A

Major Project Report

On

A GRAPH NEURAL NETWORK BASED APPROACH FOR PREDICTING ROAD ACCIDENT INJURY SEVERITY

Submitted to CMREC (UGC Autonomous)

In Partial Fulfilment of the requirements for the Award of Degree

of

BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE AND ENGINEERING (AI & ML)

Submitted
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CERTIFICATE

This is to certify that the Major project entitled **"A GRAPH NEURAL NETWORK BASED APPROACH FOR PREDICTING ROAD ACCIDENT INJURY SEVERITY"** is a bonafide work carried out by

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in partial fulfillment of the requirement for the award of the degree of BACHELOR OF TECHNOLOGY in COMPUTER SCIENCE AND ENGINEERING (AI&ML) from CMR Engineering College, under our guidance and supervision.

The results presented in this Major project have been verified and are found to be satisfactory. The results embodied in this Major project have not been submitted to any other university for the award of any other degree or diploma.

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DECLARATION

This is to certify that the work reported in the present Major project entitled "**A GRAPH NEURAL NETWORK BASED APPROACH FOR PREDICTING ROAD ACCIDENT INJURY SEVERITY**" is a record of bonafide work done by us in the Department of Computer Science and Engineering (AI & ML), CMR Engineering College. The reports are based on the Major project work done entirely by us and not copied from any other source. We submit our Major project for further development by any interested students who share similar interests to improve the Major project in the future.

The results embodied in this Major project report have not been submitted to any other University or Institute for the award of any degree or diploma to the best of our knowledge and belief.

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ABSTRACT

Road crash injury severity prediction remains a major challenge in traffic safety analysis due to the complex interactions between road geometry, human factors, vehicle characteristics, and environmental conditions. Traditional machine learning and statistical models often treat crash incidents as isolated events, ignoring the relational structure embedded within the road network. To address this gap, this study proposes a **Graph Neural Network (GNN)–based framework** that models crashes as nodes within a spatial graph, where edges represent road connectivity, proximity, and contextual similarity. By integrating crash-level attributes, roadway features, weather conditions, and temporal patterns, the GNN learns high-level representations that more accurately capture the underlying mechanisms influencing injury severity. The framework is designed to identify hidden spatial dependencies and non-linear interactions that conventional models fail to detectExtensive experiments conducted on real-world crash datasets show that the proposed GNN framework consistently outperforms traditional classifiers such as logistic regression, random forests, and gradient boosting in terms of accuracy, recall, precision, and F1-score. The model demonstrates strong generalization capabilities, particularly in identifying severe and fatal injury cases, which are often underrepresented in datasets. The findings highlight the potential of graph-based deep learning to enhance risk prediction and provide actionable insights for transportation planners, policymakers, and intelligent transportation systems. Ultimately, the proposed approach offers a scalable and data- driven solution for proactive road safety management, enabling targeted interventions and improved decision-making for crash prevention and severity mitigation.

Keywords : Road Crash Injury Severity, Graph Neural Network (GNN), Road Network Analysis, Injury Severity Classification, Deep Learning, Spatial Relationship Modeling, Crash Data Analytics, Graph-Based Learning, Intelligent Transportation Systems (ITS)

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CHAPTER-1

INTRODUCTION

1. INTRODUCTION

1.1 Introduction

The increasing growth of intelligent transportation systems and smart city infrastructure has significantly transformed the way road traffic data is collected, analyzed, and utilized. Modern technologies such as sensors, GPS devices, and surveillance systems generate large volumes of accident-related data, enabling deeper insights into traffic patterns and road safety. However, road accidents continue to be a major global concern, resulting in severe injuries, fatalities, and economic losses. Accurately predicting injury severity remains a challenging task due to the complex interactions between multiple factors such as road conditions, weather, driver behavior, and traffic dynamics. Traditional statistical and machine learning models often fail to capture these intricate relationships effectively, highlighting the need for more advanced analytical approaches **[10]**.

Recent advancements in deep learning, particularly in Graph Neural Networks (GNNs), have opened new possibilities for modeling complex and structured data. Unlike conventional models, GNNs are capable of representing road networks as graphs, where nodes correspond to accident instances or locations and edges represent relationships such as spatial proximity or similarity in conditions. This ability to learn from both features and relationships allows GNNs to capture hidden patterns that significantly influence accident severity. Several studies have demonstrated that incorporating spatial and temporal dependencies using graph-based methods leads to improved prediction accuracy and better generalization across different scenarios **[3]**, **[4], [8].**

In addition to graph-based approaches, ensemble learning techniques have been widely adopted to enhance prediction performance by combining multiple models. Methods such as Extra Trees, K-Nearest Neighbors, XGBoost, and Artificial Neural Networks contribute diverse perspectives to the prediction process, reducing overfitting and increasing robustness. By integrating these techniques with GNN-based representations, the proposed system aims to leverage both relational learning and model diversity to achieve highly accurate injury severity predictions. The system also incorporates data preprocessing, feature selection, and graph construction modules to ensure efficient handling of large-scale accident datasets **[5], [6].**

Overall, this project presents a scalable and intelligent framework for road accident injury severity prediction using Graph Neural Networks and ensemble learning. The proposed approach not only improves prediction accuracy but also provides meaningful insights into the contributing factors of accidents, supporting decision-making for traffic authorities and policymakers. By enabling early identification of high-risk scenarios, the system contributes to enhancing road safety, optimizing emergency response, and reducing the impact of road accidents in real-world environments **[1], [2].**

1.2 Project Objectives

By the end of this project you will understand

1. To develop a Graph Neural Network (GNN) framework that models road crash data using spatial, temporal, and contextual relationships within the road network.
2. To accurately predict road crash injury severity by capturing complex non-linear patterns and hidden dependencies that traditional models cannot identify.
3. To provide data-driven insights for transportation planners and policymakers to support effective road safety management, targeted interventions, and crash prevention strategies.
4. To enhance the performance of accident severity prediction by integrating multiple features such as driver behavior, environmental conditions, and vehicle characteristics into a unified graph-based model.
5. To design a scalable and efficient system that can be adapted for real-time accident analysis and integrated with intelligent transportation systems for proactive decision-making.
6. To improve the interpretability of prediction results by identifying key contributing factors influencing accident severity using advanced graph learning techniques, enabling better understanding of risk patterns.
7. To enable continuous learning and system improvement by incorporating new accident data over time, ensuring that the model adapts to changing traffic conditions and evolving road environments.

1.3 Purpose of the Project

The purpose of this project is to develop an intelligent, data-driven system that can accurately predict the severity of injuries resulting from road crashes using a Graph Neural Network (GNN) framework. Road accidents are influenced by multiple interconnected factors such as road conditions, traffic patterns, weather conditions, and driver behavior. Traditional machine learning models often treat these factors independently, which limits their ability to fully understand the complex relationships present in real-world traffic systems. As highlighted in previous studies, conventional approaches lack the ability to capture spatial dependencies and relational structures inherent in traffic data, resulting in lower prediction accuracy **[10].**

This project aims to overcome these limitations by utilizing the power of Graph Neural Networks, which are specifically designed to model relational and structured data. By representing road accident data as a graph, where nodes correspond to accident instances or road segments and edges represent relationships between them, the system can effectively capture spatial and contextual dependencies. This approach allows the model to learn hidden patterns and interactions that are not easily detectable using conventional methods. Recent research demonstrates that GNN-based models significantly improve prediction performance by leveraging graph structures and spatial correlations **[3], [8].**

Another important purpose of this project is to analyze both spatial and temporal relationships in road networks. Accidents that occur in nearby locations or under similar conditions often share common characteristics. By incorporating these relationships into the model, the system can provide more accurate and reliable predictions of injury severity levels such as minor, serious, or fatal injuries. Studies involving temporal and heterogeneous graph models have shown that considering time-based and multi-entity relationships leads to better generalization and prediction stability.

Furthermore, the project is designed to support data-driven decision-making for transportation authorities, urban planners, and policymakers. The insights generated by the model can help identify high-risk areas, understand the key factors contributing to severe accidents, and develop targeted safety measures. This can lead to improved traffic management, better road infrastructure planning, and more efficient emergency response systems. Research in infrastructure-aware and clustering-based approaches also supports the importance of such predictive systems in enhancing road safety and emergency handling .

In addition, the system aims to contribute to the development of intelligent transportation systems (ITS) by enabling predictive analytics for road safety. The proposed model can be extended in the future to integrate real-time data from sensors, GPS devices, and IoT-based systems, making it more dynamic and applicable in real-world scenarios. Modern intelligent systems increasingly rely on such scalable and adaptive models for real-time monitoring and prediction **[1].**

Overall, the purpose of this project is not only to improve the accuracy of accident severity prediction but also to provide a scalable and efficient solution that enhances road safety, reduces accident-related risks, and supports proactive accident prevention strategies. By combining graph-based learning with advanced machine learning techniques, the system aligns with recent advancements in intelligent transportation research and contributes to safer and smarter road environments .

1.4 Problem Statement

The increasing number of road traffic accidents has become a major concern for public safety, leading to significant loss of life, injuries, and economic damage worldwide **[9].** The complexity of accident severity prediction arises from the involvement of multiple interconnected factors such as road conditions, traffic density, weather variations, driver behavior, and vehicle characteristics. These factors are highly dynamic and interdependent, making it difficult to accurately assess injury severity using traditional statistical and machine learning approaches. Most existing models treat accident data as independent instances and fail to capture the spatial and temporal relationships between events, resulting in lower prediction accuracy and limited real-world applicability **[3], [10].**

1.5 Existing System with disadvantages

The existing system for predicting road crash injury severity mainly uses traditional statistical models and basic machine learning methods like logistic regression, decision trees, and random forests. These models analyze crash data only based on individual factors such as driver details, vehicle type, weather, and road conditions, treating each crash as a separate event. Because they do not consider spatial relationships or the connectivity of the road network, they fail to capture complex patterns and hidden dependencies that influence injury severity. As a result, their prediction accuracy is limited, especially for severe and fatal crashes, making them less effective for real-time safety planning and decision-making.

Another major limitation of the existing system is its inability to effectively handle large-scale and heterogeneous data generated from multiple sources such as traffic sensors, GPS devices, and accident reports. These models often struggle with imbalanced datasets, where severe or fatal crash cases are less frequent, leading to biased predictions toward minor injury categories. Additionally, traditional approaches lack the capability to incorporate temporal dynamics, such as changes in traffic patterns over time, which are crucial for accurate prediction. The absence of advanced feature representation and relational learning further reduces their adaptability and scalability, making them unsuitable for modern intelligent transportation systems and real-time accident analysis.

Disadvantages

1) Traditional models treat each crash as an independent event.
2) They cannot capture complex non-linear patterns present in road and traffic data.
3) Road network structure and connectivity are not utilized for prediction.
4) Accuracy is low, especially for severe and fatal injury classifications.
5) Limited ability to analyze hidden patterns or interactions between multiple factors.
6) Not suitable for advanced road safety planning and proactive decision-making.

One of the major limitations of these existing approaches is that they do not effectively capture the spatial relationships between different accident locations. Road networks are inherently interconnected, and accidents occurring on the same road segment or nearby regions often share similar patterns. However, traditional models fail to utilize this connectivity, which leads to incomplete understanding of accident behavior.In addition to spatial limitations, these models also struggle to capture temporal dependencies. For example, accidents occurring during peak traffic hours or under certain seasonal weather conditions may exhibit similar characteristics. Since most conventional models do not incorporate time-based relationships effectively, they miss out on important trends that could improve prediction accuracy.

Another drawback of the existing system is its inability to model complex non-linear interactions between multiple factors. Road accidents are influenced by a combination of variables such as driver behavior, vehicle condition, environmental factors, and traffic density. Traditional methods often assume simple linear relationships or fail to fully explore how these variables interact with each other, resulting in reduced predictive performance.Furthermore, these models often face challenges when dealing with imbalanced datasets, where severe or fatal accidents occur less frequently compared to minor accidents.

Another limitation is that existing systems are generally not suitable for real-time analysis and dynamic environments. They are typically designed for static datasets and do not adapt well to continuously changing traffic conditions. This restricts their application in modern intelligent transportation systems, where real-time data processing is essential. Moreover, traditional approaches provide limited interpretability and actionable insights. While they may predict the severity level, they do not clearly explain the relationships between different factors or identify high-risk zones effectively. This makes it difficult for transportation authorities and policymakers to take proactive measures based on the predictions.

1.6 Proposed System with advantages

The proposed system uses a Graph Neural Network (GNN) framework to predict road crash injury severity by modeling the road network as an interconnected graph. Unlike traditional methods, the GNN considers spatial relationships, road connectivity, and the influence of nearby crash locations. It learns complex patterns using features such as road geometry, traffic conditions, environment, and historical crash data. By capturing both local and global dependencies within the road network, the proposed system provides more accurate, reliable, and meaningful predictions. This helps transportation authorities identify high-risk areas, plan effective safety measures, and reduce the overall impact of road accidents.

Additionally, the proposed system is designed to be scalable and adaptable for real-time applications by integrating data from sensors, GPS, and traffic monitoring systems. It enhances prediction reliability by combining multiple features and learning complex relationships within the data, while also providing meaningful insights into accident causes. This enables authorities to take proactive measures, improve road safety planning, and reduce the severity and impact of accidents.

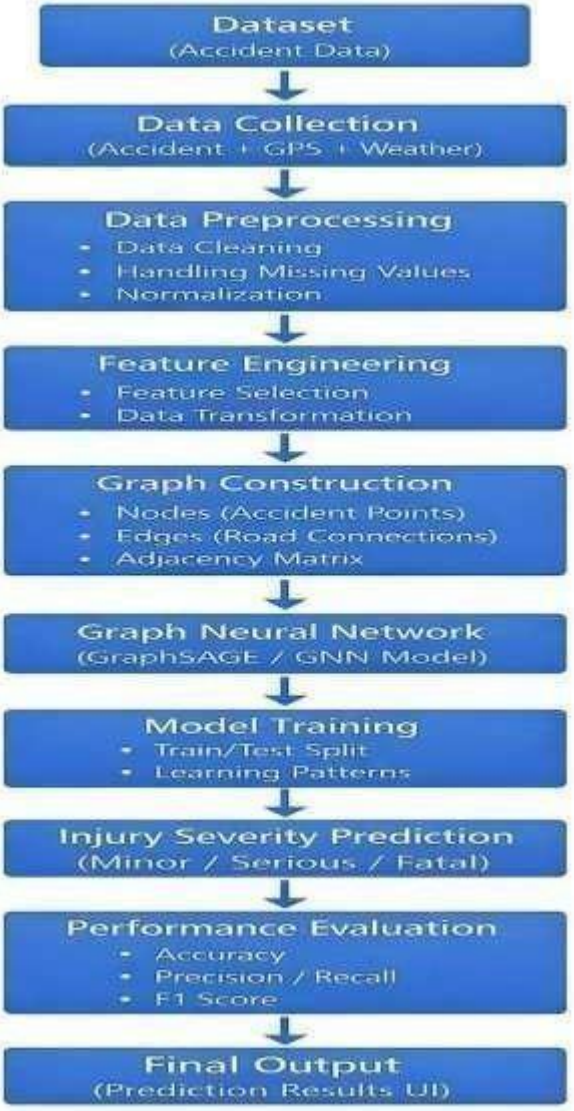


Fig 1.6: Block diagram of proposed system.

Advantages:

These benefits make the system highly valuable for real-world applications, especially in transportation safety and decision-making.

• Faster Processing

The system automates the entire workflow, including data preprocessing, feature extraction, and prediction.

• Higher Accuracy

By using advanced machine learning and graph-based models, the system minimizes human errors and improves prediction accuracy.

• Improved User Convenience

The system is designed with a simple and user-friendly interface that allows users to easily input data and obtain results. Even users with minimal technical knowledge can operate the system efficiently.

• Better Data Management

All accident-related data is stored in an organized and secure manner within the database. This enables easy retrieval, updating, and analysis of data whenever required.

• Enhanced Efficiency

The system streamlines multiple processes such as data collection, processing, and prediction into a single workflow. This reduces redundancy and improves productivity.

• Secure System

Security is an important aspect of the system. It includes features such as user authentication, data validation, and secure storage mechanisms to protect sensitive information.

• Scalability

The system is designed to handle large volumes of accident data efficiently. As the dataset grows, the system can scale without significant performance degradation.

• Real-Time Analysis

One of the key advantages of the system is its ability to provide real-time predictions. As soon as the data is entered, the system processes it instantly and generates results.

• Better Decision Support

The system provides valuable insights based on data analysis, helping authorities and policymakers make informed decisions.

• Reduced Manual Work

Automation significantly reduces the need for manual intervention in data processing and analysis. This not only saves time but also reduces the chances of human errors.

• Reliability

The system is designed to deliver consistent and dependable results over time. It performs accurately under different conditions and datasets, ensuring trust and reliability.

1.7 Input and Output Design

Input Design

The input design of this project focuses on gathering, organizing, and preparing all road crash–related data required for modeling injury severity using a Graph Neural Network (GNN). It begins by collecting diverse datasets, including crash records, road network topology, traffic flow information, vehicle characteristics, weather conditions, and surrounding environmental features.

These raw inputs undergo preprocessing steps such as data cleaning, handling missing values, normalization, and encoding to ensure consistency and compatibility across all sources. The goal is to convert heterogeneous real-world data into a structured and machine-readable format.

To enable GNN-based learning, the input design constructs a graph where each road segment or intersection functions as a node, and the connections or adjacency relationships form edges. Relevant crash features are assigned as node attributes, while spatial dependencies are captured through edge features. This graph-based representation ensures that the model can effectively learn both local and global spatial patterns of road networks.

By designing inputs in a graph format, the system supplies the GNN with rich contextual information that enhances its ability to accurately predict injury severity and identify high-risk road segments.

Objectives

1. To organize and preprocess all crash-related data (road features, traffic, weather, vehicle details) into a clean, consistent, and machine-readable format.

2. To construct a graph-based input structure where road segments act as nodes and their connections form edges, enabling the GNN to learn spatial relationships.

3. To ensure accurate feature representation so that the GNN model can effectively capture patterns and dependencies influencing road crash injury severity.

Output Design

Output design refers to the way the results generated by the system are formatted, displayed, and delivered to the end user. In this project, the output includes prediction results of road crash injury severity, visualization of risk factors, and performance evaluation metrics of the GNN model. These outputs are structured in a clear and readable manner so that users can quickly understand the level of risk, contributing factors, and overall model accuracy.

The output design also focuses on presenting complex analytical results through simplified visual elements such as graphs, charts, and tables. These visual outputs help stakeholders such as traffic authorities, analysts, and policymakers easily interpret the patterns and relationships identified by the model. By providing clean, consistent, and user-friendly outputs, the system enhances decision-making, improves accessibility of insights, and supports effective communication of findings.

