Graph-Based Learning for Multimodal Route Recommendation

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Keywords: Graph Convolutional Network, Complex Networks, Centrality Measures, Multi-Task Learning, Multimodal Transportation, Route Recommendation.

Abstract: Transportation recommendations are a vital feature of map services in navigation applications. Earlier transportation recommendation systems have struggled to deliver a satisfactory user experience because they focus exclusively on single-mode routes, such as cycling, taxis, or buses. In this paper, we represent the transportation network as a complex network (or graph). Modeling transportation as a network of nodes and edges has gained attention in the literature, generating numerous studies over the years. This approach requires a clear definition of what constitutes a node or an edge: nodes represent stops, while edges represent road segments connecting these stops. Based on this representation, we propose a framework that generates embeddings for each node and edge in the transportation network. These embeddings are created using GRU (Gated Recurrent Units) and GCN (Graph Convolutional Network) models to capture spatial and temporal patterns within the network, while incorporating centrality measures reflecting the influence of each stop. This vector representation facilitates multi-task learning for effective multi-modal transportation recommendations. The proposed framework is applied to the transportation network of Strasbourg, France. Experimental results demonstrate the framework's efficiency in recommending suitable multimodal transportation routes, considering criteria such as meteorological conditions, safety, and passenger comfort.

1 INTRODUCTION

The growing prevalence of diverse modes of transportation (such as buses, cars, bike-sharing, carpooling, ...) and the rapid expansion of transportation networks (like bus, pedestrian or road networks, ...) have offered travelers with a multitude of options to reach their destinations. Over the past few years, transport recommendation has emerged as a valuable routing service within various navigation and carpooling applications, such as Here, Didi Chuxing and Baidu Maps. The goal of transport recommendation is to assist users in finding the most suitable route from one location to another.As a result, precise and intelligent transport recommendations can allow to significantly help reduce travelers' decision-making costs and ultimately enhance the user experience (Song et al., 2018).

Recently, researchers devoted considerable attention to route recommendation because of its essential component in mapping services (Wei et al., 2012). The quality of route recommendations has been improved by leveraging massive historical datasets (such as mobile registration data (Shafique and Ali, 2016), and GPS trajectory data (Yuan et al., 2010)) with the widespread use of mobile devices and location-based services. Existing studies on transport mode recommendation can be grouped into three main categories. The first category focuses on finding the shortest path within the transport network, based on a predefined distance metric (e.g., geographic distance, travel time). Most methods in this category extend graph search algorithms to transport networks (e.g., Dijkstra, Bellman–Ford, and contraction hierarchies) (Candra et al., 2020; Iqbal et al., 2018; Geisberger et al., 2012). However, these approaches rely heavily on a predefined metric like the distance and often overlook latent factors in the data such us mode and route preferences in different situational contexts (Liu et al., 2019). The second category partially addresses this limitation by inferring transport mode preferences using supervised or unsupervised machine learning techniques. A common approach in such methods is to explicitly extract features (distance, estimated time of arrival (ETA)) from historical user data, such as GPS trajectories and in-app clicks. These methods make recommendations based on em-

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Ghalmane, Z. and Daoud, B.
Graph-Based Learning for Multimodal Route Recommendation.
DOI: 10.5220/0013356300003944
In *Proceedings of the 10th International Conference on Internet of Things, Big Data and Security (IoTBDS 2025)*, pages 313-320
ISBN: 978-989-758-750-4; ISSN: 2184-4976

pirically defined features, which heavily depend on the completeness of feature engineering. More recent studies have applied deep learning to transport mode recommendation (Chen et al., 2020; Liu and Jiang, 2022; Hopman et al., 2021). The third category uses graph-based learning, extending Graph Neural Networks (GNNs), which are well-suited to capture spatial dependencies in graph structures (Sharma et al., 2023; Hamilton et al., 2017; Jiang and Luo, 2022; Kipf and Welling, 2016; da Silva et al., 2023; MOEZZI, ; Jana et al., 2023). Recently, graph-based learning has been widely applied to many spatiotemporal exploration tasks, such as flow prediction and parking availability prediction (Wang et al., 2019). However, none of the aforementioned studies specifically address multimodal transport recommendations.

