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Original Article

Advanced Traffic Forecasting Integrating Temporal and Spatial Dependencies Using Hybrid Deep Learning Models

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Abstract - *Accurate traffic forecasting is important for refining traffic management and planning to avoid congestion on the roads and enhance road safety. Traditional models often misfire on complex, nonlinear patterns in traffic. In this study, the hybrid LSTM-CNN model proposed in this paper would overcome the limitations by modeling both temporal and spatial dependencies, thus ensuring better accuracy and reliability in prediction. The study portrays the hybrid model of LSTM-CNN to overcome all such limitations and focus on capturing the temporal and spatial dependencies pertaining to traffic features. The paper uses a rich dataset comprising variables like volume, speed, and occupancy from highway sensors. It gives a model using LSTM layers in combination with CNN to perform better in prediction. Further refinements were done in training using hyperparameters; the evaluation of performance was executed on R^2, MAPE, and RMSE. The hybrid model gave the lowest validation loss of 0.05 and the lowest test MAPE of 0.08, which is better than the conventional models. More precisely, from the LSTM model, R^2 score = 0.081, MAPE = 3.66%, and RMSE = 0.248; from the CNN model, R^2 score = 0.029, MAPE = 4.07%, and RMSE = 0.255. R^2 of 0.063, MAPE of 3.84%, and RMSE of 0.250 were found for the hybrid model, with LSTM before CNN. In reversed order—that is, the hybrid model of CNN first—the values are as follows: the model recorded an R^2 of 0.054, a MAPE of 4.15%, and an RMSE of 0.252.*

Keywords - *Traffic forecasting, Hybrid LSTM-CNN model, Temporal and spatial dependencies, Prediction accuracy, Integration of deep learning.*

1. Introduction

Factors disturbing the flow of traffic include the time of the day, weather conditions, and incidents happening on the roads. These complex, nonlinear trends are difficult to model accurately for most models currently in use and result in less than optimal predictions. The intricacies of traffic dynamics, like sudden changes due to accidents or adverse weather conditions, add layers of complexity dealt with inadequately by many traditional models. It becomes very important to develop advanced models capable of handling such multifaceted aspects and increasing the accuracy and reliability of traffic forecasts.

This is the most vital area of transportation engineering, which helps manage traffic congestion and improve road safety. An accurate, future estimation of traffic can help in the effective management and planning of traffic, reducing congestion and thereby making transportation more efficient. Temporal and spatial dependencies shall be introduced in predictive models aimed at capturing holistic features of the pattern of traffic. Recent hybrid deep learning models show great promise to provide better predictive accuracy and management of inherent complexities in traffic data. Using these hybrid models, higher-precision traffic predictions can be given with actionability, handling both temporal and spatial dynamics altogether.

A number of studies have been conducted to meet various objectives undertaken therein. For instance, Goparaju et al. [1] considered some models incorporating spatial, temporal, and periodic features. They reported that the Temporal Convolutional Network (TCN) architecture, with an optimization done by Genetic Algorithms (GA), showed better accuracy in PeMS traffic data. In this regard, Goswami and Kumar [2] proposed the Multi-Layer Bidirectional Stacked Autoencoder (MLBSAE) model, which integrated Bidirectional Long Short-Term Memory (BiLSTM) with Stacked Autoencoders (SAE) for handling the complex features of large traffic datasets. Their model worked better using California traffic data in comparison with other methods like Seasonal Autoregressive Integrated Moving Average (SARIMA), eXtreme Gradient Boosting (XGBoost), and Random Forest (RF); thus, it is more robust in handling complex datasets of traffic. Du et al. [3] extend this work, presenting a hybrid deep learning framework that makes a multi-layer deep learning architecture incorporate jointly spatial-temporal features of traffic data in support of short-term traffic flow forecasting. This framework, combining Recurrent Neural Networks (RNNs) and convolutional neural networks (CNNs), handled complex and nonlinear characteristics of urban traffic flow very well, outperforming traditional models. Zhaowei et al. [4] constructed an end-to-end hybrid deep learning network known as the Multi-Branch Long Short-Term Memory (M-B-LSTM) model, which allows online self-learning to take into the base network in a bid to alleviate distribution imbalance and overfitting. The model fuses Deep Bidirectional Long Short-Term Memory (DBLSTM) and LSTM to handle inner stochasticity and distribution imbalance of traffic data.

Chavan et al. [5] applied CNN, RNN, and hybrid CNN-LSTM models in their highway traffic flow, speed, and occupancy predictions with 36.34 million data points. Their model performed well in real-time and short-term precise traffic prediction compared to traditional methods. In another work, Zheng et al. [6] proposed a model combining CNNs and LSTMs that integrates the attention-based Convolutional Long Short-Term Memory (Conv-LSTM) module for extracting spatial features and a Bi-LSTM module for extracting temporal features. This showed superior prediction accuracy and outperformed the existing methods by dealing with the complex nonlinearity of traffic data.

Cheng et al. [7] proposed a framework of short-term traffic flow prediction that integrates econometric theory with a deep learning-based CNN-LSTM hybrid neural network model. Underlying intrinsic relationships among traffic variables and predictable relationships were represented using the Vector Autoregression (VAR) model. Their model turned in superior accuracy in speed prediction for multi-features compared to single features and other deep learning models. Similarly, various deep learning models relating to time series in Vehicular Ad-hoc Networks (VANETs) were considered by Kaushik et al. [8] in order to predict the current and future traffic patterns and analyze past data. Therefore, their model achieved an accuracy of 99.96% in prediction using Bi-LSTM and Gated Recurrent Unit (GRU).

In the domain of Web traffic prediction, Prasanth et al. [9] contributed a hybrid model in which LSTMs and Radial Basis Function Networks (RBFNs) have been integrated through an ensemble stacking algorithm. This prototype exploited the strength of both models against time series data across various Wiki pages with lower prediction error than traditional methods that take care of randomness and scale of Web traffic data.

Etengu et al. [10] focus on deep learning-assisted traffic prediction in hybrid Software-Defined Networking/Open Shortest Path First (SDN/OSPF) backbone networks. In their work, they make use of two unsupervised feature reduction techniques, Canonical Correlation Analysis (CCA) and Principal Component Analysis (PCA), all to perform short-term Traffic Matrix (TM) prediction in an SDN. Such contribution is said to reduce the dimensions and increase the accuracy of the prediction. The designed control plane forwarding with large non-recurrent networks is always better than traditional approaches. Another paper by Sarhangian et al. [11] focused on efficient traffic classification using hybrid deep learning models.

