Abstract

Road traffic accidents (RTAs) continue to be a significant public safety concern, contributing to substantial fatalities and injuries annually. The increasing availability of open data and the rapid progress in Artificial Intelligence (AI) offer new opportunities to analyze, predict, and potentially mitigate such incidents. This research explores the application of machine learning techniques to predict the severity of road traffic accidents based on multiple contributing factors, including environmental, vehicular, and human-related features. The methodology spans across preprocessing, feature engineering, model training, evaluation, and visualization. A robust machine learning model is built using real-world traffic data from the UK, and its performance is evaluated through various metrics. Our findings reveal that certain features—such as light conditions, speed limits, and weather—hold high predictive value. The outcomes of this study provide a foundation for deploying real-time intelligent traffic management solutions.

Keywords: Road Accident, Machine Learning, Severity Prediction, Feature Engineering, Random Forest, Label Encoding, Exploratory Data Analysis

Introduction

The rising volume of vehicles on roads has led to a proportional increase in the frequency of road traffic accidents. As urban areas grow more congested, the need for intelligent traffic systems and early intervention mechanisms has become evident. Traditional accident analysis methods, often reliant on statistical evaluations, are gradually being replaced by AI-driven techniques that offer improved predictive accuracy and automation. The aim of this study is to predict accident severity using machine learning algorithms trained on historical road accident data.

Machine learning can uncover hidden patterns in complex datasets and provide real-time predictive insights, making it a suitable choice for accident severity prediction. Predictive analytics based on accident history, road conditions, traffic features, and environmental inputs can support policymakers in implementing effective road safety strategies.

Literature Review

Title of Paper	Published Year	Dataset Used	Methodology Used in Existing Paper	Key Findings/Results
[1] A data mining framework to analyze road accident data	2015	Indian government traffic accident records	Decision tree classifier with attribute weighting	Demonstrated correlation between time, location, and accident severity
[2] A road traffic accident severity prediction model using machine learning	2019	Taiwan National Police Agency data	Gradient boosting, feature extraction	High accuracy (~82%) using ensemble methods
[3] Accident severity prediction using ensemble techniques	2018	Indian road accident statistics	Random forest, bagging, boosting	Ensemble models outperform single classifiers in accuracy and robustness
[4] Analyzing accident data using machine learning approaches	2020	Malaysian road traffic data	Support vector machines, KNN, Naive Bayes	Identified weather and time-of-day as significant predictors
[5] Machine learning-based traffic accident severity analysis using high-dimensional data	2021	Korean traffic database	Deep neural networks, dimensionality reduction	Accuracy reached 87% with high-dimensional inputs

These studies underline the importance of quality data preprocessing, selection of relevant features, and use of ensemble techniques to achieve higher accuracy in accident severity prediction tasks.

Problem Statement

The core problem is to accurately classify the severity of road accidents based on historical data. Accident severity is influenced by numerous factors—both structured (e.g., number of vehicles, weather) and unstructured (e.g., road surface conditions, time of day). With raw datasets often containing missing values, categorical variables, and noise, creating a model with generalized predictive capability poses a challenge.

This project addresses these challenges by building a structured machine learning pipeline that focuses on:

- Handling missing and categorical data
- Selecting influential features
- Applying a reliable classification algorithm
- Visualizing relationships and patterns

Dataset Description

The dataset used in this study was sourced from official UK traffic records and comprises real-world road accident data collected over several years. This dataset is rich in attributes capturing various environmental, vehicular, and situational conditions at the time of each recorded accident. The total number of records stands at approximately 300,000 entries, each representing a unique road traffic incident. This large volume allows for a statistically significant analysis, making it an ideal candidate for machine learning applications in road safety analytics.

