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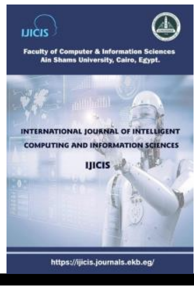

HYBRID CNN AND LSTM MODEL (HCLM) FOR SHORT-TERM TRAFFIC VOLUME PREDICTION

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Abstract: *Managing traffic on roads within cities, especially crowded roads, requires constant and rapid intervention to avoid any traffic congestion on these roads. Forecasting the volume of vehicles on the roads helps to avoid congestion on the roads by directing some of these vehicles to alternative routes. In this paper, it is studied how to deal with road congestion by using deep learning models and Time series dataset with different time intervals to predict the volume of road traffic. Hybrid CNN and LSTM model (HCLM) is developed to predict the volume of road traffic. Determining the suitable hybrid CNN-LSTM model and parameters for this problem is a major objective of this research. The results confirm that the proposed HCLM for time series prediction achieves much better prediction accuracy than autoregressive integrated moving average (ARIMA) model, CNN model, and LSTM model for Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) measures at a time interval of 25 min and, 75 min. The time required to build these models was also compared, and the model HCLM was outperformed as it required 70% of the time to build it from its nearest competitor.*

Keywords: *Traffic Volume, Time Series, Deep Learning, CNN, LSTM, CNN-LSTM ARIMA*

1. Introduction

Most cities suffer from traffic congestion, which leads to a great loss of time, an increase in the number of traffic accidents, and a rise in air pollution as a result of the large concentration of gases emitted from cars. Therefore, traffic control must be continuously developed to reduce congestion on the roads. Providing information on a continuous basis to traffic on the roads helps traffic management operations and thus prevents the occurrence of congestion on these roads [1]. The traffic flow prediction can be a short-term, mid-term and long-term prediction. In any case, the short-term prediction is the perfect fit, as

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it is able to early detect the volumes of vehicles on the roads, reducing the impact of negative congestion [2][3]. Short-term (time horizon from 5 to 30 min) traffic flow prediction is used to predict near future traffic flow. This Short-term prediction allows to monitor real-time traffic to avoid congestion on the roads around the clock [4]. Short-term traffic flow volume prediction helps manage road traffic by supporting intelligent transportation systems to deal with different situations.

There are many approaches to conducting short-term traffic flow volume predicting based on time series data, and today's most of them relied on machine learning and deep learning algorithms. Time series are things that can be observed in succession over time periods. These observations can be weather data during a year by recording hourly data, or stock market prices during a month by recording this data daily. Time series is relied upon for forecasting, as it includes essential patterns that can be relied upon in predicting future values.

In this paper, a time series prediction model is developed to predict traffic flow volume with different time interval based on time series that represent the recorded road traffic volume during regular time intervals. Improved hybrid CNN-LSTM model were used as a deep learning model to predict the future time steps of traffic flow volume. The prediction was based on the time steps 5, and 15 to avoid congestion before it occurs. The next section, it reviews a study of the previous literature related to predicting the volume of traffic flow on roads. As for the third section, how to train and build the proposed model is explained in detail. Finally, the results obtained by comparing the proposed model and other models were explained and discussed.

2. Related Work

Since the context of this paper deals with the process of predicting the volume of traffic flow on roads using the time series predicting model, this part of the paper studies previous literature reviews to predict traffic flow volumes using different methods. In previous studies, the prediction models for short-term traffic flow volume were divided into traditional methods that depend on machine learning and methods that depend on deep learning. Therefore, we will review previous studies that used machine learning and deep learning methods.

In research [5], several supervised learning algorithms were compared to predict the state of transportation on the roads, which includes everything that goes on the roads such as cars, buses and bicycles. The methods that were compared are KNN, SVM, decision tree and RF, where the RF and SVM methods being the best performing. Binary tree and K-nearest NEIGHBOR nonparametric regression are used in [6] to predict the flow of traffic in real time. The online-based SVR and weighed learning method are combined in [7] to create a model capable of predicting short-term traffic flow. This model has been compared to machine learning models with the exclusion of neural networks models, and the preference of this method over other methods has been clarified. In 1976 the Autoregressive Integrate Moving Average Model (ARIMA) was introduced [8]. This model was used in [9] to predict the volume of traffic on the highways.

