STUDY ON SHORT-TERM TRAFFIC FLOW PREDICTION USING ARTIFICIAL NEURAL NETWORK AND GENETIC ALGORITHM

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ABSTRACT

Accurate short-term traffic flow prediction is essential for the implementation of effective traffic signal control, congestion management, intelligent transportation systems, and urban mobility planning. This study develops an ANN-GA hybrid framework to predict 15-minute traffic volumes on the Daulatpur – Notun Rasta corridor in Khulna Metropolitan City. Twenty-one consecutive days of evening traffic were recorded and manually analyzed across an off-peak hour and a peak hour. Direction-wise vehicle category counts together with temporal and contextual encodings such as cyclic time of day, day of week, and holiday indicator, were considered as input variables, and total volume per 15-minute interval was predicted. A feed-forward multilayer perceptron is optimized via genetic search over architecture and learning hyperparameters, trained with mean squared error loss, and validated through a hold-out test and five-fold cross-validation with early stopping. Model performance was assessed with combined numerical metrics and graphical diagnostics, including loss and error curves, actual vs. predicted comparisons, and residual distributions. The model achieves a coefficient of determination R2 of 0.9966 on the independent test set and a low mean squared error, while additional metrics were computed and indicate consistently strong accuracy and generalization. The sensitivity analysis revealed that the vehicle composition in both directions had the strongest influence on the model's predictions, while temporal and calendar factors contributed as secondary factors. The results indicate that a well-optimized ANN–GA model can effectively learn the nonlinear and mixed traffic dynamics, and achieve reliable accuracy and interpretability.

Keywords: *Short-term traffic flow, Artificial Neural Network (ANN), Genetic Algorithm (GA), Five-fold cross-validation.*

1. INTRODUCTION

Traffic congestion has become one of the biggest challenges in city transport systems. The immense pressure put by the increasing number of vehicles creates problems such as repeated traffic jams, longer travel times, higher fuel consumption, and increased air pollution (Shu et al., 2022). In Bangladesh, traffic conditions are highly heterogeneous, with mixed motorized and non-motorized flows, weak lane discipline, and undivided roadways (Hasnat & Rahman, 2018). The Daulatpur–Notun Rasta corridor in Khulna Metropolitan City experiences such scenarios, where evening-hour congestion exhibits sharp fluctuations between off-peak and peak periods. To solve these issues and to improve traffic efficiency, researchers focused on predicting traffic flow, considering it a vital step for better traffic management

Traffic flow forecasting is done to estimate the expected traffic volume, density, or speed of vehicles in the upcoming periods. Long-term predictions help plan roads and structures, whereas short-term predictions help understand how traffic changes throughout different times of a day and on different types of days. Short-term traffic flow data is required for changing traffic lights, helping drivers choose better routes, reducing traffic jams, and spotting accidents quickly (Vlahogianni et al., 2014).

Initially, traffic flow prediction used Kalman filtering and Autoregressive Integrated Moving Average (ARIMA), which considered it as a time series (Ahmed & Cook, 1979; Okutani & Stephanedes, 1984)). Since these methods assume linearity and regularity in traffic situations, they are less effective in nonlinear and irregular traffic conditions (Ma et al., 2020; Vlahogianni et al., 2014). Machine learning techniques, particularly artificial neural networks (ANNs), were used to address the shortcomings of traditional approaches. In contrast to statistical models, ANNs can learn complex relationships from data, which makes them appropriate for traffic modelling, where significant changes are common (Ma et al., 2015; Vlahogianni et al., 2014). To increase the models' stability and durability, ANNs have recently been combined with optimization techniques like genetic algorithms (GA). The efficiency of an ANN is directly linked with the calibration of structural hyperparameters, for example, the learning rate and the activation function. Trial and error tuning is time-consuming and causes poor performance. GA enables the optimization of the optimal configuration using rules based on natural selection (Chen et al., 2020).

