International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Forecasting Traffic Volume Using Statistical and Artificial Intelligence Tools: Prophet, FbProphet, and Neural Prophet

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Submitted: 14/03/2024 **Revised**: 25/04/2024 **Accepted**: 03/05/2024

Abstract: The rising volume of vehicles on Indian roads causes congestion, accidents, and pollution levels, making solving traffic problems in Indian cities increasingly difficult. Transport networks may now function more efficiently thanks to Intelligent Transport Systems (ITS), a key solution that makes use of information and communication technologies. To achieve a complete approach, this research integrates policy initiatives, advanced technology such as ITS, and infrastructural upgrades. The use of predictive modeling methods in ITS implementations—such as Prophet, FbProphet, and Neural Prophet—becomes essential as technology develops. These models are essential to the development of sustainable and effective transport systems because they provide the ability to predict and react to dynamic traffic patterns. In this research, three traffic volume prediction models—Prophet, FbProphet, and Neural Prophet—are compared.

Keywords: *Traffic Flow Prediction, Traffic Congestion, Short-term Traffic Prediction, Prophet, FbProphet, Neural Prophet*

1. Introduction

Predicting how traffic will flow is crucial for managing vehicular traffic. Congestion, accidents, and pollution have all worsened as a result of the recent rise in both rural and urban traffic. There are several traffic issues plaguing Indian cities, including inconsistent traffic flows, high levels of congestion, excessive noise and air pollution, and a corresponding increase in traffic-related deaths and injuries. Intelligent transport systems (ITS) have made considerable strides in recent years. The term "Intelligent Transportation Systems" refers to the use of information and communication technology to enhance the effectiveness of road transportation networks and find remedies to transportation issues. ITS plays a crucial role in addressing these challenges by leveraging information and communication technology to improve the overall performance of transportation networks[1].

ITS encompasses a variety of technologies and applications designed to enhance the safety, efficiency, and sustainability of transportation systems. Addressing the traffic challenges in Indian cities requires a comprehensive and integrated approach that combines infrastructure improvements, policy initiatives, and the adoption of advanced technologies like ITS. As technology continues to advance, incorporating predictive modeling techniques such as Prophet, FbProphet, and Neural Prophet into ITS implementations can enhance the system's ability to forecast and respond to dynamic traffic patterns, thereby playing an increasingly significant role in creating more sustainable and efficient transportation systems. This paper presents a comparative study of models designed for predicting traffic volume using Prophet, FbProphet and Neural-Prophet. The emphasis is on recognizing, discussing, and proposing statistical insights, particularly in areas where analytical challenges and technological advancements converge for the future of short-term traffic forecasting research.

1.1.Literature Survey

Chikkakrishna., et al. [2] proposed research that relies on the R software's Facebook PROPHET package and the Seasonal Autoregressive Integrated Moving Average (SARIMA) for short-term traffic forecasting.The PROPHET model will provide a trend forecast and confidence interval for the future date.ChikkaKrishna, N. K., et al. [3] Proposed another study, were they use Fb-PROPHET and Neural-PROPHET to forecast traffic volumes and create Short-Term Traffic Prediction models. The pneumatic approach was used to collect data on the daily and hourly classifications of traffic on National Highway 744 in Tamil Nadu. Mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) tests were used to evaluate the created models' goodness of fit. The planned effort will aid traffic management agencies in avoiding congestion through better route design and allocation.Kumar, S. V., et al [4] They proposed a study on predicting traffic flow in areas with limited data availability, focusing on a 3-lane arterial roadway in Chennai, India. The study proposes using a Seasonal Autoregressive Integrated Moving Average (SARIMA) model for short-term predictions,