In this regard, the authors have proposed two hybrid models (integrating convolutional neural networks with recurrent neural networks, either GRU or LSTM) for the purpose of classifying network traffic. Comparing these hybrid models against traditional individual-based models on real network traffic data, they achieved significant improvements in the classification accuracies, thus proving that they are very good at processing high-dimensional datasets with high sparsity levels.

A hybrid model was proposed by Joseph et al. [12], where boosted LSTM combined with CNN for the prediction of traffic congestion in VANETs. Their model has an accuracy of 96%, tested in a real-world and simulated environment, hence promising much potential toward minimizing accidents and improving road safety. In a related study, Mahajan et al. [13] assessed network traffic prediction using a hybrid deep learning model in Wireless Mesh Networks (WMNs). In the study, various algorithms were analyzed, and they put forward a Convolutional Long Short-Term Memory (Convo-LSTM) model that demonstrated superior performance for predicting network traffic with better accuracy.

The literature gap is in the accurate prediction of traffic flow, which becomes the single most important requirement for traffic management and planning. Traditional models can never capture the complex, nonlinear nature of the changing traffic patterns, especially under the occurring conditions of incidences of different natures. Recent research on hybrid deep learning models is promising; however, much real-world testing remains to be done to prove both their efficiency in general terms and their superiority in particular cases that describe real processes. This paper concentrates on developing a hybrid model carrying LSTM and CNN archetypes for integrating both temporal and spatial dependencies with the aim of enhancing the accuracy of traffic prediction.

Table 1. Comparison of studies on traffic flow forecasting models

Study	Methods Used	Data Source	Key Findings	Evaluation Metrics
Fu et al. (2023) [14]	Hybrid LSTM-GCN	Delhi's metro rail network (2012-2017)	Accurate predictions with R^2 of 0.920, RMSE of 368.364, MAE of 549.527. Outperformed LSTM and LightGBM.	R^2, RMSE, MAE
Mohammed et al. (2022) [15]	Pelican Opt. with Hybrid DBN	Smart city traffic data	Promising performance, MSE of 17.19132, RMSE of 22.6634. Outperformed recent DL models.	MSE, RMSE, MAE
Li et al. (2023) [16]	Improved CNN-LSTM with Grouping	AIS data from CJP water area	Superior accuracy and stability, improved over 11 advanced methods.	RMSE, MAPE, REMean, RESTd
Zong et al. (2024) [17]	DATGAN and PSTTransformer	Traffic datasets PEMSD7, PEMS-BAY, METR-LA	Reduced MSE by 5%, performed well for different missing data rates/types.	MSE, RMSE, MAE, MAPE, SMAPE
Alsubai et al. (2024) [18]	Improved AOA with DL-TCC	Kaggle road traffic data	Enhanced traffic flow, reduced congestion, accuracy of 98.03%, error rate of 1.97%.	Accuracy, Error Rate, Computational Time
Casabianca et al. (2021) [19]	BiLSTM with Attention	GeoLife GPS Trajectories (Beijing)	Achieved 96% accuracy, better performance and stability.	Accuracy, MSE, RMSE, F-Score Stability
Méndez et al. (2023) [20]	Hybrid CNN-BiLSTM	Four main roadways in Madrid	Outperformed eight baseline models, with significant improvements in MAE, RMSE, and accuracy.	MAE, RMSE, Accuracy

The main objective of the work is to come up with a hybrid LSTM-CNN model for the forecast of traffic flow from such a developed dataset. This would try to draw from the strengths of LSTM in capturing temporal dependencies and CNNs in extracting features that form a spatial relationship with one another. Enhancing the accuracy and reliability of traffic predictions, along with actionable insights about traffic management and planning. The authors used a fine grain traffic-flow dataset collected from many highway sensors, capturing variables such as volume, speed, and occupancy. This paper proposes an architecture that combines LSTM and CNN layers to capture temporal and spatial dependencies more effectively. The LSTM layer can deal with sequential data, while the CNN layer extracts data from local patterns. Hyperparameter tuning was performed to optimize the models' performance. The trained models were evaluated using R^2, Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). Table 1 compares various kinds of traffic prediction models: standalone LSTM, CNN, and hybrid LSTM-CNN configurations.

The results present an overall huge level of outperformance for the hybrid LSTM-CNN compared to these traditional methods. The hybrid's best validation loss was scored at 0.05, while that of the MAPE was scored at 0.08. A number of key inputs are received from this: the standalone LSTM model scored an R^2 of 0.081, a MAPE of 3.66%, and an RMSE of 0.248. The other measures are the standalone CNN R^2 score of 0.029, a MAPE of 4.07%, and RMSE of 0.255%. The hybrid model (order of steps: LSTM-first) scored R^2: 0.063, MAPE: 3.84%, and RMSE: 0.250, while the parent model (order of steps: CNN first) scored R^2: 0.054, MAPE: 4.15%, and RMSE: 0.252. This shows that the hybrid model learns the complex temporal and spatial patterns of traffic data, giving a fittingly solid solution for accurate and reliable traffic predictions.

2. Methodology

2.1. Data Analysis

The dataset utilized in this study includes detailed traffic flow data collected from various highway sensors. The primary variables under consideration are 'from,' 'to,' and 'cost,' each contributing critical insights into traffic dynamics. The dataset comprises several thousand entries, each capturing traffic flow information at different time intervals, thus providing a comprehensive view of the traffic conditions. The dataset's key components are 'from,' 'to,' and 'cost.' Here, 'from' represents the starting point of a traffic segment, 'to' denotes the endpoint, and 'cost' signifies the associated cost, serving as a proxy for traffic density or congestion level. To understand the interrelationships between these variables, a correlation matrix was computed and visualized as a heatmap in Figure 1.

The correlation coefficients between the variables are presented in the heatmap, where a perfect positive correlation is indicated by a value of 1.00, a perfect negative correlation by -1.00, and no correlation by 0.00. Thus, the correlation between 'from' and 'to' is a weak 0.23 positively related correlation. Additionally, a weak, small positive but very small relationship is further suggested between 'from' and 'cost,' with the correlation being 0.065, while the correlation between 'to' and 'cost' is very weakly 0.06 positively related. This suggests, therefore, that although a relationship exists between the variables themselves, this is neither apparently a tight linear relationship nor strong. These correlations between the variables are shown in the heatmap of Figure 1. The strength and direction of the relationship between the other variables may, through this visualization, give some ideas on specific patterns that would greatly assist in making more accurate predictions on the flow of this traffic [21].

