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Research Article

An Artificial Neural Network Model for Short-Term Traffic Flow Prediction in Two Lane Highway in Khulna Metropolitan City, Bangladesh

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Abstract

Short-term traffic flow prediction is one of the most significant research topics in traffic engineering. It is instrumental in designing a more modern transport network to manage traffic signals and reduce congestion. Short-term traffic flow is a challenge that a third-world country like Bangladesh is all too familiar with. Like the other cities of Bangladesh, Khulna Metropolitan City is gradually becoming more aware of this situation. The Khulna-Jashore National Highway (N-7), which runs through the city and provides a linear shape, serves as the backbone of the Khulna Metropolitan City traffic flow. This study developed an Artificial Neural Network (ANN) model for the short-term Traffic Flow Prediction on Two-Lane Highway in Khulna Metropolitan City, Bangladesh. Data was collected from March 1, 2021, through June 30, 2021, during 600–900 hours and 1200–1500 hours. Good-quality electronic cameras recorded the vehicles at the full designated length. The regression graphs displayed the network outputs with targets for the training, validation, and test sets. The various speed level parameters for which the fit is reasonable for all data sets, with R values of 0.98426 in each case. The various traffic volume parameters for which the fit is reasonable for all data sets, with R values of 0.96758 in each case. The model's superiority is indicated by its low mean squared error values. This study demonstrated that the neural network has a good prediction effect on specific road traffic flow, which can achieve the goal of short-term prediction and has improved practicability through testing on real traffic data. This study provides an opportunity to provide a suitable alternative for short-term traffic flow forecasting in Khulna Metropolitan City with traffic flow conditions for two-lane undivided highways.

1. Introduction

The size of the urban transport networks is expanding, and the volume of vehicles is likewise growing as the urban grows. The challenge of traffic congestion has progressively become inescapable. It is required to accurately forecast the traffic network's short-term traffic flow and give directions based on the predictions. Also, provide competent decision-making guidance to the authorities in designing and constructing public transportation infrastructure [1]. Short-term traffic flow forecasting is an interdisciplinary study topic that combines efforts from various disciplines, including mathematics, computer science, and engineering. The dynamic, complicated, and random character of traffic makes real-time traffic parameter prediction difficult [2]. Short-term traffic flow forecasting examines past traffic datasets and predicts traffic flow for the next 5–30 minutes. When city planners and police officers estimate the traffic condition in the next 5 minutes, they can appropriately redirect traffic to alternate ways if high congestion is expected in the next few minutes [3]. Most traffic flow forecasting systems are focused on uniform traffic flow, which does not appear appropriate for mixed traffic [4]. Models that reflect mixed traffic situations are urgently needed to solve challenges related to mixed traffic flow [5, 6].

Many researchers have looked into short-term traffic flow forecasting and established different approaches. Two common techniques for traffic flow prediction are statistical techniques and Artificial Neural Network (ANN) [7]. Over the past few years, these approaches have overtaken popular research strategies. Several techniques applied for short-term traffic flow forecasting include K-nearest neighbors [8, 9, 10], Support vector machines [11], local linear regression [12], fuzzy logic-based models [13], and fuzzy-neural networks [14]. Several studies have combined different models to enhance modeling efficiency and traffic flow forecasting reliability for a given road section [15]. Because of its random and high non-linear fitting ability, ANN is popularly used in traffic flow forecasting [16-18]. The accuracy of short-term traffic flow forecasting can be increased by utilizing the characteristics of traffic patterns based on conventional prediction models. Several neural network models have been widely used to estimate short-term traffic flow as standard forecasting methodologies. Deep learning algorithms have been effectively applied over the past few years to forecast traffic flow [19].

ANN is also one of the Artificial Intelligence (AI) techniques that can forecast traffic flow better than any other model [20]. Traditional statistical models lack ANN models' flexibility, precision, generalization, and high forecasting capacity [21-23]. It is now widely acknowledged that intelligent transportation systems (ITS) must be able to estimate traffic flow, particularly short-term traffic flow forecasting. For the development of real-time, dynamic, and incredibly effective traffic management and control systems, precise short-term traffic information prediction is essential [24].

