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ENHANCING ROAD SAFETY THROUGH ADVANCED MACHINE LEARNING: A COMPARATIVE STUDY OF RANDOM FOREST AND NEURAL NETWORKS FOR MULTI-CLASS ACCIDENT SEVERITY PREDICTION

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ABSTRACT:

Traffic accidents remain a major challenge for urban planning and transportation engineering, posing continuous risks to human life and infrastructure. Despite recent advances in traffic safety measures, accurately predicting and classifying accident severity particularly under conditions of class imbalance remains difficult. This study proposes an integrated framework combining Random Forest (RF) and Artificial Neural Network (ANN) models to predict accident severity as slight, serious, or fatal. Using a large-scale UK government dataset comprising 2,047,256 accident records with 34 attributes, extensive data preprocessing was conducted, including temporal transformation, missing value imputation, and outlier removal. To mitigate class imbalance, weighted learning strategies were applied. Model performance was evaluated using confusion matrices, precision, recall, and F1-score. Results showed that while ANN and RF achieved overall accuracies of 85.99% and 70.97%, respectively, both models struggled to predict severe accidents. RF outperformed ANN in predicting fatal accidents (F1-score of 4.57% versus 0%), whereas both models performed well for slight accidents. These findings highlight the need for improved methodologies to address class imbalance in road safety severity prediction.

Keywords: *Accident severity prediction; Machine learning; Road safety; Road Design; Deep learning; Artificial Neural Networks (ANN); Random Forest (RF); Class imbalance; Multi-Class classification; Traffic analysis..*

INTRODUCTION

Traffic accidents are one of the major problems in the world today because they are primarily damaging to the health of the people, affect the socio-economic growth of society, and lower the quality of living standards. As per the WHO, road traffic crashes take about 1.3 million lives every year, alongside 20 to 50 million people suffering from other injuries [1], [2], [3]. These figures point out the importance of ad hoc approaches to minimizing the impact of road accidents along with addressing their grave repercussions [1], [2], [3], [4]. Here, predicting and categorizing the depth of the impact of traffic accidents is a relatively novel field of study, the results of which could help to formulate road safety policies and aid effective design and implementation of interventions [5], [6], [7], [8], [9].

Engineering and construction of roads are such an important factor for road safety because they form the basic structure of road safety measures. Skid-resistant materials, as well as proper road surfaces, are major contributors to safety, especially in wet conditions. As stated earlier, the geometry of a road and its components, including the horizontal and vertical alignment, cross-section design, and even the sight distance, play an important role in accident prevention. Proper road design involves safety measures and standard engineering, which leads to fewer accidents and lower injury severity [10], [11], [12], [13]. The building of roundabouts instead of intersections has been shown to drastically reduce injury crashes at stop sign intersections. Additionally, the addition of median barriers on divided highways has been known to significantly reduce head-on collisions. Intelligent transportation systems replace static road design measures with integrated technology that controls them; examples include IVHS (intelligent vehicle high traffic control system) with variable speed limits and dynamic lane control, which have shown a degree of promise in high-traffic areas.

The most important observation is that the construction and engineering control of roads has a great impact on saving lives. In cities, the idea of “complete streets,” which serves all users of the road, including people walking and riding bicycles, is related to fewer injuries to pedestrians and other vulnerable road users. In addition, the use of speed humps and chicanes can help lower vehicle speeds and the rate of accidents in residential areas. With an increasing understanding of the interplay between road layouts and safety, civil engineers are beginning to adopt the principles of a “Safe System” approach where the goal is to design a road framework that is tolerant of human mistakes and reduces serious harm from accidents through sophisticated engineering [14] [12], [15], [16].

Accident prediction analysis has changed over the years alongside the development of data acquisition, storage, and analysis technologies [17], [18], [19], [5], [6]. The earlier techniques in this field were focused on understanding the aggravating factors that description statistics and regression techniques provided, which did not account for the many complex factors that influence the probability of an accident and its severity. With the introduction of AI and machine learning, more accurate and comprehensive predictive modeling became plausible in this area [20], [21]. Techniques such as decision trees/random forests, support vector machines, and even neural networks can be employed and are optimal in identifying patterns within large complex data sets. These AI techniques are best made for understanding the non-linear relationships between the numerous factors, comprising the severity of the accidents, including road and weather conditions, behavioral aspects of the drivers, characteristics of vehicles, and time elements. The use of these techniques to road safety analysis is relatively new and has already provided a deeper understanding of the occurrence and gravity of accidents.

The major issue in predicting road accident severity is the data modeling itself, as they are fundamentally unbalanced [22], [5], [23]. While severe and fatal accidents are especially important, they are usually much rarer than minor accidents. This form of imbalance is extremely problematic for conventional machine learning techniques because they disproportionally focus on the prevalent class, which is likely to compromise the model's ability to predict severe accidents that are infrequent in number. Building models that can accurately detect and predict high-severity accidents that pose a public safety concern requires solving these data imbalance problems.
Accurate prediction of an accident’s severity demands the integration of time and space within the framework [24], [5], [25]; this is important since accidents are not singular events, rather, they are the outcome of a range of dynamic components such as daylight, traffic patterns, and seasonal changes. Furthermore, some spatial determinants also affect the frequency and gravity of accidents, such as the geometric features of the road (urban or rural), as well as its proximity to important infrastructure. The inclusion of these spatio-temporal features in an artificial intelligence model is intrinsically difficult as it can either improve or reduce the accuracy of the accident severity estimations. These advanced machine learning (ML) and deep learning (DL) approaches have often been incorporated to road accident severity prediction systems but there are still problems that must be addressed; for instance, the interpretability of DL models, particularly deep neural networks, remains a major problem. The accuracy level of these models is high, but their predictive regimes are too closed for a proper analysis by safety professionals and decision-makers.

