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A Multi-Stream Feature Fusion Approach for Traffic Prediction

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ABSTRACT

Accurate and timely traffic flow prediction is crucial for intelligent transportation systems (ITS). Recent advances in graph-based neural networks have achieved promising prediction results. However, some challenges remain, especially regarding graph construction and the time complexity of models. In this paper, we propose a multi-stream feature fusion approach to extract and integrate rich features from traffic data and leverage a data-driven adjacent matrix instead of the distance-based matrix to construct graphs. We calculate the Spearman rank correlation coefficient between monitor stations to obtain the initial adjacent matrix and fine-tune it while training. As to the model, we construct a multi-stream feature fusion block (MFFB) module, which includes a three-channel network and the soft attention mechanism. The three-channel networks are graph convolutional neural network (GCN), gated recurrent unit (GRU) and fully connected neural network (FNN), which are used to extract spatial, temporal and other features, respectively. The soft-attention mechanism is utilized to integrate the obtained features. The MFFB modules are stacked, and a fully connected layer and a convolutional layer are used to make predictions.We conduct experiments on two real-world traffic prediction tasks and verify that our proposed approach outperforms the state-of-the-art methods within an acceptable time complexity.

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].

Literature Survey

Sure, I can provide an overview of the literature survey for the topic "Multi-Stream Feature Fusion Approach for Traffic Prediction". This approach typically involves integrating multiple sources of data or features to enhance the accuracy and robustness of traffic prediction models. Here's a structured summary of what such a literature survey might include:

1.Introduction to Traffic Prediction

Define the problem of traffic prediction.

Importance of accurate traffic prediction for urban planning, transportation management, etc.

Brief overview of traditional methods and their limitations.

2.Multi-Stream Feature Fusion Techniques

Definition and Purpose: Explain what multi-stream feature fusion is and why it is relevant in traffic

prediction.

Types of Features:

Spatial Features: Include data from multiple spatial sources such as GPS data, road networks, and

geographical information.

3 IMPLEMENTATION STUDY

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 [26]–[28]. In this kind of method, the road sensor network is 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.

Disadvantages:

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

Proposed System & alogirtham

The system highlights how the proposed model tackles the challenges:

• The system harness the power of 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.

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.

