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Graph Neural Networks for Predicting Urban Traffic Congestion in Smart Cities

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***Abstract*— Urban traffic congestion is a serious issue for all smart cities in terms of sustainability and efficiency. Existing traffic prediction models do not properly account for the spatial and temporal dependencies in roads within the urban road network. This paper proposes a new methodology for modeling urban traffic congestion using a graph neural network (GNN) to design the road network as a defined dynamic graph, with the addition of multi-view traffic data (i.e. speed, volume, and occupancy), temporal sequences, and external contextual factors such as weather conditions and public events. Enhanced GNN architecture is utilized with attention and hierarchical graph pooling to learn local and universal traffic patterns. The model is validated and evaluated on a dataset collected over six months for a medium smart city, alongside three baseline models (LSTM, Xgboost and Static GCN). The proposed GNN model outperformed the three baseline models RMSE is 3.42 km/h MAE is 2.78, and -2 R^2 score 0.915 with a F1 score of 0.89 in congested hours classification. The results of the proposed methodology confirm the suitability of spatial-temporal graph learning approaches for traffic forecasting methods. To conclude, this methodology demonstrates a strong scalable approach to computing predictive traffic models as part of critical smart city infrastructure.**

Keywords— Graph Neural Networks (GNN), Traffic Congestion Prediction, Smart Cities, Spatial-Temporal Modeling, Intelligent Transportation Systems (ITS).

I. INTRODUCTION

Urbanization has increased significantly in the past decades and it is also driving the rapid development of metropolitan areas, in turn creating stress on urban transportation systems. With cities experiencing hundreds of thousands of vehicles traveling daily on roads around the city, it has become increasingly important to solve the problem of congestion by developing solutions for economic productivity, environmental sustainability, and quality of life. Intelligent transportation systems (ITS) using technologies that are data driven and systems and processes that allow cities to plan were created to analyze measures, forecast and evaluate traffic conditions. Particularly effective for traffic congestion prediction, these intelligent transportation systems (ITS) form the foundations of proactive traffic control and can be used to improve travel delays and keep infrastructure planning and real time navigation systems informed[1].

Traditionally, methods used for traffic predictions have been grounded in statistical models (most often autoregressive integrated moving average (ARIMA) models or some form of regression)[2]. Although these models are easy to interpret and simple to fit, they ultimately failed to capture non-linear dynamics and spatial dependencies that are inherent in road networks. Recent advancements in methods of ML have produced more predictive power, particularly Deep Learning (DL) methods such as Long Short- Term Memory (LSTM)[3] networks, and to a lesser extent, other sequence-based DL models which offer good predictive performance when dealing with temporal traffic patterns. However, these models simply treat each road segment independently or rely on spatial relationships that have been gleaned from previous research, ultimately neglecting to make use of the topological structure of urban road systems.

In this context , GNNs represent a competent framework to model signals of structured data, or in this case, reasonably represent traffic conditions in urban spaces. Since road networks can be organized and comprehended as graphs, with road segments or intersections signified as nodes, and road segments allow direct connections signified as edges, GNNs could learn about spatial patterns of traffic conditions, while also considering time in a cohesive framework. Recent research demonstrated that using GNNs for modeling traffic conditions yields better results than existing traditional or sequence-based models. GNNs can also propagate data through the entire road network dynamically. The creation of the neighborhood or world model is important, as traffic is conducted locally and globally[4].

Despite their potential, current GNN based traffic prediction models have limitations. Many studies do not distinguish heterogeneous set features, such as speed, volume, and occupancy, in an integrated way. Also, they do not distinguish attention to nodes, or lack of attention to nodes which can affect frames of time within the model. Finally, few studies either analyze or limit the integration of external factors (i.e. weather, events, and road incidents), all of which significantly contribute to traffic conditions.