Bangladesh, a South Asian country with a population of 161.3 million people, is a high-density-developing country [25]. In several cities across the whole country, traffic is extremely congested. The third largest city in Bangladesh is Khulna Metropolitan City, covering 45.65 km2 and housing over 1.50 million people at a population density of 67,994 persons per square kilometer. This city's total number of roads is 1215, totaling 356.64 kilometers [26, 27]. In practically all Bangladesh's cities, traffic congestion is a prevalent issue. The Khulna Metropolitan City has recently become increasingly congested. Whenever a city's transport system can no longer handle the volume of traffic, traffic congestion occurs [28]. Short-term traffic flow forecasts have received much attention due to the current increase in traffic congestion. Analyzing past traffic flow, this forecasting approach can estimate how traffic will vary soon. This study aims to develop an Artificial Neural Network Model (ANN) for short-term traffic flow prediction in a two-lane highway in Khulna Metropolitan City. Developing a more advanced transportation network capable of managing traffic signals and reducing congestion in this city will be extremely important.

2. Literature Review

In traffic planning and design operations, it is essential to forecast traffic parameters such as volume, speed, density, trip time, headways, and so on. In Intelligent Transportation System (ITS) operations, short-term forecasting of all these parameters is significant. Various techniques have been published in the research for forecasting traffic variables, including real-time methods, time series analysis, statistical methods, historical methods, and machine learning [29]. The development of traffic forecasting models can facilitate obtaining the entire potential of ITS and advancing preemptive transportation management and thorough traveler data services [30].

Considering historical traffic statistics, this study uses an ANN model to forecast traffic volume in the short term. An ANN model was developed for urban traffic flow prediction [31] and short-term inter-urban traffic predictions [32]. Ledoux [31] suggests a traffic flow approach focused on collaboration-based neural networks to incorporate them into a real-time adaptable urban traffic management network [31]. An ANN was combined with Bayes' theorem to forecast short-term traffic flow volume on a motorway [33]. Back propagation and radial basis function neural networks are separate predictors developed and merged linearly into a Bayesian mixed neural network model. A comparison study between Statistical and ANN mixed models was also developed [34] to predict traffic flow volume in an urban region. Experiments were conducted on three types of real streets, and the findings suggest that the suggested technique surpasses the best of the strategies it combines. Castro-Neto et al. [35] describe applying the supervised statistical learning technique, an Online Support Vector Machine for Regression, to forecast short-term highway traffic flow under both usual and exceptional circumstances. Online Support Vector Machine for Regression seems to be a more effective tool than Gaussian Maximum Likelihood for deployed ITS systems geared toward quickly responding to real-world unusual and event scenarios [35]. Due to the degree of complexity and randomness of the traffic flow, short-term forecasting still presents a challenge. The problem was addressed by Lu et al. [36], who suggested a combined prediction approach for short-term traffic flow based on the autoregressive integral moving average (ARIMA) model and long short-term memory (LSTM) neural network [36]. Lv et al. [19] present a unique deep-learning-based traffic flow prediction system that naturally considers temporal and spatial correlations [19]. Chen et al. [37] use the particle swarm optimization algorithm to solve the slow convergence rate and local optimal problem of the wavelet neural network (WNN) prediction algorithm. This is due to the WNN's extreme non-linear processing power, self-organization, self-adaptation, and learning ability [38]. The Levenberg-Marquardt (LM) algorithm and the hybrid exponential smoothing approach are employed in Chan et al.'s novel neural network (NN) training approach, which intends to enhance the extrapolation capabilities of earlier techniques for training NNs for short-term traffic flow prediction [39].

Bangladesh, for example, has few resources for collecting traffic flow statistics. Consequently, appropriate traffic flow studies are badly ignored [40]. Only a few studies have considered traffic flow, but their goal was not limited to short-term traffic flow predictions. Every forecasting model, according to the available research, has a specific scope of application

3. Materials and Methods

3.1. Study Area

The study area falls under the purview of the Khulna Metropolitan City (KMC). Khulna, the third largest city in Bangladesh and second port of entry, has expanded unplanned. The sites studied are Khulna Bypass Road and Khulna - Jashore Road in the Khulna Metropolitan City. The data was collected near Khulna Zero Point and Fultala.

