HIERARCHICAL GRAPH NEURAL NETWORK FRAMEWORK FOR DRIVER VIOLATION PREDICTION

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ABSTRACT: Predicting driver traffic violations is essential for enhancing road safety and advancing intelligent transportation systems. This paper proposes a Hierarchical Graph Neural Network (HGNN) framework to model driver behavior and forecast potential violations. Real-world traffic datasets are preprocessed into multidimensional indicators that capture behavioral, contextual, and temporal patterns. At the lower level, Convolutional Neural Networks (CNNs) extract short-term patterns, while Long Short-Term Memory (LSTM) networks capture sequential dependencies. These features are then integrated into a hierarchical graph attention mechanism to learn spatial–temporal interactions between drivers and violation types. A self-adaptive calibration of indicator weights further improves prediction accuracy across diverse traffic contexts. Experimental results show that the HGNN framework achieves superior performance compared to conventional deep learning and non-hierarchical methods, demonstrating its effectiveness in building safer connected vehicle and smart transportation environments.

Index Terms: Hierarchical Graph Neural Networks (HGNN), Traffic Violation Prediction, Driver Behavior Analysis, Spatial–Temporal Modeling, Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Graph Attention Networks, Intelligent Transportation Systems, Connected Vehicles, Road Safety.

1. INTRODUCTION

A Hierarchical Graph Neural Network (HGNN) framework for driver violation prediction represents a significant evolution in the field of intelligent transportation systems by integrating advanced data-driven techniques to enhance public safety and traffic management. Unlike conventional approaches that often view driver behavior and violation prediction as isolated or linear problems, this framework models the road network and driver activity as a complex, multilevel structure made up of interconnected nodes and relationships.

Significance and Motivation

The motivation for developing HGNN-based solutions is closely linked to the persistent rise in traffic violations, which contribute to increased accidents, injuries, and financial loss globally. Traditional systems generally lack the capability to incorporate multi-source, dynamic data in real time, limiting their ability to anticipate risky behaviors. Hierarchical graph neural networks can process data from various sources—such as vehicle telematics, traffic sensors, and historical violation databases—allowing for better representation of spatiotemporal dependencies and complex interactions among drivers, vehicles, and road segments.

Hierarchical Modeling Approach

HGNN frameworks construct multi-level graphs to represent different layers of driving and transportation scenarios. For example, one layer may capture individual driver behavior; another could represent local traffic conditions; while a third might reflect broader regional patterns. By aggregating data across these levels, the network identifies patterns and relationships that would otherwise be missed with traditional, flat models. The hierarchical structure allows for transfer and refinement of information from coarse to fine scales, improving both the accuracy and interpretability of predictions.

Practical Impact

The adoption of hierarchical graph neural networks enables more proactive and accurate prediction of potential driver violations. This has several practical benefits:

- **Early warning systems:** Improved prediction can trigger timely alerts to drivers or authorities, allowing preventive interventions.
- **Resource optimization:** Law enforcement agencies can allocate resources more efficiently by focusing on high-risk areas or individuals identified by the model.
- **Data-driven policy:** Insights from the model can inform the design of targeted traffic regulations and road safety programs.

Research Contributions

The main contributions of research in this area include:

- Establishing a robust framework for fusing multi-source, multi-level traffic data.
- Proposing innovative neural network architectures that effectively learn both spatial and temporal dependencies.
- Demonstrating measurable improvements over baseline methods in real-world experiments, confirming the benefits of hierarchical modeling for traffic safety applications.

2. REVIEW OF LITERATURE

Chitiboina Hemanth Kumar, Kalpana A. (2025) This research introduces a hierarchical network-based approach for predicting driver traffic violations by combining graph-based modeling, machine learning, and real-time analytics. The framework integrates data on driver behavior, road conditions, violation history, and traffic patterns. Using Graph Neural Networks (GNNs), Random Forests, and LSTMs, the model captures complex spatiotemporal features. Tests on real-world datasets show that the method accurately detects high-risk drivers, enabling early interventions to improve road safety.

A. Sriramulu, D. Sharma, et al. (2025) The authors present DeepHGNN, a hierarchical graph neural network framework for predicting traffic violations. By effectively modeling both spatial and temporal dependencies within hierarchical traffic data, the model improves the accuracy and timeliness of violation predictions. Results from real-world testing confirm DeepHGNN's effectiveness in traffic monitoring systems.