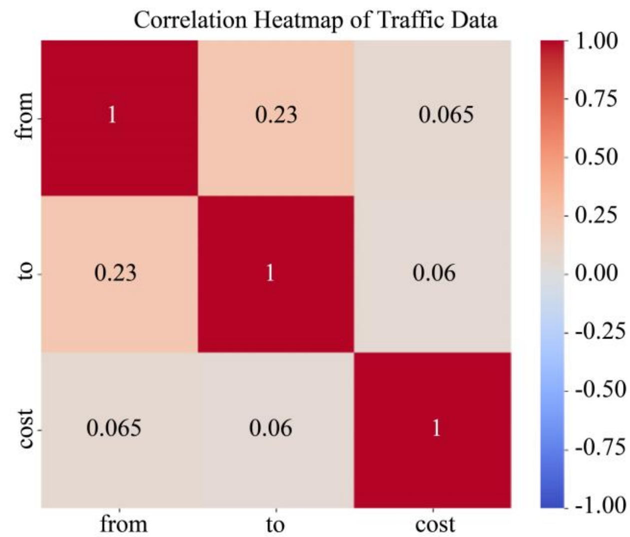


Fig. 1 The correlation matrix of the data

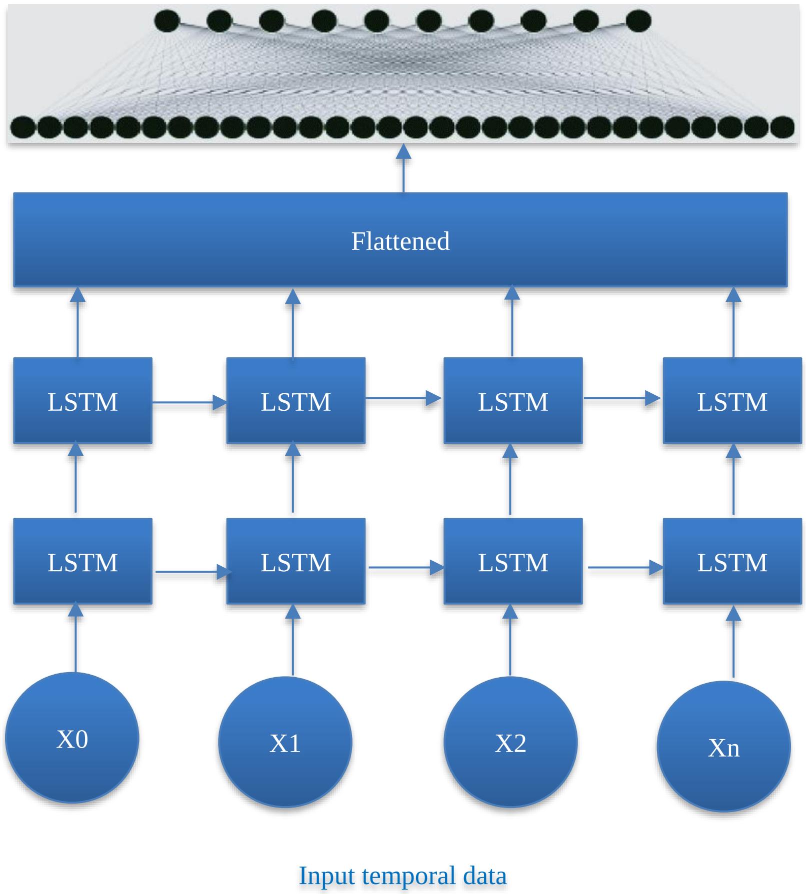
2.2. Model Architecture

The architecture of the proposed model combines the capabilities of LSTM and CNN to capture both the temporal and spatial dependencies in traffic data. This work applies an LSTM layer, as shown in Figure 2a, to capture the temporal dependency by processing sequential data through a chain of LSTM units, each retaining information from previous time steps [7], [22]. Similarly, the spatial features are extracted in the next stage, as shown in Figure 2b: it shows the essence of picking up local patterns in the data by applying several convolutional filters and then performing pooling to reduce the dimension of the convolutional output. The hybrid LSTM-CNN model flattens the output from the LSTM layer and feeds it into the CNN layer. Such integration allows for learning and generalization of both the changefulness of temporal sequences and the spatial patterns of the data. It improves predictive performance by providing very comprehensive, correct, and resilient predictions of traffic flow.

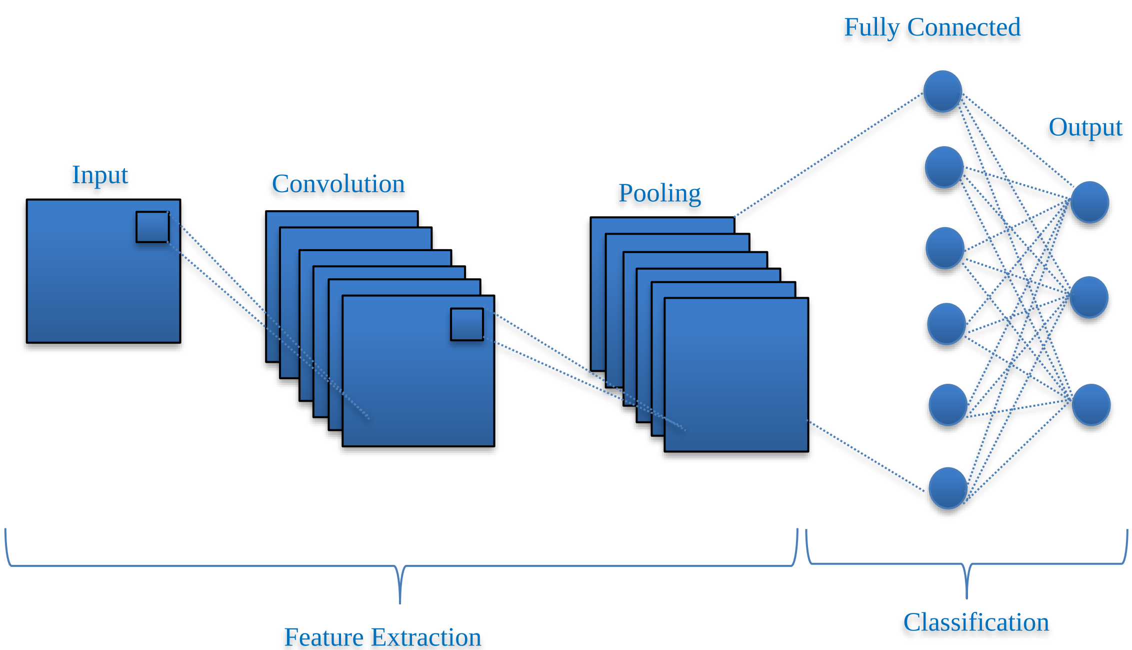
2.3. Mathematical Formulations

2.3.1. LSTM Model Equations

The LSTM model is particularly designed to grasp temporal dependencies in sequential data by devising a series of gates and state updating. Key ingredients for the LSTM model are the forget gate, input gate, output gate, and cell state, each with some equations. The forget gate determines what information about the old cell state is to be forgotten. That is mathematically represented as Equation 1. The input gate decides what new information should be written to the cell's memory state at period t. Its serial is given by Equation 2. Ultimately, the output gate defines what comes out of the LSTM cell. It is represented by Equation 3. The cell state, C_t, is updated through the activation from the input and forget gates and new candidate values. It is represented by the following Equation 4 [12], [23].