3.2. Data Collection and Preprocessing

The data for this research were gathered along a 2-lane separated roadway segment of National Highway-7 (N-7) through Khulna and Jashore. The Two locations selected for data collection were L1 (near zero point) and L2 (near Fultala). Data was collected from March 1, 2021, through June 30, 2021, during 600 - 900 and 1200 - 1500 h. Outstanding quality electronic cameras were utilized to record the vehicles at the full designated length. The traffic flow was supposed to be simple, with no directional changes. A timed effect was applied to collect all the data. On the computer, the recordings were played again, and features were retrieved. Eight groups (08) were formed out of all of the vehicles. The number of cars traveling across a selected length was physically counted to provide the vehicle number. Divide the trap length (80 m) by the time difference between entering and exiting the trap to get the speed of each vehicle in each category. Table 1 summarizes the statistical properties of speed and traffic volume observation for a 5-minute interval.

Data was obtained at 5-minute intervals in both directions. Each day, data was collected at the same location for three hours during two peak periods (in the morning and late in the afternoon). About 90 data samples were collected by analyzing monolithically on both roadsides. During the study, a total of 12,045 data samples were collected. 15% of the samples were used for validation, 15% for testing, and 70% for training after the dataset was divided into three groups.

Table 1. Summary of speed and traffic volume observation for a 5-minute interval.

Vehicle Type	Khulna-Jashore Highway							
	Average Speed (km/h)				Traffic Volume			
	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD
Car	51.428	90	72	2.27	3	9	6.83	2.19
Bus	51.428	72	60	1.07	1	3	2.33	0.94
Truck	51.428	90	60	1.09	3	19	10.09	5.84
Auto	32.73	45	40	1.00	4	9	5.25	1.15
Van	24.00	36	33	1.53	3	5	4.02	0.82
Motorcycle	40.00	90	66	1.34	9	17	12.86	2.95
Cycle	12.86	21	16	4.89	1	3	1.53	0.76
CNG	45.00	72	59	0.94	5	18	12.61	5.48

3.3. Model Development

Data An ANN has three layers: an input layer that receives external signals, an output layer that sends external signals, and one or more hidden layers (non-linear input transformations entered into the network) [30]. Figure 1 illustrates a simple Artificial Neural Network architecture.

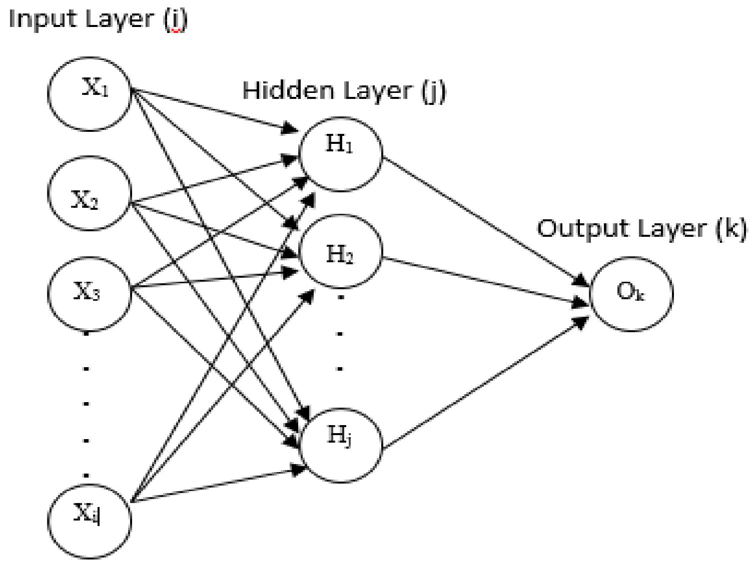

Figure 1. Simple Artificial Neural Network Architecture

The Multi-Layer Perceptron (MLP) is a common ANN network construction with a hidden layer. MLP Neural Network uses various learning algorithms, with back propagation being one of the most well-known and used in this study. We are attempting to develop an MLP Neural Network model to study its performance in predicting short-term traffic on a two-lane undivided roadway with mixed traffic scenarios. The following are the general steps of the developed model:

