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Research paper

Application of Machine Learning and Metaheuristic Optimizer Algorithm for Crash Severity Prediction in the Urban Road Network

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Abstract

This paper predicts the severity of crashes based on the analysis of multiple variables and using machine learning methods. For this purpose, data related to the years 2012 to 2024 of Tempe city in the state of Arizona USA was used. Features were selected using the metaheuristic method. Then, by using decision tree and artificial neural network, the classification of the severity of crashes was carried out. Based on the metrics, decision tree with an overall accuracy of 54% was the optimal. Finally, using the permutation feature importance method, the optimal model was interpreted. The results show that the characteristics of the year with 0.22 and the spatial characteristics with 0.11 and the collision manner with 0.1 have a higher importance in predicting the severity of crashes on urban roads.

1. Introduction

Considering that approximately 1.35 million deaths occur on the world's roads annually, addressing safety issues in transportation planning is crucial for both officials and academic researchers. The United Nations' 2030 agenda emphasizes 17 sustainable development goals, including the third goal of reducing road crash fatalities and the eleventh goal of enhancing urban road safety [1]. To align with these goals and mitigate crash impacts, it is essential to identify and classify crash causes through thorough analysis, enabling the implementation of effective countermeasures.

Crash causes can be categorized into four main groups: 1) user behavior, 2) vehicle characteristics, 3) road infrastructure, and 4) environmental conditions [2]. Recently, spatiotemporal analysis of accident data has gained attention for its importance in safety planning and management. Traditional statistical methods for analyzing large datasets and selecting key factors are computationally intensive [3]. However, advancements in data collection, storage, and transformation technologies offer new approaches to improve traffic crash prediction.

Accident prediction methods can be model-based or data-driven. Traditional statistical models often perform poorly in real-world applications. In contrast, data-driven models, such as machine learning, excel in handling complex nonlinear processes in big traffic data, yielding superior prediction performance [4, 5]. Machine learning methods enable quick and accurate selection of key features from large datasets, enhancing prediction accuracy [6]. An accurate accident prediction framework can provide traffic engineers with patterns of traffic accident conditions, allowing better crash management [7]

This study aims to predict crash severity by analyzing multiple variables such as traffic, weather conditions, road conditions, vehicle types, driver conditions, and spatiotemporal variables using machine learning methods. Innovative metaheuristic methods were employed for feature selection. By comparing the accuracy of different algorithms, the study identifies the most suitable process for quantifying crash causes and influencing factors, presenting a comprehensive framework for predicting crash severity. The study also suggests effective measures to reduce crash severity for decision-makers.

The contributions of this study are as follows: Proposing a hybrid machine learning framework for spatiotemporal crash severity prediction, outperforming advanced basic models in prediction quality and utilizing metaheuristic optimization algorithm for feature selection.

The paper is organized as follows: The “Literature Review” section provides a comprehensive review of related studies. The “Methodology” section discusses the study’s methodology, including data description and preparation. The “Results” section presents the prediction results obtained from the applied framework. Finally, the “Conclusion” section summarizes the main findings and offers recommendations.

2. Literature Review

In this study, our objective is to accurately predict the severity of crashes and identify the factors influencing them on urban roads. This section reviews prior research on modeling and analyzing the spatiotemporal characteristics of accident data, the factors affecting urban crashes, and the use of machine learning methods in predicting crash severity.

Traditional statistical analysis methods, machine learning, neural networks, time series analysis, and techniques based on spatiotemporal data mining are widely used in predicting the severity of crashes [8]. Statistical modeling relies on assumptions about data distributions and relationships between variables, but deviations from these assumptions can result in errors. In contrast, machine learning, powered by advancements in computation, does not require predefined relationships and can make predictions without in-depth understanding. Nevertheless, both applied statistics and machine learning focus on data analysis and share a significant overlap. Several machine learning approaches have proven to be effective in analyzing crash severity. These include decision trees (DTs), support vector machines (SVM), simple Bayes classifiers, Bayesian networks, random forests (RF), boosting techniques, K-nearest neighbors (K-NN), and association rule-based methods [9]. Santos et al. [5] conducted a review of 56 studies spanning from 2001 to 2021 that utilized various statistical and machine learning techniques to predict accident injury severity. Their findings revealed that RF emerged as the top-performing method in 70% of the cases following RF, SVM, DT, and K-NN were identified as the next best-performing techniques.

