Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

A Study on the Role of Optimizers in Short-Term Traffic Flow Prediction Accuracy

Sigma Sathyan[1,2], Jagadeesha S N[3]

[1]Research Scholar, College of Computer Science and Information Science, Srinivas University, Mangalore, India.
[2]Santhigiri College of Computer Sciences, Vazhithala, Kerala, India. ORCIDID: 0000-0002-0092-9114; Email ID: sigmaakhil2014@gmail.com
[3]Research Professor, College of Computer Science and Information Science, Srinivas, University, Mangalore, Karnataka, India. ORCIDID: 0000-0002-5185-2233; Email ID: jagadeesha2012@gmail.com

ARTICLE INFO

Received: 08 April 2024

Accepted: 01 May 2024

Published: 15 May 2024

ABSTRACT

This work demonstrates the creation of a strong and reliable model for predicting short-term traffic. The model utilizes Neural Prophet and is optimized using **ADAM** and (Stochastic Gradient Descent) **SGD**. Additionally, momentum is incorporated to improve the accuracy of predictions and the speed at which the model converges. Accurate anticipation of traffic congestion is crucial for effective urban planning and immediate traffic control. Conventional forecasting techniques frequently encounter difficulties in dealing with the ever-changing and intricate nature of traffic patterns. Neural Prophet is an advanced instrument for forecasting time-series data that use a complex method to accurately capture patterns in the data.This model gains advantages in efficiently managing large-scale data and reducing computational costs by including modern optimization techniques like ADAM and SGD. Incorporating momentum enhances the speed at which the convergence process occurs, ensuring stability and reducing oscillations while training.From the results we obtained the the prediction graph.Prediction graphs display data in many time intervals, including weekly, yearly, daily, and trends.

Keywords: *Short term traffic, ADAM, SGD, momentum, Neural Prophet*

Introduction

Urban regions are plagued by a widespread problem of traffic congestion, which results in substantial delays, elevated fuel usage, and increased emissions. Precise short-term traffic forecasting is essential for promoting urban mobility and optimizing transportation networks[1][2]. Short term traffic forecasting is one of the important fields of study in the transportation domain[3][4]. Short-term traffic forecasting is highly valuable for the development of a sophisticated transportation system that can effectively manage traffic signals and prevent congestion[5][6]. Multiple studies have endeavored to predict short-term traffic patterns for both divided and undivided roadways worldwide.[7]. Machine learning has made significant progress in the field of traffic forecasting, and Neural Prophet has emerged as a highly intriguing tool for this task[8][9]. Short-term traffic flow prediction is a critical aspect of traffic control and guiding, and it plays a vital role in the advancement of infrastructure[10] [1]. Forecasting the daily traffic volume in the near future is crucial for rural roads as it helps alleviate congestion, aids in trip planning, and enhances the level of service (LOS)[2]. The detrimental effects of traffic congestion, such as travel discomfort, air pollution, and economic losses, have significantly impeded the productive and sustainable growth of cities[3].

Neural Prophet is a state-of-the-art time-series forecasting tool that extends the capabilities of the original Facebook Prophet model by incorporating neural network components. It is designed to handle a variety of time-series forecasting tasks with high accuracy and flexibility. Neural Prophet excels in capturing non-linear patterns, seasonality, and trends in data, making it an ideal candidate for traffic prediction.[11]. Its proficiency is on capturing intricate patterns and seasonal variations in traffic data, rendering it a perfect contender for short-term traffic forecasting. This model is improved by including modern optimization techniques, such as the Adaptive Moment Estimation (ADAM) and Stochastic Gradient Descent (SGD) algorithms, which are further strengthened by the inclusion of momentum[12].

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

ADAM is a highly popular optimizer in the field of machine learning, renowned for its exceptional efficiency and effectiveness in managing sparse gradients and noisy data[13]. ADAM enhances the integration of neural networks by calculating adaptive learning rates for every parameter, making it well-suited for dynamic traffic data[14]. However, stochastic gradient descent (SGD), especially when used with momentum, addresses the drawbacks of basic gradient descent by making the optimization path smoother and preventing convergence to [15]local minima. This improves the resilience of the prediction model.

The objective of this study is to create a reliable model for predicting short-term traffic using the Prophet algorithm. We will optimize the model using ADAM and SGD, and also incorporate momentum to enhance the accuracy of the predictions and speed up the convergence process. The suggested approach utilizes past traffic data to forecast forthcoming traffic circumstances, offering useful insights for traffic control and urban development. According to experimental data, compared to those already in use, forecasting outcomes in respect to root mean square errors can be greatly improved[16][17].

This work aims to tackle the issues of short-term traffic prediction, such as data variability and real-time flexibility, by leveraging the capabilities of Prophet and advanced optimization approaches. The results of this study have the capacity to greatly improve the precision of traffic forecasting, thereby aiding in the development of more effective traffic management techniques and mitigating the negative consequences of traffic congestion.

Literature Review

Deekshetha H R[18] regression model was suggested to forecast traffic employing machine learning by integrating the Sklearn, Keras, and Tensorflow libraries. In order to forecast traffic patterns, the researchers employed Random Forest Regression, Support Vector Machine, K-Nearest Neighbor, and Gated Recurrent Unit models. The Random Forest approach accurately predicts the traffic volume with an 88.19% accuracy.

