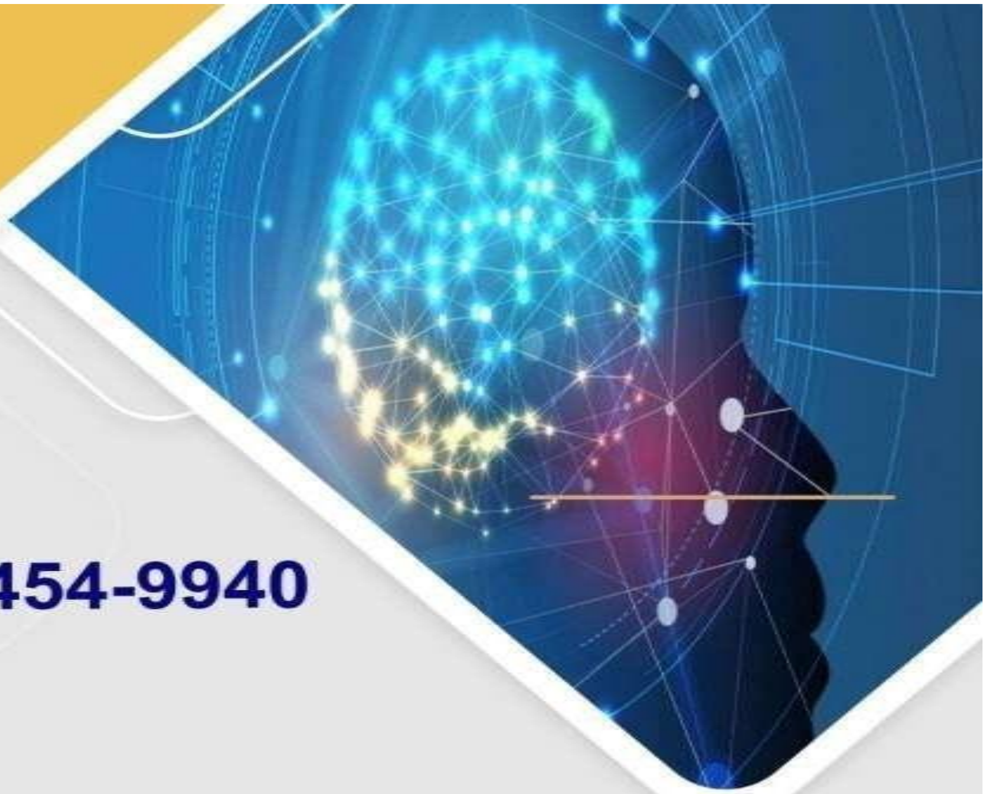

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A MULTI STREAM FEATURE FUSION APPROACH FOR TRAFFIC PREDICTION

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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

Intelligent transportation systems rely on short-term traffic predictions. How quickly and accurately ITS responds is directly impacted by the prediction's temporal complexity, quality, and dependability. Both drivers and business owners may benefit greatly from models that can anticipate traffic flows in real time and with a high degree of accuracy. The nonlinear and time-varying nature of traffic conditions—influenced by variables such as weather, events, holidays, and others—presents substantial obstacles to traffic forecast.

The geographical and temporal aspects of traffic flow exhibit a variety of characteristics. Consequently, the accuracy of the predictions is dependent on how well the characteristics can be recorded. The utilization of AI methods for traffic expectation has been made conceivable by the catch of traffic enormous information and the improvement of man-made reasoning. These methodologies obviously outflank the old ones. New possibilities and difficulties for precise traffic prediction have emerged with the advent and growth of graph-based neural networks in the last few years. A non-Euclidean structure is characteristic of the road sensor network. A traffic detection system has a predetermined number of upstream and downstream stations for each monitor station, as well as a known number and position of monitor stations overall. This means that a normally directed graph is the simplest way to represent the road sensor network. The processing of this structure is naturally better handled by graph convolutional neural networks (GCNs), although the accuracy of their predictions is highly dependent on the graph construction feature. Two difficulties with traffic prediction using a directed road sensor network are discussed in this article. A road sensor graph must be constructed as the first obstacle. When the flow distributions of two nodes are quite similar, it's probable that their link is very strong. This road sensor network assumption, however, may differ. A strong relationship cannot exist, for instance, between distant monitoring stations with identical flow distributions. A number of heuristic approaches to graph construction have been suggested in recent studies. Many people prefer distance-based approaches, which use the neighboring matrix to get the kernel-based Euclidean distance between each pair of monitoring stations. But it may not show the true spatial resemblance.

