

A MULTI STREAM FEATURE FUSION APPROACH FOR TRAFFIC PREDICTION

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ABSTRACT

Traffic prediction has become an essential component of Intelligent Transportation Systems (ITS) due to the rapid increase in urbanization, vehicle population, and road congestion. Accurate traffic flow forecasting helps transportation authorities, commuters, and smart city systems make efficient decisions related to route planning, congestion management, fuel optimization, and accident prevention. However, traffic conditions are highly dynamic and nonlinear because they are influenced by various factors such as weather conditions, public events, road construction activities, holidays, and driving behavior. Traditional statistical and machine learning approaches often fail to capture complex spatial and temporal dependencies present in traffic data, leading to reduced prediction accuracy.

1.INTRODUCTION

Transportation systems play a vital role in the economic and social development of modern society. In rapidly growing urban areas, the increase in population, vehicles, and commercial activities has led to severe traffic congestion, delays, fuel wastage, and environmental pollution. Efficient traffic

management has therefore become an essential requirement for smart cities and intelligent transportation systems. One of the major components of an intelligent transportation system is traffic prediction, which helps in forecasting future traffic conditions based on historical and real-time traffic data.

Traffic prediction refers to the process of estimating future traffic flow, speed, or congestion levels on roads using computational and analytical techniques. Accurate traffic prediction enables traffic authorities, commuters, logistics companies, and emergency services to make better decisions. For example, drivers can choose less congested routes, traffic management systems can optimize signal timings, and city planners can improve transportation infrastructure based on predicted traffic patterns.

Traditional traffic prediction methods mainly relied on statistical and mathematical models such as linear regression, autoregressive integrated moving average (ARIMA), Kalman filtering, and historical averaging techniques. Although these methods were effective for small datasets and simple traffic conditions, they failed to handle the dynamic and nonlinear nature of real-world traffic environments. Traffic conditions are influenced by multiple factors including weather conditions, road accidents, public events, road construction, holidays, and human driving behavior. Due to these complex dependencies, conventional models often produce inaccurate predictions when traffic patterns change suddenly.

2.LITERATURE REVIEW

Traffic prediction plays a vital role in Intelligent Transportation Systems (ITS) by helping authorities manage congestion, improve road safety, and optimize transportation planning. Traditional traffic forecasting methods such as Historical Average (HA), Autoregressive Integrated Moving Average (ARIMA), and Kalman Filtering were widely used for predicting traffic flow. These methods perform adequately for simple and linear traffic patterns but fail to capture complex spatial and temporal dependencies present in modern transportation networks.

With the advancement of machine learning, algorithms such as Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) have been applied to traffic prediction problems. These approaches improved forecasting accuracy by learning nonlinear traffic patterns from historical data. However, they often struggle to model long-term temporal dependencies and spatial correlations among multiple road segments.

Deep learning techniques have further enhanced traffic prediction capabilities. Recurrent Neural Networks (RNN), Long

Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) networks effectively capture temporal traffic dynamics. Similarly, Convolutional Neural Networks (CNN) can learn local spatial features from traffic datasets. Despite their success, single-model approaches cannot efficiently integrate multiple heterogeneous traffic features.

3. EXISTING SYSTEM

The existing traffic prediction systems mainly rely on traditional statistical methods and machine learning algorithms to forecast traffic flow. Commonly used techniques include Historical Average (HA), Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models. These methods analyze historical traffic data to identify patterns and generate future traffic predictions. While these approaches have shown satisfactory performance in basic traffic forecasting scenarios, they often focus on either temporal information or spatial information separately.

Most existing systems are unable to effectively capture the complex relationships between different road segments and traffic sensors. Traditional

machine learning models have limited capability in handling nonlinear and dynamic traffic patterns, especially during peak hours, accidents, road closures, and unexpected events. Furthermore, many deep learning models process only a single stream of information and fail to integrate multiple traffic-related features simultaneously. As a result, prediction accuracy decreases when dealing with large-scale transportation networks and rapidly changing traffic conditions.

