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Unleashing The Power Of Machine Learning: Enhancing Traffic Prediction In Smart Transportation Systems

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Abstract: -
Smart Transportation Systems Have Emerged As A Promising Solution For Managing Urban Traffic Congestion And Improving Overall Transportation Efficiency. One Critical Aspect Of Such Systems Is Accurate Traffic Prediction, Which Enables Proactive Traffic Management Strategies And Enhances User Experience. This Paper Proposes An Approach To Unleash The Power Of Machine Learning Techniques For Enhancing Traffic Prediction In Smart Transportation Systems. This Involves Making Predictions Based On Data From The Previous Year And Data From The Most Recent Year, Which Eventually Yields Accuracy And Mean Square Error. This Involves Making Predictions Based On Data From The Previous Year And Data From The Most Recent Year, Which Eventually Yields Accuracy And Mean Square Error.
The Traffic Statistics Is Based On A Time Gap Of One Hour. This Prediction Is Used To Analyses Current Traffic Numbers. Therefore, It Will Be Simpler To Analyses This While The User Is Also Driving. The Most Populated Routes In The City Are Identified By The System After Comparing Data From All Roads.
The Proposed Framework Is Evaluated Using Real-World Traffic Datasets From A Smart Transportation System Deployment. The Results Highlight The Potential Of Machine Learning Algorithms To Revolutionize Traffic Prediction In Smart Transportation Systems. By Accurately Forecasting Traffic Conditions, These Systems Can Optimize Traffic Management Strategies, Reduce Congestion, And Improve Overall Transportation Efficiency.
Keywords: *Intelligent Transport System (ITS), Regression, Traffic, Machine Learning, And Prediction*

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I. Introduction

Machine learning (ML) has emerged as a pivotal field within the realm of transportation engineering, with traffic forecasting garnering significant attention [1]. The economic repercussions of traffic congestion are undeniable, impacting both individuals and the overall economy through time and monetary costs. Mitigating congestion and ensuring a seamless traffic flow have become essential for enhancing people's daily lives and promoting economic progress.

To address these challenges, accurate traffic prediction on a granular level is imperative. Such predictions empower individuals to navigate their lives with reduced stress and inconvenience, while also facilitating the nation's economic advancement through improved traffic management. Intelligent transport systems (ITS) investments by governments reflect the urgency of these issues. This research aims to explore various machine learning methodologies and potentially develop Python 3 models [2].

Traffic flow prediction, as the core objective, seeks to estimate and predict traffic conditions for users. In today's congested roadways, drivers often struggle to discern the severity of traffic congestion [3]. Therefore, accurate traffic estimations derived from this research can greatly benefit users. Python scripts, executed through the command prompt, were utilized for this investigation instead of relying on software like Anaconda, which is commonly used for data prediction.

Although real-time traffic data is widely available, many users find it inconvenient due to the need for route selection. For instance, users require real-time traffic predictions during business hours or when they encounter traffic congestion, while hourly or daily traffic statistics may be more relevant in other scenarios. Hence, this research endeavours to provide real-time traffic predictions to assist users in addressing congestion-related issues.

Identifying the sources of traffic congestion is challenging. However, by comparing datasets from the most recent and previous years, this research employs two datasets to forecast congestion. By forecasting congestion levels based on historical data from the same period in the previous year, this approach offers insights into potential traffic congestion scenarios.

Traffic congestion often fluctuates with gasoline prices [4][5]. Real-time traffic forecasts aim to provide timely information on traffic jams and gridlock. However, due to the chaotic and intricate nature of today's metropolitan traffic, existing forecasting technologies often fall short.

To combat traffic congestion, machine learning techniques, including regression models and tools like pandas, os, NumPy, matplotlib, and pyplot, are employed. These implementations facilitate accessibility and traffic congestion management.

Through this strategy, users can obtain traffic information and monitor congestion flow throughout the day, utilizing one-hour data intervals [6][31]. Moreover, users can also assess weather conditions along their intended routes. Validating the accuracy of traffic predictions is accomplished by comparing mean square errors between the previous year's data and the most recent data. Additionally, users can determine the average number of vehicles per trip using the traffic forecasting tool.

In summary, by leveraging machine learning algorithms and a comprehensive range of technologies, this research aims to revolutionize smart transportation systems by enhancing traffic prediction capabilities [32]. The ultimate goal is to minimize congestion, boost economic productivity, and improve overall user experience.