CH. Devi[5] analysed live Beijing traffic data as it appears on the Baidu map. Based on this investigation, Random Forest demonstrates the highest level of accuracy among the three approaches, with an accuracy rate of 0.719. The second options are logistic regression and support vector machines (SVM). Keywords - Traffic Flow Prediction; Decision Tree; Random Forest; Support Vector Machine (SVM); Bayesian Ridge; Convolutional Neural Network (CNN); Long Short-Term Memory (LSTM); K-Nearest Neighbours (KNN); and Gated Recurrent Unit (GRU). The objective is to assess the performance of these models when implemented to a large-scale traffic dataset. The most effective model can be utilized to predict future traffic patterns.

Dai[19] A novel approach for predicting short-term traffic flow is introduced, which combines optimal variational mode decomposition (OVMD) with a long short-term memory network (LSTM).It has the capability to more effectively collect insights from traffic flow data and enhance the precision of prediction outcomes.

Kashyap[20] examined recent advancements in deep learning for predicting traffic flow. Several deep learning designs incorporate Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Restricted Boltzmann Machines (RBM), and Stacked Auto Encoder (SAE).

Zhang[21] research introduces a flow prediction algorithm that utilizes an enhanced neural network with a genetic algorithm (GA-BP). The adaptive genetic algorithm (GA) chooses the initial n individuals that are most optimal. Additionally, the self-adaptive optimization of the search step size for the population guarantees population variety and enhances the rate at which convergence occurs. Next, the neural network processing structures are encoded. The neural network is optimized using an adaptive evolutionary algorithm to identify the most effective structure and parameters, hence enhancing the accuracy of the neural network.

Yu[3] presented a novel approach for short-term traffic flow prediction utilizing data from private automobiles and minibuses operating on the Chang Tai expressway bridge, employing a diverse range of LSTM networks.

Wang[22] proposes a hybrid architecture that integrates a long short-term memory neural network (LSTM NN) and a Bayesian neural network (BNN) to anticipate real-time traffic flow and quantify uncertainty using sequence data.

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

The Caltrans Performance Measurement System (PeMS) provides traffic flow data for six freeways in Sacramento city. This data is aggregated at 15-minute intervals in order to test the suggested model.

Chan, K Y[23] proposes a novel neural network (NN) training method that employs the hybrid exponential smoothing method and the Levenberg-Marquardt (LM) algorithm, which aims to improve the generalization capabilities of previously used methods for training NNs for short-term traffic flow forecasting.

Background Study

To develop a short term traffic prediction model, we used Prophet, optimized with ADAM and SGD, incorporating momentum to improve the prediction accuracy and convergence speed.

1. **Neural Prophet:** The Neural Prophet method is an approach used to model and predict time series data using a neural network. This method was developed based on the Facebook Prophet architecture, but with an increase in the use of neural networks to overcome some of Prophet's limitations in dealing with complex data[24]. **Optimization:** The technique of iteratively improving a machine learning model's accuracy while reducing its error rate is referred to as machine learning optimization. Machine learning models can make accurate predictions on fresh live data by applying the information acquired from training data. This method approximates the essential relationship or links among both the input and the output data. A primary goal of training machine learning algorithms is to minimize the discrepancy between the actual outputs and the predicted outputs. An optimization process involves the use of a loss or cost function, which serves to measure the difference between the anticipated and actual amounts of data. The objective of machine learning models is to minimize the loss function, which entails diminishing the disparity between the actual data and the model's predictions. By employing repeated optimization, the machine learning model will gradually enhance its capacity to classify data and make predictions about outcomes.

2. ADAM optimization method

ADAM is derived from Adaptive Moment Estimation. Now, let's analyze the distinctions and similarities between ADAM and its precursors, namely the RMSprop and momentum-based techniques. ADAM is a hybrid optimization strategy that combines the benefits of momentum-based SGD and RMSprop while avoiding their disadvantages[25][13].

Mathematical aspect of Adam Optimizer

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\left[\frac{\delta L}{\delta \omega_t}\right]$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)\left[\frac{\delta L}{\delta \omega_t}\right]^2$$

3. SGD optimization method

SGD: For training linear classification machines and regressors under convex loss functions, like those of (linear) Support Vector Machines and Logistic Regression, Stochastic Gradient Descent (SGD) is a straightforward but incredibly effective method. While SGD has been around for a while in the machine learning, it has only lately attracted significant interest in the context of large-scale learning. Large-scale, sparse machine learning issues that occur frequently in the classification of texts and processing of natural languages have been successfully tackled with SGD. The classifiers in this module easily scale to situations with greater than 10^5 examples for training and more than 10^5 features since the data is sparse.

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Mathematical formulation:

$$E(\omega, b) = \frac{1}{n}\sum_{i=1}^{n} L(y_i, f(x_i)) + \alpha R(w)$$

4. **Momentum:** Momentum is a technique that enhances the gradient descent optimization procedure by allowing the search to gain momentum in a certain direction within the search space, counteract fluctuations in the gradient caused by noise, and smoothly traverse flat regions..

