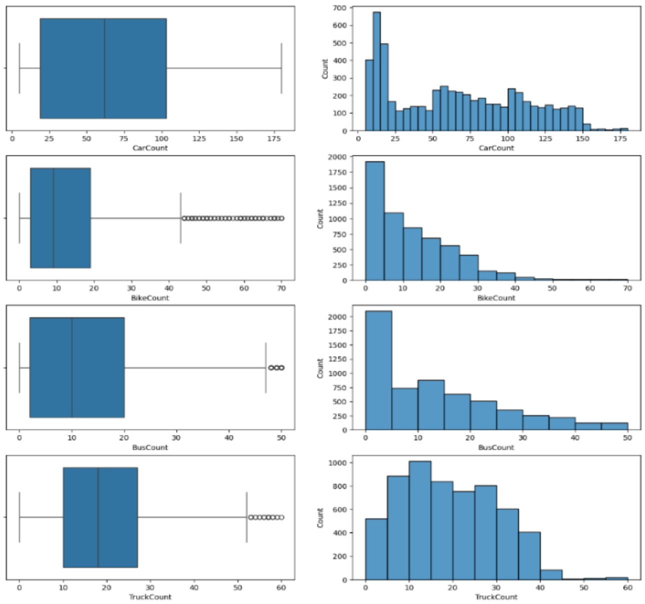

Fig. 5. The box plots and distributions (histograms) of the four vehicle types.

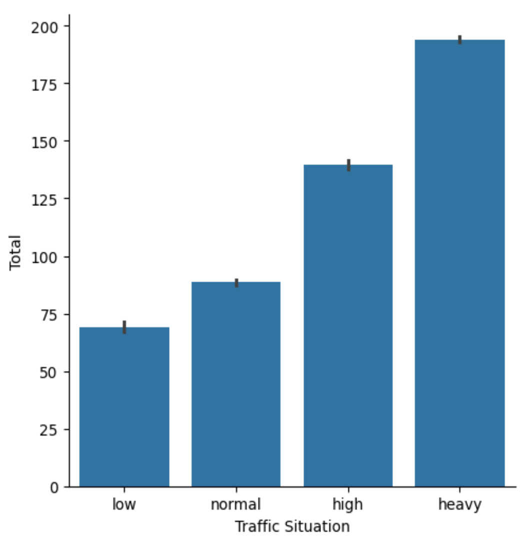

Fig. 6. The number of average total transportation for each category of traffic situations.

A pie chart of total vehicles by traffic situation has been shown in Fig. 7.

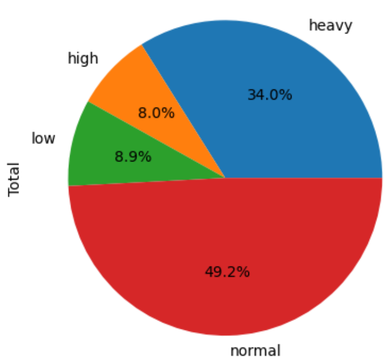

Fig. 7. Total vehicles by traffic situations.

B. *Proposed Models*

Temporal traffic pattern insights are useful for urban planners and decision-makers to reduce congestion and plan for infrastructural growth and transport system development toward building resilient cities that can withstand natural calamities and shocks such as heavy rains, floods, and earthquakes. Three algorithms are used for predicting future transportation states: XGBoost, GRUs, and LSTMs. The performance metrics used to evaluate the XGBoost model with 100 estimators included MSE, RMSE, MAE, MAPE, Error cost, Outlier sensitivity, Model complexity, etc. We compare the forecast against actual data to visualize our models' performance.

The GRU model, which consisted of a single GRU layer followed by two dense layers, underwent extensive training and evaluation. Performance measures were calculated, and predictions were compared to the real data. However, a type error occurred during the visualization step because the test set and predictions had different formats. This issue was resolved by transforming the forecasts into a NumPy array.

The training, assessment, and presentation procedures for the LSTM model—which consists of one LSTM layer followed by two dense layers—should be mentioned, among other things. It's also important to note that Fig. 8 displays the graphical representation of error distribution for each model, providing insight into the distribution and concentration sections where such errors are in the prediction cluster.

