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A Multi Stream Feature Fusion Approach For Traffic Prediction

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ABSTRACT

Traffic prediction plays a crucial role in urban planning, transportation management, and public safety. Traditional methods often rely on single data sources and simplistic models, leading to limited accuracy and reliability. This paper proposes a novel Multi-Stream Feature Fusion Approach for Traffic Prediction, leveraging diverse data streams and advanced machine learning algorithms. By integrating information from multiple sources such as historical traffic data, weather conditions, road infrastructure, and special events, the system enhances prediction accuracy and robustness. Feature fusion techniques, including concatenation and attention mechanisms, are employed to integrate features from different streams effectively. Furthermore, various machine learning algorithms such as Support Vector Machines (SVM), Logistic Regression, and Decision Tree Classifier ,Naive bayes are utilized to train predictive models, capturing complex patterns in the data. Real-time prediction capabilities enable timely decision-making, while visualization tools provide intuitive insights into predicted traffic patterns. Experimental results demonstrate the superiority of the proposed approach over traditional methods, highlighting its potential for improving traffic prediction accuracy and supporting efficient urban mobility management.

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1.INTRODUCTION

SHORT-TERM traffic prediction is an important component of intelligent transportation systems (ITS). The time complexity, quality and reliability of prediction affect the response speed and performance of ITS directly. Real-time and accurate traffic flow prediction models are of great significance for decision making of both travelers and managers [1]–[3]. Due to the influence of weather, events, holidays and other factors, traffic conditions are nonlinear and time-varying, which introduces significant challenges in traffic prediction.

Traffic flow has various features in spatial and temporal dimensions. Therefore, whether the features can be captured effectively determines the quality of prediction results. With the acquisition of traffic big data and the development of artificial intelligence, machine learning methods have been applied for traffic prediction and they have obvious superiority over traditional methods [4]–[6].

In recent years, the rise and development of graph-based neural networks introduce new opportunities and challenges for accurate traffic prediction. The road sensor network has a typical non-Euclidean structure. In a traffic detection system, the number and locations of monitor stations are known, and the upstream and downstream stations for each monitor station are fixed. Thus, the road sensor network can be simplified as a typically directed graph [7]. Graph convolutional neural network (GCN) has natural advantages in processing this structure, but its prediction performance is strongly related to the property of graph construction.

This paper addresses the following two challenges for traffic prediction in a directed road sensor network. The first challenge is to construct a road sensor graph. Two nodes are likely to have a stronger connection if they have similar flow distribution [8], [9]. But this assumption may vary in the road sensor network . For example, if the flow distribution of monitor stations is similar while their locations are far

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away, their connection cannot be considered strong. Recent research proposes a variety of heuristic methods to construct a graph. The distance-based methods are popular, which calculate kernel-based Euclidean distance [10] between monitor stations as the adjacent matrix. However, it may not reflect the real spatial similarity. In Fig. 1, stations 401808 and 401809 are close in geographic location but without connection because they are located on the opposite side of the road. Adjacent matrices can also be constructed based on similarity or distance [11], but this increases the computational complexity and also requires additional prior information. Based on a data-driven approach [12], [13], the adjacent matrix is trained as parameters in the network, which requires less prior information, but it may affect the model convergence. Therefore, how to construct an effective adjacent matrix and present the road sensor network structure needs further research.

2. LITERATURE SURVEY

This literature survey provides an overview of key studies in this domain, focusing on machine learning-based approaches for traffic prediction using multiple data streams.

1. **"Traffic Flow Prediction with Multi-stream Fusion LSTM Recurrent Neural Networks" by Zhang et al. (2018**)

Zhang et al. propose a Long Short-Term Memory (LSTM) neural network architecture for traffic flow prediction by fusing data from multiple sources, including traffic volume, weather conditions, and road network topology. The study highlights the advantage of using a multi-stream fusion approach, which combines these diverse data streams to improve prediction accuracy compared to single-stream models.