One of the primary issues facing the field at the moment is striking the right balance between a model's interpretability and complexity, which drives the creation of artificial intelligence theories that aim to address this issue. The quality and accessibility of information provide another difficulty; road accident data is often collected from many agencies and jurisdictions, which may lead to differences in data formats, definitions, and completeness. Access to comprehensive accident data may also be limited by legal restrictions and privacy concerns, particularly when it comes to the personal information of those involved. Building predictive models has become a critical problem as such models are expected to perform under certain constraints, with accuracy and relevance being the main requirements.

There is also a need to address ethical concerns related to models used to predict the severity of real accidents. Researchers must carefully examine the ethical dilemma of how prediction models may unintentionally discriminate against particular demographic groups in road safety results.

Despite these challenges, the rise of rapid autonomous vehicle transport and intelligent systems underscores the necessity to invest in the building of advanced predictive models for accident severity, which can be employed for diverse safety enhancement policies on public roads. The frameworks developed from precise predictions of disruption intensity following an accident will facilitate resource allocation and ensure enough focus on aid-based intervention techniques. The opposing perspective yields unjustified repercussions, specifically an enhancement of economic activity devoid of oversight or regulation. Given the substantial complexity of many technologies still in development, there is an increased likelihood that failures will occur suddenly, without any forewarning of the seriousness of advancements in road safety.

This paper aims to address significant challenges in the modeling of ISSR prediction; a binary classification (1-0) of accidents as fatal or non-fatal is overly simplistic; yet, most research depend on one-class or multi-class frameworks, presuming that all incidents can be categorized into three quantitative intervals: major, minor, or fatal; bridging this gap will enable policymakers to customize intervention strategies for each degree of accident severity. This project aims to address the significant deficiency of data in accidents by using innovative methods for data pre- and post-processing, in conjunction with the integration of artificial intelligence algorithmic learning. The research extends beyond only quantifying the computer-assessed severity in assisting traffic collisions; the suggested approach will focus on modeling-impaired performance, which is typically considered a factor in numerous instances of model traffic incidents. This work introduces a novel integration of conventional ML techniques to enable both the comparison of several approaches and the utilization of each method's advantages to enhance forecast accuracy. The diverse deficiencies revealed in this study will facilitate the enhancement of current systems to improve road safety via automation and modern data technologies. The results of this study may facilitate the development of pragmatic road safety policies, aid in the creation of effective intervention strategies, and substantially mitigate the negative consequences of road traffic collisions and their associated injuries.

LITERATURE REVIEW

The prediction of road accidents and the related severity levels remains a complex problem that encompasses various approaches from numerous fields; this review is focused on the existing works on road accident prediction from several categories.

2.1. Machine learning and AI-based Prediction Models

Several algorithms and artificial intelligence methods for the prediction of the likelihood and anticipated severity of road accidents are covered in this subsection; these strategies use historical data to identify patterns and forecast future incidents. A hybrid approach of K-means clustering and Random Forest (RF) for forecasting the severity of road accidents was developed by [26]; their model attained remarkable findings, with an accuracy of 99.86 %, and the criteria identified as having the most significant impact on accident severity were driver experience, lighting circumstances, driver age, and vehicle service year. A study by [27] tested various machine learning methods for assessing the severity of vehicle accidents in New Zealand; among the models, including Random Forest, Decision Jungle, AdaBoost, XGBoost, Light GBM, and CatBoost, Random Forest yielded the highest accuracy at 81.45 %; model analysis was achieved using Shapley value analysis. In India, Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models were employed to forecast road accidents in busy traffic areas [28]. Many AI methods were used to predict accident severity based on Indian road accident data [29]; gradient-boosting machines were identified as the most performing using SHAP for model interpretation.

The Chinese National Automobile Accident data was used by [30] to build prediction models for traffic accident severity; the study developed predictive features and employed RF for feature priority ranking. Accident severity prediction using many ML algorithms in India has been reported [31]; RF was found to perform best prediction at 88.89 %, followed by LR and DT variants.

2.2. Deep Learning and Neural Network Approaches

In a study by [32], a novel methodology that employs DL techniques to forecast and assess the severity of traffic accidents in cities was developed; it is a combination of CNN and DNN for accident detection with a grid-clustered feature map. A study by [33] suggested employing Convolutional Neural Networks (CNN) alongside IoT sensor networks for the detection of automobile accidents, attaining approximately 95 % accuracy. The application of graph neural networks, specifically GraphSAGE, for forecasting accident occurrences on road networks has been detailed [34]; this methodology exhibited robust efficacy, forecasting the number of accidents with a mean absolute error of under 22 % and accident occurrence with an AUROC of 87 %.

2.3. Computer Vision and Image Processing
A novel method for forecasting near-miss incidents using dashcam recordings and meteorological sensor data has been presented [35]; the prediction accuracy of the model using camera calibration, collision point forecasting, and heuristic knowledge was 96.01 %. The detection and monitoring of vehicle speed via computer vision-based algorithms was also reported by [36]; a Multi-scale Detector was used in the study for object recognition; the model also integrated DeepSORT with Centroid Sort algorithms for vehicle tracking.