The Daulatpur–Notun Rasta corridor in Khulna experiences frequent congestion due to mixed vehicular flow and minimal lane discipline. These conditions show the necessity for a data-driven model that can represent the real-world scenario of such roads. The present study investigates the applicability of an Artificial Neural Network model optimized by a Genetic Algorithm to predict short-term traffic flow volumes on the Daulatpur – Notun Rasta corridor. The study evaluates the ability of the hybrid model to learn from a limited dataset and provide reliable 15 interval predictions of total traffic volume. The specific objectives are to examine the stability and efficiency of ANN-based short-term forecasting under heterogeneous conditions, to optimize the neural architecture and learning parameters through GA for improved accuracy, and to assess model performance through statistical and graphical validation metrics. A sensitivity analysis was done to understand which input factors have the greatest influence on predicted traffic volume.

2. LITERATURE REVIEW

Prediction of traffic conditions in advance has become very important due to the growth of urban congestion. It enables more effective roadway network management, implements adaptive signal control, and dynamic route guidance (Lv et al., 2014). In developing countries, where mixed traffic streams are prominent, the prediction of traffic flow plays a crucial role. Without reliable forecasting, traffic control strategies tend to remain unresponsive. It leads to inefficient and poor utilization of existing infrastructure (Hasnat & Rahman, 2018).

Forecasting the traffic flow has evolved over several decades from a simple statistical approach to complex machine learning models. Initial traffic forecasts were made using statistical and time-series models. The ARIMA model was one of the earliest models. It did well in stationary scenarios but did not perform well in nonlinear and mixed traffic scenarios (Ahmed & Cook, 1979; Almansori et al., 2025). Real-time adaptive estimation was enabled by using the Kalman filter. But it relied on linear state assumptions and Gaussian noise. This reliance results in poor accuracy in dynamic traffic scenarios (Okutani & Stephanedes, 1984; Sun et al., 2006). Simple approaches like Historical Average (HA) and Exponential Smoothing were frequently used for comparison purposes due to their low processing complexity. However, these processes performed poorly in variable-traffic situations because they failed to account for nonlinear behaviour and real-time variations (Smith & Demetsky, 1997; Williams & Hoel, 2003). Seasonal ARIMA (SARIMA) and other additions performed better in identifying recurring daily or weekly trends, but they still needed linearity and a large amount of stationary data (Shu et al., 2022; Williams, 2001). Simultaneously, Bayesian techniques provided probabilistic forecasts that included uncertainty estimates, but they needed significant computational work and strong prior assumptions (Sun et al., 2006; Zhang et al., 2019).

The limited capacity of classical models to capture nonlinear and heterogeneous patterns led to a shift toward machine learning and ANN-based techniques. Artificial Neural Networks (ANNs) have become one of the most widely applied machine learning approaches for traffic flow prediction due to their ability to model complex nonlinear relationships. ANNs can directly learn patterns from data, which makes them particularly suitable for heterogeneous traffic environments (Ma et al., 2015; Vlahogianni et al., 2014). In traffic studies, ANNs are commonly used to forecast short-term volumes, speeds, or occupancies, offering better adaptability to fluctuations (Polson & Sokolov, 2017).

The Artificial Neural Network traffic prediction model also faces several challenges. Model performance is highly sensitive to hyperparameter selection, including the number of hidden layers, neurons, learning rate, and dropout rate. Improper tuning of these hyperparameters can lead to overfitting or underfitting (Chen et al., 2020). Moreover, ANNs typically require large and high-quality datasets to perform well. Data scarcity remains a major obstacle in developing countries. Another limitation is their “black-box” nature, which makes it difficult for traffic engineers to interpret or justify specific predictions. To overcome these issues, researchers have increasingly integrated optimization algorithms such as Genetic Algorithms (GA) to automatically determine suitable network parameters and architectures.

The performance of Artificial Neural Networks in capturing nonlinear traffic behaviour largely depends on the proper selection of hyperparameters, and manual tuning often proves inefficient. To overcome this limitation, many studies have combined ANNs with Genetic Algorithms (GA), forming hybrid ANN–GA models where the GA optimizes parameters such as the number of hidden neurons, learning rate, and activation functions, while the ANN learns the relationship between input variables and traffic flow. Through iterative processes of selection, crossover, and mutation, the GA identifies configurations that minimize prediction errors and enhance generalization (Chen et al., 2020; Liu et al., 2017). Figure 1 shows the general arrangement and relationship between the ANN and GA components. Findings indicate that these hybrid models consistently perform well while standalone ANNs and conventional time-series techniques by delivering higher accuracy, reducing overfitting, and automating the hyperparameter tuning process. Applications such as freeway flow forecasting, travel time estimation, and adaptive signal control have demonstrated the robustness and reliability of ANN–GA frameworks under both peak and off-peak conditions (Almansori et al., 2025; Polson & Sokolov, 2017b).