II. Literature Review

Smart transportation systems have gained significant attention in recent years as a means to address urban traffic congestion and enhance transportation efficiency. Within this context, accurate traffic prediction plays a crucial role in enabling proactive traffic management strategies. This literature review provides an overview of the existing research related to machine learning-based traffic prediction in smart transportation systems.

Traditional approaches to traffic prediction have relied on statistical models and time series analysis [24]. These methods often utilize historical traffic data to forecast future traffic patterns. However, they struggle to capture the complex and dynamic nature of urban traffic systems, limiting their predictive accuracy.

In contrast, machine learning techniques have emerged as powerful tools for traffic prediction. Regression models, such as Support Vector Regression (SVR) and Random Forest Regression (RFR) [27], have been widely employed to estimate traffic patterns based on diverse data sources. These models can incorporate variables such as historical traffic data, weather conditions, and social media feeds to improve prediction accuracy.

Deep learning algorithms, including Convolutional Neural Networks (CNNs) [25][28] and Recurrent Neural Networks (RNNs), have also been extensively utilized in traffic prediction. CNNs are effective in capturing spatial patterns in traffic data, while RNNs excel in modelling temporal dependencies. Hybrid models that combine CNNs and RNNs have shown superior performance by capturing both spatial and temporal characteristics of traffic.

Feature engineering techniques have been employed to enhance the predictive capabilities of machine learning models. Dimensionality reduction methods, such as Principal Component Analysis (PCA) [18], have been used to extract relevant features from high-dimensional traffic datasets. Additionally, data fusion techniques have been utilized to integrate data from various sources, such as traffic sensors, GPS devices, and social media platforms, to improve prediction accuracy.

Real-time data integration has been a focus of recent research in traffic prediction [28]. By incorporating real-time traffic data streams, such as traffic sensor readings and live GPS data, machine learning models can adapt to dynamic traffic conditions and provide up-to-date predictions [12]. Furthermore, advancements in big data analytics and cloud computing have facilitated the processing of large-scale traffic datasets, enabling faster and more accurate predictions.

Several studies have compared different machine learning models for traffic prediction, demonstrating the superiority of certain techniques over others in terms of accuracy and computational efficiency [8][29].

However, challenges such as data privacy and security, scalability, and interpretability of models remain areas of concern that need to be addressed in future research.

Machine learning techniques involving the construction and prediction of network training structures or LSTM-based prediction models have been employed in this study. The main objective is to leverage deep learning techniques to mitigate potential prediction errors that may occur during the prediction process. To achieve this, a large volume of data obtained from the performance measuring system is utilized [7][9].

The study findings demonstrate the high performance of the LSTM model in predicting traffic patterns [11][21]. Conversely, other studies employed a distinct spatial-temporal approach [1,9,10,17], with Vlahogianni utilizing an Artificial Neural Network (ANN) to generate relevant traffic information [9]. Additionally, researchers have explored hybrid neural networks and alternative methodologies to forecast traffic patterns by aggregating them and leveraging the power of neural networks [10][18].

However, it is important to note that two different types of prediction models are used in these studies. In cases of significant system changes, inaccessible past data is utilized to train models [20]. Historical data is employed to calibrate online models, while standard transport conditions obtained from v2v/v21 communication update the system [2,7].

Many researchers argue that LSTM outperforms simple machine learning models due to its ability to leverage extensive data for prediction tasks [3,6,20]. The utilization of large datasets enables real-time traffic flow prediction, and LSTM, based on deep learning principles, effectively applies previous knowledge to the current traffic situation.

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In summary, machine learning techniques have shown great potential in enhancing traffic prediction in smart transportation systems. Regression models, deep learning architectures, and feature engineering techniques have significantly improved prediction accuracy by leveraging diverse data sources.

Real-time data integration and advancements in big data analytics have further enhanced the capabilities of traffic prediction models. Future research should focus on addressing remaining challenges and developing scalable and interpretable machine learning models for effective traffic prediction in smart transportation systems.

III. Existing System

Existing systems for enhancing traffic prediction in smart transportation systems utilize various machine learning techniques to analyse and predict traffic patterns. These systems leverage large amounts of historical data, real-time data streams, and advanced algorithms to improve the accuracy of traffic predictions.

Here are a few examples of existing systems in this domain:

Google Maps: Google Maps utilizes machine learning algorithms to predict and display real-time traffic conditions. It collects data from various sources, including smartphones with location services enabled, GPS devices, and traffic sensors. By analysing this data, Google Maps can provide users with estimated travel times and suggest alternative routes to avoid congestion [26].