SYSTEM ARCHITECTURE

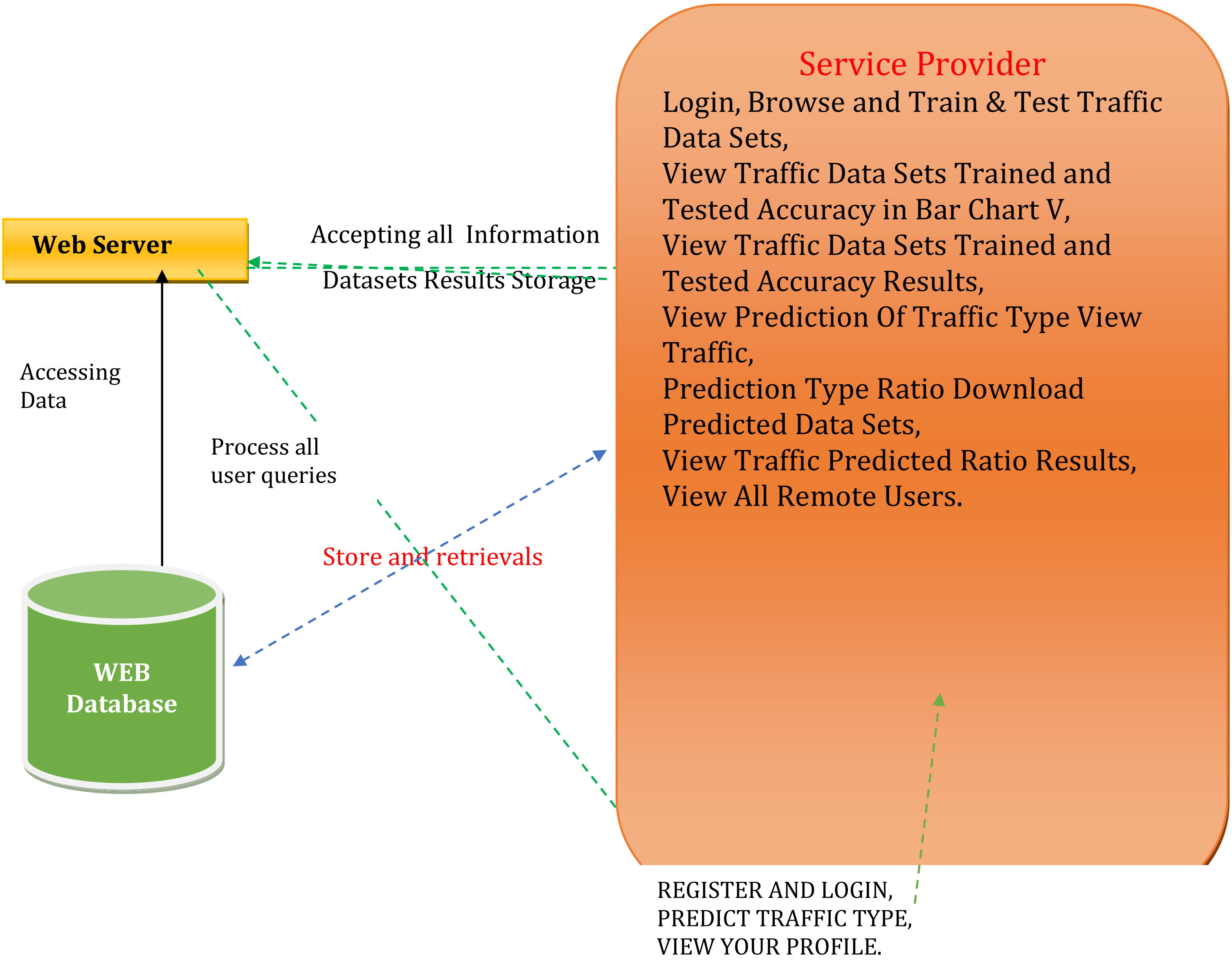


Fig:3.1 System Architecture

IMPLEMENTATION

Modules

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as

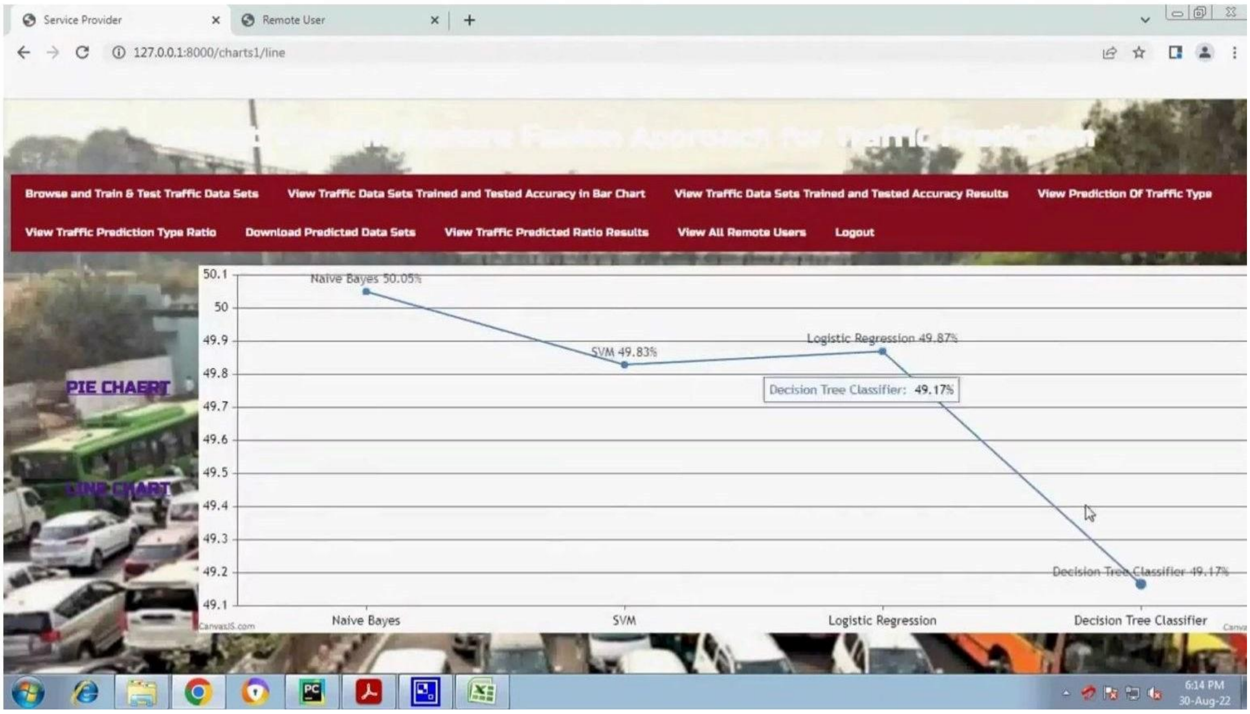
Login, Browse and Train & Test Traffic Data Sets, View Traffic Data Sets Trained and Tested Accuracy in Bar Chart V,View Traffic Data Sets Trained and Tested Accuracy Results, View Prediction Of Traffic Type View Traffic, Prediction Type Ratio Download Predicted Data Sets, View Traffic Predicted Ratio Results, View All Remote Users.