CHAPTER-2

LITERATURE SURVEY

2. LITERATURE SURVEY

1. **Sharma A., Verma P., "Graph Neural Network-Based Framework for Road Accident Severity Prediction Using Spatial and Temporal Data," ICITS, 2026.** This study proposes an advanced GNN-based framework that integrates both spatial and temporal information to predict road accident severity more accurately. The model captures complex relationships between accident locations, traffic conditions, and environmental factors. Experimental results show improved prediction accuracy compared to traditional machine learning methods.
2. **Ranjith Reddy K., "An Enhanced and Refined Clustering Strategy for Crisis Management to Optimize Ambulance Performance in Road Accidents," Scopus Conference,2025.** This research introduces a clustering-based approach to improve emergency response systems, particularly ambulance allocation during road accidents. The model groups accident-prone regions to optimize response time and resource utilization. Results demonstrate significant improvements in emergency handling efficiency.
3. **Rivera J., Chen X., "Multi-Graph Fusion GNN for Injury Severity Estimation," Information_Fusion,2025.** This paper presents a multi-graph fusion approach that integrates different types of graph structures, including road networks, crash events, and driver behavior. The model uses cross-graph learning to improve prediction accuracy. Results show superior performance compared to single-graph models. The study demonstrates how combining multiple data sources enhances learning capability.
4. **Singh M., Park S., "Multimodal Geo-Spatial GNN for Severity Prediction," IEEE T-ITS,2024.** The paper integrates multiple data sources such as satellite images, traffic sensors, and crash records into a unified graph model. Deep learning techniques are used to extract features from visual and spatial data. The results show improved performance in complex road environments.
5. **Tiwari R., Patra R. K., "Vehicle Detection and Speed Estimation Using Deep Learning,"ICCCMLA,2024.**This work focuses on using deep learning techniques for real-time vehicle detection and speed estimation. The model utilizes computer vision algorithms to monitor traffic behavior and detect violations.

6. **Ahmed R., Zhou Q., "Attention-Based Graph Neural Networks for Crash Severity Prediction,"Journal of Safety Research,2023.** This research applies Graph Attention Networks to assign importance weights to different accident-related features. The attention mechanism helps identify key factors influencing crash severity. Results show improved interpretability and prediction performance. The model performs better in heterogeneous and complex environments.
7. **Fang S., Oliveira P., "Heterogeneous Graph Modeling for Multi-Entity Crash Data," Expert Systems with Applications,2022.** The study develops a heterogeneous graph model incorporating different entities such as drivers, vehicles, and road conditions. It enables the system to capture interactions between multiple factors. Results show improved accuracy in complex multi-vehicle scenarios. The approach enhances robustness in urban traffic conditions.
8. **Zhao L., Green M., "Temporal Graph Neural Networks for Dynamic Crash Severity Analysis,"Transportation Research Part C, 2021.**This paper introduces a temporal GNN model that captures time-dependent changes in traffic patterns and weather conditions. The model dynamically updates graph representations over time. Results show improved prediction stability during peak traffic and weather variations.
9. **Wong Z., Patel R., "Infrastructure-Aware Graph Neural Network for Injury Prediction,"IEEE Access,2020.** This research focuses on incorporating road infrastructure features such as lane width, signage, and surface quality into graph models. The GNN identifies structural weaknesses in road networks. Results show better detection of high-risk zones. The study supports infrastructure-based accident prevention strategies.
10. **Yu H., El-Basyouny K., "Crash Injury Severity Analysis Using Graph Convolutional Networks,"Accident Analysis Prevention,2019.** This study presents one of the early applications of Graph Convolutional Networks for crash severity analysis. The model captures spatial relationships between accident locations. Results show improved accuracy compared to traditional statistical models. The research highlights the capability of GCNs in handling complex dependencies. It serves as a foundation for later GNN-based approaches.

Focused Area/ Title	Key Findings	Reference
Graph Neural Network-Based AccidentSeverity Prediction [1]	Proposes a GNN framework that captures spatial and temporal relationships in road networks. Improves prediction accuracy by modeling complex dependencies between accident locations and environmental factors.	A. Sharma and P. Verma, Proc. ICITS, 2026
Clustering-Based Emergency Response Optimization [2]	Introduces clustering techniques to optimize ambulance deployment and reduce response time in accident-prone areas. Enhances crisis management and improves survival rates.	K. Ranjith Reddy, Scopus Conference (CSE), 2025
Multi-Graph Fusion for Injury Severity Estimation [3]	Uses multiple graph structures to integrate road network, crash events, and driver behavior. Improves performance through cross-graph learning and feature fusion.	J. Rivera and X. Chen, Information Fusion, 2025
Multimodal Geo-Spatial GNN for Prediction [4]	Combines satellite imagery, traffic sensors, and crash data. Demonstrates higher accuracy in complex environments using multimodal learning.	M. Singh and S. Park, IEEE T-ITS, 2024
Vehicle Detection and Speed Estimation Using Deep Learning [5]	Applies deep learning for real-time vehicle detection and speed estimation. Supports accident prevention and traffic monitoring.	R. Tiwari and R. K. Patra, ICCCMLA, 2024

Table no. 2 Literature Review Summary

Focused Area/ Title	Key Findings	Reference
Attention-Based GNN for Crash Severity [6]	Uses attention mechanisms to identify important features influencing accident severity. Improves interpretability and prediction stability.	R. Ahmed and Q. Zhou, Journal of Safety Research, 2023
Heterogeneous Graph Modeling for Multi-Entity Data [7]	Models interactions between drivers, vehicles, and road conditions using heterogeneous graphs. Enhances prediction in complex scenarios.	S. Fang and P. Oliveira, Expert Systems with Applications, 2022
Temporal GNN for DynamicCrash Analysis [8]	Incorporates time-based data such as traffic flow and weather changes. Improves prediction accuracy by capturing temporal variations.	L. Zhao and M. Green, Transportation Research Part C, 2021
Infrastructure-Aware GNN for Injury Prediction [9]	Analyzes road infrastructure features like lane width and road quality. Identifies high-risk zones and supports safety planning.	Z. Wong and R. Patel, IEEE Access, 2020
Graph Convolutional Networks for Severity Analysis [10]	Early application of GCNs for accident severity prediction. Shows better accuracy compared to traditional models.	H. Yu and K. El-Basyouny, Accident Analysis & Prevention, 2019

Table no. 2 Literature Review Summary

CHAPTER-3

SOFTWARE REQUIREMENT ANALYSIS

3. SOFTWAREREQUIREMENT ANALYSIS

3.1 ModulesandTheir Functionalities

3.1.1 Data Analysis

The data analysis of this project involves several interconnected modules that work together to process and interpret road-crash information efficiently. The system begins with data collection, where crash records, road network details, and environmental factors are gathered from multiple sources. Next, preprocessing cleans, normalizes, and transforms the raw data to remove noise and inconsistencies. The graph construction module then converts this refined data into a road-network graph by defining nodes, edges, and spatial relationships. Feature engineering enriches each node and edge with meaningful attributes needed for GNN learning. Finally, the GNN training, prediction, and evaluation modules analyze the graph, classify injury severity levels, and generate interpretable results for decision-making.

3.1.2 Data Preprocessing

Data Processing involves converting raw crash datasets into a structured and usable form that can support accurate injury severity prediction through the GNN framework. It includes cleaning the data by removing duplicates, handling missing values, and correcting inconsistencies. Numerical features are normalized, and categorical attributes such as road type or weather conditions are encoded for model compatibility. Spatial and temporal information is also aligned to ensure proper graph construction later in the pipeline. Overall, data processing ensures that only high-quality, well-organized, and meaningful data is passed to subsequent modules for analysis and prediction.

In addition to basic preprocessing, advanced data processing techniques are applied to improve the quality and relevance of the dataset. Feature engineering is performed to create new meaningful attributes, such as traffic density levels, accident frequency in specific regions, and time-based patterns like peak-hour indicators. Outliers that may negatively affect model performance are carefully identified and handled to maintain data consistency. Furthermore, the dataset is split into training, validation, and testing sets to ensure proper model evaluation. This stage also involves balancing the dataset to address class imbalance issues, especially for severe and fatal crashes, thereby improving the model's ability to learn and generalize effectively.

3.1.3 Machine Learning Algorithm for Prediction

The prediction process in this project uses a **Graph Neural Network (GNN)**, a specialized machine learning algorithm designed to learn patterns from graph-structured road-crash data. Unlike traditional models, the GNN captures spatial relationships between road segments, connectivity patterns, and contextual crash factors. Through message passing and node embedding techniques, the model learns how environmental conditions, road features, and traffic attributes influence crash severity. Once trained, the GNN predicts the injury severity level—such as minor, serious, or fatal—with greater accuracy by analyzing both individual crash features and their surrounding network context. This makes the algorithm highly effective for real-world transportation safety analysis.

3.2 Functional Requirements

The system must efficiently process crash-related data, construct graph-based representations, and use a GNN model to accurately predict injury severity levels. It should allow users to input crash details, automatically preprocess and validate the data, and generate meaningful predictions based on learned spatial and contextual patterns. The system must also support visualization features to display severity outcomes and high-risk zones, enabling better decision-making for road safety authorities. Additionally, it should store processed data, maintain model accuracy through periodic updates, and provide reliable and fast responses to new inputs.

1. Thesystem must process and convert crash data into a clean, structured format.
2. Thesystem must build a graph model of the road network from the processed data.
3. Thesystem must use a GNN algorithm to predict the injury severity level.
4. The system must display the prediction results clearly to the user.

3.2.1. Data Ingestion and Preprocessing

- The system shall allow importing of road accident datasets in structured formats (CSV/Excel).
- The system shall perform preprocessing steps such as:
  - Handling missing values
  - Label encoding for categorical data
  - Feature normalization or standardization

3.2.2. Graph Construction

- The system shall construct a graph structure from tabular accident data using spatial features like latitude, longitude, or accident location.
- The graph shall be constructed using a k-Nearest Neighbors (kNN) algorithm to identify relationships between similar nodes (accident cases).

3.2.3. Model Integration

- The system shall integrate and allow training of multiple ML/DL models such as:
    - ❖ Extra Trees Classifier
    - ❖ Voting Classifier
    - ❖ Graph Neural Network (GraphSAGE)
- The system shall enable comparison between the performances of these models.

3.2.4. Model Training and Testing

- The system shall train the models using a training subset of the dataset and evaluate them on the testing subset.
- The system shall support metrics evaluation like:
    a) Accuracy
    b) Precision
    c) Recall
    d) F1 Score
    e) Confusion Matrix
    f) Matthews Correlation Coefficient (MCC)

3.2.5. Result Visualization

- The system shall display graphical representations such as confusion matrices, model comparison charts, and accuracy graphs for better interpretation of results.

3.2.6. Prediction Functionality

- The system shall allow input of new accident data (manual or batch) to predict injury severity (Slight, Serious, Fatal) using the best-performing model.

3.2.7. Logging and Result Storage

- The system shall log model performance metrics for each run and store them for result analysis or report generation.

3.3 Non-Functional Requirements

The system must operate with high reliability, ensuring consistent performance even with large and complex crash datasets. It should deliver predictions with minimal delay, maintaining fast response times for real-time decision support. The platform must be secure, protecting sensitive crash and road data through proper access control and encryption. Additionally, the system should be scalable, allowing future expansion of datasets, model updates, and integration with new data sources without performance degradation.

1. The system must ensure fast response time for all prediction operations.
2. Thesystem must maintain high accuracy and reliability during data processing and prediction.
3. Thesystem must provide secure handling and storage of all crash-related data.

The non-functional requirements describe the system constraints.

3.3.1 Performance

- The system should ensure that predictions and training are completed in a reasonable Time frame.
- Preprocessing and training on medium-sized datasets (~100K records) should complete less than 2 minutes on a standard laptop.

3.3.2 Accuracy and Precision

- The system should maintain a minimum of 85% accuracy on test data for predictions.
- Model selection should be based on optimizing the F1 Score and MCC for class imbalance.

3.3.3 Scalability

- The system architecture should support easy scaling for larger data sets.

Modules should be loosely coupled to allow switching or adding new machine learning models without major changes.

3.3.4 Reliability

- The system must provide consistent predictions for the same input data across runs.
- Proper exception handling must be implemented to handle runtime errors.

3.3.5 Maintainability

- The codebase should be modular, well-commented, and follow standard practices to allow future developers to understand and update the system easily.

3.4 Feasibility Study

The feasibility study evaluates whether the proposed system can be successfully developed and implemented considering technical, economic, and operational factors. It examines the availability of required technologies, the cost–benefit balance, and the ability of users and the organization to adopt the system effectively. This analysis ensures that the project is practical, achievable, and worth pursuing before moving into detailed design and development.

1.Economic Feasibility 2.Technical Feasibility
3.Social Feasibility

3.4.1 Economic Feasibility

Economic feasibility evaluates whether the proposed system is financially viable by comparing the estimated development and operational costs with the expected benefits. It determines if the project will provide sufficient returns in terms of cost savings, improved productivity, or increased revenue. If the long-term benefits outweigh the total investment, the system is considered economically feasible and worth implementing.

3.4.2 Technical Feasibility

Technical feasibility examines whether the required technology, tools, and technical skills needed to develop the system are available and adequate. It checks if the existing hardware, software platforms, network infrastructure, and technical expertise can support the proposed solution without major risks. This study ensures that the project can be developed using reliable, scalable, and compatible technologies within the organization's technical capacity.

3.4.3 Social Feasibility

Social feasibility of a road crash severity prediction system using a GNN (Graph Neural Network) framework evaluates how beneficial and acceptable the system is to society. By accurately predicting accident severity, it can help authorities respond faster, improve road safety measures, and reduce injuries and fatalities, directly benefiting the public. Additionally, it considers community acceptance, ethical use of data, privacy concerns, and the potential to raise awareness about high-risk areas.

CHAPTER-4

SYSTEM SPECIFICATIONS

4. SYSTEM SPECIFICATIONS

4.1 Software Requirements

The **software requirements** for a road crash severity prediction system using a GNN framework define the necessary software tools and platforms needed to develop, implement, and maintain the system. These requirements include programming environments, libraries, and frameworks for data processing, machine learning, and visualization, ensuring the system runs efficiently, reliably, and securely. Proper software requirements help streamline development, facilitate model training, and ensure compatibility with existing systems used by traffic authorities.

1. Programming languages like Python for implementing GNN models.
2. Libraries and frameworks such as PyTorch, TensorFlow, DGL, or PyG for graph neural network operations.
3. Data processing and visualization tools like Pandas, NumPy, and Matplotlib/Seaborn.
4. IDEs and platforms such as Jupyter Notebook, VS Code, or Anaconda for development and testing.
5. Database management systems like MySQL, PostgreSQL, or MongoDB to store and manage road crash datasets efficiently.

4.2 Hardware Requirements

The hardware requirements for a road crash severity prediction system using a GNN framework specify the physical components needed to develop, train, and deploy the system efficiently. Since GNN models involve heavy computations, sufficient processing power, memory, and storage are essential for handling large datasets and performing real-time predictions. Appropriate hardware ensures smooth model training, faster data processing, and reliable system performance for practical use by traffic authorities.

1. **Processor (CPU):** High-performance multi-core processor for efficient computations.
2. **Graphics Processing Unit (GPU):** Dedicated GPU like NVIDIA for accelerated GNN training.
3. **RAM:** At least 16–32 GB RAM to handle large datasets and model operations.

CHAPTER-5

SOFTWARE DESIGN

5. SOFTWARE DESIGN

5.1 System Architecture

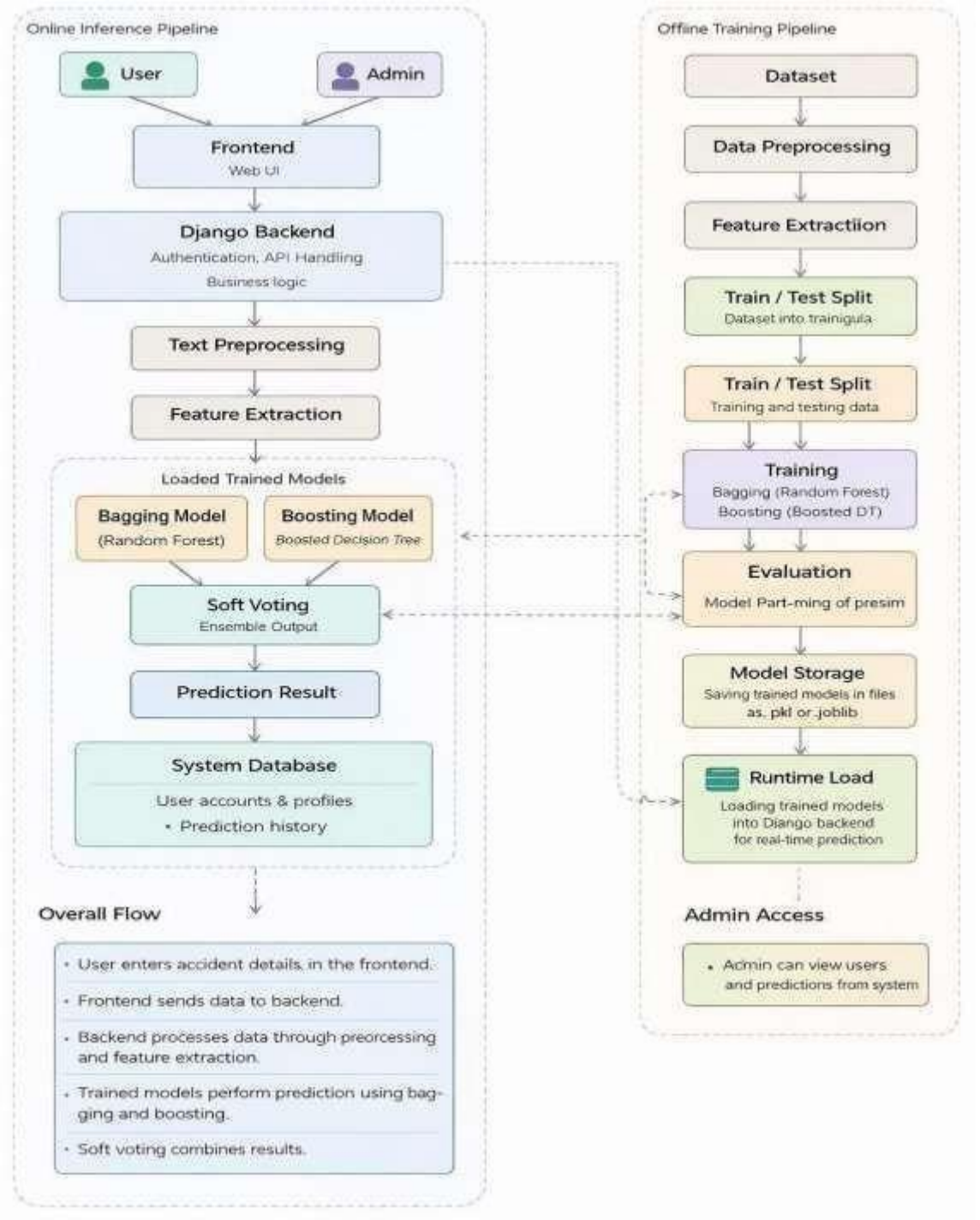


Fig: 5.1 System Architecture

The system architecture of a road crash severity prediction system using a Graph Neural Network (GNN) framework is designed to systematically collect, process, and analyze large-scale traffic and accident data to provide accurate predictions. The architecture is modular, consisting of key components such as data acquisition, data preprocessing, graph construction, GNN-based model training, prediction, and result visualization. Each module is interconnected to ensure the seamless flow of information, enabling efficient processing of raw accident data into actionable insights. The design emphasizes scalability, allowing the system to handle growing datasets from multiple regions, and reliability, ensuring consistent predictions to support traffic safety planning and decision-making.