Waze: Waze is a community-based navigation and traffic app that employs machine learning to predict and alleviate traffic congestion. It collects data from its users, who contribute information about traffic conditions, accidents, road closures, and other incidents in real time. Waze's algorithms analyse this data to provide users with the most efficient routes and real-time traffic updates [28].

IBM Intelligent Transportation: IBM offers a comprehensive intelligent transportation system that incorporates machine learning for traffic prediction. Their system integrates data from various sources, such as traffic sensors, surveillance cameras, and weather reports. By applying machine learning algorithms to this data, IBM's system can accurately predict traffic patterns, optimize traffic signal timings, and provide insights for traffic management [12].

CityBrain by Alibaba: CityBrain is an AI-powered system developed by Alibaba Cloud that focuses on urban traffic management. It utilizes machine learning algorithms to analyse diverse data sources, including traffic cameras, GPS data, and public transportation information [29]. CityBrain aims to optimize traffic flow by dynamically adjusting traffic signals, managing congestion, and predicting traffic conditions to ensure efficient transportation within cities.

INRIX: INRIX is a company that provides real-time traffic information and analytics. They employ machine learning techniques to predict traffic patterns and congestion. INRIX collects data from various sources, such as GPS devices, connected vehicles, and traffic sensors, and combines it with historical data to generate accurate traffic predictions [8]. Their predictions are used by governments, transportation agencies, and businesses to make informed decisions regarding traffic management and planning.

These systems represent just a few examples of how machine learning is being applied to enhance traffic prediction in smart transportation systems. By leveraging advanced algorithms and vast amounts of data, these systems aim to improve the efficiency of transportation, reduce congestion, and enhance the overall user experience [34].

While existing systems for enhancing traffic prediction in smart transportation systems have made significant advancements, they still face certain challenges and limitations.

Here are some common problems associated with these systems:

1. Data Quality and Availability: Accurate traffic prediction heavily relies on high-quality and up-to-date data. However, obtaining reliable and comprehensive data can be challenging. Existing systems often face issues with incomplete or inconsistent data from different sources. Additionally, accessing real-time data can be limited in certain areas, leading to less accurate predictions.

2. Scalability: As the volume of data continues to grow, existing systems may struggle to scale effectively. Processing and analysing large amounts of data in real-time can be computationally intensive. Ensuring that the system can handle the increasing data load and maintain responsiveness is crucial for accurate traffic prediction [30].

3. Model Adaptability: Traffic patterns can change over time due to factors like road construction, events, or changes in driver behaviour. Existing models may struggle to adapt to these dynamic changes without continuous updates and retraining. It is essential to develop models that can dynamically adjust and learn from new data to maintain accurate predictions.

4. Integration and Data Fusion: Integrating data from multiple sources, such as traffic sensors, GPS devices, and weather reports, can be complex [22]. Different data formats, varying levels of data quality, and data synchronization challenges can affect the accuracy and reliability of predictions. Efficient data fusion techniques are required to combine and process data effectively.

5. Privacy and Data Security: Traffic prediction systems often rely on collecting and analysing data from various sources, including user-generated data. Ensuring the privacy and security of sensitive data while maintaining the effectiveness of the system is a critical concern. Striking the right balance between data privacy and system performance is a challenge that needs to be addressed.

6. Interpretability and Transparency: Machine learning models used in traffic prediction systems can be highly complex and difficult to interpret. Understanding the factors and features driving predictions is crucial for stakeholders to have trust in the system [27]. Developing interpretable models and providing explanations for predictions can enhance transparency and user acceptance.

7. Limited Coverage: Existing systems may not have comprehensive coverage in all geographic areas. Smaller cities or rural regions may have limited or no access to advanced traffic prediction systems. Ensuring equitable access to accurate traffic information across different regions is important for a well-functioning transportation system.

