

ROAD ACCIDENT PREDICTION USING MACHINE LEARNING

**This project report is submitted in partial fulfilment of the requirement
for the award of the degree**

BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING



Submitted by

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CERTIFICATE

This is to certify that this project report entitled, “**ROAD ACCIDENT PREDICTION USING MACHINE LEARNING**” is a Bonafide work of **GUDHE JASHWANTH VEERA RAJESH**, Registration No: **218297601011** submitted in a partial fulfilment of the requirements for the award of Degree of B.Tech (CSE) during the period 2021-2025. This work carried out by him under my supervision and guidance and submitted to Department of Computer Science and Engineering, Adikavi Nannaya University.

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DECLARATION

I **GUDHE JASHWANTH VEERA RAJESH**, reg.no: **218297601011**, hereby declare that project report entitled **ROAD ACCIDENT PREDICTION USING MACHINE LEARNING** done by me under the guidance of **Dr. B. Kezia Rani, Associate Professor, Adikavi Nannaya University**, is submitted for the partial fulfilment of requirement of the award of the degree, Bachelor of Technology in Computer Science and Engineering in the academic year 2021-2025.

Signature of student

Gudhe Jashwanth Veera Rajesh

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With gratitude,

Gudhe Jashwanth Veera Rajesh
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ABSTRACT

Road accidents are a major global concern, resulting in significant loss of life, injuries, and economic costs. Predicting road accidents based on environmental, temporal, and behavioral factors of human beings can help mitigate risks and improve road safety. This project leverages machine learning techniques to analyze historical accident data and identify patterns that contribute to accident likelihood.

In this Project Machine Learning algorithms are implemented to predict the severity of an accident occurring at a particular location and time. Using Python, preprocessing and analyzing data from various sources, including weather conditions, traffic density, and road characteristics. Models such as Random Forest and Decision trees and logistic regression are trained to predict accident occurrence with high accuracy. The proposed system not only identifies high-risk scenarios but also provides actionable insights for traffic management and urban planning. This predictive approach has the potential to enhance road safety systems and support decision-making in real-time applications, ultimately reducing accidents and saving lives.

Keywords: environmental, temporal, behavioral, machine learning techniques, historical accident data, random forest, decision trees, logistic regression, decision making.

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1.INTRODUCTION

1.1 INTRODUCTION TO THE PROJECT

1. OVERVIEW

The rapid increase in global vehicle usage has led to a significant rise in road accidents, posing a serious threat to public safety. Road accidents result in severe injuries, fatalities, and substantial economic losses due to medical expenses, vehicle repairs, and traffic congestion. According to global statistics, road accidents are among the leading causes of death, affecting millions of individuals each year. The unpredictable nature of accidents makes it challenging for policymakers, urban planners, and transportation authorities to devise and implement effective preventive measures.

2. CHALLENGES IN ROAD ACCIDENT PREDICTION

Traditional accident prevention measures, such as traffic signals, speed limits, road signs, and law enforcement, have contributed to improving road safety. However, these measures alone are insufficient in completely mitigating the risks associated with road accidents. The primary challenge lies in the complex interplay of various factors, including:

- **Road conditions:** Poor infrastructure, potholes, and lack of proper signage.
- **Traffic density:** High congestion levels leading to erratic driving behavior.
- **Weather conditions:** Rain, fog, or snow reducing visibility and road grip.
- **Driver behavior:** Speeding, drunk driving, fatigue, and distraction.
- **Vehicle characteristics:** Mechanical failures, tire conditions, and brake efficiency.

Due to the dynamic nature of these variables, a more sophisticated and adaptive approach is required to predict and prevent road accidents effectively.

3. THE ROLE OF MACHINE LEARNING

Machine learning (ML) provides a data-driven approach to analyzing vast and complex datasets to identify hidden patterns and relationships influencing road accidents. Unlike traditional statistical models, ML algorithms can dynamically adapt to new data and refine predictions over time, making them highly effective for accident forecasting.

The key advantages of using machine learning in road accident prediction include:

- **Pattern recognition:** Identifying complex correlations between accident-contributing factors.
- **Real-time adaptability:** Updating predictions based on live data inputs.
- **Automation:** Reducing the manual effort required for accident analysis and prediction.
- **Scalability:** Ability to process massive amounts of data from multiple sources simultaneously.

4. DATA SOURCES FOR ACCIDENT PREDICTION

A robust accident prediction model relies on diverse datasets, which include:

- **Historical accident records:** Information on past accidents, locations, severity, and causes.
- **Traffic data:** Real-time and historical traffic density and congestion levels.
- **Weather conditions:** Data on temperature, precipitation, fog, wind speed, etc.
- **Driver behavior:** Collected through sensors, GPS, and telematics.
- **Infrastructure details:** Road conditions, lighting, lane markings, and intersections.

By integrating these datasets, ML models can estimate the probability of accidents occurring at specific locations and times, allowing authorities to take proactive measures.

Machine learning has the potential to revolutionize road safety by providing accurate and dynamic accident predictions. By leveraging historical and real-time inputs such as weather reports, traffic conditions, and human behaviour, ML models can enhance decision-making for traffic authorities, policymakers, and individual drivers. The integration of AI-driven predictive systems with existing transportation infrastructure can significantly reduce road accidents, saving lives and minimizing economic losses. As technology advances, further research and development in this domain will be crucial in creating a safer and more efficient transportation ecosystem.

2. LITERATURE SURVEY

A literature survey in a software development process is a most significant part as it shows the various analyses and research made in the field of your interest including substantive findings, as well as theoretical and methodological contributions to a particular topic. It is the most important part of the report as it gives you a direction in the area of your research; it helps in setting up the goals for the analysis. The purpose is to convey to the reader what knowledge and ideas have been established on a topic, and what their strengths and weaknesses are.

Table 1: Literature Review

| S. No. | Title | Author | Year | Objectives |
|--------|--|---------------------------------------|------|--|
| 1 | A Model of Traffic Accident Prediction Based on Convolutional Neural Network | Lu Wenqi Luo Dongyu Yan Menghua | 2017 | to predict the traffic accident severity by using convolution neural Network. |
| 2 | The Traffic Accident Prediction Based on Neural Network | Fu Huilin, Zhou Yucai | 2017 | Traditional way of linear analyses can not reveal the really situation the result of prediction is not satisfactory. Compares traditional BP network with its proposed solution. |

| | | | | |
|---|---|--|------|--|
| 3 | Evolutionary Cross Validation | Thineswaran Gunasegaran Yu- N Cheah | 2017 | This paper proposes an evolutionary cross validation algorithm for identifying optimal folds in a dataset to improve predictive modeling accuracy |
| 4 | On the Selection of Decision Trees in Random Forests | Simon Bernard, Laurent Heutte and Sebastien Adam | 2017 | This paper presents a study on on the Random Forest (RF) family of ensemble methods. |
| 5 | Hyper-parameter Tuning of a Decision Tree Induction Algorithm | Rafael G.Mantovan,, Ricardo Cerri,Joaquin Vanschoren | 2016 | This paper investigates how sensitive decision trees are to a hyper-parameter optimization process. Four different tuning techniques were explored.. |

3. PROBLEM SPECIFICATION

3.1 EXISTING SYSTEM

The traditional approach to road accident prediction and analysis relies on manual processes and outdated methodologies. Below is a detailed breakdown of the limitations of the existing system:

1. Manual Accident Reporting and Analysis

- Accident data is primarily collected through police reports, traffic surveys, and emergency services.
- The reporting process is often slow and requires human intervention, leading to data entry errors and inconsistencies.

2. Lack of Real-Time Prediction

- Most traditional systems use historical accident data to identify patterns, but they lack real-time data integration.
- Without real-time updates from traffic cameras, weather sensors, or vehicle telematics, the system cannot predict accidents dynamically.

3. Inability to Proactively Prevent Accidents

- Since no real-time alerts or preventive measures are in place, authorities can only respond after an accident occurs.
- Lack of predictive modelling makes it difficult to identify high-risk zones before accidents happen.

4. Inefficiency with Large Datasets

- Manual and rule-based approaches struggle to process large datasets efficiently.
- As data complexity increases (e.g., sensor data, GPS tracking, road conditions), legacy systems become less effective.

5. Lower Accuracy

- Traditional models rely on limited historical data and simple statistical techniques, leading to lower accuracy in predictions.
- The absence of machine learning and AI-driven techniques reduces the ability to handle complex variables such as weather conditions, driver behavior, and traffic flow.

3.2 PROPOSED SYSTEM

To address the limitations of traditional accident prediction systems, an advanced AI and machine learning-based road accident prediction system is proposed. This system integrates multiple data sources and predictive analytics to improve accuracy and real-time decision-making.