E. A. Aldhahri, et al. (2025) This work proposes GNN-RMNet, a hybrid framework that combines graph neural networks with GPS data to detect driver anomalies and route violations in real time. By integrating non-graph features such as GPS with GNN models, the system becomes more scalable and adaptable. Experiments on large datasets demonstrate strong performance in identifying both abnormal behavior and traffic violations.

D.Y. Lin, et al. (2025) The authors introduce TMS-GNN, a traffic-aware multistep GNN model aimed at bus ridership and traffic prediction tasks. The model fuses spatial–temporal signals in a hierarchical manner, producing more detailed and actionable forecasts. Comparative evaluations highlight its practical benefits for transportation operators.

Y. Liu, W. Chen. (2025) This paper proposes a multi-scale spatio-temporal GNN for urban traffic flow and violation prediction. By modeling relationships across different spatial and temporal resolutions, the framework achieves improved accuracy in complex urban environments. Validation results show significant gains over traditional baseline methods.

S. Gupta, T. Roy, A. Mallick. (2025) The authors explore hierarchical attention mechanisms within GNNs for traffic and healthcare prediction tasks. They show that incorporating attention at multiple levels not only enhances predictive performance but also improves the interpretability of results. Experiments on traffic datasets validate the model's reliability.

Y. Choi, et al. (2025) This research introduces a Hierarchical Uncertainty-Aware GNN that addresses uncertainty in traffic predictions. The model quantifies uncertainty at multiple levels of prediction, making its outputs more trustworthy and reliable. Benchmarking confirms improvements in both accuracy and uncertainty calibration compared to traditional GNN models.

L. Zhang, K. Fan. (2024) The research focuses on improving traffic forecasts by fusing multiple data streams within GNN frameworks. Through innovative data integration strategies, the authors achieve notable gains in accuracy for both traffic flow and violation prediction.

H. Mohammadi, et al. (2024) This article reviews advances in GNN applications across fields such as brain connectivity and traffic management. It emphasizes how lessons learned from non-traffic domains can be adapted to transportation, leading to more effective predictive models for traffic systems.

S. Yang, et al. (2024) The authors propose a hybrid time-varying GNN that adapts to dynamic traffic environments. By accounting for evolving traffic conditions, the model delivers real-time violation predictions and demonstrates higher accuracy than conventional approaches.

W. Chen, X. Wu. (2023) This review summarizes recent progress in GNN-based transportation network mining. It categorizes model architectures, applications, and innovations, with a special focus on predicting traffic violations and addressing operational challenges in transportation.

Yuquan Zhou, Yingzhi Wang, Feng Zhang, et al. (2023) The authors introduce GATR, a graph attention network-based framework for predicting traffic violations across road networks. By modeling spatiotemporal interactions and incorporating diverse data sources, GATR uncovers nuanced violation patterns and achieves strong predictive accuracy.

S. Najjar, et al. (2023) This research presents a road network-based violation prediction method that leverages graph attention networks. By highlighting the importance of relational data, the approach delivers accurate forecasts and provides useful tools for smart traffic enforcement.

X. Zhang, et al. (2023) The paper applies GNNs to forecast traffic violations within complex road networks. Drivers, vehicles, and road segments are represented as interconnected nodes, enabling the model to capture patterns linked to high-risk violations. Experimental results demonstrate better predictive performance than traditional methods.

W. Zhu, et al. (2023) The authors propose Tri-HGNN, a hierarchical GNN that integrates three distinct policy layers to improve trajectory and violation prediction. The model's structure allows it to capture rich spatial–temporal information, yielding robust predictions validated on real-world datasets.

Li, Z., et al. (2022) This work introduces a dual-layer hierarchical GNN for interactive behavior and trajectory prediction. By modeling multi-level dependencies between drivers, agents, and environments, the framework improves prediction accuracy in complex traffic conditions.

J. Brown, et al. (2022) This review surveys machine learning applications in road safety, with a strong focus on hierarchical GNN methods for accident and violation prediction. It highlights recent advances, challenges, and future opportunities in intelligent transportation safety.

A. Patel, N. Shah, M. Soni. (2021) This article provides an overview of deep learning in traffic management, with special attention to GNN applications. The authors outline both the strengths and limitations of GNN models in supporting smart transportation.