In this context, the objective of this work is to model the multimodal transportation network using a graph or a complex network approach. Complex network (graph) modelization is essential for uncovering hidden patterns in interconnected systems, with applications spanning diverse domains such as biology, social sciences, technology, and transportation (Ding et al., 2019; Termos et al., 2024; Termos et al., 2023; Latora et al., 2017; GHALMANE et al., 2023; Shanmukhappa et al., 2019; Zanin and Lillo, 2013; Ghalmane et al., 2020; Ghalmane et al., 2021; Ghalmane et al., 2022). To achieve this, we discretize the multimodal transportation network into a series of graph snapshots over time and construct a temporal graph, where each node represents a bus, metro, tram, or bike-sharing station, and each link represents a bus/metro/tram line or road segment. This model provides critical structural insights into the transportation network. Based on this model, we propose a framework comprising two main components: a prediction module and a recommendation module. The prediction module includes a spatiotemporal GNN-based model, which features a GRU layer for capturing temporal autocorrelations across multiple graph snapshots, and a GNN layer for capturing non-linear spatial autocorrelations from the transportation network graph. These representation-based models excel in capturing relationships and patterns in graph-structured data, making them highly suitable for transportation network modeling. In this representation, the centrality measures (Ghalmane et al., 2019; Ghalmane et al., 2018a) are also added to the embedding of each node (stop) quantifying its importance in the transportation network. The prediction module enables the forecasting of parameters for each itinerary, such as route distance, travel duration, CO2 emission, confort and safety. These predicted parameters are then used to classify different itineraries, facilitating the recommendation of the best multimodal itinerary. The recommendation process relies on an objective function that aligns with multiple goals, including minimizing carbon emissions, reducing travel time, and enhancing safety and comfort. This proposed framework was applied to the transportation network of Strasbourg, France, to assist students in navigating from their homes to their campuses. Results demonstrate that the framework accurately recommends the best multimodal itineraries for students in Strasbourg. Furthermore, the proposed framework can be generalized to other cities with different transportation infrastructures. In this paper, we focus on Strasbourg due to the availability of transportation data for the city.

The remainder of this paper is organized as follows: Section 2 outlines the methodology, detailing the graph construction, feature selection, and integration of complex network measures with the GNN and GRU models. Section 3 presents the experimental results on Strasbourg's transportation network data. Finally, Section 5 summarizes the contributions of the methodology and concludes the study.

2 MATERIALS AND METHODS

In this section, we begin by providing an overview of the proposed approach, followed by a detailed description of each step in the subsequent subsections.

2.1 General Scheme

Here, we provide an overview of the proposed methodology, as illustrated in Figure 1. First, a complex network (or graph) is constructed based on transportation data. This graph is inherently temporal, reflecting the dynamic nature of transportation networks. Each node and edge in the graph is associated with a set of features, including two centrality measures: Betweenness and Closeness (Ghalmane et al., 2019; Ghalmane et al., 2018a; Ghalmane et al., 2018b). These centrality measures offer insights into the relative importance of nodes (stops) in connecting different routes and regions within the transportation network. Once the graph is constructed with these enriched node and edge features, the prediction and recommendation modules are applied. The first component of the prediction module involves two models: GRU (Gated Recurrent Units) and GCN (Graph Convolutional Network). These models generate embeddings for each node and edge, capturing the spatial and temporal patterns within the network. Subsequently, the overall embedding of a given route is