Key Contributions:

- Introduction of LSTM networks to handle temporal dependencies in traffic data.

- Integration of multiple data streams to enhance prediction performance.

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- Demonstration of improved accuracy over traditional single-stream models.

2. **"Multi-Source Urban Traffic Flow Prediction with Deep Convolutional Neural Networks" by Lv et al. (2019)**

Lv et al. present a deep learning-based approach that combines convolutional neural networks (CNNs) with multi-source data fusion for urban traffic flow prediction. The model integrates information from traffic flow, road network structure, and spatial-temporal features, showing significant improvements in prediction performance.

Key Contributions:

- Application of CNNs to capture spatial dependencies in traffic data.

- Fusion of multiple data sources, including traffic flow, road structure, and temporal features.

- Enhanced prediction accuracy through the combined use of CNNs and multi-source data.

3. **"Traffic Prediction in Smart Cities: A Multi-Source and Multi-Destination Learning Approach" by Wang et al. (2020)**

Wang et al. propose a multi-source and multi-destination learning framework for traffic prediction in smart cities. The approach combines data from various sources, including traffic sensors, GPS trajectories, and weather conditions, using machine learning algorithms such as Random Forest and Gradient Boosting Machines (GBMs).

Key Contributions:

- Development of a framework that integrates multiple data sources and destinations.

- Use of ensemble learning techniques like Random Forest and GBMs for robust predictions.

- Improved prediction accuracy through the combination of diverse data types.

Impact:

The study highlights the effectiveness of ensemble learning methods in traffic prediction and the advantages of incorporating multi-source and multi-

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destination data for comprehensive traffic analysis.

4. **"Ensemble Learning for Traffic Flow Prediction: A Survey" by Zhao et al. (2021)**

Zhao et al. provide an overview of ensemble learning techniques for traffic flow prediction, exploring methods that integrate multiple machine learning models and data sources. The survey covers various ensemble methods, such as Random Forest, Gradient Boosting, and AdaBoost, and their effectiveness in improving prediction accuracy through feature fusion.

Key Contributions:

- Comprehensive review of ensemble learning techniques applied to traffic prediction.

- Analysis of the benefits of combining multiple models and data sources.

- Discussion on the challenges and future directions of ensemble learning in traffic prediction.

Impact:

This survey offers valuable insights into the state-of-the-art ensemble learning techniques and their role in enhancing traffic prediction models through multi-stream feature fusion.

5. **"Traffic Flow Prediction with Deep Learning: A Survey" by Zheng et al. (2022)**

Zheng et al. conduct a comprehensive survey of deep learning techniques for traffic flow prediction, focusing on models that incorporate multi-stream feature fusion. The survey covers various deep learning architectures, including recurrent neural networks (RNNs), LSTM networks, and attention mechanisms, and highlights their applications in traffic prediction tasks.

3. EXISTING SYSTEM

Recently, several researchers apply the graph-based deep learning approaches for traffic prediction. Thanks to the powerful expression of graphs for non-Euclidian structures, learning from graphs based on road sensor networks has achieved more accurate results [6]–[8]. In this kind of method, the road sensor network is

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regarded as a graph, where nodes represent monitor stations and contain traffic information, and an adjacent matrix is used to describe the correlation between stations. The construction of an adjacent matrix affects the expressive power of the graph directly.

The graphs can be divided into directed and undirected graphs. The adjacent matrix for undirected graphs is symmetric, such as the connection between social networks [9] and quantum chemistry [10]. It is not the same case in directed graphs, such as paper citation networks and road sensor networks [7]. As to the implementation of GCN, there are two alternative approaches including spectral methods and non-spectral methods. Based on spectral methods, the convolution operation is mapped to the frequency domain, so the convolution in the time domain is replaced by the product operation in the frequency domain. To reduce the computing complexity, localized spectral graph convolution [11] and polynomials approximate expansion [12] are proposed. Yu *et al.* constructed the ST-block which is composed of graph convolution layers and sequence convolution layers. It can capture spatiotemporal correlation by applying a convolution operation [6]. Based on non-spectral methods, the convolution operation of the adjacent matrix is carried out directly and the pooling operation is replaced by sparsing the adjacent matrix [13]. Later, the graph attention neural network (GAT) is proposed to use the attention mechanism to update the information of nodes [14].