Ahmed et al. [10] worked on road crash severity prediction using New Zealand dataset (2016-2020) as a classification problem. Their aim was to classify crash severity into two main classes: binary and multi-class classification. To achieve this goal, this research investigated three single mode classification algorithms and three group mode classification algorithms. Accuracy, precision, recall and F1 score were used as evaluation methods. They concluded that the RF algorithm performs better than other methods studied in the research.

Similar studies in Iran [11] and Taiwan [12] have also demonstrated the superior performance of the RF method. Consequently, advanced machine learning algorithms are employed to compute spatiotemporal correlations of accident-related features during modeling. Recent research has validated the strong performance of convolutional neural networks (CNN) in capturing spatial correlations of accident-related features using high-resolution data [13]. Today, machine learning models are attracting more attention due to their outstanding predictive performance in the field of traffic safety. Shi et al. [14] proposed a machine learning framework specifically designed for extracting features and predicting risk levels using vehicle tracking data. Bao et al. [15] introduced advanced spatiotemporal short-term networks for predicting crash risk across an entire city in the short term. Similarly, Chen et al. [12] employed LightGBM models to accurately anticipate the risk levels associated with lane-changing maneuvers.

The challenge of data imbalance has a profound impact on the performance of crash severity models, particularly in the accurate classification and interpretation of crash severity [16-18] to address this issue, prior research has often employed data resampling techniques. These methods help rebalance datasets with an uneven distribution of class labels by either reducing the number of samples from the majority class (under-sampling) or increasing the number of samples in the minority class (over-sampling). For instance, under-sampling methods have been applied in studies like those of Yang et al. [19] and Wang et al. [20] while over-sampling has been used in works such as [21] and [22]. Resampling techniques have been extensively employed to tackle the issue of class imbalance in datasets, leading to improved prediction accuracy in machine learning models [12, 14, 23].

While data-driven methods have demonstrated the ability to produce strong statistical predictions with minimal hyperparameter tuning, they are inherently limited in their capacity to identify causal relationships. Additionally, the outputs of these models tend to be complex and can often be challenging to interpret effectively in relation to the application of meta-heuristic optimization algorithms, their use has mostly been confined to accident frequency analysis. For instance, Beeramoole et al. [24] introduced a comprehensive hypothesis testing framework for discrete outcome models, where an optimization strategy was used to identify key explanatory variables while maintaining both interpretability and advanced model specification testing. However, when it comes to predicting crash severity, innovative optimization techniques or escape algorithms have not yet been applied in this domain.

Therefore, according to the literature review, there is still a research gap to develop a comparative machine learning approach to find the best prediction method to analyze the severity of road traffic crashes. This means that road accident data patterns should be studied and processed to find the most meaningful features of prediction and correlation and dependence on the model of road accident behavior. Therefore, the contribution of this study to the innovation of using the grey wolf metaheuristic algorithm is to use it for features selection - which is the most important part in predicting the severity of crashes. According to the review of previous studies, the proposed comprehensive method has not been used until now regarding the selection of features and the prediction of the severity of crashes.

Feature selection is a necessary step for machine learning as it can reduce computational costs, remove irrelevant features, and improve models' prediction performance [25]. Based on the literature review it was found that until now previous studies have tried to use different methods such as statistical and regression models to predict the severity of crashes, and in recent years, the use of machine learning methods has become widespread. One of the most important parts related to predicting the severity of crashes is the feature selection that have the greatest impact on predicting the severity of crashes. So far, feature selection has been done based on statistical methods and machine learning, but the use of metaheuristic method due to their great potential and ability is a new method that has been used in this study to select features.

The aim of this study is to predict the severity of crashes based on the analysis of multiple variables such as traffic, weather conditions, road conditions, types of vehicles, driver status and temporal and spatial variables using machine learning methods from different families such as DT, NAA, K-NN and Logistic Regression. For this purpose, the metaheuristic algorithm of grey wolf is used to select the features, and also by comparing the accuracy of various algorithms, the most suitable process for quantifying the causes of crashes and the factors affecting it is identified, and a comprehensive method for predicting the severity of crashes is presented. We will propose mutually effective measures to reduce the severity of crashes for the decision of the authorities.