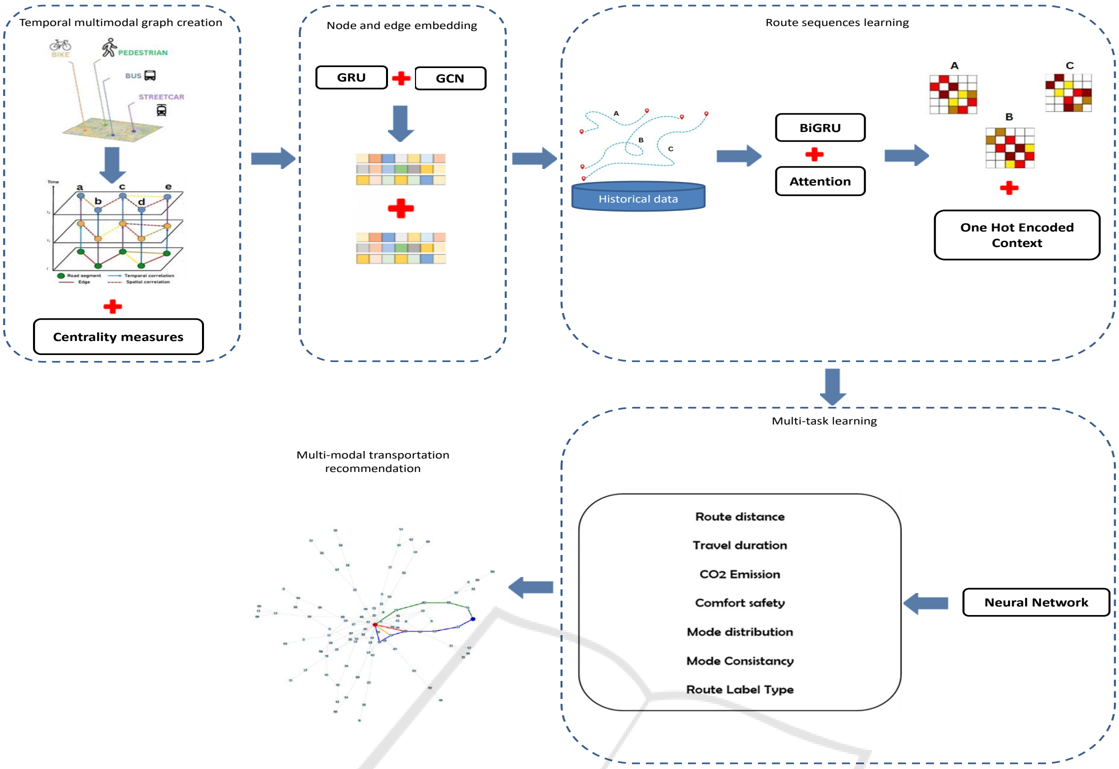

Figure 1: General scheme of the proposed framework.

computed using a BiGRU model, leveraging the embeddings of the sequence of nodes and edges that constitute the input route. In the second component of the prediction module, these route embeddings are combined with contextual data—such as safety, comfort, and meteorological conditions—and are fed into a multi-layer neural network. This network performs multiple regression and classification tasks to predict various parameters for each route, including route distance, travel duration, CO2 emissions, comfort level, safety, mode consistency, and route type. Finally, the recommendation module ranks the different routes based on these predicted parameters. This ranking is achieved using an objective function.

2.2 Temporal Multimodal Graph Creation

The transportation network is modeled as a multimodal graph representing bus, tram, and bike-sharing systems, with nodes for stations and edges for connections. Data from General Transit Feed Specification (GTFS) and General Bikeshare Feed Specification (GBFS) files is used to create the graph, linking bus/tram stops and bike stations based on proximity and transfer points. Each node and edge is enriched with spatial and temporal features, such as geographic coordinates, centrality measures (closeness and betweenness), and estimated daily passenger flow. Temporal data is added to capture network dynamics, including passenger counts and route capacities throughout the day. This multimodal network helps optimize travel routes and analyze urban transportation patterns, considering both static and time-dependent network changes.

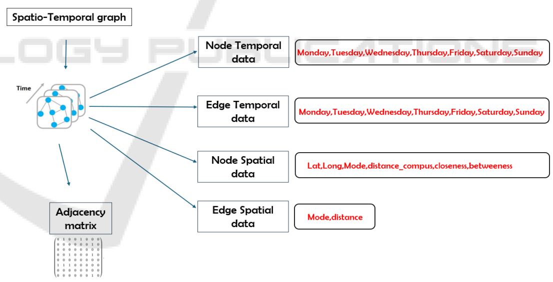

Figure 2: The spatial, temporal and network features of the multimodal network.