In [10], the Beidou navigation satellite system was used to collect data and train an LSTM-based method to build a model to predict traffic speed in the presence of unusual congestion. Researchers in [11] designed a framework to predict traffic flow based on LSTM method. This framework addressed the problem of noise in the data, such as the presence of road maintenance, by using Empirical Mode Decomposition, Ensemble Empirical Mode Decomposition and Wavelet. In research [12] a model is developed to predict traffic flows in real time, using LSTM. Traffic flows data for the previous 24 hours is used to predict the flow of traffic on the roads in the next hour, taking into account some weather phenomena. Also, LSTM was used in [13] to build a short-time model to predict traffic taking into account missing data by inferring it using multiscale temporal smoothing.

LSTM and CNN methods are combined in [14] to design a Conv-LSTM model to predict traffic flow by extracting the features of spatial-temporal information for traffic flow. The researchers at [15] also developed a method based on one-dimensional convolution neural network and LSTM to predict short-term traffic flow. The spatial information in the traffic flow data is obtained by 1DCNN, while the temporal information is obtained by the LSTM. Finally, this information is used in multiple layers to get the prediction results, which were good. A framework (HMDLF) is proposed in [16] for short-term traffic flow prediction, using one-dimensional Convolutional Neural Networks (1D CNN) and Gated Recurrent Units (GRU). Where CNN and GRU are combined to develop a hybrid multimodal to improve prediction accuracy in real time.

TrafficWave was used in Research [17] to analyze time series traffic forecasting. TrafficWave is a deep learning architecture for time series analysis and relies on RNN methods. Addressing the effects of weather on traffic flow was the goal of the researchers in [18], where a gated recurrent unit-based (LSTM) deep learning was used to predict traffic flow on highways. Now, after reviewing the previous literature, we will focus on the shortcomings which are the accuracy and speed of prediction, in order to be able to provide a model capable of predicting in real time and with high reliability by choosing the best CNN structure suitable for this problem.

There are several key differences between the proposed approach in this research and those studied above in related work. We present a new architecture for integrating CNN and LSTM techniques in addition to controlling network parameters and number of nodes in each layer, which provides a model with high accuracy within a short time compared to previous approaches.

3. Proposed Model

The performance of deep learning models varies greatly depending on the architecture of network and the values of Hyper-parameters. Therefore, determining the architecture and Hyper-parameters is a major challenge when developing the deep learning models. In this section, the proposed HCLM we relied on to solve the time-series prediction problem is explained. Firstly, the nature of the problem that we are dealing with in this research has been clarified by the dataset used to train and evaluate the proposed model. The best parameter for HCLM, such as the epoch number and the learning rate parameters, is also selected. Finally, the architecture of HCLM, which gave the best results when dealing with the problem of predicting time series, was explained in detail.

3.1. Dataset

To train and test the HCLM that proposed in this research, a dataset in [19] for a road in a California was used. This data records the traffic volume on this road for two months for training data and one month and half for testing, and this data is recorded every 5 minutes. Vehicle's Volume for this period of both the Training and testing data shown in Figure 1. Table 1 shows a sample of Training and testing data containing the details and features of the data that was recorded for the movement of vehicles.