(a)



(b)

Fig. 2 Architecture of the a) LSTM b) CNN Model

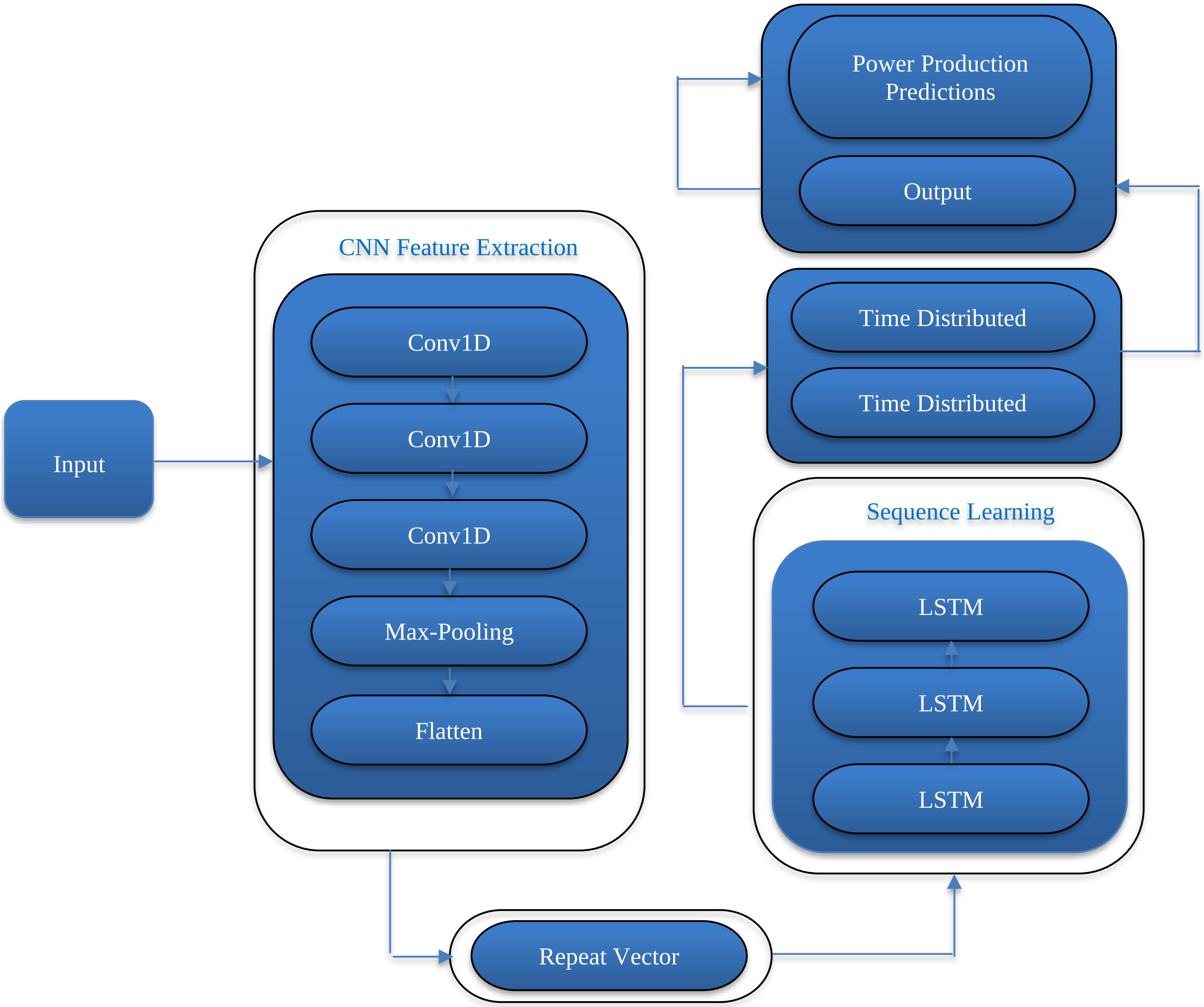


Fig. 3 Architecture of the LSTM-CNN model

$$f_t = \sigma\left(\sum_{i=1}^{n} W_{f_i} \cdot [h_{t-1}, x_{t-i}] + b_f\right) \quad (1)$$

$$i_t = \sigma\left(\sum_{j=1}^{m} W_{i_j} \cdot [h_{t-1}, x_{t-j}] + b_i\right) \quad (2)$$

$$o_t = \sigma\left(\sum_{k=1}^{p} W_{o_k} \cdot [h_{t-1}, x_{t-k}] + b_o\right) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \tanh\left(\sum_{l=1}^{q} W_{c_l} \cdot [h_{t-1}, x_{t-l}] + b_c\right) \quad (4)$$

Where, f_t is the forget gate activation, σ denotes the sigmoid function, W_{f_i} represents the weight matrix for the $i - th$ component, h_{t-1} is the previous hidden state, x_{t-i} is the input at time step $t - i$, and b_f is the bias term. In this equation, i_t is the input gate activation, W_{i_j} represents the weight matrix for the $j - th$ component and b_i is the bias term. where o_t is the output gate activation, W_{o_k} represents the weight matrix for the $k - th$ component and b_o is the bias term. In this equation, C_t is the cell state, tanh denotes the hyperbolic tangent function, W_{c_l} represents the weight matrix for the $l - th$ component and b_c is the bias term.

2.3.2. CNN Model Equations

The CNN model is utilized to extract spatial features from the input data through convolutional and pooling layers. The convolutional layer applies filters to the input data to capture local patterns. It is represented by Equation 5 [24].

$$y = f\left(\sum_{m=1}^{r} W_m * x_m + b\right) \quad (5)$$

Here, y is the output feature map, W_m represents the filter weights for the $m-th$ filter, x_m is the input data, b is the bias term, and f denotes the activation function. The pooling layer reduces the spatial dimensions of the feature map, retaining only the most significant features. It is represented by Equation 6:

$$y = \max_{j}\left(x_j\right) \tag{6}$$

In this equation, y is the pooled feature map, and $\max_{j}$ represents that we take the maximum inside the operation over the $j-th$ region.