1. Efficient Handling of Large Datasets

- The system can process vast amounts of accident-related data, including historical records, real-time sensor inputs, and GPS-based traffic data.
- Unlike traditional methods, which struggle with data overload, the use of big data technologies allows seamless handling of large datasets.

2. Machine Learning-Based Classification Algorithms

- The system employs supervised learning algorithms such as Random Forest, Decision Trees and logistic regression to predict accident severity.
- Feature selection techniques are used to identify the most relevant factors influencing accident risk.

3. Integration of Diverse Data Sources

To enhance prediction accuracy, the system incorporates various real-time and static data inputs:

- **Traffic Flow Data:** Real-time vehicle count, speed variations, and congestion patterns from road sensors and GPS devices.
- **Environmental Conditions:** Weather parameters like rainfall, fog, temperature, and visibility levels.

- **Driver Behaviour Data:** Speed violations, sudden braking, alcohol consumption.
- **Road Infrastructure:** Historical accident locations, road curvature, presence of intersections, and traffic signals.

By integrating these factors, the system moves beyond conventional statistical models and provides data-driven accident risk assessments.

4. Scalability for Real-Time Predictions

- The system must be able to scale to handle increasing data sources, traffic volume, and users, especially as more sensors and data streams by integrating real-time data.

5. Higher Prediction Accuracy

- With AI-driven data processing, the proposed system significantly outperforms traditional models in terms of accuracy.
- Continuous model training using new accident data and real-time updates ensures improved predictions over time.

3.3 SCOPE OF THE SYSTEM

The scope of the system includes various aspects aimed at improving road safety, reducing accidents, and assisting authorities in better traffic management.

1. Accident Risk Prediction

- The system will analyze historical accident data, weather conditions, road conditions, and traffic flow to predict accident-prone areas.
- It will help authorities and drivers take preventive actions before an accident occurs.

2. Real-Time Data Analysis

- Integration of real-time data from IoT sensors, GPS, and traffic monitoring systems to predict accident likelihood dynamically.

- Immediate alerts to drivers, emergency response teams, and traffic authorities to prevent accidents.

3. Machine Learning-Based Decision Making

- Utilizes ML algorithms like Random Forest, Decision Trees, and Logistic Regression to analyze complex datasets and improve prediction accuracy.
- Continuous learning and self-improvement of models based on new accident data.

4. Government and Traffic Management Support

- Helps urban planners and traffic management authorities identify high-risk areas and optimize traffic flow.
- Can be used for policy-making, road infrastructure improvements, and safety enhancements.

5. User-Friendly Visualization and Reporting

- Provides an interactive dashboard for real-time monitoring and accident risk visualization.
- Generates reports and statistical insights for further analysis.

4. REQUIREMENTS SPECIFICATION

4.1 FUNCTIONAL REQUIREMENTS

1. Data Collection and Integration

- Collects real-time and historical accident data.
- Gathers road condition details, weather reports, traffic patterns, and geographical data.
- Integrates data from multiple sources, including traffic cameras, sensors, and weather APIs.

2. Data Preprocessing

- Cleans and structures data to remove inconsistencies.
- Handles missing values by filling gaps or removing incomplete records.
- Identifies and removes outliers to improve prediction accuracy.

3. Machine Learning Model Development

- Selects suitable machine learning algorithms such as Decision Trees, Random Forest, Logistic Regression.
- Trains models on historical accident data to learn patterns and risk factors.
- Evaluates model performance and fine-tunes parameters for higher accuracy.

4. Prediction Engine

- Uses trained ML models to predict accident probabilities based on real-time inputs.
- Classifies accident severity levels (Severe, Moderate, Mild).
- Continuously updates predictions based on dynamic environmental and traffic conditions.

5. User Interface (UI) and Visualizations

- Provides an interactive dashboard displaying real-time accident risks.
- Visualizes traffic conditions, road safety warnings, and prediction results.
- Allows users (authorities, drivers, urban planners) to access and interpret data easily.

4.2 NON-FUNCTIONAL REQUIREMENTS

1. Response Time

- The system must provide real-time predictions of accident risk with minimal latency.

2. Scalability

- The system should be capable of handling an increasing number of data sources, traffic volume, and users.
- It should be able to integrate more sensors and data streams in the future.

3. Availability

- The system should be available 99.9% of the time, ensuring minimal downtime for updates or maintenance.

4. Fault Tolerance

- The system should automatically handle failures and provide meaningful error messages to users.

5. User Interface (UI) Design

- The UI should be intuitive, easy to use, and provide clear visualizations for accident risk and traffic conditions.
- Navigation should be user-friendly for better usability.

4.3 HARDWARE REQUIREMENTS

The Hardware consists of the physical components of the computer that input storage processing control, output devices. Most hardware only has operating system requirements or compatibility. For example, a printer may be compatible with Windows XP but not compatible with newer versions of Windows like Windows 10, Linux, or the Apple macOS.

The kind of hardware used in the project is

- Processor: Intel Core i5 or higher
- RAM: 8GB or higher
- Hard Disk :256 GB

4.4 SOFTWARE REQUIREMENTS

Software is a set of programs to do a particular task. Software is an essential requirement of computer systems. The system requirements or software requirements is a listing of what software programs are required to operate the program properly.

The kind of software used in the project is

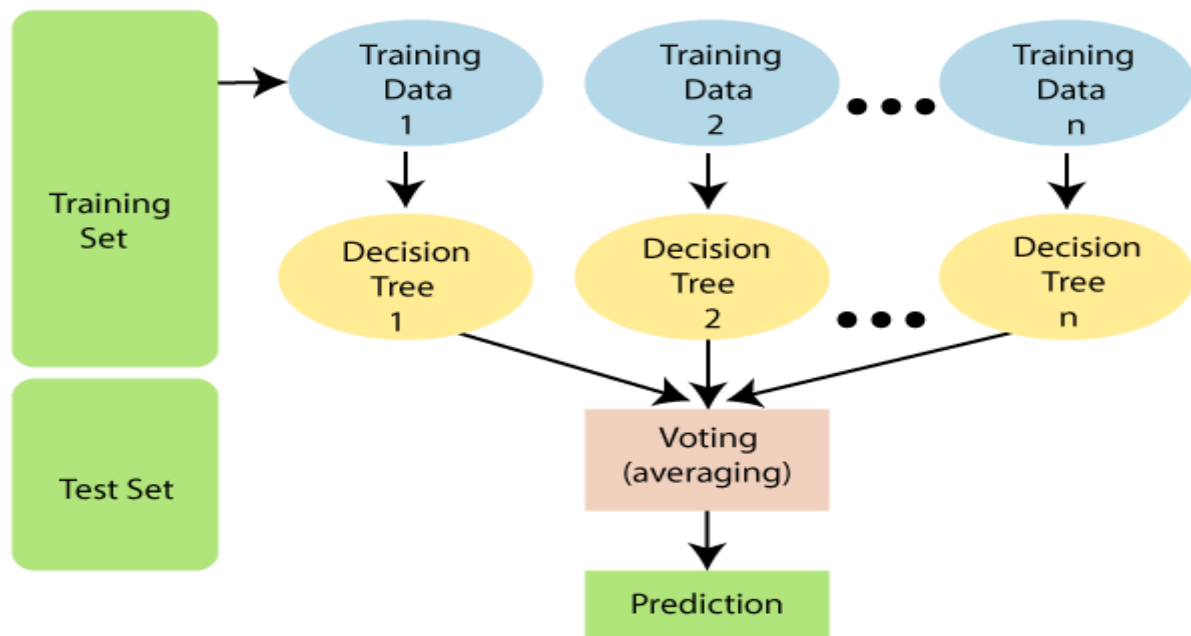
- Operating System: Windows 11
- Programming Language: Python
- Framework: Flask, Django
- Development : VS Code
- Libraries: Scikit-Learn, Pandas, NumPy, Joblib

5. ALGORITHMS USED

5.1 RANDOM FOREST

Random Forest algorithm is a powerful tree learning technique in Machine Learning to make predictions and then we do voting of all the trees to make prediction. They are widely used for classification and regression task.

- It is a type of classifier that uses many decision trees to make predictions.
- It takes different random parts of the dataset to train each tree and then it combines the results by averaging them. This approach helps improve the accuracy of predictions. Random Forest is based on ensemble learning.