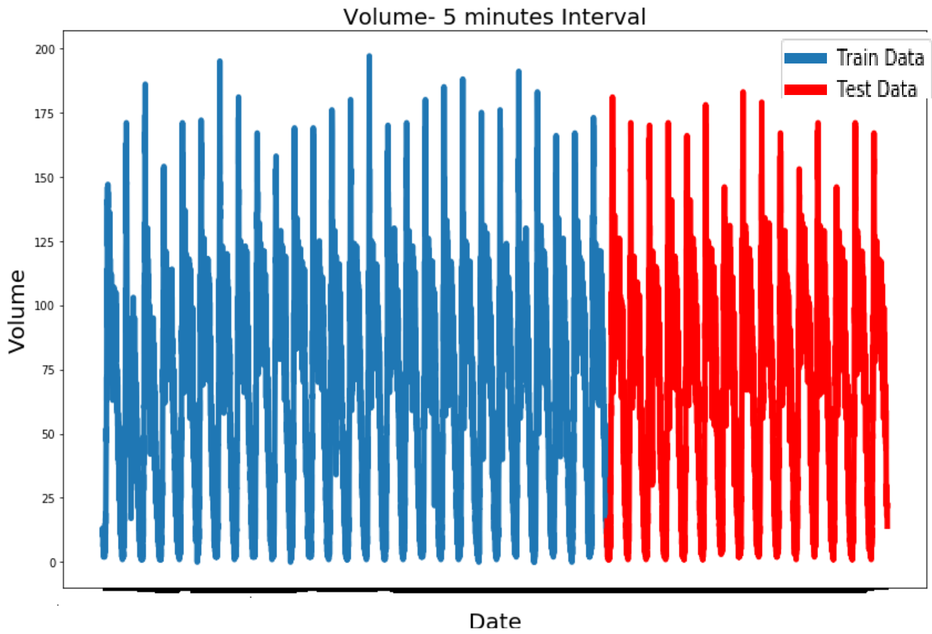

Figure. 1: Vehicle’s volume for the training and testing data

Table 1: Vehicle’s Volume Dataset Sample

Time	Flow (Veh/5 Minutes)
4/1/2016 0:00	12
4/1/2016 0:05	13
4/1/2016 0:10	11
4/1/2016 0:15	13
4/1/2016 0:20	10
4/1/2016 0:25	10
4/1/2016 0:30	13

Due to the impact of large input values on the stability of deep learning models, its weakness and its inability to generalize, so a pre-processing process (rescaling for input data) was used on the dataset before using it in the training and testing processes for the CNN-LSTM model. MinMaxScaler in python is used to perform normalization on input data according to the following equation:

$$y = \frac{(x - min)}{(max - \min)} \quad (1)$$

Where max and min are x values that represent the volume of vehicles on the road. We can now split the dataset into the set of features (x) and label (y) that we want to predict. Due to the nature of the problem, features (x) represent successive traffic volumes for the number of past observations (lag) while y represents the next traffic volume to be expected as explained in the following equations:

$$x = x_1, x_2 \dots \dots x_{lag}$$
$$y = x_{lag+1}$$

The time series is a series of real values recorded during a predefined time step, where in this research it is 5 minutes. The number of vehicles passing through the road is recorded regularly every time period t (five minutes). The features and labels that will be used to train and evaluate proposed CNN-LSTM model and other models for lag=5 can be represented as follows:

$$[\,[x_1, x_2 \dots \dots x_5]\ [x_2, x_3 \dots \dots x_6] \dots \dots \dots \dots \dots \dots [x_{n-5}, x_{n-4} \dots \dots x_{n-1}]] \quad (2)$$
$$y = [x_6, x_7 \dots \dots x_n]$$

$$where\ n = dataset\ size$$

3.2. HCLM Architecture

CNN has the ability to perform automatic feature extraction, so it will be relied upon to be the first layer in HCLM. Since the problem is a time series prediction we will use 1D CNN layer to receive the input that has a sequence form. This layer provides a more accurate representation of the features, which are then passed to the LSTM layer in HCLM. The accurate representation of these features leads to the ability to learn temporal dependencies more accurately by LSTM layer. The HCLM architecture that got the best results in time series prediction is shown in Figure 2, which consisted of one input layer, one output layer and through them the next layers, CNN layer (128 nodes, relu), Max Pooling Layer, Batch Normalization Layer, LSTM layer (20 nodes, relu), Flatten Layer, Dropout layer, and finally dense (32 nodes, relu) layer.

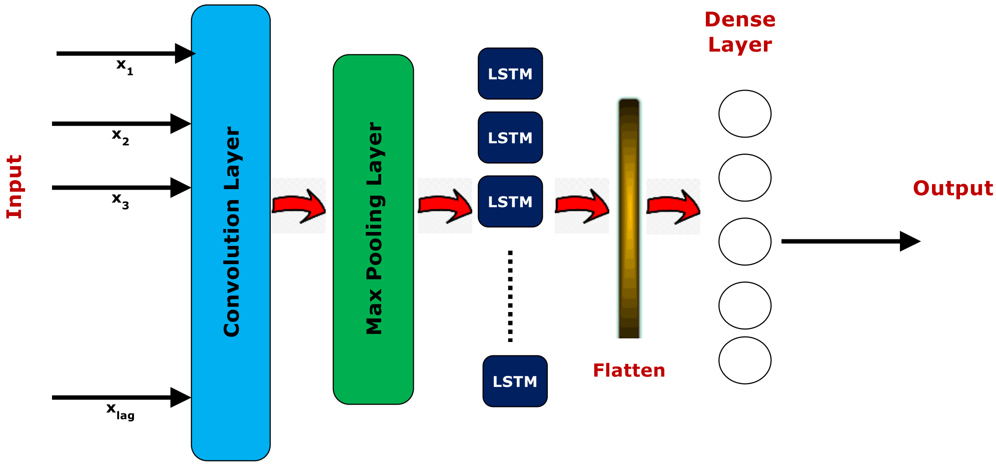

Figure. 2: The proposed hybrid CNN and LSTM model architecture (HCLM)