To address these gaps, a GNN based traffic jams model is introduced to propose a novel GNN framework that provides higher options for predicting the urban traffic jam patterns in smart cities in a precise manner. The model will build distributed representations based on multi-views of traffic data, it will include recurrent neural layers that provide temporal encoding and it will have an attention based hierarchical graph learning module capable of learning the complex space-time relationships. In designing this model, we will use enriched features used to embrace real-world uncertainty through exogenous contextual data. Research Question and Problem Statement How can spatiotemporal dependence and contextual information be integrated into GNNs to improve the accurateness and robustness of urban traffic jam forecasting in smart cities? In this research, we pointed out the limitations in spatial awareness and the absence of contextual dimensions in existing traffic forecasts. In line with this, we intend to advance a graph based deep learning strategy which has the ability to model, and dynamically predict traffic congestion patterns in an intricate time variant urban context. The main objectives of the study are as follows

- To design a new GNN-based model that integrates multiple traffic features from different perspectives and can learn spatial and temporal dependencies from urban road networks.
- To leverage attention approaches and improve predictive accuracy through hierarchical pooling to better capture the patterns and scales of drivers in traffic flows.
- To assess the proposed model against standard baselines using real smart city traffic data to show improved predictions.

The rest of the paper is organized as follows. Section 2 describes related work on traffic prediction and GNNs. Section 3 describes the proposed method, including graph construction and model architecture. Section 4 describes experimentation and results, and Section 5 contains the conclusion and future work.

II. RELATED WORKS

Recent progress in smart transportation systems employs graph-based deep learning to improve traffic forecasting and city mobility. Graph Neural Networks (GNNs) capture spatial and temporal relationships in road networks, enhancing precision and scalability. Techniques encompass attention mechanisms, clustering, and multimodal frameworks via RNNs or Transformers. They also advocate for privacy safeguarding and the incorporation of various sources. Collectively, they provide robust adaptive approaches for handling traffic in intelligent urban areas.

da Silva et al., (2023) introduce a privacy-friendly approach to learning topology in VANETs using Graph Learning frameworks that improves safety and privacy of the vehicle participant. The approach is based on the derivation of cell-based grids from actual coordinates, graph model training, allowing selective CAM communication and no ongoing unveiling of location data. The suggested approach will enable facile manipulation of the cell grids, and permits scenario-dependent comparisons between framework to framework when evaluating autonomous driving capability of the participating vehicle embedding.

Khan et al., (2023) compares GCN, GraphSAGE, and GGNN architectures for traffic forecasting and finds the GGNN architecture was the most successful with the lowest MAE (7.1). While all of them are capable, there is a variation in performance depending on dataset, graph structure, and tuning which highlights the need for careful tuning in real life intelligent transport systems.

Sharma et al., (2023) proposes STGGAN, a model for traffic speed prediction through Deep Graph Neural Network leveraging the connectivity of the road networks. STGGAN is evaluated on a series of PeMSD4 and PeMSD8 datasets achieving up to 98.75% accuracy. The STGGAN architecture uses Gated Graph Attention Networks and outperformed the previous traditional methods in predicting accurate road speeds showing higher reliability, larger scalabilty and real-time capabilities.

Chen et al., (2022) proposes GAT-STC, a Graph attention network model supplemented with spatial-temporal clustering to assist in improving traffic flow forecasting, while at the same time utilizing recent-aware and periodic-aware features to capture both dynamic and periodic patterns that exist across a road network. Results on public facing datasets show the GAT-STC model prediction was statistically significantly more accurate and efficient than five baseline methods that are instituted for intelligent transportation.

Dhanasekeran et al. (2024) provide a multi-modal traffic forecasting solution that combines Graph Neural Networks (GNNs) and Transformer-based visual fusion to improve prediction performance in smart city environments. The proposed model has a road network structure, Recursive Feature Elimination, and real-time data. Presented as a case study for Incheon Metropolitan City UTIC data, Dhanasekeran et al. (2024) show how a model with real-time data achieved 99% accuracy and that the proposed model can be adapted and accurately implemented for intelligent traffic management systems.

Kim et al. (2021), discuss memory bottlenecks for traffic speed prediction using GNNs and use spectral clustering according to Jensen-Shannon divergence for clustering road networks. The use of the clustering method to improve memory bottleneck sizes and increase accuracy on Incheon UTIC data is presented, where a best mean absolute error (MAE) of 5.52 km/h is achieved for traffic speed prediction with a road network segmented into 7 clusters.