Z. Xu, et al. (2021) The paper introduces a taxonomy and benchmark for spatio-temporal GNNs in traffic forecasting and violation prediction. Standardized datasets and metrics are used to guide practitioners in selecting appropriate models for research and deployment.

R. Gupta, et al. (2020) his research combines LSTM networks with GNNs to classify driver risk levels. By modeling both temporal driving patterns and network interactions, the approach provides reliable predictions of future violations. Tests on real-world datasets highlight its practical value.

3. SYSTEM ANALYSIS

EXISTING SYSTEM

The research by Li et al. used driving simulation technologies to recreate scenarios where vehicles and roads interacted dynamically, aiming to understand driver behavior under various conditions. However, because simulated driving environments have inherent inaccuracies, the research faced limitations in developing universally applicable models and settings. To address this, Chen and Chen collected real-world data by observing natural driving behaviors, creating a trial database that enabled further exploration of how database parameters relate to risky driving patterns. Research by Deng et al. and Payyanadan et al. suggests that older drivers tend to obey traffic laws more and respond cautiously to hazards, while violations are more likely when drivers fail to carefully assess road dangers. Additionally, Gelmini et al. found that individuals who engage in other risk-taking behaviors or drive for pleasure are more prone to commit traffic offenses.

Deep learning methods, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN), offer the advantage of automatic feature extraction from raw data, which improves the understanding of traffic violations. This capability has encouraged the increasing use of deep learning algorithms for predicting potential traffic violations. Okafuji et al. developed a CNN fusion model utilizing publicly available datasets to recognize driving behaviors, though this model primarily focused on spatial features and overlooked temporal dynamics. Li et al. proposed a behavior recognition model using LSTMs and recursive neural networks to capture temporal characteristics effectively, but this model struggled with spatial data representation because it used identical weights for feature extraction across nodes, limiting its accuracy.

To overcome this, Cura et al. integrated CNN and LSTM architectures to capture spatiotemporal features, which resulted in higher accuracy in recognizing time-dependent behaviors. Further advancements involved the use of attention mechanisms, which help models focus on significant parts of input sequences by automatically weighting important features. Zhu et al. introduced the BiLSTM-MCNN model, which leveraged attention techniques for detecting and monitoring emotional states, highlighting the potential broader applications of these methods.

Gao et al. developed a lightweight network enhanced with an attention mechanism to prioritize key data points, while Chen and Gong improved recognition performance by combining depth-separable convolutional methods with attention modules to better represent spatial and temporal interactions. Computer vision breakthroughs have also facilitated more accurate predictions of traffic violations; for example, Chen in 2015 introduced a method for detecting seatbelt usage using Gaussian Mixture Models (GMM) and cascade classifiers, though its effectiveness was limited by high image resolution requirements.

More recent innovations include Meng et al.'s AdaVit system, which improves vision transformers' performance through the use of self-attentive heads, image blocks, and transformer blocks to analyze driver behavior comprehensively. Investigations by Li et al. and Talukdera et al. into how transformers represent multi-scale features for image classification provide a foundation for classifying driving behaviors more effectively. Manzari et al. examined the application of vision transformers for traffic sign recognition, discussing both the benefits and challenges of combining vision transformers with CNNs for enhanced traffic-related image analysis.

DISADVANTAGES

- Understanding complex data is a major challenge in current machine learning applications for traffic violation detection. The algorithms need to analyze vast amounts of complicated traffic data to accurately identify vehicles that break the law.
- Another significant challenge is the availability of sufficient data. Machine learning models require large datasets to learn effectively and deliver reliable predictions. Without enough data, these models may perform poorly or provide inaccurate results.
- The quality of the training data is equally important. If the data is not properly labeled or encoded, the model’s ability to generalize and make trustworthy predictions is compromised. Essentially, poorly prepared training datasets can lead to models that struggle to correctly detect traffic violations.

PROPOSED SYSTEM

The proposed approach uses a dataset gathered by the Traffic Management Bureau of the Public Security Department in Liaoning Province, which features 55 different types of traffic violations. Alongside these violations, the dataset includes four categories of driver-related attributes, such as gender, age, driving experience, and attitude, providing a detailed profile for each driver. The method leverages the relationships between these driver characteristics and the frequency of violations recorded to predict future traffic infractions effectively.