4. PROPOSED SYSTEM

The proposed system introduces a Multi-Stream Feature Fusion Approach for Traffic Prediction that combines multiple deep learning techniques to improve forecasting performance. The system extracts spatial features using Graph Convolutional Networks (GCN), temporal features using Gated Recurrent Units (GRU), and additional contextual features using Fully Connected Neural Networks (FNN). These features are processed through separate learning streams and then integrated using a feature fusion mechanism to create a comprehensive representation of traffic conditions.

To further enhance prediction accuracy, the proposed model employs an attention mechanism that dynamically identifies and assigns importance to the most relevant

features. This enables the system to learn complex spatial-temporal relationships among road networks and traffic sensors more effectively. By combining multiple sources of information into a unified framework, the proposed approach significantly reduces prediction errors and improves forecasting accuracy. The system is capable of supporting real-time traffic monitoring, congestion management, route optimization, and intelligent transportation systems, making it more efficient and reliable than conventional traffic prediction methods.

5.METHODOLOGY

The proposed Multi-Stream Feature Fusion Approach for Traffic Prediction follows a systematic process to accurately forecast future traffic conditions. Initially, traffic data is collected from various sources such as traffic sensors, surveillance cameras, GPS devices, and intelligent transportation systems. The collected data may include traffic flow, vehicle speed, traffic density, road occupancy, weather conditions, and historical traffic records. This raw data undergoes preprocessing steps such as data cleaning, normalization, missing value handling, and feature selection to improve data quality and model performance.

After preprocessing, the system constructs a traffic network representation where road

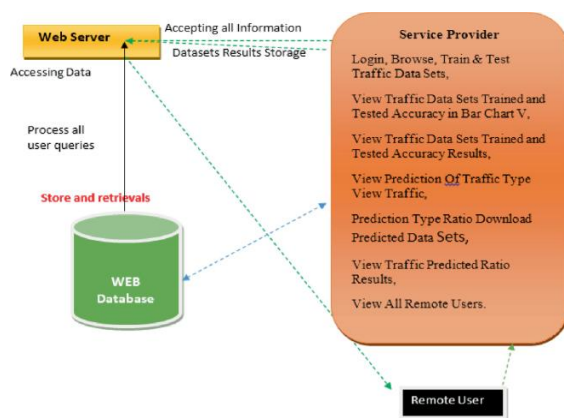
segments and traffic monitoring stations are modeled as interconnected nodes. Spatial features are extracted using Graph Convolutional Networks (GCN), which capture the relationships and dependencies among different road segments. Simultaneously, temporal features are extracted using Gated Recurrent Units (GRU), enabling the system to learn traffic variations and trends over time. Additional contextual information, such as weather conditions and special events, is processed using Fully Connected Neural Networks (FNN) to provide supplementary insights into traffic behavior.

The extracted spatial, temporal, and contextual features are then passed through a Multi-Stream Feature Fusion Block, where information from different streams is combined into a unified feature representation. An Attention Mechanism is incorporated to dynamically assign weights to important features and eliminate irrelevant information. This allows the model to focus on the most significant traffic patterns affecting prediction accuracy.