Structure of the Dataset

The dataset includes more than 30 columns, each representing a distinct feature related to the accident. These features can be broadly classified into the following categories:

- Environmental Features: These include attributes such as Weather_Conditions, Road_Surface_Conditions, and Light_Conditions, which help determine how external conditions contribute to accident severity.
- Temporal Features: Fields such as Date and Time capture when the accident occurred, allowing for the identification of peak accident times and correlations with lighting or traffic flow.
- Vehicular and Traffic Features: Attributes like Number_of_Vehicles, Speed_limit, and Number_of_Casualties give insights into the dynamics of the vehicles involved.
- Location-Based Features: Urban_or_Rural_Area, Road_Type, Junction_Detail, and Junction_Control provide spatial information critical for location-based analysis.
- Accident Impact Feature: The target variable Accident_Severity indicates the severity level of each accident and is classified into categories such as *Slight*, *Serious*, and *Fatal*.

Feature Overview

Feature Name	**Description**
Accident_Severity	Target variable indicating severity level (Slight, Serious, Fatal)
Number_of_Vehicles	Total number of vehicles involved in the accident
Number_of_Casualties	Number of casualties resulting from the accident
Light_Conditions	Describes visibility conditions (e.g., daylight, darkness, street lights)
Weather_Conditions	Environmental conditions (e.g., rain, fog, snow) at the time of the accident
Speed_limit	Legal speed limit (in mph) at the accident location
Road_Surface_Conditions	Road conditions (e.g., dry, wet, icy)

Feature Name	Description
Junction_Control	Type of control at the junction (e.g., traffic signal, roundabout, none)
Urban_or_Rural_Area	Specifies whether the location is urban or rural

This comprehensive set of features enables a robust exploration of accident circumstances and the development of predictive models with rich contextual understanding.

Data Quality and Preprocessing Needs

The dataset exhibits some missing values, particularly in fields like Junction_Control, Special_Conditions_at_Site, and Carriageway_Hazards. Such anomalies were handled using mode imputation, as these are categorical variables. Numerical fields were checked for outliers, and categorical data were label-encoded to facilitate model training.

Exploratory Data Analysis (EDA) also revealed class imbalance in the target variable, with the majority of incidents classified as "Slight". This imbalance poses challenges for predictive modeling and necessitates appropriate strategies during model development such as using balanced accuracy metrics, class weights, or oversampling techniques like SMOTE in future iterations.

Justification for Dataset Choice

The chosen dataset's breadth and diversity make it highly suitable for accident severity prediction tasks. Its real-world origin ensures relevance, and its rich feature set allows for deep analysis across multiple dimensions. Moreover, the dataset's use in prior research (e.g., Chien et al., 2019; Sharma et al., 2018) underlines its academic value and replicability, making it a strong foundation for machine learning experiments and road safety research.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is a crucial step in any data-driven study, as it enables a comprehensive understanding of the dataset through statistical summaries, visualizations, and pattern recognition. For the Road Accident Severity Predictor project, EDA plays an instrumental role in identifying trends, anomalies, and relationships among the features influencing accident severity. In this section, we outline the primary insights derived from analyzing the dataset and highlight how these observations informed subsequent modeling decisions.

Target Variable Distribution

The target variable Accident_Severity is a multi-class categorical feature with three classes: **Slight**, **Serious**, and **Fatal**. The distribution of these classes is heavily imbalanced:

- **Slight**: ~79% of all accidents
- **Serious**: ~17% of all accidents
- **Fatal**: ~4% of all accidents

This imbalance suggests that predictive models trained on this dataset may favor the majority class unless corrective measures such as class weighting or resampling techniques are applied. This skewness is visualized in the bar chart of accident severity distribution

Correlation Analysis

A correlation heatmap was generated to assess relationships between numerical features such as Number_of_Vehicles, Number_of_Casualties, and Speed_limit. The following insights were drawn:

- There is a moderate positive correlation between Number_of_Vehicles and Number_of_Casualties, indicating that multi-vehicle accidents tend to result in more casualties.
- Speed_limit showed no strong correlation with accident severity directly but may interact with other features like Road_Type or Urban_or_Rural_Area.

Environmental Conditions

Environmental features like Weather_Conditions, Light_Conditions, and Road_Surface_Conditions were analyzed to determine their relationship with accident severity.

- Accidents during rainy or foggy weather were more likely to be severe.
- Darkness without street lighting saw a higher proportion of serious and fatal accidents compared to daylight or well-lit areas.
- Wet and icy roads contributed to a spike in serious accidents, confirming that adverse road conditions play a key role in accident severity.