2.3.3. LSTM-CNN Model Equations

Hybrid LSTM-CNN combines the strengths of the LSTM and CNN in capturing the temporal and spatial dependencies. Inferences will be made based on the developed model with the fused traffic flow dataset, and evaluation will be done using coefficients like R^2, MAPE, and RMSE. Table 3 reveals the hyperparameter tuning results of LSTM, CNN, and hybrid LSTM-CNN models with various configurations.

The LSTM model reported a best validation loss of 0.06, with a MAPE of 0.1, for learning rate—0.001, batch size—64 for this model, and 50 epoch training. The CNN model reported a best validation loss of 0.07, with a MAPE of 0.15, under these same hyperparameters. The hybrid LSTM-CNN models, again both LSTM-first and CNN-first architectures, performed better, with each attaining a best validation loss of 0.05 and MAPE of 0.08.

Such clearly leads to the expectation that LSTM-CNN hybrids yield higher predictability and generalization than either individual LSTM or CNN models do. Inputs are passed through an LSTM layer. See the figure below for time dependency modeling of an input sequence x_t. Equation 7 presents that step.

$$h_t = \text{LSTM}\left(\sum_{s=1}^{u} x_{t-s}\right) \tag{7}$$

Where, h_t is the output from the LSTM layer. Finally, the output h_t is forwarded into the CNN layer, where further processing occurs to help extract spatial features. This process can generally be shown in Equation 8:

$$y = \text{CNN}\left(\sum_{v=1}^{w} h_{t-v}\right) \tag{8}$$

y is the ultimate output of a combined LSTM-CNN model. The hybrid model in this equation captures the very essence of the two dependencies—temporal and spatial—present in traffic data, whereby this model is effective in predictive performance.

2.4. Model Development and Selection Process

Figure 4 shows the traffic prediction workflow and model selection. This chart illustrates the step-by-step process in the methodology to provide a systematic approach toward data preparation, model training, evaluation, and then selection. It shows at a glance the critical decisions and iterative steps to establish with clarity that each step flows with systematics and thoroughness for a good approach in model development and selection [24]–[26].

- Data Preparation: This is the initial step involved in collecting and preprocessing the raw traffic data. These can be done by way of data cleaning, handling problems regarding missing values, feature normalization, and perhaps transforming data into a model-trainable format. Data preparation thus needs to be accorded utmost importance, which can properly ensure dataset quality and consistency for better performance of the model developed.
- Choice of Model Architecture: With the data preparation complete, an appropriate model architecture must be chosen for traffic prediction. Among them are LSTM and CNN or their hybrids. Each of these models specializes in capturing either temporal or spatial dependencies in traffic flow records.
- Splitting Data into Training and Testing Sets: Having chosen a model, a complemental division of the formerly singular dataset into respective subsets for training and testing is carried out. Normally, most of the data is for training, except a small amount used for testing, that fine-tuning exercise reserved for finally evaluating how the model is. This is critical to the decision that gives the appropriate confirmation to know if, indeed, the model generalizes well with examples that are not observed.
- Training and Optimization of the Chosen Model: The chosen model is trained with the training set. The model is optimized for its parameters to learn the patterns and relations between the data out of it. Tune the hyperparameters to learn at what learning rate, what the batch size will be, and how many iterations of epochs the model will be maximally performing.
- Model Performance Evaluation: For performance testing, the model is tested on the testing dataset. In doing so, the evaluation metric will involve R^2, MAPE, and RMSE in checking the accuracy of the model's prediction. This is an essential step to take so that the model performs well on what remains new data.
- Model Selection Decision: Using evaluation results, select the optimal model. If the model meets all performance criteria as predefined, then it is an optimal model, and feeding moves to the last phase. If a model does not fall under the criteria, tuning is done, and retraining and revaluation of the model are performed.
- Deployment Ready: The process culminates with the selection of the best predictive performance model that is ready for deployment in traffic prediction applications.

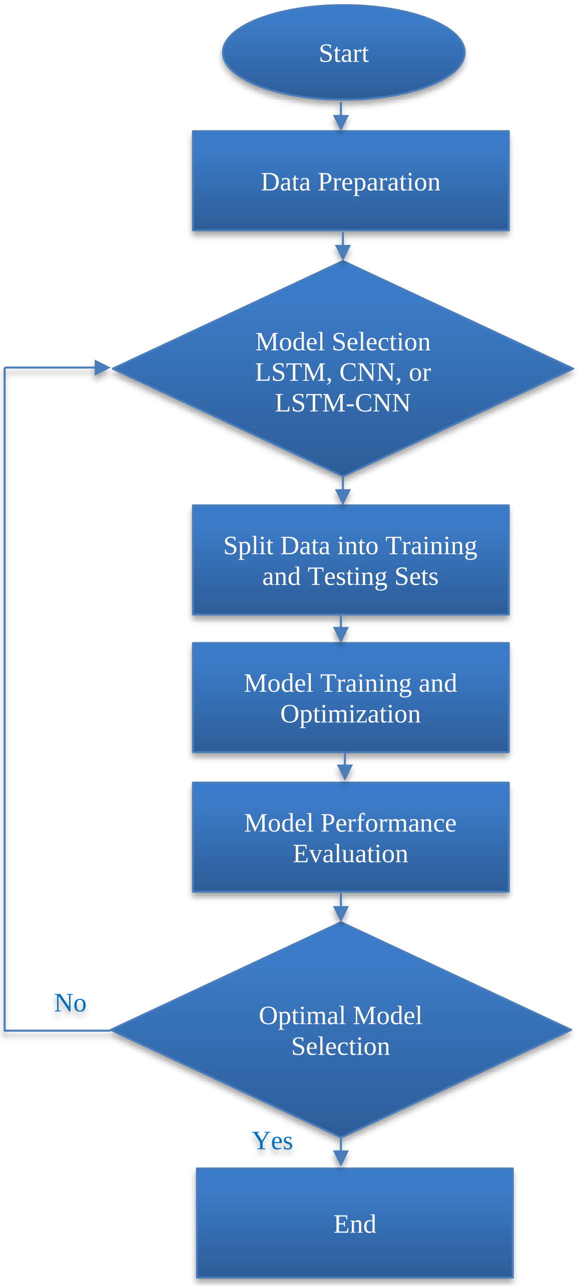


Fig. 4 The workflow and model selection flowchart for traffic prediction

3. Results and Discussion

Table 4 shows the performance metrics for different traffic prediction models with respect to LSTM, CNN, Hybrid LSTM-CNN (LSTM first), and Hybrid LSTM-CNN (CNN first). The metrics used are R^2 Score, MAPE, and RMSE. For the LSTM model with an R^2 score of 0.081 with values for MAPE and RMSE of 3.66% and 0.248 correspondingly, this model goes fairly well. Although it has a relatively high R^2 score, the error rates reflected in the MAPE and RMSE are somewhat high, thus indicating some room for improvement in prediction accuracy.