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utilizing only three consecutive days of flow data. The process involves differencing for stationarity and determining model parameters through the maximum likelihood method in R. Validation includes a 24-hour ahead forecast, comparing predicted flows with actual values, and assessing performance against historic average and naive methods. The proposed SARIMA model shows a mean absolute percentage error (MAPE) in the range of 4–10%, suggesting its applicability in Intelligent Transportation Systems where data constraints exist.Yu, Z., et al [5] proposed a new Long Short-Term Memory (LSTM) -NeuralProphet (NP-LSTM) hybrid forecasting model built using a parallel-series hybrid structure. Neural Prophet was created to extract primary trends and seasonal effects while also providing interpretability, and the suggested model makes use of LSTM to describe these nonlinear interactions. In this paper's tests, they use four different datasets to evaluate their model against both existing standalone models and hybrids based on traditional architectures. Their experimental findings demonstrate the higher performance of NP-LSTM which is a hybrid model achieves good forecasting result in various criteria.Hindarto, D.,et al [6] They proposed Neural Prophet's ability to predict rice sales at major food kiosks by discerning data trends and fluctuations results in accurate sales estimates. The model performs well: MAE = 12.90, RMSE = 15.80, and Loss = 0.0313. This research empowers basic food stall owners and suppliers to streamline inventory management, avoid stockouts, and reduce overstocking by using the Neural Prophet algorithm's rice demand forecasting.Ersöz, N. Ş., et al [7] COVID-19 has seen the greatest global spread in recent years. After hundreds, the death toll rose to thousands and millions. Since January 2020, researchers have been developing COVID-19 models and projections to help governments prepare hospitals and reduce deaths. This analysis predicts the European COVID-19 pandemic using ARIMA, Prophet, and Holt-Winters Exponential Smoothing. Compare and contrast the three approaches' performance. This dataset contains WHO-classified COVID-19 case data from 2020 to 2022 in Europe. Holt-Winters Exponential Smoothing outperformed ARIMA and Prophet with an RMSE of 0.2080 and MAE of 0.174.Adigopula, V.K.,et al[8] his study examines Indian smart transportation systems. Both academics and industry are ITS priorities. Modern data communication has merged commuter networks, roadways, and automobiles using information, communication, computers, and other integrated technologies. Indian ITS research has shortcomings, according to the literature. This evaluation stresses ITS and ICT assessment. Improve current and future programs. India's high population density, lack of lane discipline, and range of vehicle speeds (pedestrians, light motor vehicles, bicycles) make ITS deployment difficult. Early ITS solutions focused on traffic management criteria. ITS data can give real-time network conditions, improving coordination and network use. Second, research comparing India's ITS implementation to chosen overseas countries. This study included SWOT analysis, technical solutions, planning, finance, and Indian ITS implementation measures.

This report helps governments and politicians in emerging nations like India remove barriers to ITS expansion and smart city efforts.Hussein, H., et al [9] ICT advancements have created smart cities with many pieces, and artificial intelligence is essential. Smart Health improves healthcare via illness predicting, early diagnosis, and more. Machine learning algorithms can aid S-Health, but which is best for disease prediction. Gedaref State, Sudan's wettest, has malaria and pneumonia year-round. Researchers have predicted these diseases' future tendencies to enable Gedaref's administration and the state's ministry of health to avoid and control them and establish a suitable pharmaceutical store. Thus, Gedaref's government needs a trustworthy forecasting model to develop economic and medical strategies for these diseases and allocate medical resources. Use of a state ministry of health time series dataset estimates malaria and pneumonia as prevalent infections in Gedaref state, Sudan, five months later. ARIMA and Prophet forecast disease cases using the disease dataset. This study compares Gedaref State malaria and pneumonia forecasting using ARIMA and FB-Prophet. State health ministry data from January 2017 to December 2021 was used. The ARIMA approach outperforms the FB-Prophet forecasting method in malaria (182.8, MAE: 141.6, MAPE: 0.0057, and MASE: 0.0537) and pneumonia (1400.3, MAE: 1001.4, MAPE: 0.0513, and MASE: 0.9136).

1.2. Problem Statement

Urban traffic congestion is a pressing issue that affects the efficiency of transportation systems, increases travel time, and contributes to environmental pollution. Accurate short-term traffic flow prediction is crucial for developing effective traffic management strategies to mitigate these adverse effects. Traditional statistical and machine learning models often fall short in capturing the complex, non-linear patterns inherent in traffic data, necessitating the development of more advanced forecasting methods. Facebook's Prophet tool has gained popularity for its simplicity and effectiveness in handling time series data, especially for capturing seasonality and trends. However, while Prophet is robust and user-friendly, it has limitations in dealing with highly dynamic and non-linear datasets such as traffic flow data.To address these limitations, the development and application of Neural Prophet—a hybrid model combining the strengths of Facebook's Prophet and neural network techniques—offers a promising solution. Neural Prophet aims to enhance the forecasting capabilities by incorporating non-linear components and leveraging the flexibility of neural networks. This study focuses on comparing the performance of Prophet, FbProphet (an enhanced version of Prophet with additional capabilities), and Neural Prophet in short-term traffic flow prediction. Preliminary results show that while Prophet and FbProphet are effective in capturing general trends and seasonality, they may struggle with the intricate patterns of traffic flow data. Neural Prophet, on the other hand, integrates neural network methodologies to better handle these complexities, potentially providing more accurate and reliable predictions. The problem, therefore, is to develop and validate a short-term traffic flow prediction model that can effectively utilize the strengths of Prophet, FbProphet, and Neural Prophet. The goal is to achieve higher accuracy and reliability in predictions, enabling more efficient traffic management and reduction in urban congestion. This involves comprehensive evaluation of these models on real-world traffic datasets to identify the most effective approach for real-time traffic flow forecasting.

