DOI: https://doi.org/10.52756/ijerr.2024.v45spl.019 *Int. J. Exp. Res. Rev.*, Vol. 45: 237-250 (2024)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)
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ISSN: 2455-4855 (Online)
www.iaph.in

Evaluation of a Probabilistic Framework for Traffic Volume Forecasting Using Deep Learning and Traditional Models

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Article History:

Received: 09th Jul., 2024
Accepted: 20th Nov., 2024
Published: 30th Nov., 2024

Keywords:
Traffic forecasting, autoregression, deep learning, dynamic probability assignment, stacked autoencoder, real-time traffic management.

How to cite this Article:
Abhay Narayan Tripathi and Bharti Sharma (2024). Evaluation of a Probabilistic Framework for Traffic Volume Forecasting Using Deep Learning and Traditional Models. *International Journal of Experimental Research and Review*, *45*, 237-250.
DOI: https://doi.org/10.52756/ijerr.2024.v45spl.019

Abstract: Forecasting is a very important issue in the present times to optimize urban traffic management systems and their proper planning. It is often found that traditional forecasting models cannot fully approximate the non-linear and dynamic nature of traffic patterns. The presented paper proposes a framework that integrates multiple traditional models such as Autoregression (AR), Support Vector Regression (SVR), Exponential Smoothing, Historical Average, Random Walk and Artificial Neural Network (ANN) with deep learning models, especially Stacked Autoencoders, and enhances their predictive efficiency phenomenally. The forecast accuracy is then further enhanced through a dynamic probabilistic model integration strategy that adapts to real-time traffic conditions by dynamically weighting the models based on their performance. It is found that the hybrid framework proposed in the present paper performs much better than the traditional models in predicting traffic volume. Deep learning models with RMSE of 26.9976, AR (RMSE: 22.6679) and SVR (RMSE: 28.2221) provided remarkable prediction accuracy. Based on the results, the authors are confident that the integrated models are useful for real-time traffic management applications. However, they still have great potential for further refinement and optimization.

Introduction

At present, traffic congestion in urban areas is a growing challenge that directly affects economic productivity, environmental sustainability, and the quality of life of city dwellers. Due to this, the demand for efficient traffic management systems is also increasing tremendously. It has been found that traffic volume forecasting is an essential component in traffic management that can help urban planners and policymakers make appropriate decisions by anticipating future traffic conditions (Tripathi and Sharma, 2023; Kazmi et al., 2023). However, accurate traffic forecasting is a very complex task, as many factors affect traffic patterns, such as weather conditions, time of day, day of the week, special events, and accidents. Due to their predetermined capabilities, traditional traffic forecasting models often fail to capture the non-linear and stochastic nature of traffic. Based on this limitation, researchers have observed that they have to employ more advanced forecasting approaches (Tripathi and Sharma, 2022). Based on these recommendations by previous researchers, in the present research, authors proposed a probabilistic framework based on hybrid forecasting method to address the present research problem integrated with traditional models.

The problem of traffic volume prediction has been studied extensively over the past few decades. Early models were primarily based on statistical methods such as autoregressive integrated moving average (ARIMA) models, which assume that future traffic volume depends linearly on its historical values (Ghanbari and Zare, 2020). On the other hand, ARIMA and its related approaches have given enhanced accuracy for non-linear traffic data predictions (Smith and Demetsky, 1997;

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Zhang et al., 2011). Moreover, various machine learning models like support vector regression (SVR) and neural networks (NNs) have also shown their ability to predict complex relationships between input and output variables (Karlaftis and Vlahogianni, 2011). However, their proper tuning and sensitivity are also crucial for implementation (Van Lint and Van Hinsbergen, 2012; Tripathi and Sharma, 2024).

In past years, deep learning models like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have gained popularity in time-series forecasting (Ma et al., 2015). These models are basically designed to portray time-based dependencies and accomplish non-linearity in time-series data (Tang et al., 2018; Zhu et al., 2018; Tripathi and Sharma, 2022). Thus, it has been observed that a more acceptable and robust approach is needed for traffic forecasting.

In the present research paper, the authors tried to develop a hybrid deep learning-based traditional model for traffic volume forecasting. In this study, deep learning models were used, using stacked autoencoders. The main contribution of this research is to provide a novel probabilistic model integration mechanism that can dynamically adjust each model's weights based on its historical performance.

Generally, traffic forecasting models can be classified into short-term and long-term (Vlahogianni et al., 2014; Fu et al., 2016). Short-term forecasting is required for real-time traffic management, like adaptive traffic signal control and dynamic route guidance, while long-term forecasting is crucial for infrastructure planning and policy development. The dataset used in this study is the traffic volume data gathered from Delhi-NCR area on a busy road for a time. Then, the data is classified into different vehicle types, such as two-wheelers, four-wheelers, heavy vehicles, light vehicles, and other vehicle types, while the total traffic volume is considered as an output variable. All models' performance is evaluated based on root mean squared error (RMSE). Thereafter, coupled approaches are developed for probability-driven forecasting based on various strategies. At last, the findings are summarized by providing directions for future research.

Literature Review

Traffic prediction has been a challenging task for researchers, engineers, and city planners for a long time. Various researchers employed different techniques for traffic volume prediction in the past, but due to the non-linearity of traffic data, it is always a tough task (Bokde et al., 2020). Zhang et al., 2013 employed ARIMA models for the same purpose. Their findings showed that ARIMA has various limitations due to its inability to handle the non-stationary and non-linearity nature of traffic data. On the other side, different machine learning models, such as SVR, Kalman filter etc. are used by various researchers. Wu et al. (2004) and Karlaftis and Vlahogianni (2011) employed SVR and other machine learning methods for short-term traffic forecasting. They found that if traffic data exhibited non-linear patterns, SVR could outperform ARIMA. Wu et al. (2004) also observed that the quantity and quality of traffic data highly affected the SVR's performance. Stathopoulos and Karlaftis (2003) stated that the Kalman filter is used for traffic forecasting and observed that its recursive nature makes it suitable for real-time traffic forecasting. They also employed Exponential Smoothing technique for urban traffic prediction and observed that it surpasses ARIMA's performance. Chien et al. (2003) mentioned that ARIMA and Kalman filters face difficulties due to non-linear traffic data patterns. Thus, it has been observed that the non-linearity in traffic data restricts their ability to perform accurately. Researchers also try to employ different advanced machine learning and deep learning models for traffic forecasting.

Deep learning methods in traffic forecasting came into the scenario due to their ability to handle big data easily. Long Short-Term Memory (LSTM) network, which is a type of recurrent neural network (RNN), is designed to capture long-term dependencies in time-series data. It is suited for traffic prediction (Ma et al., 2015). They found that LSTM enhanced the prediction accuracy over traditional methods like ARIMA and Kalman filter. They mentioned that it is extremely suitable for highly dynamic environments. Autoencoders, another type of deep learning architecture, were also successfully employed by Bengio et al. (2013) for traffic forecasting. Lv et al., 2015 used stacked autoencoders for short-term traffic prediction and observed that the model could capture both linear and non-linear relationships in the traffic data with improved forecasting accuracy. Yu et al. (2017) introduced a spatiotemporal graph convolutional network for traffic forecasting, which coupled the CNNs with graph theory. They observed that the developed hybrid model confirmed state-of-the-art performance in traffic flow prediction.