The CNN model has a lower R^2 score of 0.029 and a higher MAPE of 4.07% with an RMSE of 0.255. This, therefore, dictates that there is a greater struggle by the CNN model as compared to the LSTM in capturing variance in traffic data and had large prediction errors. The result for the Hybrid LSTM-CNN with LSTM first was an R^2 score of 0.063, a MAPE of 3.84%, and an RMSE of 0.250. This hybrid model is better than the CNN model in terms of MAPE but still cannot beat the R^2 score obtained by the LSTM model.

The hybrid LSTM-CNN model—CNN first—cores an R^2 score of 0.054, a MAPE of 4.15%, and an RMSE of 0.252. This setting also integrates CNN layers first, but the performance is not very high when compared to other models, thus proving that the order of integration is critical to the effectiveness of the model. Thus, in comparison with the rest of the models, the LSTM model strikes a better balance between explaining variance and minimizing errors.

The hybrid models, however, especially the configuration LSTM-CNN with LSTM first, obviously show improvements in MAPE and RMSE; thus, they are better at tracing some intricate patterns underlying the data. Hybrid models retain advantages from the architectures of both LSTM and CNN; therefore, they result in higher predictive accuracy and robustness in traffic-flow forecasting.

Figure 5 illustrates the comparison of model loss across epochs for different traffic prediction models. Effective learning and convergence are indicated by the LSTM model's consistent loss reduction Figure 5(a), which aligns with its relatively low MAPE and RMSE. The CNN model Figure 5(b) shows a less pronounced loss reduction, reflecting its limitations in capturing temporal dependencies. The hybrid LSTM-CNN model (LSTM first) Figure 5(c) shows a smoother and more significant loss reduction compared to individual LSTM and CNN models, indicating better learning and convergence. The hybrid LSTM-CNN model (CNN first) Figure 5(d) exhibits a similar pattern to the LSTM-first hybrid but with slightly higher loss values, indicating that the LSTM-first configuration is more effective.

Figure 6 compares the MAPE across epochs. The LSTM model Figure 6(a) shows a consistent decline in MAPE for both training and validation sets, indicating good generalization. The CNN model Figure 6 (b) exhibits larger MAPE values, especially for validation sets, highlighting its limitations in handling temporal patterns.

The hybrid LSTM-CNN model (LSTM first) Figure 6(c) displays a more noticeable and smoother decline in MAPE, reflecting the combined strengths of LSTM and CNN layers. The hybrid LSTM-CNN model (CNN first) Figure 6(d) demonstrates better performance in MAPE reduction compared to the CNN model but is not as effective as the LSTM-first hybrid.

Table 3. Hyperparameter tuning results for the hybrid LSTM-CNN model

Model	Learning Rate	Batch Size	Epochs	Best Validation Loss	Best Validation MAPE
LSTM	0.001	64	50	0.06	0.1
CNN	0.001	64	50	0.07	0.15
Hybrid LSTM-CNN (LSTM first)	0.001	64	50	0.05	0.08
Hybrid LSTM-CNN (CNN first)	0.001	64	50	0.05	0.08

Table 4. A comparison between the traffic prediction models' performance

Model	R^2 Score	MAPE	RMSE
LSTM	0.081472406	3.658087202	0.247960299
CNN	0.028916215	4.072279317	0.254955508
Hybrid LSTM-CNN (LSTM first)	0.062918688	3.838256188	0.250452105
Hybrid LSTM-CNN (CNN first)	0.054123389	4.146928275	0.251624712

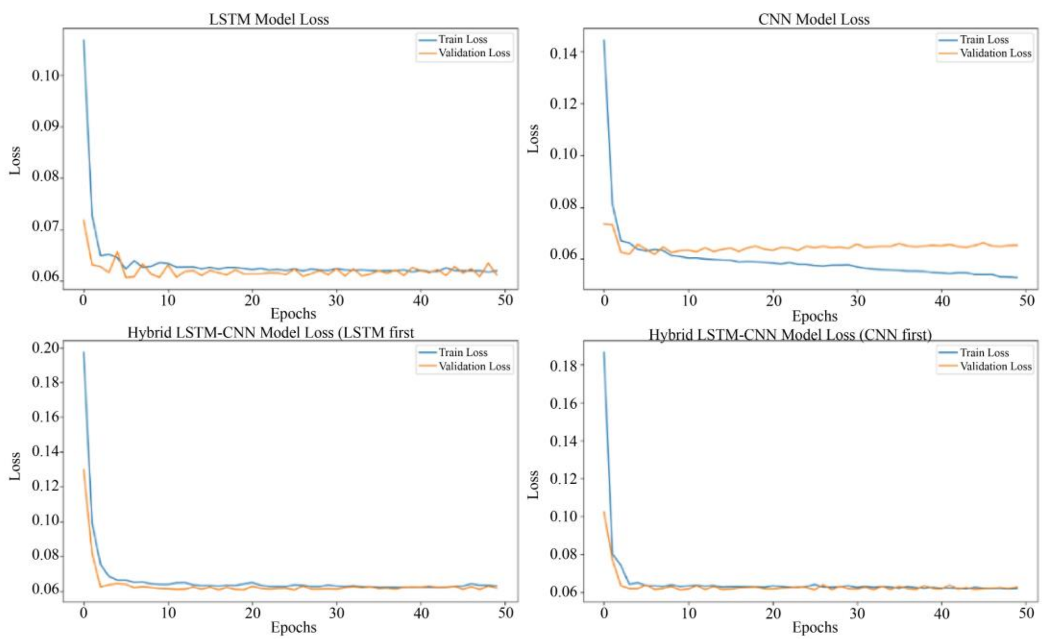


Fig. 5 Comparison of model loss across epochs for traffic prediction (a) LSTM model loss, (b) CNN model loss, (c) Hybrid LSTM-CNN model loss (LSTM first), (d) Hybrid LSTM-CNN model loss (CNN first)

Figure 7 provides residual analysis for traffic volume and speed predictions. The distribution of residuals for traffic volume Figure 7(a) and traffic speed Figure 7(b) are closely centered around zero, indicating minimal prediction errors and high accuracy for the LSTM-first hybrid model. This confirms the model's robustness in predicting both traffic volume and speed.