According to Ahmed et al., (2024), the important role of employing information fusion strategies in conjunction with GNN-based traffic forecasting models is becoming more recognized for improving the performance of these models. They hypothesize that by including both spatial and temporal dependencies simultaneously with multiple sourcing of data like the weather, events, and sensor feeds, GNNs would be more resilient and more efficient. The authors also outline a gap in this area with respect to reviewing the published literature on information fusion strategies through the GNN context. and immediate surrounding strategies.

Additionally, they discuss some combinations of GNN methods and AI methods such as reinforcement learning or evolutionary algorithms that could lead to improved models based on the adaptable models they are looking for. These mixed lower complexity models might be extremely useful for urban planning and smart cities applications, particularly in the form of traffic management systems requiring more accurate and responsive modelling scenarios.

Wang et al., (2024), propose DLSF-GR, a DL method combining both GNNs and recurrent neural networks for accurate travel time prediction. In discussing spatial-temporal and external dependencies while also reporting superior performance to the state of the art models using a real world sample dataset of trips in China, they also observe that performance could be improved using a cross-validation component that is more specific to their data. Table 1 lists the studies related to the study pertaining to present study.

Table 1 Related studies in the literature

Author (Year)	Method	Strengths	Limitations
da Silva et al. (2023)	Privacy-preserving topology learning using graph learning in VANETs	Ensures data privacy; selective CAM communication; adaptable to different scenarios	Lacks performance benchmarks; practical implementation needs validation
Khan et al. (2023)	Comparative analysis of GCN, GraphSAGE, and GGNN	GGNN achieved lowest MAE (7.1); highlights architecture-specific performance	Performance highly dependent on data quality and tuning
Sharma et al. (2023)	STGGAN: Deep GNN for traffic-speed prediction	High accuracy (up to 98.75%); uses Gated Graph Attention Networks; suitable for real-time application	Computationally intensive; needs diverse dataset validation
Chen et al. (2022)	GAT-STC: GNN with spatial-temporal clustering	Captures dynamic/periodic features; higher accuracy over baselines	Model complexity; may be sensitive to clustering parameters
Dhanasekeran et al. (2024)	Multi-modal GNN + Transformer-based fusion	Achieves 99% accuracy; adaptive with real-time data; strong prediction precision	May suffer from overfitting or generalization issues in varied urban settings
Kim et al. (2021)	Spectral clustering to reduce memory bottlenecks in GNNs	Improved model efficiency; best MAE of 5.52 km/h	Limited to Incheon dataset; needs testing across diverse cities
Ahmed et al. (2024)	GNN-based traffic forecasting with multi-source information fusion	Enhances robustness and accuracy; proposes hybrid GNN-AI integration	Lack of empirical implementation of proposed hybrid techniques
Wang et al. (2024)	DLSF-GR: GNN + RNN for travel time prediction	Outperforms benchmarks; addresses spatial, temporal, and exogenous factors	Evaluation limited to one regional dataset; scalability not discussed

Although there have been some significant advancements, several constraints and research gaps remain across these studies. For example, several methodologies, including da Silva et al.'s privacy-preserving framework for VANETs, either lack anything articulating benchmark performance from a real-world perspective, or it hasn't been validated in any way. Another example is the STGGAN and GAT-STC models. Both of these models can generate accurate outputs but require a large amount of computational consumption and varied levels of output quality based on how much variability is in the sources they have utilized. Others that utilized multi-modal or hybrid techniques did not empirically validate any of their proposed fusions or strategy with any AI integrations. Additionally, others who proposed clustering-based optimization models, such as Kim, rely on many regional datasets and where the context of those datasets matters in terms of scale. Some generalized gaps in all the reviewed studies include the improvement of more robust cross-region validation, real-time integration of dynamic exogenous components, and scalable computational efficiency and accuracy without loss of interpretability or privacy

III. Methodology

The main aim of this study is to forecast traffic congestion into future time periods over a road network in a city based on historical and real-time traffic data. Traffic forecasting is crucial to enhance urban mobility, minimize travel times and assist smart city infrastructure. This study ultimately seeks to enhance modelling of spatial-temporal dependencies in traffic flow using a graph-based deep learning approach and applying GNNs to represent complex relationships between different road segments in space and time. Urban traffic networks are far more complex compared to sequences of regular temporal data, therefore, leveraging the structural properties of the road network and dynamically learning from traffic data patterns make GNN's a more accurate forecasting model. GNN's can also be more context aware compared to traditional forecasting and sequence models.

