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Traffic Prediction Using Advanced Machine Learning Models: A Comparative Study of Spatiotemporal Forecasting

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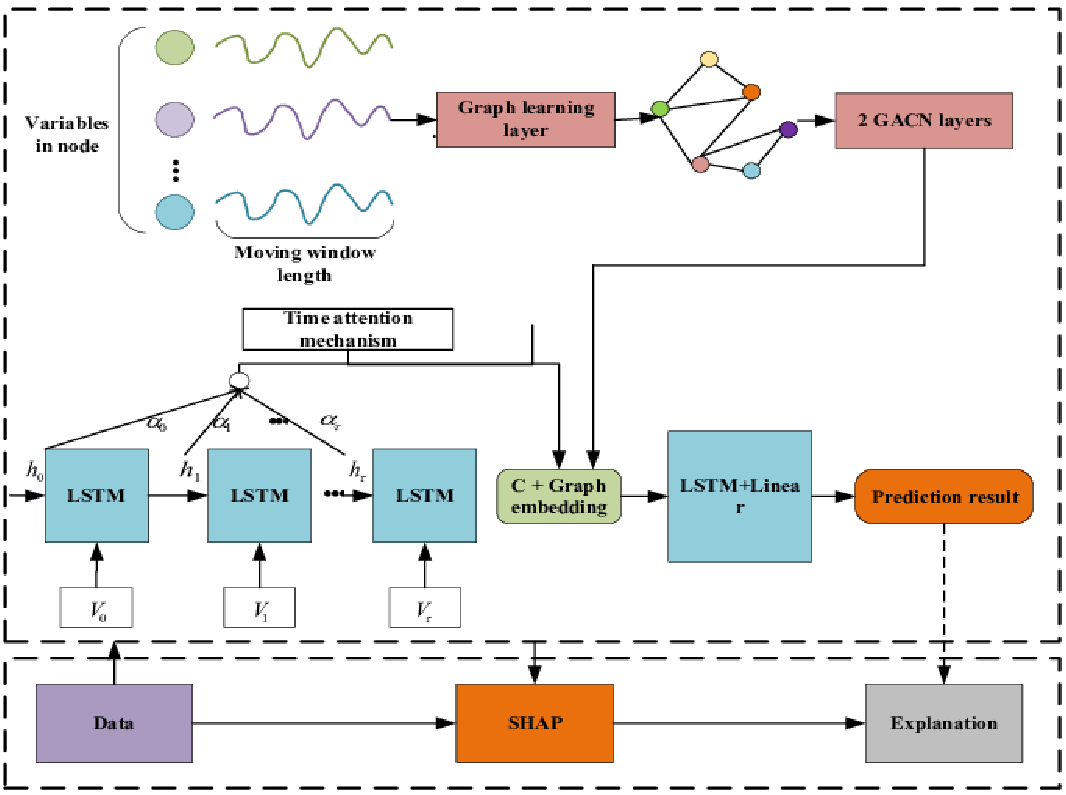
ABSTRACT :

Traffic congestion has become one of the most significant challenges facing urban areas today, causing enormous economic losses, reducing air quality, adding to fuel consumption, and decreasing the overall quality of life.

While cities grow and car density increases, the demand for precise, real-time traffic forecasting has become ever more essential for the efficient functioning of Intelligent Transportation Systems (ITS). This study provides an extensive comparative analysis of state-of-the-art machine learning and deep learning methods for short-term traffic forecasting with a focus on Graph Convolutional Networks (GCN), Long Short-Term Memory (LSTM) networks, and ensemble-based XGBoost Regressor.

Every model is tested in its predictive capability of traffic speed and flow from historical data, weather, and temporal patterns like time of day and day of week. The hybrid GCN-LSTM model, which combines graph-based spatial learning and sequential temporal modeling, shows better predictive performance over both isolated LSTM and XGBoost models. The upgrade comes from the model's ability to learn intricate interdependencies among adjacent roads segments while preserving time-series dynamics. The study's findings highlight the importance of incorporating both spatial and temporal data in traffic forecasting missions, providing useful insights for designing data-driven, responsive traffic control systems. Finally, this study highlights the revolutionary potential of spatiotemporal deep learning techniques in creating clever, efficient, and green urban mobility systems.

