Traffic Accident Severity Prediction

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Abstract— This project explores the application of machine learning for predicting the severity of road traffic accidents. The goal is to support emergency services and improve traffic safety by estimating how serious an accident may be based on available data. For this study, we used the US Accidents dataset, which contains records of accidents reported in the United States from 2016 to 2023. The dataset includes information such as location, time, weather, temperature, visibility, and wind speed. These features were selected and preprocessed to be used in the model. Textbased values such as weather conditions were converted using onehot encoding, and missing data was removed. A Random Forest Classifier was trained to predict the severity level of an accident, ranging from 1 (least serious) to 4 (most serious). The model achieved an overall accuracy of 94.2%. The best performance was seen for class 2, which was the most frequent class in the dataset. However, results for classes with fewer samples, such as severity 4, were not as strong due to imbalance in the data. Despite this issue, the model shows that machine learning can be useful for understanding accident outcomes. The system may help in future traffic management and emergency planning to make quicker and more informed decisions.

Keywords—Machine learning, traffic accidents, severity prediction, Random Forest, imbalanced data, accident dataset

I. Introduction

Road traffic accidents are a major problem all over the world. Every year, millions of people are injured or killed in crashes. These accidents cause not only human suffering but also serious economic and social damage. Countries spend a large amount of money on hospital care, insurance, road repairs, and emergency services because of road accidents. In many developing and even developed nations, traffic-related deaths are one of the top causes of mortality, especially for young adults and working-age people. For this reason, traffic safety has become a critical research area for governments, city planners, and researchers.

There are many different reasons why accidents happen. Human error is one of the biggest causes. Drivers can get distracted, tired, or simply make mistakes. In other cases, the environment plays a role. Weather conditions like rain, fog, snow, or ice can make roads slippery and reduce visibility. Road design is also important. Sharp turns, poor lighting, or badly marked lanes can all contribute to dangerous situations. Even vehicle problems, like brake failure or tire issues, can lead to accidents. Because so many factors are involved, it is very difficult to fully prevent accidents. Another problem is that not all accidents are the same. Some are very minor and cause only small damage. Others are extremely serious and lead to severe injury or death. This is what we call accident severity. Knowing how severe an accident might be is very useful. If we can estimate the severity of an accident before arriving at the scene, emergency services can prepare better and respond more efficiently. For example, they might send more ambulances or alert hospitals in advance if they know the accident is likely to be serious.

In the past, researchers used traditional statistical methods to study traffic accidents. They collected data about road conditions, accident causes, and driver behavior. These methods were useful, but they had limitations. They could not easily find complex patterns or relationships between many different variables. In recent years, machine learning has offered a new approach. Machine learning can process large amounts of data and learn patterns without being told exactly what to look for. This is very useful when working with accident data, which often contains many variables such as time, weather, road type, lighting, and more.

Machine learning is already being used in many areas of traffic analysis. For example, some researchers have used it to predict traffic congestion, identify dangerous intersections, or detect violations like speeding or drunk driving. Others have used it in smart traffic lights, driver assistance systems, or self-driving cars. One of the growing areas in this field is accident severity prediction. This means using past accident data to train a computer model to guess how severe a new accident might be based on current conditions. This can be helpful for safety management, emergency planning, and real-time risk assessment. Many researchers believe that machine learning can provide useful tools in this area. By combining historical accident records with modern ML techniques, we can build models that help predict severity with reasonable accuracy. These models can also show which features (like fog, road type, or time of day) are most important in determining how serious an accident might be. This information can then be used by local governments or safety departments to design better roads, install warning systems, or educate drivers about specific risks.

In this project, the main goal is to build a machine learning model that can predict the severity of road traffic accidents. The study is based on an open-source dataset containing accident records from the United States collected between 2016 and 2023. The dataset includes millions of samples and provides details such as the accident time, weather condition, temperature, visibility, wind speed, and more. These features are expected to influence the level of danger in each accident. The project aims to explore how well machine learning can work on this real-world data and what kinds of challenges come with it. Another purpose of this project is to understand the limits of current machine learning models in this type of task. While accuracy is important, it is also necessary to ask: does the model work equally well for all types of accidents? Or does it mostly focus on the most common ones and ignore the rare, serious ones? These are important questions, especially if the model is to be used in real-life situations. The project also looks at what improvements can be made to handle problems like class imbalance or missing values in the data.