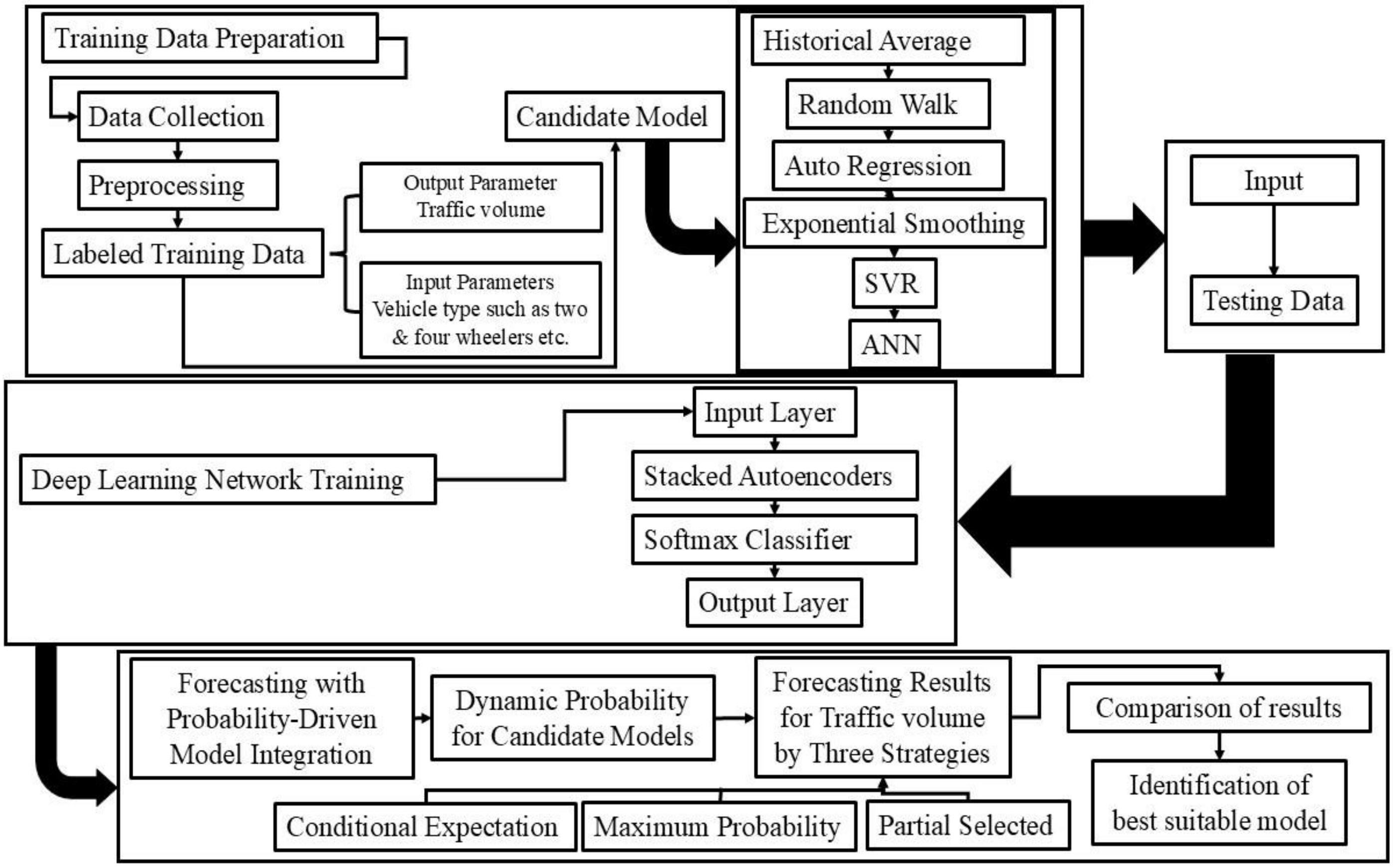

Figure 1. Flowchart of the proposed methodology.

However, CNNs and LSTMs are highly effective, but they are computationally intensive and require significant processing power with a huge amount of data for training. This has provoked the researchers to investigate various hybrid models that possess both the strengths of traditional and deep learning methods. Zhang et al. (2013) employed a weighted averaging hybrid approach of ARIMA and SVR models for traffic forecasting and observed that the hybrid method is more powerful as compared to the individual models. Van Lint & Van Hinsbergen (2012) observed the same results when they coupled ARIMA, SVR and Kalman filter models for short-term traffic prediction.

As traffic systems are highly dynamic in nature and non-linear, the authors attempt to develop coupled approaches with deep learning and traditional prediction models in the present research article.

Methodology

Initially data was collected in Delhi-NCR area for 31 days on a busy road for a particular day time. Thereafter, it has been ensured that data is clean without any missing entries and it is structured. In this step, outliers' data values are also corrected or removed. The data was then normalized and structured into a consistent format, ensuring compatibility for further analysis and model training. These preprocessing steps were crucial for enhancing the reliability of the predictive models. The final, cleaned dataset, as shown in Table 1, provides a solid foundation for accurate traffic volume forecasting.

Table 1. Descriptive statistics of collected Traffic Data.

Variable	N	Mean	SE Mean	St Dev	Median
Two wheelers	400	159.92	0.604	12.09	160
Four wheelers	400	56.465	0.427	8.544	55
Heavy Vehicles	400	32.980	0.469	9.371	280
Light Vehicles	400	26.352	0.338	6.764	27
Others	400	19.425	0.299		5.977
Traffic Volume	400	195.51	0.784	15.68	192

The proposed methodology for this work, as shown in Figure 1, integrates traditional models, such as Autoregression, SVR, and Exponential Smoothing, with deep learning models, including Stacked Autoencoders with a Softmax Classifier. By using a dynamic probability-driven model integration approach, forecasts are generated based on three strategies: Conditional Expectation, Maximum Probability, and Partial Selection, optimizing traffic volume prediction.

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Data Collection & Preprocessing

The collected dataset spans 31 working days and captures traffic data across five distinct vehicle categories. These categories include two-wheelers (motorcycles, scooters), which contribute significantly to urban traffic; four-wheelers (cars, sedans), a vital component of daily commuter traffic; heavy vehicles (trucks, buses), which often influence traffic flow due to their size; light vehicles (vans, SUVs), which serve both personal and commercial transportation needs; and other vehicles, encompassing specialized or utility vehicles. This comprehensive dataset provides a diverse and dynamic traffic pattern record, essential for accurate traffic volume forecasting. Pre-processing involved handling missing data, normalization, and feature engineering to ensure the dataset was suitable for model training and analysis. After data collection, pre-processing of data is performed to make it suitable for model training.

Candidate Model Selection

Six different forecasting models are selected for traffic volume prediction at this stage. Gautam & Shrivastava, 2024 provide a comprehensive review of metaheuristic optimization techniques, highlighting their potential applications in improving predictive models, which could be adapted for traffic forecasting scenarios requiring complex, real-time decision-making. In this step, all six models are employed individually for prediction purposes. Later, the best suitable mode is determined based on their Root Mean Squared Error (RMSE). Basically, the RMSE value indicates the model's prediction power and capacity to supervise a complex environment such as traffic volume forecasting.

Historical Average

In the present research work, the first evaluated candidate model is Historical Average model. This can compute the mean of the historical traffic volumes. It also uses these means as a constant prediction for all future points and provides a baseline for comparison. After performing this approach, an RMSE of 27.6766 was achieved. This revealed that this model is unsuitable for dynamic changes in traffic patterns. However, this approach works effectively in stable traffic conditions or with a simple baseline. Figure 2 visually depicts this approach's variation of actual and predicted traffic volume values. Based on the acquired RMSE value we can identify the limitations of this simplistic static model.

Random Walk

Thereafter, the Random Walk model was employed on the same data sets. This time, the value of RMSE is slightly decreased as 26.8732, showing it is slightly better than the Historical Average approach (Figure 3). This technique has the ability to handle problems with short-term fluctuations like traffic volume. However, this tends to fail at significant changes in the data over time. Thus, it has been absolved that this approach is not suitable for long-term trends and affects its predictive power.

Autoregression (AR)

Apart from previously employed techniques, the Autoregression (AR) model shows a less RMSE value of 22.6679 (Figure 4). This technique can capture the linear dependencies between the current traffic volume and previous values, making it suitable for short-term traffic volume prediction. This has the potential to learn from linear relationships in the data and used it for better prediction. However, this has been limited to non-linear patterns or sudden changes in traffic flow environments.

Support Vector Regression (SVR)

When we applied the Support Vector Regression (SVR) model, we achieved the RMSE value of 28.2221, which is remarkably higher than the Historical Average and Random Walk models (Figure 5). This approach is highly used to solve complex regression problems. The major limitation of this approach is that it requires extensive hyperparameter tuning. However, SVR is suitable for non-linear data sets, but it struggled to capture the underlying traffic patterns in the present case. This may be due to the inherent noise or complexity in the traffic dataset.

Exponential Smoothing

The RMSE value achieved by the Exponential Smoothing model is 24.0968, which is also short of the Autoregression model (Figure 6). This model is suitable for the prediction of simpler models. However, in the present case, it has been identified that this model is not able to properly capture the underlying linear dependencies in the data over time.

Artificial Neural Network (ANN)

Finally, the ANN model was employed to predict the traffic volume data. An RMSE value of 26.5927 was achieved using this approach (Figure 7). It is a well-known fact that ANN is suitable for complex no-linear problems, but in the present case, it provides a higher value of RMSE, which shows that this model is not the best fit for provided traffic data. This may be due to the simple architecture of the developed ANN model or the requirement for more parameter tuining.

