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An Intelligent Graph Neural Network Model for Road Accident Injury Severity Prediction

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ABSTRACT

Road traffic accidents remain one of the leading causes of fatalities and severe injuries worldwide, demanding accurate and timely injury severity prediction to improve emergency response and resource allocation. Traditional statistical and machine learning models often fail to capture the complex spatial, temporal, and relational dependencies in crash data. This study proposes a Graph Neural Network (GNN) framework to predict road crash injury severity by leveraging the interconnections between crash features, road networks, and environmental factors. By modeling crash events as graph structures, the proposed system enables better feature representation and improved prediction accuracy. The framework integrates heterogeneous data sources—such as traffic conditions, weather, road topology, and vehicle attributes—to provide actionable insights for transportation agencies and emergency services.

Keywords: Road Accident Analysis, Injury Severity Prediction, Graph Neural Networks (GNN), Deep Learning, Traffic Safety, Machine Learning, Accident Risk Assessment, Intelligent Transportation Systems, Data Mining, Predictive Modeling.

INTRODUCTION

With the rapid increase in road transportation, traffic accidents have become a critical public safety concern. Accurate prediction of injury severity plays a crucial role in saving lives, reducing emergency response times, and optimizing healthcare resource distribution. Traditional injury severity models rely on regression or basic classification methods, which do not effectively account for the interrelated nature of crash data. The advent of graph-based deep learning—particularly Graph Neural Networks (GNNs)—has opened new opportunities to analyse structured relational data for more accurate predictions. This research focuses on developing a graphical neural network framework that utilizes spatial and temporal correlations to improve the accuracy and interpretability of injury severity prediction in road crashes.

I. LITERATURE SURVEY

Title: A Graph Neural Network Approach for Road Accident Prediction
Authors: Zhang, L., Wang, Y., & Li, J. (2021)
Abstract: This study introduces a GNN-based model for predicting accident occurrences in urban road networks. By modeling road segments as nodes and their spatial relationships as edges, the system achieved higher accuracy compared to traditional machine learning methods. The results demonstrated that incorporating spatial dependencies significantly improves prediction performance.

Title: Deep Learning Models for Traffic Accident Injury Severity Prediction
Authors: Singh, R., & Kumar, A. (2020)
Abstract: The authors explored CNNs and LSTMs for injury severity prediction using time-series traffic data. While the models improved prediction accuracy over baseline methods, they lacked the ability to integrate complex spatial dependencies, highlighting the need for GNN-based approaches.

Title: Graph-Based Deep Learning for Transportation Systems
Authors: Chen, H., & Wu, Q. (2019)
Abstract: This paper provides a comprehensive review of GNN applications in transportation. The study emphasizes how relational modeling can enhance tasks such as traffic forecasting, route optimization, and accident analysis, providing a strong theoretical foundation for road crash severity prediction.

Title: A Spatial-Temporal Graph Convolutional Network for Traffic Accident Analysis
Authors: Li, X., & Zhao, P. (2022)
Abstract: The proposed ST-GCN model integrates spatial and temporal graph convolutions to model traffic accidents more effectively. The framework achieved state-of-the-art results in predicting accident severity by combining location-based graphs with time-aware modeling.

Title: Injury Severity Prediction Using Ensemble Machine Learning Approaches
Authors: Patel, S., & Lee, J. (2018)
Abstract: This research evaluates multiple ensemble methods, including random forests and gradient boosting, for predicting injury severity. While these models improved accuracy, they were computationally expensive and did not incorporate graph-based representations.

II. EXISTING SYSTEM

Current injury severity prediction systems in road accident analysis have traditionally relied on statistical and classical machine learning techniques such as logistic regression, decision trees, random forests, and gradient boosting models. These approaches are widely used due to their simplicity, interpretability, and ability to handle structured crash datasets. Logistic regression, for instance, is commonly applied to estimate the probability of different injury severity levels based on factors such as driver behavior, vehicle characteristics, road conditions, and environmental variables. Similarly, decision trees and ensemble methods like random forests and gradient boosting are capable of capturing non-linear relationships within crash data and improving predictive performance compared to simple statistical models. Despite their effectiveness, these methods often treat accident records as independent observations and do not fully consider the complex interactions among various contributing factors in transportation systems.