Figure 8 shows the comparison between predicted and actual values for traffic volume and speed using the hybrid LSTM-CNN model. The predicted values for traffic volume in Figure 8(a) align closely with actual values, demonstrating high accuracy. Similarly, the strong correlation between predicted and actual traffic speed values in Figure 8(b) further validates the model's effectiveness. While in figure 9 presents the feature importance analysis, highlighting the most significant factors impacting traffic flow predictions. Temporal features (time of day, historical traffic data) and spatial features (road conditions, weather) are shown to play crucial roles in prediction accuracy, providing valuable insights for model improvement and application in traffic management. Finally, Figure 10 shows the confusion matrix for traffic congestion level predictions, illustrating the model's accuracy in classifying different congestion levels. The high accuracy rates indicate the model's reliability in practical traffic management applications.

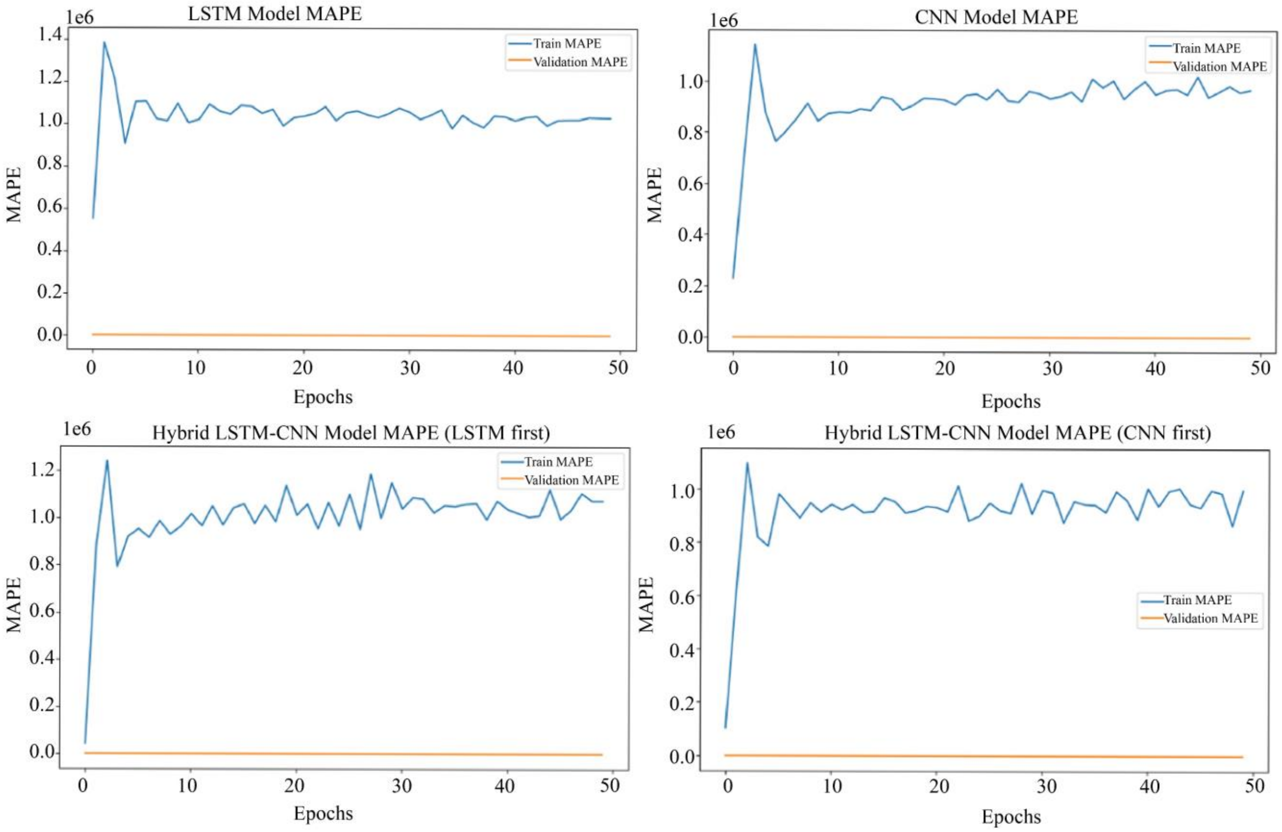


Fig. 6 Comparison of model MAPE across epochs (a) LSTM model MAPE (b) CNN model MAPE (c) Hybrid LSTM-CNN model MAPE (LSTM first) (d) Hybrid LSTM-CNN model MAPE (CNN first)

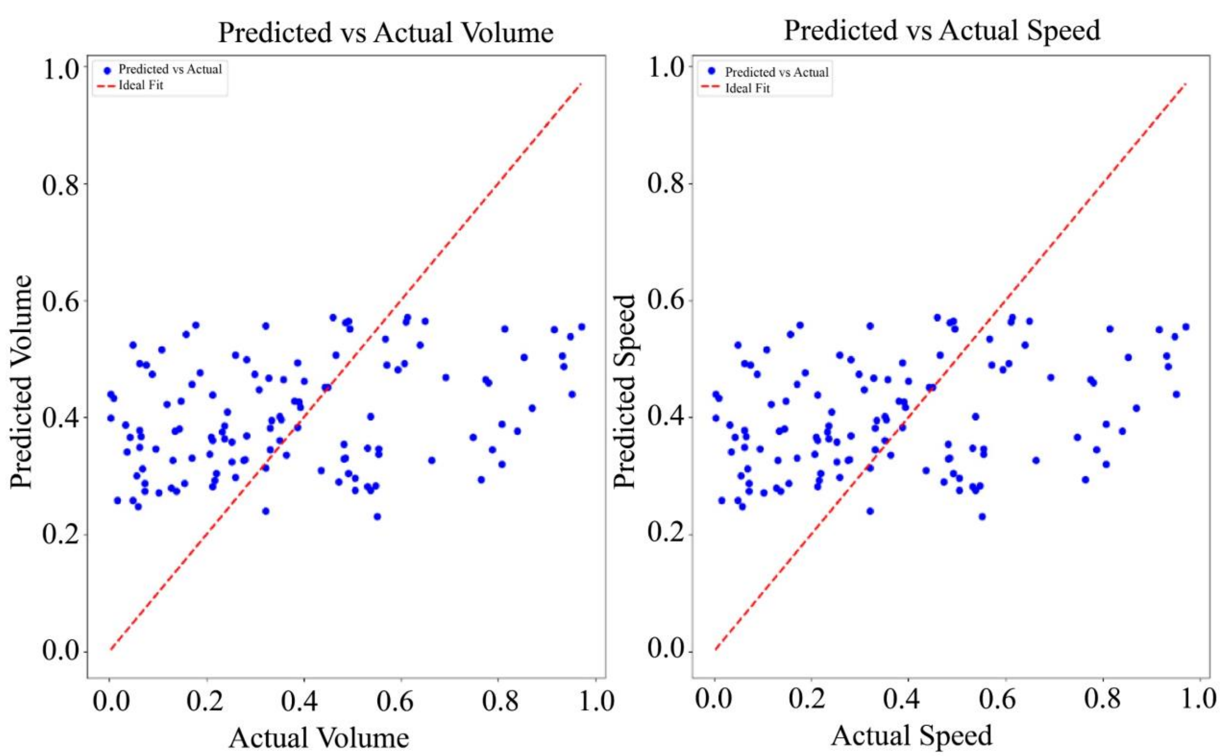


Fig. 8 Prediction vs. Actual values for (a) Traffic volume and (b) Traffic speed using the hybrid LSTM-CNN model.