2.4. Big Data and Data Mining Approaches
Studies that leverage large datasets and data mining techniques for the extraction of meaningful patterns for accident prediction are covered in this subsection. A study has proposed the use of Big data from GPS trajectory patterns in combination with self-reported accident information for the prediction of motorcycle accident likelihood [37]; the RF-based model showed that dangerous overtaking event-based features most significantly impacted accident prediction. A tool for road accident risk prediction using data from the Portuguese National Guard has been presented [38]. The presented data mining approach identified peak accident times and influential factors like weather conditions. Deep learning methods have been evaluated for accident occurrence prediction on road networks [34] based on a large-scale analysis of 9 million traffic accident records from various US states.

2.5. Autonomous and Connected Vehicles
Research related to accident prediction and prevention in the context of autonomous and connected vehicles is covered in this subsection. The study by [39] focused on the relationship between expected accident numbers/fatalities involving vulnerable road users and the number of automated vehicles on the road. Their approach combined analysis of current accident causes with projections of how automated vehicles could mitigate these causes. A novel approach for predicting collisions in collaborative and autonomous driving systems has been developed [40]; the study also presented a spatial-clock stochastic specification language (SCSSL) for safety invariants description in self-driving systems. The use of machine learning and IoT-based technology for reducing accidents in autonomous vehicles has been presented by [41]; they proposed a system to predict a car's manufacturing tolerance without defecting the car.

2.6. Demographic and Geographic Analysis
Approaches that relied on demographic or geographic data to predict accident likelihood or identify high-risk areas are covered in this subsection. The study by [42] reported the utilization of demographic data to forecast road accident frequency in England and the UK; the proposed regression-based ML models indicated that census data might account for more than 28 % of the variance in per capita traffic accident rates. In another study [43], the scholars strived to identify accident-prone locations on the road network of Northern Greece; they employed LR and ML algorithms to compare efficiency.

2.7. IoT and Sensor-based Approaches
Studies that utilize IoT devices and sensors for accident prediction and prevention are covered in this subsection. The use of ML methods in road traffic analysis and vehicle Internet of Vehicles (IoV) safety systems has been evaluated [41]; the study aims to highlight the efficacy of federated learning (FL) in addressing most ML-related problems. To demonstrate the concept of IoT and AI-driven accident prediction, an automobile accident detection system that employs IoT sensor networks in conjunction with DL was proposed [33].

2.8. Near-Miss and Proactive Accident Prevention
This subsection focused on the prediction and prevention of near-miss incidents that could be precursors to actual accidents. The study by [41] used dashcam footage and weather sensor data to develop an approach to near-miss accident prediction; their lightweight model aims to provide drivers with real-time assistance for proactive accident prevention; the model was designed for edge client deployment.

2.9. Literature Reviews and Meta-analyses
The relevant studies on road accident prediction are reviewed and analyzed in this subsection. A systematic evaluation of the application of ML for road traffic analysis and vehicle safety within the context of the Internet of Vehicles (IoV) was conducted by [44]; the study assessed existing research endeavours and pinpointed areas requiring future investigation. An article [45] concentrated on enhancing accident analysis by employing RF algorithms and Gini impurity tests to evaluate the significance of predictors in accident prediction.

The multi-sectoral approach to road accident prediction has been highlighted in this review, ranging from the use of ML, DL networks, and computer vision to big data analysis to enhance accident prediction and prevention technologies; emerging technologies such as IoT and autonomous vehicles renew the research prospects, supported by the demographic and geographical analyses of accident occurrence. With the advancement of technology, combining these approaches will make it possible to improve road safety in the future. In Table 1, the summary of the existing approaches for traffic accident prediction is presented.

Table 1. Summary of the recent methods and approaches to road accident prediction

Category	Reference	Key Method/Approach	Main Findings/Contributions
Machine Learning and AI-based Prediction Models	[26]	Hybrid K-means and Random Forest	99.86% accuracy; identified key contributing factors
Machine Learning and AI-based Prediction Models	[27]	Comparison of multiple ML models	Random Forest is best at 81.45% accuracy
Machine Learning and AI-based Prediction Models	[28]	MLR vs ANN comparison	ANN showed superior performance
Machine Learning and AI-based Prediction Models	[29]	Various AI techniques	Gradient boosting machines are most effective
Machine Learning and AI-based Prediction Models	[30]	Random Forest for feature ranking	High-accuracy prediction model
Machine Learning and AI-based Prediction Models	[31]	Comparison of ML algorithms	Random forest is highest at 88.89% accuracy
Deep Learning and Neural Network Approaches	[32]	CNN and DNN combination	Novel system for urban traffic accident prediction
Deep Learning and Neural Network Approaches	[33]	CNN with IoT sensors	95% accuracy in auto accident detection
Deep Learning and Neural Network Approaches	N/A	Graph neural networks	Strong performance in accident prediction
Computer Vision and Image Processing	[35]	Dashcam footage analysis	96.01% accuracy in near-miss prediction
Computer Vision and Image Processing	[36]	Multi-scale Detector & tracking algorithms	High accuracy in vehicle speed detection
Big Data and Data Mining Approaches	[37]	GPS trajectory data analysis	Identified key factors in motorcycle accidents
Big Data and Data Mining Approaches	[38]	Data mining on police data	Identified peak accident times and factors
Autonomous and Connected Vehicles	[39]	Analysis of Automated Vehicle Impact	Projected accident reduction with automated vehicles
Autonomous and Connected Vehicles	[40]	SCSSL for autonomous driving	Novel approach for collision prediction
Demographic and Geographic Analysis	[42]	Demographic data analysis	Census data explained 28% of the accident rate variance
Demographic and Geographic Analysis	[43]	Black spot identification	Compared logistic regression and ML algorithms
IoT and Sensor-based Approaches	[44]	Systematic literature review	Highlighted the potential of federated learning
IoT and Sensor-based Approaches	[33]	IoT sensor network with deep learning	Integrated IoT and AI for accident detection
Near-Miss and Proactive Accident Prevention	[35]	Dashcam and sensor data analysis	Real-time assistance for proactive prevention
Literature Reviews and Meta-analyses	[44]	Systematic literature review	Overview of ML in Road Traffic Analysis
Literature Reviews and Meta-analyses	[45]	Discussion on analysis methods	Highlighted the importance of Random Forest and the Gini impurity test