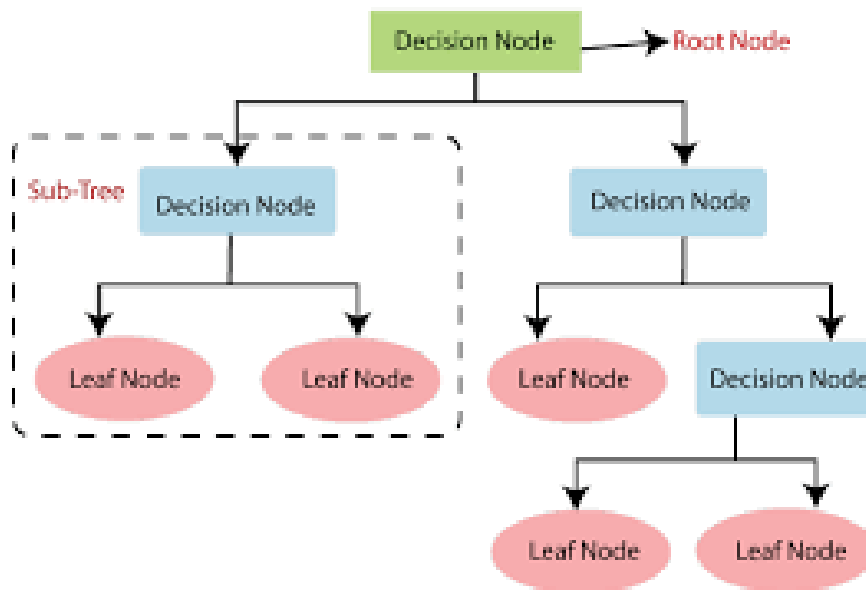


Since the random forest combines multiple trees to predict the class of the dataset, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random forest classifier:

- There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.
- The predictions from each tree must have very low correlations.

5.2 DECISION TREES

A decision tree is a supervised learning for both **classification** and **regression** tasks. It models decisions as a tree-like structure where internal nodes represent attribute tests, branches represent attribute values, and leaf nodes represent final decisions or predictions. Decision trees are versatile, interpretable, and widely used in machine learning for predictive modelling.



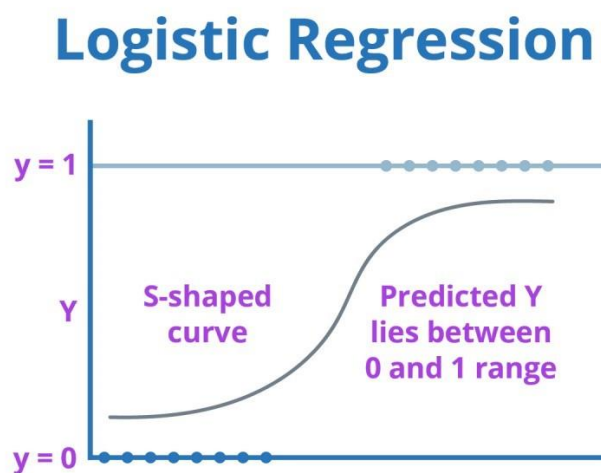
In a decision tree, for predicting the class of the given dataset, the algorithm starts from the root node of the tree. This algorithm compares the values of root attribute with the record (real dataset) attribute and, based on the comparison, follows the branch and jumps to the next node.

For the next node, the algorithm again compares the attribute value with the other sub-nodes and move further. It continues the process until it reaches the leaf node of the tree.

- Decision Trees usually mimic human thinking ability while making a decision, so it is easy to understand.
- The logic behind the decision tree can be easily understood because it shows a tree-like structure.

5.3 LOGISTIC REGRESSION

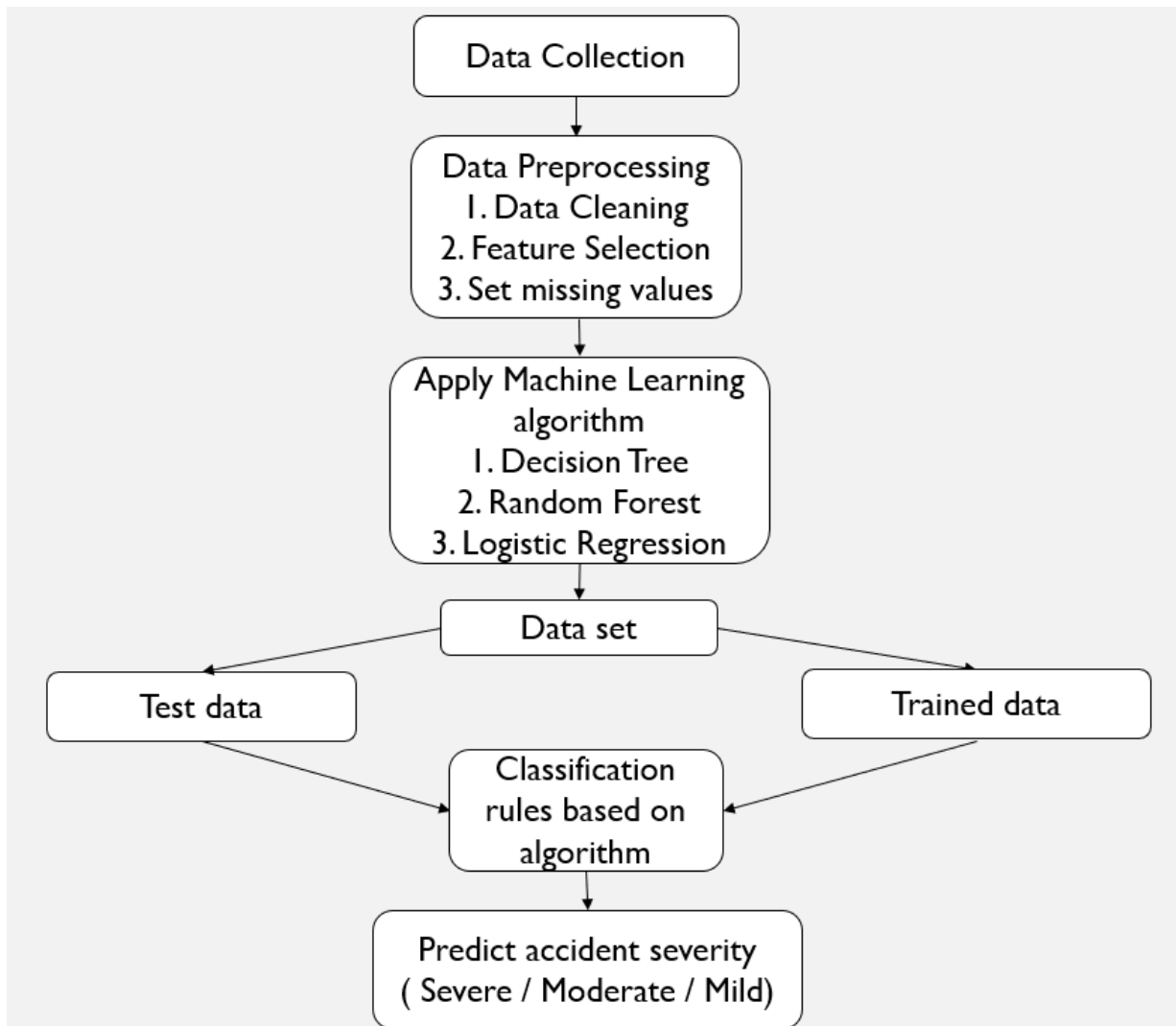
Logistic regression is a supervised machine learning algorithm used for classification tasks where the goal is to predict the probability that an instance belongs to a given class or not. Logistic regression is a statistical algorithm which analyze the relationship between two data factors. Logistic regression is used for binary classification where we use **sigmoid function**, that takes input as independent variables and produces a probability value between 0 and 1.



- Logistic Regression is much similar to the Linear Regression except that how they are used. Linear Regression is used for solving Regression problems, whereas Logistic regression is used for solving the classification problems.
- In Logistic regression, instead of fitting a regression line, we fit an "S" shaped logistic function, which predicts two maximum values (0 or 1).
- The curve from the logistic function indicates the likelihood of something such as whether the cells are cancerous or not, a mouse is obese or not based on its weight, etc.

6. PROJECT ARCHITECTURE

The architecture of the Road Accident Prediction System consists of multiple stages, integrating data collection, preprocessing, machine learning model application, and prediction visualization.



1. Data Collection

- The process begins with collecting relevant road accident-related data from various sources such as:
 - Traffic police reports
 - GPS and telematics data
 - Weather reports
 - Traffic surveillance cameras

- Publicly available accident databases (e.g., U.S. NHTSA, UK DfT, Indian NCRB)
- This data typically includes information about accident locations, severity, weather conditions, driver behavior, and road infrastructure.

2. Data Preprocessing

Before applying machine learning algorithms, raw data needs to be cleaned and transformed to improve prediction accuracy.

- **Data Cleaning:**
 - Removing duplicate or irrelevant entries
 - Handling missing or inconsistent data
 - Removing outliers that may affect model performance
- **Feature Selection:**
 - Selecting the most relevant attributes (features) that influence accident severity, such as:
 - Vehicle speed
 - Road surface conditions
 - Traffic density
 - Driver fatigue levels
 - Unimportant features are removed to improve efficiency.
- **Handling Missing Values:**
 - Missing data is filled using:
 - Mean/median values for numerical data
 - Most frequent values for categorical data
 - Advanced methods like K-Nearest Neighbours (KNN) imputation

3. Apply Machine Learning Algorithm

Various machine learning algorithms are applied to the processed dataset to create a predictive model.