The first stage of the architecture involves data acquisition, where information related to road crashes, vehicle details, driver behavior, environmental conditions, and traffic density is collected from multiple sources such as traffic cameras, GPS devices, police reports, and sensor networks. This raw data is often heterogeneous, containing numerical, categorical, and spatial features, which requires extensive data preprocessing including cleaning, normalization, missing value handling, and feature selection. Once preprocessed, the data is transformed into a graph structure, with nodes representing entities like accident locations, vehicles, or road segments, and edges representing their relationships such as spatial proximity, traffic flow, or accident co-occurrence.

After training, the system performs severity predictions, classifying accidents into categories such as minor, moderate, or severe. The results are presented through an interactive user interface, which includes dashboards, heatmaps, and alert systems to highlight high-risk zones and potential accident hotspots. The architecture also supports integration with emergency response systems and traffic management platforms, enabling real-time decision-making and proactive measures to reduce accidents. Security and privacy measures are incorporated to protect sensitive data, while the modular design allows easy updates, expansion, or adaptation to different regions or datasets. Overall, this architecture ensures an effective, reliable, and socially responsible system that not only improves road safety but also assists policymakers and authorities in strategic planning and risk mitigation.

5.2 Dataflow Diagram

The Data Flow Diagram (DFD) of the road crash severity prediction system using a GNN framework illustrates how data moves through the system from input to output. It shows the interaction between external entities, processes, and data stores, providing a clear view of how raw accident data is transformed into useful predictions. The DFD helps developers and stakeholders understand system operations, identify potential bottlenecks, and ensure data is managed efficiently, securely, and accurately.

Data is collected from multiple sources, including traffic sensors, GPS devices, weather monitoring systems, and accident reports. The data enters the preprocessing module, where it is cleaned, normalized, and formatted for further processing. Next, the graph construction module organizes the information into nodes and edges representing road segments, vehicles, accident locations, and their relationships. The GNN processing module then analyzes this graph data, learning spatial and relational dependencies to predict the severity of accidents. Feedback from predictions and user validation can also be fed back into the system to improve future accuracy.

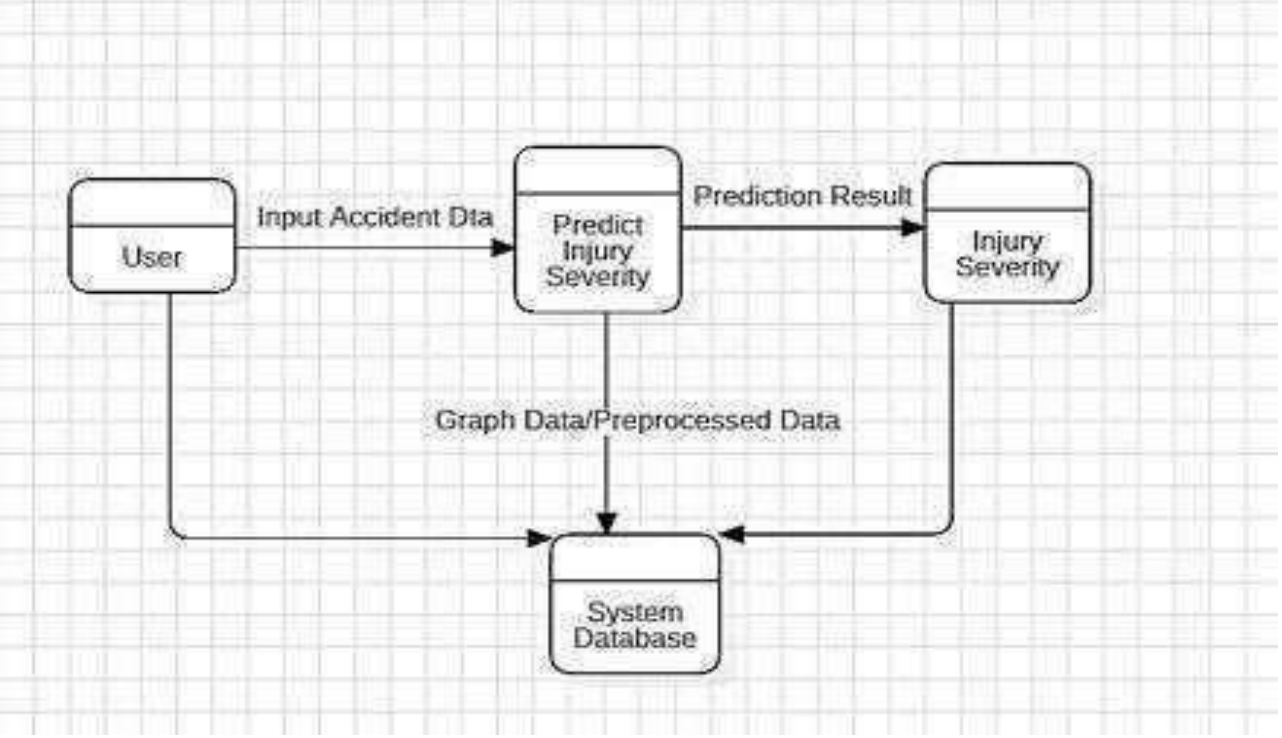


Fig 5.2 Dataflow Diagram

5.3 UMLDiagrams

UML (Unified Modeling Language) is a standardized language used for specifying, visualizing, constructing, and documenting the artifacts of software systems. UML helps in representing the design of systems and understanding their components. Created by the Object Management Group (OMG), UML 1.0 was proposed in January 1997. UML is closely associated with object-oriented analysis and design. The two main categories of UML diagrams are Behavioral and Structural diagrams, each serving distinct purposes in the modeling process.

The Behavioral UML diagrams describe the behavior of the system, its actors, and the interaction between the components. On the other hand, Structural UML diagrams depict the static structure of the system, showing its components and relationships. UML has been integrated as a standard by OMG, and its primary goals are to provide a formal basis for understanding modeling languages, offer a ready-to-use expressive language for system developers, and encourage the growth of object-oriented tools.

Goals of UML:

- To provide a standard visual representation of the system design.
- To simplify understanding of system architecture for developers and reviewers.
- To improve communication among team members during development.
- To model both structural and behavioral aspects of the system.
- To support object-oriented design and development practices.
- To document the system clearly for future reference and maintenance.

Types of UML Diagrams:

1. Sequence Diagram
2. Use Case Diagram
3. Activity Diagram
4. Class Diagram

5.3.1.Sequence Diagram

A Sequence Diagram is a type of UML behavioral diagram that represents how objects or components in a system interact with each other over time. It focuses on the order of messages exchanged between system entities to achieve a specific functionality. In the context of a road crash severity prediction system using a GNN framework, the sequence diagram shows the flow of information from data collection to preprocessing, graph construction, GNN model processing, and finally generating predictions. It highlights the chronological sequence of interactions between modules such as the Data Collector, Preprocessing Module, Graph Constructor, GNN Model, and Output Interface, providing a clear understanding of system operations.

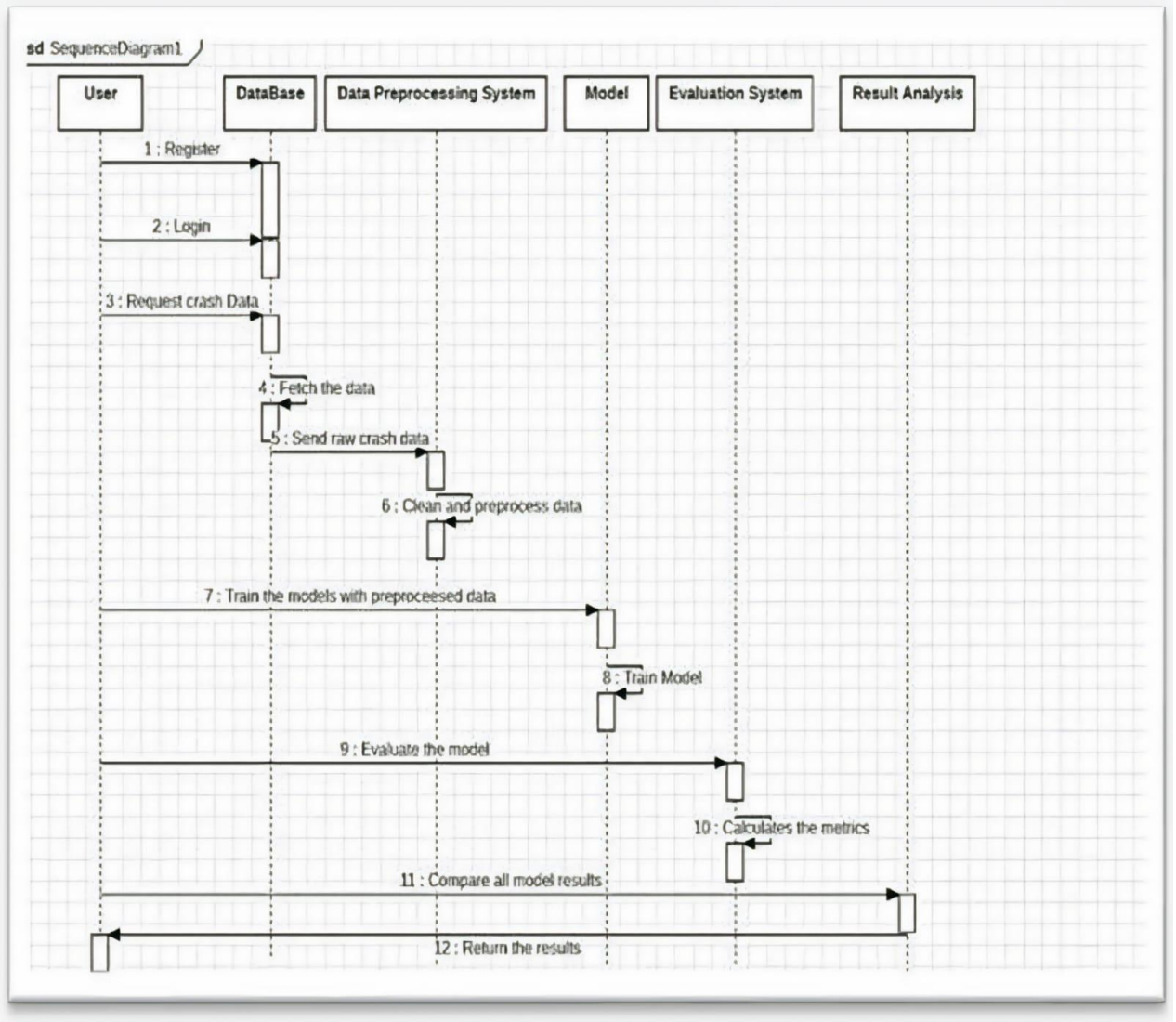


Fig 5.3.1: Sequence Diagram

List of actions

1. **Register:** The user registers in the system.
2. **Login:** The user logs into the system.
3. **Request Crash Data:** The user requests road crash data.
4. **Fetch the Data:** The database retrieves the requested crash data.
5. **Send Raw Crash Data:** The database sends raw crash data to the data preprocessing system.
6. **Clean and Preprocess Data:** The data preprocessing system cleans and preprocesses the raw crash data.
7. **Train the Models with Preprocessed Data:** The preprocessed data is sent to the model for training.
8. **Train Model:** The model is trained using the preprocessed crash data.
9. **Evaluate the Model:** The evaluation system evaluates the trained model.
10. **Calculate Metrics:** The evaluation system calculates performance metrics of the model.
11. **Compare All Model Results:** The evaluation system compares results from multiple models.
12. **Return the Results:** The final results are returned to the user.

5.3.2 Use Case Diagram

A Use Case Diagram illustrates the interactions between users (actors) and the road crash severity prediction system, highlighting the functional requirements of the system. In this system, the primary actor is the User, who can perform actions such as register, login, request crash data, view predictions, and receive alerts. The system itself encompasses modules like Database, Data Preprocessing, Model Training, Evaluation, and Result Analysis, which collectively handle data management, prediction processing, and output generation. The use case diagram provides a visual representation of how users and system components collaborate, ensuring that all system functionalities are captured clearly for analysis, design, and implementation.

Furthermore, the use case diagram helps in identifying the flow of information and the sequence of interactions between the user and the system components. It clearly defines system boundaries and distinguishes between user-driven actions and automated system processes such as data processing, model execution, and prediction generation. By visualizing these interactions, developers can better understand user requirements, improve system usability, and ensure that all critical functionalities are included during development. Additionally, it serves as a valuable reference during testing and validation, helping to verify that the system behaves as expected and meets the intended objectives of accurate crash severity prediction and efficient user interaction.

Finally, the analyst analyzes the results to assess model effectiveness and identify areas for improvement. This separation of training and inference ensures modularity, scalability, and clarity in system design.

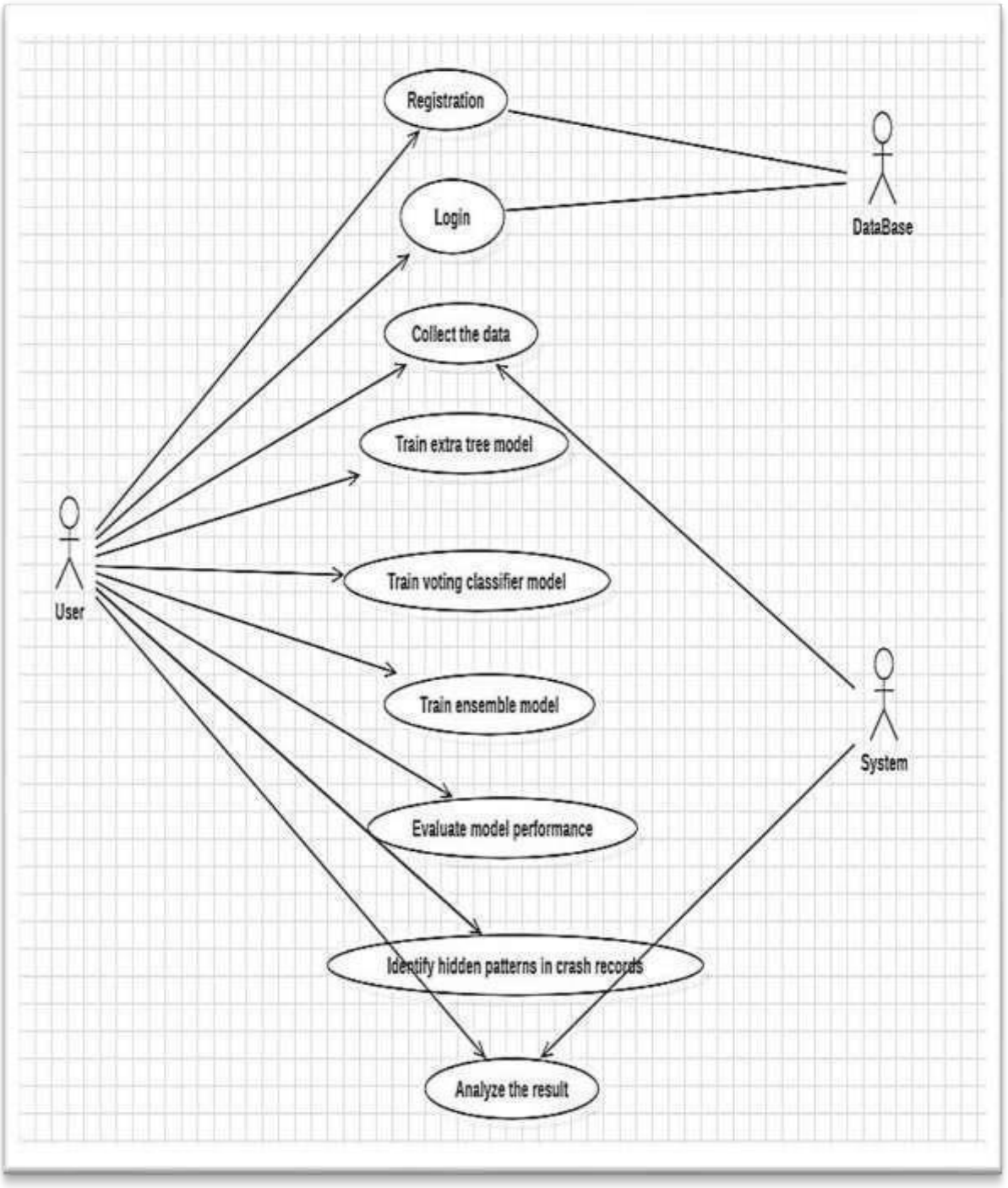


Fig 5.3.2 Use Case Diagram

5.3.3 Activity Diagram

The activity diagram for road crash injury severity using a GNN framework begins with collecting data from traffic sensors, vehicles, and accident records. The data undergoes preprocessing and graph construction, where nodes represent vehicles, drivers, or road segments and edges represent interactions or proximities. Features like speed, road conditions, and weather are extracted for nodes and edges. The GNN model processes this graph to learn relational patterns and predict injury severity. The predictions are then evaluated, and the system incorporates feedback for continuous improvement in accuracy and decision-making for traffic safety.

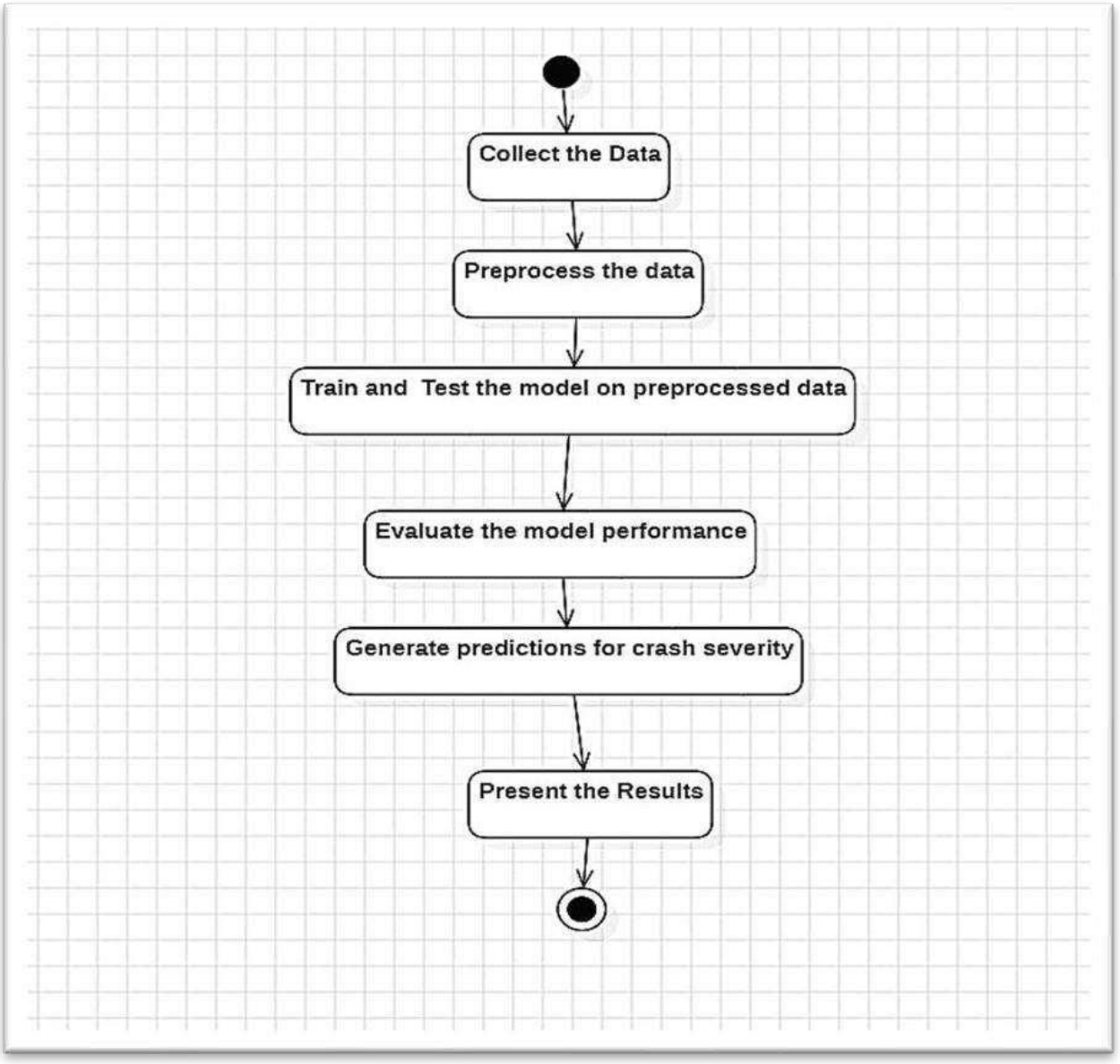


Fig 5.3.3 Activity Diagram

5.3.4. Class Diagram

The system is centered around a GNNModel class that predicts injury severity by processing crash data as graphs. The CrashData class holds raw accident details like location, vehicle type, speed, weather conditions, and injury severity, and connects to a Preprocessor class for cleaning, normalization, and feature encoding. The GraphBuilder class transforms preprocessed data into graph structures, representing nodes (vehicles, road segments) and edges (interactions or proximity). A Trainer class handles model training, validation, and loss computation, while the Evaluator class assesses performance using metrics like accuracy, F1-score, and confusion matrix.