5. **Autoencoder**

An autoencoder is a common example of an unsupervised learning algorithm. The objective is to establish the target values to be identical to the original values. A typical model typically consists of three distinct phases. An autoencoder is a conventional feed-forward neural network. It connects multiple basic "neurons" together. A neuron's output can serve as the input for another neuron. The variables can be calculated using the back-propagation process. This Autoencoder is mostly used for deep feature extraction.[26]

- **Input**: Encoder: a collection of linear feed-forward filters defined by the weight matrix and bias parameters. A feed-forward neural network.
- **Activation**: a non-linear function that converts the encoded coefficients into values ranging from 0 to 1.
- **Decoder:** A decoder refers to a collection of reverse linear filters that generate a new representation of the input. Back-propagation.

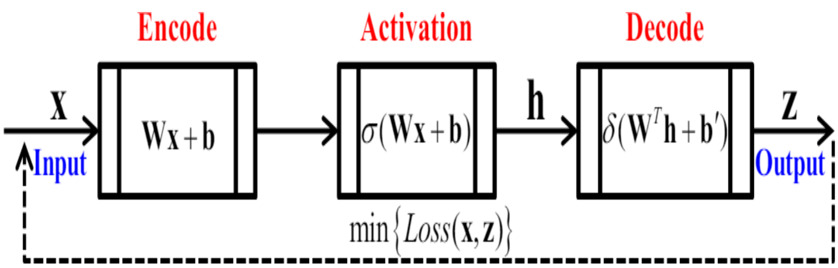


Figure 1:Agentic flow chart of Autoencoder

Methodology

Data Set

Data collected in this paper are from the Kaggle website for the implementations of machine learning algorithms using python3 to show outputs in the traffic prediction. Two datasets are collected in which one is the 2012 to 2013 traffic data which comprises of date, time, and number of vehicles, junction. The unwanted data has been deleted by pre-processing the data aggregated from 1 to 24 hours time interval to calculate traffic flow prediction with each 1 hour interval.

EDA

Exploratory Data Analysis (EDA) is the systematic examination and analysis of datasets to discover their distinctive features, detect trends, pinpoint outliers, and establish connections between variables. Analyze and visualize data is a crucial initial stage to understand its fundamental characteristics, reveal patterns, and identify links among variables. Exploratory Data Analysis (EDA) is commonly conducted as an initial step before to undertaking more formal statistical investigations or modeling.

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Model Building

We develop a hybrid model that combines the ADAM and SGD optimizers to estimate traffic flow using Prophet. We incorporate momentum to enhance the accuracy of the predictions and improve the pace at which the model converges. Features were extracted from the data using an Autoencoder.

Model Evaluation

Model evaluation refers to the process of assessing a model's ability to be applied to new data in order to determine its generalizability. Several metrics, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Median Absolute Percentage Error (MDAPE), and Symmetric Mean Absolute Percentage Error (SMAPE).

Performance Metrics

Mean Squared Error (MSE): The Mean Squared Error (MSE) is calculated by taking an average of the average squared discrepancies between the projected values and the actual values. The estimation accuracy of an estimator is quantified by a metric that is always greater than or equal to zero, with values nearer to zero indicating better performance[27][28].

Root Mean Squared Error (RMSE):

RMSE, or Root Mean Square Error, is the mathematical operation of taking the square root of the Mean Square Error (MSE). It quantifies the magnitude of mistake using the identical units as the initial data[27][28].

Mean Absolute Error (MAE):

The Mean Absolute Error (MAE) is calculated as an average of the actual discrepancies between the projected values and the actual values. The metric quantifies the mean absolute value of inaccuracies in a collection of forecasts, irrespective of their orientation[28].

Mean Absolute Percentage Error (MAPE):

MAPE, or Mean Absolute Percentage Error, is a measure that calculates an average of the actual percentage differences between anticipated values and actual values. It is commonly represented as a percentage[27][28].

Median Absolute Percentage Error (MDAPE)

Median Absolute Percentage Error (MDAPE) is a statistical measure used to assess the accuracy of a forecast or prediction. It calculates the median of the absolute percentage differences between the predicted values and the actual values[27][28].

SMAPE

The Symmetric Mean Absolute Percentage Error (SMAPE) is a metric used to measure the accuracy of a forecast or prediction. SMAPE, short for Symmetric Mean Absolute Percentage Error, is a modified version of MAPE (Mean Absolute Percentage Error) that assigns equal importance to both over- and under-forecasts. The metric is calculated by taking the mean of the absolute distinctions between the actual and predicted values, and then dividing it by the mean of the actual and predicted values[27][28].

Tools and Software for Analysis

Our research extensively utilized the language of programming, Python, and its extensive environment for analyzing deep learning models. Furthermore, our main computing platform was Google Colab.

The table provided displays traffic data that has been processed using an Autoencoder model. The purpose of this model is to extract features and reduce the dimensionality of the data. The 'ds' column denotes the timestamp, encompassing dates from October 2, 2012, to October 1, 2013, with hourly intervals. The 'y' column denotes the initial traffic count data for each date. The columns denoted as '0', '1', and '2' are features that have been produced by the

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Autoencoder. These columns capture intricate patterns in the original data and decrease its complexity, simplifying the identification of underlying trends and abnormalities in traffic

patterns. The Autoencoder algorithm takes the input data ('y') and converts it into novel

feature depictions, which can then be utilized for additional analysis or forecasting tasks.In summary, this table illustrates the effectiveness of using Autoencoder-generated features to compress complex traffic data into an additional manageable format, while still retaining

important information for future forecasting and analysis.