- Decide on the starting weights w_{ij} (0),
- The procedure below should be repeated until convergence (samples from k=1 to k=S):
  - Forward process: begin at the input node and compute, layer by layer, the input value I^l_{jk} and the output value O^l_{jk} of each node until you reach the network output value y'k,
  - Backward process: determine each layer's δ^l_{jk} and adjust the weights in accordance with the equation that follows:

$$w_{ij}(t+1) = w_{ij}(t) - \mu \frac{\partial Ek}{\partial Wij} \qquad \mu > 0$$

With much simulation effort, the resulting model has been applied to short-term traffic prediction. The entire architecture of the developed system is shown graphically in Figure 2.

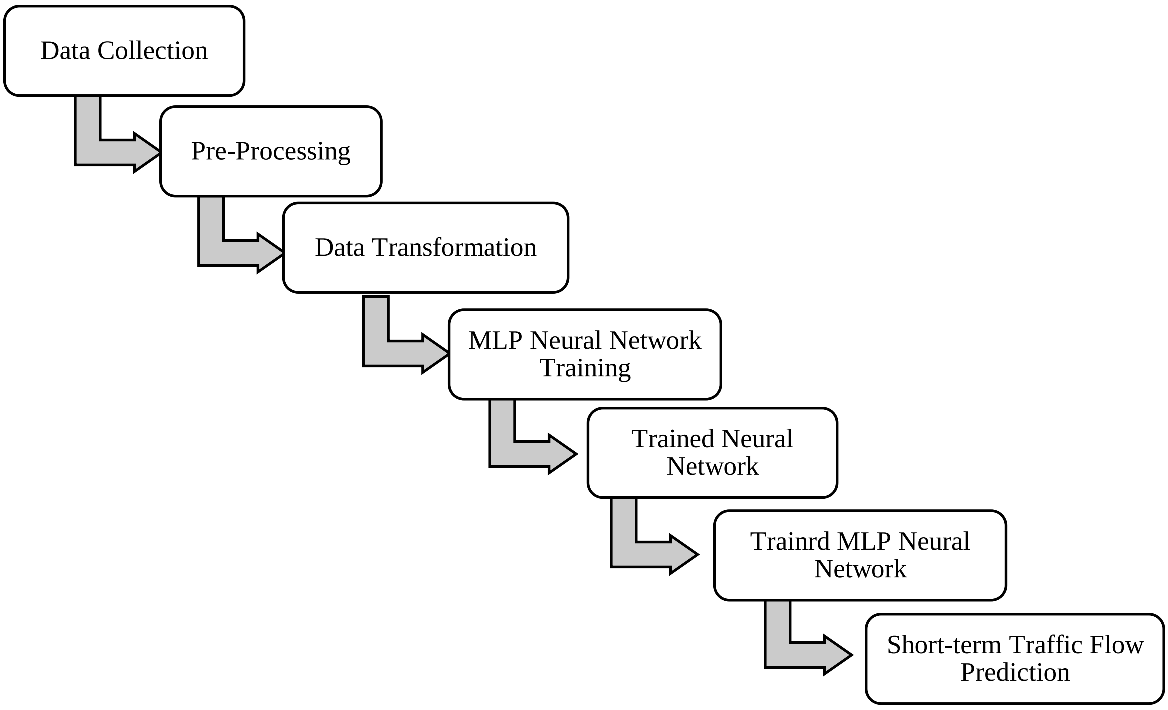

Figure 2. The Training Architecture of the developed system

MLP Neural Network training aims to achieve ANN output weight values that closely resemble the real target values. The MLP Neural Network was used in this study to predict traffic flow for the following 5 minutes. This model was built using 200 data samples, each with numerous properties such as location, time of day, eight vehicle categories, and the average speed of each type of vehicle. The average speed of many vehicle classes is applied to forecast traffic flow on an undivided two-lane highway: Microsoft Excel and MATLAB tools formulated and developed the ANN model. The trial-and-error strategy was used to obtain appropriate values for network parameters. The Least Mean Square Error (MSE) was adopted as a criterion for completing training sessions.