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There is still a critical gap in solving the challenges of multi-class severity prediction while concurrently managing imbalanced datasets, despite the fact that previous research has made great progress in road accident prediction utilizing a variety of machine learning and deep learning techniques. This study integrates traditional machine learning models and deep learning models for accident severity prediction to provide new insights into the problem. Unlike other works that limit themselves to single model frameworks or simple classes such as binary classification, this study enforces a complex framework that predicts accident severity across diverse categories and class imbalance using weighted learning. Addressing these issues implies accurately predicting road accident severity, a problem this study works towards for the sake of improving safety policy and intervention approaches.

PROBLEM FORMULATION

Assume a given dataset that consists of vehicle and accident; the major aim is to come up with a predictive model that would map the input features to accident severity class (often categorized as minor, major, and fatal). Hence, the problem formulation could be seen as a supervised classification problem as follows.

Let:

- be the dataset where is the number of samples.
- is the feature vector for the -th sample, with being the number of features.
- t is the target variable representing the severity category (e.g., 1: minor, 2: major, 3: fatal) for the -th sample.

The models are trained to minimize the classification error, as given in Equation (1):

(1)

Where represents the parameters of the model, and is the loss function, typically the cross-entropy loss for classification problems.

DATA PREPROCESSING

The quality and reliability of predictive models often rely on the type of data used for training; hence, data preprocessing is a critical step in the pipeline to ensure model quality and reliability. Several key operations are performed during data preprocessing to enhance usability; the first step is data transformation into a suitable format. Temporal data, such as the date and time of accidents, must be transformed into a suitable date-time format before training the model. In such an instance, let represent the original timestamp vector, where each element. is a string; the transformation applied is as given in Equation (2):

(2)

where represents the date-time-formatted vector. The timestamps are then categorized into discrete periods (e.g., morning rush, office hours), defined as Equation (3):

(3)

Where is a function mapping each date-time value to its respective category.
Next, the handling of missing values involves identifying and removing columns and rows with NaNs. Let denote the original feature matrix, and the cleaned matrix. The process is defined as Equation (4):

(4)

To combine the vehicle and accident data frames, assume that the accident data frame is while is the vehicle data frame; then, the combined data frame could be as given in Eq (5):

(5)

Where = the union operation on data frames that ensures a complete dataset for modeling.
Then, one-hot encoding is used to convert the categorical variables in into a numerical format. Let represent the categorical feature set, and the encoded matrix. The encoding function is in Equation (6):

(6)

Outliers in numerical columns are detected and handled. For each numerical feature , the interquartile range (IQR) method is used, defining lower and upper bounds as Equation (7):

(7)

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Outliers in numerical columns are detected and handled. For each numerical feature , the interquartile range (IQR) method is used, defining lower and upper bounds as Equation (8):

(8)

where and are the first and third quartiles of the feature , respectively. Data points outside these bounds are considered outliers and are treated accordingly.
The 'Age of Vehicle' feature is binned into categories. using defined age intervals. The binning function is in Equation (9):

(9)

Finally, the comprehensive preprocessing pipeline, encompassing these transformations and cleanups, ensures a robust and high-quality dataset , ready for subsequent modeling stages. The idea of this structured approach is to ensure data integrity and facilitate accurate and reliable predictive model development for accident severity.

MODEL FORMULATION AND DATA SPLITTING

This study aims to come up with predictive models for the classification of road accident severity using a dataset that consists of accident and vehicle data; the dataset consisted of samples, where is the feature vector for the -th sample, and is the target variable that indicates the level of severity (1: minor, 2: major, 3: fatal). The dataset is divided into two sets – the training dataset and the testing dataset ; and represent the number of samples contained in the training and testing datasets, respectively, as in Equation (10):

(10)

HANDLING IMBALANCED CLASSES

To address the issue of class imbalance, class weights are assigned to each class . These weights are inversely proportional to the frequency of each class in the training set in Equation (11):

(11)

where is the number of samples of class in the training set.

RANDOM FOREST CLASSIFIER

A Random Forest classifier is trained on the training set . The model parameters are optimized to minimize the entropy-based criterion with balanced class weights. The Random Forest model is represented as Equation (12):

(12)

NEURAL NETWORK MODELS

For neural network models, the input features are normalized, and the outputs are one-hot encoded.
Artificial Neural Network (ANN)

The ANN model comprised one input layer, one hidden layer with 512 neurons using ReLU activation, and an output layer with softmax activation; the model parameters are optimized to minimize the cross-entropy loss in Equation (13):

(13)

where is the predicted probability of class for sample .