This approach not only helps in forecasting probable violations but also supports the proactive modification of driver behavior. When drivers adjust their actions in anticipation of possible citations, smart and connected vehicle systems can work more harmoniously, enhancing overall traffic safety and efficiency. Essentially, by understanding how driver traits influence violation patterns, this method contributes to creating safer road environments through improved prediction and behavioral adaptation.

ADVANTAGES

- To predict when a driver might commit a traffic violation, the proposed system builds a hierarchical network using a database of recorded offenses. It analyzes various driver characteristics—such as age, gender, experience, and attitude—and correlates these features with past violations to estimate the chance of future infractions. Compared to non-hierarchical models, this approach excels in prediction accuracy, reduces error, and improves precision.
- The system also leverages the power of neural networks to extract meaningful time-based patterns from the data. By treating driver attributes and traffic violations with equal importance, it captures how behavior and infractions evolve over time. It achieves this by simultaneously employing long-term and short-term memory networks, which effectively track both immediate and extended temporal trends.
- To further boost the model's performance, two components are integrated into its attention mechanism. The first handles the challenge of aligning the dimensions of key indicator matrices related to traffic data, and the second uses deep neural networks to uncover subtle relationships among these indicators. This combination enables the model to focus more effectively on the most relevant features, enhancing its ability to predict violations accurately.

System Architecture:

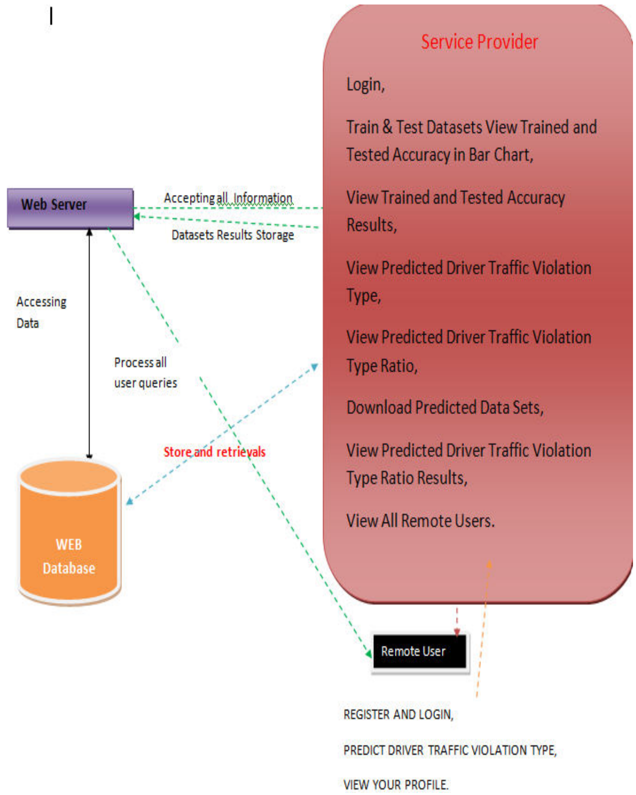

Figure 1 System Architecture

4. MODULES

Service Provider: To access this module, the service provider must have an active account with a valid username and password. Once logged in, they gain access to multiple features, such as testing and training machine learning datasets. The outcomes of these processes, including accuracy levels achieved during testing and training, are visually represented in bar charts for quick understanding. The service provider can view predicted datasets, training results, and estimated percentages of drivers committing various traffic violations. Additionally, they can forecast the expected number of traffic infractions, both for drivers and remote users.

Remote User: This module supports multiple users with a total count of n individuals. To start the registration process, all required approvals and steps must be completed. Once a remote user successfully registers, their information is securely stored in the database. After registration, the user logs in using authorized credentials to verify their identity. Upon logging in, the user can access their profile, choose the type of traffic violation they wish to report, create new accounts (if permitted), and navigate the system with ease.