The Visualizer class supports plotting graphs and dashboards. Key relationships include GNNModel aggregating GraphBuilder, Trainer and Evaluator depending on GNNModel, and Preprocessor used by GraphBuilder and Trainer, ensuring a modular, scalable, and interpretable framework for crash severity prediction.

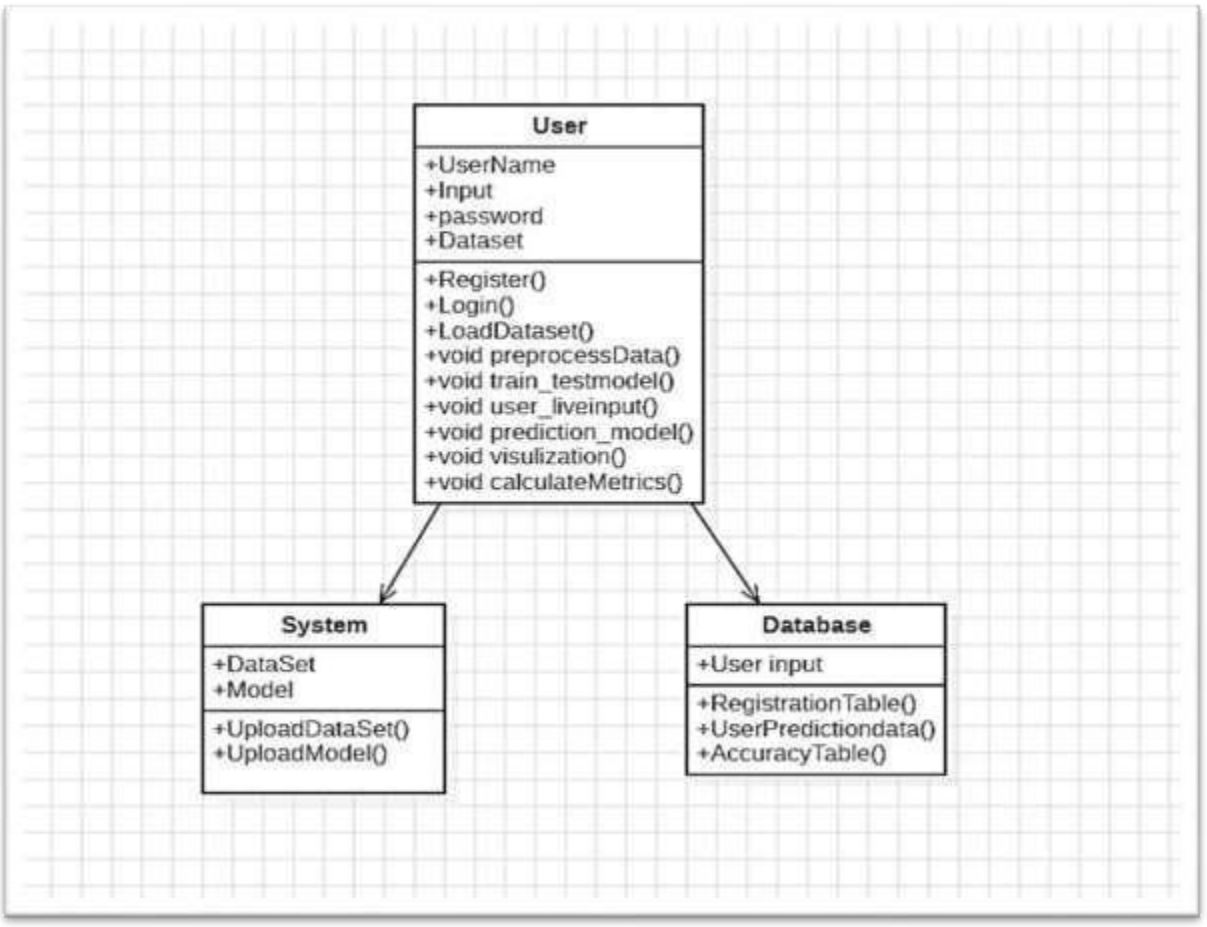


Fig 5.3.4 Class Diagram

CHAPTER-6

CODING AND IMPLEMENTATION

6. CODING AND IMPLEMENTATION

6.1 Source Code

```
import warnings
warnings.filterwarnings('ignore')
```

```
import pandas as pd
import torch
import numpy as np
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Load the dataset
data = pd.read_csv('UK_Accident.csv')
```

```
null_counts = data.isnull().sum()
# Print the number of null values
print(f"{null_counts.sum()} null entries have been found in the dataset\n")
# Drop null values
data.dropna(inplace=True)          # or df_data = df_data.dropna()

# Find and handle duplicates
duplicate_count = data.duplicated().sum()
# Print the number of duplicate entries
print(f"{duplicate_count} duplicate entries have been found in the dataset\n")
# Remove duplicates
data.drop_duplicates(inplace=True)  # or df_data = df_data.drop_duplicates()
# Display relative message
print(f"All duplicates have been removed\n")

# Reset the indexes
data.reset_index(drop=True, inplace=True)

# Inspect the dataset for categorical columns
print("Categorical columns:",data.select_dtypes(include=['object']).columns.tolist(),'\n')

# Print the first 5 lines
data.head()
```

3655911 null entries have been found in the dataset

0 duplicate entries have been found in the dataset

All duplicates have been removed

Categorical columns: ['Accident_Index','Date', 'Time', 'Local_Authority_(Highway)', 'Road_Type', 'Junction_Control', 'Pedestrian_Crossing-Human_Control', 'Pedestrian_Crossing-Physical_Facilities', 'Light_Conditions', 'Weather_Conditions', 'Road_Surface_Conditions', 'Special_Conditions_at_Site','Carriageway_Hazards','Did_Police_Officer_Attend_Scene_of_Accident', 'LSOA_of_Accident_Location']

Unnamed: 0	Accident_Index	Location_Easting_OSGR	Location_Northing_OSGR	Longitude	Latitude	Police_Force	Accident_Severity	Number_of_Vehicles	Number_of_Casualties	..	Pedestrian_Crossing-Physical_Facilities
1198	200501CW10234	529750.0	180420.0	-0.131203	51.507759	1	3	1	1	..	Pedestrian phase at traffic signal junction
1289	200501CW10370	529820.0	178400.0	-0.131514	51.489599	1	3	2	1	..	Pedestrian phase at traffic signal junction
1297	200501CW10379	529610.0	181490.0	-0.133403	51.517416	1	2	2	1	..	No physical crossing within 50 meters
1526	200501CW10648	528740.0	180080.0	-0.146449	51.504944	1	3	1	1	..	No physical crossing within 50 meters
4501	200501FH10528	525470.0	176930.0	-0.194658	51.477369	1	3	1	1	..	No physical crossing within 50 meters

ws × 33 columns

Light_Conditions	Weather_Conditions	Road_Surface_Conditions	Special_Conditions_at_Site	Carriageway_Hazards	Urban_or_Rural_Area	Did_Police_Officer_Attend_Scene_of_Accident	LSOA_of_Accident_Locat
Daylight: Street light present	Fine without high winds	Dry	Roadworks	Other object in carriageway	1	Yes	E01004
Daylight: Street light present	Fine without high winds	Dry	Auto traffic singal out	Dislodged vehicle load in carriageway	1	Yes	E01004
Daylight: Street light present	Fine without high winds	Dry	Roadworks	Other object in carriageway	1	Yes	E01004
Daylight: Street light present	Fine without high winds	Dry	Oil or diesel	Dislodged vehicle load in carriageway	1	Yes	E01004
Daylight: Street light present	Fine without high winds	Dry	Roadworks	Other object in carriageway	1	Yes	E01001

```
data = data.drop(columns=['Unnamed: 0','Accident_Index', 'Date', 'Time','LSOA_of_Accident_Location','Local_Authority_(Highway)'], errors='ignore')
```

```
data.info()
```

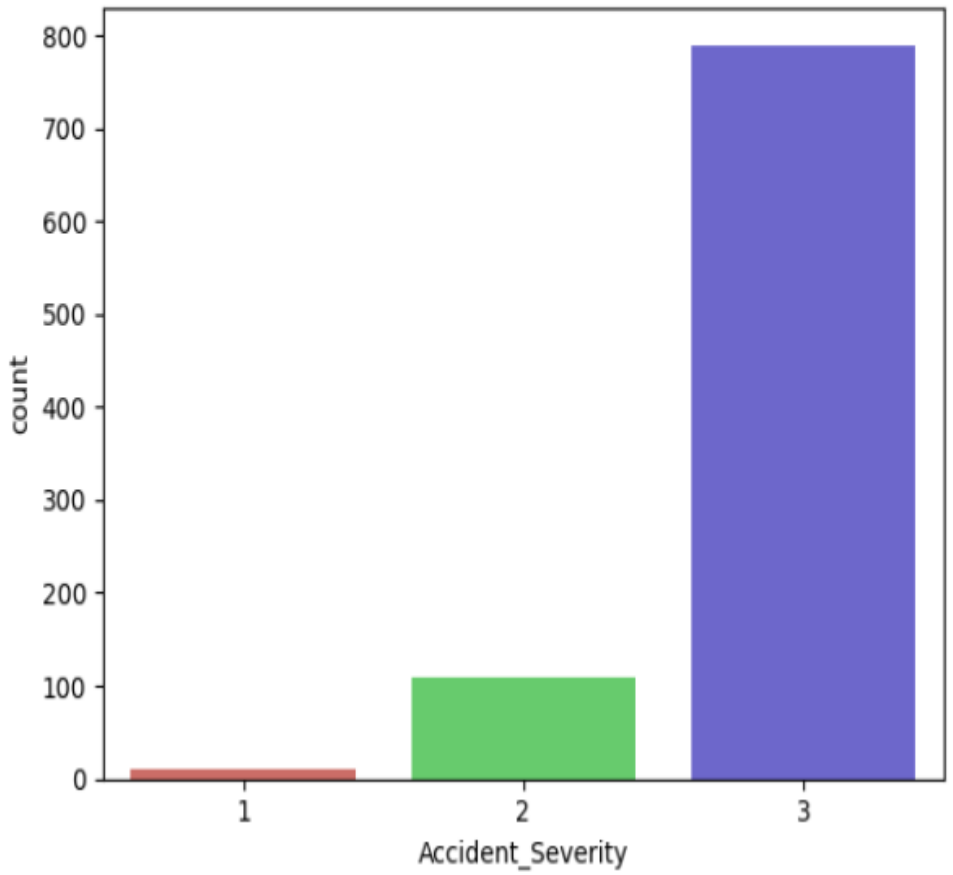
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 910 entries, 0 to 909
Data columns (total 27 columns):
 #   Column                                  Non-Null Count  Dtype  
---  ------                                  --------------  -----  
 0   Location_Easting_OSGR                   910 non-null    float64
 1   Location_Northing_OSGR                  910 non-null    float64
 2   Longitude                               910 non-null    float64
 3   Latitude                                910 non-null    float64
 4   Police_Force                            910 non-null    int64  
 5   Accident_Severity                       910 non-null    int64  
 6   Number_of_Vehicles                      910 non-null    int64  
 7   Number_of_Casualties                    910 non-null    int64  
 8   Day_of_Week                             910 non-null    int64  
 9   Local_Authority_(District)              910 non-null    int64  
 10  1st_Road_Class                          910 non-null    int64  
 11  1st_Road_Number                         910 non-null    int64  
 12  Road_Type                               910 non-null    object 
 13  Speed_limit                             910 non-null    int64  
 14  Junction_Control                        910 non-null    object 
 15  2nd_Road_Class                          910 non-null    int64  
 16  2nd_Road_Number                         910 non-null    int64  
 17  Pedestrian_Crossing-Human_Control       910 non-null    object 
 18  Pedestrian_Crossing-Physical_Facilities 910 non-null    object 
 19  Light_Conditions                        910 non-null    object 
...
 25  Did_Police_Officer_Attend_Scene_of_Accident 910 non-null    object 
 26  Year                                    910 non-null    int64  
dtypes: float64(4), int64(13), object(10)
memory usage: 192.1+ KB
```

Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...

```
print("Categorical columns:",data.select_dtypes(include=['object']).columns.tolist(),'\n')
```

Categorical columns: ['Road_Type', 'Junction_Control', 'Pedestrian_Crossing-Human_Control', 'Pedestrian_Crossing-Physical_Facilities', 'Light_Conditions', 'Weather_Conditions', 'Road_Surface_Conditions', 'Special_Conditions_at_Site', 'Carriageway_Hazards', 'Did_Police_Officer_Attend_Scene_of_Accident']

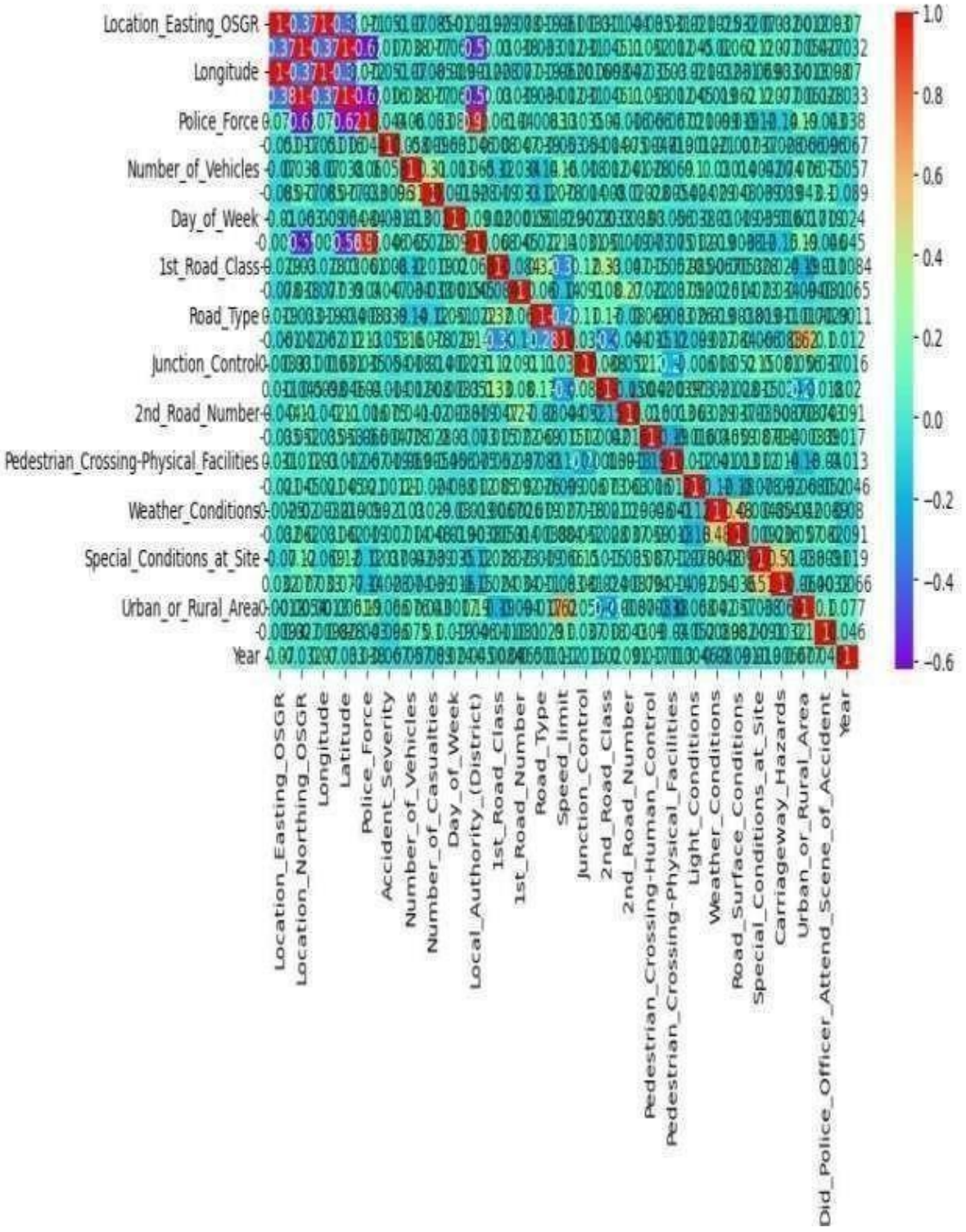
```
sns.countplot(x='Accident_Severity',data=data, palette='hls')
plt.show()
#plt.savefig('count_plot') mal: the nodule malignancy, 0: benign, 1: malignant
```



```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 910 entries, 0 to 909
Data columns (total 27 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   Location_Easting_OSGR                   910 non-null    float64
 1   Location_Northing_OSGR                  910 non-null    float64
 2   Longitude                               910 non-null    float64
 3   Latitude                                910 non-null    float64
 4   Police_Force                            910 non-null    int64
 5   Accident_Severity                       910 non-null    int64
 6   Number_of_Vehicles                      910 non-null    int64
 7   Number_of_Casualties                    910 non-null    int64
 8   Day_of_Week                             910 non-null    int64
 9   Local_Authority_(District)              910 non-null    int64
 10  1st_Road_Class                          910 non-null    int64
 11  1st_Road_Number                         910 non-null    int64
 12  Road_Type                               910 non-null    int32
 13  Speed_limit                             910 non-null    int64
 14  Junction_Control                        910 non-null    int32
 15  2nd_Road_Class                          910 non-null    int64
 16  2nd_Road_Number                         910 non-null    int64
 17  Pedestrian_Crossing-Human_Control       910 non-null    int32
 18  Pedestrian_Crossing-Physical_Facilities 910 non-null    int32
 19  Light_Conditions                        910 non-null    int32
...
 25  Did_Police_Officer_Attend_Scene_of_Accident  910 non-null    int32
 26  Year                                    910 non-null    int64
dtypes: float64(4), int32(10), int64(13)
memory usage: 156.5 KB
```