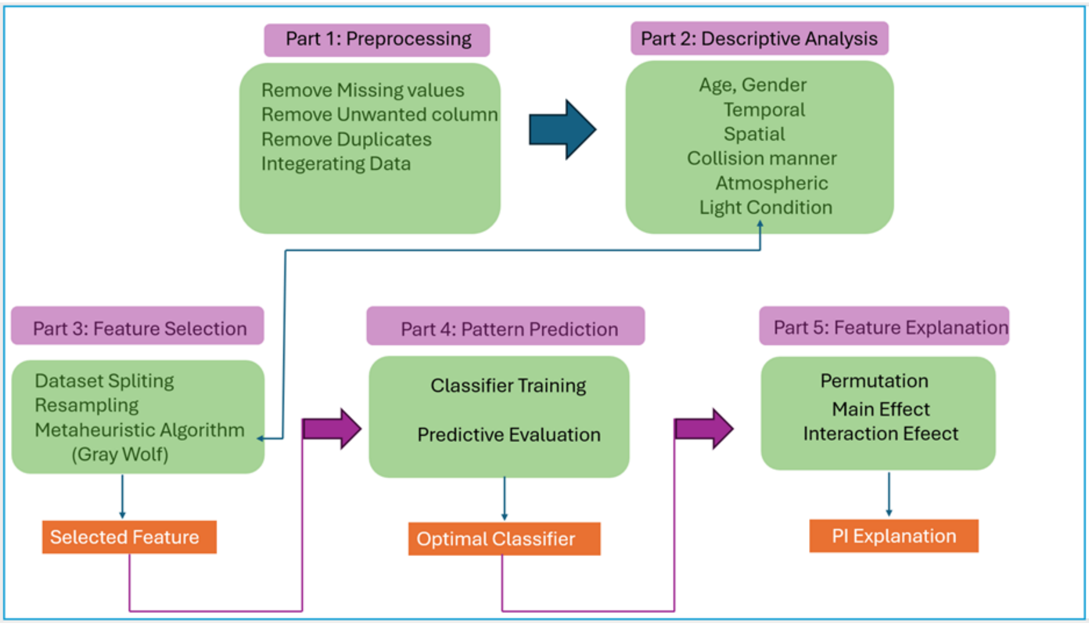

Figure 1. Overal framework of urban crash severity prediction model.

3. Methodology

3.1. Model framework

The model proposed in this study aims to predict crash severity by analyzing multiple variables such as individual characteristics, weather conditions, road conditions, driver conditions, and temporal and spatial variables using machine learning methods. The feature selection is performed using the grey wolf metaheuristic optimizer algorithm. The proposed model includes five main parts, as illustrated in Figure 1. This comprehensive framework not only predicts crash severity but also explains the influence of various factors within the model.

3-2- Data preprocessing

The quality of analysis results hinges on the quality of the dataset used, including factors like consistency, accuracy, and the presence of valuable, non-missing information. Therefore, data cleaning is essential to extract accurate insights and build the desired model. In this study, preprocessing was performed to clean and integrate the data. The dataset was refined by removing 17 irrelevant attributes, such as street addresses and mileage, narrowing the focus to 16 essential attributes. These essential attributes include infrastructure conditions, traffic, weather, accident types, and other factors potentially impacting accident severity.

3-3- Data collection

This study uses a comprehensive dataset of traffic crashes in the city of Tempe, Arizona, USA, from January 2012 to August 2024.

These records are publicly available through an open data portal at https://data.tempe.gov/api/download/v1/items, originally containing approximately 17,529,452 entries spread across 33 properties. In this study, we considered seven categories to represent the types of accident severity:

No injury: crashes in this category did not result in physical injuries, although financial damage may have occurred.

Possible injury: an injury may have occurred, but it was not recorded at the scene of the accident.

Non-Incapacitating Injury: The injury has occurred but has not caused disability.

Suspected Minor Injury: This category includes incidents that usually involve minor cuts, bruises, or sprains.

Incapacitating Injury: Significant non-fatal injuries, such as broken bones, severe lacerations or head trauma, are characteristic of serious crashes.

Suspect of serious injury: injury that is determined after visiting the hospital.

Fatal: The most severe category, "fatal" includes crashes that lead to one or more deaths.

Figure 2 shows the distribution of accident severity categories. Fatal crashes represent only 0.003% of all recorded crashes, while crashes with suspected serious injuries account for 0.01%. Suspected minor injury crashes include 0.06% and the majority of crashes, 68.00%, are crashes without injuries.