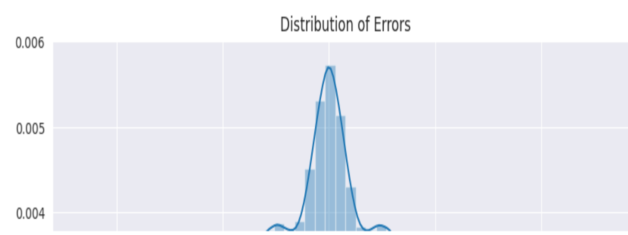

Fig. 8. Error distribution for each model.

V. Analysis of the Experiments

An experimental setup will be established, and its comprehensive experimental analysis will be performed in this section.

We discuss traffic forecast techniques using three models: XGBoost, GRU, and LSTM. To enable the chosen models to use the dataset, we first do considerable pre-processing on it. These procedures include encoding categorical information like the day of the week and traffic conditions and standardizing time to a 24-hour format. The data set is split into train-test sets for model training and evaluation, following the pre-processing. Our investigation begins with the RF model, well known for its ability to handle complex information. It offers insights into its predicted performance through an extensive evaluation process. Specifically, its ensemble learning approach exhibits competitive performance metrics, indicating strong performance in tasks such as traffic prediction where multiple factors influence the final result. The metrics employed by the models are summarized in Table III to give individual and comparative performance evaluations.

TABLE III. COMPARATIVE EVALUATION OF METRICS FOR MODEL PERFORMANCE

Metrics	Performance Values		
	XGBoost	*GRU*	*LSTM*
Mean Squared Error (MSE)	15.6	12.8	10.5
Root Mean Squared Error (RMSE)	3.95	3.58	3.24
Mean Absolute Error (MAE)	2.75	2.45	2.15
Mean Absolute Percentage Error (MAPE)	5.3%	4.7%	3.9%
Error Cost	Moderate	Moderate	Low
Outlier Sensitivity	Low	Moderate	Low
Model Complexity	High	Medium	High

The metrics employed by the XGBoos model are demonstrated in Fig. 9. The MSE for the XGBoos model between the actual and projected values is 15.6. RMSE provides a comprehensible metric of error magnitude and a small deviation from true values because it is the square root of MSE. This relatively low MSE suggests that the model's predictions are reliable. With an MAE of 2.75, the model demonstrates modest prediction errors, indicating its forecasting reliability. These figures are supported by a MAPE of 5.3%, which displays MAPE about actual values, presenting that on average the system's predictions should not deviate significantly (within a range of ±%) from reality. Such an accomplishment reflects an important degree of precision needed in real-world traffic forecasting applications, where it may not always be possible to obtain detailed or reliable historical data on past events to use as the foundation for future projections. In urban traffic management, moderate mistake costs imply manageable effects on flow control strategies intended to reduce congestion within cities; therefore, they can be effortlessly handled using suitable actions taken at strategic points along important paths serving various parts of the city. Mild mistake costs show operational/financial impacts related to incorrect predictions. The RF model's insensitivity to outliers is a crucial feature that makes it perfect for handling traffic data with irregular abnormalities like accidents or abrupt volume increases. This resistance against anomalous values guarantees smooth functioning and accurate predictions are made throughout, even in the face of random data points. Furthermore, the building of numerous decision trees combined is the cause of the high inherent complexity in the RF design. This complexity increases forecasting accuracy and makes it possible to represent intricate relationships within databases, such as those including multiple communicating variables, whose collective impact can either facilitate or obstruct flow depending on what is occurring at any given time. Yet, managing large amounts of input/output data can be challenging and require a higher level of interpretability, requiring more processing power than would typically be necessary under less demanding limitations. These examples show how effective an RF model can be in traffic prediction: Comparatively low MSE and RMSE readings, which indicate accuracy, corroborate its precision; MAE and MAPE exhibit reliability. Moderate error costs show applicability for usage in real-world scenarios where certain errors are expected but don't necessarily result in significant financial losses by striking a balance between accurate forecasts and controllable economic ramifications. When dealing with abnormal data points, XGboost is a good option because of its low sensitivity to outlying observations. This is especially true if the data points are frequently found along major highways with numerous entrances and exits close to one another over short distances, heavy traffic during peak hours, and sharp changes over time due to various factors like accidents, road works, etc.