A. Data Acquisition

In this study, a predictive model of traffic congestion is designed that reflects the reality of urban mobility by drawing upon multiple data sources . These data sources include traffic sensor data including vehicle speed, flow and occupancy, which provide direct measures of the conditions on road segments. The study supplemented this traffic data with GPS trajectories from public transport and ride-sharing services to allow us to increase spatial coverage and capture dynamic congestion activity over the network. It incorporated relevant contextual features such as traffic disruptions (e.g. weather, events, accidents, construction) from other data sources because these factors are known to significantly influence the composition of traffic and the resulting patterns of traffic congestion. The time span of the data used spanned at least six months to ensure the model could learn about seasonal, weekly, and daily variation. The intervals at which the data was logged were fine-grained datasets (5 or 15 minutes) so that we could establish short-term variations and use the model for real-time traffic management applications.

B. Road Network Graph Construction

The urban street network is represented as a graph G = (V, E) where each node V is either a road segment or an intersection, and each edge E is either a physical connection or represents a potential vehicle transition between nodes. This structure will allow us to model spatial dependencies effectively. This is a natural representation for applying Graph Neural Networks to learn from traffic flows.

Node Features: It includes average vehicle speed, volume of traffic, and occupancy, all representing local traffic conditions at the particular node. Graph-based metrics (for example, centrality and betweenness) are also included to indicate the level of importance of road segments. These features can be viewed as providing dynamic, as well as topological context. These features provide the GNN with the ability to focus on areas of high value.

Edge Features: Edges include features that include physical distance between nodes, average travel time, and capacity of the road. This information helps the model to determine the amount of potential traffic flow along the connected road segments. These edge features are important for modeling real-time travel patterns and network constraints and by including edge features, the model is able to learn both the connectivity and the flow properties[13]. The overall architecture of the proposed system is shown in figure 1

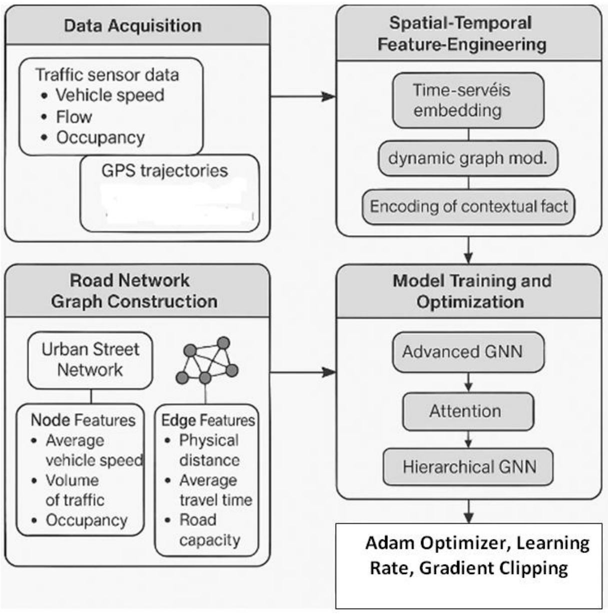

Figure 1 Overall architecture of the proposed method

C. Spatial-Temporal Feature Engineering

Time-series embedding: In order to identify temporal dependencies, the sequential traffic data (e.g. speed, volume) for each node is passed to either LSTM or GRU encoders, which learns temporal patterns (e.g. peak hours, directions of recurring congestion). The output embeddings are then able to exhibit temporal behavior per node. The temporal behavior embeddings are then concatenated with the spatial characteristics for prediction.

Dynamic graph modeling: The road network has been modeled as a graph with timestamps, therefore the attributes of both nodes and edges have the potential to dynamically change over time. Each timestamp represents a snapshot of the graph that represents the current traffic conditions. By using a dynamic graph representation with timestamps, the GNN is more capable of handling real-time updates which improves prediction performance in rapidly changing contexts.