2. Method

In this paper, models were developed to predict traffic flow using Prophet, Fb-PROPHET and Neural-PROPHET with a clear focus on recognizing, discussing, and proposing statistics on extents where the analytical challenges and technological recline for the future generation using short term traffic forecasting research. Figure1 explains the working methodology of these three-model creation [10].Daily historic data is captured and is subjected to preprocessing which consist of enhancement and/or error reduction of the data. From the cleansed data training and testing data set is splits for the model creation and prediction. And finally, evaluation and comparison of the model prediction results were done [11]. The result of errors in a developed system like false acceptance and false rejection determines the accuracy of the system.Figure 1 shows the model creation and stimuation details.

2.1. Prophet, Fbprophet, Neural Prophet &Trend

Prophet and FbProphet are based on an additive time series decomposition model that includes components for trend, seasonality, and holidays. They use a piecewise linear model for capturing trend changes and provide flexibility in handling various time series patterns. Neural Prophet extends the original Prophet framework by incorporating neural networks for more complex modeling. It allows for capturing non-linear patterns in the data, which can be beneficial for datasets with intricate relationships. Both tools handle seasonality well and allow for the inclusion of custom seasonality components [12]. Holidays and special events can be incorporated to account for their impact on the time series. Neural Prophet provides more advanced options for trend modeling, allowing users to specify the trend flexibility and include additional features like yearly seasonality. The Neural Prophet has improved handling of missing data compared to the original Prophet [13].

2.1.1 Prophet

PROPHET is an additive model in which non-linear trends are fitted with annual, weekly, daily, and holiday-related seasonality. For optimal results, use a time series with robust seasonal effects and multiple years of data [14]. Prophet is robust against outliers and missing data, and it can tolerate trend changes.The Prophet framework can be expressed by the following formula:

$$Y(t) = g(t) + s(t) + h(t) + € t \ (4) \qquad (1)$$

where, g(t) is the trend item, modeling the aperiodic changes in time series; s(t) is a seasonal periodic item, reflecting the nature of periodic changes in the day, week, or year; h(t) is a holiday item, indicating the influence of special events on time series; €t is an error term, meaning that it does not react abnormally in the model and obeys normal distribution.

2.1.2 FbProphet

FbProphet is a forecasting technique which is fast and is completely automated with no manual effort. It works fine with time series as it is robust to missing information and changes in the trend which typically handles irregularities well[15]. The Fb-PROPHET model gives the predicted traffic flow the form of trends and the upper and lower limits, allowing the data to fit into the best model. FbProphet uses an additive decomposition model, meaning that the various components (trend, seasonality, holidays) are added together to obtain the predicted value. FbProphet includes functionalities for handling missing data, automatic changepoint detection, and flexible handling of outliers[16]. It adds features and improvements to the original Prophet, making it more robust and versatile.

2.1.3 Neural-Prophet

Neural-Prophet holds the design philosophy of Prophet and delivers similar basic model components. Deep clusters at large-scale networks can effectively cluster the road segments and predictions based on group-based models can achieve comparable performance against individual-based models with a smaller number of models. Neural Prophet is more complex than both Prophet and FbProphet due to the incorporation of a neural network component [17]. Neural Prophet is better equipped to capture nonlinear and intricate patterns in the data compared to Prophet and FbProphet.

2.1.4 Trend Attributes

Trend parameter is used in all the three algorithms and trend is modelled by fitting a piecewise linear curve over the trend or the non-periodic part of the time series. The linear fitting exercise ensures that it is least affected by spikes/missing data. Here are two growth models in the Prophet framework, g(t), one is the logistic model and the other one is the linear model. The difference between which is whether the carrying capacity is limited[18]. Trend items are affected by change points. The expression of the growth trend of logistic regression nonlinear saturation is:

$$g(t) = \frac{C(t)}{1+e-e^{-k(t)(t-m(t)}} \tag{2}$$

where C(t) is the bearing capacity; k(t) is growth rate; m(t) is the offset. All three parameters are functions of time (t).The expression of piecewise linear growth trend is:

$$g(t) = (k(t) + a(t)^T\,\partial)t + (m(t) + a(t)^T\,)\gamma \tag{3}$$

where k(t) is the slope variation; a(t) is the parameter adjustment vector; m(t)indicates the offset.