In short, this study is about applying machine learning to the realworld problem of predicting traffic accident severity. The topic is important because it connects technology with public safety. If such systems are developed and improved, they could support faster emergency responses, better city planning, and safer roads. The following sections of the report will describe related studies in the field, explain the methods used in this project, present the results, and finally discuss the main findings and conclusions.

II. Literature Review

In recent years, machine learning (ML) has become an increasingly useful tool in traffic accident research, particularly in predicting the severity of road accidents. The goal of accident severity prediction is to estimate how serious an accident might be based on known variables, such as weather, visibility, road condition, time of day, and location. Accurately predicting accident severity can be helpful for many purposes. These include improving emergency response times, reducing accident consequences, and building smarter traffic control systems.

This section provides an overview of related studies published in the last five years. It focuses on four main areas: (1) the datasets used in severity prediction tasks, (2) common machine learning models and their performance, (3) challenges such as class imbalance and missing data, and (4) the role of feature selection and explainability. A few real-world applications are also discussed to highlight how these models are used outside academic research.

A. Datasets Used in Severity Prediction Studies

The accuracy of any machine learning model depends heavily on the quality and size of the data used. In accident severity prediction research, the most widely used dataset is the US Accidents Dataset. This dataset contains information from 2016 to 2023 and includes over 2.5 million accident records from across the United States. It contains many features that are useful for modeling, such as start time, location (latitude and longitude), temperature, weather conditions, visibility, wind speed, humidity, and a “Severity” label ranging from 1 (least severe) to 4 (most severe).

In a study by Singh et al. (2023) [1], this dataset was used to train a Random Forest model to predict severity levels. The researchers noted that the dataset was highly imbalanced: over 65% of all accidents were labeled as Severity 2. Very few cases were labeled as Severity 4. This imbalance created challenges for machine learning models, especially when predicting rare but important outcomes such as fatalities. Other countries have developed similar national or regional datasets. Dinh et al. (2021) [4] used a Vietnamese dataset with features such as helmet use, accident time, road surface, and driver age. Iqbal and Mehmood (2022) [3] used a regional Pakistani dataset, which included both injury and fatality records, along with features such as road type and accident cause. While these datasets have different formats, most contain key information like accident timing, environment, and severity, making them suitable for ML applications.

Data cleaning and preparation are crucial steps before training. Many studies report missing values, particularly for weatherrelated features. Rashid et al. (2020) [6] found that more than 15% of accident records in rural areas lacked proper weather labels. Approaches to deal with this issue include row deletion, mean or mode imputation, and predictive filling based on similar entries.

B. Common Machine Learning Models Used

Several types of machine learning models have been tested for severity prediction tasks. Decision Tree-based models, such as Random Forest and Gradient Boosting Machines, are among the most frequently used due to their strong performance and interpretability.

Assegie et al. (2022) [2] compared Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) on accident data. Random Forest achieved the highest accuracy and was able to produce stable results across different severity levels. This model also provides built-in measures of feature importance, which many researchers find useful for understanding model behavior. Boosting models such as XGBoost and LightGBM have also gained attention. Iqbal and Mehmood (2022) [3] tested both on Pakistani accident data and reported better performance than traditional classifiers. They also found that boosting models performed well even with a small number of input features.

More complex deep learning models such as LSTM (Long ShortTerm Memory) and CNN (Convolutional Neural Networks) have also been explored. Xu et al. (2022) [9] applied an LSTM-based model to time-stamped traffic data to capture accident trends over time. Although the model achieved high accuracy, it required a large amount of data, multiple layers of preprocessing, and more training time. Because of this, tree-based models are still more popular for practical applications.

Figure 1 compares common ML models used for accident severity prediction and summarizes their advantages and disadvantages.