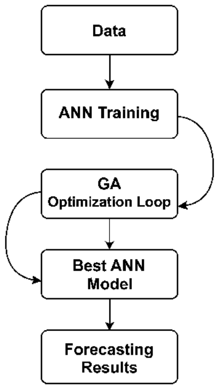

Figure 1: Hybrid ANN–GA Framework for Traffic Flow Forecasting

Traffic flow prediction in developing countries faces different problems than in developed countries. In developed countries, sensor and GPS systems collect continuous data, whereas traffic data in developing countries like Bangladesh is usually gathered manually or from short video surveys. This results in small datasets, which makes model training harder and can reduce accuracy (Almansori et al., 2025; Zhang et al., 2019). Traditional statistical models often fail to handle such mixed and unpredictable traffic, but ANN-based methods perform better because they can learn from noisy data (Chen et al., 2020; Polson & Sokolov, 2017). When combined with Genetic Algorithms, ANNs become even more effective, as GA helps to automatically adjust the network for small datasets.

Recent studies have applied various machine learning and deep learning models, such as Support Vector Machines, Random Forests, and Long Short-Term Memory (LSTM) networks, for short-term traffic flow prediction. While these models can perform well, they often require large datasets and higher computational resources. In developing countries, traffic data are usually limited and collected manually, which reduces the practicality of data-intensive deep learning approaches. Compared to standalone ANN models, the ANN–GA framework offers a systematic way to optimize model parameters while maintaining good accuracy, making it a practical choice for short-term traffic prediction under mixed traffic conditions.

3. METHODOLOGY

This study develops a hybrid Artificial Neural Network-Genetic Algorithm (ANN-GA) model to predict short-term traffic flow under heterogeneous traffic conditions. The research methodology covers data collection, data processing, model design, optimization, and validation

3.1 Study Area and Data Collection

The study was conducted on the Daulatpur – Notun Rasta corridor, a section of Khulna-Jessore-Dhaka Highway (N7), Khulna, Bangladesh. This corridor experiences frequent congestion during peak hours, and vehicles of different types and speeds share the same undivided highway. Traffic data were collected for 21 consecutive days during evening hours (4:30-6:30 pm). This period covered both off-peak (4:30-5:30 pm) and peak (5:30-6:30 pm) traffic conditions using a video camera. The recordings were analysed in slow-motion mode to ensure accurate classification and counting of vehicles. From the processed dataset, input variables included traffic counts by vehicle type, time of observation (converted into numerical form), holiday indicator, and day of the week (binary encoded). The output variable was the total traffic volume expressed as vehicles per 15 minutes (veh/15 min). A detailed overview of these variables is provided in Table 1. In total, 168 samples (21 days × 8 intervals/day) were generated for modelling.

Table 1: Description of Input and Output Variables

Variable Type	**Variable Name**	**Description**	**Data Format**
Input (Traffic)	Car count	Number of cars in 15-min interval	Integer
Input (Traffic)	Bus count	Number of buses in 15-min interval	Integer
Input (Traffic)	Motorcycle count	Number of motorcycles in 15-min interval	Integer
Input (Traffic)	Bicycle	Count of bicycles in 15-min intervals	Integer
Input (Traffic)	Truck	Count of trucks in 15-min interval	Integer
Input (Traffic)	3W1	Count of 3W1s in 15-min interval	Integer
Input (Traffic)	3W2	Count of 3W2s in 15-min interval	Integer
Input (Temporal)	Time of day	Encoded time (e.g., 16.5 = 4:30 pm)	Numeric
Input (Contextual)	Holiday indicator	1 = Holiday, 0 = Working day	Binary
Input (Contextual)	Day of week	Encoded weekday information	Binary
Output	Total traffic volume	Vehicles per 15 minutes (veh/15 min)	Numeric