MODEL EVALUATION

The test set is used to evaluate the trained models based on several performance measures to ensure reliability and robustness. Model accuracy is determined as the proportion of the correctly predicted cases against the overall number of cases; it is defined in Equation (14)

(14)

Where is the indicator function. Precision, defined as Equation (15)

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(15)

Precision is a measure of the ratio of the truly positive cases to the overall number of positive predictions.
Recall, as given in Equation (16), assesses the model for actual positive instances identification.
F1-Score, as provided in Equation (17), offers insight into the harmonic mean of recall and precision; it is a form of trade-off between recall and precision.

(16)

(17)

Confusion matrices are also computed for performance visualization across classes; the matrix has elements. that represents the number of cases of class predicted as class .

These metrics are collectively used to ensure comprehensive models' evaluation; they are also essential in making adequate comparisons of the accident severity predictive efficiency of the utilized models.

EXPERIMENTAL RESULTS AND ANALYSIS

10.1. Dataset Exploration

The dataset used in this study is the UK government's extensive traffic dataset; this dataset consists of two interrelated elements - accident data and vehicle data, thereby offering a complete perspective on road accidents nationwide. This study used a subset of data comprising over two million recordings of individual accidents, each characterized by 34 attributes. This improved dataset, inspired by the work of Dave Fisher-Hickey, includes enhancements, an extended coverage period, human-readable information from previously coded variables converted to text strings, and, most significantly, comprehensive vehicle information. There are 2,177,205 records and 24 columns in the dataset, making it suitable for study across several levels. Specifications regarding the traffic incidents in terms of their geographical location, meteorological conditions at the time, casualty figures, vehicle maneuvers, and the vehicles involved are included in the annual report of the dataset. Scholars could rely on the accident datasets to research road safety, urban planning, and environmental impacts on driving conditions; the vehicle data elucidates the influence of various vehicle kinds, models, and features in accidents. The provision of the accident cases and the involved vehicle(s) is facilitated by 34 attributes that characterize each incidence; this allows more advanced research into vehicle safety design, road safety, and traffic control systems. The distribution of traffic accidents over various days of the week in the UK is illustrated in Figure 1, which depicts the daily occurrence of accidents.

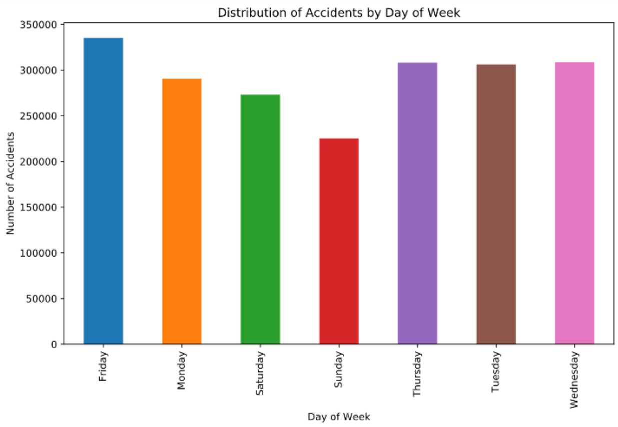

Figure 1. Distribution of traffic accidents by day of week in the UK, showing variation in accident frequency across different days, peaking on Fridays, and a trough on Sundays, likely reflecting patterns of weekly traffic flow and human activity.

Figure 1 revealed the following major observations:
- Over 350,000 incidents are recorded on Fridays (the highest number).
- There are significant decline on Saturday and Sunday compared to weekdays.
- There is a steady increase in the number of accidents from Monday to Friday.
- A similar number of accidents are encountered on Thursday, Tuesday, and Wednesday, though a bit less than cases on Fridays, but higher than cases on Mondays.

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- The fewest number of accidents is seen on Sunday, averaging 225,000 cases.

A significant observation from this pattern is that there is a positive correlation between traffic accident frequency and typical workweek patterns, as more cases of accidents do occur on busier weekdays than on weekends.
Displayed in Figure 2 is the correlation heatmap of numeric features in the traffic accident dataset; the figure highlights the connections between the quantitative variables in the dataset, where the horizontal lines illustrate perfect self-correlations of 1.0, but many clusters of strongly correlated characteristics are shown by dark red squares. Robust relationships existed between the location-related attributes (Longitude, Latitude, , Location_Northing_OSGR) as expected for geographical data. The observed positive correlation between and also indicates that accidents that involve more vehicles generally result in more casualties. Most additional feature pairings exhibit weak correlations (light blue or white), signifying that numerous quantitative features encapsulate unique facets of the incidents with low redundancy; several mild negative associations are also evident (dark blue). This heatmap can guide feature selection in predictive modelling and can improve understanding of variable interrelations; it can assist in the alleviation of probable multicollinearity concerns. It often provides a visual overview of the relationship among numeric variables in the dataset to facilitate the understanding and analysis of traffic accident patterns.

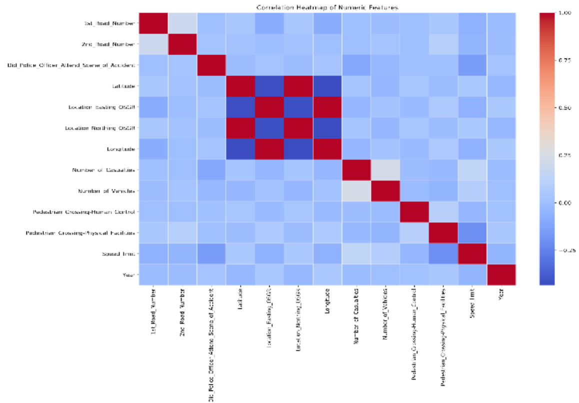

Figure 2. Correlation heatmap of numeric features in UK traffic accident data; the strength and direction of correlations between numeric variables are indicated in the heatmap, where red = positive correlations, blue = negative correlations, and intensity = strength of the relationship.