View and Authorize Users

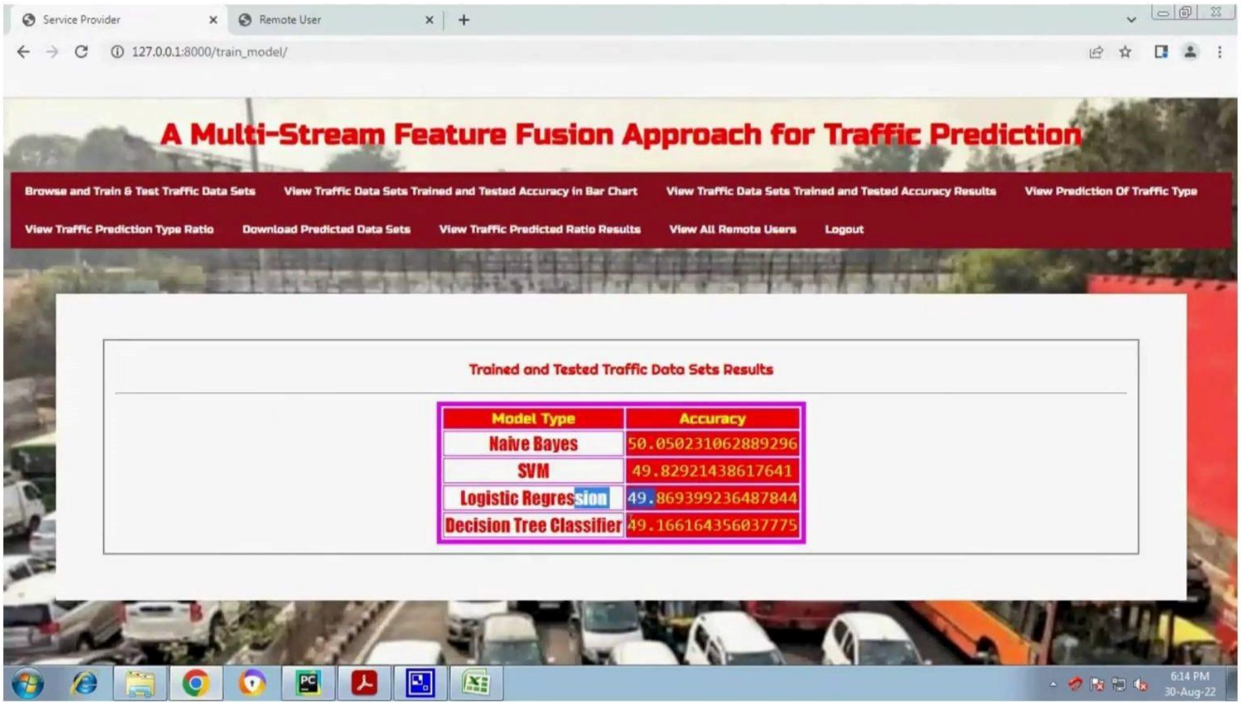
In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