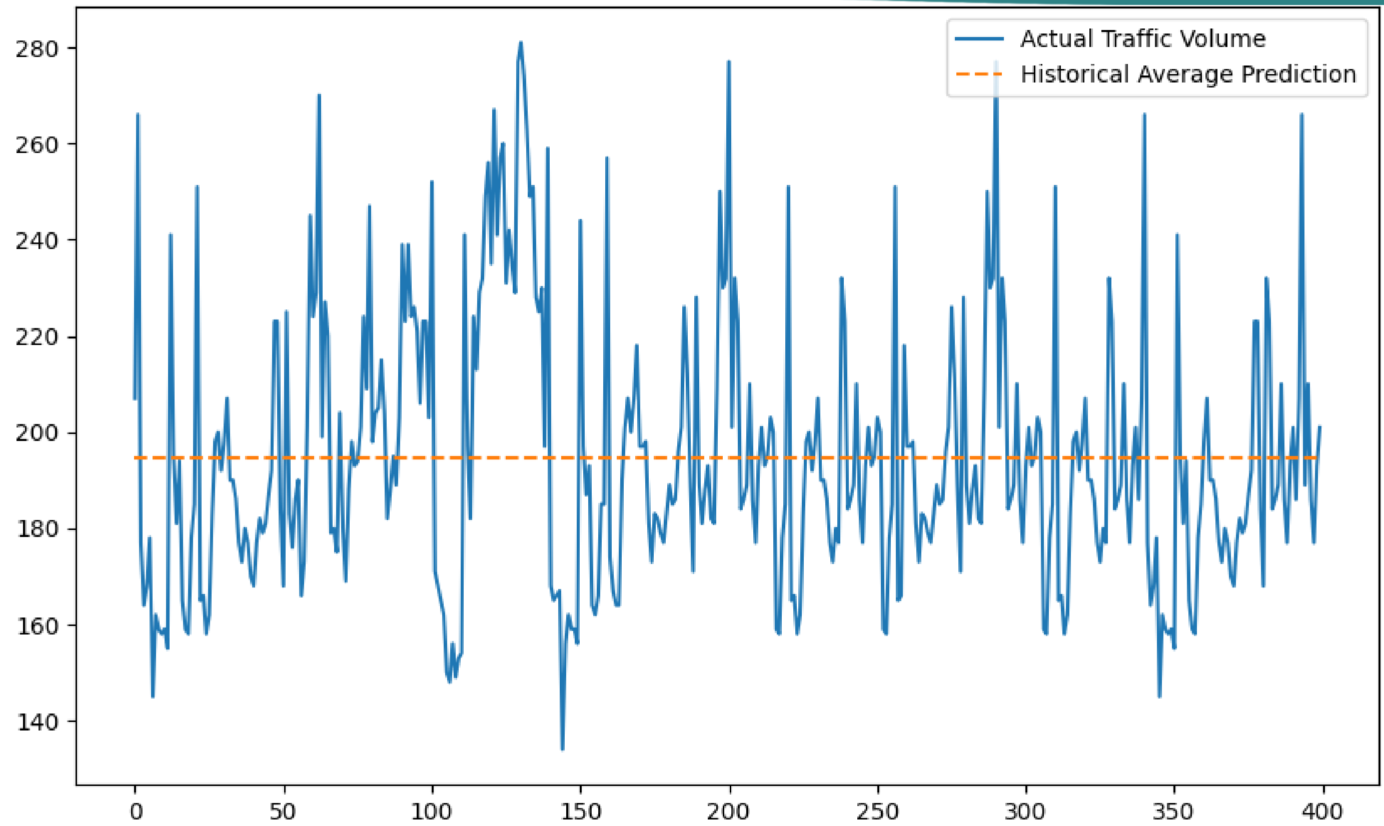

Figure 2. Variation between prediction results of historical average approach and actual traffic volume.

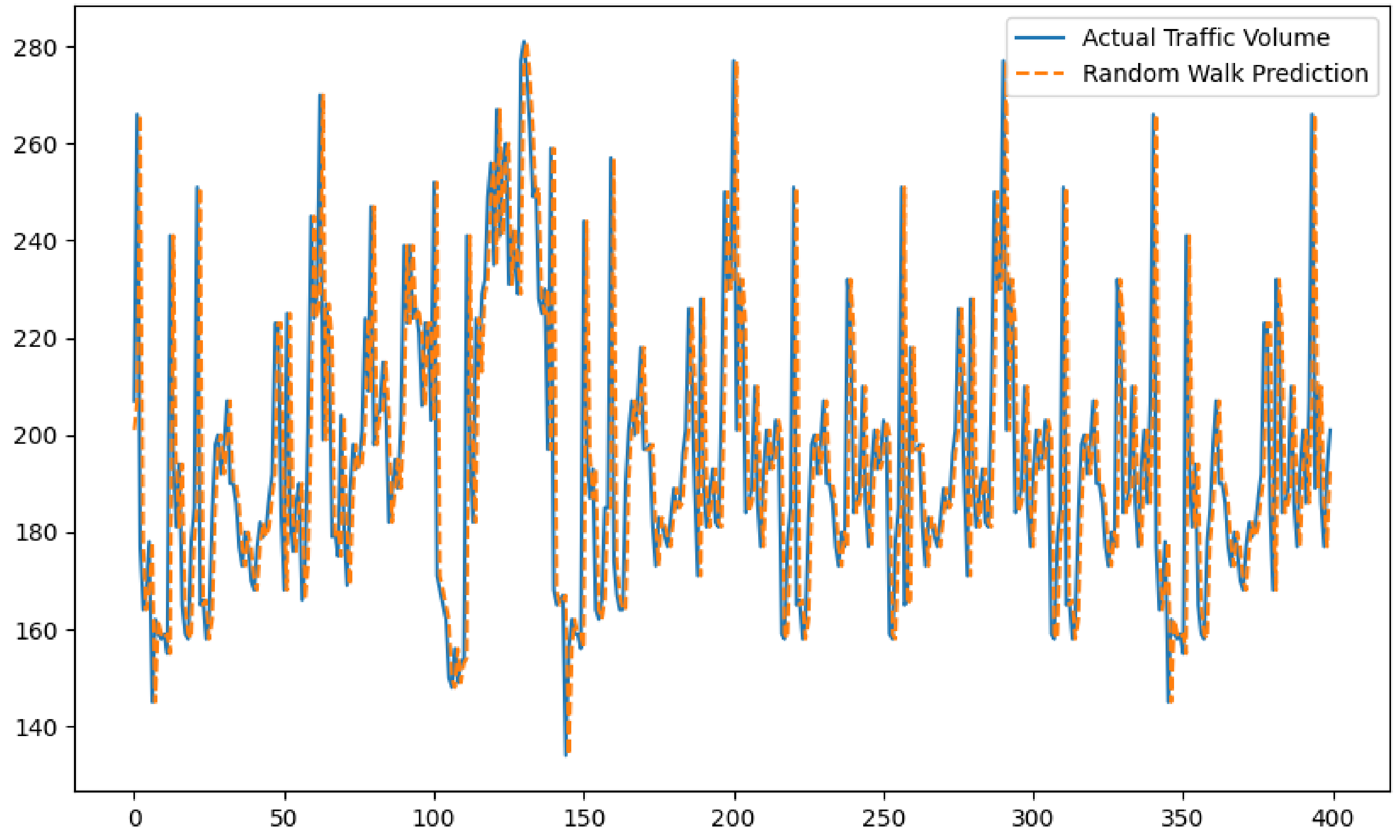

Figure 3. Variation between prediction results of Random Walk vs. actual traffic volume.