The severity of accident distribution in three distinctive categories in the UK traffic accident dataset is depicted in Figure 3; it is irrefutable that disparities exist in the frequency of various severity degrees based on the bar chart. The “Slight” category is by far the most common, accounting for around 1,700,000 of the accidents. This is followed by the “Serious” category, which is significantly lower, at roughly 300,000 cases. The “Fatal” category is at the bottom with an extremely low number of incidents that appear to be fewer than 50,000. With this distribution, it is clear that while traffic accidents do occur often, in most cases, only slight injuries or damage are done. Although infrequent, serious and fatal cases are deemed the most important in terms of concern for road safety. The discrepancy in severity levels further indicates the need for understanding what factors contribute to severe accidents, which are very uncommon. The picture aids in highlighting road safety issues for policymakers and investigators since both serious and fatal accidents need targeted reduction while still making efforts to minimize all traffic-related cases.

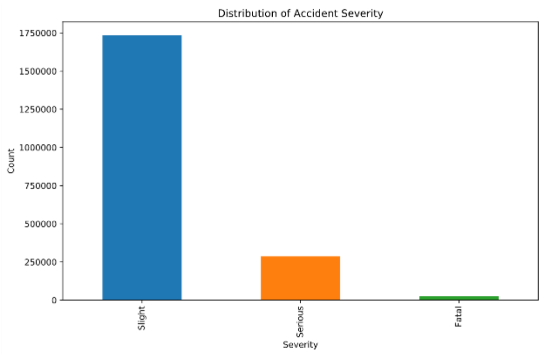

Figure 3. Distribution of accident severity in UK traffic incidents.

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Figure 4 demonstrates the hourly distribution of traffic accidents in the UK and shows some obvious, clear patterns of timing. The line graph indicates two major peaks: one in the morning from 8-9 AM and the other stronger one, from 4-6 PM, which seems to coincide with the rush hour traffic. The lowest number of accidents occurs during the wee hours of 3-5 AM and serves to indicate that traffic is almost non-existent during those hours. More accidents were recorded from 5 AM, when many people are heading to workplaces; however, the number of cases in the peak of the afternoon/evening is higher, which suggests the role of fatigue and other non-work-related travel in the risk of accidents. Nocturnal activity may account for the slight increase in the number of cases between 11 PM and 12 AM. This representation is essential as it will aid in improving traffic management, law enforcement methods, and targeted safety initiatives. The fluctuations in accident risk across a normal day, as seen in the graph, also emphasize the relationship between peak travel times and heightened accident cases.

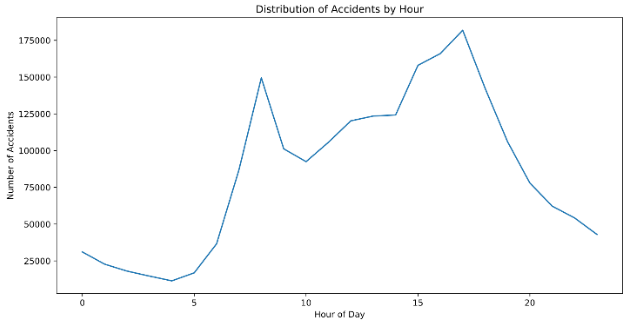

Figure 4. Distribution of traffic accidents by hour of day in the UK; the line graph illustrates the fluctuation in accident frequency over 24 hours, highlighting peak times during morning and evening commutes and the relatively safer early morning hours.

A box plot of the number of victims per accident as classified by accident severity within the dataset is seen in Figure 5. The graph indicates that most accidents result in a small number of victims due to the low placement of the boxes, regardless of severity level; yet, distinct disparities are seen within the categories.

- A lower number of casualties is often associated with slight accidents; this is indicated by the box and median line close to the bottom of the chart.
- A higher number of casualties is recorded in serious accidents, as evidenced by the wider interquartile range.
- The highest number of accidents is associated with fatal accidents, though less frequent, as shown by the higher position of the box and median line.

Each of the three categories has multiple outliers, denoted by dots above the whiskers, signifying incidents with an exceptionally high casualty count. These outliers are especially evident in the Serious and Fatal categories, with several incidents yielding more than 80 casualties. These extreme outliers across all severity levels suggest that despite the small number of casualties from most of the accidents, there are still instances of high casualties across the categories. This information can guide plans for emergency response and in comprehending the probable magnitude of various event types.

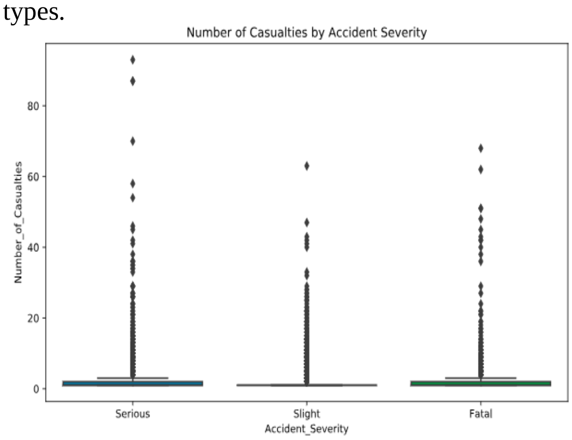

Figure 5. Box plot of number of casualties by accident severity in UK traffic incidents; the plot illustrates the distribution of casualty numbers across Serious, Slight, and Fatal accident categories, highlighting typical ranges and extreme cases for each severity level.