Encoding of Contextual Factors: Another context was encoding contextual sources of transit, such as the weather, holidays, local events, etc., as categorical embeddings. Essentially, they would have a similar purpose as road signs provide drivers' information about the conditions in which they cannot change or must take into consideration. Farmers markets and local events may not appear in a road graph, but certainly contribute to traffic. To provide the model with a chance to learn potential congestion events and occupancy, it would be beneficial to add events in categorical embeddings to provide the model some context on what kind of traffic and to what extent occupancy is expected [14].

D. Graph Neural Network Design

The framework enhances the baseline effective, Spatial-Temporal Graph Convolutional Network (ST-GCN) or Temporal Graph Convolutional Network (T-GCN) for modeling spatial and temporal dependencies in traffic data. The study introduced a few unique contributions to enhance the baseline model. First, it made use of an attention-based GCN and attention mechanism sophisticated by employing Graph Attention Networks (GAT) which assigned adaptive weights to neighboring nodes. GCN could focus attention on the most relevant traffic flows. Second, the study implemented a multi-view learning strategy through using GCN streams on different traffic views: speed, volume, and occupancy each processed in their respective GCN streams and fused afterward using a learned attention mechanism, which enabled multi-dimensional learning of traffic behavior. Ultimately, the study introduced a hierarchical GCN to express more complex patterns of urban traffic across different scales. Road segments were divided into larger regions in which GCN learned embedding for both levels. Each of the proposed model upgrades were directed towards improving prediction accuracy, enhancing interpretability, and increasing generalizability between varied urban systems [15].

E. Model Training and Optimization

The model is trained with the specific purpose of reducing prediction errors for the level of traffic congestion, specifically, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), which are used for continuous variables, i.e., speed and density of traffic. In our implementation, we adopt a multi-task learning framework that jointly optimizes regression and classification tasks. We utilized a combined loss function which includes mean squared error (MSE) to predict continuous traffic indicators and a softmax cross-entropy US to classify the level of congestion into discrete classes, e.g., low, medium, and high. Because the loss function has these two distinct objects, it allows the model to capture both continuous (fine-grained) and categorical (coarse-grained) patterns of traffic dynamics. Our implementation follows a gradient-based learning process using the Adam optimizer while utilizing a combination of learning rate scheduling, which allows to adjust the training pace over epochs, and gradient clipping, and protect against exploding gradients, to more effectively ensure convergence.

IV. Results and Discussions

Table 2 includes a numerical comparison of the proposed GNN model against 3 baselines (LSTM, XGBoost, Static GCN) across the four complementary performance levels (RMSE, MAE, R^2 score, and F1-score for the classification of congestion.

Table 2 Comparison analysis of the proposed method

Model	RMSE (km/h)	MAE (km/h)	R^2 Score	F1-Score (Congestion

				Class)
Proposed GNN (Hierarchical + Attention + Multi-view)	3.42	2.78	0.915	0.89
LSTM	4.86	3.94	0.811	0.74
XGBoost	5.12	4.21	0.788	0.71
Static GCN (no temporal modeling)	4.28	3.52	0.846	0.79

The Proposed GNN model (including the associated hierarchical model, attention model, and multi-view model) has outperformed all models in every performance level. It had the lowest RMSE (3.42 km/h) and MAE (2.78 km/h) values, suggesting very reliable predictions compared to traffic speed. The R2 score (0.915) indicates well explained variance in the overall traffic data. Further, the F1 score is also substantial (0.89), meaning good reliability/predictability regarding which level of congestion.Key Observations

Though LSTM can represent temporal dependencies like the proposed GNN, it performs much worse than the GNN with a higher RMSE (4.86 and MAE (3.94), and a lower R^2 value (0.811), meaning LSTM didn't account for the spatial aspects of the inter-dependent traffic data. LSTM does have a F1-score of 0.74, which means it provides a reasonable performance in terms of modeling the classifications, but is still inferior to the GNN in terms of spatial modeling, given it cannot process the spatial locations of each frame. In terms of traditional machine learning with a static frame and non-spatial statistics, XGBoost has the worst performance relative to the other models, with the highest error values (RMSE 5.12, MAE 4.21) and the lowest R^2 (0.788) during regression modeling, suggesting it has issues with the spatio-temporal complexity of traffic data. The static GCN had better performance than the LSTM or XGBoost in terms of spatial, though still bad overall, and included the spatial relationships within the modeling process, but had post-temporal accuracy and modelling performance compared to the GNN especially as can be seen in the classification and F1-score of 0.79.