3-4- Descriptive statistics

Descriptive statistics refers to the data analysis methods that help describe, display, or summarize data meaningfully. Descriptive statistics allow us to present data in a more meaningful way, enabling

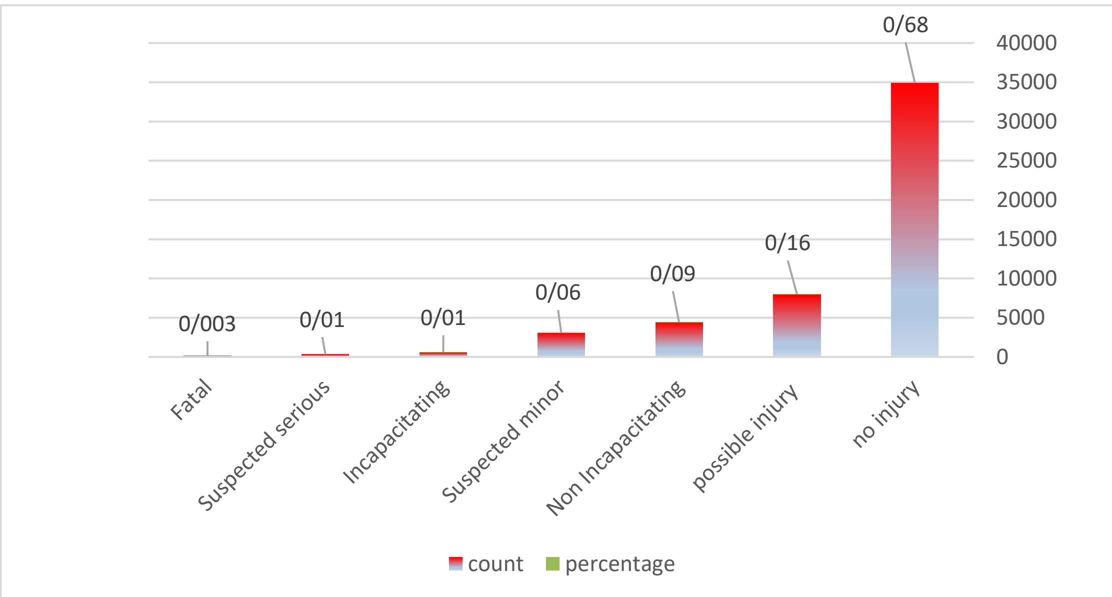

Figure 2. Distribution of types of accident severity based on number and percentage.

easier interpretation. In this study, a comprehensive descriptive analysis was conducted on the dataset, providing valuable insights into various aspects of road crashes.

Figure 3 presents an analysis of the age conditions of drivers involved in crashes by gender. It shows that men under 30 years old and women over 40 years old are the most frequently involved in crashes. Figure 4 displays the number of crashes based on the type of collision. The results indicate that rear-end collisions account for the largest number of crashes, with approximately 15,800 incidents. This is followed by collisions involving left turns, sideswipe collisions in the same direction, and angle (front-to-side) collisions.

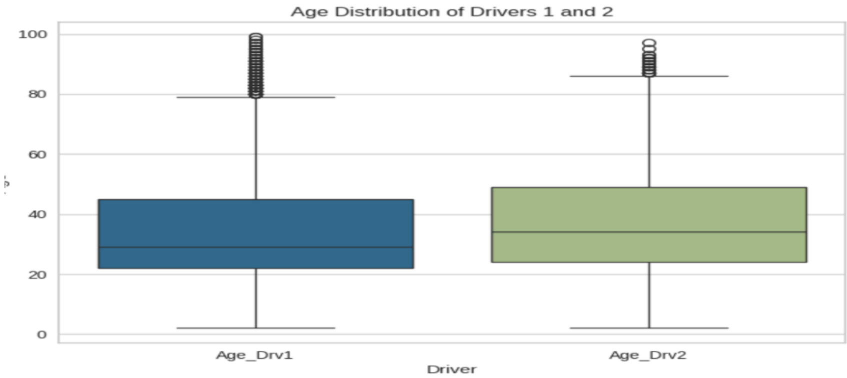

Figure 3. Age distribution of drivers.

Additionally, a smaller number of head-on collisions, sideswipe collisions in the opposite direction, U-turns, and rear-to-side collisions are observed, as depicted in the diagram. In terms of weather conditions based on Figure 5, most of the crashes happened in a situation where there were no atmospheric phenomena and the weather was completely clear.

With a clear difference, cloudy and then rainy conditions are in the next ranks, Also, by analyzing the results based on Figure 6, it is clear that most of the crashes happened during the day and when the weather is clear, and about 25% of the crashes happened at night. Also, crashes at dawn are almost a third of crashes at dusk.