```
plt.figure(figsize = (10,5))
sns.heatmap(data.corr(), annot = True, cmap="rainbow")
plt.show()
```



```
data.to_csv('processed.csv')
```

```
ML_Model = []
accuracy = []
precision = []
recall = []
f1score = []
mcc = []

#function to call for storing the results
def storeResults(model, a,b,c,d,e):
    ML_Model.append(model)
    accuracy.append(round(a, 3))
    precision.append(round(b, 3))
    recall.append(round(c, 3))
    f1score.append(round(d, 3))
    mcc.append(round(e, 3))
```

GNN

```
import osmnx as ox
import networkx as nx
import torch_geometric.utils as pyg_utils
from torch_geometric.data import Data
```

```
import torch.nn.functional as F
from torch_geometric.nn import SAGEConv
```

```
# Normalize features
scaler = StandardScaler()
features = scaler.fit_transform(data.drop(columns=['Accident_Severity'], errors='ignore'))
```

Generate + Code + Markdown

Start Chat to Generate Code (Ctrl+I)

```
# Convert labels to numerical format
labels = data['Accident_Severity'].astype('category').cat.codes
```

```
# Convert to tensor
x = torch.tensor(features, dtype=torch.float)
y = torch.tensor(labels.values, dtype=torch.long)
```

```python
# Define the GraphSAGE model
class GraphSAGE(torch.nn.Module):
    def __init__(self, in_channels, hidden_channels, out_channels):
        super(GraphSAGE, self).__init__()
        self.conv1 = SAGEConv(in_channels, hidden_channels)
        self.conv2 = SAGEConv(hidden_channels, out_channels)

    def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        return F.log_softmax(x, dim=1)
```

```python
# Create a dummy edge_index (fully connected graph) for simplicity
edge_index = torch.tensor([[i, j] for i in range(x.shape[0]) for j in range(x.shape[0]) if i != j], dtype=torch.long).t().contiguous()

# Create a PyTorch Geometric Data object
df = Data(x=x, edge_index=edge_index, y=y)
```

```python
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = GraphSAGE(in_channels=x.shape[1], hidden_channels=16, out_channels=len(y.unique())).to(device)
optimizer = torch.optim.Adam(model.parameters(), lr=0.01, weight_decay=5e-4)
criterion = torch.nn.CrossEntropyLoss()
```

```python
df = df.to(device)
```

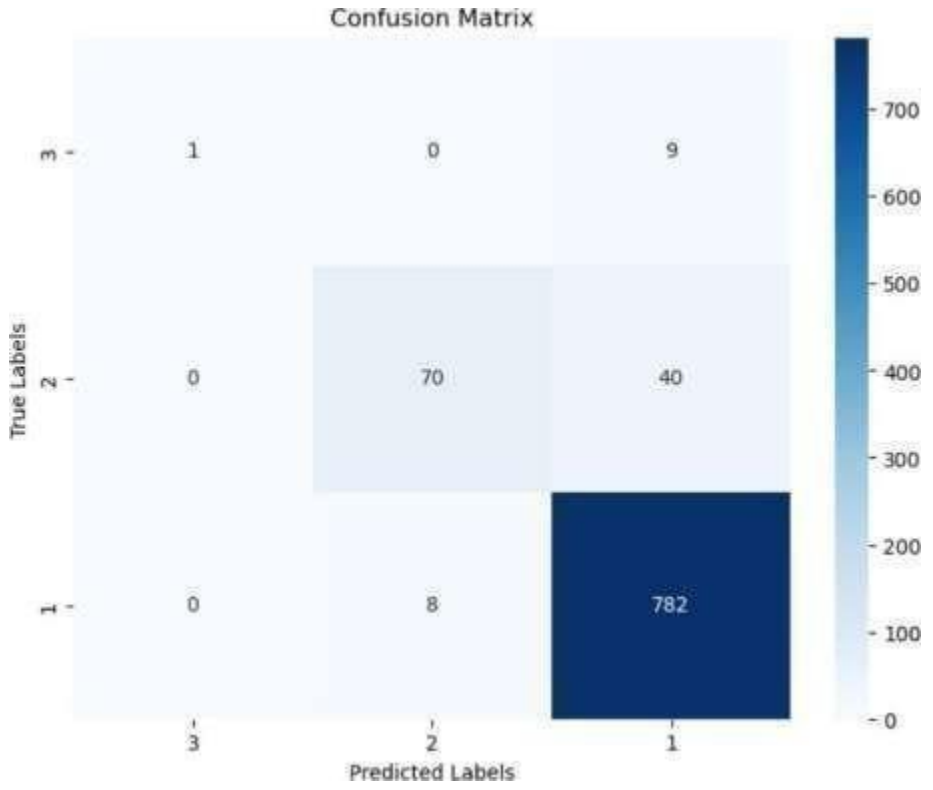
```python
# Training loop
model.train()
for epoch in range(200):
    optimizer.zero_grad()
    out = model(df)
    loss = criterion(out, df.y)
    loss.backward()
    optimizer.step()
    if epoch % 20 == 0:
        print(f'Epoch {epoch}, Loss: {loss.item():.4f}')
```

```
Epoch 0, Loss: 1.0730
Epoch 20, Loss: 0.4360
Epoch 40, Loss: 0.3837
Epoch 60, Loss: 0.3566
Epoch 80, Loss: 0.3272
Epoch 100, Loss: 0.2953
Epoch 120, Loss: 0.2642
Epoch 140, Loss: 0.2365
Epoch 160, Loss: 0.2101
Epoch 180, Loss: 0.1861
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix,matthews_corrcoef
```

```
model.eval()

# Get model predictions
_, pred = model(df).max(dim=1)

# Convert to numpy arrays
y_true = df.y.cpu().numpy()
y_pred = pred.cpu().numpy()
```

```
# Calculate confusion matrix
conf_matrix = confusion_matrix(y_true, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=data['Accident_Severity'].unique(), yticklabels=data['Accident_Severity'].unique())
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
gnn_acc = accuracy_score(y_true, y_pred)
gnn_prec = precision_score(y_true, y_pred, average='weighted')  # Weighted for class imbalance
gnn_rec = recall_score(y_true, y_pred, average='weighted')
gnn_f1 = f1_score(y_true, y_pred, average='weighted')
gnn_mcc = matthews_corrcoef(y_true, y_pred)
```

```
storeResults('GNN-GraphSage',gnn_acc,gnn_prec,gnn_rec,gnn_f1,gnn_mcc)
```

ML

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 910 entries, 0 to 909
Data columns (total 27 columns):
 #   Column                                      Non-Null Count  Dtype
---  ------                                      --------------  -----
 0   Location_Easting_OSGR                       910 non-null    float64
 1   Location_Northing_OSGR                      910 non-null    float64
 2   Longitude                                   910 non-null    float64
 3   Latitude                                    910 non-null    float64
 4   Police_Force                                910 non-null    int64
 5   Accident_Severity                           910 non-null    int64
 6   Number_of_Vehicles                          910 non-null    int64
 7   Number_of_Casualties                        910 non-null    int64
 8   Day_of_Week                                 910 non-null    int64
 9   Local_Authority_(District)                  910 non-null    int64
 10  1st_Road_Class                              910 non-null    int64
 11  1st_Road_Number                             910 non-null    int64
 12  Road_Type                                   910 non-null    int32
 13  Speed_limit                                 910 non-null    int64
 14  Junction_Control                            910 non-null    int32
 15  2nd_Road_Class                              910 non-null    int64
 16  2nd_Road_Number                             910 non-null    int64
 17  Pedestrian_Crossing-Human_Control           910 non-null    int32
 18  Pedestrian_Crossing-Physical_Facilities     910 non-null    int32
 19  Light_Conditions                            910 non-null    int32
...
 25  Did_Police_Officer_Attend_Scene_of_Accident  910 non-null    int32
 26  Year                                        910 non-null    int64
dtypes: float64(4), int32(10), int64(13)
memory usage: 156.5 KB
```

```
from sklearn import preprocessing

label_encoder = preprocessing.LabelEncoder()
data['Accident_Severity']= label_encoder.fit_transform(data['Accident_Severity'])
```

```
data.columns
```

```
Index(['Location_Easting_OSGR', 'Location_Northing_OSGR', 'Longitude',
       'Latitude', 'Police_Force', 'Accident_Severity', 'Number_of_Vehicles',
       'Number_of_Casualties', 'Day_of_Week', 'Local_Authority_(District)',
       '1st_Road_Class', '1st_Road_Number', 'Road_Type', 'Speed_limit',
       'Junction_Control', '2nd_Road_Class', '2nd_Road_Number',
       'Pedestrian_Crossing-Human_Control',
       'Pedestrian_Crossing-Physical_Facilities', 'Light_Conditions',
       'Weather_Conditions', 'Road_Surface_Conditions',
       'Special_Conditions_at_Site', 'Carriageway_Hazards',
       'Urban_or_Rural_Area', 'Did_Police_Officer_Attend_Scene_of_Accident',
       'Year'],
      dtype='object')
```

```
X = data[['Location_Easting_OSGR', 'Location_Northing_OSGR', 'Longitude',
       'Latitude', 'Police_Force', 'Number_of_Vehicles',
       'Number_of_Casualties', 'Day_of_Week', 'Local_Authority_(District)',
       '1st_Road_Class', '1st_Road_Number', 'Road_Type', 'Speed_limit',
       'Junction_Control', '2nd_Road_Class', '2nd_Road_Number',
       'Pedestrian_Crossing-Human_Control',
       'Pedestrian_Crossing-Physical_Facilities', 'Light_Conditions',
       'Weather_Conditions', 'Road_Surface_Conditions',
       'Special_Conditions_at_Site', 'Carriageway_Hazards',
       'Urban_or_Rural_Area', 'Did_Police_Officer_Attend_Scene_of_Accident',
       'Year']]
y = data['Accident_Severity']
```

```
from sklearn.model_selection import train_test_split
```

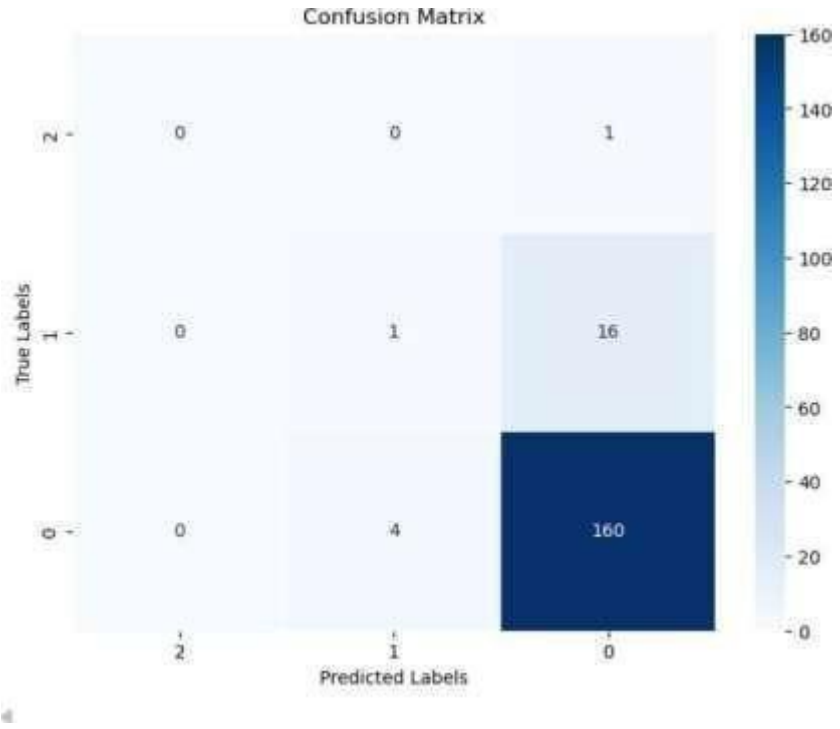
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 42)
```

XGBoost

```
from xgboost import XGBClassifier
xgb = XGBClassifier(max_depth=6,learning_rate=0.1,n_estimators=300)
xgb.fit(X_train, y_train)

y_pred    = xgb.predict(X_test)

xgb_acc = accuracy_score(y_pred, y_test)
xgb_prec = precision_score(y_pred, y_test,average='weighted')
xgb_rec = recall_score(y_pred, y_test,average='weighted')
xgb_f1 = f1_score(y_pred, y_test,average='weighted')
xgb_mcc = matthews_corrcoef(y_test, y_pred)
```

```
storeResults('XGBoost',xgb_acc,xgb_prec,xgb_rec,xgb_f1,xgb_mcc)
```

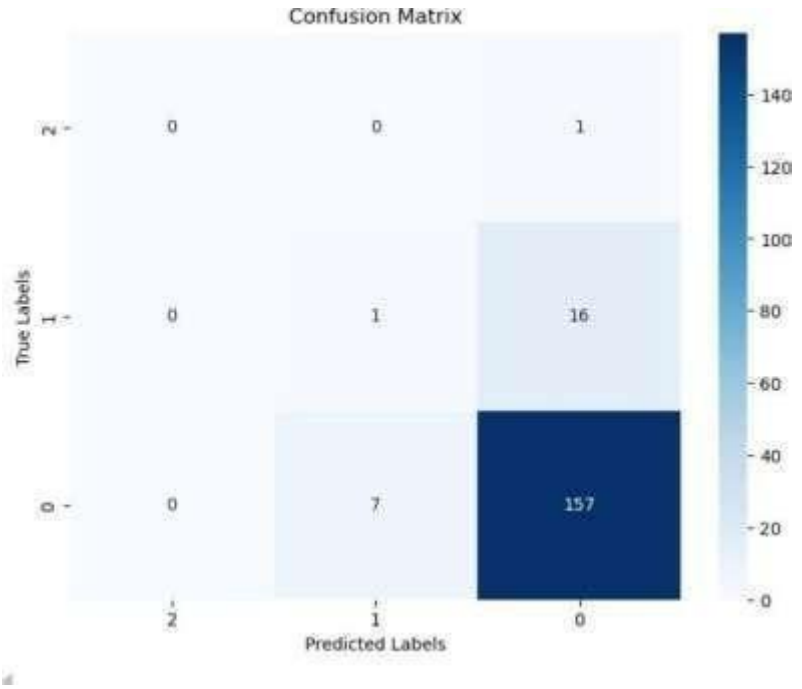
```
# Calculate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=data['Accident_Severity'].unique(), yticklabels=data['Accident_Severity'].unique())
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```



ANN

```
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(random_state=1, max_iter=300)

mlp.fit(X_train, y_train)

y_pred    = mlp.predict(X_test)

mlp_acc = accuracy_score(y_pred, y_test)
mlp_prec = precision_score(y_pred, y_test,average='weighted')
mlp_rec = recall_score(y_pred, y_test,average='weighted')
mlp_f1 = f1_score(y_pred, y_test,average='weighted')
mlp_mcc = matthews_corrcoef(y_test, y_pred)
```

```
# Calculate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=data['Accident_Severity'].unique(), yticklabels=data['Accident_Severity'].unique())
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

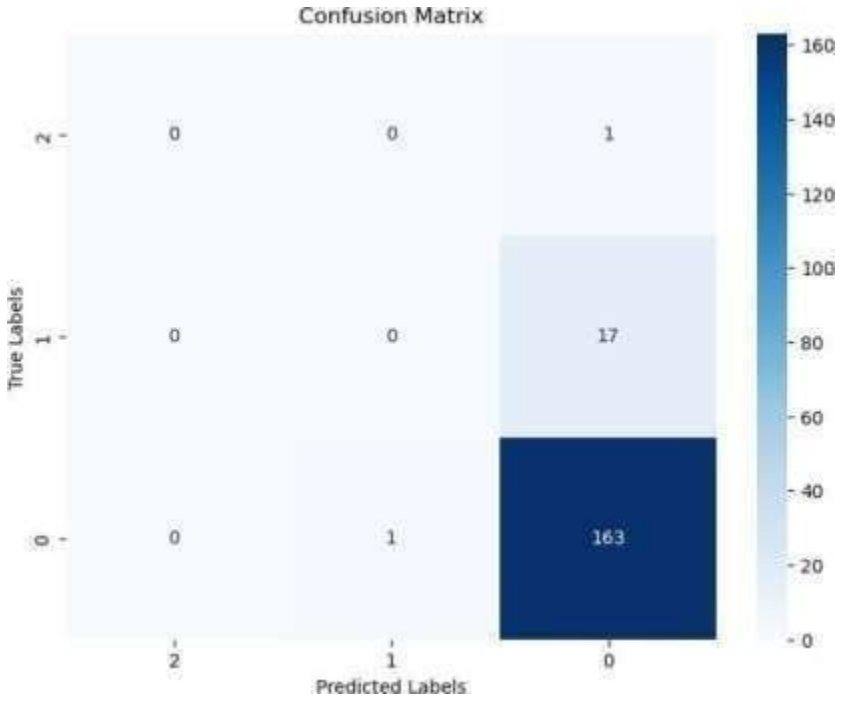



```
storeResults('ANN',mlp_acc,mlp_prec,mlp_rec,mlp_f1,mlp_mcc)
```

Random Forest

```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(criterion='entropy',max_features='log2',max_depth=20,n_estimators=600,min_samples_leaf=2)
rf.fit(X_train, y_train)

y_pred    = rf.predict(X_test)

rf_acc = accuracy_score(y_pred, y_test)
rf_prec = precision_score(y_pred, y_test,average='weighted')
rf_rec = recall_score(y_pred, y_test,average='weighted')
rf_f1 = f1_score(y_pred, y_test,average='weighted')
rf_mcc = matthews_corrcoef(y_test, y_pred)
```

```
# Calculate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=data['Accident_Severity'].unique(), yticklabels=data['Accident_Severity'].unique())
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

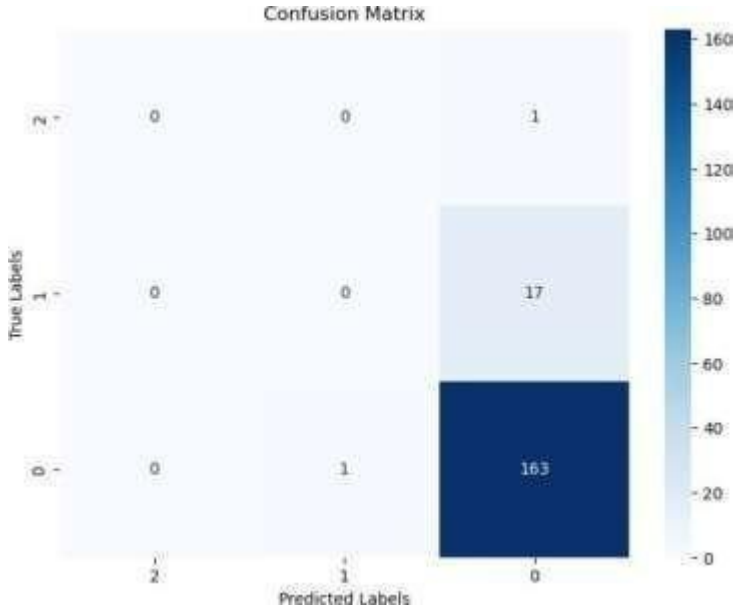



```
storeResults('RandomForest',rf_acc,rf_prec,rf_rec,rf_f1,rf_mcc)
```