- **Decision Tree:**
 - A tree-like structure that splits the dataset based on feature values.
 - It classifies accident severity by following decision paths based on input features.
- **Random Forest:**
 - An ensemble learning technique that creates multiple decision trees.
 - It improves prediction accuracy by reducing overfitting.
- **Logistic Regression:**
 - A statistical model used for binary and multi-class classification.
 - It assigns probabilities to different severity levels (Severe, Moderate, Mild).

4. Dataset Splitting

- The data is divided into two subsets:
 - **Training Data:** Used to train the machine learning model.
 - **Test Data:** Used to evaluate the model's performance.
- This ensures the model generalizes well to unseen accident scenarios.

5. Classification Rules Based on Algorithm

- After training, classification rules are generated based on the selected algorithm.
- These rules help in making predictions by identifying which input features contribute the most to accident severity.

6. Prediction of Accident Severity

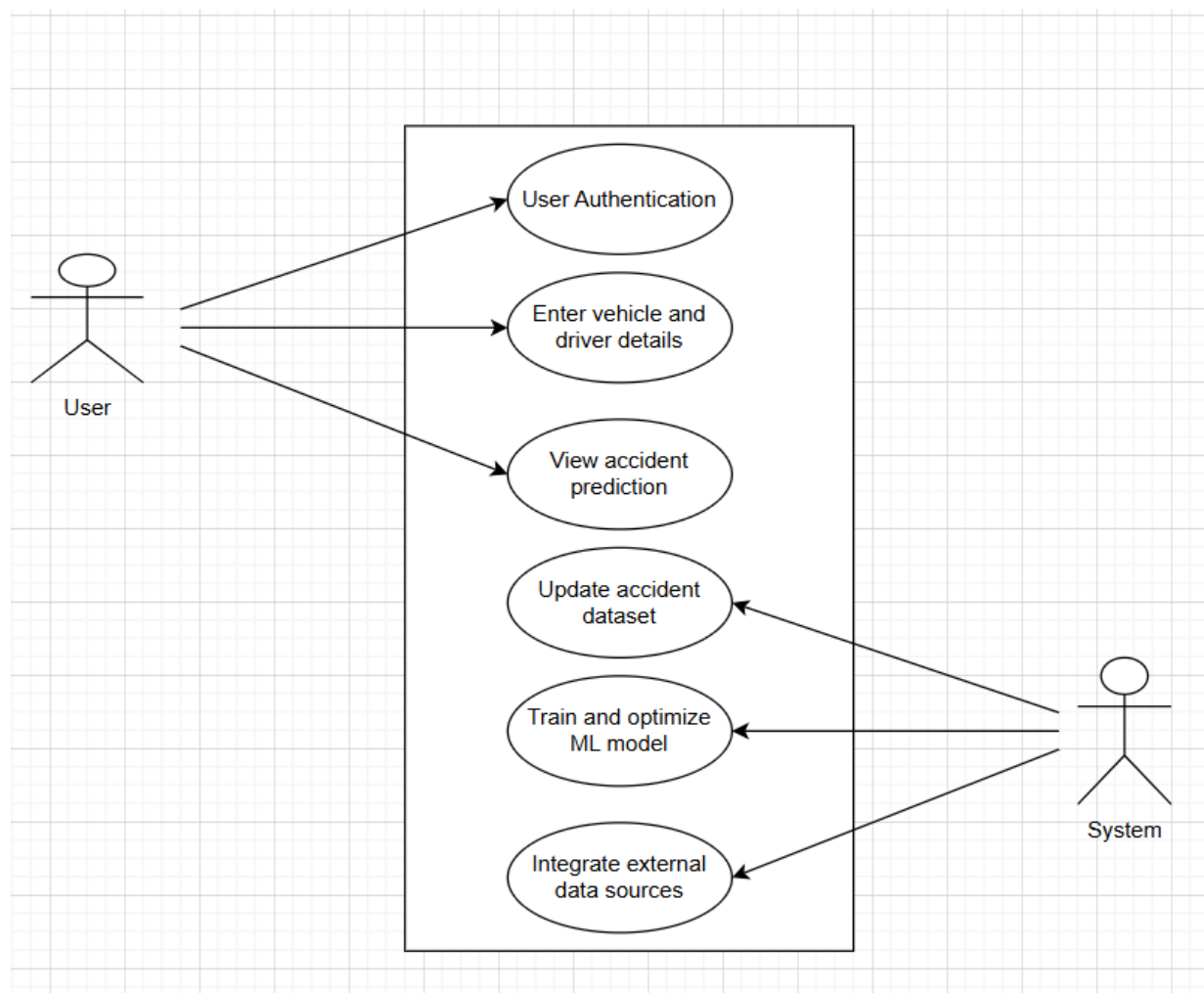
- The trained model classifies accidents into three categories:
 - **Severe:** High-risk accidents with fatalities or major injuries.
 - **Moderate:** Medium-risk accidents with minor injuries.
 - **Mild:** Low-risk accidents with little or no injuries.
- The prediction is based on real-time input factors like road conditions, weather, and traffic density.

7. UML DIAGRAMS

A UML diagram is a diagram based on the UML (Unified Modeling Language) with the purpose of visually representing a system along with its main actors, roles, actions, artifacts or classes, in order to better understand, alter, maintain, or document information about the system.

7.1 USECASE DIAGRAM

A Use Case Diagram represents the functional requirements of a system. It shows the interactions between users (actors) and the system's functionalities (use cases). This diagram is useful for understanding what a system does rather than how it does it.



Detailed Breakdown of the Workflow

1. User Authentication

- The process begins with the user being authenticated by the system. This step ensures that only authorized individuals can access the platform, safeguarding sensitive data and functionalities. Authentication might involve username/password combinations, biometric verification, or other security protocols.

2. Enter Vehicle and Driver Details

- Once authenticated, the user inputs specific details about the vehicle and driver. This could include vehicle identification numbers (VIN), model, age, maintenance history, driver demographics, driving history, or behavioral data (e.g., speed tendencies, adherence to traffic rules). This data forms the foundation for subsequent analysis.

3. View Accident Prediction

- The system processes the entered data and generates an accident prediction. This step likely involves running the input through a pre-trained ML model that assesses risk factors and predicts the likelihood of an accident. The output might include a probability score, potential risk areas, or recommended preventive actions.

4. Update Accident Dataset

- Based on the predictions or real-world feedback (e.g., actual accidents), the system updates its accident dataset. This iterative process ensures that the dataset remains current, incorporating new incidents, trends, or environmental factors (e.g., weather conditions, road types). This step is crucial for maintaining the relevance and accuracy of the predictive model.

5. Train and Optimize ML Model

- The updated dataset is used to retrain and optimize the machine learning model. This involves adjusting parameters, refining algorithms, and improving prediction accuracy. Techniques such as cross-validation, hyperparameter tuning, or reinforcement learning might be employed to enhance the model's performance.