In this procedure, we employed the prophet model to fit the multivariate data. We utilized hybrid optimization techniques, specifically ADAM and SGD, while incorporating momentum.

FLOW CHART FOR ALGORITHM

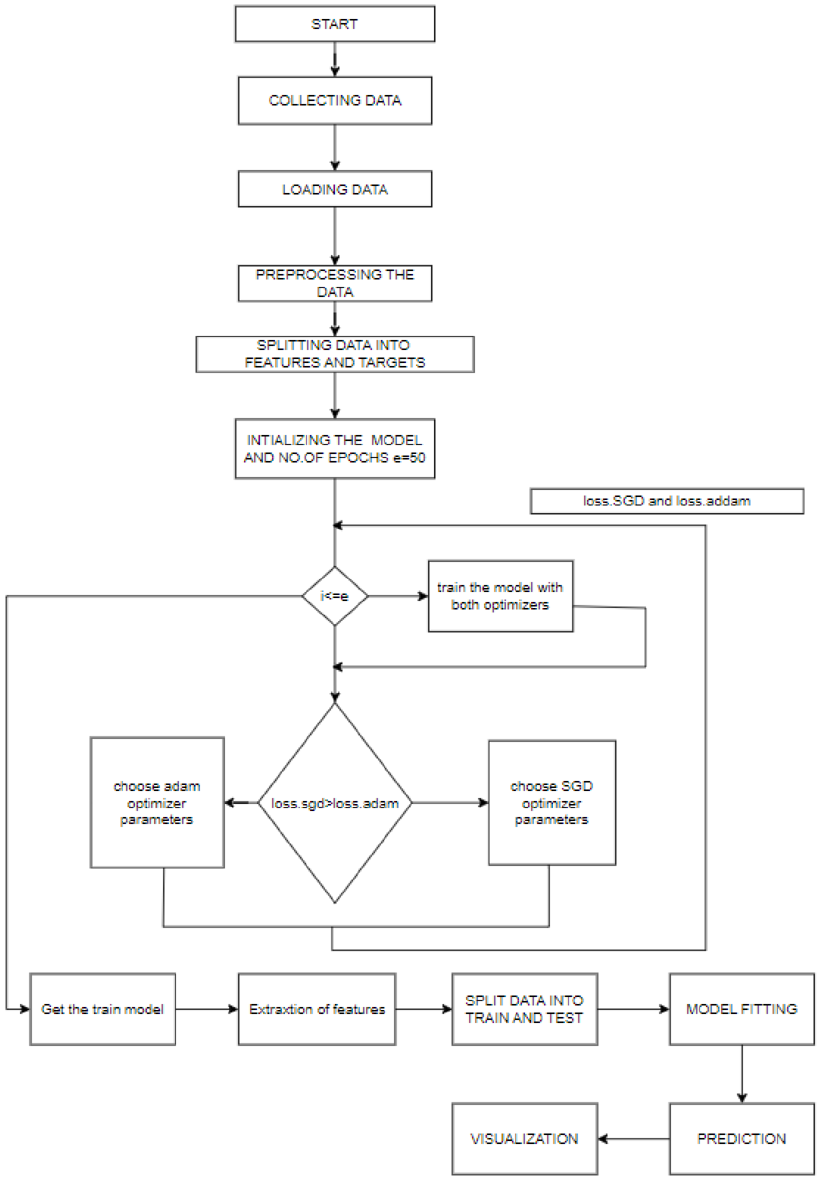


Figure 2:Autorncoder_Deep_feature_Exctraction

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Results and Discussions

Table 1: Dataset values

ds	0	1	2	y
02-10-2012 10:00	0.151234	0.574555	0	4516
02-10-2012 11:00	0.069663	0.496628	0	4767
02-10-2012 12:00	0.06812	0.284865	0	5026
02-10-2012 13:00	0.15809	0.188115	0	4918
02-10-2012 14:00	0.542933	0.235561	0	5181
...	...	...	...	...
30-09-2013 20:00	0.525231	0.29151	0	3041
30-09-2013 21:00	0.528989	0.172103	0	2371
30-09-2013 23:00	0.520673	0.547931	0	1917
01-10-2013 21:00	0.512583	0.352693	0	3050
01-10-2013 23:00	0.514892	0.006638	0	679