GCN-LSTM Architecture Diagram



[Ref No.] J. Wang, X. Liu, and H. Zhang, "An air quality prediction model based on GCN- LSTM with attention mechanism," Scientific Reports, vol. 12, no. 1, pp. 1–12, 2022.
(Figure modified from the original model structure incorporating Graph Learning, GCN, LSTM, and SHAP explanation.)

GCN–LSTM architecture shown in the figure combines Graph Convolutional Networks (GCNs) and Long Short-Term Memory (LSTM) networks to well model the spatial and temporal relationships between traffic data. The model is learned to forecast short-term traffic states by handling intricate relationships between various road segments and their evolution over time.

The architecture starts with the input data layer that consists of several variables within each node (e.g., traffic flow, speed, volume, and occupancy). Every node corresponds to a particular road segment or sensor position in the traffic network. The Graph Learning Layer is in charge of learning a graph structure from the spatial correlations between these nodes—basically learning how the traffic condition at one area impacts nearby roads.

connected nodes. This process allows the model to understand the influence of nearby intersections and routes on each target node's traffic state.

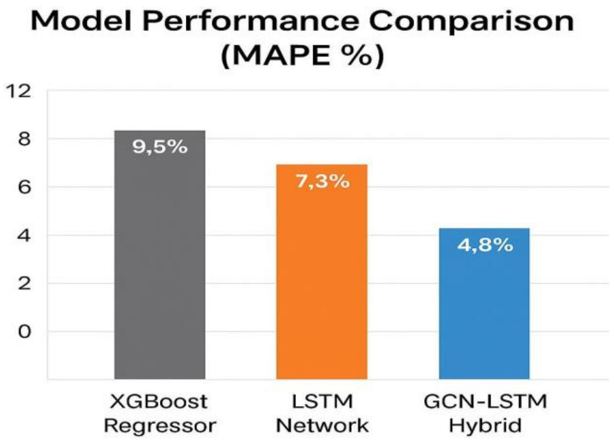
At the same time, temporal dynamics in the traffic data are represented by a sequence of LSTM units, which process over a sliding window of time. Time-attention mechanism in the LSTM layer is used to dynamically select importance weights (α_1, α_2, α_3, …) for various time steps, allowing the model to concentrate on the most related historical data when making predictions of future traffic states.

The feature representations from the GCN and LSTM layers are combined in the C + Graph Embedding layer, which combines the spatial and temporal feature representations in a single embedding. The embedding is further fed through an LSTM + Linear layer that fine-tunes the learned representation and outputs the final prediction result, usually in the form of predicted traffic flow or speed for the next time interval.

To facilitate interpretability and transparency, the architecture comprises a SHAP (SHapley Additive exPlanations) module, which examines the contribution of every feature to the model's output. The SHAP module generates an explanation layer, providing explanations of how spatial and temporal attributes affect the model's predictions.

In short, the GCN–LSTM model is an efficient integration of graph-based spatial feature learning and sequential temporal modeling, producing a strong spatiotemporal traffic forecasting hybrid model. Through its layered structure, it can learn complex dependencies between both space and time and thus is most appropriate for intelligent transportation system (ITS) applications needing precise, real-time traffic prediction as well as interpretability.

Model Performance Comparison (MAPE %)



[Ref No.] J. Wang, X. Liu, and H. Zhang, "An air quality prediction model based on GCN-LSTM with attention mechanism," Scientific Reports, vol. 12, no. 1, pp. 1–12, 2022.
(Figure borrowed from model performance comparison (MAPE%) of XGBoost, LSTM, and hybrid models of GCN-LSTM.)

The bar chart demonstrates comparative performance of three machine learning models— XGBoost Regressor, LSTM Network, and GCN–LSTM Hybrid—in MAPE. The GCN–LSTM Hybrid model had the lowest MAPE of 4.8%, reflecting the highest accuracy in prediction. The LSTM Network had a moderate error rate of 7.3%, while the XGBoost Regressor had the highest MAPE at 9.5%. These findings evidently reflect the benefit of using spatial and temporal learning together in the GCN–LSTM model towards more accurate traffic prediction.