3.5. Spatial analysis of accident

Regarding the spatial distribution of crashes, the most common places are intersections located in the city center, which include a high percentage of all registered crashes. Also, more crashes have occurred in the main roads and arteries, and minor roads have accounted for a smaller volume of crashes.

According to Figure 7, it is clear that the northern parts of the city have far more crashes than the southern parts, and the central area in the northern part has many crashes. A spatial survey of accident density indicates that there are fewer crashes in the southern parts of the city than in the northern parts.

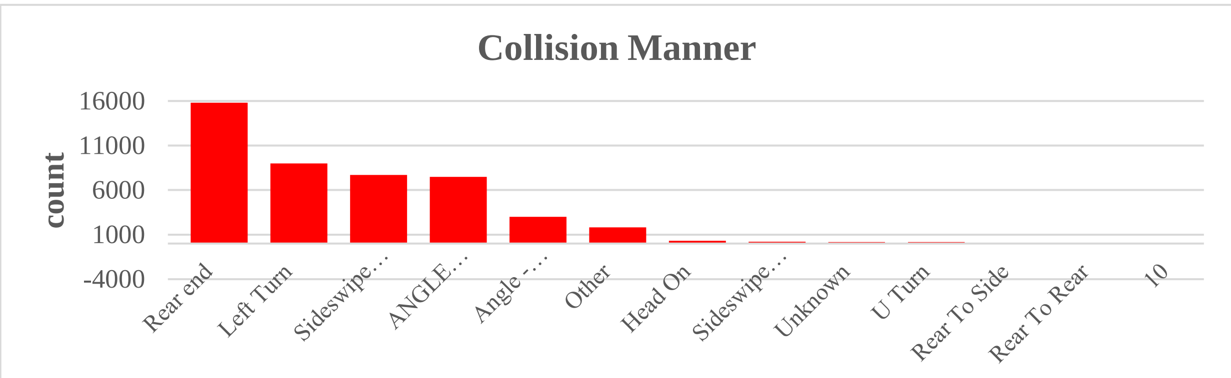

Figure 4. The number of crashes based on the type of collision.