The computational complexity and amount of previous knowledge required to generate adjacent matrices based on similarity or

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distance are both increased. Although it may impact the model's convergence, training the neighboring matrix as network parameters based on a data-driven method reduces the amount of prior knowledge needed. So, further study is required to determine how to effectively build an adjacent matrix and display the road sensor network architecture. Second, we want to find a happy medium between the model's performance and the temporal complexity. Models pertaining to deep neural networks are becoming more and more challenging to store and implement on devices with limited resources.

The predictive approach isn't practical for low-power applications because of the high computation and storage overhead. You should give serious thought to finding a deep learning model that is straightforward to implement. We plan to upgrade the forecast exhibition while keeping a reasonable time intricacy in this examination. Our proposed traffic expectation model utilizes the multi-stream include combination technique to overcome the aforementioned issues. An MFFB is built using a fully connected neural network (FNN), a gated recurrent unit (GRU), and a graph convolutional neural network (GCN). Space, time, and other physical characteristics are the primary areas of concentration for each of them. The GCN network displays the road sensor network via its data-driven adjacent matrix. Afterwards, the several traits that were retrieved are combined using the soft-attention method.

We emphasize the ways in which the suggested model addresses the obstacles:

By combining GCN, GRU, and FNN into a single model, we are able to better express traffic characteristics by capturing the convoluted

nonlinear relations of the traffic elements seen by the street sensor organization. To accelerate the model's preparation and inducing processes, the element extraction engineering is parallelized as opposed to in cascade. This study primarily offers three contributions:

• We suggest a data-driven adjacent matrix as an alternative to a distance-based matrix for graphing the road sensor network. This technique provides equivalent performance to the former while reducing the human design load.

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• We construct a multi-stream include combination module that incorporates spatial-transient and different qualities separated from a three-channel organization using the soft-attention method.

• The prediction model's performance and complexity are balanced. In two genuine expectation challenges, our model beats cutting edge approaches while keeping a satisfactory fleeting intricacy.

2.LITERATURE SURVEY

Title: MuSeFFF: A framework for traffic prediction using multi-stage feature fusion.

Authors: Arunkumar, R.Sunitha

This study introduces MuSeFFF, a new method for predicting future traffic using a computer program.MuSeFFF is more accurate at understanding how traffic behaves in different places and times compared to older methods. When tested with real traffic data, MuSeFFF predicted traffic 1.25% more accurately for short-term predictions and 2.76% more accurately for long-term predictions compared to other methods. This means MuSeFFF is better at telling us what traffic will be like in the future, helping us plan our journeys more effectively.

Title: A Spatiotemporal Graph Convolutional Network-Based Deep Learning Method for Multi-Factor Fusion Used in Long-Term Traffic Flow Prediction.

Authors: Xiaoyu Qi, Gang Mei, Jingzhi Tu, Ning Xi, and Francesco Piccialli Intelligent transportation systems rely on accurate long-term traffic flow predictions, and this work presents a novel approach for doing just that using deep learning techniques. Unlike previous studies that focus mainly on short-term predictions and overlook external factors, this approach considers various factors like temperature and weather conditions. This is how the technique enhances the reliability of traffic flow predictions over the long run. Experimental results show that incorporating external factors enhances prediction performance compared to traditional models, making it a promising solution for traffic prediction in real-world scenarios.

Title: Making Use of Multi-stream Data Fusion for Trajectory Forecasting in Low-light Conditions: Method Using Multi-Channel Graph Convolution

Authors: Hailong Gong1, Zirui Li

This paper proposes a method for predicting vehicle trajectories in low-light conditions for autonomous vehicles. The data from images, optical flows, and object trajectories are combined using CNN, LSTM, and ST-GCN. Even in low-light situations, the approach reliably predicts future trajectories by combining data from various sources. Evaluation on urban intersection datasets, including HEV-I and Dark-HEV-I, shows superior performance over existing methods, highlighting its versatility across different perception data types.

Title: Predicting Traffic using a Multi-Stream Feature Fusion Method

Authors: Zhishuai Li , Gang Xiong

Using a multi-stream feature fusion methodology, the authors provide a new method for predicting traffic flow in ITS. For the purpose of building graphs, they provide a data-driven nearby matrix that is acquired using Spearman rank correlation coefficients between monitoring stations. A multi-stream feature fusion block (MFFB) module is a part of their model that combines features obtained from several types of neural networks, To make predictions, we utilize stacked MFFB modules with fully connected and convolutional layers, and we apply the soft-attention technique to fuse the extracted features. While keeping the temporal complexity acceptable, experimental findings show that the technique outperforms state-of-the-art methods.