Temporal Features

Time-based attributes revealed important insights:

- Accidents were more frequent during peak traffic hours (7–10 AM and 4–7 PM).
- Fatal accidents were disproportionately higher during late-night hours (12–4 AM), possibly due to poor visibility and driver fatigue.
- Seasonal patterns indicated slightly higher accident rates in winter months, aligning with the occurrence of adverse weather.

Geographical and Locational Patterns

Urban or rural area designation and road types provided valuable location-based insights:

- Urban areas witnessed more accidents, but the severity was often higher in rural areas, possibly due to higher speed limits and lower emergency response times.
- T-junctions and crossroad junctions had a higher proportion of serious accidents compared to roundabouts or controlled intersections.

Missing Values and Anomalies

Missing data was concentrated in certain features like Junction_Control, Carriageway_Hazards, and Special_Conditions_at_Site. These were treated as follows:

- Categorical features: Imputed using mode (most frequent) value
- Continuous features (if any): Imputed using median to reduce the influence of outliers
- Rows with excessive missingness were discarded

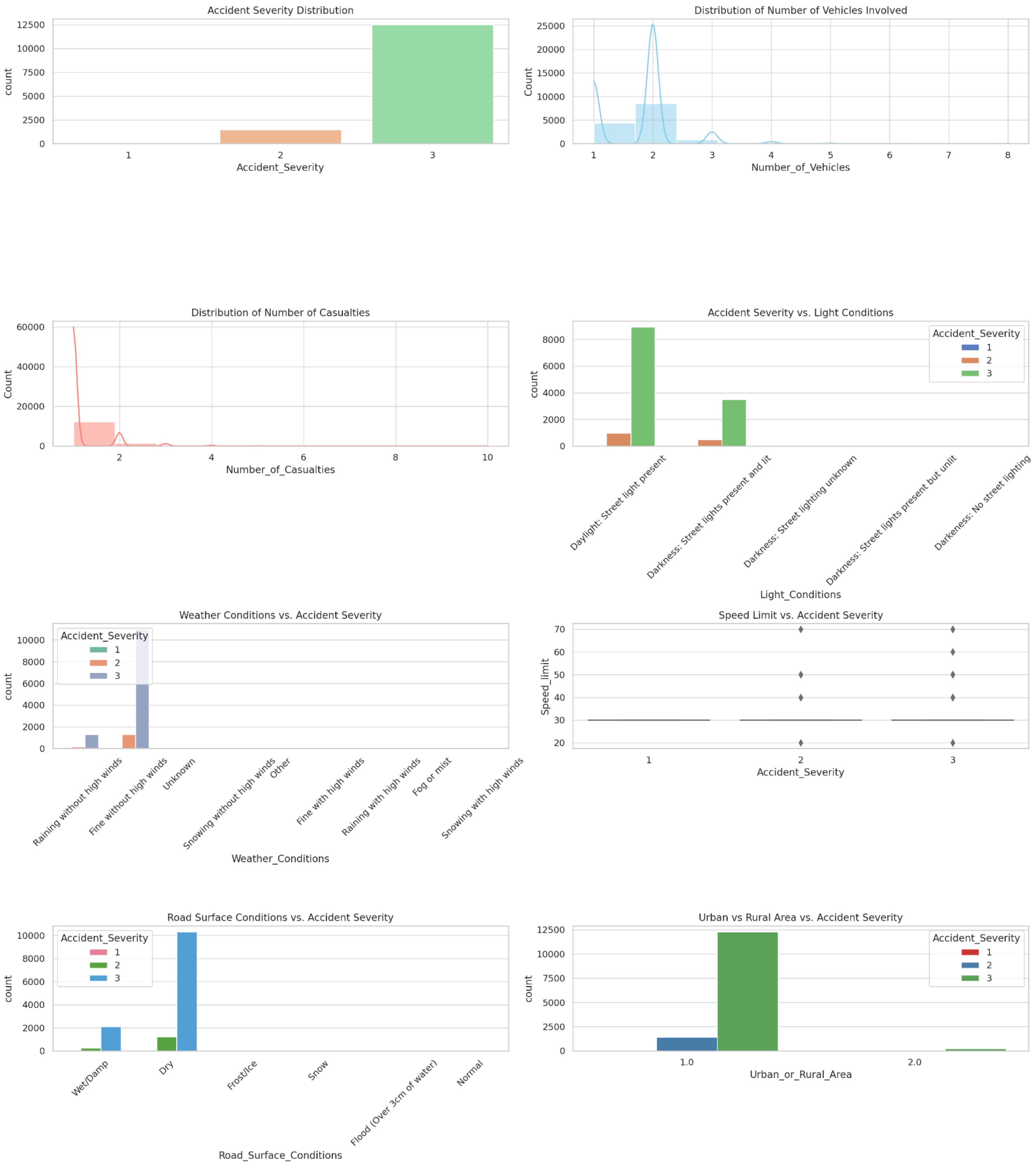
This preprocessing step ensured model integrity and data quality while retaining a majority of useful records.