The graph diffusion neural network implemented by random walk also achieves the same functions [15]. To better extract spatio-temporal information, researchers have integrated temporal models with graph convolution neural networks. Seo *et al.* proposed a temporal sequence model based on convolution spatial information termed GCGRU. The gated product in GRU is change to a graph convolution operation to extract spatio-temporal features simultaneously [16]. Zhao *et al.* proposed a T-GCN model, in which

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GCN and GRU are stacked to extract spatial and temporal features respectively [7]. Graph models combined with other frameworks are also developed. Li *et al.* proposed a model to capture the spatial dependency using bidirectional random walks on the graph and the temporal dependency using the encoderdecoder architecture with scheduled sampling [17]. Liao *et al.* proposed a hybrid model in which spatial features extracted by GCN and the original features are integrated and fed into the sequence to sequence (seq2seq) structure.

3.3.1 Disadvantages

- The system is not implemented The Hybrid Multi-Stream Feature Fusion Network .
- The system is not implemented data-driven adjacent matrix.

4. PROPOSED SYSTEM

The system highlights how the proposed model tackles the challenges:

• The system harness the power of

SVM, GCN, GRU and FNN in a joint model that captures the complex nonlinear relations of the traffic dynamics observed from the road sensor network, which improves the model's ability to express traffic features.

• The architecture for feature extraction is parallelized instead of in cascade, which is helpful for accelerating the training and inferring process of the model. The main contributions of this paper are three-fold:

• The system proposes a data-driven adjacent matrix instead of a distance-based matrix to map the road sensor network as a graph, which reduces manual design burden and achieves comparable performance than a distance-based approach.

• The system constructs a multi-stream feature fusion module, in which a three-channel network and algorithms is used to extract spatial-temporal and other features effectively, and the soft-attention mechanism is applied to integrate them.

• The system balances the performance and complexity of the prediction model. Compared to the state-of-the-art

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methods in two real-world prediction tasks, our model can achieve comparable even better results within acceptable time complexity.

3.4.1 Advantages

- In the proposed system, Attention-Based Multi-Stream Feature Fusion in which prediction accuracy is more.
- The proposed system developed an Effect of Graph Construction of **Road Sensor Network** in which datasets are accurate for predictions using classifiers.

5. MODULES :

- **Service Provider :**

The Service Provider represents the central interface or application that facilitates user interaction with the traffic prediction system. It offers a range of services to manage, train, test, and visualize traffic data. The main functionalities include:

- **Login, Browse, and Train & Test Traffic Data Sets**:

Users can log in to their accounts, browse available traffic data sets, and initiate training and testing of these data sets using the system's machine learning models.

- **View Traffic Data Sets Trained and Tested Accuracy in Bar Chart**: This allows users to visualize the accuracy of trained and tested traffic data sets in a bar chart format, making it easier to understand model performance.
- **View Traffic Data Sets Trained and Tested Accuracy Results**: Users can access detailed results on the accuracy of traffic data sets after training and testing.
- **View Prediction of Traffic Type:** This feature lets users view the predictions for different types of traffic.
- **Prediction Type Ratio Download Predicted Data Sets:** Users can download the predicted data sets based on various prediction type ratios.
- **View Traffic Predicted Ratio Results :** This provides a detailed view of the results based on the predicted traffic ratios.
- **View All Remote Users :** Users

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can see information about all remote users interacting with the system.