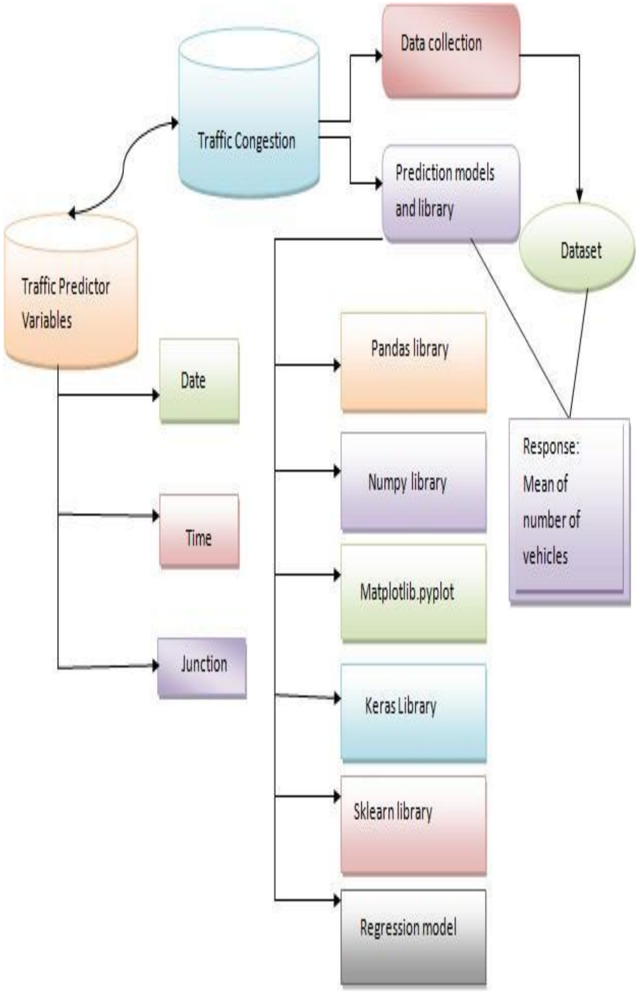
Addressing these challenges requires ongoing research and development in the field of traffic prediction and machine learning.

Efforts should focus on improving data quality, developing scalable and adaptable models, enhancing data integration techniques, ensuring privacy and security, and promoting transparency and accessibility of the system [33]. By overcoming these limitations, the power of machine learning can be fully harnessed to enhance traffic prediction in smart transportation systems.

IV. Proposed System

The process of traffic congestion forecasting involves data collection and a prediction model.

Figure: -1 Overview of Traffic Prediction



To ensure accurate predictions, the process must be carried out appropriately. After data collection, data processing becomes crucial, including training and testing datasets as input [8]. The model is then evaluated using the required models. Figure 1 provides an overview of machine learning-based traffic prediction. Several methodologies have been employed by researchers [21].

This study focuses on traffic prediction using regression models and various libraries such as Pandas, NumPy, OS, Matplotlib.pyplot, Keras, and Sklearn.

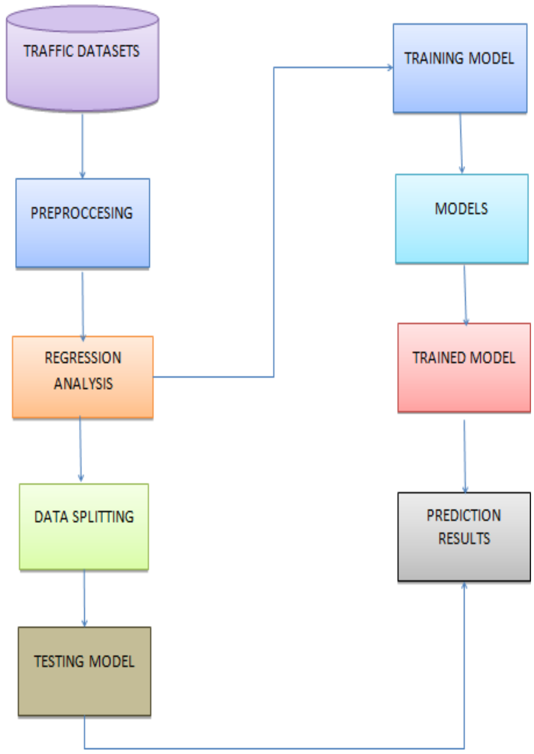
Dataset

Traffic congestion has been on the rise due to factors like increasing urban populations, irregular traffic light timing, and a lack of real-time data. The data used in this study were obtained from the Kaggle website and were utilized to showcase the results of machine learning algorithms implemented in Python 3 for traffic prediction [12]. Two datasets were collected for simple and accurate comparison: one consisting of traffic data from 2015, including date, time, number of vehicles, and junction, and the other consisting of traffic data from 2017 [12]. Pre-processing involved removing unnecessary data by focusing on 1-hour intervals within the collected data from 1 to 24 hours [19].

Regressor Model

A regressor model is a mathematical technique used to establish the relationship between a dependent (criterion) variable and one or more independent (predictor) variables [22].

Figure: -2 Regression of Traffic Prediction



The evaluation generates a predicted value for the benchmark, which is the scalar vector sum of the predictors [13]. Mean-square-error is used to measure accuracy. The anticipated error can then be calculated by comparing the observed and true values, similar to the standard deviation used in statistical approaches. Figure 2 illustrates the Regression Model for Traffic Prediction [14].