3. EXISTING SYSTEM

A number of scholastics have as of late utilized chart based profound learning techniques to conjecture traffic designs. Gaining from charts in view of street sensor networks has delivered more exact discoveries, made conceivable by the solid plan of diagrams for non-Euclidian designs. This approach sees the street sensor network as a chart, with hubs addressing the many checking stations that gather and store traffic information, and a contiguous lattice portraying the relationship between's the stations. The expressive capability of the graph is directly impacted by the creation of an adjacent matrix.

It is possible to classify graphs as either directed or undirected. An example of an undirected graph is the link between quantum

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chemistry and social networks; in this case, the adjacent matrix is symmetric. Directed graphs, such those used in paper citation networks and road sensor networks, provide a different situation. Regarding the use of GCN, two other ways exist: spectral techniques and non- spectral methods. We suggest using polynomials approximation and localized spectral graph convolution to decrease processing complexity. Two types of convolutional layers—graph and sequence—make up the ST-block that Yu et al. built. By using a convolution process, it is able to capture correlation between space and time. The non-spectral approaches allow for direct convolution of the neighboring matrix and sparsing of that matrix in lieu of pooling Similarly compelling is the chart dissemination brain network prepared utilizing an irregular walk. Analysts have joined transient models with chart convolution brain organizations to work on the extraction of spatio-fleeting data.

The GCGRU model, put out by Search engine optimization et al., is a worldly grouping model that utilizes convolutional spatial data.To extract spatio-temporal characteristics concurrently, GRU changes the gated product to a graph convolution process. In their T-GCN model, Zhao et al. layered GCN with GRU to extract temporal characteristics and spatial features, respectively. There is also development of graph models that integrate with various frameworks. presented a model that could capture both the spatial and temporal dependencies. In their hybrid model, Liao et al. suggested integrating and feeding the original data into the sequence-to-sequence (seq2seq) structure, together with spatial information derived by GCN.

Disadvantages

 The system is not implemented The Hybrid Multi-Stream Feature Fusion Network.

 The system is not implemented data-driven adjacent matrix.

3.1 PROPOSED SYSTEM

The system emphasizes the ways in which the suggested model addresses the obstacles:

• By consolidating GCN, GRU, and FNN into a solitary model, the framework can more readily communicate traffic qualities by catching the confounded nonlinear relations of the traffic elements seen by the street sensor organization.

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• To accelerate the model's preparation and surmising processes, the element

extraction engineering is parallelized as opposed to in flow. There are three essential

advantages to perusing this paper:

• The framework proposes an information driven neighboring grid to plan the street sensor network as a chart, rather of a distance-based lattice. This procedure limits the plan intricacy and conveys execution that is identical to the distance-based strategy.

• The framework fabricates a multi-stream highlight combination module that incorporates spatial-fleeting and different qualities separated from a three-channel network utilizing the delicate consideration technique.

• The framework makes a fair compromise between the expectation model's intricacy and its presentation. In two genuine forecast difficulties, our model outflanks cutting edge approaches while keeping a satisfactory worldly intricacy.

Advantages:

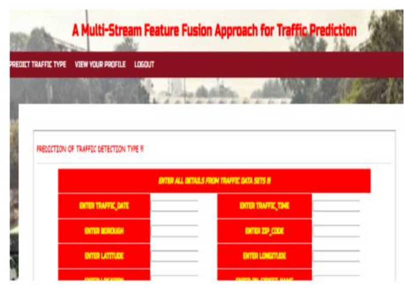
• Attention-Based Multi-Stream Feature Fusion, the suggested approach, has higher prediction accuracy

• To ensure that datasets used for classifier predictions are valid, the suggested method created an Effect of Graph Construction of Road Sensor Network.