The input is passed to the first layer, which is the CNN layer responsible for extracting features and creating feature maps. The Max pooling layer is used in HCLM to reduce the number of parameters, by relying on summarization for features in a region. This works on generalizing the features that extracted and reduce the computing time of the training process.

The feature map generated from the Max Pooling Layer after summarization is passed to the LSTM layer to perform the learning process. Each cell in LSTM layer have three gates which is forget gate, input gate and the last one is the output gate as illustrated in figure 3. This gates are responsible for learning the complex dependencies between dataset, where the forget gate determines the amount of information that must be saved while removing the ineffective information using the input xt and hidden state ht. The data generated from the forget gate is passed to the next gate, the input gate, to update the cell status. Finally, the output gate gets the input and new cell status, Ct, to compute the new hidden state, ht, that contains information about previous input. A flatten Layer follows the LSTM layer to flatten its output to be ready to calculate the final output.

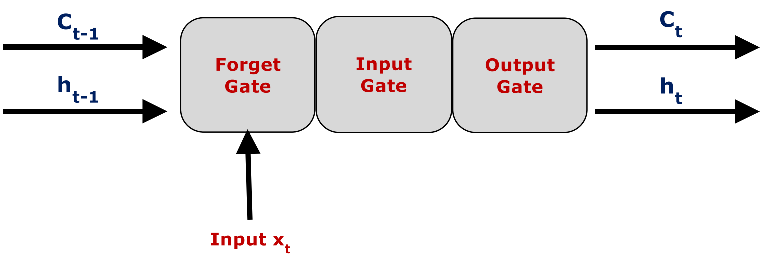

Figure. 3: LSTM cell

A dense layer with 16 nodes takes the generated output from every neuron of LSTM layer to apply nonlinear transformation. And finally a dense layer with only one node is responsible for generate the final output.

3.3. HCLM Hyper-Parameters Optimization

The epochs size tested were 10 to 100, and the best value was achieved at 40 epochs, and the results were stable after that and did not improved with increasing number of epochs. In addition, the best value for Batch size was determined as 25 where the results for MAE and RMSE were the best. The learning rate that gave the best results was 0.0001 and the effect of changing this value on the results was good for choosing the best learning rate for HCLM enhancement. It was observed that the value of 0.0001 for the learning rate was the best because the output was Good Fit learning curves, which represent the model's ability to generalize and avoid over-fitting and under-fitting. Adam Optimizer is always the best choice for deep learning algorithms, featuring fast boot time with low memory requirements and finally less tuning. Table 2 shows the value of all these hyperparameters.

Table 2 Optimum Hyper-Parameters for HCLM

Hyper-Parameters	**Value**
Epoch	*40*
Batch Size	*25*
Learning Rate	*0.0001*
Optimizer	*Adam*

The results in the next section show the ability of HCLM to predict time series with high accuracy compared to other models.

4. Results and Discussion

The experiment was aimed at evaluating HCLM, which can predict the volume of vehicles on roads, and comparing it with several other models. In this section, the metrics that we relied on for evaluation and comparison were reviewed, then the results were presented and discussed.

4.1. Performance Measurement

In this paper, three criteria were used to evaluate the proposed HCLM that was built using hybrid CNN-LSTM against ARIMA, LSTM and CNN Models. These criteria are mean absolute error (MAE), and Root Mean Squared Error (RMSE). MAE and RMSE reflect the accuracy of the predictions of the proposed model in this research, and the deviation of the predicted values from the actual values. Where MAE represents the average size of errors between the predicted values and the actual values without addressing their direction, i.e. the absolute value. As for RMSE, it measures the Root of the Mean of the Square of Errors, and the difference between MAE and RMSE can be used to determine the variation in the errors in a set of forecasts. These criteria can be defined for real traffic flow volume y_i and prediction volume yˆ as follows:

$$MAE = \frac{1}{n}\sum_{1}^{n} |\, y_i - \hat{y} \,| \tag{3}$$

$$MSE = \frac{1}{n}\sum_{1}^{n} (y_i - \hat{y})^2 \tag{4}$$

$$RMSE = \sqrt{MSE} \tag{5}$$

In addition, the time required to build a deep learning model is an important factor in evaluating the proposed HCLM that was built using hybrid CNN-LSTM against ARIMA, LSTM and CNN Models, especially with the increasing size of time series data.