6. Integrate External Data Sources

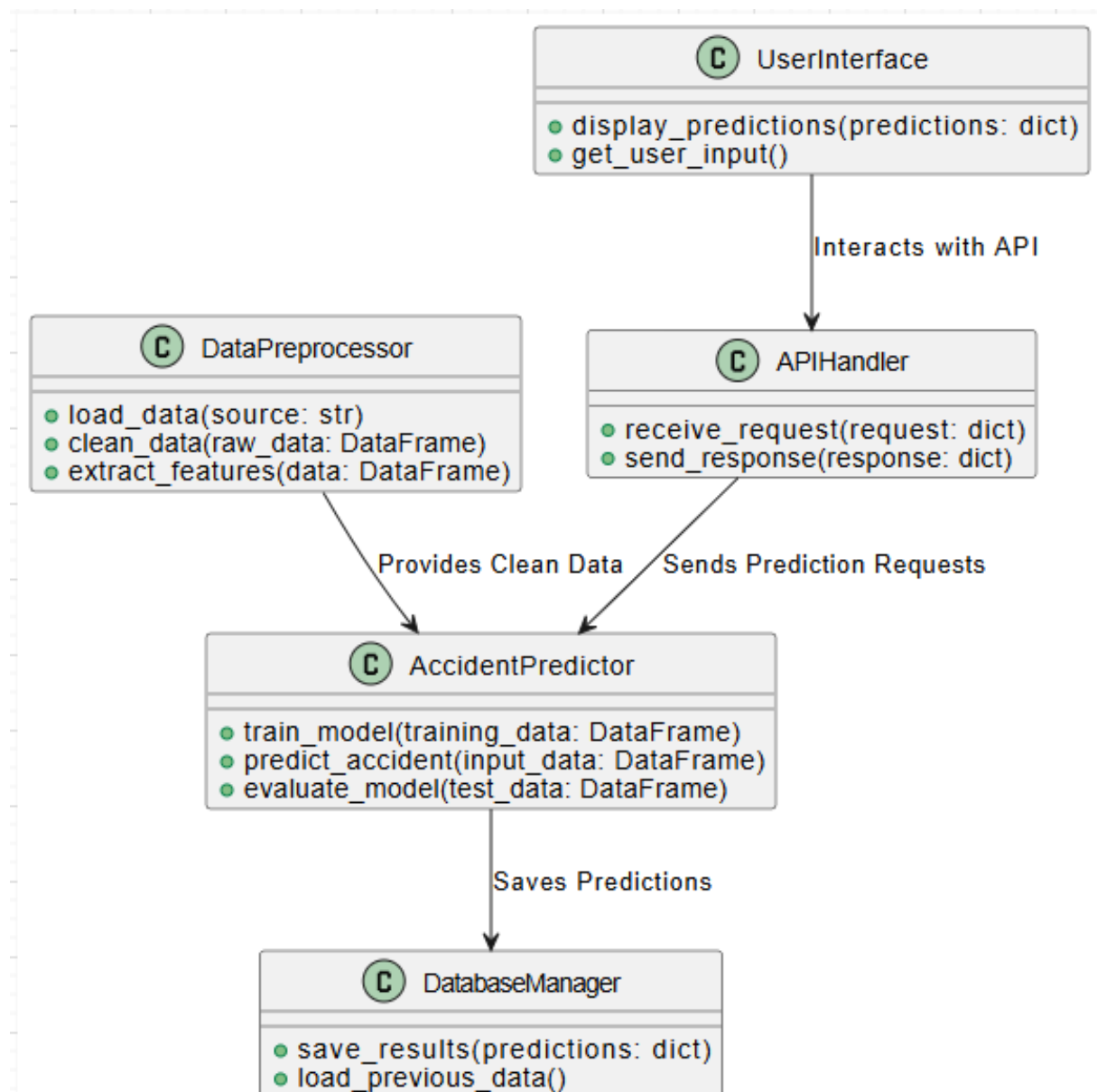
- The system integrates external data sources to enrich its dataset and improve predictions. These sources could include traffic reports, weather data, road condition updates, or historical accident statistics from public or private databases. This integration broadens the context of the analysis, enabling more robust and comprehensive predictions.

Interaction Between User and System

- The flowchart illustrates a bidirectional interaction between the "User" and the "System." The user initiates the process by providing authentication and data, while the system responds with predictions and requires user input for dataset updates. This collaborative dynamic suggests a user-centric design where human oversight complements automated processes.

7.2 CLASS DIAGRAM

Class diagrams are the blueprints of your system or subsystem. You can use class diagrams to model the objects that make up the system, to display the relationships between the objects, and to describe what those objects do and the services that they provide.



1. User Interface

- This component serves as the entry point for user engagement with the system. It is responsible for facilitating interaction between the user and the underlying processes..
- The UserInterface interacts with an API to relay user data and receive prediction outcomes, ensuring a seamless flow of information.

2. API Handler

- This component acts as the intermediary that manages communication between the UserInterface and the backend prediction system.
- The APIHandler facilitates the exchange of prediction requests and responses, maintaining the system's connectivity and efficiency.

3. Data Preprocessor

- This component is responsible for preparing raw data for analysis, ensuring it is clean and suitable for the prediction model.
- The DataPreprocessor provides the resulting clean data to the AccidentPredictor, forming a critical step in ensuring accurate predictions.

4. Accident Predictor

- This component is the core of the system, where the actual prediction of accidents occurs using a trained model.
- The AccidentPredictor saves the generated predictions for storage and further use, bridging the analysis phase with data management.

5. Database Manager

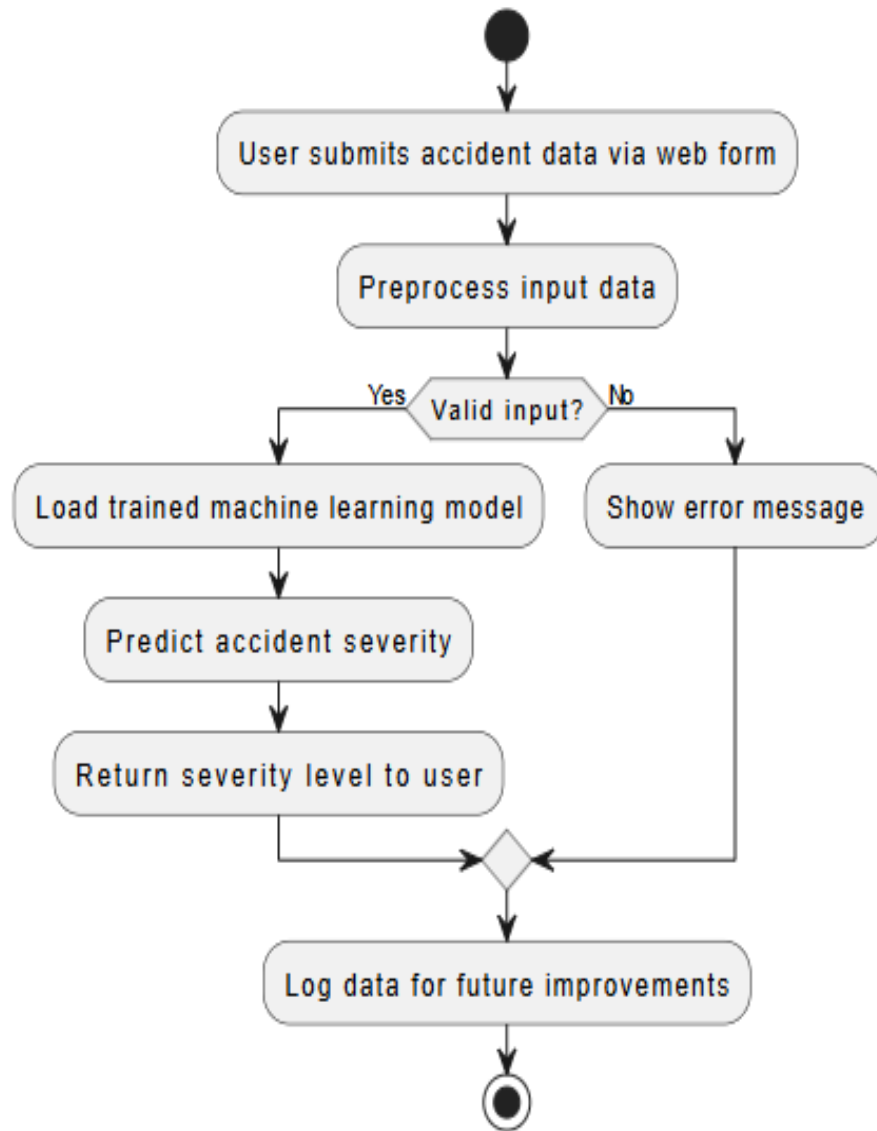
- This component handles the storage and retrieval of prediction results and historical data, ensuring the system maintains a record for future analysis.
- The DatabaseManager acts as the system's memory, preserving valuable insights for ongoing and future operations.

Interaction Between Components

- The workflow follows a structured sequence:
 - The `UserInterface` collects input and displays results, interacting with the `APIHandler` to transmit data.
 - The `APIHandler` sends prediction requests to the backend and returns responses, coordinating the flow.
 - The `DataPreprocessor` refines the data and provides it to the `AccidentPredictor`.
 - The `AccidentPredictor` generates predictions and saves them to the `DatabaseManager`.
 - The `DatabaseManager` stores results and supplies previous data for model training or evaluation.
- This interconnected process ensures that data flows smoothly from user input to actionable insights, with each component playing a specialized role.

7.3 ACTIVITY DIAGRAM

Class diagrams are the blueprints of your system or subsystem. You can use class diagrams to model the objects that make up the system, to display the relationships between the objects, and to describe what those objects do and the services that they provide.



Detailed Breakdown of the Workflow

1. User Submits Accident Data via Web Form

- The process begins with the user, who interacts with the system through a web-based interface.
- Action: The user submits accident data, which could include details such as the location of the incident, time of occurrence, vehicle types involved, environmental conditions (e.g., weather, road state), or injury reports. This data serves as the input for the severity prediction.

2. Preprocess Input Data

- The submitted data is received and subjected to an initial preparation phase.
- Action: Preprocessing involves cleaning the data by removing inconsistencies (e.g., missing values, duplicates) and standardizing formats to ensure compatibility with the prediction model. This step transforms raw input into a usable form for analysis.