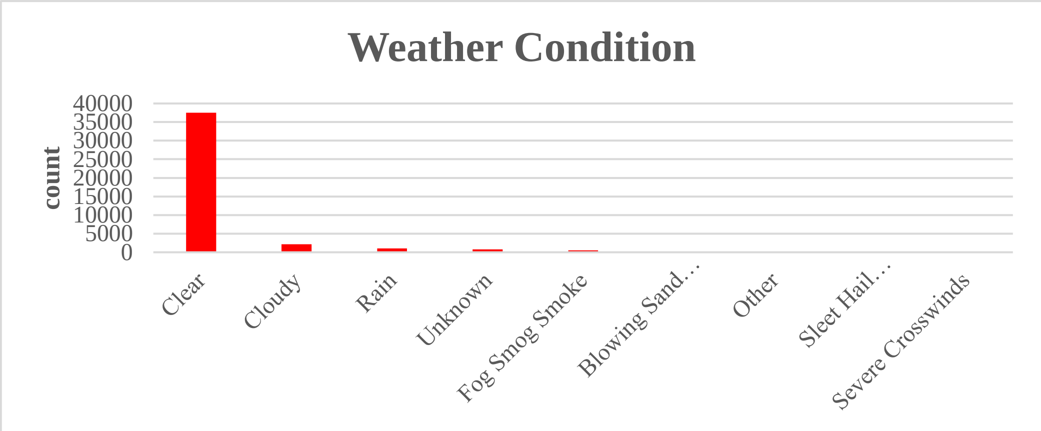

Figure 5- Atmospheric condition during crashes

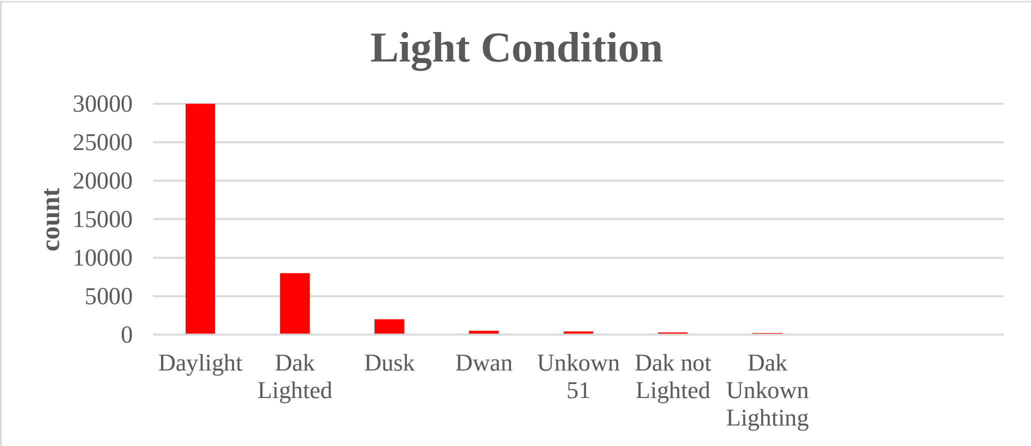

Figure 6. Lighting conditions during crashes.

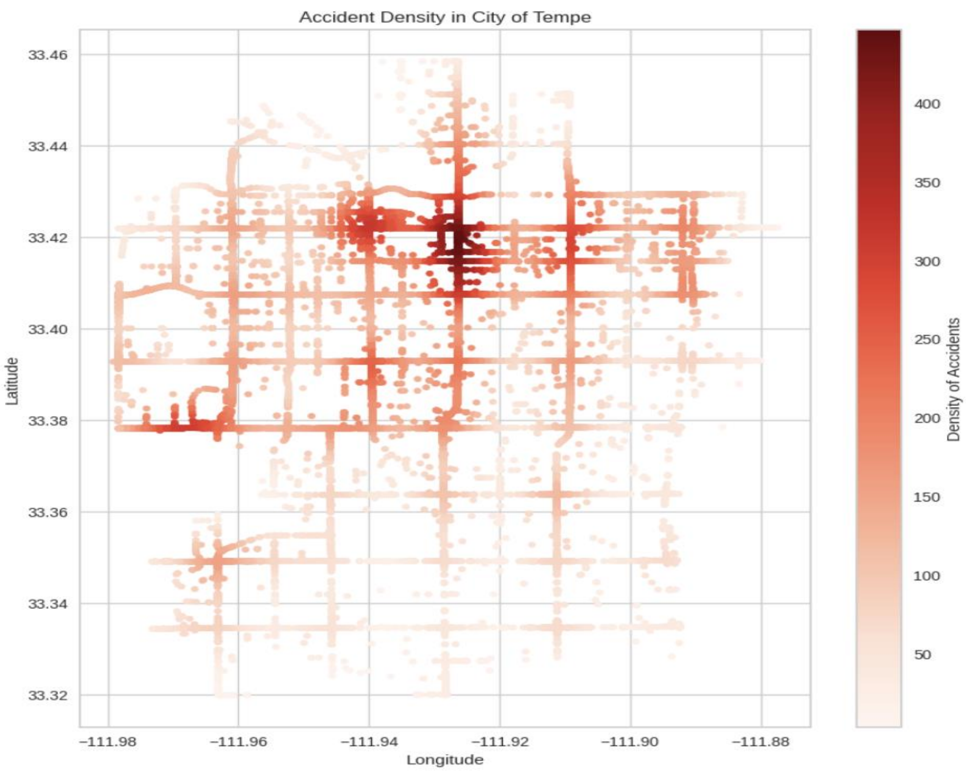

Figure 7. Spatial distribution of crashes in Tempe city.

3.6. Temporal analysis of crashes

The temporal distribution of road crashes indicate that the frequency of crashes has unfortunately increased between 2012 and 2019. Accident numbers are significantly lower in 2020 and 2022, respectively, due to Covid-19 restrictions and incomplete data. But again after 2021 we see an increasing trend. Of course, do not pay attention to the bar of 2024 because the information for that year is not complete. The Figure 8 left shows the distribution of accident severity in different months, which recorded the highest number of crashes in October, November and January. In contrast, July records relatively fewer crashes during this period. Regarding the day of the week, the data show distinct patterns. It is worth noting that all injury crashes occur mostly on Fridays, followed by Thursdays, Tuesdays and Wednesdays, which show an almost equal number of crashes.

On the contrary, Sundays saw the least number of crashes in all categories and emerged as the safest day of the week.

A 24-hour investigation of crashes shows that we see a lot of crashes at the daylight (between 12 to 24 in the chart), and on the contrary, we see the lowest number of crashes in the darkness as we approach night. In the next part, we will deal with the temporal analysis and statistical description of the accident severity data. In figure number 8, we have shown the temporal analysis of the severity of crashes by year, month, day of the week and hour.