DOI: https://doi.org/10.52756/ijerr.2024.v45spl.019

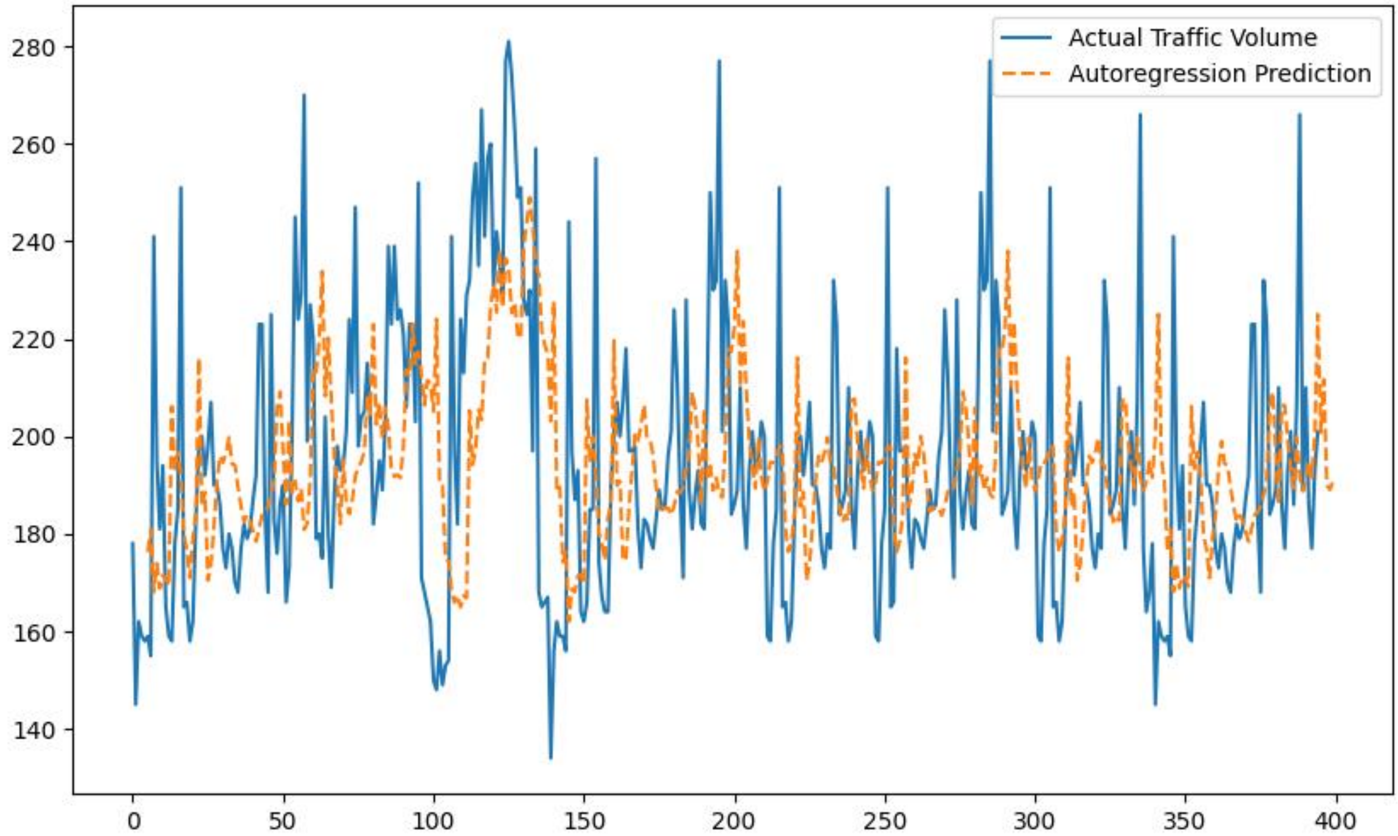

Figure 4. Variation between prediction results of Autoregression (AR) vs. actual traffic volume.

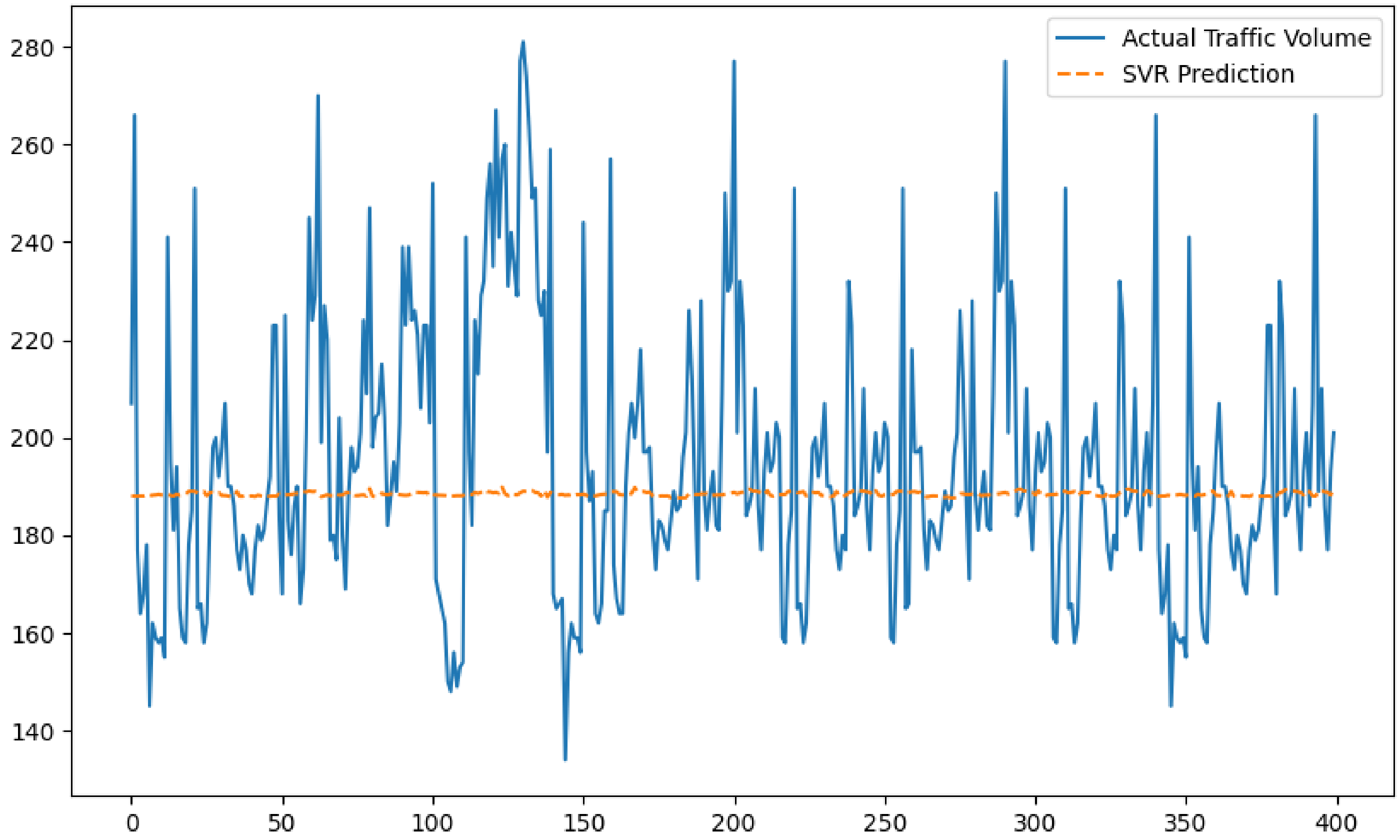

Figure 5. Variation between Support Vector Regression (SVR) prediction results vs. actual traffic volume.

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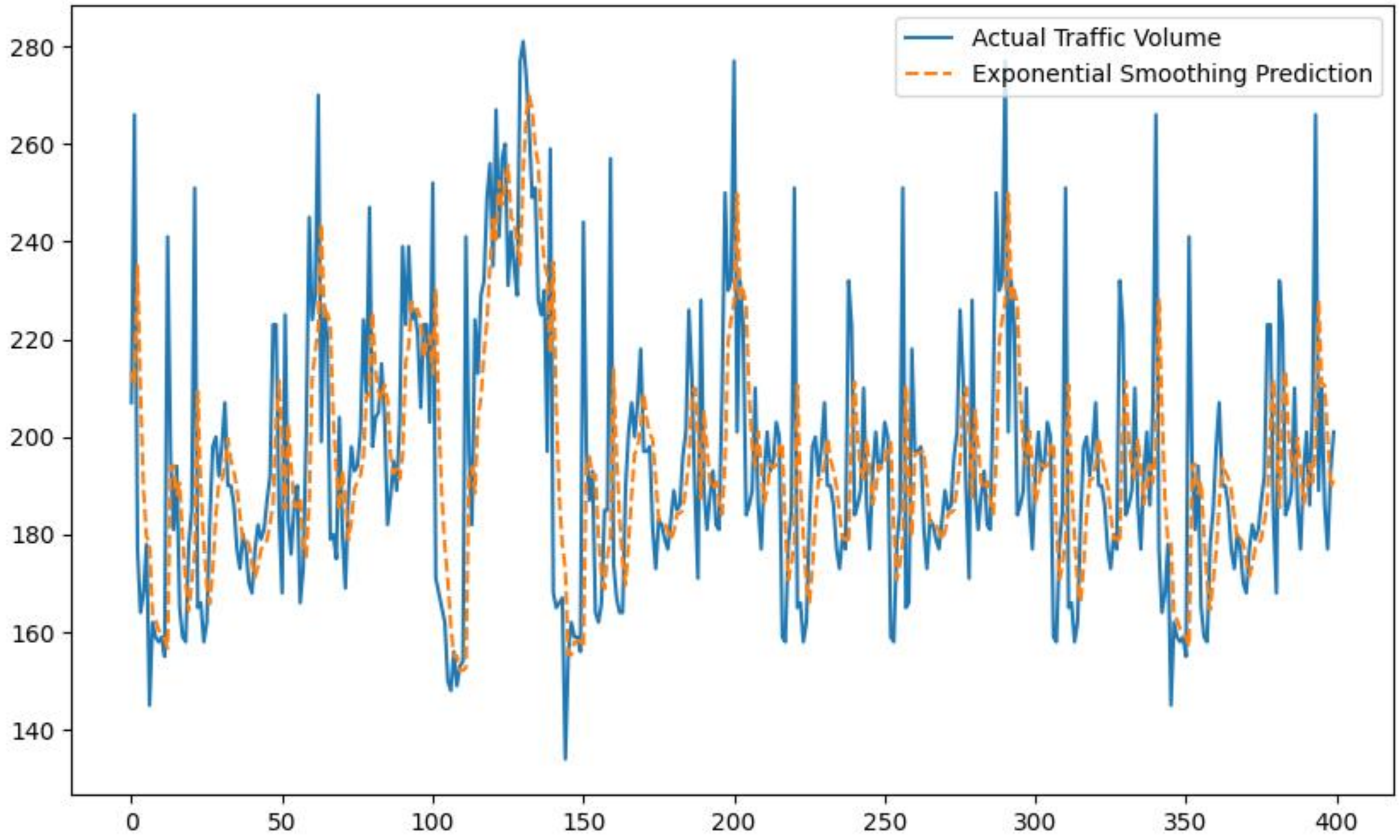