V. Implementation

To implement the project "Unleashing the Power of Machine Learning: Enhancing Traffic Prediction in Smart Transportation Systems" using a regression model and machine learning techniques, while leveraging the Sklearn, Keras, and TensorFlow libraries, you can follow these steps:

1.) Data Collection and Pre-processing: -Gather relevant traffic data from various sources, such as traffic sensors, GPS devices, and historical traffic records [30]. Pre-process the data by handling missing values, outliers, and data inconsistencies. Normalize or scale the data as necessary.

2.) Feature Engineering: - Extract meaningful features from the collected data that can capture traffic patterns and characteristics. Consider factors like time of day, day of the week, weather conditions, road network topology, and historical traffic flow. Encode categorical variables using techniques like one-hot encoding or label encoding.

3.) Splitting the Dataset: -Split the pre-processed dataset into training and testing sets. Typically, use a majority portion of the data for training (e.g., 80%) and reserve the rest for testing the model's performance [32].

4.) Model Selection and Development: - Choose a regression model suitable for traffic prediction, such as Linear Regression, Decision Tree Regression, or Random Forest Regression [38]. Sklearn provides implementations for these models. Train the chosen model using the training dataset. Fit the model to the features and target variable (e.g., traffic flow or travel time).
Tune hyperparameters of the model, such as regularization parameters, tree depth, or ensemble size, to optimize performance. Sklearn provides tools like Research for hyperparameter tuning.

5.) Model Evaluation: -Evaluate the trained regression model using the testing dataset. Calculate evaluation metrics like mean absolute error (MAE), root mean square error (RMSE), or coefficient of determination (R^2) to assess the model's accuracy.

Visualize the model's performance by comparing predicted traffic values with the ground truth data using plots or charts [24] [37].

6.) Model Optimization and Fine-tuning: -Explore techniques to optimize the model's performance further, such as feature selection, dimensionality reduction, or ensemble methods like boosting or bagging [35].
Experiment with different variations of the regression model, fine-tuning hyperparameters, or exploring more advanced regression algorithms available in Sklearn.

7.) Integration with Keras and TensorFlow: -If desired, explore neural network-based regression models using Keras and TensorFlow libraries [36]. Design and train a deep learning model, such as a feedforward neural network or a recurrent neural network (RNN), for traffic prediction.
Utilize Keras and TensorFlow's functionalities to define the network architecture, compile the model, and train it using the pre-processed dataset.

8.) Deployment and Utilization: - Integrate the trained regression model (either the Sklearn or the Keras/TensorFlow model) into the smart transportation system infrastructure [39]. Deploy the model to a production environment, such as a web service or an application programming interface (API), to provide real-time traffic predictions.
Ensure proper data input and output handling within the smart transportation system for seamless integration and utilization of the traffic prediction model.

9.) Ongoing Monitoring and Maintenance: -Continuously monitor the model's performance in the production environment. Monitor data quality, prediction accuracy, and system reliability. Address any issues or anomalies promptly by monitoring logs, implementing error handling mechanisms, or performing regular model retraining and updates as new data becomes available [10].
Continuously monitor the performance of the traffic prediction model in real-world scenarios. Gather feedback, evaluate the model's accuracy, and make necessary improvements over time.
Throughout the implementation process, import the required libraries, such as Sklearn for regression modelling, Keras for deep learning models, and TensorFlow as the underlying machine learning framework. Utilize the functionalities provided by these libraries to pre-process the data, train the model, make predictions, and evaluate the performance.

VI. Result & Analysis

The results of the traffic are as follows by the matplotlib library.