5 RESULTS AND DISCUSSION

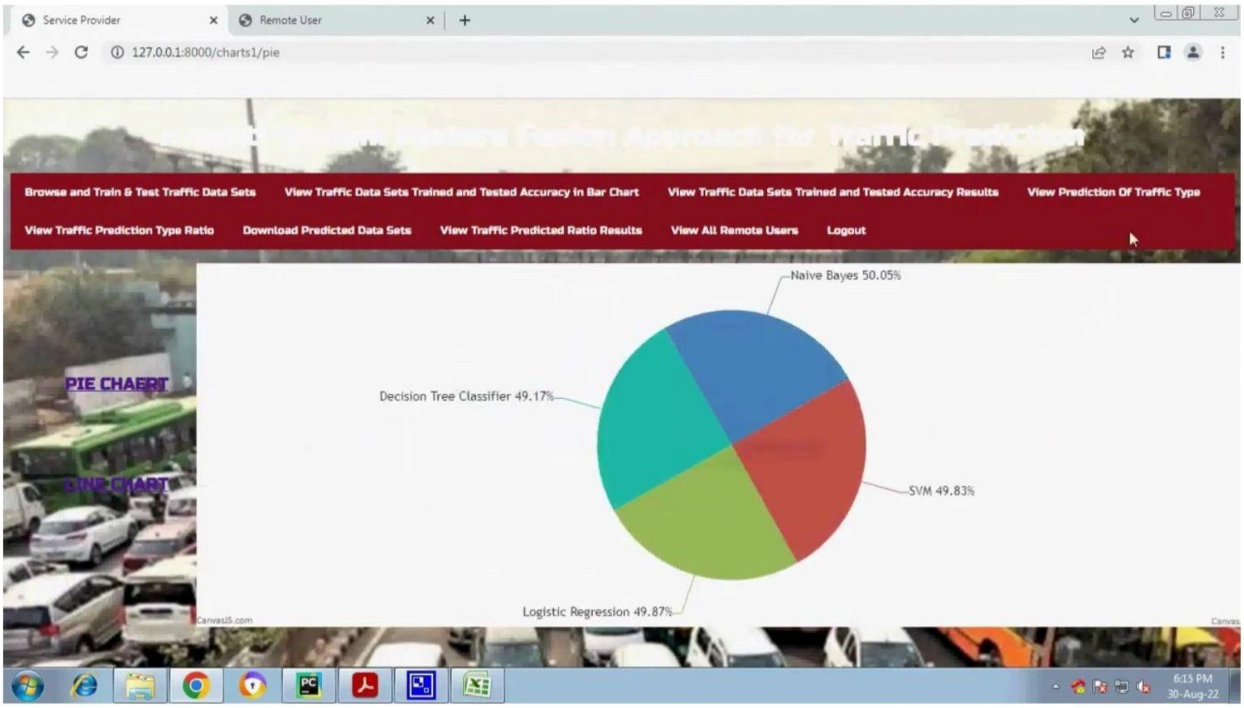
SCREEN SHOT-1



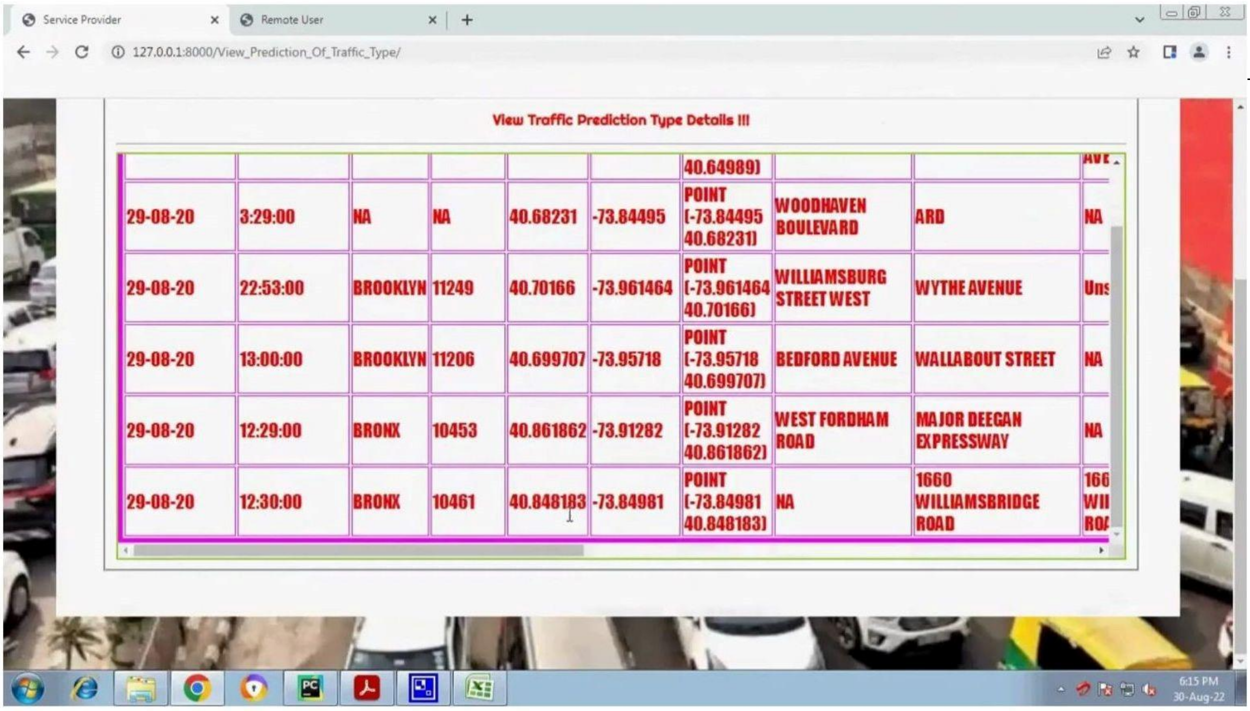
SCREEN SHOT-2



SCREEN SHOT-3



SCREEN SHOT-4



						40.64989)			AVE
29-08-20	3:29:00	NA	NA	40.68231	-73.84495	POINT (-73.84495 40.68231)	WOODHAVEN BOULEVARD	ARD	NA
29-08-20	22:53:00	BROOKLYN	11249	40.70166	-73.961464	POINT (-73.961464 40.70166)	WILLIAMSBURG STREET WEST	WYTHE AVENUE	Uns
29-08-20	13:00:00	BROOKLYN	11206	40.699707	-73.95718	POINT (-73.95718 40.699707)	BEDFORD AVENUE	WALLABOUT STREET	NA
29-08-20	12:29:00	BRONX	10453	40.861862	-73.91282	POINT (-73.91282 40.861862)	WEST FORDHAM ROAD	MAJOR DEEGAN EXPRESSWAY	NA
29-08-20	12:30:00	BRONX	10461	40.848183	-73.84981	POINT (-73.84981 40.848183)	NA	1660 WILLIAMSBRIDGE ROAD	166 WII ROA

6. CONCLUSION AND FUTURE WORK

CONCLUSION

This paper proposes a multi-stream feature fusion method, which leverages a data driven approach to construct graphs. We calculate the Spearman rank correlation coefficient between monitor stations to obtain the initial adjacent matrix and fine-tuning it while training the network. We perform experiments on two real-world traffic datasets, demonstrates that our proposed model outperforms the state-of-the-art traffic prediction methods, and achieves comparable performance compared with the distance-based graph constructing approach while relieving the burden of constructing the adjacent matrix.

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