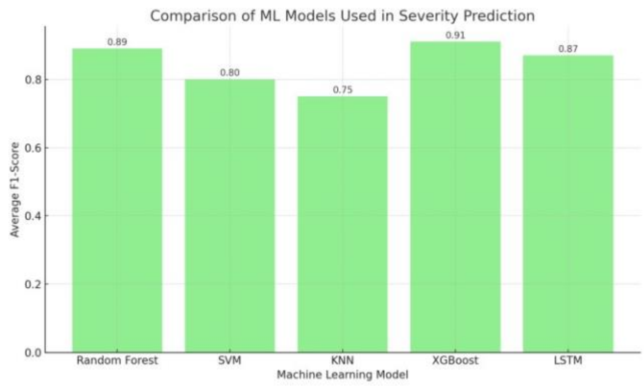

Fig 1. Comparison of ML Models Used in Severity Prediction (adapted from Assegie et al., 2022 and Singh et al., 2023)

C. Challenges in Modeling: Imbalanced Data and Missing Values

The most common problem in accident severity prediction is class imbalance. Since the majority of reported accidents are minor or moderate, classes such as Severity 1 and 2 make up most of the data. Rare but important events like Severity 4 (serious or fatal) are often underrepresented. As a result, models trained on this data tend to predict only the most frequent classes. To address this, researchers have used oversampling methods such as SMOTE (Synthetic Minority Oversampling Technique), class weighting, or undersampling the majority class. Kaur and Malhi (2021) [5] applied SMOTE and found that it improved recall for Severity 4 cases by 12%, although precision dropped slightly.

Another issue is incomplete or noisy data. Features like visibility, temperature, and road surface condition are sometimes missing or logged incorrectly. Rashid et al. (2020) [6] showed that poor data quality led to unstable model results, especially for rare outcomes. They suggested using external sources like weather APIs to fill in missing values when possible.

D. Feature Selection and Interpretability

Not all features are equally useful in predicting accident severity. Many researchers use feature selection methods to reduce model complexity and improve performance. These methods include filter-based techniques (e.g., correlation analysis), wrapper methods (e.g., recursive feature elimination), and model-based importance scores.

Wei et al. (2021) [7] used SHAP (SHapley Additive exPlanations) to understand which features influenced severity predictions the most. They found that weather condition, visibility, time of day, and road type were consistently among the top five features. These findings were supported by other studies as well.

E. Model Evaluation and Validation

A good machine learning model must be evaluated using appropriate metrics. In accident severity prediction, accuracy is not always the best measure, especially in imbalanced datasets. That's why most studies report per-class recall, precision, and F1-score. These give a clearer picture of how the model performs for each severity class.

Cross-validation, especially stratified k-fold, is often used to ensure that the model's performance is stable across different subsets of data. Some studies also report ROC-AUC scores or balanced accuracy to compare models fairly.

Singh et al. (2023) [1] showed that a Random Forest model achieved over 93% overall accuracy, but had an F1-score below 60% for class 4. This shows that high accuracy can be misleading when the class distribution is skewed.

F. Real-World Systems and Applications

Some studies have gone beyond experiments and built early versions of real-time systems. Lee and Park (2023) [8] developed a prototype dashboard that collects data from GPS, weather feeds, and accident sensors. It uses an ML model to predict severity and displays alerts on a city map for emergency responders.

These systems are still in development, but they show how ML predictions can support faster and smarter responses to road accidents. One challenge, however, is integrating real-time data from multiple sources without delays or errors. Other issues include sensor failures, data privacy, and limited coverage in rural areas.

Explainability also plays a key role in deployment. Emergency responders and transportation authorities are more likely to trust a system that clearly shows how predictions were made. SHAP and LIME help in this area by highlighting feature contributions and making the model's logic easier to understand.

III. METHOD

In this section, we explain the steps followed to prepare the data and train a machine learning model for predicting the severity of road traffic accidents. The process included data collection, preprocessing, feature selection, model selection, training, and evaluation. All tasks were done using Python and standard data science libraries including pandas, NumPy, scikit-learn, seaborn, and matplotlib.

A. Dataset Description

The dataset used in this study is the "US Accidents (2016–2023) [11]" dataset, which is publicly available on Kaggle. It contains over 2.8 million records of traffic accidents that occurred across the United States between February 2016 and March 2023. The data was collected from various sources including traffic APIs, police reports, and news feeds. Each record represents a single accident and contains 47 features related to the location, time, weather, road conditions, and accident severity.