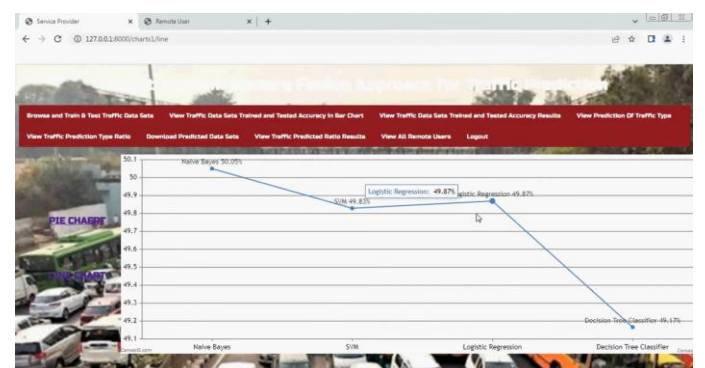
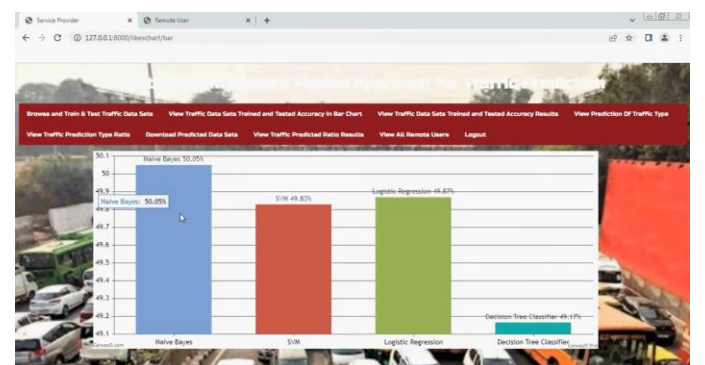
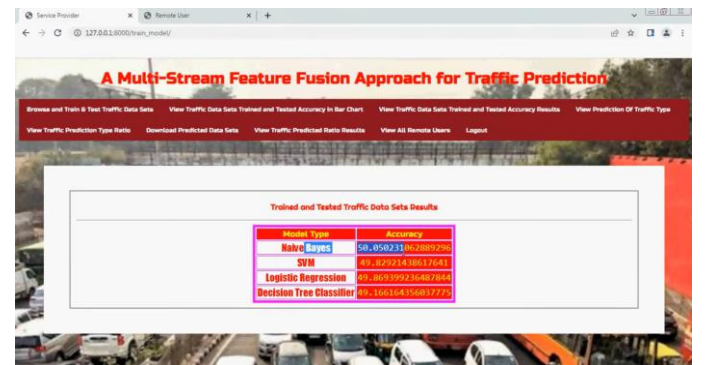
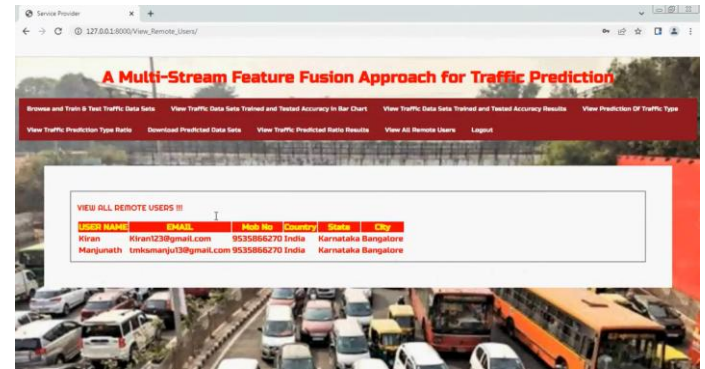
Finally, the fused feature set is fed into the prediction layer, which generates short-term and long-term traffic forecasts. The model is trained and validated using historical traffic datasets, and performance

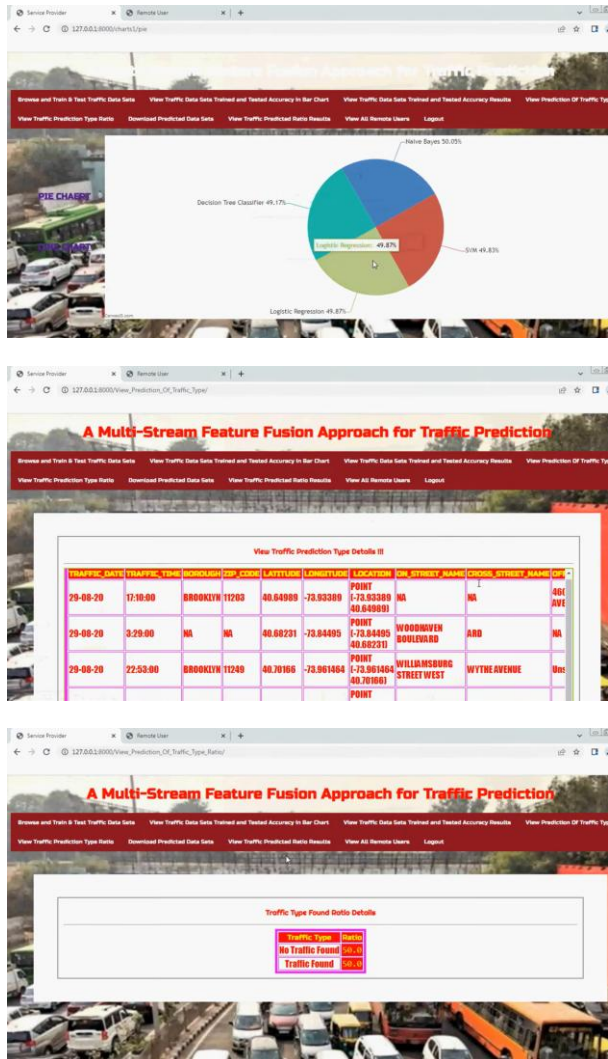
is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The generated predictions can be utilized for traffic management, congestion control, route planning, and smart city transportation applications.