3W1= Three wheelers (CNG, Auto, Mahindra), 3W2= Three wheelers (Rickshaw, van)

3.2 Data Processing:

The manually extracted raw data were first checked for errors and inconsistencies. Missing entries were filled by interpolating similar data from the same time interval on other days, and the dataset was then cleaned for analysis. Timestamp was converted into a numeric form, and the holiday indicator and day of week were converted into a binary. The dataset was divided into three subsets: 70% for model training, 10% for validation, and 20% for testing. Due to a small dataset size, data augmentation was performed by introducing noise within realistic limits to improve generalization and reduce overfitting tendencies.

3.3 Development of ANN Model:

Artificial Neural Networks (ANNs) are widely used for traffic flow prediction due to their ability to approximate nonlinear and complex relationships. In this study, a feed-forward multi-layer perceptron (MLP) was developed, trained, and optimized to forecast short-term traffic volume from the prepared dataset.

The ANN was structured as follows:

- Input layer: Consisted of all pre-processed features, including traffic counts, encoded time, holiday indicator, and day-of-week. Additional sine and cosine encodings of time were included to capture cyclic patterns.
- Hidden layers: The number of layers (1–3) and neurons per layer (10–100) were determined through GA optimization.
- Output layer: A single neuron producing continuous predictions of traffic volume (veh/15 min).
- Regularization: Dropout (0.0–0.3) and L2 weight penalties were applied to prevent overfitting.

Python code used for model construction using Dense layers, Dropout, and L2 regularization techniques. Figure 2 also illustrates the whole feed-forward ANN design graphically, illustrating the transition from input features to hidden layers with regularization and ultimately to the output neuron for traffic volume prediction.

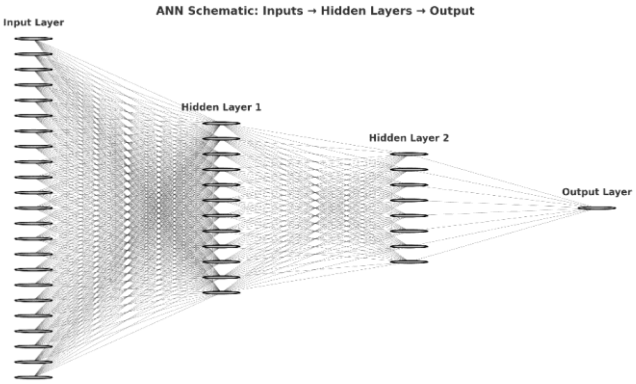

Figure 2: Schematic diagram of a feed-forward ANN

Different activation functions, such as ReLU, Sigmoid, Tanh, and ELU were tested to select the most suitable one for this dataset. The model was trained using Mean Squared Error (MSE) as the loss function. In addition, Mean Absolute Error (MAE) was tracked during training to provide an interpretable measure of average prediction deviation. The ANN was trained using gradient-based optimization with different optimizers (Adam, RMSProp, SGD, Nadam), chosen adaptively by GA. Training was carried out for up to 300 epochs, with early stopping (patience = 20) to prevent overfitting. Batch sizes of 16, 32, and 64 were tested during optimization.

3.4 Integration of Genetic Algorithm (GA):

Artificial Neural Networks rely heavily on hyperparameter choices such as the number of hidden layers, neurons, learning rate, optimizer, dropout rate, and activation functions. Manually tuning these settings is inefficient and may lead to poor results. The Genetic Algorithm (GA) was applied to automatically optimize the ANN's hyperparameters. The GA searched for optimal values for network configuration parameters. The GA mimics the process of natural selection, evolving a population of candidate solutions over generations to identify architectures with superior performance. Each candidate ANN configuration was represented as a chromosome. Number of hidden layers (1-3), Neurons per layer (10-100), Activation function (ReLU, Sigmoid, Tanh, ELU), Optimizer (Adam, RMSProp, SGD, Nadam), Dropout rate (0.0-0.3), Batch size (16,32,64), Learning rate (0.0001-0.01) were encoded in hyperparameter optimization. This flexible representation allows the GA to explore a wide search space of possible models. The fitness of each individual was based on validation loss (MSE) after limited training epochs.