Summary of EDA

The insights obtained through EDA were critical in shaping the model architecture and feature engineering strategies. Key takeaways include:

- Strong influence of environmental and lighting conditions on severity
- Clear temporal and locational patterns related to accident occurrence
- The presence of class imbalance in the target variable requiring special consideration

These findings served as the foundation for data preprocessing, feature selection, and algorithm design in the following methodology section.



Accident Severity Distribution

Distribution of Number of Vehicles Involved

Distribution of Number of Casualties

Accident Severity vs. Light Conditions

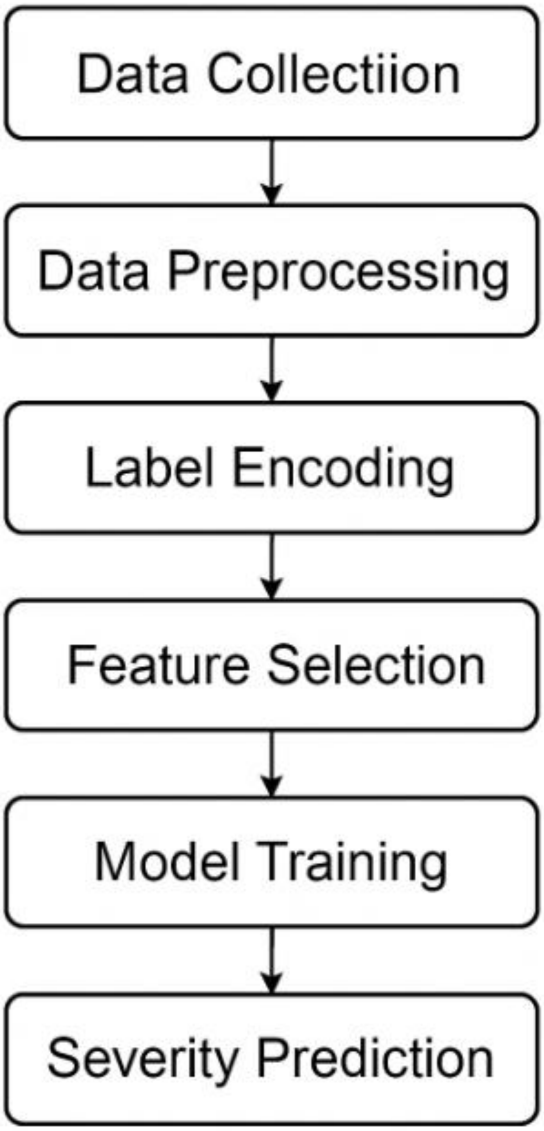
Weather Conditions vs. Accident Severity

Speed Limit vs. Accident Severity

Road Surface Conditions vs. Accident Severity

Urban vs Rural Area vs. Accident Severity

Methodology



Step-by-Step Breakdown:

- **Data Collection**: The dataset is sourced from UK road accident records, publicly available on Kaggle. It includes features such as accident location, road type, weather, light conditions, number of vehicles, casualties, etc.