4.2. Experiment Result

The HCLM proposed in this research to predict time series is evaluated and compared with CNN, LSTM, and ARIMA models using a number of time lags. Where the prediction was made within 5, 15 lags, that is, within 25, and 75 minutes, since each lag represents 5 minutes. The traffic volume that was predicted by the proposed model was compared with the original traffic volume data contained in the test data to obtain the values of the two criteria (MAE, and RMSE). These values were compared with the values of the models CNN, LSTM, and ARIMA to clarify the efficiency of the proposed model, HCLM, that presented in this research. Table 3 shows the results for the two measures, MAE, and RMSE, for each of the CNN, LSTM, HCLM, and ARIMA models for different lags. Figure 4 illustrates also the comparison between the four models with respect to MAE, and RMSE values. As we note from the results of these experiments, the HCLM for analysing time series to predict future values succeeded with a great degree of accuracy compared to the ARIMA, CNN, and LSTM models Where the lowest value of the RMSE scale is the best value as it expresses the square root of the deviation of the expected values from the real values.

Table 3: The Prediction Results for HCLM, CNN model, LSTM Model, and ARIMA Model

Lag	*Metric*	*CNN*	*LSTM*	**HCLM**	**ARIMA**
5	*MAE*	7.6	*7.6*	*7.4*	*10.4*
	MSE	106.1	*106.5*	*101.7*	*211.3*
	RMSE	10.30	*10.32*	*10.08*	*14.53*
15	*MAE*	*7.2*	*7.2*	*6.9*	*10.4*
	MSE	*96.3*	*95.9*	*89.9*	*211.4*
	RMSE	*9.8*	*9.7*	*9.4*	*14.5*

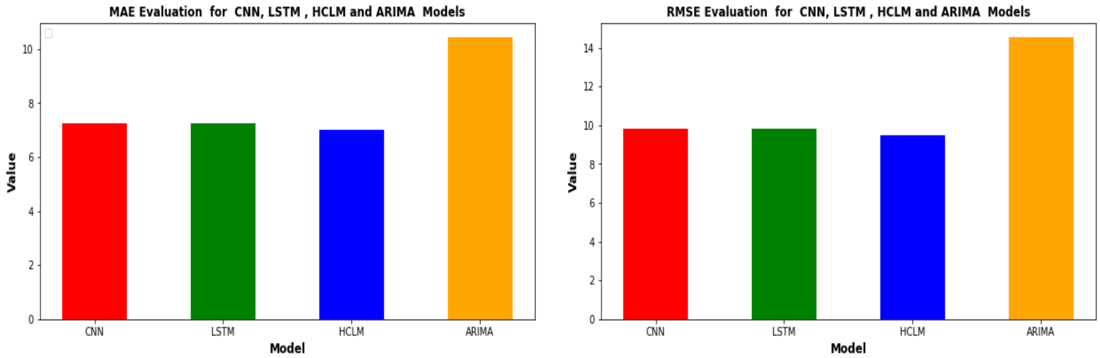

Figure. 4: MAE and RMSE comparison for CNN, LSTM, HCLM and ARIMA model

The time required to build the four models, as illustrated in table 4, was also compared to show the speed of building the HCLM model compared to the CNN model, LSTM Model, and ARIMA models. In Figure 5, it can be seen that the construction of the proposed model in this research, HCLM, was done faster than other models, especially when the values of lag are increased.