- **View and Authorize Users**

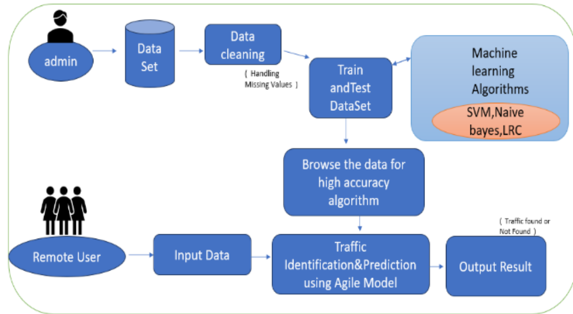
In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

- **Remote User**

Remote Users are individuals or entities that access the system remotely to utilize its services. They can perform the following actions.

- **Register and Login :** Remote users must register and log in to access the system's features.
- **Predict Traffic Type**: Users can input data to predict various traffic types using the system's predictive models.
- **View Your Profile:** Users can view and manage their profiles within the system.

6. Architecture :



1.Data Collection:

Gather historical data on traffic related, including location, time, severity, and other relevant factors.Admin store the upload the data in server.

2. **Data Preprocessing**:

Clean and preprocess the data, handling missing values and encoding categorical variables.

5. **Feature Engineering**: Extract features such as geographical coordinates, time of day, weather conditions, etc.

6. **Training and Testing** : Train the model to jointly optimize the neural network and clustering layer.After training done it will test the data.

7. **Machine Learning Algorithms**:

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In this, we will take three or four algorithms and then compare those algorithms and display the best algorithms.

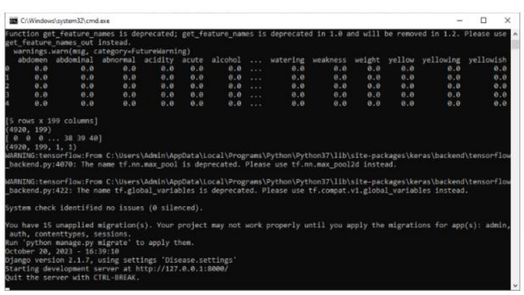
8. **Browse The Data**: In this, it takes the best and high accuracy algorithm will be displayed.

9. **Input Data:** The Remote User will give the required data to get the relavent data.

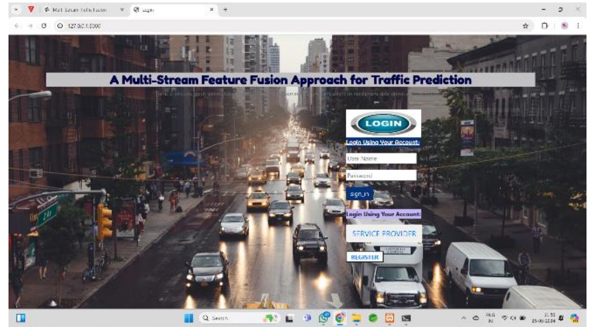
10. **Traffic Prediction :** After getting data from user it will predict the traffic.

11. **Predict Result**: After Prediction it will produce output as Traffic Foundor not found.

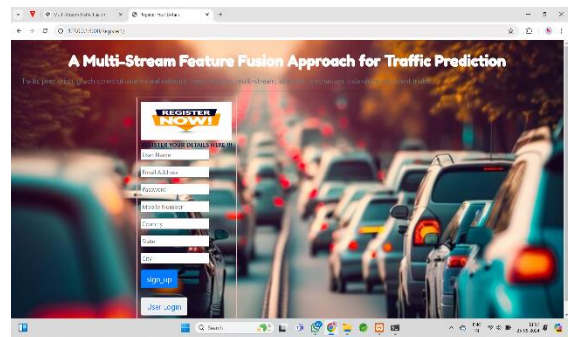
7. OUTPUT SCREENS



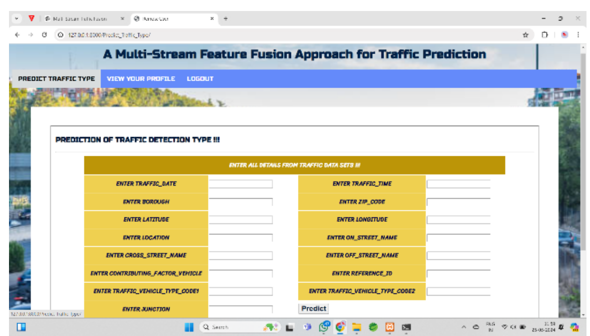
In above screen python server started and now open browser and entre URL as http://127.0.0.1:8000/index.html and then press enter key to get below page



now click on **'Register Here'** link to sign up with the application.