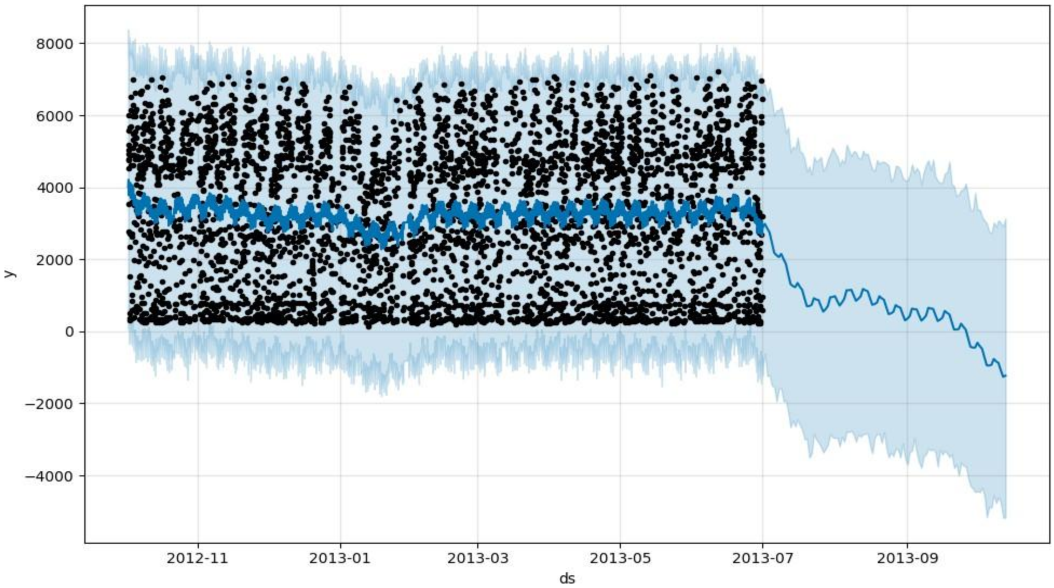


Figure 3:Neural Prophet Traffic Prediction with Uncertainty Bands

Upon visual examination, it was determined that the model well reflected the overall trend and seasonal variations of traffic patterns when comparing the projected values with the actually observed data points. The blue forecast line closely tracked the black data points for most of the time period. The expansion of the uncertainty range towards the conclusion of the forecast period demonstrated the model's escalating uncertainty in making predictions for distant future time points, as anticipated in time-series forecasting.

Below is the prediction graph we obtained. Prediction graphs display data in many time intervals, including weekly, yearly, daily, and trends. The traffic flow prediction graph is displayed in the above figure. It includes predictions for daily, weekly, annual, and trend patterns.

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Trend Prediction Graph

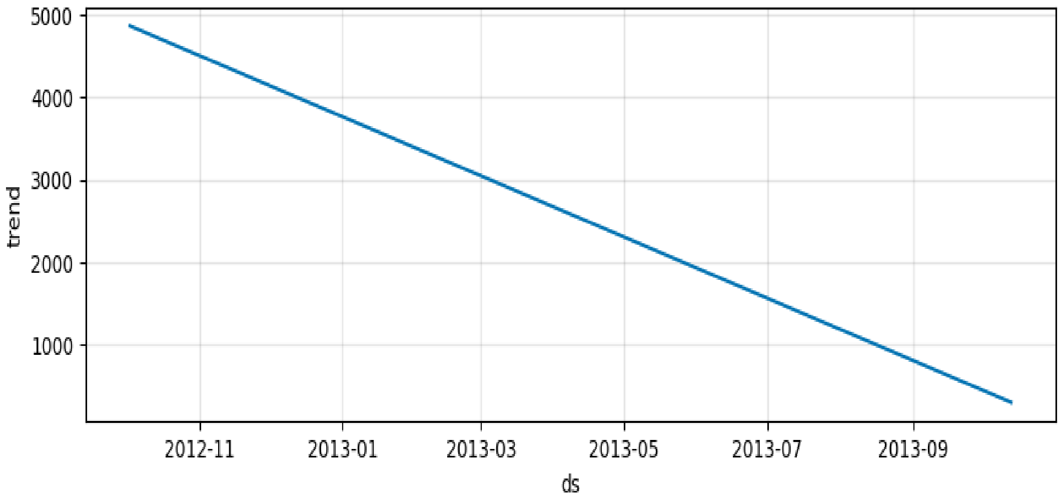


Figure 4:Trend Graph

Figure 4 shows the trend component, which is a continuous linear fall that occurs between November 2012 and September 2013. This decline can suggest a steady decline in the underlying variable being studied. Technical modeling-wise, a segmented linear function that uses identified changepoints to signify underlying or external influences on the time series to calculate slope variations best describes this trend.