A tournament selection approach was used, where a small group of individuals was randomly chosen from the population, and the best-performing one was selected as a parent. This balances exploration (trying new solutions) and exploitation (favouring good solutions). Selected parents underwent two-point crossover, where two random cut points were chosen along the chromosome and the segments between them were exchanged. This operation produced offspring that inherited characteristics from both parents. To maintain diversity in the population, mutation was applied with a probability of 0.2 per gene, including changing the number of neurons, switching activation functions. adjusting the dropout rate. replacing the optimizer. This prevented premature convergence to local optima.

The Genetic Algorithm was executed with a population size of 10 and evolved over five generations, with each experiment repeated five times to ensure robustness. In every run, the best-performing configuration was preserved for final model training. The algorithm terminated automatically after reaching a maximum of five generations, and the overall best solution among all runs was selected as the final output. The implementation of this process was carried out using the DEAP library.

3.5 Model Evaluation:

The final ANN–GA model was tested on the reserved test dataset using both statistical and graphical techniques. In addition to a single hold-out test, five-fold cross-validation was conducted to confirm model stability.

3.5.1 Statistical and Graphical Evaluation:

Model accuracy was assessed using several indicators, including R^2, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Logarithmic Error (MSLE). These metrics describe the model accuracy. Graphical analysis was also performed to visually interpret performance. Actual versus predicted plots, scatter plots, and residual diagrams were used to identify bias and correlation strength, while error distribution histograms confirmed the randomness of residuals.

3.5.2 Cross-validation:

A five-fold cross-validation was carried out using the best GA optimized ANN model. Each fold was used once for testing, while the remaining folds were used for training. The averaged results across folds provided a reliable estimate of generalization performance.

3.5.3 Sensitivity Analysis:

A sensitivity analysis was conducted to identify which input features most influenced short-term traffic flow prediction. Each variable was increased by 10% while keeping others constant, and the resulting change in predicted traffic volume was measured. This analysis helped determine the relative importance of different traffic components and time-related variables, offering insights into how key factors shape flow variation under mixed traffic conditions.

4. RESULTS AND DISCUSSION

The ANN-GA model was validated by monitoring training dynamics, evaluating regression metrics on the test set, and verifying robustness through cross-validation. The results confirm the strong predictive capability and generalization of the hybrid model under mixed urban traffic conditions.

The training and validation losses were calculated by using Mean Squared Error (MSE). Figure 3 shows the training and validation losses over epochs. The training loss curve declines steeply at first, indicating that the model learns the traffic pattern very quickly. After some epochs, the curve flattens, indicating that the model has learned most of the relationships, and small oscillations are present due to batch updates and optimizer adjustments. The validation curve also declines steeply following a nearly identical path to the training loss, which indicates no significant overfitting of the model. The use of an early stopping strategy prevented unnecessary iterations once no further improvement was observed for 20 patience epochs, and the model weights were restored to the epochs with the lowest validation loss.

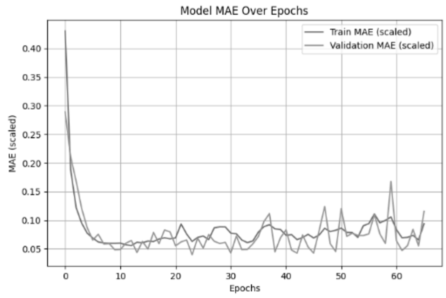

Figure 3: Training and validation loss values across epochs

In addition to loss, Mean Absolute Error (MAE) was tracked to provide a sensitive measure of average prediction deviation. Figure 4 shows the train MAE and validation MAE across epochs. Initially, both curves drop steeply, which represents the quick learning of the model about the traffic pattern.