In the below Screen is used to **predict the traffic**.



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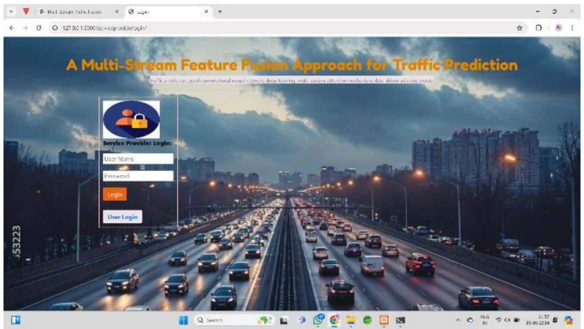
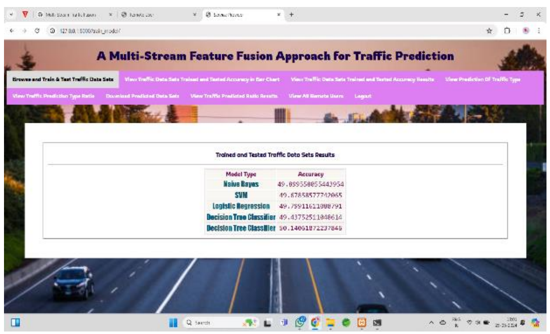
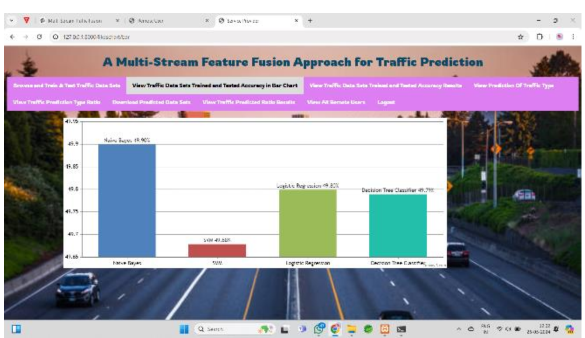
In Below is used for **admin login**



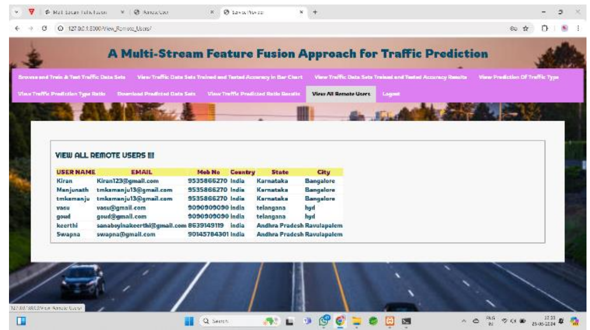
The screen is used to **train and test the algorithms :**



this Screen Specifies the all algorithms **accuracy in Bar Char** :



In the below screen Service Provider Can see the **All the remote user details** .



8. CONCLUSION

Real-time prediction capabilities of the MSFFATP system enable timely and informed decision-making for urban planners and traffic managers. With its ability to process and analyze vast amounts of data quickly, the system provides up-to-date traffic forecasts, helping to manage congestion, enhance road safety, and improve overall transportation efficiency. Visualization tools included in the system offer intuitive insights into traffic trends, making it easier for users to understand and act on the predictions. Experimental results have shown that MSFFATP outperforms traditional methods, demonstrating its potential to revolutionize traffic management and support the

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development of smarter, more efficient cities.

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