3. Decision: Valid Input?

- A critical decision point follows the preprocessing stage to verify the quality of the data.
- **Condition:** The system checks whether the preprocessed data is valid. Validity might be assessed based on completeness, accuracy, or adherence to expected formats (e.g., numerical values for distances, categorical data for weather).
- **Outcomes:**
 - Yes: If the data is deemed valid, the process proceeds to the next step.
 - No: If the data is invalid, an alternative path is taken to address the issue.

4. Show Error Message (if Invalid)

- In the case of invalid input, the system provides feedback to the user.
- Action: An error message is displayed, informing the user of the issue (e.g., missing fields, incorrect data types). This step allows the user to correct and resubmit the data, looping back to the preprocessing stage for re-evaluation.

5. Load Trained Machine Learning Model

- Once the input data is validated, the system prepares for prediction.
- Action: A pre-trained machine learning model is loaded. This model has been developed using historical accident data to recognize patterns and correlate factors with severity levels (e.g., minor, moderate, severe). Loading the model sets the stage for applying it to the new data.

6. Predict Accident Severity

- The core analytical step involves using the loaded model to assess the submitted data.
- Action: The system predicts the accident severity by analyzing the preprocessed data against the patterns learned by the model. This could involve evaluating factors like impact force, number of vehicles, or injury extent to estimate the severity level.

7. Return Severity Level to User

- After the prediction is generated, the result is communicated back to the user.
- Action: The severity level is returned to the user through the web interface, presented in an understandable format (e.g., a categorical label like "low," "medium," "high," or a detailed report). This step provides actionable insights for the user, such as informing emergency response or insurance claims.

8. Log Data for Future Improvements

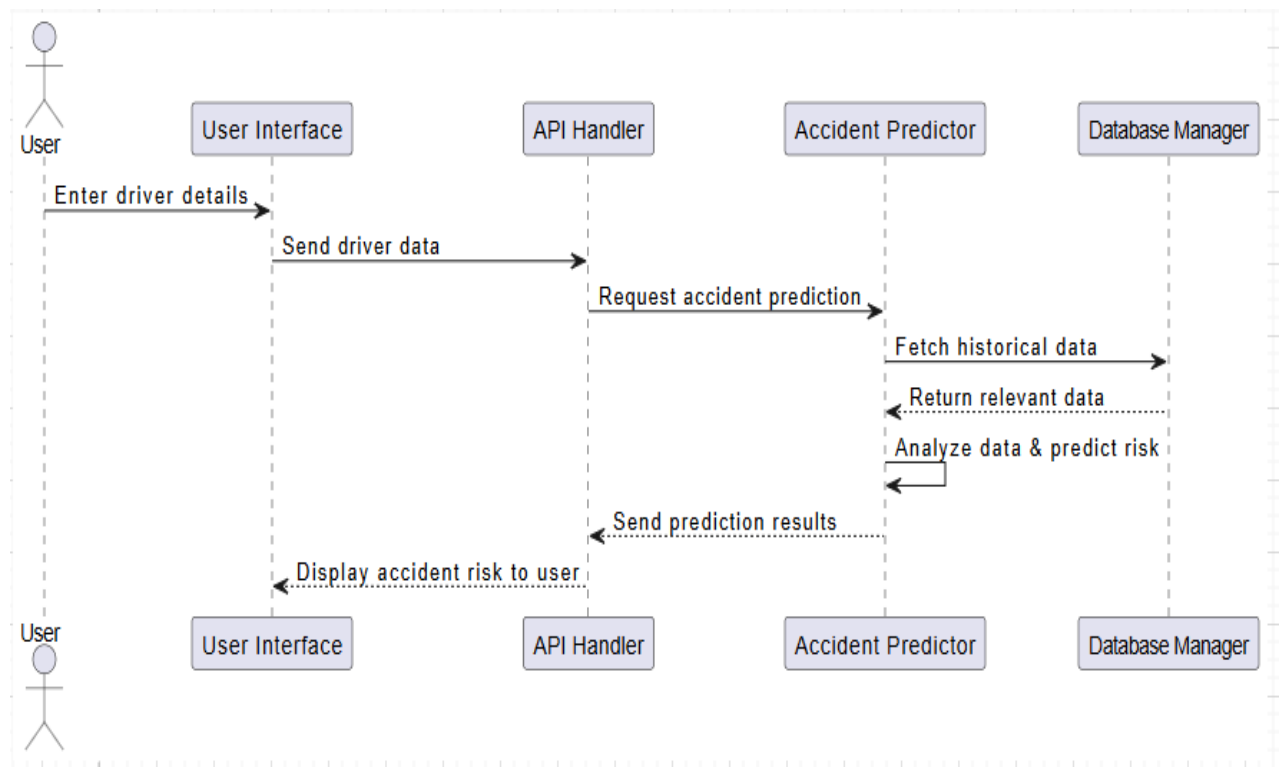
- The final step involves storing the processed data for ongoing enhancement of the system.
- Action: The submitted data, along with the predicted severity and any relevant metadata, is logged for future use. This data can be used to retrain or refine the machine learning model, ensuring the system adapts to new trends or improves its accuracy over time.
- The process then concludes, with the potential for the user to submit new data and restart the cycle.

Interaction and Flow

- The flowchart follows a linear progression with a conditional branch:
 - The user initiates the process by submitting data via a web form.
 - The data is preprocessed and validated, with an error message loop if validation fails.
 - Upon validation, a trained model is loaded, and the severity is predicted.
 - The result is returned to the user, and the data is logged for future improvements.

7.4 SEQUENCE DIAGRAM

A sequence diagram is a type of UML (Unified Modeling Language) diagram that illustrates how objects interact in a particular scenario of a system. It focuses on the sequence of messages exchanged between different components over time.



Detailed Breakdown of the Workflow

1. User Initiates Interaction

- The process starts with the user, represented as an external entity, engaging with the system through the User Interface.
- **Action:** The user enters driver details, which could include information such as the driver's age, driving experience, history of incidents, or behavioral patterns. This input serves as the foundation for the risk assessment.

2. User Interface Sends Driver Data

- The User Interface, the first system component, receives the driver details from the user.
- **Action:** It forwards this data to the API Handler by sending the driver data. This step ensures that the raw input is transmitted to the backend for processing, acting as the initial bridge between the user and the system's analytical capabilities.

3. API Handler Requests Accident Prediction

- The API Handler, responsible for managing communication between components, receives the driver data from the User Interface.
- **Action:** It sends a request for an accident prediction to the Accident Predictor. This request encapsulates the driver details and signals the system to analyze the data and generate a risk assessment.

4. Accident Predictor Fetches Historical Data

- The Accident Predictor, the core analytical component, receives the prediction request from the API Handler.
- **Action:** It interacts with the Database Manager to fetch relevant historical data. This data might include past accident records, driver performance trends, or environmental factors (e.g., weather or road conditions) associated with similar profiles, providing context for the prediction.

5. Database Manager Returns Relevant Data

- The Database Manager, responsible for storing and retrieving data, responds to the Accident Predictor's request.
- **Action:** It returns relevant historical data to the Accident Predictor. This information enriches the analysis by providing a baseline for comparison and pattern recognition.

6. Accident Predictor Analyzes Data and Predicts Risk

- With the driver details and historical data in hand, the Accident Predictor performs its primary function.

- **Action:** It analyzes the combined data to predict the accident risk. This involves assessing factors such as the driver's history against historical trends to estimate the likelihood of an accident. The result is a risk assessment, which could be expressed as a probability score or a qualitative rating (e.g., low, medium, high).

7. Accident Predictor Sends Prediction Results

- After generating the risk prediction, the Accident Predictor shares the outcome.
- **Action:** It sends the prediction results back to the API Handler. This step ensures that the analyzed data is relayed to the communication layer for distribution.

8. API Handler Sends Prediction Results to User Interface

- The API Handler receives the prediction results from the Accident Predictor.
- **Action:** It forwards these results to the User Interface, maintaining the flow of information from the backend to the user-facing component.

9. User Interface Displays Accident Risk to User

- The User Interface receives the prediction results from the API Handler.
- **Action:** It displays the accident risk to the user in a clear and understandable format, such as a visual graph, a numerical score, or a written summary. This final step completes the cycle, providing the user with actionable insights based on the analysis.

10. User Receives Feedback

- The user, now back in focus, receives the displayed risk assessment.
- **Outcome:** This information can inform decisions such as adjusting driving habits, scheduling training, or implementing safety measures, closing the interaction loop.

Interaction Between Components

- The sequence diagram illustrates a linear yet interconnected process:
 - The user initiates the process by entering data through the User Interface.
 - The User Interface and API Handler facilitate data transmission to the Accident Predictor.

- The Accident Predictor collaborates with the Database Manager to gather historical context.
 - The Accident Predictor analyzes the data and returns results via the API Handler to the User Interface.
 - The User Interface presents the final risk assessment to the user.
- This structured interaction ensures efficient data flow and accurate risk prediction, with each component playing a specialized role in the pipeline.