Figure 6. Variation between prediction results of Exponential Smoothing vs. actual traffic volume.

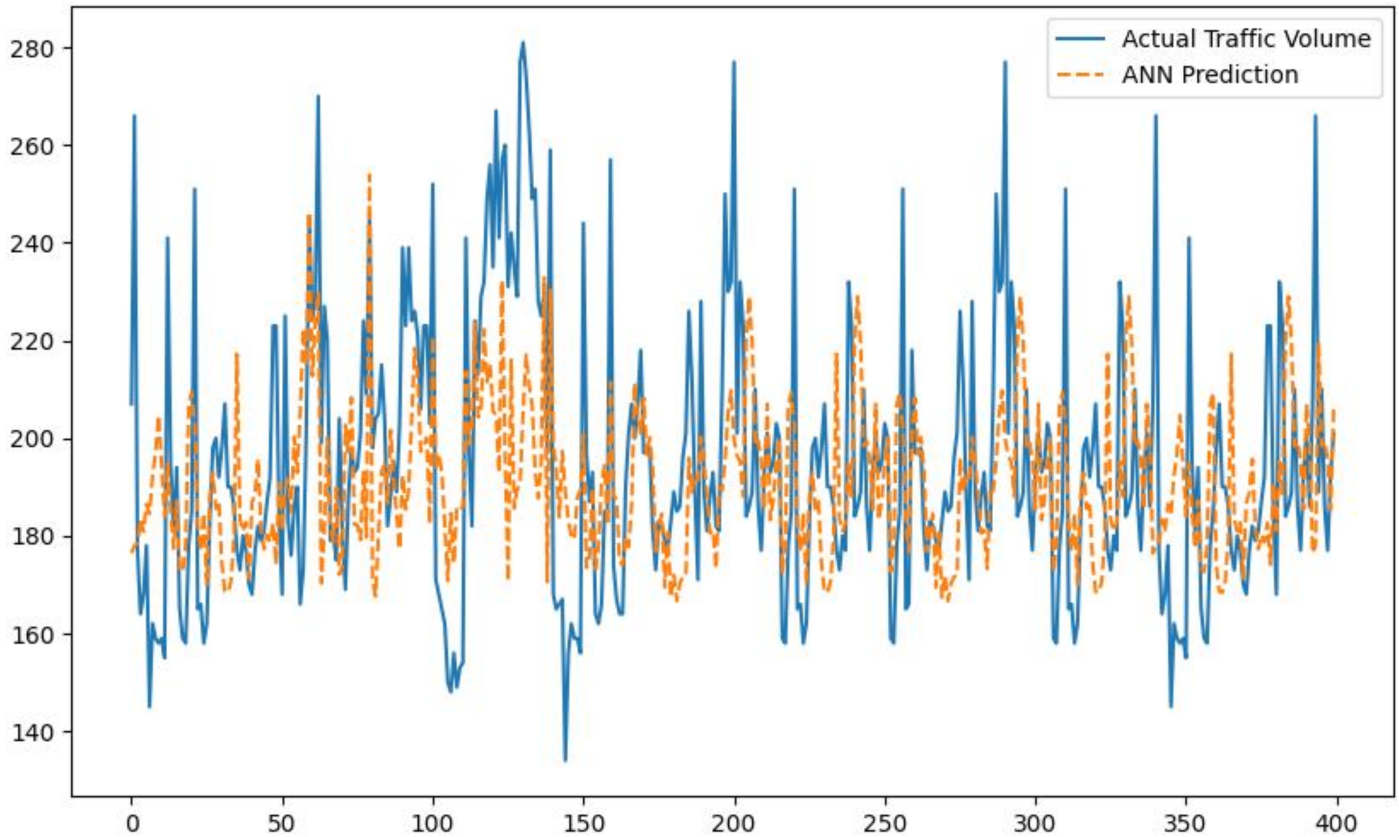

Figure 7. Variation between Artificial Neural Network (ANN) model prediction results and actual traffic volume.

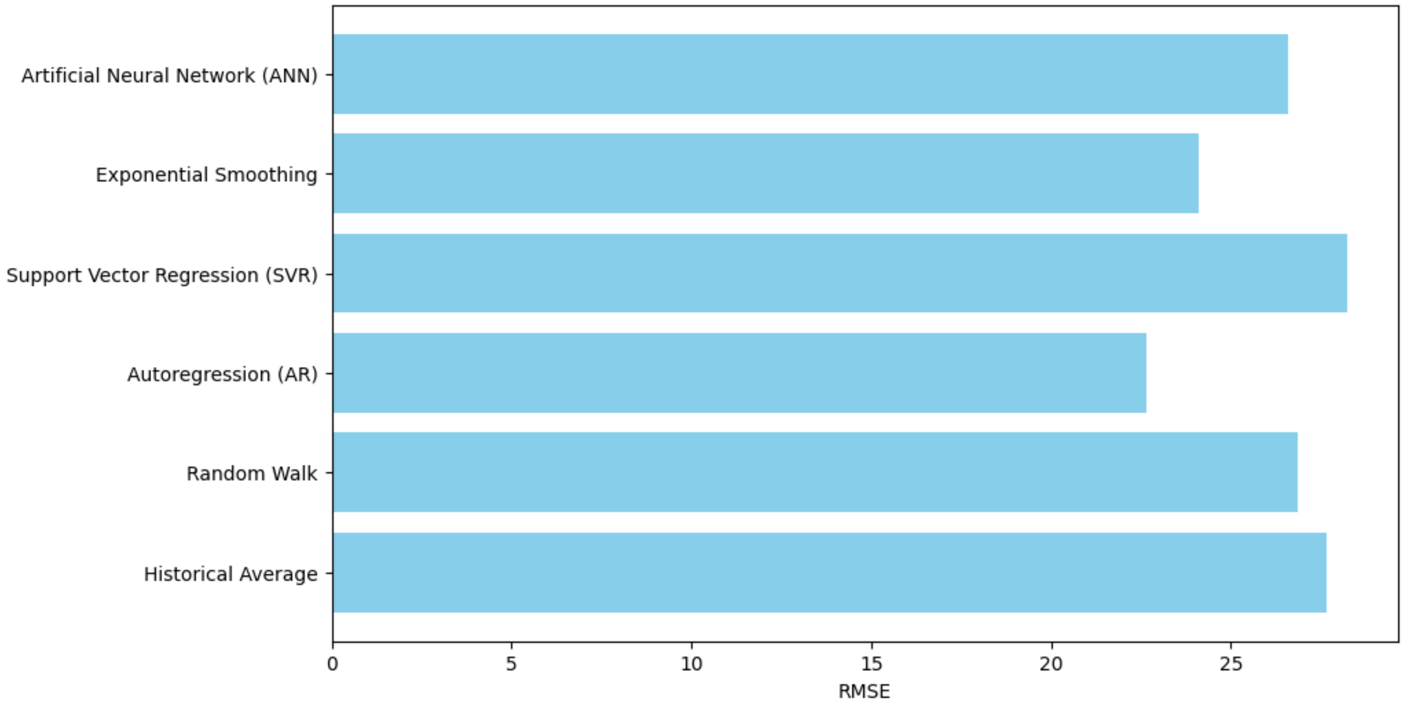

Figure 8. Comparison of RMSE of Various Traffic Forecasting Models.