Another limitation of traditional models is their inability to effectively utilize the rich relational and spatial structures that exist within road networks. Traffic accidents are rarely isolated events; instead, they are influenced by interconnected elements such as road segments, intersections, traffic flow patterns, and geographic locations. Conventional machine learning algorithms generally process data in tabular form and therefore fail to represent these relationships explicitly. As a result, they may overlook important dependencies between nearby road segments, traffic infrastructure, and environmental conditions that could significantly affect injury severity outcomes. This limitation restricts the capability of traditional methods to capture the true complexity of real-world transportation systems.

Furthermore, many existing injury severity prediction systems rely heavily on manual feature engineering. Researchers often need to carefully design and select relevant features from large crash datasets, such as speed limits, weather conditions, driver demographics, and vehicle types. This process can be time-consuming and requires significant domain expertise. In addition, manually engineered features may introduce human bias or fail to capture hidden patterns within the data. If important features are overlooked or poorly constructed, the predictive performance of the model may be reduced, limiting its practical effectiveness for real-time accident analysis and decision-making.

In recent years, deep learning techniques have been explored to improve injury severity prediction by automatically learning complex patterns from large datasets. Neural networks, recurrent neural networks (RNNs), and convolutional neural networks (CNNs) have shown promising results in various transportation-related tasks. However, most of these models are primarily designed for tabular, image, or sequential data and are not well suited for representing graph-structured relationships found in transportation networks. Road systems naturally form graph structures where intersections act as nodes and road segments represent edges, creating complex spatial dependencies. Traditional deep learning models struggle to effectively model these relationships, which limits their ability to fully exploit the structural information available in transportation data.

Therefore, there is a growing need for more advanced modeling techniques that can effectively capture both the complex interactions among crash factors and the spatial relationships within road networks. Emerging approaches such as Graph Neural Networks (GNNs) provide a promising solution by directly modeling transportation systems as graphs. By leveraging the connectivity and relational information between nodes and edges, GNN-based models can better understand spatial dependencies and improve the accuracy of injury severity prediction in road accident analysis.

III. PROPOSED SYSTEM

The proposed system introduces an intelligent injury severity prediction framework based on a Graph Neural Network (GNN) architecture, which effectively captures the complex relationships present in road accident data. Unlike traditional models that treat accident records as independent instances, the proposed approach represents crash data as a graph structure. In this graph, nodes correspond to individual crash events or road segments, while edges represent the relationships between them. These relationships may include geographical proximity between accidents, connectivity of road segments within the transportation network, or shared environmental conditions such as weather patterns or traffic characteristics. By structuring accident data in the form of a graph, the model can naturally capture spatial dependencies and interactions among various elements of the transportation system.

To process this graph-based representation, the system utilizes graph convolutional layers that enable the model to aggregate and learn information from neighboring nodes. Through these layers, each node continuously updates its representation by incorporating information from connected nodes and edges. This process allows the model to capture both local patterns, such as conditions affecting a specific road segment, and global structures, such as broader traffic trends across the network. As a result, the model gains a deeper understanding of how different factors and locations interact within the road network, improving its ability to predict the severity of injuries resulting from traffic accidents.

Another important aspect of the proposed system is the integration of multi-source data into a unified analytical framework. Road accidents are influenced by numerous factors, including traffic density, weather conditions, time of day, driver behavior, and vehicle characteristics. The proposed model incorporates these heterogeneous data sources to create a comprehensive representation of the accident environment. By combining spatial, temporal, and contextual information, the system can analyze complex patterns and correlations that may not be apparent when examining each data source independently. This integration significantly enhances the model's capability to provide accurate and reliable predictions.