2.3 Node and Edge Embedding

2.3.1 Temporal Embedding

The temporal pattern of the multimodal network is captured by using Gated Recurrent Unit (GRU) model (Yu et al., 2019). The output of the GRU layer is a temporal embedding for each node and edge. This embedding condenses the temporal patterns captured over the week into a lower-dimensional space, allowing the model to focus on the most relevant temporal dynamics for subsequent learning tasks. The temporal data is processed by a GRU, a common sequence modeling layer. The GRU is configured with:

- **Input Shape:** 7, representing the number of days in the week as temporal features.
- **Output Shape:** 3, indicating that the GRU reduces the temporal data into a 3-dimensional embedding for each node.
- **Number of Hidden Units:** 32, which defines the number of neurons in the hidden layers of the GRU, controlling the capacity to capture temporal dependencies.
- **Recurrent Dropout:** 0.15, applying dropout to prevent overfitting during the learning process.
- **Number of Layers:** 2, meaning that the GRU has two layers to ensure deeper processing of sequential information.
- **Activation Function:** ReLU, which introduces non-linearity in the model and helps in capturing complex temporal interactions.

Following the generation of the temporal embedding for nodes and edges, the temporal information is concatenated with spatial features. The spatial information complements the temporal embedding, allowing the model to integrate both spatial and temporal correlations. This combination is critical for understanding how transportation modes and distances vary over time in the multimodal network. It is illustrated in Figure 3 for temporal nodes embedding (the same process is applied to edges).

2.3.2 Spatio-Temporal Embedding

In this section, we observe that the input to the GCN (Zhang et al., 2019) consists of both node and edge embeddings, which capture the spatial and temporal properties of the graph. The concatenation of spatial and temporal embeddings for both nodes and edges provides a comprehensive representation of the transportation network. Additionally, the adjacency matrix

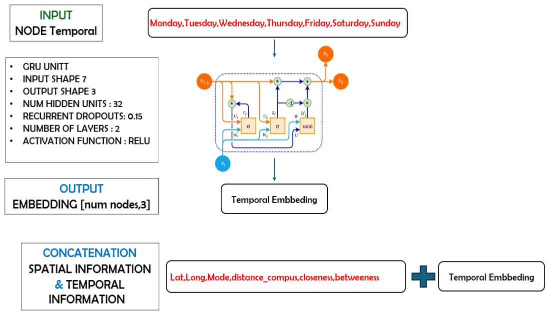

Figure 3: Temporal node embedding.

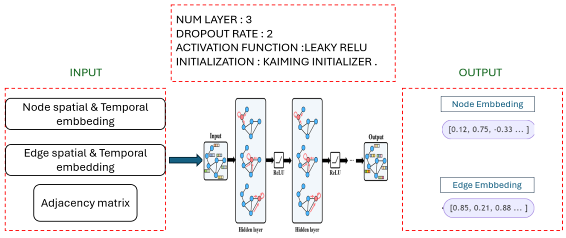

Figure 4: Spatio-temporal correlation.

is included to encode the graph's structure, describing the relationships between nodes (i.e., the connectivity of the network). The GCN processes the input embeddings over multiple layers to produce refined representations. The configuration of the GCN is as follows:

- **Number of Layers:** 3, providing the network with the depth to capture higher-order neighborhood information in the graph.
- **Dropout Rate:** 2, to prevent overfitting and ensure robust generalization during training.
- **Activation Function:** Leaky ReLU, which introduces non-linearity while allowing for a small gradient when the unit is not active.
- **Initialization:** Kaiming initializer, used for weight initialization to ensure faster convergence and prevent vanishing gradients, particularly in deeper layers.

As depicted in Figure 4, the graph convolution operation is applied iteratively across hidden layers. At each layer, the GCN aggregates information from neighboring nodes and edges, thus refining the node and edge embeddings. The ReLU activation function is used after each convolution to introduce non-linearity and capture more complex relationships in the data. The final output of the GCN is a set of refined embeddings for both nodes and edges. These embeddings are used for downstream tasks, such as prediction or classification. The node embeddings

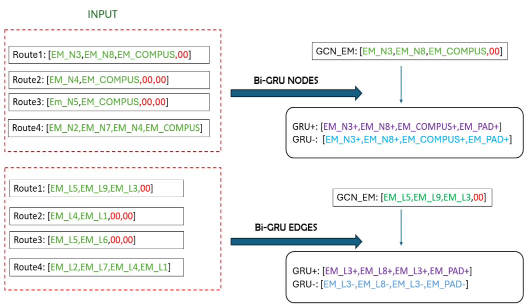

Figure 5: Route sequence learning.

capture the latent spatial and temporal features of each location (bus/tram/bike stop), while the edge embeddings encode the dynamic relationships between connected locations. The embeddings are represented as multidimensional vectors, as illustrated in the output boxes.