6. SYSTEM MODEL



7. RESULTS AND DISCUSSIONS





8.CONCUSION

Traffic prediction has become one of the most important research areas in intelligent transportation systems because of the rapid increase in urban traffic congestion and transportation challenges. Accurate traffic forecasting helps improve road safety, reduce travel time, minimize fuel consumption, and support smart city infrastructure. However, traffic flow prediction is a difficult task because traffic conditions are highly dynamic, nonlinear, and influenced by multiple external factors

such as weather conditions, road accidents, public events, holidays, and varying driving patterns.

The main objective of this project was to develop an intelligent traffic prediction system using a Multi Stream Feature Fusion Approach capable of extracting and integrating multiple traffic features effectively. The proposed system successfully combined Graph Convolutional Networks (GCN), Gated Recurrent Units (GRU), Fully Connected Neural Networks (FNN), and a soft attention mechanism to improve prediction accuracy and traffic forecasting performance.

The project addressed several limitations found in traditional traffic prediction systems and existing graph-based neural network models. Conventional statistical methods often fail to capture the complex spatial and temporal relationships present in real-world traffic networks. Similarly, distance-based graph construction techniques do not always represent actual traffic behavior accurately. To overcome these problems, the proposed system introduced a data-driven adjacency matrix using the Spearman rank correlation coefficient. This approach enabled the model to identify hidden relationships between traffic monitoring stations based

on traffic similarity rather than only geographical distance.

The Graph Convolutional Network component successfully captured spatial dependencies among traffic stations by processing graph-structured traffic data. The Gated Recurrent Unit effectively learned temporal traffic patterns such as daily traffic trends, peak-hour congestion, and sequential traffic variations. The Fully Connected Neural Network extracted additional hidden and nonlinear features from the traffic dataset. These extracted features were integrated using a soft attention mechanism, which dynamically assigned importance to different feature streams and improved feature fusion performance.

9. REFERENCES

- [1] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd Edition, Morgan Kaufmann Publishers, 2011.
- [2] C. C. Aggarwal, *Neural Networks and Deep Learning: A Textbook*, Springer, 2018.
- [3] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.
- [4] C. M. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006.
- [5] T. M. Mitchell, *Machine Learning*, McGraw-Hill Education, 1997.
- [6] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, Vol. 521, No. 7553, pp. 436–444, 2015.
- [7] T. N. Kipf and M. Welling, "Semi-Supervised Classification with Graph Convolutional Networks," *International Conference on Learning Representations (ICLR)*, 2017.
- [8] K. Cho, B. Van Merriënboer, D. Bahdanau, and Y. Bengio, "Learning Phrase Representations Using RNN Encoder-Decoder for Statistical Machine Translation," *Proceedings of EMNLP*, pp. 1724–1734, 2014.
- [9] A. Vaswani et al., "Attention Is All You Need," *Advances in Neural Information Processing Systems (NeurIPS)*, pp. 5998–6008, 2017.
- [10] M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems," *USENIX Symposium on Operating Systems Design and Implementation*, 2016.
- [11] J. Leskovec, A. Rajaraman, and J. Ullman, *Mining of Massive Datasets*, 3rd Edition, Cambridge University Press, 2020.
- [12] M. E. J. Newman, *Networks: An Introduction*, Oxford University Press, 2010.