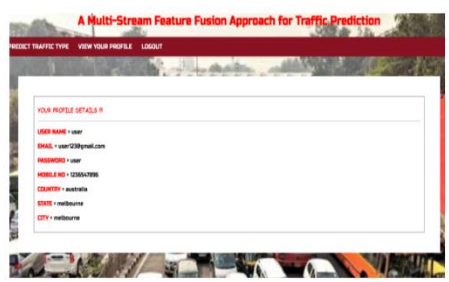
4.OUTPUTSCREENS

Remote User:

Predict Traffic Type



View Your Profile



Service Provider:

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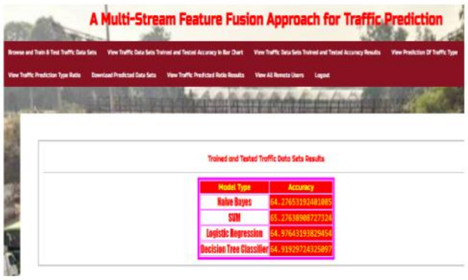
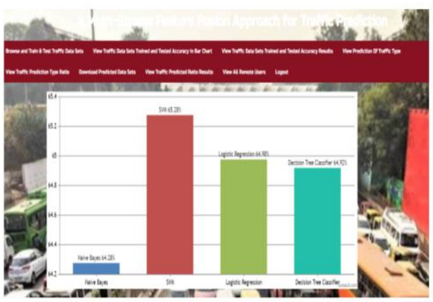
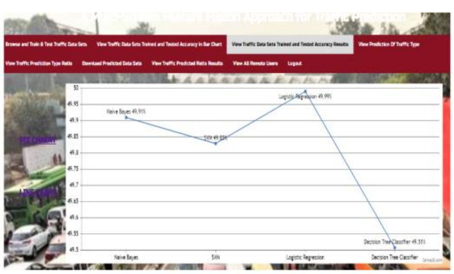
Browse and Train & Test Traffic DataSets



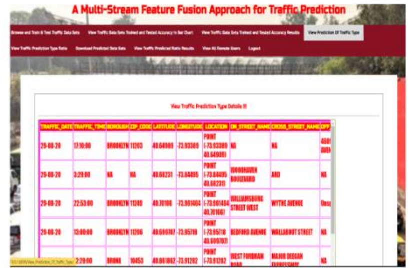
View Traffic Data Sets and Accuracy In Bar Chart



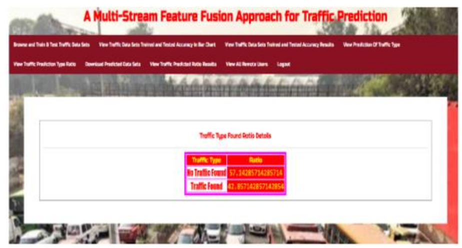
View Traffic Data Sets Trained and Tested Accuracy Results



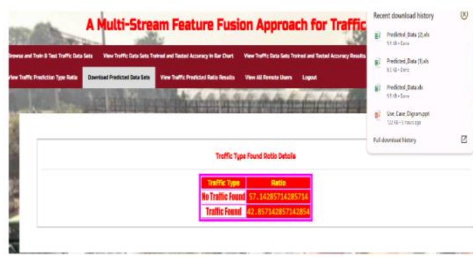
View Prediction Of Traffic Type



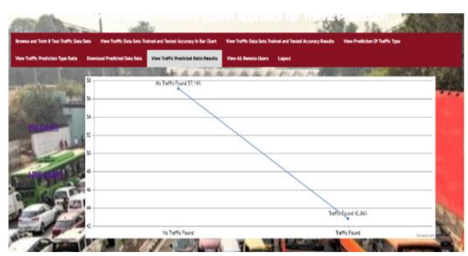
View Traffic Prediction Type Ratio



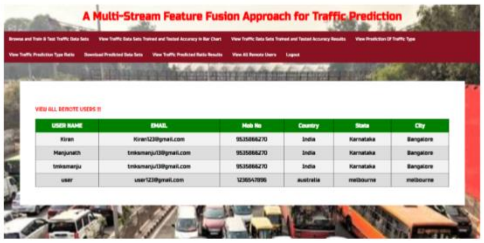
Download Predicted Data Sets



View Traffic Predicted Ratio Results



Logout



5.CONCLUSION

In order to build graphs, this research suggests a data-driven methodology called multi-stream feature fusion. We get the initial adjacent matrix by calculating the Spearman rank correlation coefficient between the monitor stations, then we tweak it during training the network. By conducting experiments on two real-world traffic datasets, we prove that our suggested model is superior to the current best practices for traffic prediction and can achieve results that are on par with those of the distance-based graph construction method, all without having to worry about building the adjacent matrix. Our method's drawback is that additional training parameters are needed for the neighboring matrix fine-tuning procedure. As the number of monitor stations in a road sensor network increases, the network will inevitably grow in size and training efficiency will decline. Hence, in our next study, we will explore the strategy of fine- tuning nearby matrices with fewer training parameters. For more conventional prediction jobs, such electricity demand forecast, the suggested technique works as well. In addition, other structures like GAN or sequence to sequence may be used to further our work.

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