Figure: -3 Traffic prediction of Junction 1 from the datasets

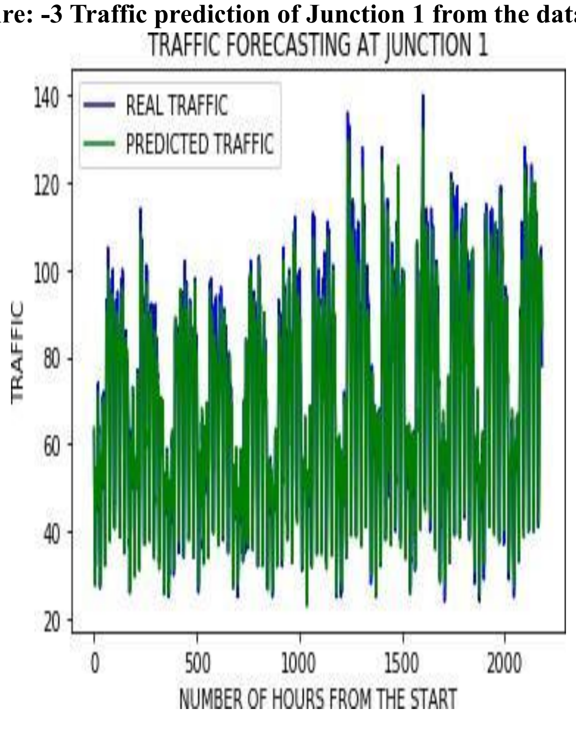


Figure: -4 Traffic prediction of Junction 2 from the datasets

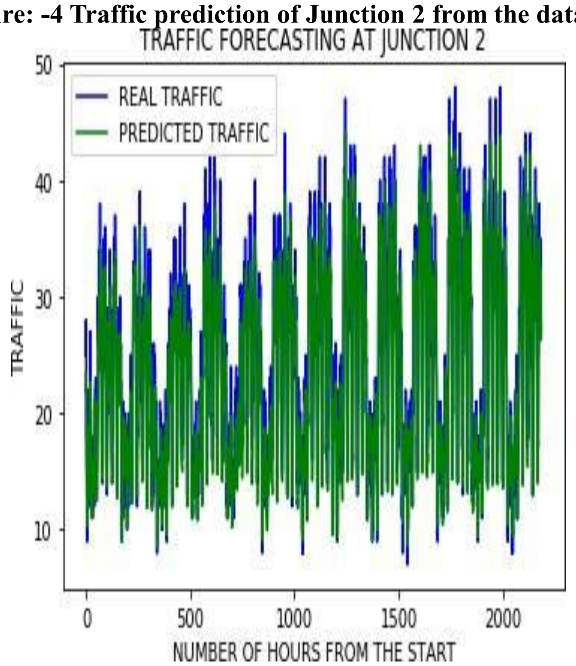
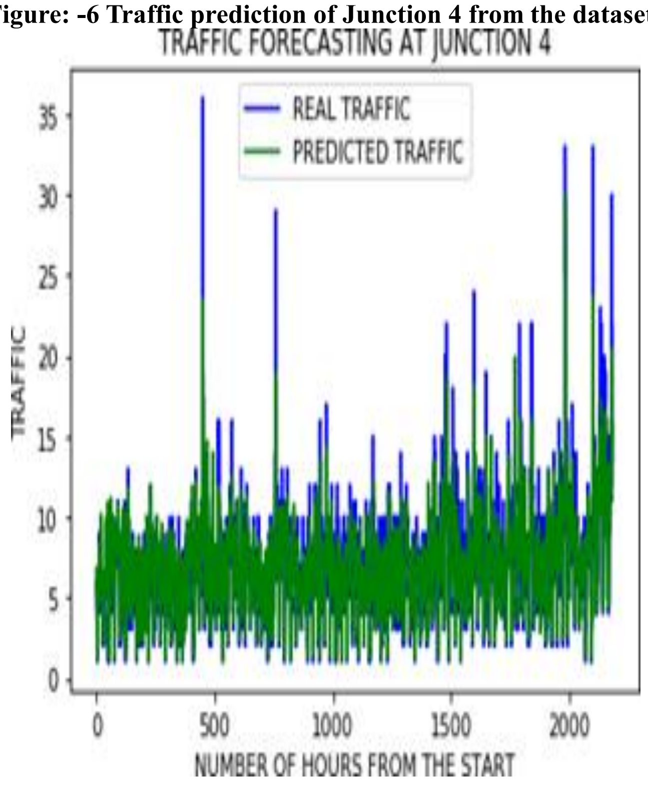


Figure: -6 Traffic prediction of Junction 4 from the datasets



VII. Conclusion

The traffic flow forecasting mechanism of the system utilizes a machine learning algorithm [15][17]. It employs regression model analysis for accurate predictions. This benefits the general public by providing insights into future traffic conditions and current traffic flow. Additionally, it enables them to assess road conditions by knowing the average vehicle speed at junction number four [12]. Changes in meteorological conditions and fuel prices impact the transportation sector [23]. High fuel costs may limit vehicle ownership, leading to varying traffic figures. Furthermore, individuals' preference for solo travel affects traffic congestion [13]. By comparing data from two years, this prediction aids in evaluating traffic flow. It empowers individuals to make informed decisions about route selection, leveraging the prediction and navigation system. The findings of this study pave the way for future research and development of intelligent transportation systems that leverage machine learning techniques to enhance traffic prediction capabilities.

In today's world, traffic forecasting plays a crucial role in almost all regions. Therefore, such predictions are valuable for anticipating and planning for traffic conditions.