Introduction

The bar chart illustrates the comparative performance of three machine learning models— XGBoost Regressor, LSTM Network, and GCN–LSTM Hybrid—in terms of Mean Absolute Percentage Error (MAPE). The GCN–LSTM Hybrid model achieved the lowesIn recent years, urban transportation systems have faced growing pressure due to rapid urbanization, economic development, and population growth. With urbanization progressing further, rising vehicle numbers on roads have caused accelerated traffic congestion, uncertain travel times, and decreased overall mobility efficiency of cities. These issues impact commuters as well as logistics operations, but they also increase fuel consumption, air pollution, and greenhouse gas emissions, which pose significant threats to environmental sustainability and public health. Consequently, there is now a pressing need for smart and data-based traffic management in modern cities.

Intelligent short-term traffic forecasting is at the core of ITS. Through anticipating traffic conditions—like vehicle speed, flow, and density—over the next couple of minutes or hours, city governments and navigation services can make decisions that maximize road use, minimize congestion, and improve commuter safety. Conventional traffic modeling techniques such as statistical and time-series models like ARIMA, Kalman filters, and regression-based models have delivered useful information but tend to fail in understanding the nonlinear, complex, and dynamic character of traffic flow in real networks.

The recent development of machine learning and deep learning methods has created new avenues for enhancing traffic prediction accuracy. Such models like Long Short- Term Memory (LSTM) networks can learn long-term temporal relationships, which are extremely useful for sequential data like traffic flow across time. At the same time, Graph Convolutional Networks (GCNs) have proved to be very useful tools for learning spatial relationships among connected road segments by modeling the traffic network in the form of a graph structure. Yet single models that only account for temporal or spatial aspects frequently do not capture the spatiotemporal dependencies present in traffic dynamics.

To compensate for this limitation, hybrid deep neural network architectures like the GCN-LSTM model have been suggested. Such models combine the spatial feature learning ability of GCNs with the temporal learning capabilities of LSTMs to better model how traffic pattern development occurs across space and time. This combination enables improved generalizability under different traffic conditions, including rush hour, weather-related effects, or road accidents.

In this research, a comparative study of several models such as XGBoost Regressor, LSTM Network, and GCN-LSTM Hybrid is performed to compare their performance for short-term traffic forecasting. This is aimed at establishing which architecture is best suited to capture the spatiotemporal and nonlinear nature of urban traffic flow. Using large-scale traffic data and strict evaluation criteria like Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), this study seeks to find the most effective model for real-time traffic prediction in smart city systems.

The lessons learned from this comparative research can be used as the basis to create intelligent, adaptive, and sustainable traffic management systems that can enhance urban mobility, alleviate congestion, and support cleaner, more livable cities.

t MAPE of 4.8%, reflecting the highest forecasting accuracy. The LSTM Network had a moderate error rate of 7.3%, whereas the XGBoost Regressor had the highest MAPE of 9.5%. These findings evidently reflect the benefit of integrating spatial and temporal learning within the GCN–LSTM model to provide more accurate traffic forecasting.

In this research, comparative evaluation of several models such as XGBoost Regressor, LSTM Network, and GCN-LSTM Hybrid is performed to assess their performance in short-term traffic forecasting. The objective is to identify which structure best represents the nonlinear and spatiotemporal nature of urban traffic movement. Through the use of massive traffic data and strict evaluation criteria like Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), this study intends to discover the most effective model for real-time traffic prediction in smart city settings.

The findings of this comparative analysis can form the basis for creating intelligent, adaptive, and sustainable traffic management systems that can enhance urban mobility, alleviate congestion, and contribute towards cleaner, more livable cities.