Weekly Prediction graph

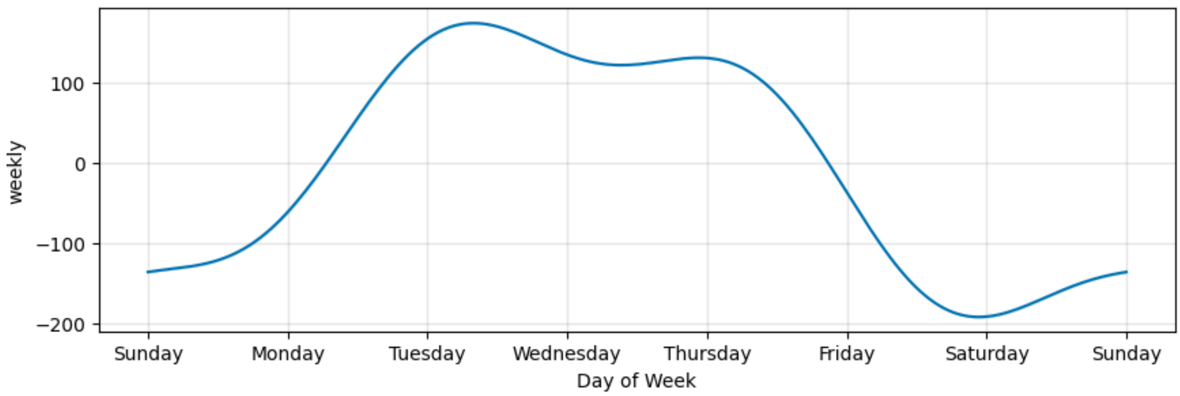


Figure 5:Weekly Graph

Figure 5 shows that weekly component depicts the recurrent patterns that appear each week. Throughout the week, the values vary, reaching their highest point on Tuesdays and Wednesdays and then precipitously falling approaching Saturday. The shape of the weekly pattern is determined by the amplitudes and stages of the Fourier terms in the Fourier series model used to represent this component. The data's cyclical nature within a week is highlighted by the weekly seasonality, which may be affected by operating scheduling or customer behaviour.

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Yearly Prediction Graph

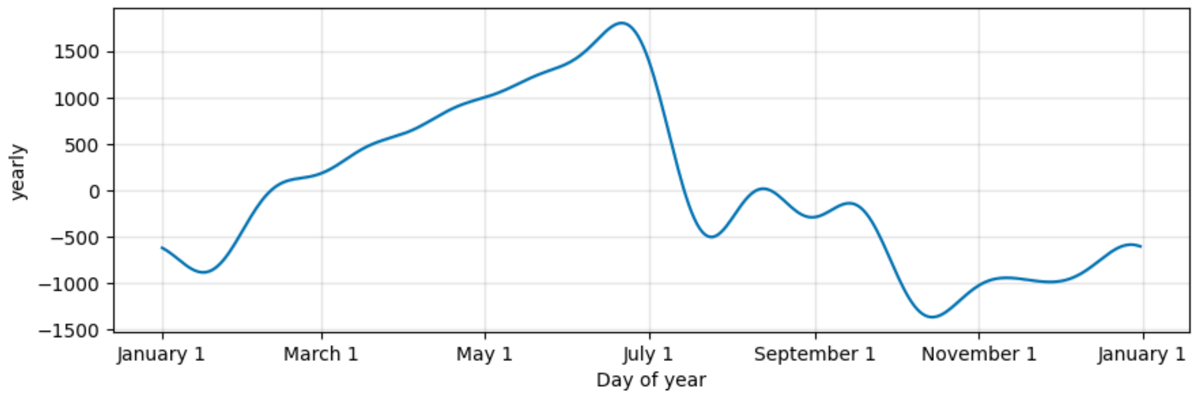


Figure 6:Yearly Graph

Figure 6 illustrates the yearly component, which shows peaks around July's midpoint and troughs toward the end of the year. This component captures the annual seasonality in the data. Fourier series is also used to represent this pattern, with higher-order components helping to precisely mimic the intricate yearly cycles. Understanding the larger cyclic tendencies that take place inside a year, driven by things like vacations, the weather, or fiscal seasons, is made easier with the aid of the annual seasonality component..

Daily Prediction Graph

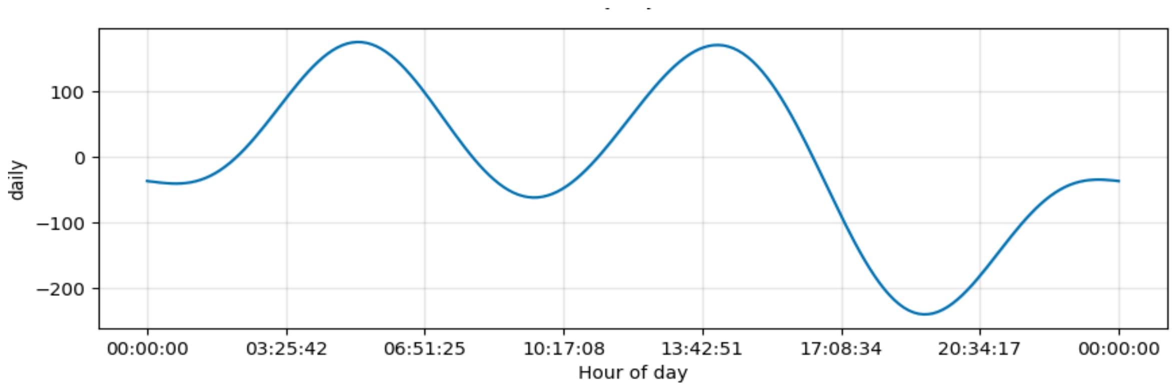


Figure 7:Daily Graph

Figure 7 shows the daily component, depicted in the lower graph, illustrates the recurring intra-day patterns that occur every 24 hours. This graph displays cyclical patterns with distinct periods of time showing high and low points, such as peaks in the early morning and mid-afternoon. The daily seasonality is represented by utilizing Fourier series with a shorter duration to accurately reflect the daily fluctuations. This component is essential for comprehending the patterns inside a single day, which may be influenced by customary daily routines, working hours, or other intra-day cyclic elements.

Conclusion

The objective of creating a strong short-term traffic prediction model utilizing Prophet, optimized with ADAM and SGD, and integrating momentum, has demonstrated encouraging potential in improving forecast accuracy and convergence speed. The model accurately captures the complicated pattern in traffic data by utilizing the features of Neural Prophet, a strong tool for time-series forecasting.