10.2. Random Forest

The RF model's classification performance revealed that it performed inconsistently at various accident severity levels; the model has significant issues with fatal and serious accidents, but shows competence in predicting small accidents (87.31% precision, 78.89% recall, and 82.89% F1-score). For example, the model obtains a precision of 16.43%, a recall of 23.83%, and an F1-score of 19.45% for large accidents, but an accuracy of 3.07%, a recall of 8.96%, and an F1-score of 4.57% for fatal accidents. The macro average (35.64% F1-score) and the weighted average (73.79% F1-score) differ significantly, indicating a serious class imbalance issue. The model's performance on small incidents, which make up the majority of the dataset (293,021 out of 340,811 cases), has a considerable impact on the total accuracy of 70.97%. The absence of equilibrium, coupled with deficiencies in predicting fatal and severe accidents, is profoundly concerning, particularly given the significance of precisely predicting these extremes. To enhance the accuracy of model fatality predictions, it is prudent to utilize advanced techniques for addressing class imbalance, such as SMOTE, engage in discriminative feature building, and implement alternative, less conventional algorithms for imbalanced data. A thorough examination of the most predictive variables can be carried out to help with the design of data collection and model-building techniques, and the model's classification thresholds may also be modified. Table 2 shows the micro average, macro average, and weighted average values for each severity class along with the precision, recall, F1-score, and support measures.

Table 2. Classification report for RF model predicting accident severity.

	F1-score	Precision	Recall	Support
Fatal	0.045697	0.030673	0.089565	4600
Serious	0.194507	0.164335	0.23825	43190
Slight	0.828862	0.873094	0.788896	293021
micro avg	0.709675	0.709675	0.709675	340811
macro avg	0.356355	0.356034	0.372237	340811
weighted avg	0.737902	0.771905	0.709675	340811

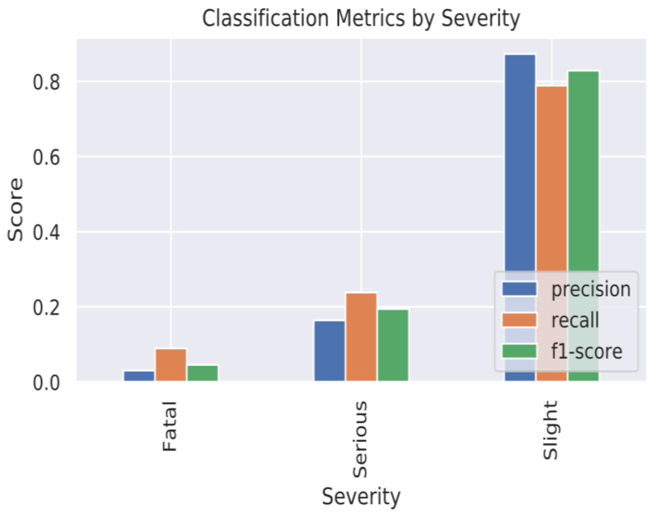

Figure 6. Classification metrics by accident severity using RF

The precision, recall, and F1-score values for each accident severity level captured using the RF model have been presented in Figure 6; the graph is a virtual representation of the strong performance of the model in Slight accidents, as well as its challenges with Fatal and Serious accidents; it highlights the issue of class imbalance and its impact on the predictive performance of models. The confusion matrix in Figure 7 portrays the performance of the ML model in predicting accident severity level across different categories; it provides details of the model's accuracy and the error types as follows:

- The diagonal elements (413, 10290, and 231183) represent correct predictions for each severity level.
- Off-diagonal elements show misclassifications. For example, 1122 Fatal accidents were incorrectly predicted as Serious.

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- The model performs best at predicting Slight accidents, with 231,183 correct predictions.
- There's significant confusion between Serious and Slight accidents, with 31204 Serious accidents misclassified as Slight.
- The model struggles most with Fatal accidents, often misclassifying them as less severe.

This graph shows the model's strengths (light accidents) and weaknesses (differentiating fatal and serious accidents from less serious ones); the observed differences in prediction accuracy between severity levels indicate the need for further model improvement, which may entail addressing the class imbalance in the training data.

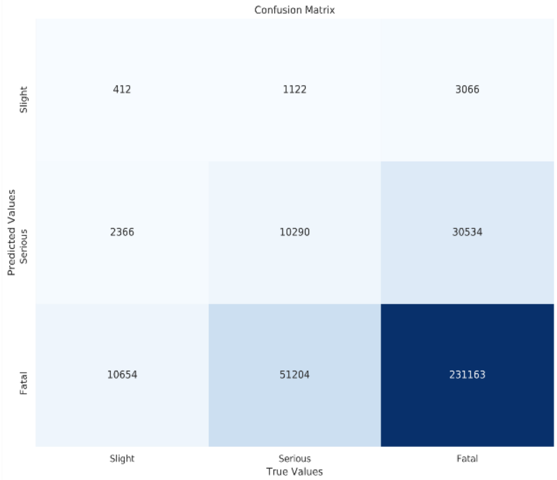

Figure 7. Confusion matrix for accident severity prediction using RF

10.3. Neural network

In this work, the neural network model for accident severity prediction consisted of an input layer, a hidden layer with 512 ReLU-activated neurons, and an output layer. The convergence curves in Figure 8 show the training process of the model; after being trained on 1,363,242 data and verified on 340,811 samples over 20 epochs, the model exhibited strong early performance with 85.90% training accuracy and 85.97% validation accuracy. However, both accuracies show little improvement during training, peaking at 85.92% and 85.99%, respectively, whereas loss values decrease somewhat from 0.4398 to 0.4249 (training) and 0.4293 to 0.4228 (validation). Overfitting was not an issue based on the close match between the training and validation measures; however, the model rapidly reached its learning capacity for this architecture and dataset, as shown by the ensuing performance plateau and rapid convergence. The consistency of accuracy and loss values during training are the measure of the robustness of a model, although the modest improvements over time raise the possibility of improvement through feature engineering, architectural modifications, or possible class imbalance-related issues. Overall, the model predicts accident severity with a moderate degree of accuracy, even though there is still room for improvement considering the convergence pattern.