VIII. Future Work

The system continuously improves in future versions by incorporating additional variables that influence traffic management, along with advanced techniques like deep learning, artificial neural networks, and big data analysis. Users can leverage this method to determine the most convenient route for reaching their destination.

This technology not only helps users choose the optimal search option but also assists in identifying the least congested path in low-traffic areas. Various forecasting techniques have already been employed for predicting traffic congestion. There is potential for more precise congestion prediction and obtaining accurate and precise results from the predictions. By utilizing the latest forecasting algorithms and improved traffic data, the accuracy of predictions can be significantly enhanced.

To ensure better congestion prediction, it is essential to focus on the grade and accuracy of traffic predictions. Future developments aim to estimate prediction accuracy in a simpler and more user-friendly manner, allowing users to benefit from the prediction model without wasting time on complex data interpretation. Moreover, providing accessible options such as weather forecasts, GPS navigation with road conditions, and accident-prone areas will discourage users from selecting risky routes and enable traffic prediction. This will be facilitated through the utilization of big data, artificial neural networks, and deep learning techniques.

References

[1]. Vlahogianni, E. I., M. G. Karlaftis, and J. C. Golias. Optimized and Meta-Optimized Neural Networks for Short Term Traffic Flow Prediction: A Genetic Approach. Transportation Research Part C: Emerging Technologies, Vol. 13, No. 3, 2005, pp. 211–234.
[2]. Machine Learning Approach to Short-Term Traffic Congestion Prediction in a Connected Environment AmrElfar1, Alireza Talebpour2, and Hani S. Mahmassani1, National Academy of Sciences: Transportation Research Board 2018.
[3]. Big data-driven machine learning-enabled traffic flow prediction Fanhui Kong1 Jian Li1 Bin Jiang2 Tianyuan Zhang3 Houbing Song3, 2018.
[4]. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2845248/
[5]. Hong, J. S., and Kim, Y. J. (2015). Using a multi factor pattern recognition paradigm, the urban TFP system. 16(5),2744–2755, IEEE Transactions on ITS.
[6]. Bao G, Zeng Z, Shen Y. Region stability analysis and tracking control of memristive recurrent neural network. Neural Netw. 2017;5(1):74-89.
[7]. Jiang, X., and H. Adeli.Dynamic Wavelet Neural Network Model for Traffic Flow Forecasting. Journal of Transportation Engineering, Vol. 131, No. 10, 2005, pp. 771– 779.
[8]. Identification Traffic Flow Prediction Parameters AnuchitRatanaparadorn Department of Industrial Engineering, Kasetsart University, Thailand, AnuchitRatanaparadorn, Sasivim olMeeampol, ThaneeratSiripachana, Pornthep, Anussornnitisarn, 19-21 2013, Zadar, Croatia, international conference.
[9]. YuhanJia, Jianping Wu, and Ming Xu, Traffic Flow Prediction with Rainfall Impact Using a Deep Learning Method, Journal of Advanced Transportation, 2017.
[10]. Felix Kunde Alexander Hartenstein Stephan Pieper Petra Sauer, Traffic prediction using a Deep Learning paradigm, CEUR-WS.org, 2017.
[11]. https://www.kaggle.com/fedesoriano/traffic prediction-dataset.
[12]. https://www.hindawi.com/journals/jat/2021/8878011/
[13]. https://machinelearningmastery.com/how-to-connect model-input-data-with- predictions-for-machine-learning/
[14]. https://www.shanelynn.ie/pandas-iloc-loc-select-rowsand-columns-dataframe/
[15]. https://matplotlib.org/2.0.2/api/pyplot_api.html.
[16]. Azzouni A, Pujolle G. A long short-term memory recurrent neural network framework for network traffic matrix prediction. Comput Sci. 2017;3(6):18-27.
[17]. Ioannis LoumiotisRoad Traffic Prediction Using Artificial Neural Networks 2018.
[18]. https://www.catalyzex.com/s/Traffic%20Prediction.
[19]. https://www.geeksforgeeks.org/formatting-dates-in python/
[20]. https://www.scitepress.org/Papers/2016/58957/pdf/index.html
[21]. Malik S., Mire A., Tyagi A.K., Arora V. (2020) A Novel Feature Extractor Based on the Modified Approach of Histogram of Oriented Gradient. In: Gervasi O. et al. (eds) Computational Science and Its Applications – ICCSA 2020. ICCSA 2020. Lecture Notes in Computer Science, vol 12254. Springer, Cham. https://doi.org/10.1007/978-3- 030-58817-5_54.
[22]. B. Gudeti, S. Mishra, S. Malik, T. F. Fernandez, A. K. Tyagi and S. Kumari, "A Novel Approach to Predict Chronic Kidney Disease using Machine Learning Algorithms," 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, 2020, pp. 1630-1635, doi: 10.1109/ICECA49313.2020.9297392.
[23]. Gillala Rekha, V. Krishna Reddy, and Amit Kumar Tyagi, "KDOS - Kernel Density based Over Sampling - A Solution to Skewed Class Distribution", 2020, Journal of Information Assurance and Security (JIAS), Vol. 15 Issue 2, p44-52. 9p.
[24]. Ambildhuke G.M., Rekha G., Tyagi A.K. (2021) Performance Analysis of Under sampling Approaches for Solving Customer Churn Prediction. In: Goyal D., Gupta A.K., Piuri V., Ganzha M., Paprzycki M. (eds) Proceedings of the Second International Conference on Information Management and Machine Intelligence. Lecture Notes in Networks and Systems, vol 166. Springer, Singapore. Https://doi.org/10.1007/978-981-15-9689-6_3.
[25]. Mahmuda Akhtar, Sara Moridpour, \"A Review of Traffic Congestion Prediction Using Artificial Intelligence\", Journal of Advanced Transportation, vol. 2021, Article ID 8878011, 18 pages, 2021. https://doi.org/10.1155/2021/8878011