2.4 Route Sequences and Multi-Task Learning

In this step, the historical routes, consisting of both nodes and edges, are transformed into their corresponding spatial and temporal embeddings. They are, then, input into a BiGRU model to obtain an overall embedding for each route. These route embeddings as well as the contextual data (such as time duration, meteorological conditions, safety and comfort level) are fed into a neural network model designed to predict various route-related metrics as illustrated in Figure 5. This neural network, depicted as a fully connected layer in the diagram, takes the input embeddings and processes them through several hidden layers, resulting in a set of predictions related to the routes. The output of the model consists of several key metrics related to the routes. These include:

- **Route Distance:** The predicted distance for the route.
- **Travel Duration:** The estimated time required to travel along the route.
- **CO2 Emission:** An estimate of the carbon dioxide emissions for the route, based on the transportation mode and other factors.
- **Comfort Safety:** A metric that evaluates the comfort and safety of the route.
- **Mode Distribution:** The distribution of transportation modes used in the route.
- **Mode Consistency:** A measure of how consistently the same transportation mode is used throughout the route.
- **Route Label Type:** A classification of the route, such as whether it is a high-speed or scenic route.

This route prediction model described in Figure 1 enables the system to predict multiple key attributes of a route based on the node and edge embeddings. By considering both spatial and temporal features, the model is able to provide accurate and comprehensive predictions that are useful for various applications such as route optimization, environmental impact assessment, and safety evaluations.

2.5 Recommendation System

The route recommendation system utilizes the predicted parameters of the routes from the historical dataset to rank and suggest the best itinerary for passengers traveling from a given starting point. This recommendation is based on a weighted linear function that prioritizes CO2 emissions, safety, and distance. While other parameters such as travel duration, mode distribution, mode consistency, and route type are primarily used for training the models within our framework, they can be integrated into the multi-objective function if necessary. The function is defined as follows:

$$f(e,s,d) = \alpha \cdot e + \beta \cdot s + \gamma \cdot d \qquad (1)$$

Here, e, s, and d represent the predicted values for CO2 emissions, safety, and distance of a given route, respectively. The coefficients α, β, and γ are set to 0.5, 0.3, and 0.2, respectively, to assign greater importance to CO2 emissions, aligning with the primary goal of this study to promote low-carbon itineraries.

The recommendation system integrates multiple factors, including route characteristics, environmental context, and user preferences, to provide personalized route suggestions. This ensures that the recommended routes reflect both objective metrics (e.g., distance) and subjective preferences (e.g., safety and emission reduction). The proposed multimodal route recommendation system offers passengers a comprehensive framework for making well-informed decisions.

3 RESULTS

This section presents the results of training our multimodal route recommendation model, tested in the city of Strasbourg, France. The model aims to recommend optimal multimodal itineraries for students commuting to their campus while minimizing CO2 emissions. We trained the model using historical data, which includes four potential paths from each node in

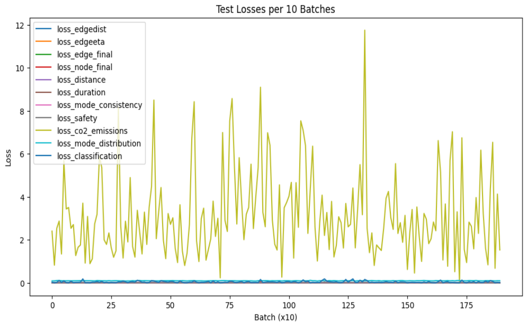

Figure 6: Loss with attention mechanism in test dataset.

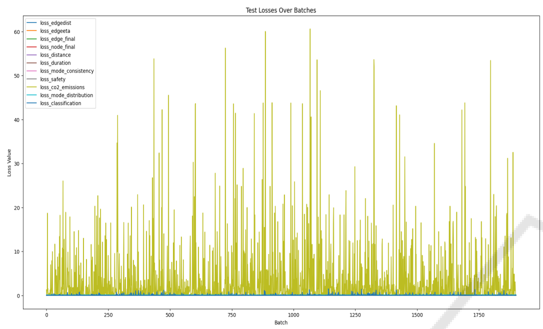

Figure 7: Loss without attention mechanism in test dataset.