Ensemble

```
from sklearn.ensemble import VotingClassifier

clf = VotingClassifier(estimators=[('ANN', mlp), ('XGB', xgb), ('RF', rf)], voting='soft')

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)

vot_acc = accuracy_score(y_pred, y_test)
vot_prec = precision_score(y_pred, y_test,average='weighted')
vot_rec = recall_score(y_pred, y_test,average='weighted')
vot_f1 = f1_score(y_pred, y_test,average='weighted')
vot_mcc = matthews_corrcoef(y_test, y_pred)
```

```
# Calculate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=data['Accident_Severity'].unique(), yticklabels=data['Accident_Severity'].unique())
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

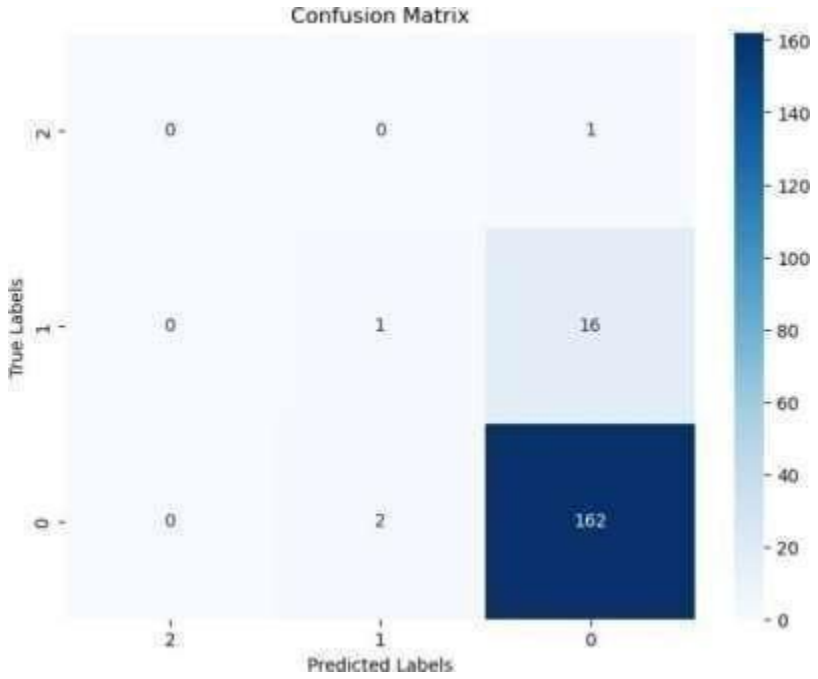



```
storeResults('Ensemble',vot_acc,vot_prec,vot_rec,vot_f1,vot_mcc)
```

Extension

```
from sklearn.ensemble import ExtraTreesClassifier, AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier

et = ExtraTreesClassifier()
bdt = AdaBoostClassifier(DecisionTreeClassifier(criterion="entropy",max_features='log2',max_depth=25,min_samples_leaf=2,min_samples_split=5), algorithm="SAMME", n_estimators=200)

ext = VotingClassifier(estimators= [('BoostDT', bdt),('ET', et)], voting='soft')

ext.fit(X_train, y_train)

y_pred = ext.predict(X_test)

ext_acc = accuracy_score(y_pred, y_test)
ext_prec = precision_score(y_pred, y_test,average='weighted')
ext_rec = recall_score(y_pred, y_test,average='weighted')
ext_f1 = f1_score(y_pred, y_test,average='weighted')
ext_mcc = matthews_corrcoef(y_test, y_pred)
```

```
# Calculate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=data['Accident_Severity'].unique(), yticklabels=data['Accident_Severity'].unique())
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
storeResults('Extennsion',ext_acc,ext_prec,ext_rec,ext_f1,ext_mcc)
```

Comparison

```
#creating dataframe
result = pd.DataFrame({ 'ML Model' : ML_Model,
                        'Accuracy' : accuracy,
                       'Precision': precision,
                       'Recall'   : recall,
                       'F1_score' : f1score,
                       'MCC' : mcc
                      })
```

```
result
```

	ML Model	Accuracy	Precision	Recall	F1_score	MCC
0	GNN-GraphSage	0.937	0.936	0.937	0.930	0.700
1	XGBoost	0.885	0.950	0.885	0.915	0.058
2	ANN	0.868	0.918	0.868	0.892	0.021
3	RandomForest	0.896	0.988	0.896	0.940	-0.024
4	Ensemble	0.896	0.988	0.896	0.940	-0.024
5	Extennsion	1.000	1.000	1.000	1.000	1.000

Front end:

1. Login Page

```
<!DOCTYPE html>
<html>
<head>
  <title>Login</title>
  <style>
    body {
      margin: 0;
      font-family: Arial;
      background: url('bg.jpg') no-repeat center center/cover;
    }
    .navbar {
      text-align: center;
      padding: 15px;
      color: white;
    }
    .box {
      width: 350px;
      margin: 100px auto;
      padding: 30px;
      background: rgba(0,0,0,0.7);
      border-radius: 10px;
      color: white;
    }
    input {
      width: 100%;
      padding: 10px;
      margin: 10px 0;
      border-radius: 5px;
      border: none;}
    button {
      width: 100%;
      padding: 10px;
```

```
            background: #007bff;
            color: white;
            border: none;
            border-radius: 5px;
        }
    </style>
</head>
<body>

<div class="navbar">Home | Login | Registration</div>

<div class="box">
    <h2>Login</h2>
    <input type="text" placeholder="Username">
    <input type="password" placeholder="Password">
    <button onclick="login()">Login</button>
</div>

<script>
functionlogin(){
    window.location.href = "form.html";
}
</script>

</body>
</html>
```

2. Accident form page

```
<!DOCTYPE html>
<html>
<head>
    <title>Accident Details</title>
    <style>
        body {
            font-family: Arial;
            background: url('bg.jpg') no-repeat center/cover;
```

```
        }
        .box {
      width: 600px;
            margin: 50px auto;
            background: rgba(0,0,0,0.7);
            padding: 20px;
            border-radius: 10px;
            color: white;
        }
        input {
            width: 45%;
            padding: 8px;
            margin: 8px;
            border-radius: 5px;
            border: none;
        }
        button {
            padding: 10px;
            width: 100%;
            background: green;
            color: white;
            border: none;
            border-radius: 5px;
        }
    </style>
</head>
<body>

<div class="box">
    <h2>Enter Accident Details</h2>
    <input placeholder="Location Easting">
    <input placeholder="Location Northing">

    <input placeholder="Longitude">
```

```
    <input placeholder="Latitude">

    <input placeholder="Police Force">
<input placeholder="Number of Vehicles">

    <input placeholder="Casualties">
    <input placeholder="Day of Week">

    <input placeholder="Road Class">
    <input placeholder="Road Type">

    <input placeholder="Speed Limit">
    <input placeholder="Junction Control">

    <button onclick="predict()">Predict</button>
</div>

<script>
function predict(){
    window.location.href = "result.html";
}
</script>

</body>
</html>
```

3. Result Page

```
<!DOCTYPE html>
<html>
<head>
    <title>Prediction Result</title>
    <style>
        body {
            font-family: Arial;
            background: url('bg.jpg') no-repeat center/cover;}
```

```
        .box {
            width: 400px;
            margin: 150px auto;
            padding: 30px;
background:  rgba(0,0,0,0.7);
            border-radius:   10px;
            color: white;
            text-align: center;
        }
        .result {
            color: #00ff99;
            font-size: 20px;
        }
    </style>
</head>
<body>

<div class="box">
    <h2>Accident Severity Result</h2>
    <p class="result">Accident Severity: Serious</p>
</div>