8. IMPLEMENTATION

8.1 Code Design Characteristics

1. Modular Structure

- The code is divided into separate files for training, preprocessing, and predictions.
- Advantages: Easier maintenance, debugging, and scalability.

2. Model Persistence

- Trained models are saved as .pkl (pickle) files for reuse without retraining.
- Advantages: Faster predictions, efficient storage.

3. Preprocessing Pipeline

- The preprocess.py script likely cleans and transforms raw data before model training.
- Advantages: Ensures high data quality and prevents missing/inconsistent data from affecting predictions.

4. Web Interface Integration

- The presence of app.py and index.html suggests that the system supports a web-based UI.
- Likely built using Flask or Django, allowing real-time accident risk visualization.

5. Machine Learning Model Variety

- Uses Decision Tree, Logistic Regression, and Random Forest models.
- Advantages: Allows comparison of different models for better accuracy.

6. Script-Based Execution

- Training and prediction are handled through separate scripts (train_model.py, predict.py).
- Advantages: Command-line or automated execution is possible.

8.2 SAMPLE CODE

Code for training the model:

```
import pandas as pd

import joblib

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.preprocessing import LabelEncoder

df = pd.read_csv("dataset/accident_data.csv")

random_forest = RandomForestClassifier(n_estimators=200)

random_forest.fit(X_train,y_train)

Y_pred = random_forest.predict(X_test)

random_forest.score(X_test, y_test)

acc_random_forest1 = round(random_forest.score(X_test, y_test) * 100, 2)

sk_report = classification_report(

    digits=6,

    y_true=y_test,

    y_pred=Y_pred)

print("Accuracy" , acc_random_forest1)

print(sk_report)

pd.crosstab(y_test, Y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True)
```

```

decision_tree = DecisionTreeClassifier()

decision_tree.fit(X_train, y_train)

Y_pred = decision_tree.predict(X_test)

acc_decision_tree1 = round(decision_tree.score(X_test, y_test) * 100, 2)

sk_report = classification_report(

    digits=6,

    y_true=y_test,

    y_pred=Y_pred)

print("Accuracy", acc_decision_tree1)

print(sk_report)

### Confusion Matrix

pd.crosstab(y_test, Y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True)

lr = LogisticRegression()

# Fit the model on the training data.

lr.fit(X_train, y_train)

y_pred = lr.predict(X_test)

sk_report = classification_report(

    digits=6,

    y_true=y_test,

    y_pred=y_pred)

print("Accuracy", round(accuracy_score(y_pred, y_test)*100,2))

print(sk_report)

pd.crosstab(y_test, y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True)

```



```

# Encode categorical values if needed

label_encoders = {}

for col in df.select_dtypes(include=["object"]).columns:

    label_encoders[col] = LabelEncoder()

    df[col] = label_encoders[col].fit_transform(df[col])

# Split data

X = df.drop(columns=["Accident_Severity"]) # Target column

y = df["Accident_Severity"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train model with new features

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)

rf_model.fit(X_train, y_train)

# Save updated model

joblib.dump(rf_model, "models/random_forest.pkl")

print("✅ Model retrained with new features & saved successfully!")

```

Code for making prediction:

```

import pandas as pd

import joblib

# Load the trained model

model = joblib.load("models/random_forest.pkl")

# Load the test data

test_data = pd.read_csv("dataset/test_data.csv")

```

```

# Print columns for debugging

print("◆ Columns in test_data.csv:", list(test_data.columns))

print("◆ Expected Features in Model:", list(model.feature_names_in_))

# Define categorical encodings (MUST MATCH training data)

encoding_map = {

    "Weather_Condition": {"Rain": 0, "Clear": 1, "Fog": 2},

    "Traffic_Density": {"Low": 0, "Medium": 1, "High": 2},

    "Road_Type": {"Highway": 0, "Urban": 1, "Rural": 2},

}

# Convert categorical values to numerical

for col, mapping in encoding_map.items():

    if col in test_data.columns:

        test_data[col] = test_data[col].map(mapping)

# Check for missing values after encoding

if test_data.isnull().values.any():

    raise ValueError("✗ Test data contains unrecognized categorical values! Please check input.")

# Ensure the test data contains only the required columns

trained_feature_names = model.feature_names_in_

missing_features = [col for col in trained_feature_names if col not in test_data.columns]

if missing_features:

    raise ValueError(f"✗ Test data is missing required columns: {missing_features}")

# Select only the required columns

```

```

X_test = test_data[trained_feature_names]

# Make predictions

predictions = model.predict(X_test)

# Save predictions

test_data["Predicted_Severity"] = predictions

test_data.to_csv("dataset/predictions.csv", index=False)

print("✅ Predictions saved to dataset/predictions.csv")

```

Code for incorporating factors:

```

from flask import Flask, request, render_template

import pandas as pd

import joblib

app = Flask(__name__)

# Load trained model

model = joblib.load("models/random_forest.pkl")

# Define severity levels

severity_levels = ["Mild", "Moderate", "Severe", "Fatal"]

# Define feature encoding

encoding_map = {

    "Weather_Condition": {"Rain": 0, "Clear": 1, "Fog": 2},

    "Traffic_Density": {"Low": 0, "Medium": 1, "High": 2},

    "Road_Type": {"Highway": 0, "Urban": 1, "Rural": 2},

    "Light_Condition": {"Day": 0, "Night": 1, "Street Light": 2, "No Light": 3},

```

```

"Vehicle_Type": {

    "Car": 0, "Motor Cycle": 1, "Bus": 2, "Mini Bus": 3,

    "Electric Motor Cycle": 4, "Pedal Cycle": 5, "Other Vehicle": 6

},

"Gender": {"Male": 0, "Female": 1},

"Human_Behavior": {"Non Drunk": 0, "Drunk": 1},

}

@app.route("/", methods=["GET", "POST"])

def index():

    prediction_text = None

    if request.method == "POST":

        # Get user input

        user_input = [

            encoding_map["Weather_Condition"][request.form["weather_condition"]],

            encoding_map["Traffic_Density"][request.form["traffic_density"]],

            encoding_map["Road_Type"][request.form["road_type"]],

            encoding_map["Light_Condition"][request.form["light_condition"]],

            encoding_map["Vehicle_Type"][request.form["vehicle_type"]],

            int(request.form["vehicle_speed"]),

            encoding_map["Gender"][request.form["gender"]],

            encoding_map["Human_Behavior"][request.form["human_behavior"]],

        ]

        # Convert to DataFrame

```

```

df = pd.DataFrame([user_input], columns=[

    "Weather_Condition", "Traffic_Density", "Road_Type",

    "Light_Condition", "Vehicle_Type", "Vehicle_Speed",

    "Gender", "Human_Behavior"

])

# Make prediction

prediction = model.predict(df)[0]

prediction_text = severity_levels[prediction]

return render_template("index.html", prediction_text=prediction_text)

if __name__ == "__main__":

    app.run(debug=True)

```

Main:

```

from flask import Flask, render_template, request

import pandas as pd

import joblib

import numpy as np

import urllib.request

import urllib.parse

app = Flask(__name__)

model = joblib.load('litemodel.sav')

def cal(ip):

    input = dict(ip)

    weather_condition = input['weather_condition'][0]

```

```

traffic_density = input['traffic_density'][0]

road_type = input['road_type'][0]

light_condition = input['light_condition'][0]

vehicle_type = input['vehicle_type'][0]

vehicle_speed = input['vehicle_speed'][0]

gender = input['gender'][0]

human_behavior = input['human_behavior'][0]


data = np.array([weather_condition, traffic_density, road_type, light_condition, vehicle_type,
vehicle_speed, gender, human_behavior])


print("logging",data)

data = data.astype(float)

data = data.reshape(1, -1)

x = np.array([1, 3.73, 3, 0.69, 125, 4, 1, 1, 1, 1, 30]).reshape(1, -1)

try: result = model.predict(data)

except Exception as e: result = str(e)

return str(result[0])

@app.route('/', methods=['GET'])

def index():

    return render_template('index.html')

@app.route('/visual/', methods=['GET'])

def visual():

```

```
        return render_template('visual.html')

@app.route('/', methods=['POST'])

def get():

    return cal(request.form)

if __name__ == '__main__':

    app.run(host='0.0.0.0', debug=True, port=4000)
```

9. DEPLOYMENT

OVERVIEW

The Accident Severity Prediction System is a web-based tool designed to estimate the severity of road accidents based on factors such as weather conditions, traffic density, road type, lighting, vehicle type, speed, driver gender, and human behavior. The system uses a machine learning model trained on historical accident data and is deployed as an accessible online application. This section details the deployment strategy, infrastructure, and steps to ensure the system is operational for end users.