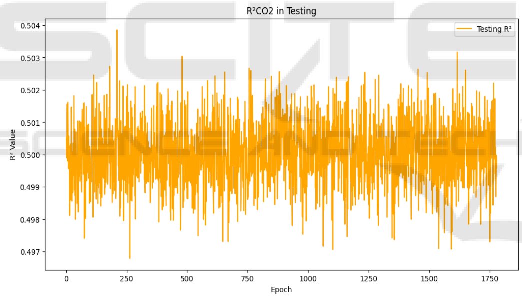

Figure 8: R2 CO2 in test dataset.

the network to the campus in Strasbourg. The input to our multimodal route prediction model consists of a combination of route embeddings (based on node and edge embeddings) along with relevant contextual information. The model's output includes several route-related metrics as outlined in subsection 2.4. The multi-task model performs regression predictions for metrics such as distance, travel duration, CO2 emissions, comfort, safety, mode distribution, and mode consistency, as well as a classification prediction for the route type label. The model's optimization parameters are detailed in Table 1.

Figure 6 presents the loss function trends for the various prediction metrics. Initially, the attention mechanism is employed to help the model focus on the most relevant parts of the node and edge se-

Table 1: Optimization parameters utilized in the framework's models.

Learning Rate	Batch Size	Weight Decay	Gradient Clipping
0.001	4	0.0001	5

Table 2: Performance results of the classification task after 450 epochs.

Accuracy	Recall	Precision
0.9	0.75	0.79

quences during route embedding. The CO2 emissions loss curve is the most prominent, fluctuating significantly throughout training, with values ranging from 0 to 12. These fluctuations indicate varying performance across batches, suggesting that CO2 emissions prediction remains challenging for the model and may require further tuning to improve stability in this area. In contrast, other loss components show much lower values, remaining near zero throughout the test batches. This minimal variation suggests that the model has effectively learned these aspects, with little contribution to the overall error. In Figure 7, the same losses are plotted without using the attention mechanism. Here, the CO2 emissions loss curve shows pronounced instability, with values reaching as high as 60 and significant spikes across the entire batch range. This high variability highlights the model's instability without the attention mechanism, likely due to the model's reduced ability to consistently focus on the most relevant features. This underlines the importance of incorporating attention mechanisms into the proposed framework to stabilize and enhance model performance, particularly for tasks that demand emphasis on specific features or relationships within the data.

Table 2 reports the accuracy, recall, and precision for the classification task after 450 epochs. The classification accuracy is around 0.9, indicating that the model is highly effective in making correct predictions. Precision and recall also show high values, demonstrating strong performance in the classification task. For the regression tasks, the R^2 values are computed across all metrics. An example of CO2 emissions is shown in Figure 8. The testing R^2 fluctuates around 0.5 without a clear upward or downward trend, suggesting that the model's performance on unseen data remains relatively consistent. Similar behavior is observed for the other metrics. These fluctuations indicate some instability in the predictions, implying that while the model generalizes to the test data, further refinement is necessary to improve stability and reduce variance during testing.

After training, we also tested our recommendation system based on Equation 1. The system con-

Table 3: Recommendation Results. The ranking of four itineraries when the starting point is the stop at node 51 and the destination is the Strasbourg campus located at node 44.

Ranks	CO2 (gram/km)	Safety	Distance (km)	Score	Duration (min)	Mode Distribution	Context
1	9.67	0.67	0.79	5.29	1.99	walk	Snow, Morning
2	15.45	0.24	0.72	8.04	7.25	Bus, walk	Snow, Morning
3	16.4	0.21	0.84	9.5	8.01	Bus	Snow, Morning
5	16.7	0.21	0.87	9.87	8.9	Bus	Snow, Morning

siders multiple factors when making route recommendations, including CO2 emissions, user safety, and distance. These parameters are integrated into the ranking algorithm to ensure that suggested routes not only optimize efficiency but also prioritize environmentally friendly options and user well-being. This holistic approach allows users to make informed choices based on their preferences for sustainability and safety. The recommendation system results are presented in Table 3, where weights of 0.5, 0.3, and 0.2 were assigned to CO2 emissions, safety, and distance, respectively. The results reveal that distance is not the primary criterion for selecting the top-ranked route; instead, CO2 emissions and safety factors are more heavily weighted. This outcome underscores the emphasis on environmental impact and user safety in the recommended routes.