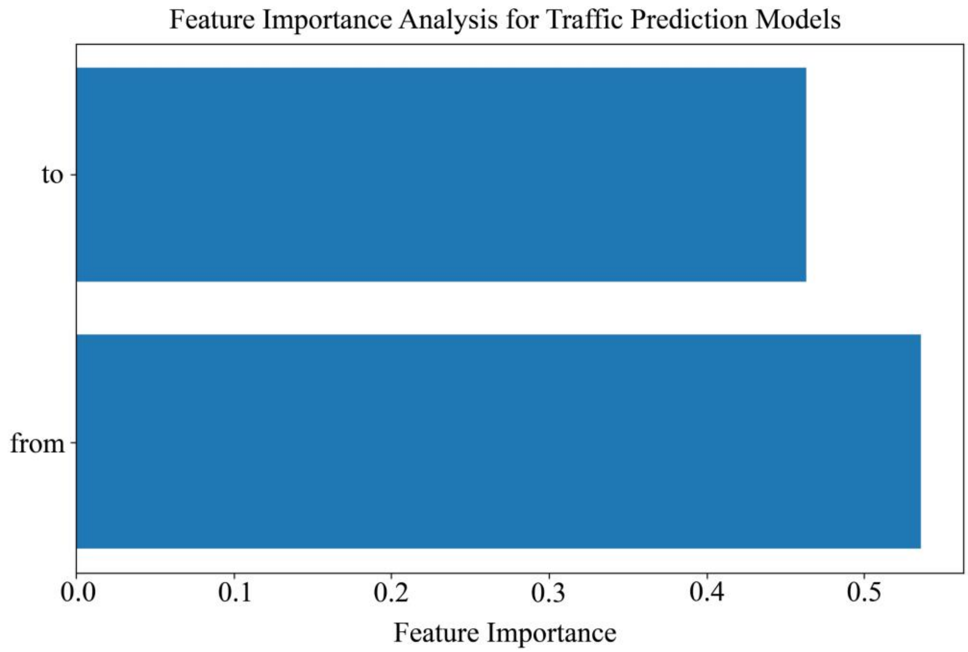


Fig. 9 Feature importance analysis for traffic prediction models

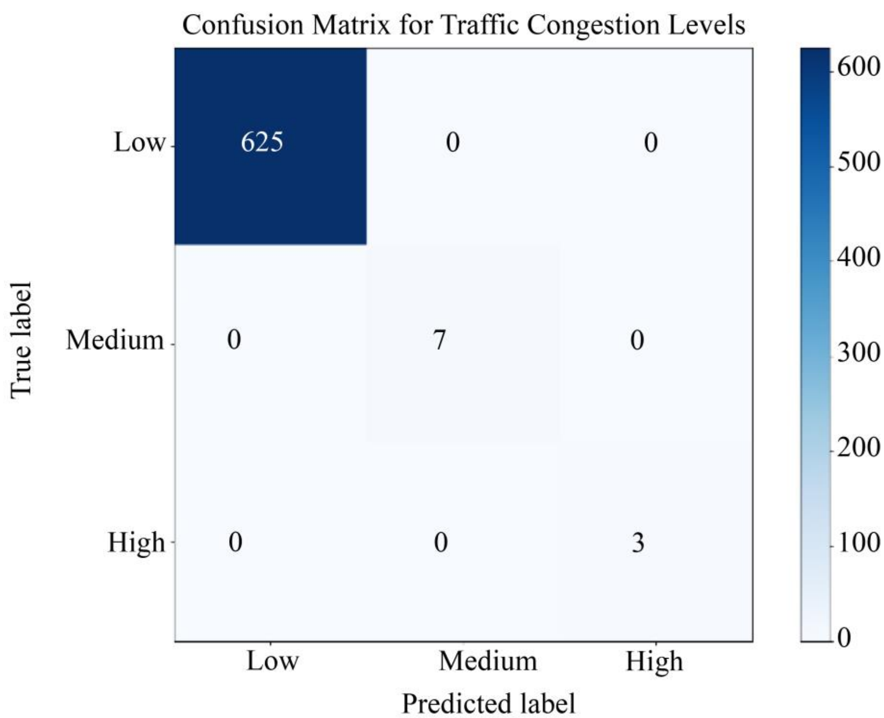


Fig. 10 Confusion matrix for traffic congestion levels

4. Conclusion

This study showed the enormous potential of the hybrid model of LSTM and CNN for improved accuracy in traffic-flow forecasting models derived from its ability to capture the temporal and spatial dependencies embedded in traffic data. The model was exhaustively tested on a completely established dataset that originated from diverse sources of inputted data—the three lane-wise sensors, reports of volume, speed, as well as occupancy collected from highway leased line sensors. The metrics R-squared, MAPE, and RMSE were persistently directed to the hybrid model, dominating the basic LSTM and CNN models. For LSTM-CNN, again, the much better predictive accuracy is proved by the best validation loss obtained equal to 0.05 with a MAPE of 0.08. Concretely, the hybrid univariate model performed with an R^2 of 0.063, a MAPE value of 3.84%, and an RMSE value of 0.250 with the first added transformation LSTM, whereas having the first added transformation CNN arrived with an R^2 value of 0.054, MAPE 4.15%, and RMSE 0.252. On the other hand, the LSTM-only model resulted in an R^2 score of 0.081 and MAPE and RMSE of 3.66% and 0.248, respectively. The CNN-only model had an R^2 score of 0.029, MAPE of 4.07%, and RMSE of 0.255. These results emphasize that the hybrid model is very effective in dealing with different intrinsic complexities in traffic patterns for a much stronger solution in making traffic predictions with greater accuracy and action. The enhanced accuracy of the hybrid model can hugely aid traffic management and planning, including the rough reduction of congestion and rise in road safety.

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