3.7. Prediction of accident severity pattern

3.7.1. Feature selection

To select the key features that are significantly related to the patterns of accident severity, the metaheuristic algorithm of the grey wolf optimizer is used along with the application of the random forest algorithm as a modeler, and among the number of features in the dataset, the feature those that are relevant to the severity of crashes are selected. All available features in dataset are presented in table 1 and the results of feature selection are highlighted.

3.7.1.1. Metaheuristic algorithm of the novel hybrid grey wolf optimizer

As a key method for reducing the dimensions of high-dimensional data, feature selection focuses on identifying the most relevant subset of features from the original dataset. The GWO is a powerful intelligence optimization algorithm that has been successfully applied to feature selection tasks. GWO was first introduced by Mirjalili et al. in 2014, drawing inspiration from the social hierarchy and hunting strategies of grey wolves in the wild. In nature, grey wolves exhibit a strict hierarchical structure, which is divided into four levels based on social ranking:

- Alpha Wolf (α): The leader of the pack, responsible for decision-making and guiding the group.
- Beta Wolf (β): The second in command, assisting the alpha wolf in decision-making and serving as the likely successor.
- Delta Wolf (δ): A subordinate to both alpha and beta wolves, yet dominant over omega wolves.
- Omega Wolf (ω): The lowest-ranking member, submitting to all others but playing a vital role in the social structure of the pack.

In the mathematical model of the GWO, the top three agents with the highest fitness values are identified and designated as the alpha, beta, and delta wolves, respectively. These agents guide the search process, simulating the behavior of grey wolves encircling prey. The mathematical model for this encircling process is based on certain equations, which govern the exploration and exploitation phases of the algorithm.

By imitating these natural behaviors, GWO has proven effective in solving optimization problems, including feature selection, by balancing between exploration (searching for new areas in the solution space) and exploitation (refining the most promising solutions). In this context, the variable *t* represents the current iteration of the optimization process, while *A* and *C* are coefficient vectors. *Xp* denotes the position vector of the prey (which represents the target solution), and *X* is the position vector of a grey wolf. The coefficient vectors *A* and *C* are computed as follows:

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}\cdot D \tag{1}$$

$$\vec{D} = \left|\vec{C}\cdot\overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{2}$$

where t indicates current iteration, A and C are coefficient vectors, Xp is the position vector of the prey, and X indicates the position vector of a grey wolf. The vector A and C are calculated as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{4}$$

Where $\vec{r_1}$ and $\vec{r_2}$ are random vectors in [0,1] and $\vec{a}$ is linearly decreased from 2 to 0 over the course of iterations.

3.7.2. Splitting the dataset

In this study, the dataset was divided into two parts: 67% for training and 33% for testing. Additionally, the training data was further randomly split, with 90% designated for training and 10% set aside as calibration data.

3.7.3. Resampling

Resampling methods are commonly used to address class imbalance in datasets and enhance the prediction performance of machine learning models [12, 14, 23]. Figure 12 reveals a significant imbalance in the number of samples for each class in the training data. To address this, the Synthetic Minority Oversampling Technique (SMOTE) is applied [26]. SMOTE generates artificial samples for the minority class to achieve a balanced class distribution by identifying the minority class and selecting its “k” nearest neighbors, where “k” is an adjustable parameter. It’s crucial to apply SMOTE only to training samples during training to avoid bias in test data. This oversampling method enhances the machine learning classifier’s understanding of the minority class, improving its prediction accuracy and reducing class imbalance impact during classification, resulting in more accurate and reliable model performance.