4 CONCLUSION

This paper presents a novel approach to multimodal route recommendation that utilizes advanced graph-based learning techniques, specifically GRU and GCN models, to improve the effectiveness and relevance of route suggestions in urban environments. By modeling the transport network as a complex graph and incorporating essential contextual factors such as weather, safety, and passenger comfort, our methodology captures intricate spatial and temporal patterns often overlooked by traditional systems. The proposed recommendation system is grounded in a multi-task model that predicts key urban metrics, including route distance, travel duration, CO2 emissions, comfort, safety, mode distribution, mode consistency, and route type. Experimental results demonstrate high classification accuracy, highlighting the model's strong performance in predicting route types. These predicted factors are integrated into our system to ensure the suggested routes prioritize environmental sustainability and user well-being. The ranked routes show that CO2 emissions and safety take precedence over distance, aligning with our objective of promoting eco-friendly transportation choices. Our work contributes to the growing body of knowledge on intelligent transportation systems and provides a robust framework for future research in this domain. Future perspectives will focus on enhancing the model's performance by exploring additional graph properties.

REFERENCES

Candra, A., Budiman, M. A., and Hartanto, K. (2020). Dijkstra's and a-star in finding the shortest path: A tutorial. In *2020 International Conference on Data Science, Artificial Intelligence, and Business Analytics (DATABIA)*, pages 28–32. IEEE.

Chen, L., Zhang, L., Cao, S., Wu, Z., and Cao, J. (2020). Personalized itinerary recommendation: Deep and collaborative learning with textual information. *Expert Systems with Applications*, 144:113070.

da Silva, E. S., Pedrini, H., and dos Santos, A. L. (2023). Applying graph neural networks to support decision making on collective intelligent transportation systems. *IEEE Transactions on Network and Service Management*, 20(4):4085–4096.

Ding, R., Ujang, N., Hamid, H. B., Manan, M. S. A., Li, R., Albadareen, S. S. M., Nochian, A., and Wu, J. (2019). Application of complex networks theory in urban traffic network researches. *Networks and Spatial Economics*, 19:1281–1317.

Geisberger, R., Sanders, P., Schultes, D., and Vetter, C. (2012). Exact routing in large road networks using contraction hierarchies. *Transportation Science*, 46(3):388–404.

Ghalmane, Z., Brahmia, M.-E.-A., Zghal, M., and Cherifi, H. (2022). A stochastic approach for extracting community-based backbones. In *International Conference on Complex Networks and Their Applications*, pages 55–67. Springer.

Ghalmane, Z., Cherifi, C., Cherifi, H., and El Hassouni, M. (2020). Exploring hubs and overlapping nodes interactions in modular complex networks. *IEEE Access*, 8:79650–79683.

Ghalmane, Z., Cherifi, C., Cherifi, H., and El Hassouni, M. (2021). Extracting modular-based backbones in weighted networks. *Information Sciences*, 576:454–474.

Ghalmane, Z., Cherifi, C., Cherifi, H., and Hassouni, M. E. (2019). Centrality in complex networks with overlapping community structure. *Scientific reports*, 9(1):10133.

Ghalmane, Z., El Hassouni, M., Cherifi, C., and Cherifi, H. (2018a). K-truss decomposition for modular centrality. In *2018 9th International Symposium on Signal, Image, Video and Communications (ISIVC)*, pages 241–248. IEEE.

Ghalmane, Z., El Hassouni, M., and Cherifi, H. (2018b). Betweenness centrality for networks with non-overlapping community structure. In *2018 IEEE workshop on complexity in engineering (COMPENG)*, pages 1–5. IEEE.

GHALMANE, Z., Zghal, M., et al. (2023). Road networks: A new filtering approach to extract backbones using community structure.