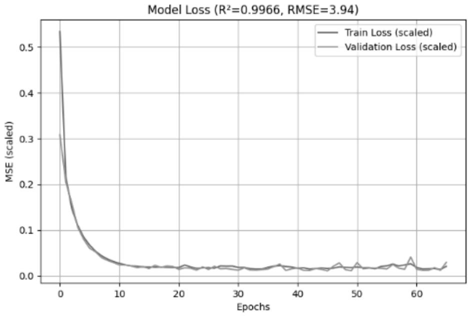

Figure 4: Training and validation MAE values across epochs

After training, the model was evaluated on the independent test dataset. Table 2 summarizes the results using five regression metrics: coefficient of determination (R^2), RMSE, MAE, MAPE, and MSLE. The high R^2 score (0.9966) and low RMSE (3.94 veh/15 min) and MAE (3.30 veh/15 min) demonstrate that the ANN–GA framework can accurately forecast short-term traffic volume under mixed traffic conditions.

Table 2: Performance metrics on the hold-out test

Metrices	R^2	RMSE	MAE	MAPE	MSLE
Values	0.99659	3.9421	3.3058	0.00471	3.20E-05

To ensure robustness, a five-fold cross-validation was conducted, and the averaged results are presented in Table 3. The consistently high R^2 values (mean 0.9956) and low error terms across folds confirm that the model generalizes well beyond the training data.

Table 3: Five-fold cross-validation results

Metrices	R2	RMSE	MAE	MAPE	MSLE
Mean	0.99564	3.8418	2.98214	0.00415	3.44E-05
Standard Deviation	0.0043355	1.9228147	1.53856	0.002273	3.69E-05

To visualize predictive performance, Figures 5–7 illustrate the close agreement between actual and predicted traffic volumes. The line plot (Figure 5) and bar chart (Figure 6) both show that the predicted values nearly overlap with the observed counts, while the scatter plot (Figure 7) displays points clustered around the 45° line, confirming a near-perfect correlation between actual and estimated volumes.

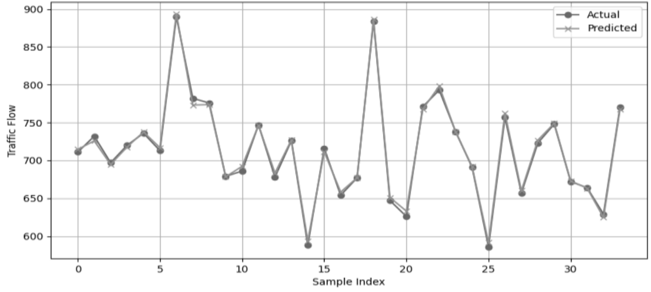

Figure 5: Line plot of actual vs predicted traffic flow for selected test samples