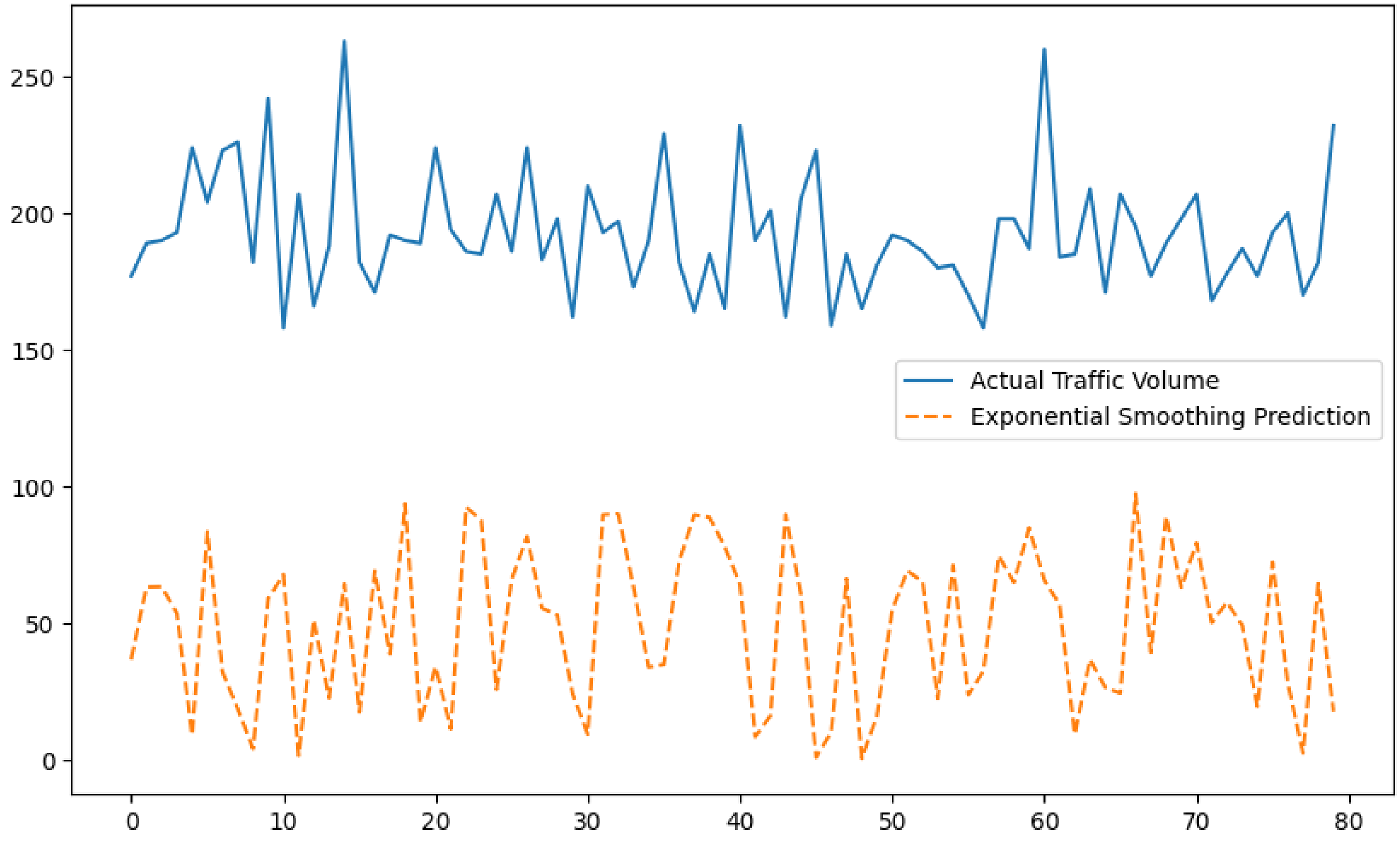

Figure 9. Comparison of Exponential Smoothing Vs. Actual Traffic Volume.

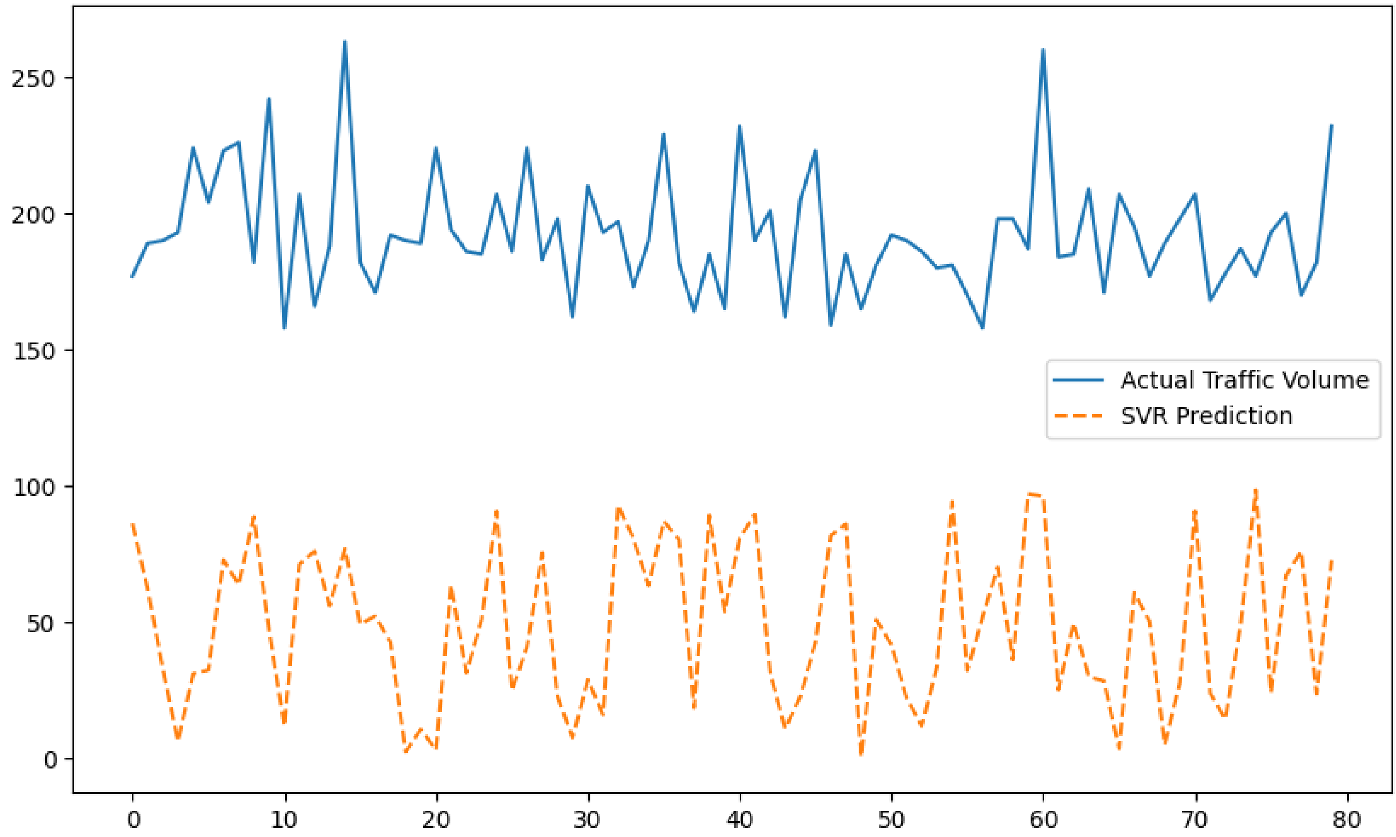

Figure 10. Comparison of SVR Prediction Vs. Actual Traffic Volume.