Hamilton, W., Ying, Z., and Leskovec, J. (2017). Inductive representation learning on large graphs. *Advances in neural information processing systems*, 30.

Hopman, D., Koole, G., and Mei, R. V. D. (2021). A machine learning approach to itinerary-level booking prediction in competitive airline markets. *International Journal of Revenue Management*, 12(3-4):153–191.

Iqbal, M., Zhang, K., Iqbal, S., and Tariq, I. (2018). A fast and reliable dijkstra algorithm for online shortest path. *Int. J. Comput. Sci. Eng*, 5(12):24–27.

Jana, D., Malama, S., Narasimhan, S., and Taciroglu, E. (2023). Edge ranking of graphs in transportation networks using a graph neural network (gnn). *arXiv preprint arXiv:2303.17485*.

Jiang, W. and Luo, J. (2022). Graph neural network for traffic forecasting: A survey. *Expert systems with applications*, 207:117921.

Kipf, T. N. and Welling, M. (2016). Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*.

Latora, V., Nicosia, V., and Russo, G. (2017). *Complex networks: principles, methods and applications*. Cambridge University Press.

Liu, H., Tong, Y., Zhang, P., Lu, X., Duan, J., and Xiong, H. (2019). Hydra: A personalized and context-aware multi-modal transportation recommendation system. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2314–2324.

Liu, S. and Jiang, H. (2022). Personalized route recommendation for ride-hailing with deep inverse reinforcement learning and real-time traffic conditions. *Transportation Research Part E: Logistics and Transportation Review*, 164:102780.

MOEZZI, R. Enhanced vehicle arrival time prediction with graph neural networks (gnn) using gps data.

Shafique, S. and Ali, M. E. (2016). Recommending most popular travel path within a region of interest from historical trajectory data. In *Proceedings of the 5th ACM SIGSPATIAL International Workshop on Mobile Geographic Information Systems*, pages 2–11.

Shanmukhappa, T., Ho, I. W.-H., Chi, K. T., and Leung, K. K. (2019). Recent development in public transport network analysis from the complex network perspective. *IEEE Circuits and Systems Magazine*, 19(4):39–65.

Sharma, A., Sharma, A., Nikashina, P., Gavrilenko, V., Tselykh, A., Bozhenyuk, A., Masud, M., and Meshref, H. (2023). A graph neural network (gnn)-based approach for real-time estimation of traffic speed in sustainable smart cities. *Sustainability*, 15(15):11893.

Song, C., Guan, W., and Ma, J. (2018). Potential travel cost saving in urban public-transport networks using smartphone guidance. *Plos one*, 13(5):e0197181.

Termos, M., Ghalmane, Z., Fadlallah, A., Jaber, A., Zghal, M., et al. (2023). Intrusion detection system for iot based on complex networks and machine learning. In *2023 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)*, pages 0471–0477. IEEE.

Termos, M., Ghalmane, Z., Fadlallah, A., Jaber, A., Zghal, M., et al. (2024). Gdlc: A new graph deep learning framework based on centrality measures for intrusion detection in iot networks. *Internet of Things*, 26:101214.

Wang, Y., Yin, H., Chen, H., Wo, T., Xu, J., and Zheng, K. (2019). Origin-destination matrix prediction via graph convolution: a new perspective of passenger demand modeling. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*, pages 1227–1235.

Wei, L.-Y., Zheng, Y., and Peng, W.-C. (2012). Constructing popular routes from uncertain trajectories. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 195–203.

Yu, Y., Si, X., Hu, C., and Zhang, J. (2019). A review of recurrent neural networks: Lstm cells and network architectures. *Neural computation*, 31(7):1235–1270.

Yuan, J., Zheng, Y., Zhang, C., Xie, W., Xie, X., Sun, G., and Huang, Y. (2010). T-drive: driving directions based on taxi trajectories. In *Proceedings of the 18th SIGSPATIAL International conference on advances in geographic information systems*, pages 99–108.

Zanin, M. and Lillo, F. (2013). Modelling the air transport with complex networks: A short review. *The European Physical Journal Special Topics*, 215(1):5–21.

Zhang, S., Tong, H., Xu, J., and Maciejewski, R. (2019). Graph convolutional networks: a comprehensive review. *Computational Social Networks*, 6(1):1–23.