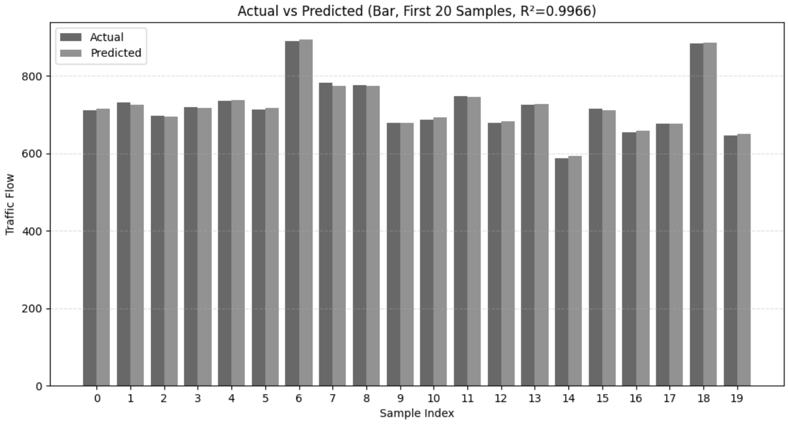

Figure 6: Bar plot of actual vs predicted traffic flow for selected test samples

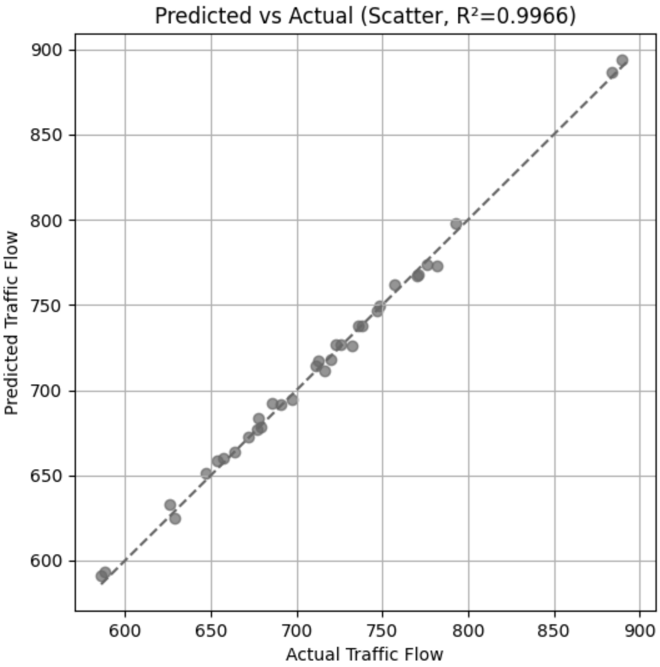

Figure 7: Scatter plot of predicted vs actual traffic flow

Error analysis reveals whether the model consistently overestimates or underestimates traffic flow, and whether variations are concentrated in specific value ranges or not. Figure 8 shows the residuals (differences between actual and predicted values) plotted against the actual traffic volumes. The residuals are scattered closely around zero without any clear trend, indicating that the model does not exhibit systematic bias across different traffic levels. The histogram in Figure 9 displays the distribution of residuals. The distribution is approximately centered around zero with most errors falling within a narrow band, confirming that the majority of predictions are close to actual values.

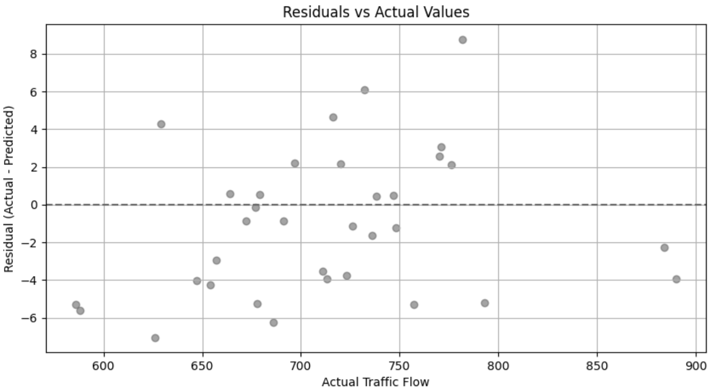

Figure 8: Residuals plotted against actual traffic volumes

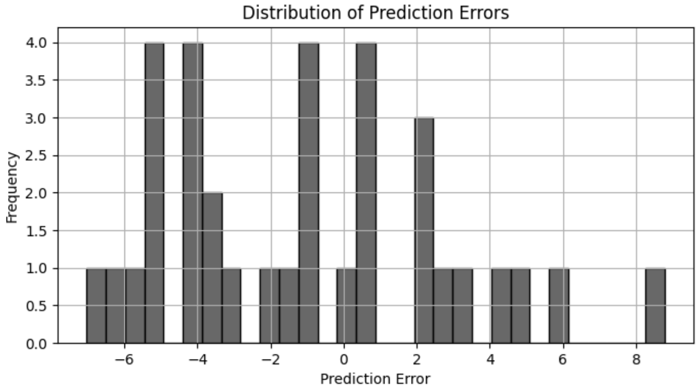

Figure 9: Histogram of prediction errors

A sensitivity analysis was also carried out to identify the influence of individual features on the model output. Each variable was increased by 10% while others were held constant, and the corresponding change in predicted flow was measured. The results (Figure 10) show that three-wheelers (3W1A and 3W1B) exert the highest influence on total traffic volume, followed by cycles, motorcycles, and buses. Cars, trucks, and 3W2 vehicles contributed moderately, while temporal and contextual variables (such as day type or time of day) showed lesser effects.