The trend item growth model should be selected according to the characteristics of the predicted objects. FbProphet automatically detects changepoints in the time series, identifying points where the data exhibits a significant change in its trajectory. In both Prophet and FbProphet, trend change is automatically handled through a piecewise linear model [19]. The algorithms identify changepoints in the historical data where the trajectory of the time series exhibits significant changes. These changepoints allow the model to adapt to variations in the trend over time. Neural Prophet, being an extension that incorporates neural networks, allows for a more flexible and dynamic representation of the trend [20]. The neural network component in Neural Prophet can inherently capture non-linear patterns and adapt to more complex changes in the trend. All three algorithms are capable of handling trend changes, but they use different mechanisms for doing so. Prophet and FbProphet use a piecewise linear model with automatic changepoint detection, while Neural Prophet leverages the flexibility of neural networks to capture more complex trend changes. Table1 describes the trend attributes in the models. Table 2 describes attributes in the dataset.

Table 1. Trend attributes of the specified models

Parameter	Description
Growth	Linear or Logistic trend
Changepoints	List of dates at which to include the changepoints
n_Changepoints	Default Changepoint

Table 2. Attributes of the Dataset

Parameter	Description
ID	Junction ID with 5 Minutes interval
Timestamp	Date &Time
hourly_traffic_count	No. of vehicles pass at that timestamp