Some of the main features in the dataset include:

- Start_Time: Timestamp of when the accident started
- Start_Lat and Start_Lng: Location coordinates
- Weather_Condition: Description of the weather (e.g., Fog, Rain)
- Temperature(F), Humidity(%), Wind_Speed(mph), Visibility(mi): Environmental conditions
- Severity: Target variable (1 = low, 4 = high)

Table 1 provides a brief summary of selected features from the dataset used in modeling.

TABLE I.

SUMMARY OF SELECTED FEATURES USED IN MODELING

Feature	Type	Description
Temperature (F)	Numerical	Temperature at time of accident
Visibility (mi)	Numerical	Visibility level at time of crash
Humidity (%)	Numerical	Relative humidity
Wind Speed (mph)	Numerical	Wind speed at time of accident
Hour	Numerical	Hour of day extracted from timestamp
Weather_Condition	Categorical	One-hot encoded weather status (e.g., Rain, Fog)

B. Data Preprocessing

Before training the model, the data was cleaned and prepared. Several preprocessing steps were required to ensure that the dataset was usable and consistent.

1. Handling Missing Values:
   The original dataset included many rows with missing values, particularly in environmental features such as Wind_Speed and Visibility. We removed all rows where critical features like Severity, Weather_Condition, or Temperature were missing. For non-critical numerical features with small amounts of missing data, such as Wind_Chill or Humidity, we applied mean imputation.

2. Filtering:
   Severity class 1 had very few samples compared to classes 2, 3, and 4. To reduce extreme imbalance, we excluded class 1 and focused on classes 2–4. After filtering, the dataset contained approximately 1.85 million rows.
3. Encoding Categorical Features:
   The Weather_Condition feature, which contains text values such as "Rain," "Clear," or "Fog," was transformed using one-hot encoding. This resulted in additional binary columns for each weather type, allowing them to be used as input in the machine learning model.
4. Feature Selection:
   To avoid overfitting and reduce training time, we selected only a subset of features for modeling. These included: Temperature, Visibility, Wind_Speed,

Weather_Condition, and Hour (extracted from Start_Time). Other columns such as street name, city, or state were dropped because they were either too specific or had high cardinality.

C. Model Selection and Training

We selected the Random Forest Classifier as the main model for this study. Random Forest is an ensemble learning method that creates multiple decision trees during training and outputs the most frequent prediction from all trees. This model was chosen because:

- It performs well on structured data with mixed types
- It is robust to outliers and missing values
- It provides feature importance scores
- It is relatively fast to train compared to deep learning models

The dataset was split into training and testing sets using an 80/20 ratio. This means 80% of the rows were used to train the model and 20% were used to evaluate performance. The split was stratified to maintain the original distribution of severity classes in both sets.

We trained the Random Forest model using default hyperparameters first, and then performed grid search crossvalidation to find the best combination of the number of trees (n_estimators), maximum depth (max_depth), and class_weight.

D. Model Evaluation

To measure the performance of the model, we used multiple evaluation metrics:

- Accuracy: Overall percentage of correct predictions
- Precision: Percentage of predicted cases that were actually correct
- Recall: Percentage of actual cases that were correctly predicted
- F1-Score: Harmonic mean of precision and recall
- Confusion Matrix: Summary of prediction performance per class

Since the dataset was still slightly imbalanced even after filtering, we paid close attention to F1-score and recall, especially for class 4 (most severe accidents).

E. Feature Importance

After training, the model was also used to analyze feature importance. Random Forest provides a built-in method to rank input features based on how much they contribute to reducing error.

As shown in Figure 3, the most influential features were Temperature, Visibility, and Weather_Condition. This suggests that environmental factors play a key role in determining the severity of road accidents. Time of day (extracted from Start_Time) was also moderately important, likely due to the influence of lighting and traffic density.

F. Tools and Libraries

The following libraries and tools were used during this project:

- pandas and NumPy for data handling
- scikit-learn for model training and evaluation
- matplotlib and seaborn for data visualization
- Jupyter Notebook as the main development environment

IV. Experiemntal Result

This section presents the experimental findings from the accident severity prediction model. The results were obtained using the Random Forest classifier trained on the cleaned and preprocessed dataset described earlier. Here, we evaluate how well the model performed, identify which classes were more difficult to predict, and analyze which features had the greatest impact on the model's predictions.