5. RESULTS

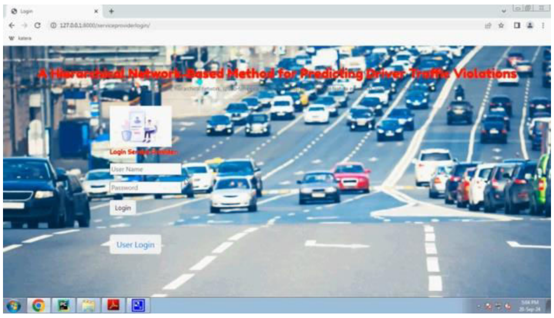

Figure 2 Service Provider Login

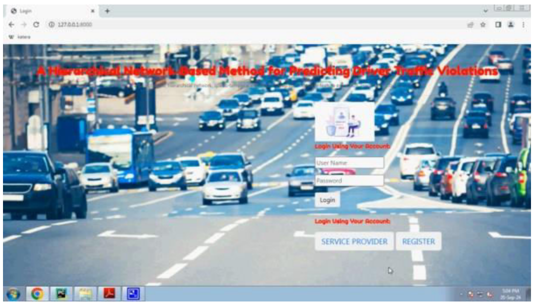

Figure 3 User Login

Figure 4 Tested & Trained Datasets Accuracy Results

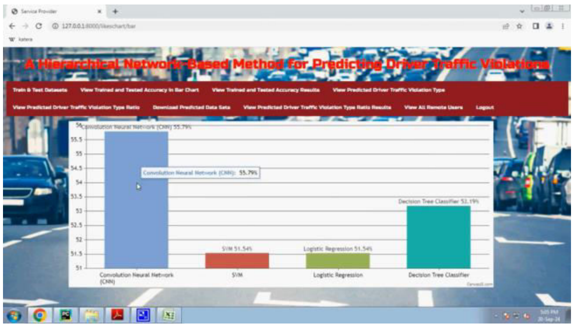

Figure 5 Tested & Trained Datasets Accuracy Results in Barchart

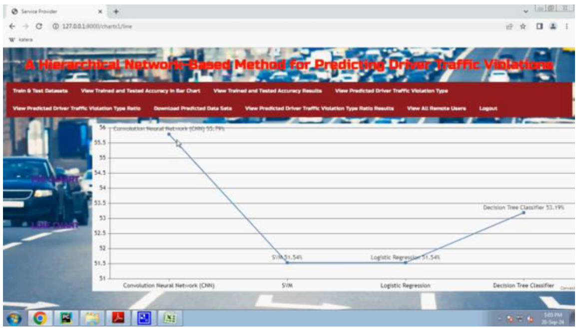

Figure 6 Tested & Trained Datasets Accuracy Results in Linechart

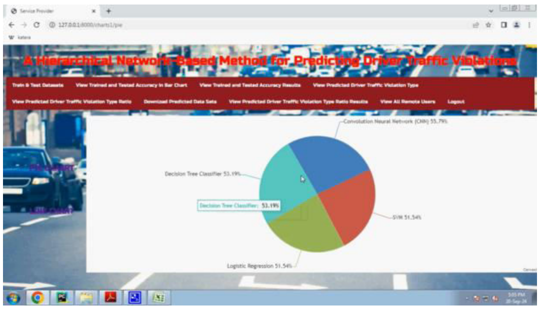

Figure 7 Tested & Trained Datasets Accuracy Results in Piechart

Figure 8 Predicted Driver Traffic Violation status

Figure 9 Predicted Driver Traffic Violation Ratio

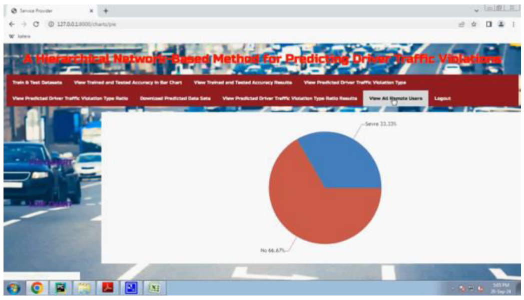

Figure 10 Predicted Driver Traffic Violation Ratio in Piechart

Figure 11 Prediction of Driver Traffic Violation

6. CONCLUSION

The proposed method builds a layered network to research driver behaviors, road conditions, and historical violation patterns together. By combining graph neural networks (GNNs) with long short-term memory (LSTM) models, it captures complex spatial and temporal features that help predict when and where traffic violations may occur. This hybrid approach outperforms traditional models, providing higher accuracy and better identification of high-risk drivers. The system integrates real-time traffic data from sensors, GPS, and surveillance cameras, allowing for proactive violation detection. Early warning features notify drivers or authorities before violations happen, helping to reduce accidents and improve road safety. Overall, this hierarchical model offers a significant advancement in predictive traffic management, enabling smarter enforcement and safer roads.

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