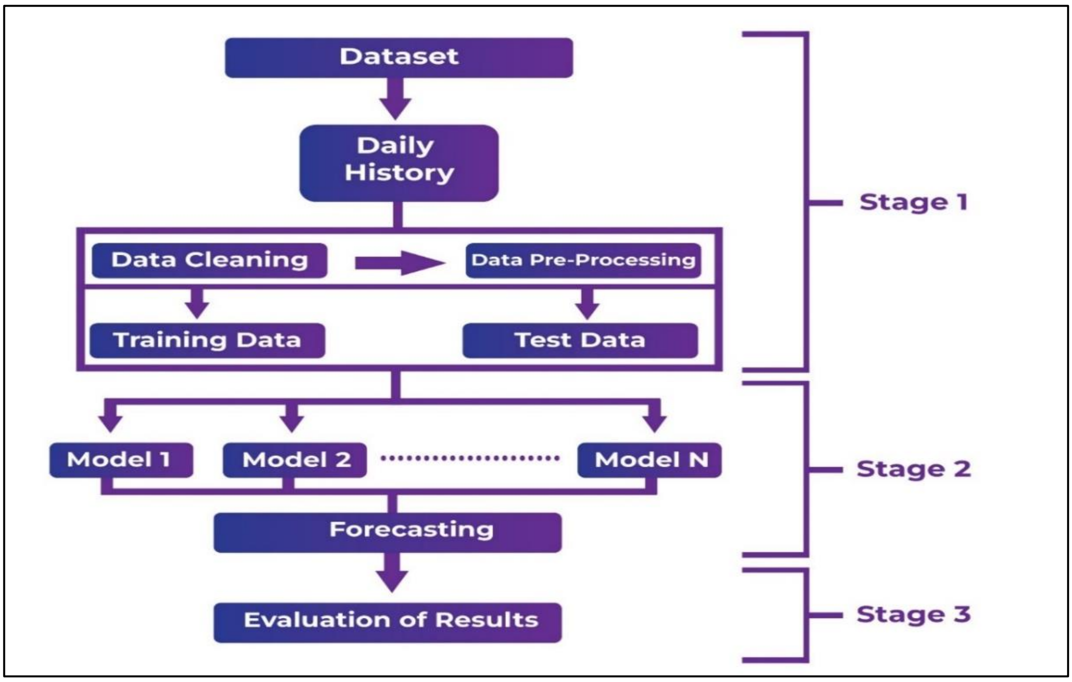

Fig 1. Simulation model creation

2.1.5 Dataset & Experiment Discusssion

The algorithms are implemented using Jupyter Notebook. Prediction experiments are carried out with sample data from the Kaggle database. The Dataset used here contains the traffic count of a certain road at each 5-minute interval [21]. There are two columns in the dataset: the timestamp and the hourly traffic count (which is counted in each five-minute interval). The dataset contains 26396 rows of data starting from 2015-10-04 00:00:00 and which ends at 2016-01-03 23:55:00. Figure 2 shows the details of the dataset.Each day, with a 5-minute interval, the traffic is counted. So, for each day, we get 24x60/5 = 288 rows or timestamps of traffic data [22].We do some preprocessing of the data. This is because FbProphet needs the dataset to have two columns in specific names: ds and y. Also, the ds column needs to be in datetime format. So, we will check and tune our dataset accordingly [23]. The dataset is seasonal, that means it has a repeating pattern to it. That's a good thing. But the problem here is it has missing values, but they are not NaN, they are zero (0). This missing value is because the dataset was created using a machine which eventually ran into some error. That's why the machine could not count traffic. Hence it placed zero at those places. There are several approaches to handle those missing values. But for simplicity's sake, we are going to exclude the values with error. To be more specific, in Figure 2 and 3, we will be using only a month's data starting from 2015-10-04 00:00:00 to 2015-11-03 00:00:00 for training purpose (31days x 288 rows each day = 8928 timestamps) and will try to predict the next 3 days traffic (3x288 = 864 timestamp) for testing purpose. So, in total we are going to extract 9792 timestamps or rows from our dataset and get a visualization [24][25].Figure 3 shows the visualization of the dataset used.

```
df=pd.read_csv('train27303.csv')
df
```

	timestamp	hourly_traffic_count
0	2015-10-04 00:00:00	3
1	2015-10-04 00:05:00	16
2	2015-10-04 00:10:00	9
3	2015-10-04 00:15:00	12
4	2015-10-04 00:20:00	19
...	...	...
26491	2016-01-03 23:35:00	16
26492	2016-01-03 23:40:00	15
26493	2016-01-03 23:45:00	10
26494	2016-01-03 23:50:00	19
26495	2016-01-03 23:55:00	15

26496 rows × 2 columns

Fig 2. Description of Dataset

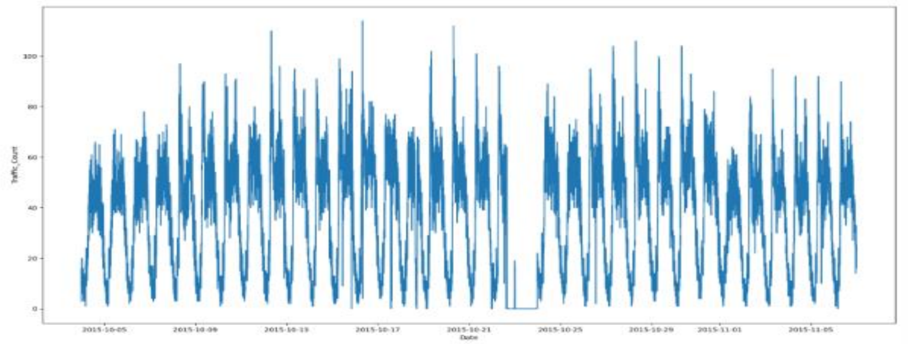

Fig 3. Visualization of the Dataset used

3. Result Prediction And Discussion

The collected characterized hourly traffic dataset is used for time series modeling using PROPHET, Fb-PROPHET, and Neural-PROPHET in Jupyter Notebook. As we discussed, we will predict the outcome for the next three days i.e., from 04/11/2015 Midnight to 06/11/2015 Midnight. For this, we need a matrix of the timestamps for which our model will predict the traffic count. So, for that, we used the ds column of our test dataset and used the prediction method to predict the outcome. The developed model is then tested for its accuracy from R2 SCORE and RMSE tests and the results compared. Figure 4 Shows the real traffic volume or count of the Testing dataset from the date mentioned. We are going to create a model by calling the Prophet. But as the core purpose of FbProphet was to deal data on day, month, and year basis, we need to add a parameter: changepoint_prior_scale=0.01 which will help us handle minute-wise data for the model. Also, we will calculate the time required for fitting the data with our model. Figure 5 shows the observed Prediction from Prophet and Figure 6 shows the trend analysis of Prophet Algorithm. Figure 7 shows the Fb-Prophet Prediction and Figure 8 shows the Neural-Prophet Prediction result.