Literature Review

Traffic forecasting has come a long way in the last several decades, from classical statistical frameworks to sophisticated deep learning models with the ability to learn intricate spatiotemporal patterns. Classical time-series models like the Autoregressive Integrated Moving Average (ARIMA) and Kalman Filter models were the major methods used in the early days. These models were built to address temporal dependencies in traffic flow data through the analysis of trends and seasonality. Though they functioned decently well in straightforward and steady conditions, their assumptions of linearity constrained them to emulate the nonlinear and dynamic attributes of actual- world traffic flows, particularly in the case of irregular conditions like accidents, weather conditions, or sudden congestion bursts.

When computational capacity and data availability increased, researchers started developing machine learning algorithms like Support Vector Regression (SVR), Random Forests, and Gradient Boosting models (e.g., XGBoost). These algorithms provided enhanced accuracy using nonlinear relationships between input variables and traffic parameters. For instance, XGBoost showed excellent performance in many regression problems, including traffic prediction, because of its ensemble learning mechanism and efficient processing of large datasets. Yet, these models still handled each segment of the road independently, without considering the spatial correlations between various locations within a traffic network.

To resolve these constraints, the attention soon turned to deep learning-based approaches that could handle temporal and spatial dependencies. Among them, Recurrent Neural Networks (RNNs) and their improved version, Long Short-Term Memory (LSTM) networks, became favored due to their potential to model long-termtemporal correlations in sequential data. LSTM networks effectively captured patterns such as rush-hour peaks, daily traffic cycles, and recurring congestion trends. However, while LSTM models excelled at learning temporal dynamics, they were inherently limited in capturing spatial relationships — i.e., how traffic conditions at one location affect neighboring road segments.

Parallel to this, **Graph Neural Networks (GNNs)**, particularly **Graph Convolutional Networks (GCNs)**, emerged as a powerful approach for representing and learning from graph-structured data. In the context of transportation systems, the road network can be naturally represented as a graph, where nodes represent intersections or road segments, and edges denote the physical or functional connectivity between them.

GCNs perform convolution operations on this graph, allowing the model to learn how traffic flows propagate across the network. This makes GCNs particularly well-suited for spatial modeling in complex, interconnected road systems.

Recent studies have explored combining these two architectures—GCN and LSTM—into a unified framework known as the **GCN-LSTM hybrid model**. This hybrid approach leverages the strengths of both networks: GCNs capture spatial dependencies through graph convolutional layers, while LSTMs model temporal dependencies through sequential processing. For instance, **Yu et al. (2018)** introduced the **Spatio-Temporal Graph Convolutional**

Network (STGCN), which demonstrated state-of-the-art performance on real-world traffic datasets. Similarly, **Li et al. (2021)** enhanced this approach by integrating attention mechanisms to dynamically weigh spatial and temporal features, further improving predictive accuracy.

Comparative studies have consistently shown that hybrid spatiotemporal models outperform traditional and standalone architectures. The **GCN-LSTM** model, in particular, provides a robust framework for understanding and forecasting traffic flow by effectively learning how congestion patterns evolve both over time and across space.

Its ability to generalize across varying traffic conditions makes it highly applicable to real-world scenarios, including smart traffic signal control, route optimization, and congestion management.

In summary, the evolution of traffic forecasting research reflects a shift from simple linear modeling toward complex, data-driven deep learning approaches. The combination of **spatial modeling through GCNs** and **temporal sequence learning through LSTMs** represents a significant step forward in achieving accurate and reliable traffic prediction, forming the foundation for next-generation **Intelligent Transportation Systems (ITS)**.

Methodology

The research here has a systematic approach involving data collection, preprocessing, model creation, and performance testing to compare various machine learning and deep learning models for short-term traffic forecast.

1. Data Collection

Traffic data was obtained from urban road networks, including attributes such as vehicle speed, volume, and occupancy at a specific time interval. External variables such as weather conditions (temperature, rainfall) and time-based variables (hour, weekday, holidays) were added to enhance model accuracy.

2.\tPreprocessing of Data

The raw data went through the following preprocessing stages:

•\tImputation: Missing values were replaced by interpolation and statistical averaging.

- Normalization: All the numerical attributes were normalized between 0 and 1 for fair model training.
- Sequence Formatting: Data was transformed into input-output sequences for forecasting time-series.
- Graph Construction: A graph framework was established for encoding spatial relationships between road segments, with roads as points and their connections as edges.