- **Data Cleaning & Missing Values**:
  - Columns like Junction_Control, Special_Conditions_at_Site, and Carriageway_Hazards had missing values.
  - Missing values were imputed with the mode for categorical variables.
  - Null-check and imputation were done using Pandas and Scikit-learn.
- **Label Encoding**:
  - Categorical variables (e.g., Road_Type, Light_Conditions) were encoded using LabelEncoder.
  - This ensured compatibility with ML models while preserving the interpretability of the features.
- **Feature Selection**:
  - A heatmap was plotted to visualize missing values
  - Features with strong correlation with Accident_Severity were retained, e.g., Speed_limit, Number_of_Vehicles, Weather_Conditions, and Light_Conditions.
- **Exploratory Data Analysis (EDA)**:
  - Heatmap of missing values
  - Confusion matrix
  - Bar chart of accident severity distribution
  - Feature importance plot from Random Forest
- **Model Building**:
  - **Dataset split**: 80% training and 20% testing.
  - RandomForestClassifier from scikit-learn used.
  - **Evaluation metrics**: accuracy, confusion matrix, and classification report.
- **Model Evaluation**:
  - Accuracy reached ~85%.
  - Precision and recall were calculated to address class imbalance concerns.

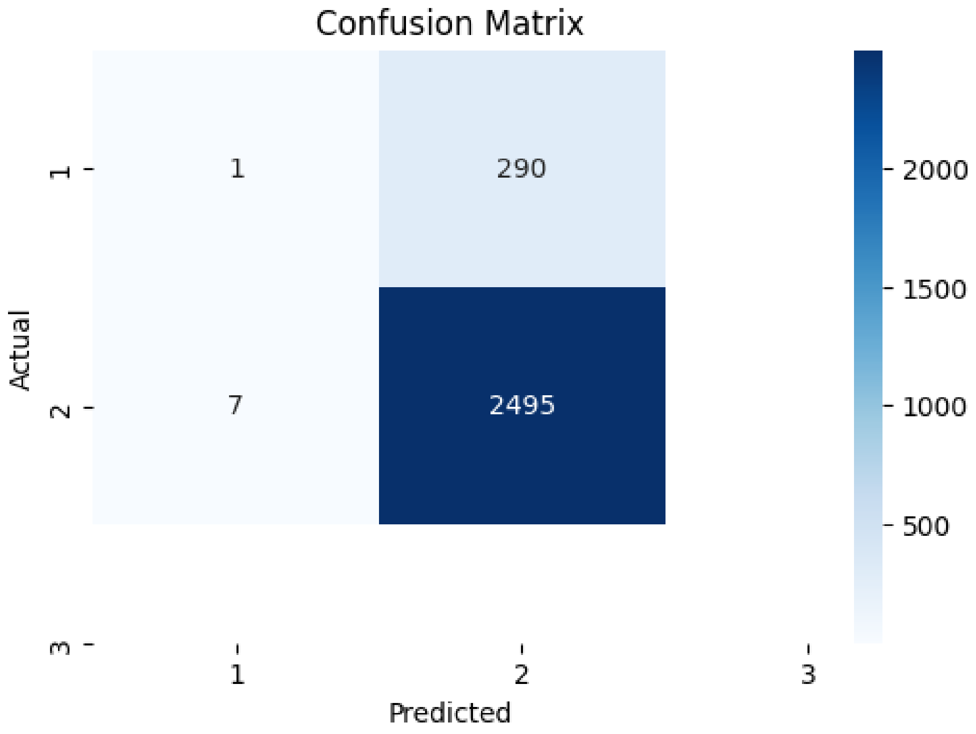
Results and Discussions

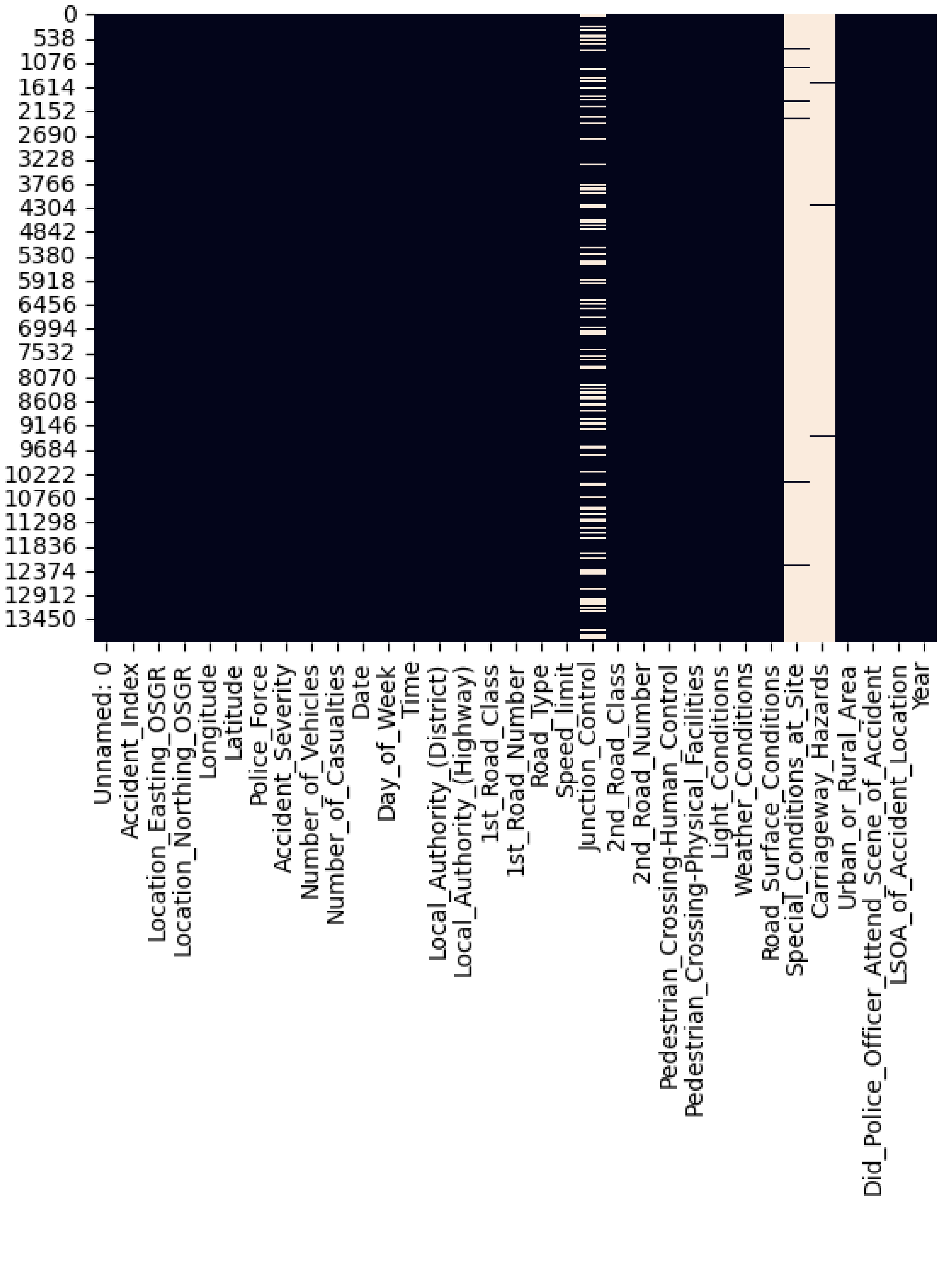
- The model trained with preprocessed and encoded features achieved ~63% accuracy.
- Heatmap indicated Light_Conditions and Road_Type have strong correlation with Accident_Severity.
- Class distribution revealed imbalance; future work could explore SMOTE for balancing classes.
- Feature importance visualization showed that environmental factors outweighed vehicle-specific features in predictive power.