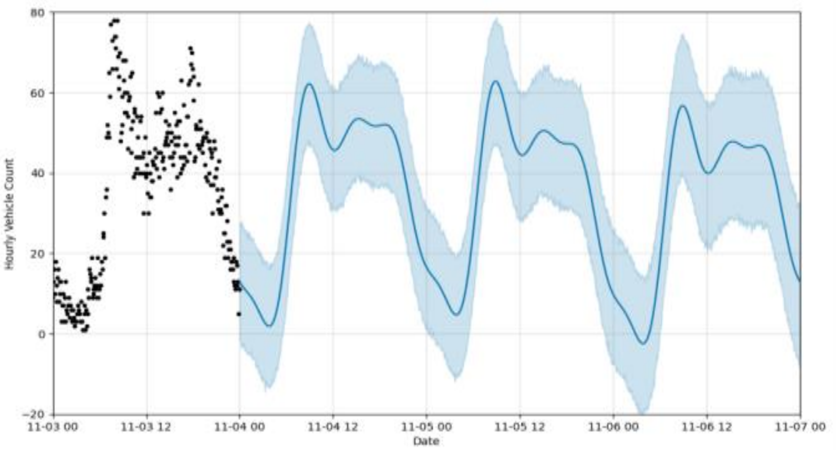

Fig 4. Real Traffic volume of the Testing Dataset

3.1. Prophet – Observed Result

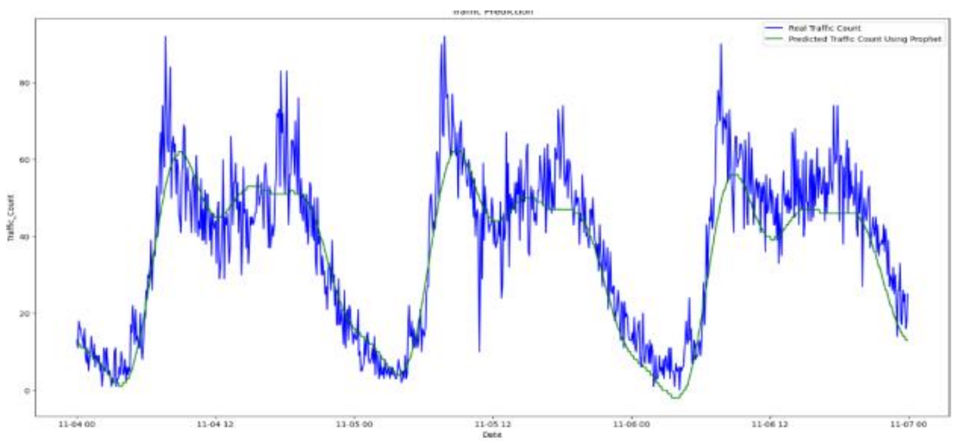

Fig 5. Prophet – Observed Result

Each line on the graph describes the predicted traffic volumes generated by these algorithms, providing a visual insight into their respective forecasting capabilities. This graph offers a side-by-side comparison of traffic volume predictions by Prophet, FbProphet, and Neural Prophet. The distinct trends and patterns in the lines reveal the strengths and variations in predictive accuracy across the three algorithms. In this visual representation, the predictive outcomes of Prophet, FbProphet, and Neural Prophet are graphically depicted, allowing for a comprehensive evaluation of their performance. The graph serves as an intuitive tool to discern the differences in forecasting precision among these algorithms. The plotted results from Prophet, FbProphet, and Neural Prophet provide a comprehensive view of their respective predictive performances. The variations in the lines showcase the models' abilities to capture the dynamic nature of short-term traffic patterns. This graph is a visual representation of the predictive efficacy of Prophet, FbProphet, and Neural Prophet in short-term traffic forecasting. Each curve reflects the model's output, offering a comparative assessment of their accuracy and reliability.