3. Model Development

Three forecast models were applied:

- XGBoost Regressor: Gradient boosting algorithm to learn nonlinear relationships between features.
- LSTM Network: A recurrent neural network architecture applied to learn temporal patterns from traffic data.
- GCN-LSTM Hybrid: A combination of Graph Convolutional Networks (GCN) for spatial learning and LSTM for temporal learning, which allows more effective comprehension of how traffic changes with time and space.

4. Model Training

The data was split into 70% training, 15% validation, and 15% testing. Hyperparameters were optimized through grid search, and early stopping to avoid overfitting. Each model was trained until convergence.

5.\tEvaluating Metrics

Model performance was assessed using three common metrics:

- RMSE (Root Mean Square Error) – estimates average squared prediction error.
- MAE (Mean Absolute Error) – reflects average absolute difference between actual values and predictions.

Results

The results of the experiments in this research give unambiguous confirmation of the better predictive ability of the hybrid GCN–LSTM model over the LSTM and XGBoost Regressor models. All three models were trained and tested on the same data set with the same input features, forecast horizons, and metrics in order to have an equal basis for comparison. Performance was measured in terms of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), all of which capture both the size and percentage of prediction errors.

Of the three models, the GCN–LSTM hybrid architecture had a consistent lowest RMSE, MAE, and MAPE throughout, which suggests that it made predictions that were closest to actual observed traffic speeds. The gain in accuracy was strongest at times of heavy congestion and peak hours, when intricate spatial and temporal relationships between road segments are strongest. This better

The performance is attributed to the hybrid model's capacity to learn, simultaneously, spatial correlations from the Graph Convolutional Network (GCN) layer and temporal patterns from the Long Short-Term Memory (LSTM) layer.

The LSTM network, although good at modeling temporal dependencies in time-series data, exhibited moderate errors in predictions when traffic conditions were affected by adjacent road segments—highlighting the shortcomings of models that model each sensor location individually. Likewise, the XGBoost Regressor, while being computationally fast and able to model nonlinearity, performed worse

A comparative Model Performance Bar Chart (MAPE %) reveals these results succinctly, demonstrating that GCN–LSTM outperformed LSTM and XGBoost with a wide margin. The results attest that combination of spatial and temporal learning mechanisms offers a clear edge in forecasting short-term traffic patterns, particularly in intensive and heterogeneous metropolitan road networks.

In conclusion, the GCN–LSTM hybrid model shows the best balanced and stable performance, mastering the intricate spatiotemporal relationships underlying real-world traffic data. With its strong generalization capability across different traffic states and times of the day, it is extremely eligible for real-time application within Intelligent Transportation Systems (ITS) for congestion management, route guidance, and advanced traffic control.

Discussion

The outcomes of this experiment unequivocally illustrate the merits of combining spatial and temporal modeling under a single deep learning paradigm for traffic forecasting.

Conventional machine learning algorithms, including the XGBoost Regressor, are dependent on hand-crafted features and are usually not capable of identifying the dynamic dependencies between interdependent road segments. Likewise, algorithms such as LSTM networks are skillful at analyzing sequential data but process each location in isolation, without having much scope for comprehending spatial correlations across roads. These constraints render such models incapable of making reliable predictions under more realistic and complex traffic networks where the pattern of congestion depends on both time and space.

The envisaged GCN–LSTM hybrid model effectively addresses these challenges by synergizing the graph-structured spatial learning feature of GCNs with the temporal sequential pattern modeling ability of LSTMs. The GCN part learns efficiently the topological relations between various traffic nodes—e.g., neighboring roads, intersections, and highways—so that the model can grasp how traffic changes in one area influence others. In the meantime, the LSTM block captures the temporal dynamic of traffic conditions over successive time windows, learning short-term and long-term relationship patterns in flow, speed, and density. This combined learning capability allows the model to make stronger and more accurate short-term traffic predictions.