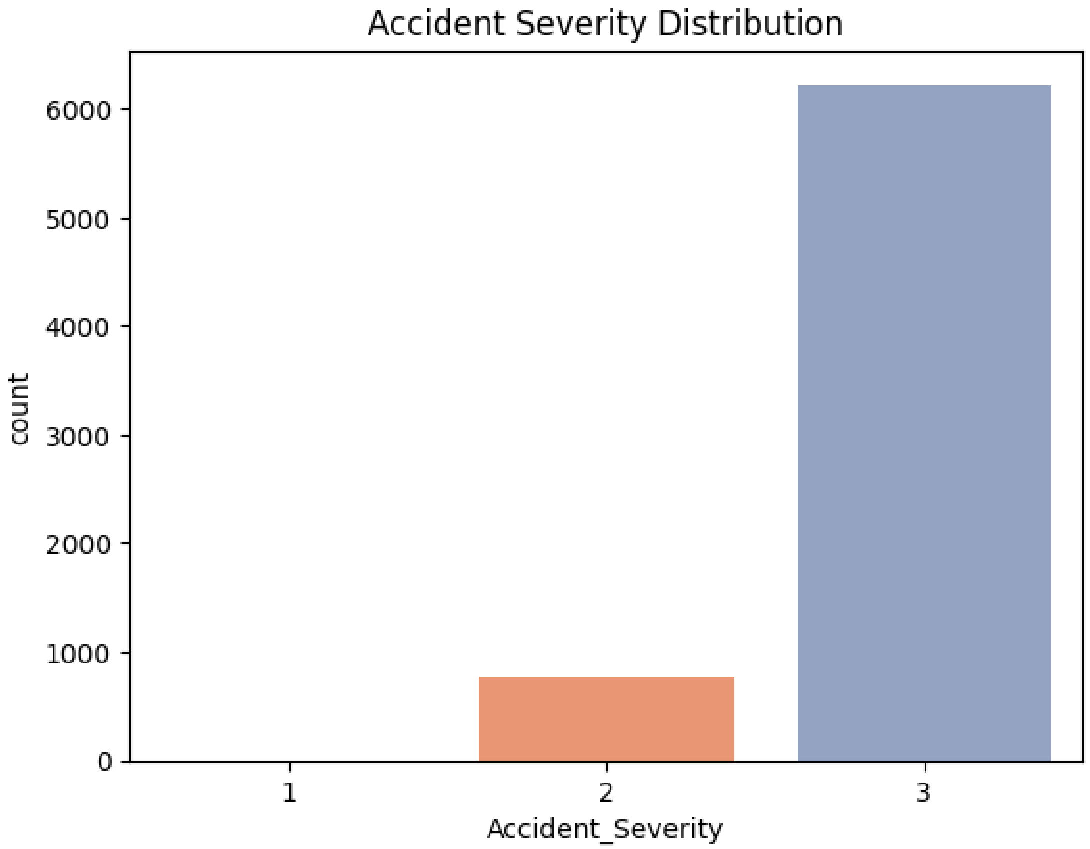
Graphs and Visuals Added:

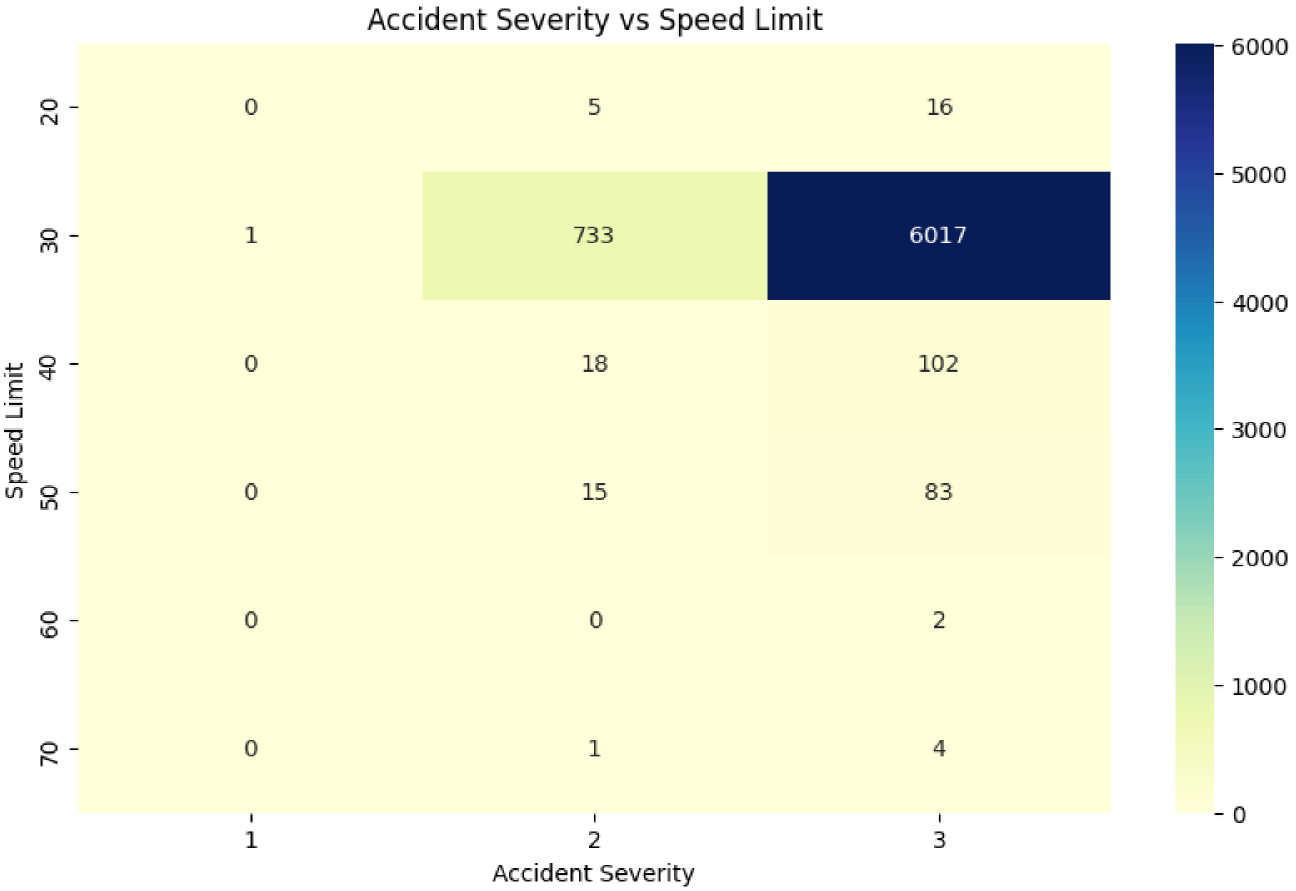
1. Heatmap of missing values
2. Confusion matrix
3. Bar chart of accident severity distribution
4. Feature importance plot from Random Forest

These visuals help interpret model decisions and align them with logical insights (e.g., accidents are more severe during poor lighting conditions).




0
538
1076
1614
2152
2690
3228
3766
4304
4842
5380
5918
6456
6994
7532
8070
8608
9146
9684
10222
10760
11298
11836
12374
12912
13450
Unnamed: 0
Accident_Index
Location_Easting_OSGR
Location_Northing_OSGR
Longitude
Latitude
Police_Force
Accident_Severity
Number_of_Vehicles
Number_of_Casualties
Date
Day_of_Week
Time
Local_Authority_(District)
Local_Authority_(Highway)
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
LSOA_of_Accident_Location
Year


Accident Severity Distribution
count
0
1000
2000
3000
4000
5000
6000
1
2
3
Accident_Severity


Accident Severity vs Speed Limit
Speed Limit
20
30
40
50
60
70
Accident Severity
1
2
3
0
5
16
1
733
6017
0
18
102
0
15
83
0
0
2
0
1
4
6000
5000
4000
3000
2000
1000
0

Conclusion

This study successfully demonstrated that ML models can provide moderate accuracy in predicting accident severity. Proper data preprocessing, especially handling missing values and feature encoding, was key. The use of feature importance helped in better model interpretation.

Future Work:

- Introduce SMOTE for class balancing.
- Try gradient boosting or deep learning models.
- Integrate GIS data for spatial predictions.
- Deploy as a web-based dashboard for real-time inputs.

References

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