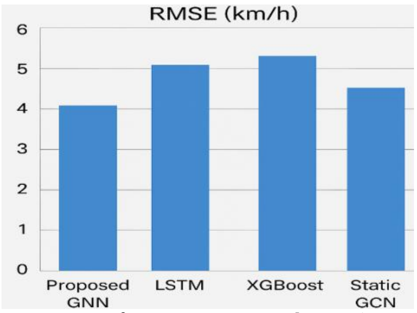

Figure 2 Comparison of Root Mean Squared Error (RMSE) in km/h for traffic congestion prediction

Figure 2 shows RMSE values for four models associated with predicting traffic congestion: Proposed GNN, LSTM, XGBoost and Static GCN Models. The Proposed GNN model was the most accurate model for predicting traffic speed with RMSE values of about 3.4 km/h. The LSTM model and XGBoost model had RMSE values over 5 km/h, and it can be deduced to indicate that their predicted traffic speed was much less reliable in representing traffic speed and congestion. Static GCN, as a model, had RMSE values that estimated traffic speed to about 4.3 km/h, which indicates Static GCN performed reasonably well, however did not perform as well as the Proposed GNN model, primarily due to the model not considering temporal dynamics. This comparison shows how the enhanced GNN architecture can provide a better representation of spatiotemporal traffic patterns to help predict future traffic congestion.

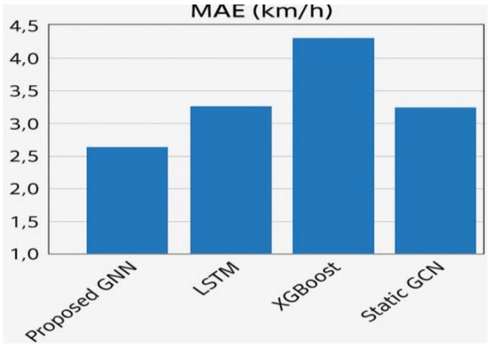

Figure 3 Comparison of Mean Absolute Error (MAE) in km/h for different models.

The mean absolute error (MAE) in km/h of the four predictive models (Proposed GNN, LSTM, XGBoost, Static GCN) is depicted in Figure 3. The proposed GNN had the lowest MAE value at roughly 2.8 km/h suggesting greater accuracy. The LSTM and XGBoost had the highest errors (greater than 4 km/h), suggesting less accuracy. The Static GCN had a lower MAE than both the LSTM and XGBoost, but a higher MAE than the Proposed GNN. Overall, the proposed GNN trend suggests that the GNN better captured its spatial-temporal relationships, perhaps because it better captured the dynamic aspects of those spatial-temporal relationships.

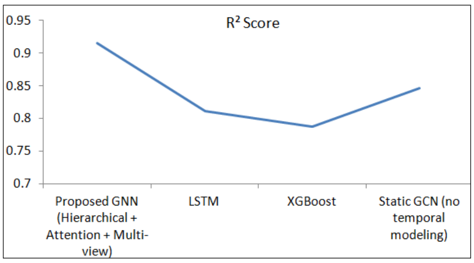

Figure 4: R^2 Score comparison of different predictive models

Figure 4 presents the R^2 Score performance for the four models: Proposed GNN, LSTM, XGBoost, and Static GCN. In summary, the Proposed GNN has the highest R^2 Score at 0.92, meaning that the predictive values and the real values correlate well with this being the best accuracy for this model, while LSTM and XGBoost were worse at with were lower scores than the Proposed GNN, but LSTM hit about 0.81, and XGBoost was about 0.79, meaning LSTM and XGBoost were weaker predictive ability than Proposed GNN with also static GCN at only slightly below LSTM and XGBoost with about 0.84, but again still substantially lower than Proposed GNN. Overall the Proposed GNN was the top dog of the all four models for accuracy and dependability