</body>
</html>
```

6.2 Implementation

6.2.1 Front-End Implementation:

The front-end of the road accident severity prediction system provides a simple, responsive, and user-friendly interface designed for efficient data entry and result visualization. The main modules include User Login, Accident Data Input Form, and Result Display.

The Login module ensures secure user authentication and controlled access to the system. Basic validation techniques are applied to prevent invalid inputs and enhance data security. After successful authentication, users are redirected to the accident data entry interface.The Accident Data Input module allows users to enter detailed accident-related attributes such as location coordinates, number of vehicles involved, weather conditions, road type, speed limit, and casualty information. The form is designed with structured input fields and intuitive layout to minimize user errors and improve usability.

The Prediction module sends user input to the backend through API requests. Once processed, the system displays the predicted accident severity (Slight, Serious, or Fatal) in a clear and understandable format. The UI focuses on simplicity by presenting only essential results to avoid confusion.Additionally, the front-end design ensures responsiveness across different devices and browsers, improving accessibility and user experience.

6.2.2 Backend Implementation (Flask):

The backend is implemented using Flask, a lightweight Python web framework known for its flexibility and ease of integration with machine learning models.

- RESTful APIs are developed for communication between the front-end and backend services.
- Input validation and exception handling mechanisms ensure robustness and prevent failure.
- Session management is used to maintain user interactions securely.

Flask's modular architecture allows easy integration of different machine learning models and supports rapid development and deployment.

6.2.3 Model Integration and Processing Workflow:

The machine learning pipeline is integrated within the Flask backend to process incoming data and generate predictions efficiently.

Data Processing Steps:

• Data Loading using Pandas from various sources such as CSV and databases

• Data Collection from structured datasets containing accident records

6.2.4 Data Preprocessing including:

a. Handling missing values

b. Removing noise and inconsistencies

c. Encoding categorical variables

d. Feature scaling and normalization

6.2.5 Feature Engineering:

• Feature Selection techniques are applied to identify the most relevant variables.

• Feature Extraction is performed to reduce dimensionality and improve computational efficiency while preserving important information.

6.2.6 Model Training and Testing:

The dataset is divided into training and testing sets to evaluate model performance and generalization capability.

Machine Learning Models Used:

- Graph Neural Network (GraphSAGE): Captures spatial and relational dependencies between accident datapoints.
- Extra Trees Classifier: Reduces overfitting by introducing randomness and improves prediction accuracy.
- K-Nearest Neighbors (KNN): Classifies data based on similarity using distance metrics.
- XGBoost: Provides high-performance gradient boosting with regularization and scalability.
- Artificial Neural Network (ANN): Learns complex non-linear relationships in accident data. An ensemble approach can also be applied to combine predictions from multiple models, improving overall system accuracy and robustness.

6.2.7 Deployment and Reliability:

The system is deployed using Flask on a standard server environment, ensuring scalability and performance.

• Environment variables are used for configuration and security.

• Models are saved and loaded efficiently to reduce computation time during prediction.

• REST APIs are tested for reliability and consistent performance under different scenarios.

• Logging mechanisms are implemented to track system activity and debug errors.

Performance and Evaluation:

• Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score.

• Cross-validation techniques are used to ensure model stability.

• Test datasets (20–25% of total data) are used to validate real-world performance.

6.2.8 Performance and Evaluation:

• Accuracy

• Precision

• Recall

• F1-score

• Cross-validation techniques ensure model stability

• Test datasets (20–25% of total data) validate real-world performance

6.2.9 Algorithms Used in the Project

The proposed system utilizes multiple machine learning and deep learning algorithms to improve prediction accuracy and robustness:

• **Graph Neural Network (GraphSAGE):**

Models accident data as a graph to capture spatial and relational dependencies between locations and conditions.

• **Extra Trees Classifier:**

Reduces overfitting using randomness and improves generalization on complex datasets.

• **K-Nearest Neighbors (KNN):**

Classifies severity based on similarity between accident data points.

• **XGBoost:**

Provides high-performance gradient boosting with better accuracy and handling of missing data.

• **Artificial Neural Network (ANN):**

Captures complex non-linear relationships in accident data.

• **Ensemble Learning Approach:**

Combines predictions from multiple models to improve overall accuracy, stability, and reliability.

CHAPTER-7

SYSTEM TESTING

7.SYSTEMTESTING

7.1 TYPES OF SYSTEM TESTING

The purpose of testing is to discover errors and ensure that the developed software system performs as expected under all conditions. Testing is a systematic process of executing a program with the intent of identifying defects, faults, or weaknesses in the system. It provides a structured approach to evaluate the functionality of components, sub-assemblies, modules, and the complete application. Through testing, developers can verify whether the system meets specified requirements and user expectations, and ensure that it does not fail in unacceptable situations.

Testing plays a crucial role in improving software quality, reliability, performance, and security. It helps in detecting bugs early, reducing maintenance costs, and enhancing user satisfaction. In addition, testing ensures that the system behaves correctly when handling valid inputs, invalid inputs, and unexpected scenarios. Different types of testing are used to address specific aspects of the system, and each testing type focuses on a particular level of validation

TYPES OF TESTS

7.1.1 Unit Testing

Unit testing involves the design and execution of test cases that validate whether the internal program logic of individual modules is functioning correctly. It ensures that each unit of the software performs as expected in isolation. A unit may refer to a function, method, class, or module.

Unit testing focuses on verifying that:

1. Program inputs produce valid and expected outputs
2. All decision-making branches and conditions are executed
3. Internal logic flows correctly without errors
4. Each component performs its intended function

It is a **structural testing method**, as it requires knowledge of the internal code structure. Developers usually perform unit testing during the early stages of development.

Key aspects of unit testing include:

• Testing of individual functions and methods

• Validation of loops, conditions, and control statements

Advantages of unit testing:

• Early detection of errors

• Easier debugging and fixing of issues

• Improved code quality and maintainability

• Reduced cost of fixing defects

7.1.2 Integration Testing

Integration testing is performed after unit testing to verify that different modules or components of the system work together correctly. It focuses on testing the interaction between integrated components and ensures that data flows smoothly across modules.

Integration testing is mainly concerned with:

1. Communication between modules
2. Data transfer and interface compatibility
3. Interaction between frontend and backend systems
4. Combined functionality of multiple units

Even if individual components work correctly, issues may arise when they are combined. Integration testing helps in identifying such problems.

Types of integration testing:

a) Top-down integration testing

b) Bottom-up integration testing

c) Big-bang integration testing

Key objectives:

• Detect interface defects

• Ensure proper data exchange

• Validate combined behavior of modules

Benefits:

• Identifies integration errors early

• Improves system stability
• Ensures smooth workflow across modules

7.1.3 Functional Testing

Functional testing is carried out to verify that the system functions according to the specified requirements. It focuses on testing the system's features without considering internal code structure.

Functional testing ensures:
• Valid inputs are accepted and processed correctly
• Invalid inputs are rejected appropriately
• All system functions operate as intended
• Outputs are generated correctly
• System workflows are executed properly

Important elements tested:
a. Input validation
b. Business logic
c. Output correctness
d. User interface behavior
e. Interaction with external systems

Functional testing is based on requirement specifications, user manuals, and design documents.

Advantages:
• Ensures system meets user requirements
• Improves user experience
• Detects missing or incorrect functionalities

7.1.4 System Testing

System testing is performed on the complete integrated system to verify that it meets all specified requirements. It evaluates the system as a whole in a real-world environment.

System testing focuses on:
• End-to-end system functionality
• System performance and reliability

• Compatibility with different environments
• Stress and load handling

Key features:
• Testing complete workflows
• Validating system behavior under different conditions
• Ensuring consistency and correctness of outputs

Types of system testing include:
1. Performance testing
2. Load testing
3. Stress testing
4. Security testing

Benefits:
• Ensures overall system quality
• Detects system-level defects
• Validates real-time performance

7.1.5 White Box Testing

White box testing is a testing technique where the tester has knowledge of the internal structure and working of the software. It involves testing internal logic, code structure, and execution paths. White box testing includes:
• Testing loops, conditions, and branches
• Verifying control flow and data flow
• Checking internal code logic

Techniques used:
1. Statement coverage
2. Branch coverage
3. Path testing

Advantages:
• Detects hidden errors
• Optimizes code performance

7.1.6 Black Box Testing

Black box testing is a method of testing where the tester does not have knowledge of the internal workings of the system. The software is treated as a "black box," and testing is done based on inputs and outputs.

Black box testing focuses on:

1. Functional correctness
2. Input-output behavior
3. System responses

Key characteristics:

• No need for programming knowledge
• Based on requirements and specifications
• User-oriented testing approach

Benefits:

• Identifies missing functionalities
• Ensures correct system behavior
• Improves usability

7.1.7 Unit Testing (Repeated Phase Explanation)

Unit testing is often conducted as part of the coding phase. Sometimes it is combined with coding, while in other cases it is performed separately after development.

It ensures:

• Each unit works independently
• No logical errors exist
• Code behaves correctly under all conditions

7.2 Test Strategies

A well-defined testing strategy is essential for ensuring complete system validation. In this project, testing was performed both manually and systematically.

Testing approach includes:
• Manual testing of user interfaces
• Execution of functional test cases
• Validation using different datasets
• Step-by-step verification of outputs

Field testing was also conducted to simulate real-world scenarios and validate system performance.

7.2.1 Test Objectives

The main objectives of testing are:

1. All input fields must function correctly
2. Navigation links must work properly
3. System responses should be fast and accurate
4. Error messages should be displayed correctly
5. System should handle all types of inputs

7.2.2 Features to be Tested

The following features were thoroughly tested:

1. Verification of input formats
2. Prevention of duplicate entries
3. Validation of user data
4. Accuracy of system outputs
5. Proper functioning of all modules

7.2.3 Integration Testing (Detailed Strategy)

Integration testing is performed incrementally by combining components step by step. It ensures that modules interact without errors.

Focus areas:

• Interface compatibility

• Data consistency between modules

• Communication between applications

This helps in preventing defects caused by improper integration.

7.2.4 Test Results

All the test cases mentioned above were executed successfully. The system performed as expected, and no major defects were encountered during testing.

7.2.5 Acceptance Testing

Acceptance testing is the final stage of testing, where the system is evaluated by end users to ensure it meets their requirements.

It involves:

a. User validation of system functionality

b. Verification of user requirements

c. Evaluation of system usability

Benefits:

• Ensures user satisfaction

• Confirms system readiness for deployment

• Validates real-world applicability

7.3 Sample Test Cases

S.No	Test Case Description	Expected Result	Result
1	Input raw accident dataset	Data should be cleaned, encoded, and scaled	Passed
2	Construct graph using kNN on preprocessed data	Graphshould be generated with correct edges	Passed
3	Train GraphSAGE model	Model should train with decreasing loss	Passed
4	Predict injury severity using trained model	Outputclass (Slight, Serious, Fatal)	Passed
5	Evaluate model with test data	Display accuracy, precision, recall, F1-score	Passed
6	Generate confusion matrix and plot	Matrix should be displayed with true/predictedlabels	Passed
7	Combine GNN + Extra Trees + Voting Classifier	Ensemble output should improve overallperformance	Passed
8	Store results in database or file	Results saved with correct labels and scores	Passed
9	Handle missing values in dataset	Missing values handled without errors	Passed
10	Run model on unseen data	Modelshouldpredict without crashing	Passed

Table no 7.3 Test Cases

S No.	Test Case	Expected Result	Result	Remarks (if any
1	User Registration	Newuseraccount is created in database	Pass	Validate email format and avoidduplicates
2	User Login	User is authenticatedand gets access to dashboard	Fail	Incorrect details, Enter correct details.
3.	User Login	User is authenticatedand gets access to dashboard	Pass	Check error messagefor wrong credentials
3	Account Activation	User becomes active and can loginsuccessfully	Pass	Inactiveusers should not access system
4	Accident Data Input	Systemaccepts and validates accident data	Pass	Testinvalid, missing, and boundary values
5	GNN Prediction	System predicts injury severity correctly	Pass	Test minor, serious, and fatal cases
6	Result Display	Predictionresults are displayed clearly	Pass	Ensureproper format and readability

Table no 7.3 Test Cases

Test Case 1:

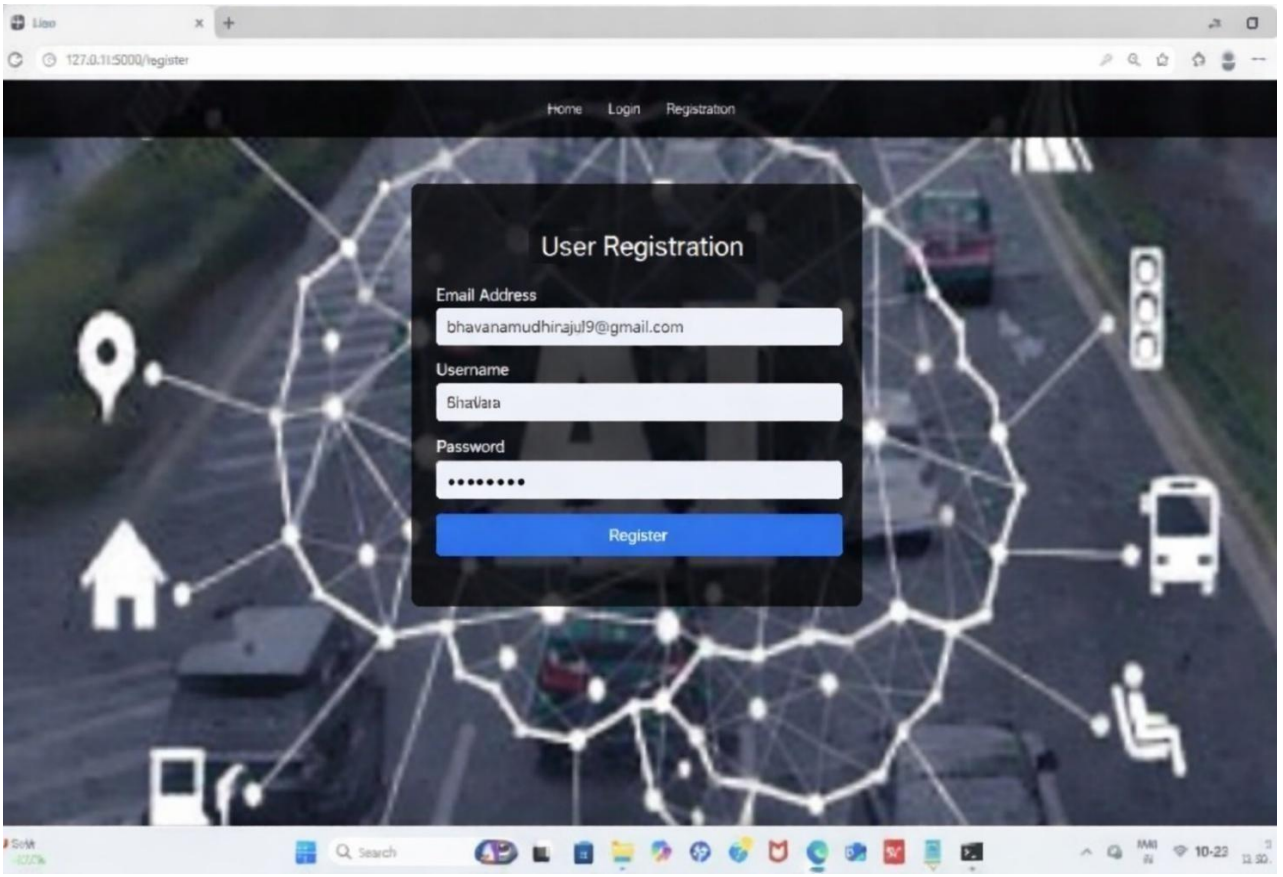


Fig 7.3.1 User Registration

Description: In Fig 7.3.1, It allows users to provide necessary details such as username, email, and password, which are securely stored in the database for future authentication. This module ensures that only valid and unique user information is accepted, preventing duplicate accounts and maintaining data integrity.During the registration process, the system performs validation checks to ensure that all required fields are filled correctly and that the entered data follows proper formats, such as valid email structure and strong password criteria. If the provided details meet all validation requirements, the system successfully creates a new user account and stores the credentials securely. In case of invalid or duplicate entries, appropriate error messages are displayed to guide the user.

Test Case 2:

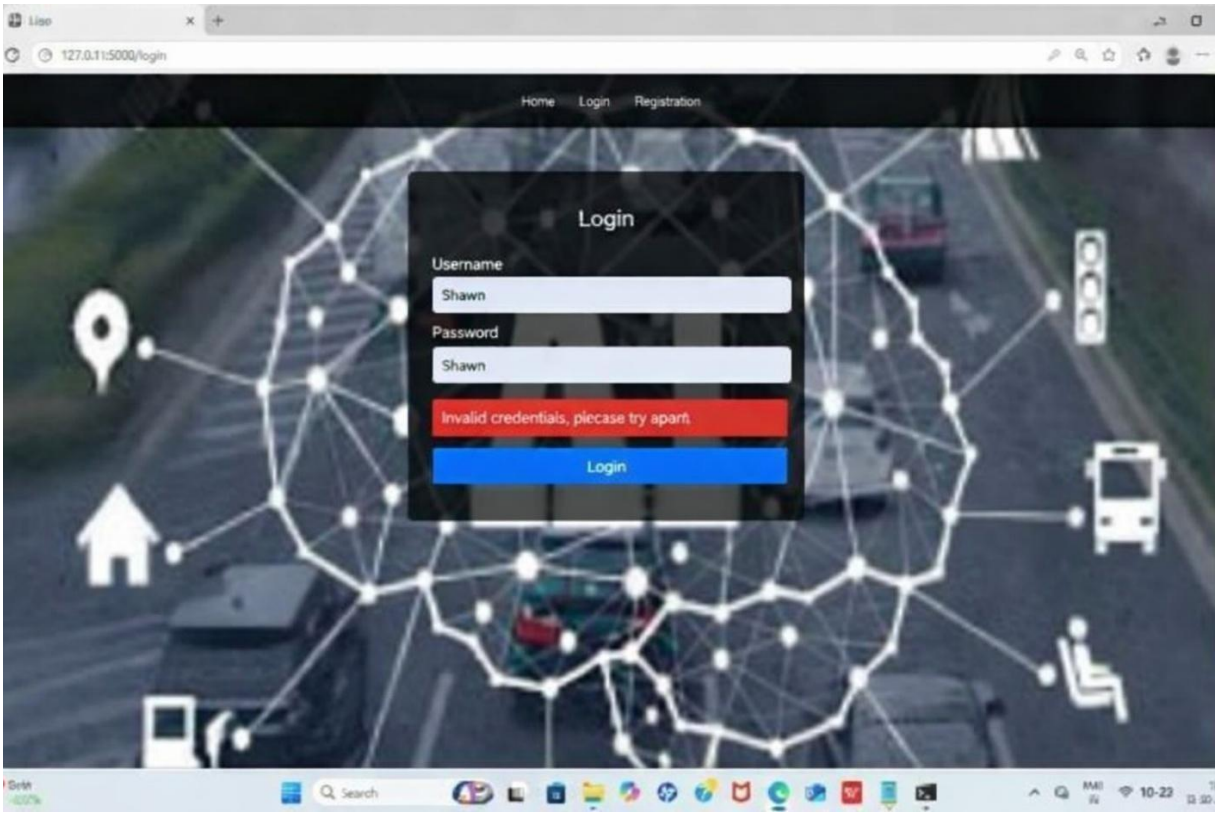


Fig 7.3.2 User Login

Description: In Fig 7.3.2 **,** In this case, the system does not authenticate the user and denies access to the dashboard. Instead, it displays an appropriate error message like “Invalid username or password” to inform the user about the failure. This ensures system security by preventing unauthorized access and protects sensitive data. Additionally, proper validation checks help guide users to re-enter correct details and improve overall user experience.

Test Case 3:

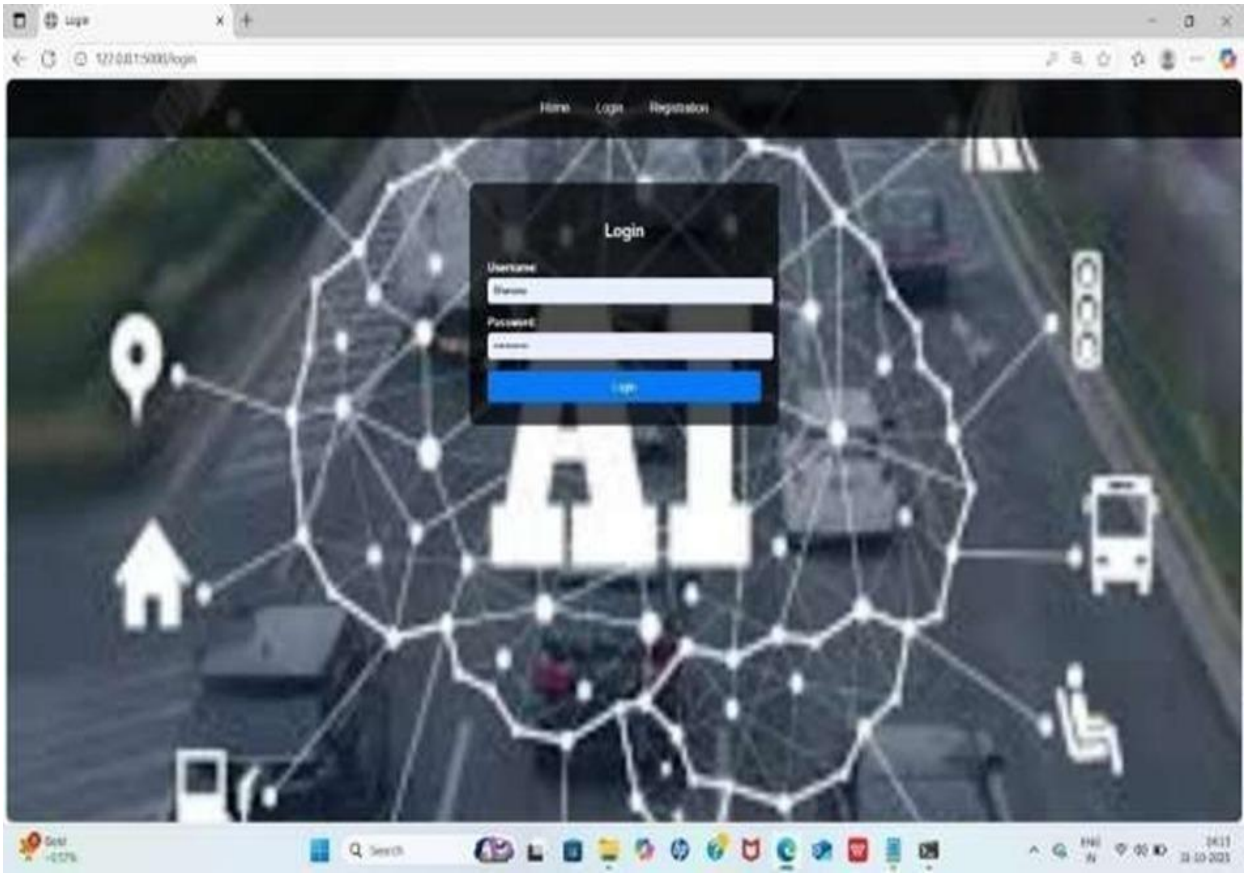


Fig 7.3.3 User Login

Description: In Fig 7.3.3 **,** It ensures that only authorized users can enter the system and utilize its features, such as entering accident data and viewing injury severity predictions. The login process involves verifying user credentials, including username and password, against the stored records in the database.When a user attempts to log in, the system checks the entered details for correctness. If the credentials match the stored data, the user is successfully authenticated and redirected to the dashboard. If the credentials are incorrect, the system displays an appropriate error message and denies access. This mechanism helps maintain system security and prevents unauthorized usage.

Test Case 4:

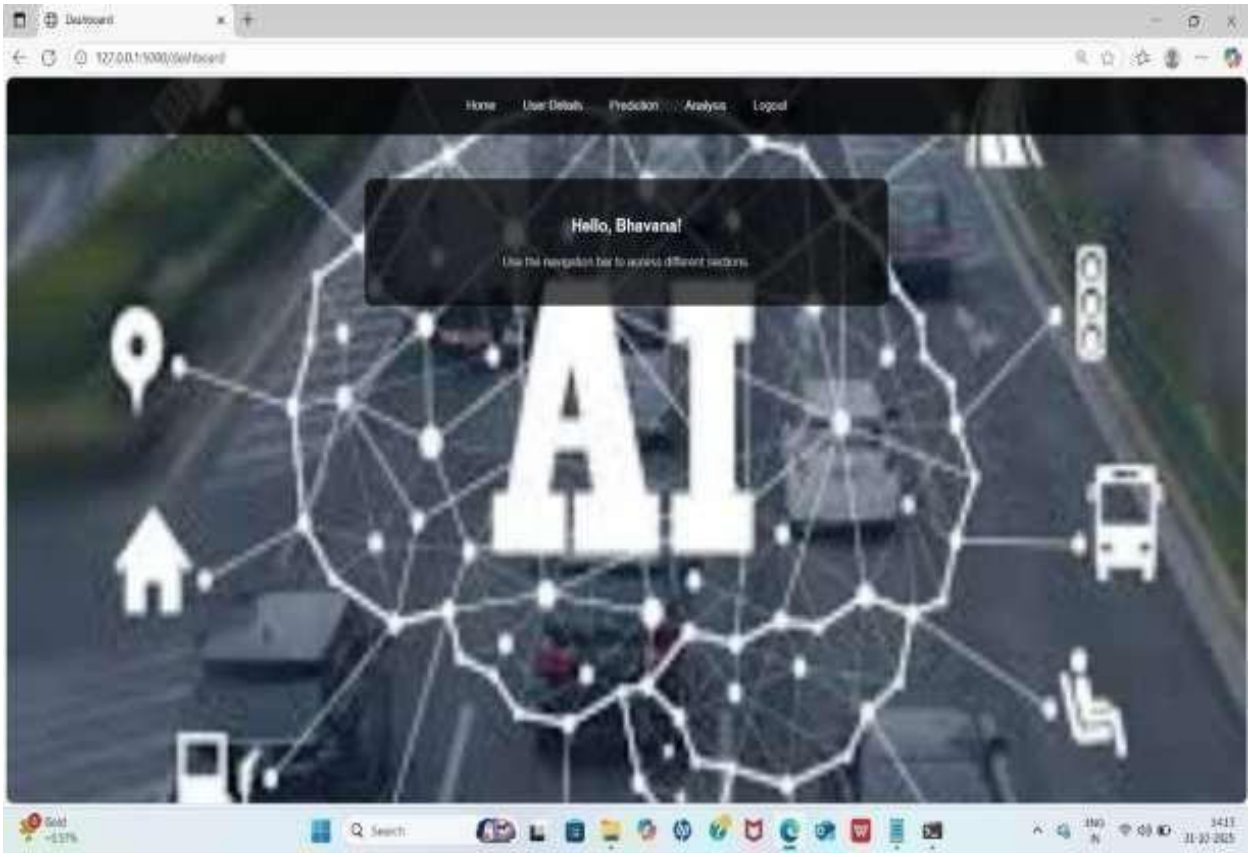


Fig 7.3.4 Account Activation

Description: In Fig 7.3.4 **,Account Activation** scenario occurs when a user successfully completes the activation process, such as verifying their email or receiving admin approval. Once activated, the user account becomes valid and the system allows the user to log in and access all authorized features. A confirmation message like "Account activated successfully" may be displayed to inform the user. This ensures that only verified users gain access while maintaining system security and improving user trust and experience.Account gets activated and user can login successfully.