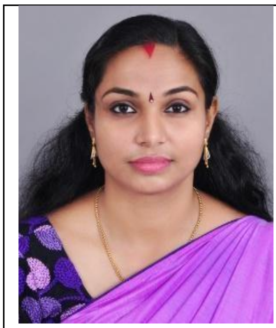
The utilization of modern optimizers such as ADAM and SGD, renowned for their efficacy in managing extensive datasets and minimizing computing expenses, greatly enhances the performance of the model. By including momentum, the convergence process is accelerated as it stabilizes the updates and reduces oscillations during training

References

[1] T. Dinh Toan and V.-H. Truong, 'Support Vector Machine for Short-Term Traffic Flow Prediction and Improvement of Its Model Training using Nearest Neighbor Approach', *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2675, Dec. 2020, doi: 10.1177/0361198120980432.
[2] A. Khan, M. M. Fouda, D.-T. Do, A. Almaleh, and A. U. Rahman, 'Short-Term Traffic Prediction Using Deep Learning Long Short-Term Memory: Taxonomy, Applications, Challenges, and Future Trends', *IEEE Access*, vol. 11, pp. 94371–94391, 2023, doi: 10.1109/ACCESS.2023.3309601.
[3] L. Yu, J. Zhao, Y. Gao, and W. Lin, 'Short-Term Traffic Flow Prediction Based On Deep Learning Network', in *2019 International Conference on Robots & Intelligent System (ICRIS)*, 2019, pp. 466–469. doi: 10.1109/ICRIS.2019.00122.
[4] G. Wang, 'Short-term Traffic Flow Prediction Based on Neuron Network Model', in *2023 Prognostics and Health Management Conference (PHM)*, 2023, pp. 12–16. doi: 10.1109/PHM58589.2023.00011.
[5] D. Kang, Y. Lv, and Y. Chen, 'Short-term traffic flow prediction with LSTM recurrent neural network', in *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, 2017, pp. 1–6. doi: 10.1109/ITSC.2017.8317872.
[6] A. Raut, M. K. Maurya, V. K. Chaurasiya, and M. Kumar, 'Adaptive hyperparameter optimization for short term traffic flow prediction with spatial temporal correlated raster data', *Evol. Syst.*, vol. 15, no. 2, pp. 469–488, 2024, doi: 10.1007/s12530-023-09513-0.
[7] B. Sharma, S. Kumar, P. Tiwari, P. Yadav, and M. I. Nezhurina, 'ANN based short-term traffic flow forecasting in undivided two lane highway', *J. Big Data*, vol. 5, no. 1, p. 48, 2018, doi: 10.1186/s40537-018-0157-0.
[8] N. A. M. Razali, N. Shamsaimon, K. K. Ishak, S. Ramli, M. F. M. Amran, and S. Sukardi, 'Gap, techniques and evaluation: traffic flow prediction using machine learning and deep learning', *J. Big Data*, vol. 8, no. 1, p. 152, 2021, doi: 10.1186/s40537-021-00542-7.
[9] J. Y. Kim, 'A Traffic Prediction Using Machine Learning: Literature Survey', *SSRN Electron. J.*, pp. 1–4, 2022, doi: 10.2139/ssrn.3976059.
[10] X. Xu, X. Jin, D. Xiao, C. Ma, and S. C. Wong, 'A hybrid autoregressive fractionally integrated moving average and nonlinear autoregressive neural network model for short-term traffic flow prediction', *J. Intell. Transp. Syst.*, vol. 27, no. 1, pp. 1–18, Jan. 2023, doi: 10.1080/15472450.2021.1977639.
[11] Y. Li, Z. Ma, Z. Pan, N. Liu, and X. You, 'Prophet model and Gaussian process regression based user traffic prediction in wireless networks', *Sci. China Inf. Sci.*, vol. 63, no. 4, pp. 1–8, 2020, doi: 10.1007/s11432-019-2695-6.
[12] N. K. ChikkaKrishna, P. Rachakonda, and T. Tallam, 'Short - Term Traffic Prediction Using Fb-PROPHET and Neural-PROPHET', in *2022 IEEE Delhi Section Conference (DELCON)*, 2022, pp. 1–4. doi: 10.1109/DELCON54057.2022.9753459.
[13] R. B. Sarooraj and P. Shyry, 'Analysis of traffic flow prediction from spatial-temporal data using hybrid GSA-Adam optimizer based LSTM network for intelligent transport system', *Multimed. Tools Appl.*, vol. 83, pp. 1–27, Jul. 2023, doi: 10.1007/s11042-023-16253-5.
[14] E. Hassan, M. Y. Shams, N. A. Hikal, and S. Elmougy, *The effect of choosing optimizer algorithms to improve computer vision tasks: a comparative study*, vol. 82, no. 11. Multimedia Tools and Applications, 2023. doi: 10.1007/s11042-022-13820-0.
[15] C. Zhang, H. Zhang, D. Yuan, and M. Zhang, 'Citywide Cellular Traffic Prediction Based on Densely Connected Convolutional Neural Networks', *IEEE Commun. Lett.*, vol. 22, no. 8, pp. 1656–1659, 2018, doi: 10.1109/LCOMM.2018.2841832.
[16] Y. Zhang *et al.*, 'Prophet: Traffic Engineering-Centric Traffic Matrix Prediction', *IEEE/ACM Trans. Netw.*, no. 01, pp. 1–11, 5555, doi: 10.1109/TNET.2023.3293098.
[17] X. Yin, G. Wu, J. Wei, Y. Shen, H. Qi, and B. Yin, 'Deep Learning on Traffic Prediction: Methods, Analysis, and