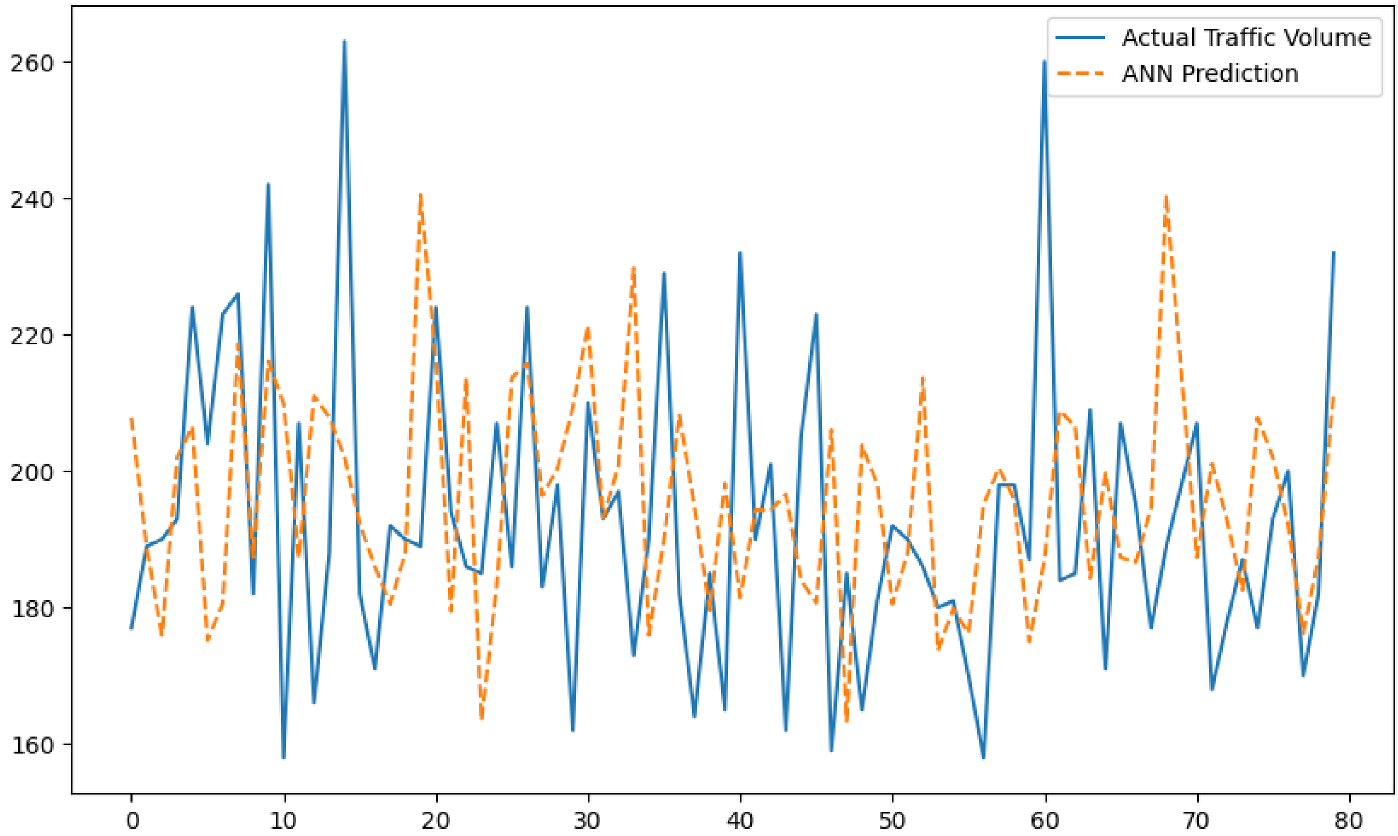

Figure 11. Comparison of ANN Vs. Actual Traffic Volume.

DOI: https://doi.org/10.52756/ijerr.2024.v45spl.019

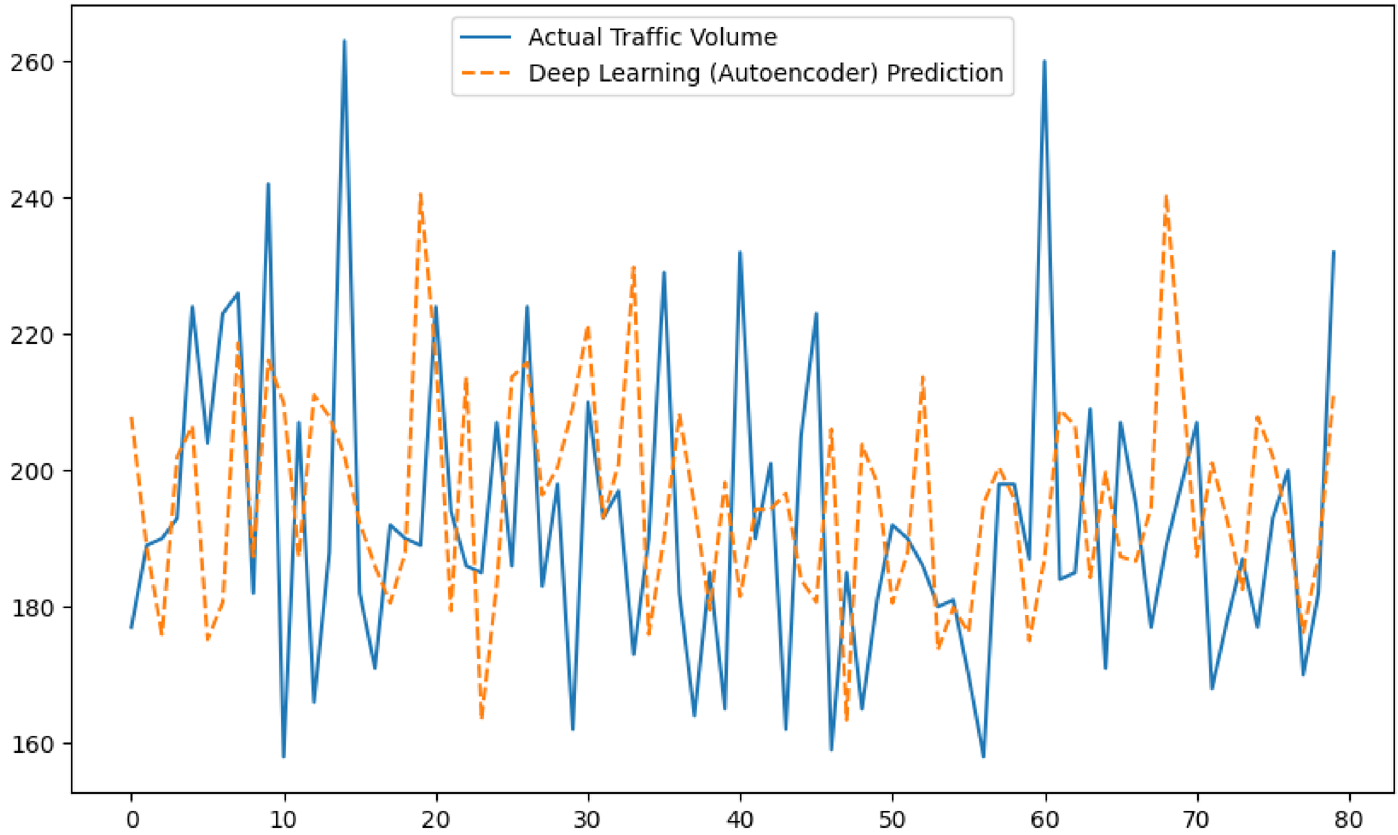

Figure 12. Comparison of Deep Learning (Autoencoder) prediction Vs. Actual Traffic Volume.