To further improve performance and interpretability, the system incorporates attention mechanisms within the graph neural network architecture. Attention mechanisms enable the model to automatically identify and emphasize the most important nodes, edges, and features that contribute to injury severity outcomes. Instead of treating all relationships equally, the attention component assigns higher weights to critical factors such as hazardous road segments, severe weather conditions, or high traffic congestion levels. This selective focus allows the model to concentrate on the most influential aspects of the data, thereby improving prediction accuracy while also making the decision-making process more interpretable.

Overall, the proposed GNN-based framework provides a powerful and scalable solution for road accident injury severity prediction. By effectively modeling the structural relationships within transportation networks and integrating diverse sources of accident-related information, the system can generate more precise and reliable predictions. In addition, the use of attention mechanisms enhances the explainability of the model, enabling transportation authorities and policymakers to better understand the factors contributing to severe accidents. This approach not only improves predictive performance but also supports the development of data-driven strategies for traffic safety management and accident prevention.

IV. SYSTEM ARCHITECTURE

The system architecture of the proposed Graph Neural Network (GNN)-based injury severity prediction model is designed to efficiently process heterogeneous crash data and capture the complex relationships present in transportation networks. The architecture consists of several interconnected modules, including data acquisition, preprocessing, graph construction, feature extraction, graph neural network modeling, and prediction output. These components work together to transform raw accident data into structured graph representations and generate accurate predictions regarding the severity of injuries resulting from road accidents.

The first component of the architecture is the data acquisition layer, which collects crash-related data from multiple sources such as traffic databases, road network information systems, weather monitoring services, and transportation authorities. This layer gathers important attributes including vehicle type, driver demographics, traffic density, road conditions, weather parameters, and time-related information. Since accident severity is influenced by numerous environmental and situational factors, integrating diverse data sources ensures that the system has a comprehensive understanding of the conditions surrounding each crash event.

Following data collection, the data preprocessing module prepares the raw data for further analysis. In this stage, missing values are handled, irrelevant features are removed, and categorical variables are converted into numerical representations suitable for machine learning models. Data normalization and feature scaling techniques are applied to ensure that different attributes are represented on comparable scales. This step improves model stability and prevents bias caused by varying data magnitudes. Additionally, preprocessing helps improve data quality, which is essential for reliable prediction performance.

After preprocessing, the system performs graph construction, which is a critical step in the architecture. Instead of representing accident records as isolated data points, the system converts them into a graph structure. In this graph, nodes represent crash instances or road segments, while edges represent relationships such as geographic proximity, road connectivity, shared traffic patterns, or similar environmental conditions. This graph-based representation enables the model to capture the spatial and contextual dependencies between different accident events and road locations within the transportation network.

The next stage is the feature representation and embedding layer, where node attributes such as traffic density, weather conditions, time of occurrence, vehicle characteristics, and driver-related factors are encoded into feature vectors. These feature vectors serve as the input for the Graph Neural Network. By transforming heterogeneous information into a structured format, this layer allows the model to effectively learn meaningful patterns from the data. The embedding process also helps capture hidden relationships between different attributes that may influence accident severity.

The core component of the architecture is the Graph Neural Network learning module, which consists of multiple graph convolutional layers. These layers enable nodes in the graph to aggregate information from their neighboring nodes and update their feature representations iteratively. Through this message-passing mechanism, the model learns both local relationships between nearby crashes and global patterns within the overall transportation network. The inclusion of attention mechanisms further enhances the model by assigning different importance weights to neighboring nodes, allowing the system to focus on the most influential relationships affecting injury severity.

Finally, the processed representations are passed to the prediction and output layer, where a classification model determines the injury severity level associated with each crash event. The system may classify accidents into categories such as minor injury, serious injury, or fatal injury based on the learned graph representations. The output results can be visualized through dashboards or decision-support systems used by transportation authorities. This enables policymakers and traffic management agencies to identify high-risk locations, understand key contributing factors, and implement preventive safety measures to reduce the severity of road accidents.