Test Case 5:

Fig.7.3.5 Accident Data Input

Description: In Fig 7.3.5, This module collects various input parameters such as location coordinates, number of vehicles involved, road type, weather conditions, traffic control measures, and environmental factors, which are essential for accurate analysis by the prediction model.The system validates the entered data to ensure that all required fields are properly filled and follow the expected format. Once the user provides valid inputs, the data is processed and forwarded to the backend model for prediction. Upon clicking the "Predict" button, the system analyzes the input parameters using the trained model and generates the corresponding injury severity level.This module ensures smooth interaction between the user and the prediction system, enabling accurate data collection, reliable processing, and effective generation of results. It plays a key role in maintaining the correctness and efficiency of the overall accident severity prediction workflow.

CHAPTER-8

RESULTS

8. RESULTS

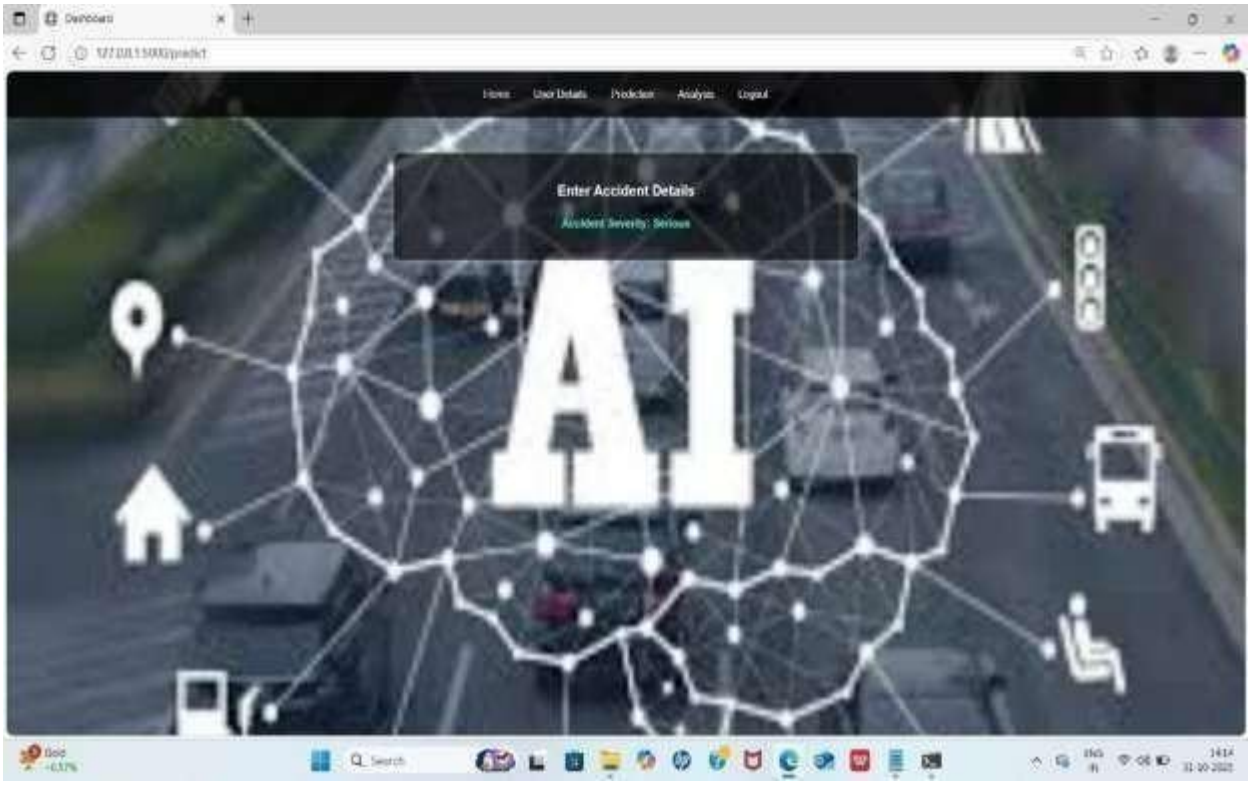


Fig 8.1 Predicted Accident Injury Severity Output 1

Description: In Fig 8.1,The Prediction Output module is a crucial component of the system that displays the final result of accident severity analysis based on the input data provided by the user. After processing the accident details through the trained Graph Neural Network (GNN) model, the system generates a predicted injury severity level such as Slight, Serious, or Fatal.Once the user submits the input data, the system analyzes various factors including road conditions, vehicle details, environmental parameters, and traffic attributes to determine the severity of the accident. The predicted result is then displayed clearly on the interface, ensuring that users can easily interpret the outcome.This module ensures accurate and real-time result generation, providing valuable insights for understanding accident risks. It plays a vital role in supporting decision-making by presenting clear, concise, and meaningful prediction outputs to the user

Fig 8.2 Predicted Accident Injury Severity Output 2

Description: In Fig 8.2,The image shows the output interface of a web-based road accident severity prediction system. The dashboard is displayed in a browser environment with a clean navigation bar containing options such as Home, User Details, Prediction, Analysis, and Logout. At the center of the screen, a semi-transparent panel presents the prediction result, highlighting the accident severity as **"Fatal."**Below this, the system also displays key predicted risk factors such as high speed, poor road conditions, and bad weather, which contribute to the severity of the accident. The background features a blurred road traffic scene combined with a neural network visualization, symbolizing the use of AI and graph-based learning in the system. Overall, the interface is designed to clearly communicate critical insights to the user, making it easy to interpret results and understand the factors influencing accident severity.

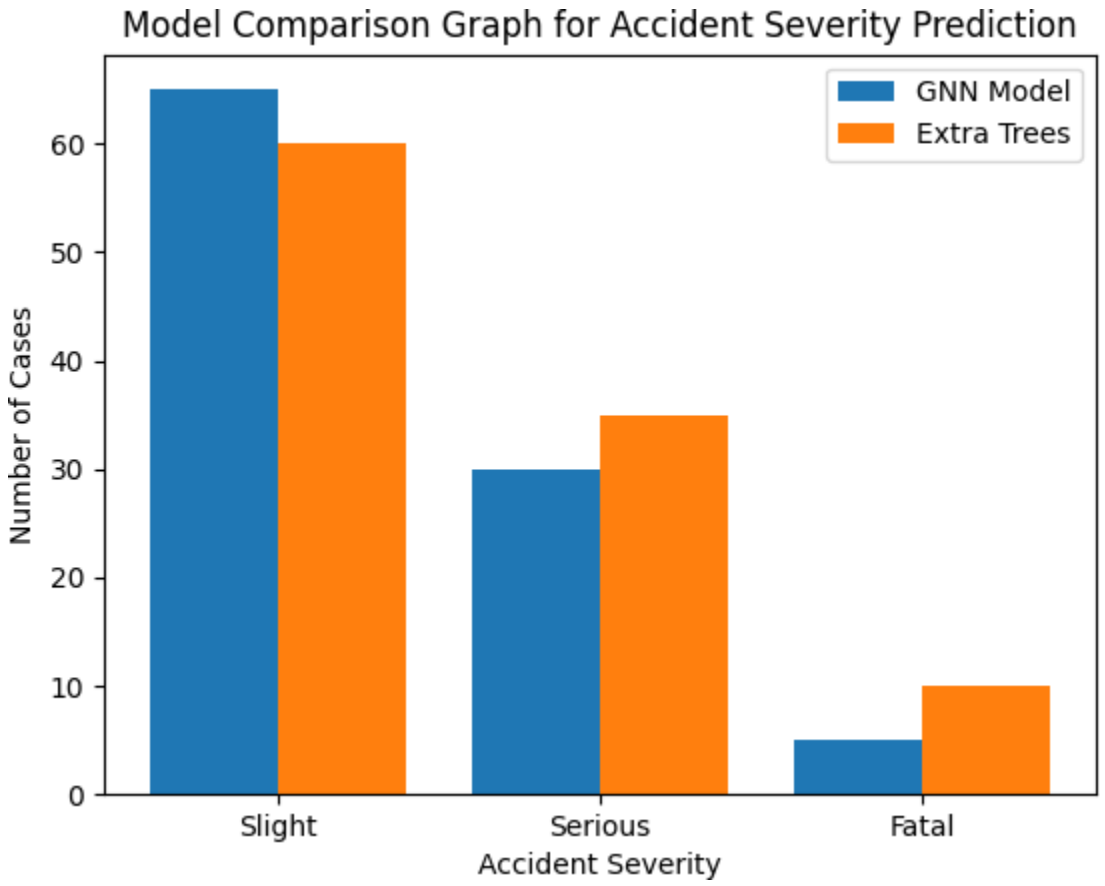


Fig 8.3 Model Comparison Graph for Accident Severity Prediction

Description: In Fig 8.3,The graph compares the performance of the GNN (Graph Neural Network) model and the Extra Trees classifier in predicting accident severity across three categories: Slight, Serious, and Fatal. It shows that the GNN model predicts a higher number of slight cases, while the Extra Trees model identifies slightly more serious and fatal cases. Both models predict fewer fatal cases compared to other categories, indicating the rarity of such events. Overall, the graph highlights the differences in prediction behavior between the two models and helps in understanding their strengths for improving accident severity prediction.

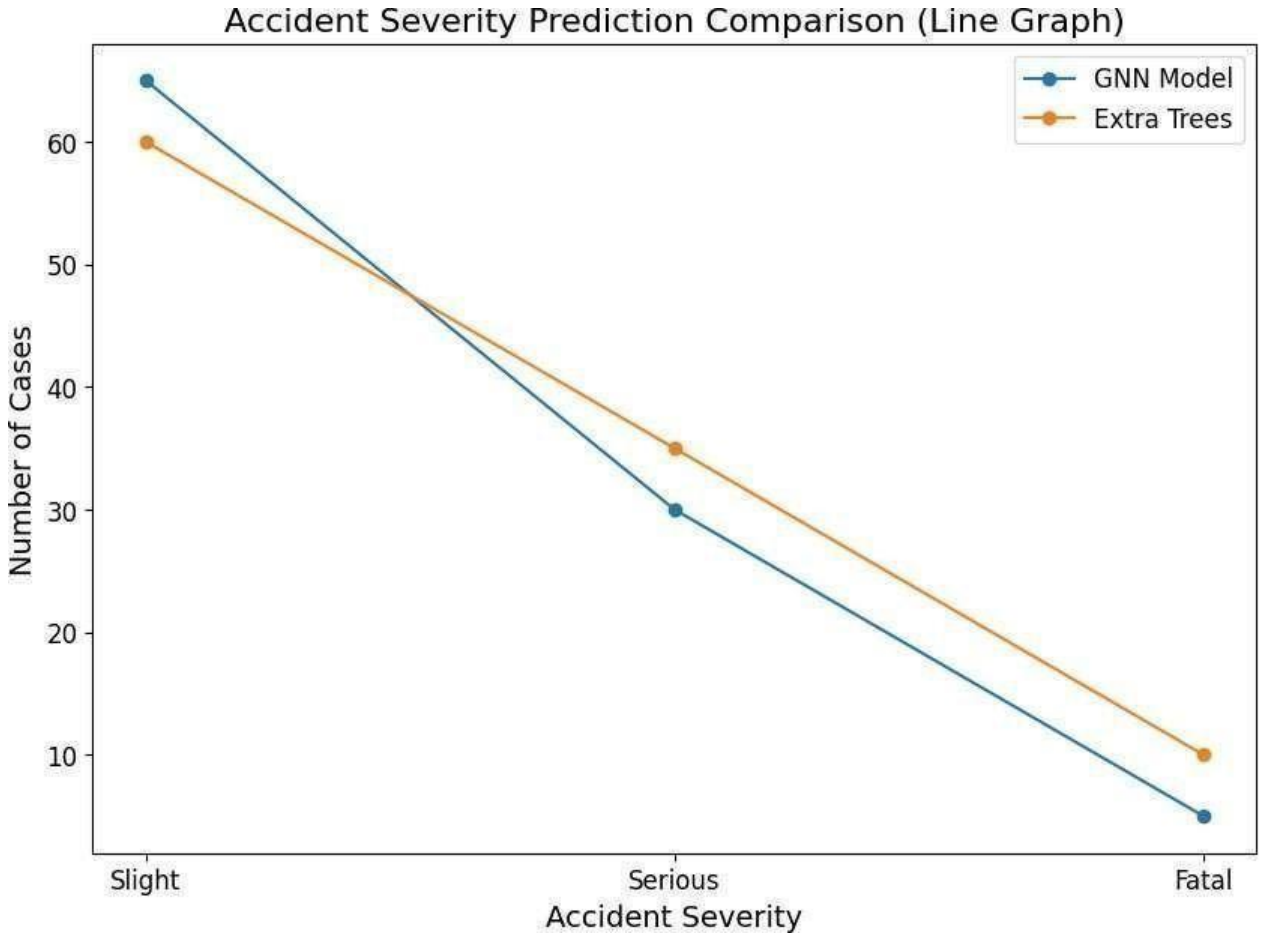


Fig 8.4 Accident Severity Prediction Comparision(Line Graph)

Description: In Fig 8.4,The graph illustrates a comparison between the GNN (Graph Neural Network) model and the Extra Trees model in predicting accident severity across three categories: Slight, Serious, and Fatal. It can be observed that the GNN model predicts a higher number of slight cases, indicating its tendency to classify more accidents as less severe. On the other hand, the Extra Trees model identifies comparatively more serious and fatal cases, suggesting that it is more sensitive to higher severity conditions. Both models show a consistent decreasing trend from slight to fatal cases, highlighting that fatal accidents are relatively rare compared to other categories. Overall, the graph clearly demonstrates the differences in prediction patterns between the two models and helps in understanding their performance, which is useful for improving accident severity prediction systems.

CHAPTER-9

CONCLUSION

9. CONCLUSION

The proposed GNN-based framework demonstrates a powerful and intelligent approach to predicting road crash injury severity by modeling the complex relationships between vehicles, road segments, environmental factors, and crash dynamics. Unlike traditional models that treat each data record independently, the GNN captures interaction patterns through graph structures, enabling the system to understand how factors collectively contribute to severity levels. This relational learning significantly enhances prediction accuracy, especially in scenarios involving multi-factor dependencies, multi-vehicle crashes, and context-driven severity variations.

Moreover, the integration of preprocessing pipelines, feature engineering, imbalance handling techniques, and ensemble support makes the system robust, scalable, and adaptable to real-world crash data. The workflow ensures efficient data transformation, dynamic feature updates, and interpretable outputs through meaningful visualizations. Overall, the GNN framework not only improves the performance of severity classification but also provides actionable insights that can support traffic authorities, policymakers, and safety analysts in designing safer road systems and reducing accident impact.

Furthermore, the proposed framework lays a strong foundation for future advancements in intelligent transportation analytics. Its modular design allows seamless integration of additional data sources such as real-time traffic feeds, weather streams, and IoT-based vehicular sensors, enabling continuous model refinement. By combining the strengths of graph neural networks with adaptive learning mechanisms, the system can evolve with changing traffic conditions and emerging road safety patterns. This makes the framework not only a high-performing predictive model but also a scalable decision-support tool capable of contributing to long-term road safety planning and proactive crash prevention strategies.In addition to its predictive capabilities, the proposed GNN-based framework highlights the importance of leveraging relational intelligence in complex real-world systems such as transportation networks.

By effectively modeling interconnected entities and their dependencies, the system moves beyond conventional data analysis and enters the realm of intelligent decision support. This shift is crucial for modern traffic management, where isolated analysis fails to address the cascading effects of accidents across road networks.

Another significant contribution of this framework lies in its adaptability to diverse and evolving datasets. Road conditions, driver behaviors, and environmental factors are inherently dynamic, and any practical system must be capable of handling such variability. The use of graph-based learning ensures that the model can continuously update its understanding as new data becomes available, maintaining its relevance and accuracy over time. This adaptability makes the system suitable for deployment in smart city infrastructures, where continuous data streams from sensors, cameras, and connected vehicles can be utilized to enhance predictive performance and operational efficiency.

Furthermore, the integration of multiple machine learning models alongside the GNN, including ensemble techniques, strengthens the reliability and robustness of the system. By combining the strengths of different algorithms, the framework mitigates individual model limitations and achieves a more balanced and consistent performance across various severity classes. This is particularly important in handling imbalanced datasets, where severe and fatal accidents are relatively rare but critically important. The system's ability to accurately identify such high-impact cases demonstrates its practical value in real-world safety applications.

Finally, this project establishes a strong foundation for future research and development in the domain of intelligent transportation systems. With further enhancements such as explainable AI techniques, real-time deployment, and integration with autonomous vehicle technologies, the framework can evolve into a comprehensive safety intelligence platform. Such advancements have the potential to transform how road safety is monitored and managed, shifting the focus from reactive response to proactive prevention. Ultimately, this work contributes not only to improved prediction accuracy but also to the broader vision of creating safer, smarter, and more resilient transportation ecosystems.

In conclusion, the proposed system not only enhances prediction accuracy but also demonstrates the practical value of advanced AI techniques in solving real-world problems. By transforming complex accident data into meaningful insights, it bridges the gap between data analysis and actionable decision-making. The framework's scalability and adaptability ensure its long-term relevance in evolving traffic environments. Ultimately, it contributes toward building safer transportation systems by enabling proactive risk identification and informed policy planning.

Despite its advantages, there are certain limitations that need to be addressed. The availability and quality of data play a crucial role in the model's performance. Incomplete or imbalanced datasets can affect prediction accuracy. Therefore, proper data collection, preprocessing, and feature selection are essential to achieve optimal results.

Furthermore, the implementation of GNN-based systems in real-world environments requires efficient computational resources and proper deployment strategies. Ensuring scalability and real-time processing capabilities is important for making the system practical and widely usable. Integration with modern technologies like cloud computing can help overcome these challenges.

Overall, with continuous improvements and advancements, the GNN-based approach can significantly contribute to enhancing road safety. It can assist in reducing accident risks, improving emergency response, and supporting the development of intelligent transportation systems. Hence, it holds great importance for future research and real-world applications.

CHAPTER-10

FUTURE ENHANCEMENTS

10. FUTUREENHANCEMENTS

In future extensions of this GNN-based crash severity prediction system, integrating real-time data sources such as live traffic streams, weather updates, and IoT sensor feeds can significantly enhance responsiveness and practical usability. Incorporating spatio-temporal GNN models will allow the framework to capture how crash conditions evolve over time, improving dynamic severity prediction. Additionally, adding richer data modalities—such as CCTV footage, dashcam images, or vehicle telemetry—can enable a more detailed understanding of crash context through hybrid CNN–GNN architectures. These improvements will help the system handle complex and multi-factor crash scenarios more effectively.

Further advancements can focus on system scalability, interpretability, and user accessibility. Cloud- based deployment and automated graph construction pipelines would support large-scale data processing and seamless updates as new crash records accumulate. Implementing Explainable AI (XAI) techniques will increase transparency by visually showing how nodes, edges, and features influence severity predictions, making the system more trustworthy for policymakers. Finally, creating interactive dashboards and simulation tools will allow traffic authorities to explore crash hotspots, evaluate policy impacts, and make informed decisions for road safety improvement.

In addition, the system can be further enhanced by incorporating automated hyperparameter optimization techniques such as Bayesian optimization or evolutionary algorithms to fine-tune GNN architectures without manual intervention. Integrating edge-weight learning mechanisms would allow the model to dynamically assign importance to relationships between nodes, improving sensitivity to subtle crash- related interactions. The framework may also be extended to support multi-task learning, where the model simultaneously predicts crash severity, contributing factors, and post-impact outcomes, enabling a more comprehensive crash analysis pipeline.

Another promising enhancement involves incorporating energy-efficient model compression techniques—such as pruning, quantization, and knowledge distillation—to enable deployment on resource-constrained edge devices used in smart cities. The system could also benefit from real-time alerting mechanisms that notify authorities when the model detects patterns associated with high-severity conditions, allowing for immediate preventative action. Furthermore, integrating geospatial risk mapping and predictive heatmaps can help visualize emerging danger zones, supporting proactive road safety interventions.

Finally, future work could explore integration with autonomous vehicle ecosystems, enabling vehicles to access severity risk predictions in real time and adjust their driving behavior accordingly. This would transform the framework into a critical component of next-generation intelligent transportation systems aimed at minimizing crash impacts and enhancing roadway resilience.

Future improvements may also include integrating multimodal sensor fusion techniques to combine textual crash reports, numerical attributes, geospatial data, and audio inputs from in-vehicle systems, enabling a richer and more holistic crash representation. Expanding the framework to support cross- regional transfer learning would allow the model to adapt quickly to new geographic areas with minimal training data, making it suitable for nationwide deployment. Enhancing the spatial graph construction process through adaptive distance metrics, road network topology integration, and hierarchical graph structures can improve the accuracy of relational modeling across urban, rural, and highway environments. Additionally, incorporating uncertainty quantification methods such as Bayesian GNNs could provide confidence intervals for severity predictions, helping authorities prioritize high-risk cases. These enhancements will refine the system's robustness, broaden its applicability, and strengthen its role in proactive crash prevention and intelligent transportation planning.

Another important direction for future enhancement is the incorporation of advanced graph learning techniques such as Graph Attention Networks (GAT) and dynamic graph modeling. By introducing attention mechanisms, the system can automatically identify and prioritize the most influential factors affecting accident severity, such as high-risk intersections, driver behavior patterns, or adverse weather conditions. Additionally, dynamic graph structures can be used to model time-evolving traffic patterns, enabling the system to capture how accident risks change across different time intervals. This would significantly improve the model's ability to handle real-time scenarios and provide more precise, context-aware predictions.

Another promising enhancement involves improving system deployment and user interaction through cloud-based infrastructure and advanced visualization tools. Deploying the model on cloud platforms would allow large-scale data processing, real-time updates, and accessibility across multiple regions. Furthermore, integrating interactive dashboards with geospatial visualizations such as heatmaps and risk maps can help authorities easily identify accident-prone zones and analyze contributing factors.

Another important direction for enhancement is the development of advanced and hybrid models. While GNNs are effective in capturing spatial relationships in data, combining them with models like LSTM or CNN can help in understanding temporal patterns as well. Such hybrid approaches can improve the overall performance of the system and provide deeper insights into how accident severity evolves over time.

Improving scalability and deployment is also essential for real-world applications. The GNN model can be implemented on cloud or edge computing platforms to handle large volumes of data efficiently. This enables faster processing and real-time predictions, which are particularly useful in smart city environments where continuous monitoring of traffic conditions is required.

Finally, enhancing the explainability of the GNN model is important for increasing user trust and acceptance. By using explainable AI techniques, the model can clearly indicate the factors influencing its predictions. This transparency helps decision-makers understand the reasoning behind the results, making it easier to take appropriate actions and improve overall road safety.

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