Table 4: The Model Building Execution Time for HCLM, CNN model, LSTM Model, and ARIMA Model

Lag	*Metric*	*CNN*	*LSTM*	HCLM	ARIMA
5	*Time*	88	*120*	*81*	*166*
15	*Time*	*176*	*234*	*109*	*169*

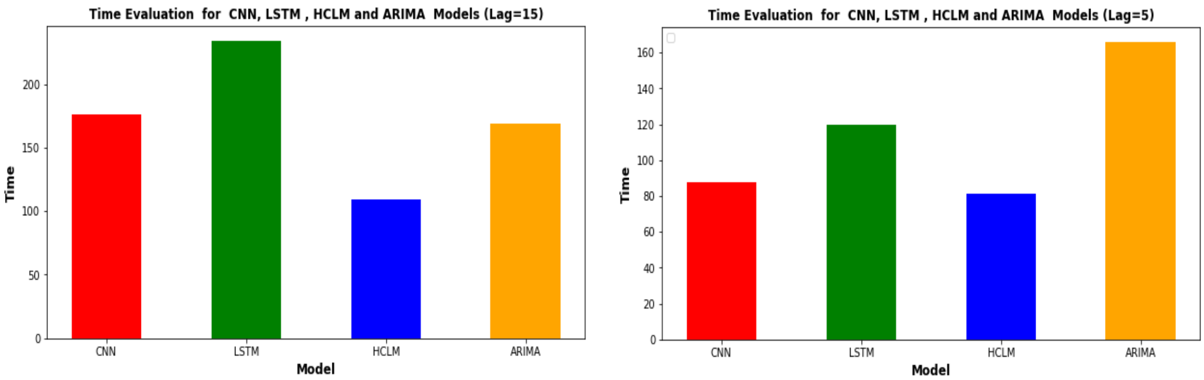

Figure 5: Execution time comparison for CNN, LSTM, HCLM and ARIMA model

During the training process, HCLM performance is measured at each epoch by using learning curves which illustrates training and validation loss. According to learning process, the HCLM does not suffer from overfitting and underfitting problems, which makes it capable of generalization.

From the previous results, we can confirm that the proposed HCLM predict the vehicles volume with high accuracy. Figure 6 illustrates the volume forecasting against the actual volume using the proposed HCLM for the first 100 sample from test data at lag values equal to 5 and 15.

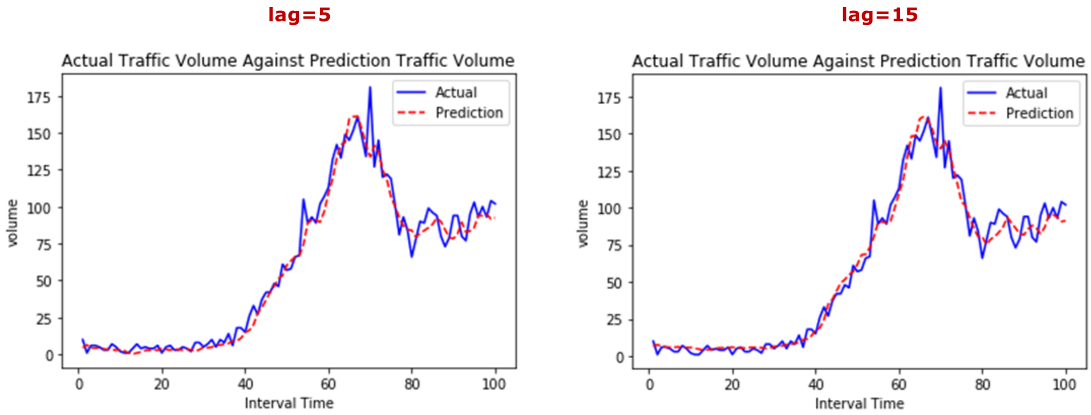

Figure 6. Actual vs predicted traffic volume by using HCLM

5. Conclusions

Traffic congestion on the roads drains a lot of countries' resources, so proactive measures must be taken to avoid congestion on the roads. There are several techniques that have been used to analyze traffic volume data over a period of time to predict future traffic volume to help direct traffic to alternative routes. In this paper, a road traffic prediction model is designed using CNN and LSTM models to obtain reliable and accurate results. The results of this model, HCLM, were compared with three models, the first designed using the LSTM model, the second using the CNN model, and finally the third using the ARIMA model. Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) measures at a time interval of 25 min and, 75 min was used to compare these models. The results were accurate for the proposed HCLM, and the overfitting and underfitting of this model was disappeared due to the use of maximum pooling and dense layers allowing it to be generalized. In addition, the HCLM model clearly outperformed when comparing the build time with other models, especially with the increase in the size of the lag.

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