Figure 8. Convergence curves for the neural network model on accident severity prediction

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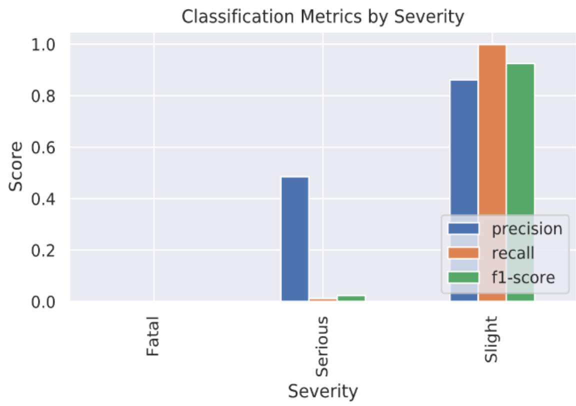

Figure 9. Classification metrics by accident severity using ANN.

Figure 9 displays the precision, recall, and F1-score for each accident severity level as recorded by the RF model, while Table 3 displays the micro-, macro-, and weighted average metrics, as well as the accuracy, recall, F1-score, and support for each accident severity class. The figure illustrates the class imbalance effect on the model's predictive performance by showing the model's optimal performance in minor accidents and its struggles with fatal and serious accidents.

Table 3. Classification Report for ANN Predicting Accident Severity.

	F1-score	Precision	Recall	Support
0	0	0	0	4600
1	0.023099	0.48482	0.011831	43190
2	0.9247	0.861101	0.998444	293021
micro avg	0.859937	0.859937	0.859937	340811
macro avg	0.315933	0.44864	0.336758	340811
weighted avg	0.797962	0.801793	0.859937	340811

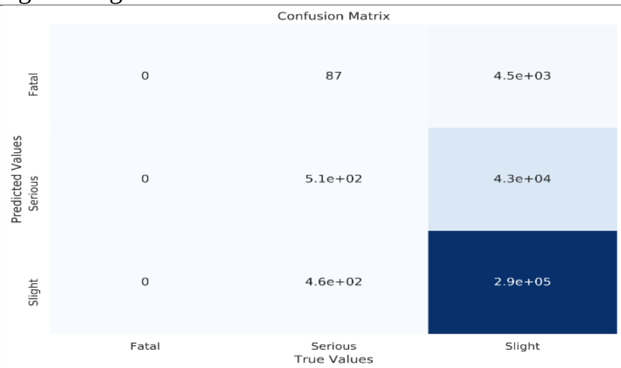

Figure 10: Confusion Matrix for Accident Severity Prediction using ANN

CONCLUSION AND FUTURE WORKS

Advanced ML techniques were used in this work to predict the degree of accident severity in a bid to address the nagging class imbalance problem. RF and ANN models were hybridized to form a strong and reliable accident severity prediction and classification model. The class imbalance effect on the prediction performance of models was demonstrated by the striking disparity in performance across the severity scale, despite the excellent overall accuracy. Although the two models performed well in minor accident prediction, their performance in serious and fatal cases was poor, and this is probably most important for road safety initiatives. Fatal accidents were accurately identified by other annexed methods or ensemble models, including RF, possibly due to their resilience to class imbalance; however, ANN performed best, suggesting fitness for capturing intricate data patterns.

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With these findings, this study has highlighted the importance of employing several modeling techniques for a given task, as well as giving careful thought to evaluation criteria other than overall accuracy when working with unbalanced datasets. The major conclusions from this study can be itemized thus:

- Rush hours and weekdays recorded a higher number of accident cases, possibly due to higher vehicular movement during such days; hence, there is a need for more safety measures during these peak periods. Also, the number of casualties per accident is directly a function of the number of vehicles involved; this demonstrates the necessity for multi-vehicle accident mitigation strategies.
- The issue of Imbalance in accident class and severity remains a major hindrance to predictive models development and implementation; there is a sustained search for novel ways to enhance model performance on minority classes.

To improve the predictive power of accident severity models, there is a need to consider:

- Exploration of advanced techniques that can handle extreme class imbalance; such techniques may include generative adversarial networks (GANs) or adaptive synthetic sampling (ADASYN) for minority class augmentation.
- Integration of spatial-temporal features and external data sources (such as weather patterns, traffic flow data) to capture more contextual information.
- Adaptation of interpretable ML models to provide actionable insights to road safety experts.
- Exploration of ensemble methods that merge the strengths of different algorithms to improve performance on all severity levels.
- Building of DL models for tackling multi-class problems in the transportation sector.

Reliable prediction models can be developed only if these problems are addressed; such models can assist in data-driven decision-making in road safety policy and intervention. This model's ability to save lives and minimize the societal impact of road accidents becomes more realistic as it is continuously improved.

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