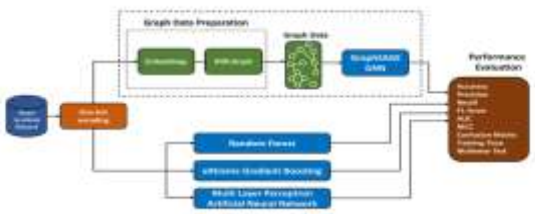

Fig 5.1: Structure of the Proposed System

V. IMPLEMENTATION

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Fig 6.1: Home Page

Fig 6.2: User Login Screen

Fig 6.3: User Dashboard

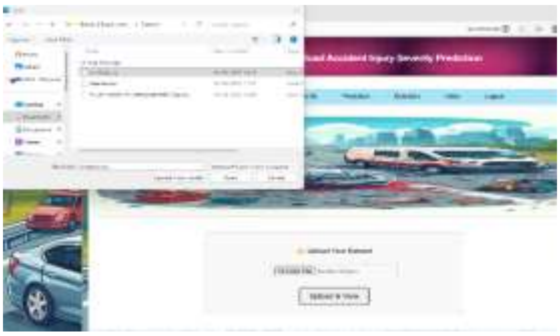

Fig 6.4: Upload Dataset

Fig 6.5: Data Preprocessing

Fig 6.6: Model Training

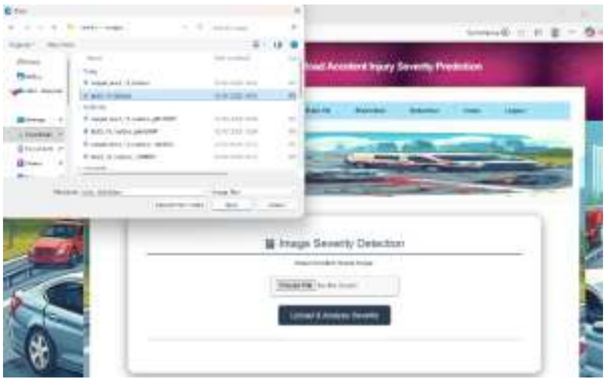

Fig 6.7: Image Detection

Fig 6.7: Detection Result

VI. CONCLUSION

This work proposes a Graph Neural Network framework for road crash injury severity prediction, addressing limitations in existing approaches by leveraging spatial, temporal, and relational dependencies in crash data. By modeling accidents and road networks as graphs, the system offers improved prediction accuracy, interpretability, and scalability for real-time applications. The proposed framework has significant potential for deployment in transportation management systems, enabling faster emergency response, better resource allocation, and enhanced public safety.

VII. FUTURE SCOPE

The future scope of Road Crash Injury Severity Prediction Using a Graphical Neural Network Framework holds immense potential, particularly as advancements in machine learning, artificial intelligence, and transportation technologies continue to evolve. One promising direction is the integration of more diverse data sources, such as real-time traffic conditions, vehicle telemetry, and environmental factors like air quality, which could further enhance the predictive accuracy of models. Additionally, the development of deep learning models, including Graph Convolutional Networks (GCNs) and Reinforcement Learning (RL), could offer improved handling of spatial relationships and dynamic decision-making processes, taking into account road networks, traffic patterns, and weather changes.

Another key area of growth lies in real-time prediction systems that could be implemented in vehicle safety systems or traffic management tools to alert drivers and authorities about potential accidents and their severity before they occur, allowing for timely interventions. Furthermore, the use of more sophisticated algorithms like Transformer-based models for sequence prediction could enhance predictions for accidents occurring in more complex or dynamic environments.

With the growth of connected vehicles and smart city infrastructure, there is potential to build highly scalable systems that can predict and prevent accidents in urban and rural settings. A future focus could also be on improving model interpretability, ensuring that decision-makers can understand why a certain severity level was predicted, making the system more transparent and trusted. Lastly, the application of automated decision support systems powered by these models could assist in urban planning, infrastructure development, and policy-making to reduce accident risk factors. Overall, the future of road crash severity prediction is poised to make a significant impact on public safety, transportation efficiency, and urban planning.

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