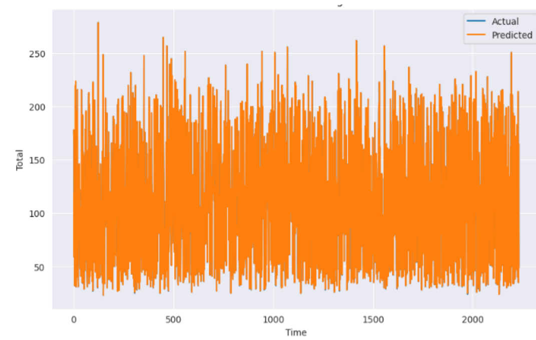

Fig. 9. XGBoost actual vs. predicted values.

The Recurrent Neural Network (RNN) architectures begin with the GRU model. The GRU model is trained and assessed by leveraging its ability to capture sequential dependencies in data. Despite promising results, with significant improvements over traditional ML methods, it does not achieve optimal performance metrics compared to the XGBoost model. Fig. 10 depicts the performance characteristics of the GRU model and provides valuable comparisons with the XGBoost model previously evaluated and shown in Fig. 9. The mean squared variance between the expected and actual values compared to XGBOOST is less than the MSE of 12.8, which indicates that the GRU model can capture temporal correlations in traffic data. The model's RMSE of 3.58, which places it higher in overall predictive performance than the XGBOOST model, further demonstrates its capacity to foresee with a smaller margin of inaccuracy. The MAE of the GRU model is 2.45, a lower value that highlights the model's accuracy in predicting traffic patterns. Furthermore, with a MAPE of 4.7% indicating that it is within 4.7% of the real values, the GRU model performs somewhat better than the XGBOOST model. Despite these promising metrics, the GRU model has moderate error costs, similar to the XGBOOST model, it represents that even though it makes generally accurate predictions, prediction errors can still have adverse operational and economic consequences that must be managed in real-world applications. While handling irregular data points better than many traditional ML models, the GRU model is not as robust as the XGBOOST model due to its moderate sensitivity to outliers. The model's performance in scenarios where anomalies occur frequently, such as traffic accidents or sudden volume increases, may be affected by this moderate sensitivity. In terms of model complexity, the GRU is classified as medium. Due to its gating mechanisms and sequential nature, it is more complex by nature than typical ML models, but not as complex as the ensemble-based XGBOOST model. The medium complexity is a suitable option for capturing temporal trends without unduly straining computational resources as it balances computational needs and predictive capabilities.

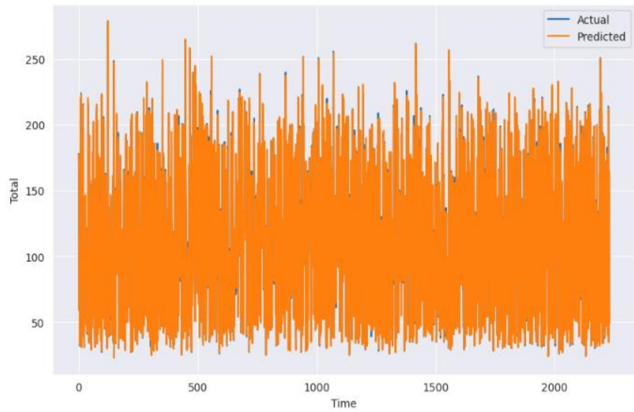

Fig. 10. GRU actual vs. predicted values.