4. Results and Discussions

Various possibilities can be developed by varying the number of hidden layers in Neural Networks. Different ANN models were developed and trained on the dataset. The models were employed to estimate the coefficient of determination for various parameters. All of these models were trained at distinct epochs to alter the weight parameters in the network. The following regression graphs plot the network outputs against targets for training, validation, and test sets. The data should fall along a 45-degree line for a good fit, with the network outputs equal to the targets.

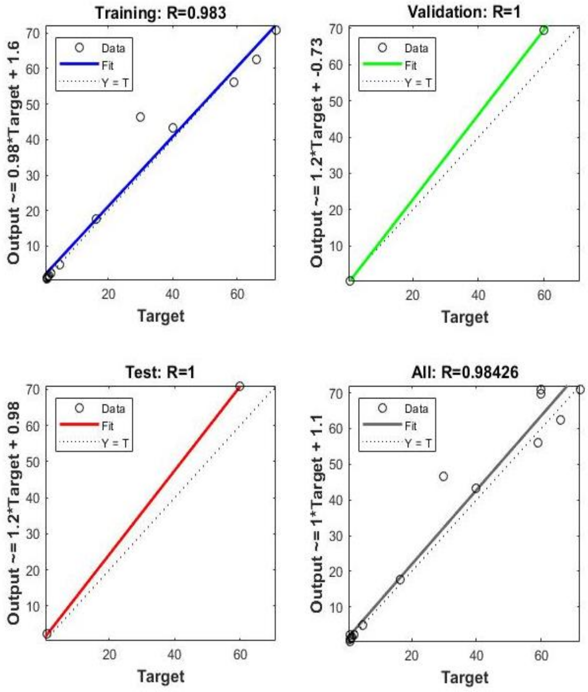

Figure 3. ANN output for different speed levels

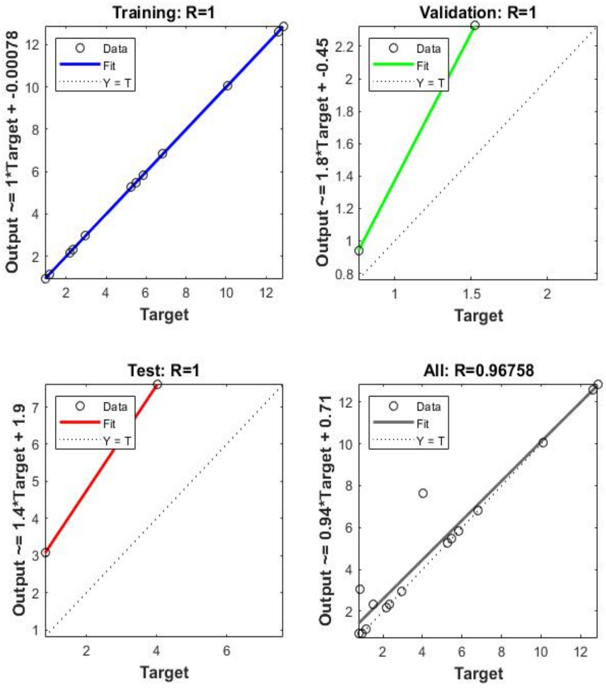

Figure 4. ANN output for different traffic volume

The prediction model is better if the R-value is as near 1 as possible. Figure 3 illustrates the various speed level parameters for which the fit is reasonable for all data sets, with R values of 0.98426 in each case. Figure 4 depicts the various traffic volume parameters for which the fit is reasonable for all data sets, with R-values of 0.96758 in each case.

A training, validation, and test error plot appeared in the training window to obtain the performance. The performance of the best two models trained on different numbers of epochs is shown in Figure 5. Figure 5 also shows that increasing the number of epochs decreased the MSE and enhanced the model's performance in both the training and validation stages.