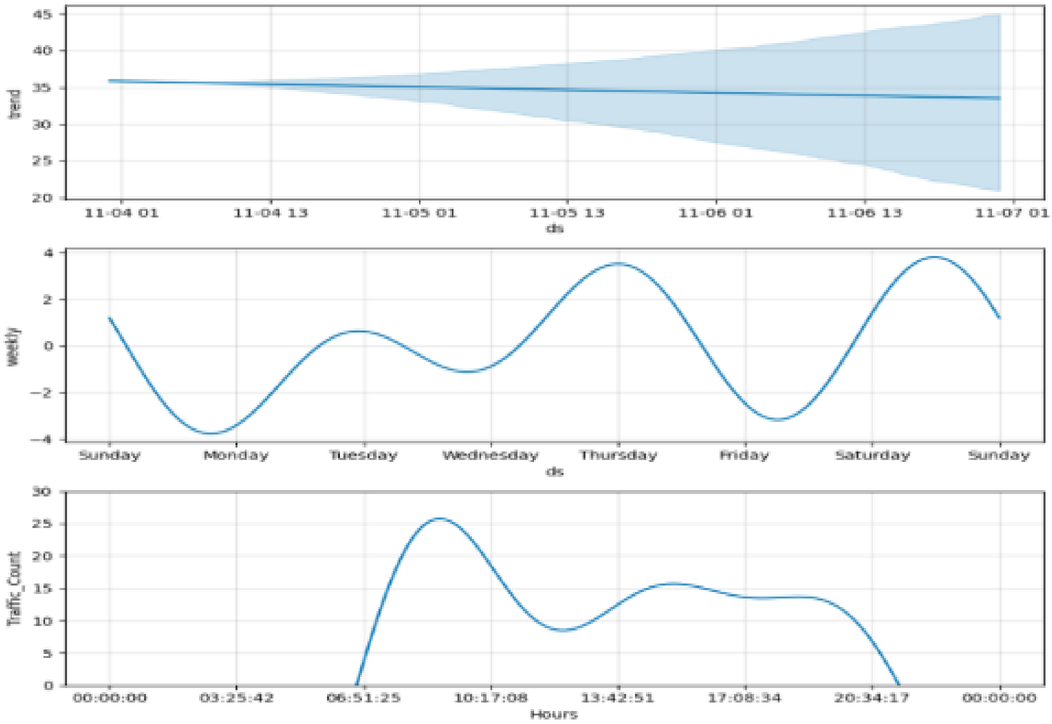

Fig 6. Prophet Trend Component Variations

3.2. FbProphet -Observed Result

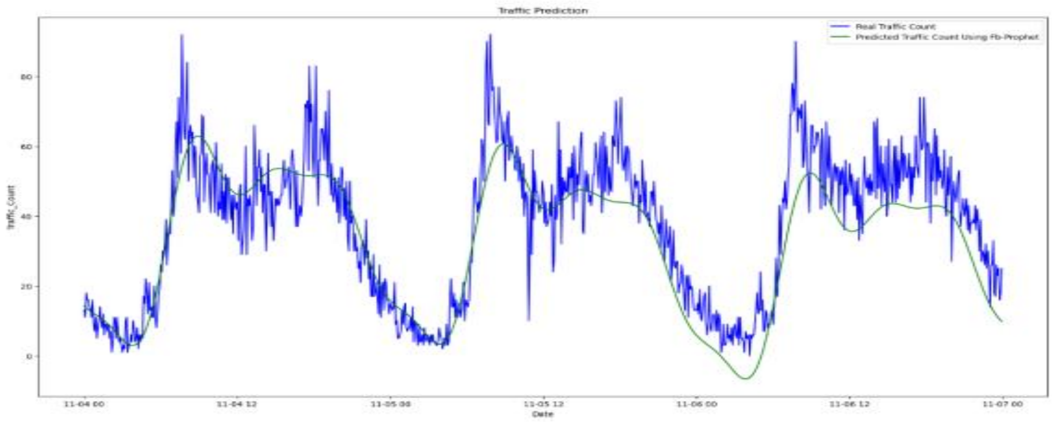

Fig 7. FbProphet -Observed Result

3.2.1. Neural Prophet-Observed Result

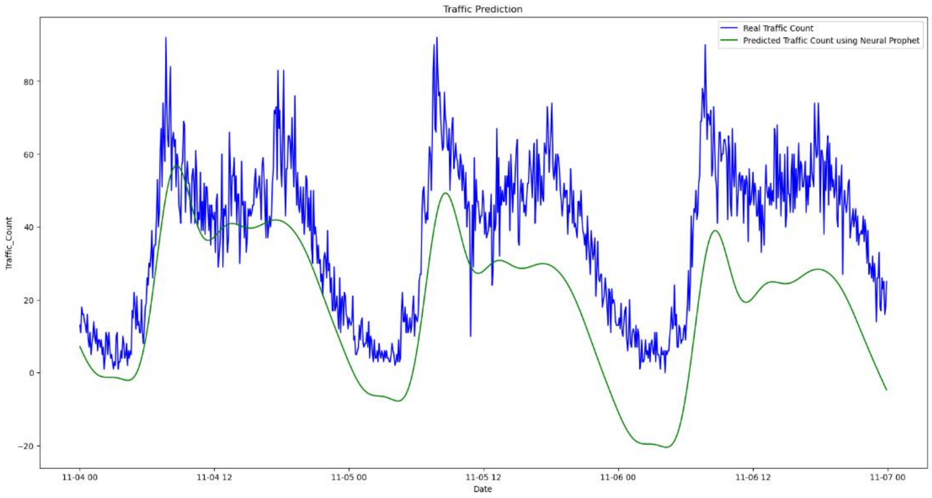

Fig 8. Neural Prophet-Observed Result

3.2.2. Prophet FbProphet and Neural Prophet-Combined Result Analysis

The present work comprises three prediction models for finding out the best algorithm. Figure 9 represents the observed outputs from Prophet, Fb-Prophet, and Neural-Prophet. The graphical representation illustrates the comparative performance of three prominent traffic forecasting tools.Table 3 indicates the model performance measures RMSE, R2 Score, Accuracy Score for calibrating dataset and testing dataset indicating that the FbProphet model performs well than the other models: Prophet & Neural prophet.

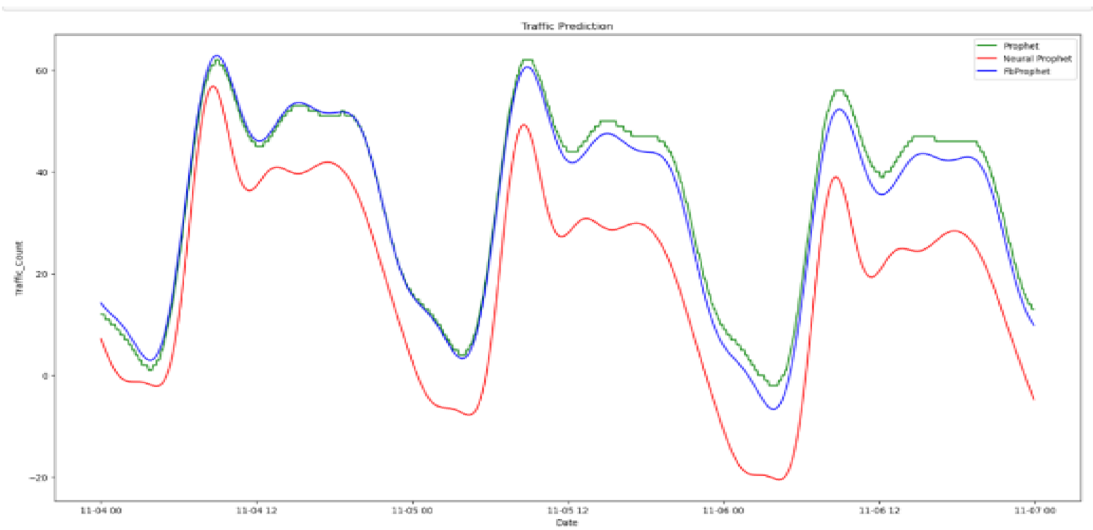

Fig 9. Neural Prophet-Observed Result

Table 3. Traffic Volume Prediction Evaluation for Designed Models

Evaluation Metrics	PROPHET	NEURAL PROPHET	FbPROPHET
RMSE	0.010797	0.025268	0.012502
R2 SCORE	0.89669	0.83774	0.96658
ACCURACY SCORE	0.973387	0.801157	0.973704

4. Conclusion

Several prediction models are used in this work to estimate traffic flow prediction for the data gathered from the Kaggle dataset. The current research has led to the following conclusions: Three brand-new, cutting-edge methods were employed in the study to forecast future traffic volume by helping to comprehend the temporal variances in the historical data. According to the model outputs, FbProphet prediction for the collected data is more accurate than Prophet & Neural Prophet. Finally, the thorough analysis of model performance metrics, namely RMSE and R2 Score, over calibration and validation datasets demonstrates that the FbProphet model outperforms its competitors, Prophet and Neural Prophet when it comes to short-term traffic forecasting

Declarations

Ethics Approval And Consent To Participate

We submitted this manuscript to the Ethics Committee of the institution. This board reviews the ethical aspects of my study, ensuring it complies with institutional and governmental regulations regarding the treatment of human subjects.

Consent For Publication

Not applicable

Availability Of Data And Materials

Not applicable

Competing Interests

The authors have no conflicts of interest to declare.

Funding

Not applicable

Authors' Contributions

SS: Conceived and designed the study, conducted experiment in the Jupyter Notebook-Python, collected and analyzed data and drafted the manuscript. JSN: Guided the Research directions and reviewed the manuscript. All authors have read and approved the final manuscript.

Acknowledgements

None

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