DEPLOYMENT ENVIRONMENT

The application is hosted on a cloud-based platform to ensure scalability, reliability, and broad accessibility. The deployment environment includes:

1. **Server:** A cloud-hosted virtual machine capable of running web applications.
2. **Operating System:** A Linux-based system for compatibility with the application's runtime environment.
3. **Web Server:** A production-grade server setup with a WSGI application server and a reverse proxy to manage incoming requests and serve static content efficiently.
4. **Model Storage:** The trained machine learning model is stored in a secure directory and loaded into memory when the application starts.

DEPLOYMENT WORKFLOW

The deployment process involves the following steps:

1. Code Preparation:

- The web application integrates the trained model and processes user inputs through an interactive interface.
- Input features are encoded consistently with the training phase to ensure accurate predictions.

2. Local Testing:

- The system was tested locally to confirm that it correctly processes inputs and delivers predictions matching predefined severity levels (e.g., Mild, Moderate, Severe, Fatal).

3. Containerization (Optional):

- For improved portability, the application can be packaged into a container using a tool that standardizes the runtime environment across different systems.
- The container is built and validated locally before being deployed.

4. Cloud Deployment:

- **Step 1:** The application files, trained model, and static assets are transferred to the cloud server.
- **Step 2:** The server is configured with the necessary runtime environment and tools to run the application.
- **Step 3:** The web server is set up to handle multiple concurrent users, and a reverse proxy is configured to route traffic appropriately.
- **Step 4:** The system is made accessible via a public URL or IP address (e.g., <http://accident-severity-prediction.com>).

5. Monitoring and Scaling:

- Logs are maintained to track system performance and identify potential issues.
- The infrastructure supports scaling to accommodate increased user demand during high-traffic periods.

Security Considerations

- **Input Validation:** User inputs are checked to prevent malicious data from compromising the system.
- **Data Encryption:** Secure communication protocols (e.g., HTTPS) are implemented to protect data during transmission.
- **Model Integrity:** The trained model is safeguarded and verified during deployment to prevent unauthorized modifications.

Performance Metrics

- **Response Time:** Predictions are delivered within 1-2 seconds under typical conditions.
- **Accuracy:** The model performs reliably based on testing with historical data.
- **Uptime:** The system targets a 99.9% uptime, supported by the cloud provider's service guarantees.

Future Enhancements

- Incorporate real-time data sources, such as traffic and weather feeds, to enhance prediction accuracy.
- Extend the system as an API for integration with mobile applications or external platforms.
- Add user authentication to limit access to authorized individuals, such as traffic management officials.

10. TESTING

The Testing Phase is crucial to ensure the system functions correctly, accurately predicts accident severity, and meets performance expectations. Below is a detailed breakdown of testing methodologies and test cases for the Road Accident Prediction System .

1. Testing Phases in Road Accident Prediction System

a) Unit Testing

- Tests individual components of the system (functions, modules).
- Ensures correctness of data preprocessing, model training, and prediction functions.

b) Integration Testing

- Verifies the interaction between different modules (data collection, preprocessing, machine learning models, UI).
- Ensures smooth data flow and prediction accuracy.

c) System Testing

- Validates the entire system against functional and non-functional requirements.
- Includes performance testing and stress testing.

d) User Acceptance Testing (UAT)

- Involves real-world users testing the system.
- Checks if predictions, UI, and visualization meet user expectations.

2. Types of Testing in the Project

a) Functional Testing

Verifies whether the system functions as expected.

| Test Case ID | Test Scenario | Expected Output | Status |
|--------------|--|------------------------------------|-----------|
| TC-01 | System should load trained ML model correctly | Model loads without errors | Pass/Fail |
| TC-02 | User enters accident parameters (weather, traffic, road type) | System should process input | Pass/Fail |
| TC-03 | System should return accident severity prediction (Mild/Moderate/Severe) | Valid severity output | Pass/Fail |
| TC-04 | Test prediction accuracy using test dataset | Accuracy > 80% | Pass/Fail |
| TC-05 | UI should display accident probability clearly | Graphs, text, alerts should appear | Pass/Fail |

b) Performance Testing

Checks response time, scalability, and system load handling.

| Test Case ID | Test Scenario | Expected Output | Status |
|--------------|---|-----------------------------|-----------|
| PT-01 | Test prediction response time | Response time < 2 sec | Pass/Fail |
| PT-02 | System handles 1000 simultaneous requests | No crashes, stable response | Pass/Fail |
| PT-03 | Large dataset (1M+ records) processed | No memory issues | Pass/Fail |

c) Security Testing

Ensures data protection and user authentication.

| Test Case ID | Test Scenario | Expected Output | Status |
|--------------|---|------------------------|-----------|
| ST-01 | Unauthorized user tries to access API | Access denied | Pass/Fail |
| ST-02 | Data input contains SQL injection attempt | System prevents attack | Pass/Fail |
| ST-03 | System prevents data tampering | Integrity maintained | Pass/Fail |

d) Compatibility Testing

Tests compatibility across browsers, devices, and platforms.

| Test Case ID | Test Scenario | Expected Output | Status |
|--------------|---|------------------|-----------|
| CT-01 | Run application on Chrome, Firefox, Edge | Works correctly | Pass/Fail |
| CT-02 | Access system from mobile, tablet, and PC | UI is responsive | Pass/Fail |


The testing phase ensures that the Road Accident Prediction System is reliable, secure, and performs efficiently under different scenarios. By conducting thorough functional, performance, security, and compatibility testing, the system can be validated for real-world deployment.

11. OUTPUT SCREENS

Cases:

1. Mild Accidents (☑ Low Severity)

- Minor vehicle damage (scratches, dents).
- No or very minimal injuries (e.g., bruises, minor cuts).
- No road blockage; traffic flow remains unaffected.

 **Road Accident Prediction**

Weather Condition

Clear

Traffic Density

Low

Road Type

Urban

Light Condition

Day

Vehicle Type

Car

Vehicle Speed (km/h)

40

Gender

Male

Human Behavior

Non Drunk

Predict

Predicted Severity: Mild



Road Accident Prediction

Weather Condition

Clear



Traffic Density

Medium



Road Type

Highway



Light Condition

Street Light



Vehicle Type

Electric Motor Cycle



Vehicle Speed (km/h)

40

Gender

Male



Human Behavior

Non Drunk




Predict

Predicted Severity: Mild

2. Moderate Accidents (⚠ Medium Severity)

- Vehicle damage is noticeable but repairable.
- Injuries may require medical attention (e.g., fractures, concussions).
- Partial road blockage, causing temporary traffic delays.

 **Road Accident Prediction**

Weather Condition

Rain

Traffic Density

Low

Road Type

Highway

Light Condition

Day

Vehicle Type

Bus

Vehicle Speed (km/h)

80

Gender

Male

Human Behavior

Non Drunk

Predict

Predicted Severity: Moderate



Road Accident Prediction

Weather Condition

Rain



Traffic Density

Low



Road Type

Urban



Light Condition

Night



Vehicle Type

Motor Cycle



Vehicle Speed (km/h)

60

Gender

Male



Human Behavior

Non Drunk



Predict

Predicted Severity: Moderate

3. Severe Accidents (🚚 High Severity)

- Major vehicle damage (total loss, fire, overturning).
- Severe injuries or fatalities involved.
- Full road blockage, causing significant traffic disruptions.



Road Accident Prediction

Weather Condition

Fog



Traffic Density

Medium



Road Type

Rural



Light Condition

No Light



Vehicle Type

Motor Cycle



Vehicle Speed (km/h)

120

Gender

Male



Human Behavior

Drunk



Predict

Predicted Severity: Severe



Road Accident Prediction

Weather Condition

Rain



Traffic Density

High



Road Type

Highway



Light Condition

Street Light



Vehicle Type

Mini Bus



Vehicle Speed (km/h)

100

Gender

Female



Human Behavior

Drunk



Predict

Predicted Severity: Severe

12. CONCLUSION AND FUTURE SCOPE

CONCLUSION

The Road Accident Prediction System is a significant step towards improving road safety using machine learning techniques. By analyzing real-time and historical accident data, the system can:

- Predict accident severity (Severe, Moderate, Mild)
- Identify high risk traffic zones and hazardous conditions.
- Help authorities take preventive actions to reduce accidents.
- Improve decision-making for urban planning and traffic management.

By utilizing Decision Trees, Random Forest, and Logistic Regression models, the system achieves high accuracy in accident predictions, ultimately saving lives and enhancing road safety policies.

FUTURE SCOPE

The project has potential for further enhancements, including:

- Integration with IoT for Real-Time Accident Detection.
- Enhancing ML Models with Deep Learning Techniques.
- Deployment as a Mobile or Web-Based Application.
- Collaboration with Traffic Management Systems.

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