Future Directions', *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 6, pp. 4927–4943, 2022, doi: 10.1109/TITS.2021.3054840.
[18] H. R. Deekshetha, A. V. Shreyas Madhav, and A. K. Tyagi, 'Traffic Prediction Using Machine Learning', *Lect. Notes Data Eng. Commun. Technol.*, vol. 116, no. March, pp. 969–983, 2022, doi: 10.1007/978-981-16-9605-3_68.
[19] G. Dai, J. Tang, and W. Luo, 'Short-term traffic flow prediction: An ensemble machine learning approach', *Alexandria Eng. J.*, vol. 74, 2023, doi: 10.1016/j.aej.2023.05.015.
[20] A. A. Kashyap, S. Raviraj, A. Devarakonda, S. R. Nayak K, K. V. Santhosh, and S. J. Bhat, 'Traffic flow prediction models–A review of deep learning techniques', *Cogent Eng.*, vol. 9, no. 1, 2022, doi: 10.1080/23311916.2021.2010510.
[21] L. Zhang, W. Liu, and L. Feng, 'Short-term Traffic Flow Prediction Based on Improved Neural Network with GA', in *2021 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, 2021, pp. 312–315. doi: 10.1109/ICAICA52286.2021.9498033.
[22] Y. Wang, S. Ke, C. An, Z. Lu, and J. Xia, 'A Hybrid Framework Combining LSTM NN and BNN for Short-term Traffic Flow Prediction and Uncertainty Quantification', *KSCE J. Civ. Eng.*, vol. 28, no. 1, pp. 363–374, 2024, doi: 10.1007/s12205-023-2457-y.
[23] K. Y. Chan, T. S. Dillon, J. Singh, and E. Chang, 'Neural-Network-Based Models for Short-Term Traffic Flow Forecasting Using a Hybrid Exponential Smoothing and Levenberg–Marquardt Algorithm', *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 2, pp. 644–654, 2012, doi: 10.1109/TITS.2011.2174051.
[24] D. Hindarto, F. Hendrata, and M. Hariadi, 'The application of Neural Prophet Time Series in predicting rice stock at Rice Stores', *J. Comput. Networks, Archit. High Perform. Comput.*, vol. 5, no. 2, pp. 668–681, 2023, doi: 10.47709/cnahpc.v5i2.2725.
[25] S. Mehta, C. Paunwala, and B. Vaidya, *CNN based Traffic Sign Classification using Adam Optimizer*. 2019. doi: 10.1109/ICCS45141.2019.9065537.
[26] G. Dong, G. Liao, H. Liu, and G. Kuang, 'A Review of the Autoencoder and Its Variants: A Comparative Perspective from Target Recognition in Synthetic-Aperture Radar Images', *IEEE Geosci. Remote Sens. Mag.*, vol. 6, no. 3, pp. 44–68, 2018, doi: 10.1109/MGRS.2018.2853555.
[27] P. Cembaluk and J. Aniszewski, 'Forecasting the network traffic with PROPHET', *3rd Polish Conf. Artif. Intell.*, pp. 215–218, 2022.
[28] B. Hussain, M. K. Afzal, S. Ahmad, and A. M. Mostafa, 'Intelligent traffic flow prediction using optimized GRU model', *IEEE Access*, vol. 9, pp. 100736–100746, 2021, doi: 10.1109/ACCESS.2021.3097141.

BIOGRAPHIES OF AUTHORS

	**Ms. Sigma Sathyan** completed her bachelor degree in Computer Science from Mahatma Gandhi University, Kottayam, Kerala in the year 2010.She received her master's in computer applications from Mahatma Gandhi university in 2013. Her area of interests includes Machine Learning, Deep Learning and Artificial Intelligence. She is a Ph.D. student at College of Computer Science & Information Science, Srinivas University, Mukka, Mangalapuram, Karnataka, India

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

<table>
<tr>
<td></td>
<td>Prof.Dr. Jagadeesha S N received his B.E., in Electronics and Communication Engineering, from University B. D. T College of Engineering., Davangere affiliated to Mysore University, Karnataka, India in 1979, M.E. from Indian Institute of Science (IISC), Bangalore, India specializing in Electrical Communication Engineering., in 1987 and Ph.D. in Electronics and Computer Engineering., from University of Roorkee (I.I.T, Roorkee), Roorkee, India in 1996. He is an IEEE member and Fellow, IETE. His research interest includes Array Signal Processing, Wireless Sensor Networks and Mobile Communications. He has published and presented many papers on Adaptive Array Signal Processing and Direction-of-Arrival estimation. Currently he is Professor in the Department of Computer Science and Engineering, Jawaharlal Nehru National College of Engg. (Affiliated to Visvesvaraya Technological University), Shimoga, Karnataka, India</td>
</tr>
</table>