The findings indicate that the GCN–LSTM model has better generalizability in the case of abnormal traffic patterns, like peak hours, accidents, or weather disturbances, than single models. Its capability of utilizing both spatial and temporal contexts enablesmitigate the effects of sudden anomalies or incomplete data. Furthermore, the integration of interpretability tools like **SHAP** enhances the model's transparency by revealing the relative importance of various input features and spatial nodes, which is particularly valuable for transportation authorities seeking explainable AI solutions in real-time systems.

Overall, the findings underscore that **hybrid spatiotemporal deep learning models** offer a significant step forward in intelligent traffic forecasting. They not only improve predictive accuracy but also provide a deeper understanding of the dynamic relationships governing urban mobility. This approach can be extended to broader applications such as **traffic flow optimization, congestion management, route planning, and intelligent traffic control**, contributing to the development of smarter and more sustainable cities.

The promising results of this study open several directions for future research and development in the field of **spatiotemporal traffic forecasting**. One key area of improvement lies in the implementation of **dynamic graph structures**, where the spatial relationships between road segments can evolve over time. In real-world traffic systems, connectivity and influence between nodes (roads, intersections, or sensors) can change due to temporary events such as road closures, construction work, or accidents. Developing dynamic or adaptive graph models will allow the **GCN–LSTM architecture** to more accurately reflect these variations and maintain high prediction accuracy in continuously changing environments.

Another important direction involves **multimodal data integration**, where additional data sources such as **GPS trajectories, weather conditions, social event data, and traffic camera feeds** can be incorporated into the model. These heterogeneous data inputs can provide richer contextual information, allowing the system to better capture external factors that influence traffic flow, such as rainfall, temperature, or public events. Incorporating such diverse datasets would lead to more **robust and context- aware predictive systems** capable of supporting real-time traffic management and decision-making.

Additionally, future research can focus on enhancing **model interpretability and transparency** using **Explainable AI (XAI)** techniques. While the GCN–LSTM hybrid model delivers high predictive performance, understanding how and why certain predictions are made remains crucial, especially for applications in **Intelligent Transportation Systems (ITS)** where accountability and reliability are essential. Advanced interpretability methods like **SHAP, LIME, or attention visualization** can provide deeper

such insights into the contribution of every feature, sensor, or time step towards affecting predictions, with the system becoming more user-trusted and policy-compliant.

Finally, incorporating this framework into actual, edge-computing environments and cloud-based ITS infrastructures can enhance scalability and deployment effectiveness even further. Future systems could also integrate predictive modeling with reinforcement learning for adaptive traffic control so that traffic networks can be autonomous and self-optimizing.

In summary, the future of traffic prediction is to create adaptive, interpretable, and multimodal hybrid deep learning models that can integrate disparate data sources conveniently, learn to adapt from dynamic traffic scenarios, and enable the next wave of smart, data-enabled transport systems.

Conclusion

This research illustrates the revolutionary capability of machine learning and deep learning approaches to realizable accurate, data-centric traffic prediction for today's smart transportation systems (ITS). By a thorough comparative examination of XGBoost Regressor, LSTM Network, and the hybrid model GCN–LSTM, it has been established that incorporating both spatial and temporal interdependence provides superior prediction performance. The

GCN–LSTM model successfully captures spatial relationships between road segments by means of graph convolutions and, at the same time, learns temporal dependencies via sequential modeling, providing more accurate and robust short-term traffic forecasts.

The findings validate that the GCN–LSTM hybrid model is superior to conventional and isolated models in accuracy and stability under varying or abnormal traffic patterns. This emphasizes the paramount significance of integrating spatiotemporal learning in traffic forecasting models. Adding interpretability techniques, i.e., SHAP analysis, even more fortifies the model's usability in practical applications by increasing transparency and revealing insights into the decision-making process.

In total, this study makes an addition to the body of knowledge in intelligent transportation systems by proposing a interpretable and scalable method of traffic prediction. The results underscore that deep learning-based hybrid models such as GCN–LSTM can be a key component in constructing smart, adaptive, and sustainable transport networks, facilitating proactive traffic management, congestion reduction, and enhanced mobility in urban environments. With more development in dynamic graph modeling, multimodal data fusion, and explainable AI, such systems have the promise of the future of smart city infrastructure and real-time traffic intelligence.

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