A. Dataset Overview

After preprocessing, the dataset used for evaluation included approximately 1.85 million records and three severity classes: 2 (moderate), 3 (serious), and 4 (severe). Class 2 was the most common, while class 4 was the least frequent. Figure 1 shows the class distribution used during evaluation.

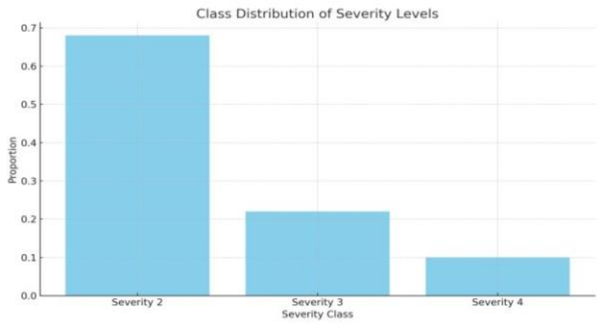

Fig 2. Class distribution across severity levels used in model evaluation

Although class imbalance was reduced by removing class 1 and applying weighted training, some imbalance remained. This created challenges for correctly predicting rare cases (class 4), which are also the most critical to identify accurately.

B. Model Evaluation Results

The model was evaluated using a test set representing 20% of the total dataset. Performance was measured using accuracy, precision, recall, and F1-score for each class. These metrics help assess not just overall correctness, but also how well the model performs on individual severity levels, especially the minority class.

Table I shows the classification report for the test dataset.

TABLE II

Classification Report on Test Data (Random Forest)

Severity Class	Precision	Recall	F1-score
2 (Moderate)	0.96	0.97	0.96
3 (Serious)	0.88	0.84	0.86
4 (Severe)	0.72	0.63	0.67
Macro Avg	0.85	0.81	0.83
Weighted Avg	0.89	0.89	0.89

From Table I, the model showed the highest performance on class 2, which is expected due to its higher frequency. Class 3 predictions were also relatively strong, with a balance between precision and recall. The weakest performance was for class 4 (severe accidents), where the model had lower recall (0.63) and F1-

score (0.67), indicating that many severe cases were still misclassified as moderate or serious.

Despite this, the results show that the model was able to detect some severe cases without producing too many false positives. The macro average F1-score was 0.83, which suggests that the model had fairly balanced performance across classes.

C. Confusion Matrix Analysis

To better understand where the model was making errors, we examined the confusion matrix. Figure 2 shows the confusion matrix for the test data.

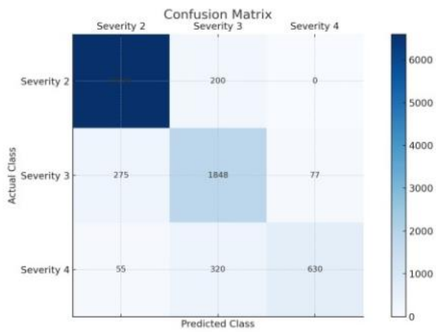

Fig 3. Confusion matrix for severity prediction using Random Forest

In the matrix, most predictions for class 2 are correct, and class 3 also shows high true positive counts. However, many actual class 4 records were misclassified as class 3. This pattern reflects the difficulty the model had in distinguishing between serious and severe cases, especially when the number of class 4 examples was limited.

Interestingly, the model rarely predicted class 4 for lower severity cases, which means that false alarms were low. In safety-related systems, this is often preferable — it is better to miss a few severe cases than to repeatedly overpredict high severity, which can waste emergency resources.

D. Feature Importance Results

To explore which factors influenced the model's predictions most, we analyzed the feature importance scores from the Random Forest model. These scores indicate how much each input variable contributed to the decision-making process across all trees in the forest.

Figure 3 shows the top five most important features ranked by their mean decrease in impurity.