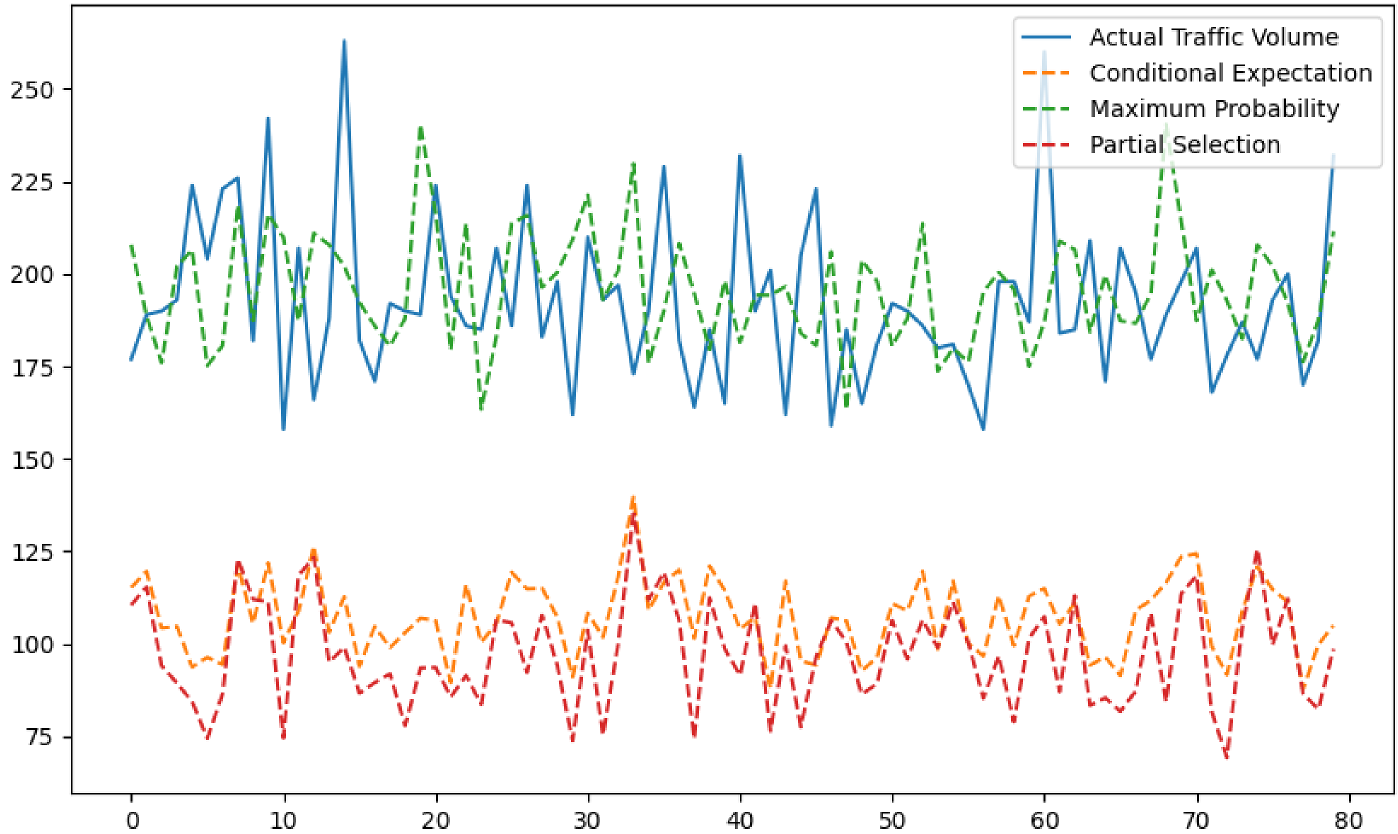

Figure 13. Forecasting results by Three strategies.

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Thereafter, a comparison of achieved RMSE values of each model is shown in Table 2 and Figure 8, and it is found that for the provided data, the Autoregression (AR) model outperforms. In this case, the high RMSE values of the Historical Average and Random Walk models make them unsuitable for prediction purposes. However, it has been assumed that the results could be changed if we provide more advanced machine learning models or coupled with them.

Table 2. RMSE values were obtained through various models.

Sr. No.	Model Technique	RMSE
1	Historical Average	27.676612
2	Random Walk	26.873221
3	Autoregression (AR)	22.667893
4	Support Vector Regression (SVR)	28.222095
5	Exponential Smoothing	24.096784
6	Artificial Neural Network (ANN)	26.592718

Forecasting with Probability-Driven Model Integration

After performing all six candidate models, we employed deep learning model coupled with traditional approaches. Before performing the models, we classified that 80% of the data is used for training, while the remaining 20% is used for testing the unseen data. After performing the models, we observed that the AR, SVR, and Exponential Smoothing resulted in higher RMSE values as 150.75, 147.40, and 148.39, respectively. While, ANN and Deep Learning (Autoencoder) models showed a low RMSE value of 26.99, indicating their superiority in handling non-linearity in the traffic data. These models were trained on compressed representations of the data, leading to more accurate predictions.

The comparisons of each model's predictions versus actual traffic volume are depicted in Figures 9, 10, 11 & 12, illustrating how deep learning models closely track actual traffic patterns.

Three strategies were tested in the Forecasting with Probability-Driven Model Integration: Conditional Expectation, Maximum Probability, and Partial Selection. The Maximum Probability strategy, driven by the best-performing Deep Learning model, achieved the lowest RMSE of 26.99, outperforming Conditional Expectation (RMSE: 88.49) and Partial Selection (RMSE: 98.54) as shown in Figure 13.

Result and Discussion

The traffic forecasting models were evaluated using data collected over 31 working days, capturing traffic across five vehicle categories: two-wheelers (motorcycles, scooters), four-wheelers (cars, sedans), heavy vehicles (trucks, buses), light vehicles (vans, SUVs), and other specialized vehicles. Pre-processing involved handling missing data, normalization, and feature engineering, ensuring the dataset was suitable for model training. The dataset was split into 80% for training and 20% for testing. The models' performance was evaluated using the RMSE metric to assess their predictive accuracy.

The Autoregressive (AR) model achieved an RMSE of 22.6679, indicating its effectiveness for short-term traffic predictions in stable conditions. However, AR struggled with non-linear traffic dynamics and experienced increased prediction errors during sudden spikes in traffic volume. Evidently, the SVR model has RMSE 28.2221, which is worse than AR. This may be due to its high sensitivity towards the noise. Therefore, extensive tuning of hyperparameters is required. However, in the same noisy environment, the performance of Exponential Smoothing is satisfactory, but it has also struggled with non-linear patterns. The RMSE values of the Historical Average and Random Walk models are 27.6766 and 26.8732, respectively and were found to be worse. Thus, it is observed that these models are suitable only for stable traffic environments. The best performance came from the Stacked Autoencoder with Softmax Classifier, which achieved an RMSE of 26.9976. This may be due to its ability to extract high-level features from the input data, which allowed it to gain complex and non-linear relationships between input and output variables and make it the most accurate and suitable model. Overall, the deep learning model outperformed traditional models by better handling non-linear traffic patterns and fluctuating traffic conditions. However, training deep learning models requires significant computational resources. The SVR model performed relatively well but showed reduced accuracy in noisy environments.

After the training of individual models, dynamic probabilities are assigned to each model based on their performance. This gives more weight and allows the model integration process for dynamic data. Higher probabilities are assigned to the AR and Exponential Smoothing models during stable traffic conditions. However, the system selected the Stacked Autoencoder and SVR models due to high traffic fluctuation. This may be due to their better performance in non-linear traffic patterns.

Over time, the dynamic probability weights adjusted smoothly, confirming that the system remained adaptable

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for real-time changes in traffic conditions. This dynamic probability assignment process improves the robustness of the prediction performance by dynamically adjusting the assigned weights.

Then, various strategies of conditional forecasting, such as conditional expectation, maximum probability, and partial selection, are selected and employed in the model. Minimum RMSE was achieved by the Conditional Expectation strategy, which is based on calculating the weighted sum of predictions from all models. It provides the lowest overall prediction error and is found effective for moderate traffic fluctuation. On the other hand, the maximum probability strategy, which relied on the prediction from the highest-probability model, performed well in stable traffic conditions, but it has limitations in highly volatile environments due to its dependency on a single model's prediction. Meanwhile, based on average predictions from the top-performing models, the partial selection strategy performs well during traffic fluctuations. Thus, it has been revealed that the Conditional Expectation strategy is the most consistent forecasting strategy among others.

The results of this study are important for real-time traffic management systems in urban environments. Using dynamic probability assignment and probability-driven model integration, the system can adapt to real-time changes in traffic conditions, making it highly effective for traffic management applications requiring accurate, up-to-the-minute predictions.The probability-driven model integration approach offers a promising solution for real-time traffic forecasting, as it dynamically adjusts model weights based on current traffic conditions. Future work should focus on optimizing these models or exploring more efficient architectures like LSTM to reduce the computational overhead. Another limitation is the reliance on historical data for model training. In real-world applications, incorporating real-time data streams and handling missing or incomplete data remain challenges that must be addressed to improve the system's accuracy and practical applicability. Incorporating real-time data into the forecasting system would help ensure more timely and accurate traffic predictions.

Conclusion

In this research paper, the authors used both traditional and deep learning models on a traffic dataset for 31 working days to forecast traffic volumes based on various vehicle categories. For this purpose, initially they performed dataset pre-processing to ensure the suitability of data for model training and analysis. Thereafter, they employed different models for traffic forecasting and evaluated their performance based on RMSE. Based on the results, they observed that the traditional models, such as AR were suitable for the same, with RMSE value of 22.6679. However, they employed a deep learning model coupled with an autoencoder and softmax classifier. They achieved RMSE of 26.9976, demonstrating its superiority over other models for non-linear relationships and dynamic traffic conditions.

Additionally, the authors found that the system's adaptability to real-time traffic changes can be significantly enhanced when dynamic probability assignment and probability-driven models are integrated. Based on the results obtained, the authors believe that the presented research underlines the importance of employing advanced deep-learning techniques and dynamic model integration strategies to improve the accuracy of traffic forecasting in environments where traffic patterns fluctuate rapidly.

Acknowledgement

The authors are highly thankful to the management of DIT University, Dehradun, UK, India, for providing fruitful support to complete this work.

Conflict of Interest

The authors declare no conflict of interest.

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How to cite this Article:

Abhay Narayan Tripathi and Bharti Sharma (2024). Evaluation of a Probabilistic Framework for Traffic Volume Forecasting Using Deep Learning and Traditional Models. *International Journal of Experimental Research and Review*, *44*, 237-250.

DOI : https://doi.org/10.52756/ijerr.2024.v45spl.019