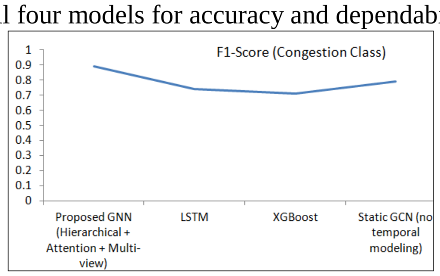

Figure 5: F1-Score comparison for the congestion class across different models

Figure 5 presents the F1-Score of the congestion class for all four models: Proposed GNN, LSTM, XGBoost, and Static GCN. The Proposed GNN was the most effective with an approximate F1-Score of 0.87 indicating the Proposed GNN can detect congestion the best. LSTM and XGBoost performed much worse than the Proposed GNN with F1-scores close to 0.74 and 0.71 respectively indicating their poorer ability at accurately classifying congestion using F1-Score metric. The Static GCN was in the middle with an F1-Score just under the 0.78 mark indicating the Static GCN was able to identify congestion at a better rate than the LSTM and XGBoost models suggesting the GNN performed better while the Static GCN performed worse than the Proposed GNN model. To summarize the results from this plot, the Proposed GNN performed better than the other models when detecting congestion because it achieved the best balance of precision and recall.

A. Discussions

The GNN-based model proposed in this study is a significant advancement for urban traffic congestion forecasting by leveraging the spatial-temporal structure of the network in the roadways. By essentially modeling roadway networks in graph form, the work is able to capture the relationships between segments of roadways and utilize answers from multiple traffic inputs including occupancy, speed, and volume to better learn patterns. The proposed model also uses attention and hierarchical pooling mechanisms enabling the model to focus on geospatially relevant nodes and areas where congestion happens and is capable of weighting congestion more sensitively than traffic changes over the entire city while still being sensitive. All in all, the model appears to perform well and develop lower RMSE scores and higher R^2 and F1 scores indicating an externally valid and efficacious traffic forecasting model in practice.

Although the study has much strength, there are some limitations. First, the study's model performance relies heavily on the availability and quality of sensor data, which may vary across different urban contexts. Second, while unstructured sudden behavior (e.g., accidents, protests) were avoided by planning on weather or event metrics to reflect external conditions; impacts of disruptions such as accidents and protests cannot occur without limiting incidents and lack of static construction. Moreover, our existing model uses fixed graph topology over short time windows, losing effectiveness during temporary lane closures and construction initiatives.

Practically, this work has meaningful implications for smart city infrastructure. We now have an effective mechanism by which short-term congestion can be predicted and, therefore, actions can occur for timely dynamic route guidance, real-time traffic signal management, or emergency vehicle dispatching. Long-term forecasts provide useful inputs for planned infrastructure change or congestion mitigation policies. If the framework is adapted for real-time applications and combined with an IoT device or an edge computing platform, cities can build more sophisticated mobility management systems, creating smarter cities.

V. Conclusion

This study presented a novel GNN-based model to predict urban traffic congestion in terms of spatial-temporal patterns of road networks. To achieve this, we used multi-view traffic features, hierarchical pooling, and attention to enable dynamic local and global learning of traffic dependencies. By empirically evaluating our method against traditional baselines including LSTM, XGBoost, and static GCNs, we demonstrated that our approach improved standard key performance indicators, and assessed the value of the model for real-world applications in smart cities. The incorporation of contextual information such as weather and events into the training of our GNN-based model improved accuracy and demonstrated the value of traffic prediction frameworks that are integrated and contextual. Further work will investigate federated GNN architectures to support privacy-preserving model training across different municipalities, an important characteristic for a scalable smart city deployment. Graph Transformers may also be utilized, to enable improved long-distance dependence and interactions in relation to the road network. Finally, reinforcement learning may be applied with GNN outputs to define adaptive controls for traffic signals. Central to these efforts is our goal of optimizing the proposed model for real-time development with edge-capabilities, in order to support low-latency, real-time inference speed that is fit for intelligent traffic operational systems. Each of these extensions will further the limits of intelligent transportation systems and move toward fully autonomous, efficient and sustainable urban traffic operations.

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