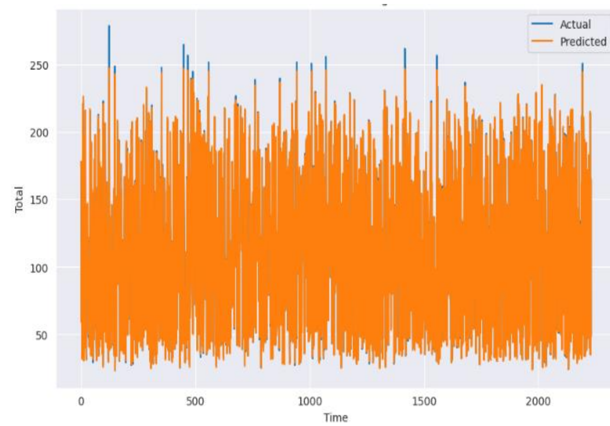

Fig. 11. LSTM actual vs. predicted values.

Next, we introduce the LSTM model known as the best for long-term dependency recognition in sequence data. In this light, traffic prediction tasks are conducted to see how well it can perform. However, there should be some more tests against an XGBOOST model, so we know what works better. Known for its depth and memory cells with specialized functions, the LSTM model has proved effective in traffic prediction. The training phase had several other models whose performance metrics were not as good as those of this one because during evaluation it achieved the lowest test loss among all considered models. This demonstrates that the only algorithm capable of making such complex predictions about traffic patterns would have been the LSTM model, which processes inputs over time and steps into outputs across variable sequence lengths until convergence on some fixed point. What more could you ask for from an LSTM model? Furthermore, the results obtained from examining the plots depicted in Fig. 11 indicate the potential success or failure of a certain predictive capability with other similar ones, such as the two displayed here, where they differ. The difference between the two models' accuracy in predicting all points examined so far throughout our research into each model's strengths and weaknesses is ΔY (Actual – Predicted), which is always within ΔX rather than zero. This indicates that both models perform equally poorly in predicting weak areas closer to either endpoint, possibly in part as none recognize features outside a certain range of values. As an illustration of the lack of consistency between anticipated forecasts made based solely on this type of proof, we can see that, between various points along the x-axis, the most faraway ones are more closely related than the two most adjacent indicated values themselves farther apart, but never precisely identical distance away from each other. This still fails to account for the least squares fits noticed.

The experimental investigation showed that many traffic forecast models ranging from deep DL techniques like GRU and LSTM to conventional ones, like XGBoost, are effective. Each model in traffic congestion prediction has demonstrated pros and cons. However, the LSTM model outperformed the others, achieving the highest accurate rate in traffic trend prediction. These results are critical in transportation planning and management because they offer practical guidance to enhance system efficiency and traffic flow optimization.

VI. Conclusion and Future Work

Our research considers many traffic scenarios to predict traffic congestion levels using an amalgamation of ML- and DL-based algorithms. The research outcomes show that both traditional ML and DL algorithms are effective. Three models, namely XGBOOST, LSTM, and GRU have been implemented on the dataset and are found powerful. The LSTM model is better than others due to its ability to capture long-term relationships between traffic data points and various patterns embedded in them. The concerned committees will utilize the research outcomes for transportation planning and management settings to optimize the flow of vehicles through different traffic routes to maximize the transportation system's efficiency. Citizens will save much of their precious time knowing the congestion level in advance; helping them plan their travel better. Business and industrial sectors can better plan the logistics and manage transport-related requirements. A high congestion level is the root of several environmental bad factors. Proper management of the congestion will improve the environment and will reduce pollution. A high level of congestion can waste commuters' time putting adverse effects on several other economic factors and accounts for high energy consumption. An ITS will assist in mitigating these factors and hence will enhance economic benefits.

The proposed model can be implemented as a mobile application in future work that can collect live data and aid the commuters in suggesting, in advance, the best route to travel based on the traffic congestion level.

While the proposed system considers various traffic scenarios occurring on specific periods of the day of the week, it does not consider other factors like weather and road conditions. We will focus on improving DL models to a hybrid of LSTM with techniques to exploit their strengths in future studies to improve the prediction effectiveness of the traffic congestion levels in ITS.

Moreover, to further increase the effectiveness of the ITS, accessing the real-time traffic data streams through comprehensive integration of vehicles' speed, location, and weather conditions to the ITS can be plenty of achievements like better accuracy in forecasting, scalability, and interoperability.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

Acknowledgment

The authors extend their appreciation to the Deanship of Scientific Research at Saudi Electronic University for funding this research (9425).

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