[26]. GEORGE EP Box, Gwilym M Jenkins, and G Reinsel. Time series analysis: forecasting and control holden-day San Francisco. BoxTime Series Analysis: Forecasting and Control Holden Day1970, 1970.

[27]. W. Zhang, Y. Yu, Y. Qi, F. Shu, and Y. Wang, "Short-term traffic flow prediction based on spatio-temporal analysis and CNN deep learning," Transportmetrica A: Transport Science, vol. 15, no. 2, pp. 1688–1711, 2019.

[28]. J. Wang, Y. Mao, J. Li, Z. Xiong, and W.-X. Wang, "Predictability of road traffic and Congestion in urban areas," PLoS One, vol. 10, no. 4, Article ID e0121825, 2015.

[29]. T. Adetiloye and A. Awasthi, "Multimodal big data fusion for traffic congestion prediction," Multimodal Analytics for Next-Generation Big Data Technologies and Applications, Springer, Berlin, Germany, 2019.

[30]. Accident Analysis and Prevention, 132, 105226.https://doi.org/10.1016/j.aap.2019.07.002

[31]. Dr. K Gomathy, Article: A Semantic Quality of Web Service Information Retrieval Techniques Using Bin Rank, International Journal of Scientific Research in Computer Science Engineering and Information Technology (IJSRCSEIT) Volume 3 | Issue 1 | ISSN :2456-3307, P. No:1563-1578, February-2018.

[32]. Travel time prediction under different traffic conditions using global positioning system and its data come from buses. IET Intelligent Transportation Systems. 3(1), 1–9 (2009).

[33]. Hemalatha. C.Kand N. Ahmed Nisar (2011)., Explored teachers' commitment in self-financing engineering colleges, International Journal of Enterprise Innovation Management Studies (IJEIMS), Vol2. No2. July-Dec 2011 ISSN: 076-2698.

[34]. Mehul Mahrishi and Sudha Morwal. Index point detection and semantic indexing of videos – a comparative review. Advances in Intelligent Systems and Computing, Springer, 2020.

[35]. C. Zhang, P. Patras, and H. Haddadi. Deep learning in mobile and wireless networking: A survey. IEEE Communications Surveys Tutorials, 21(3):2224–2287, third quarter 2019.

[36]. Z. Zhao, W. Chen, X. Wu, P. C. Y. Chen, and J. Liu. Lstm network: a deep learning approach for short-term traffic forecast. IET Intelligent Transport Systems, 11(2):68–75, 2017.

[37]. Jason Brownlee. Bagging and random forest ensemble algorithms for machine learning. Machine Learning Algorithms, pages 4–22, 2016.

[38]. Olabarrieta, I. I, Lana, I., and Del Ser, J., (2016). Analysing traffic flow to understand everyday mobility trends in urban road networks. IEEE/IFIP Network Operations and Management Symposium, NOMS 2016-2016, 1(1),1157-1162.

[39]. Zhao, Q., Liu, S., Yang, L., Li, D., and Qi, Y. Qu, W., Li, J., and others (2020). Temporal intersection anticipating the flow of traffic. Sustainability, 12(19), 1-13.