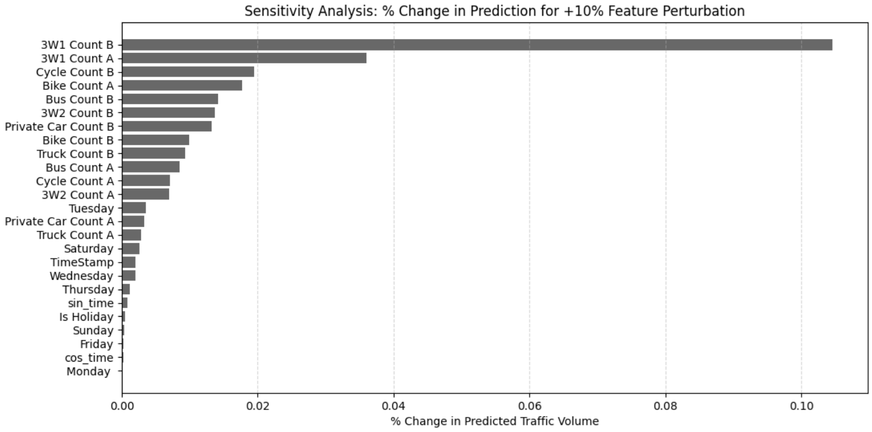

Figure 10: Sensitivity analysis of ANN–GA model

These findings align with the real-world situation in Khulna, where three-wheelers and small vehicles dominate the road space, especially on undivided corridors. The model correctly captured this dynamic, relying primarily on direct vehicle composition while maintaining interpretability.

Overall, the ANN–GA framework delivers reliable performance, with R^2 above 0.99, with low RMSE and MAE values. Its stability across five-fold cross-validation confirms that the approach is robust and not overly sensitive to data partitioning. A sensitivity analysis also emphasized that the model properly ranked vehicle classes and time trends so that predictions reflected legitimate traffic dynamics. Integration of genetic algorithms for hyperparameter tuning proved effective, offering a systematic and efficient alternative to manual adjustments. The model requires limited computational resources and produces traffic flow predictions almost instantaneously, which supports its applicability in real-time traffic management systems.

The study also has some limitations. The dataset only covers 21 days and was limited to a fixed two-hour observation window. Manual traffic count is very time-consuming and may contain some inaccuracies. In addition, the data was collected only from a single point on the corridor and was limited to a single corridor. Thus, it raises concerns about this model's performance on other road networks without further retraining. Despite these limitations, the results declare that the model can be a reliable tool for short-term traffic forecasting. Once the optimal network architecture is obtained, the prediction stage is computationally lightweight. The trained ANN produces traffic flow estimates almost instantaneously, making it suitable for real-time traffic forecasting.

5. CONCLUSIONS & RECOMMENDATIONS

This study investigated the application of an Artificial Neural Network optimized with a Genetic Algorithm (ANN–GA) for short-term traffic flow prediction on the Daulatpur–Notun Rasta corridor in Khulna Metropolitan City. The model was trained and validated under both peak and off-peak conditions to capture variations in mixed urban traffic. The results showed that the ANN–GA framework can accurately forecast traffic volumes in heterogeneous flow environments, achieving a high coefficient of determination ($R^2 = 0.9966$) along with low RMSE, MAE, and MAPE values. Cross-validation further confirmed the model's robustness and stability across different data partitions. Sensitivity analysis revealed that vehicle composition, particularly the counts of dominant vehicle types such as three-wheelers and motorcycles, had the most significant influence on traffic flow, while contextual and temporal factors had secondary effects.

Based on these results, future research should consider extending the observation period to include different times of the year and varying weather conditions to capture broader traffic variations. Data from multiple locations or additional corridors could also be used to assess model adaptability and scalability. Integrating the proposed ANN–GA framework into urban traffic control systems could provide a practical solution for real-time traffic management and congestion reduction in mixed-traffic environments.

DECLARATION OF USE OF AI

The authors declare that AI tools were used only to assist in language refinement, grammar correction, and improving the clarity of sentences. All core ideas, methodology, experimental design, data analysis, interpretation of results, and conclusions were entirely developed by the authors. The authors maintained full oversight over the content generated and verified all text for accuracy and originality. No AI tools were used for generating research ideas, analyzing data, or drawing scientific conclusions.

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