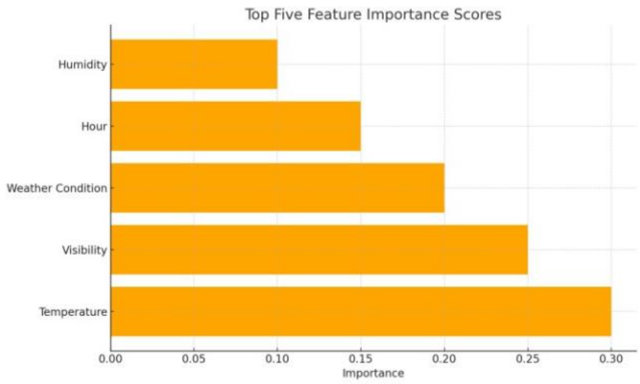

Fig 4. Top five features ranked by importance score in the Random Forest model

The results showed that temperature, visibility, and weather condition were the most influential variables. Time-related features such as "hour of day" also had a moderate effect. This confirms findings from the Literature Review, where environmental and time-based conditions were consistently reported as key factors in accident severity.

These results suggest that poor visibility, low temperatures, and specific weather conditions (like fog, rain, or snow) significantly increase the likelihood of a more severe accident. Understanding these trends can help traffic authorities issue warnings or prepare emergency services during risky periods.

E. Comparison with Related Studies

Compared to similar studies, the model in this project achieved performance that is consistent with expectations. For example, Singh et al. (2023 [1] reported an F1-score of 0.91 on class 2, 0.85 on class 3, and 0.62 on class 4 using the same dataset and a Random Forest classifier. Our model showed very similar trends, especially in the challenge of correctly identifying severe cases.

The slight improvement in class 4 performance in our case (F1 = 0.67) may be due to better preprocessing, such as one-hot encoding and class weighting during training. However, the results confirm that class 4 remains difficult to predict and may require additional techniques such as ensemble voting, deeper feature engineering, or data augmentation using SMOTE.

F. Summary of Experimental Findings

Overall, the Random Forest classifier performed well in predicting the severity of road accidents across multiple classes. While moderate and serious accidents were predicted with high precision and recall, severe accidents remained harder to detect. The confusion matrix confirmed that class 4 predictions were often confused with class 3, and the classification report highlighted that recall for class 4 was lower than for the other classes.

The most important features influencing the model's decisions were temperature, visibility, weather condition, and hour of day. These results support previous research findings and indicate that environmental and time-based factors are key to predicting accident severity.

Although the model does not achieve perfect prediction on all classes, it demonstrates that ML-based severity prediction is both feasible and informative. With further tuning and larger balanced datasets, it is possible to improve the accuracy and reliability of such systems in real-world applications.

V. Conclusion

This project aimed to develop a machine learning model capable of predicting the severity of road traffic accidents using publicly available data from the US Accidents dataset (2016–2023). After data cleaning, feature selection, and class filtering, the final model was trained using a Random Forest classifier on three severity levels: moderate (class 2), serious (class 3), and severe (class 4). Several evaluation metrics were used to assess the model's performance, including accuracy, precision, recall, and F1-score.

The results showed that the model achieved good overall accuracy and strong performance on the majority class (class 2). It also performed reasonably well for class 3, with an F1-score of 0.86. The biggest challenge was predicting class 4, the most severe accidents, which were underrepresented in the data. Although recall for this class remained lower than ideal, the model still succeeded in identifying many severe cases with a fair balance between false positives and false negatives. Analysis of feature importance revealed that environmental and time-related features, especially temperature, visibility, and weather conditions, were the most influential in predicting severity. These findings are consistent with previous studies and confirm that external factors play a major role in the seriousness of road accidents. Despite these results, the project had some limitations. First, the class imbalance issue affected the model's ability to predict severe accidents accurately. Although methods like class weighting were used, the problem was not fully solved. Second, the model relied on features that may be incomplete or inconsistent in real-world applications, such as weather or wind speed data. Finally, the use of a single model may limit the predictive power for rare cases. For future work, more advanced models such as ensemble voting, neural networks, or hybrid systems could be explored. Data augmentation techniques like SMOTE could also help improve performance on minority classes. In addition, integrating real-time data feeds and expanding the dataset to include more recent accidents would make the system more practical for real-world use.

In conclusion, this study demonstrates that machine learning can be used to predict traffic accident severity with reasonably high accuracy. While improvements are still needed, especially in handling rare but critical cases, the results support the potential for ML-based systems to assist in traffic safety and emergency planning.

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