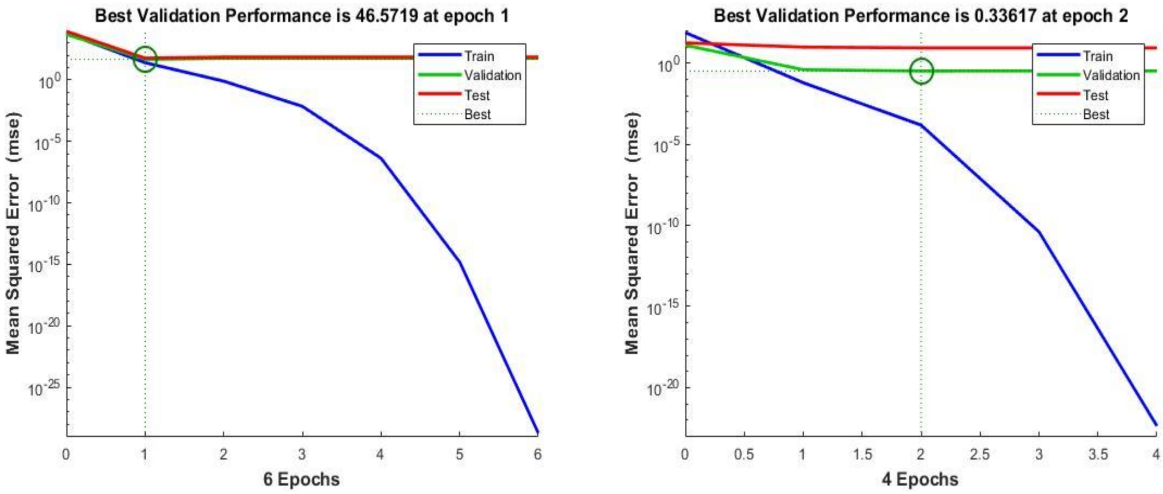

Figure 5. Error graph (MSE) versus learning epochs for best two models

Because of the following points, the finding in this research is appropriate: i) The mean-square error is minimal in the end, ii) The properties of the test set error and the validation set error are analogous, and iii) There has been no considerable over-fitting. Due to varying initial weight and bias values and different partitions of data into training, validation, and test sets, every time a neural network is trained, it can produce a different output. After a certain number of epochs, if there are no further improvements in prediction accuracy, this training can be stopped.

Using a back propagation neural network technique, the study developed a short-term forecasting model for two-lane, undivided highways with mixed traffic conditions. The main benefit of a back-propagation neural network is that, with more training, it can improve prediction accuracy by computing the prediction error and propagating back to the previous layers to adjust the weights. After a predetermined number of epochs, the training can be terminated without achieving any additional gains in prediction accuracy. This approach is highly methodical and precise in forecasting traffic volume performance.

In order to handle realistic circumstances of heterogeneous (mixed) traffic, this model considers the average speed of each vehicle category independently as an input variable. The results show that, even with less training, cross-validation, and testing data, ANNs remain consistently and steadily performant in traffic flow prediction, even when time intervals grow. However, ANN modeling offers many benefits over analytical and statistical methods. However, this study does have certain drawbacks. One of the study's primary limitations is that it only looks at the quality of traffic flow during off-peak hours. The data only includes daytime traffic flow characteristics; nighttime traffic flow patterns are not considered, which is another limitation. Subsequent research endeavours would prioritise gathering data sets over extended durations to encompass all plausible and achievable scenarios related to traffic movement.

5. Conclusions

This research work developed an Artificial Neural Network Model (ANN) model for predicting short-term traffic flow on a two-lane highway in Khulna Metropolitan City. The important advantage of an artificial neural network is that it evaluates the forecast error and continues to perpetuate it back to the earlier layers to change the weights, leading to increased predictive performance with further training. The model's superiority is indicated by its low mean squared error values. The ANN technique was used to model the short-term traffic flow data because it is a more flexible and assumption-free methodology capable of evaluating all traffic flow parameters. The findings unequivocally show that even when vehicle categories and related speeds were considered independent input variables, the ANN model could still accurately predict the number of vehicles. Even with an extended prediction time interval, the consistency of ANN performance is readily apparent. Therefore, it is concluded that this study can potentially provide effective solutions for short-term traffic forecasting for two-lane undivided highways in Khulna Metropolitan City with mixed traffic flow conditions. This study could also help with short-term traffic forecasts in Advanced Traveler Information Systems.

More specific informative datasets regarding traffic flow might be included in this study to improve it. Deep neural networks such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN), known to handle large data sets efficiently, should be used to evaluate massive data sets.

Declaration of Competing Interest: The authors declares they have no known competing interests.

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