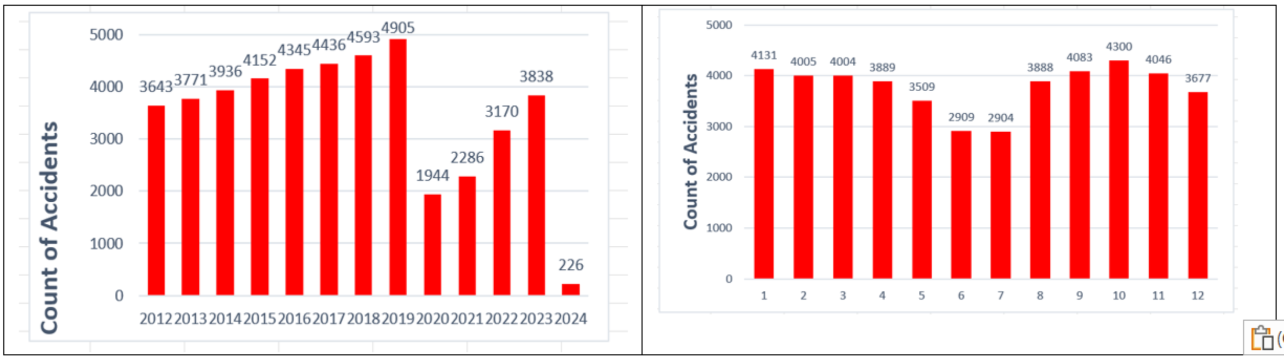

Figure 8. left- Temporal distribution of crashes by year and right Temporal distribution of crashes by month .

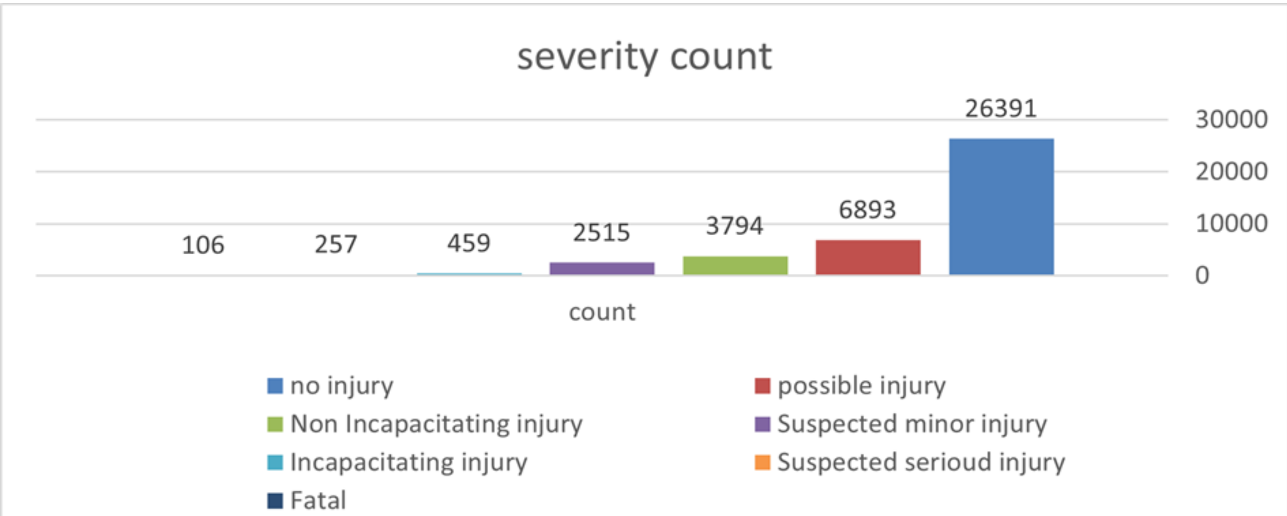

Figure 9. accident severity diagram - data imbalance.

Table 1. Available and selected features.

	Feature	Nunique	Nulls
1	OBJECT ID	51407	0
2	Incident ID	51407	0
3	StreetName	525	206
4	CrossStreet	708	663
5	JunctionRelation	35	1
6	Distance	3063	1
7	DateTime	50940	0
8	Year	13	0
9	Totalinjuries	10	1
10	Totalfatalities	4	1
11	Injuryseverity	7	1
12	Collisionmanner	14	1
13	Lightcondition	8	1
14	Weather	9	1
15	SurfaceCondition	9	1
16	Unittype_One	4	1
17	Age_Drv1	111	48
18	Gender_Drv1	3	954
19	Traveldirection_One	10	1
20	Unitaction_One	23	1
21	Violation1_Drv1	28	48
22	AlcoholUse_Drv1	2	48
23	DrugUse_Drv1	2	48
24	Unittype_Two	4	3387
25	Age_Drv2	107	4753
26	Gender_Drv2	3	4855
27	Traveldirection_Two	10	3387
28	Unitaction_Two	24	3387
29	Unitaction_Two	23	4753
30	AlcoholUse_Drv2	2	4753
31	DrugUse_Drv2	2	4753
32	Latitude	15143	326
33	Longitude	14484	326

3.8. Selection of models and classification algorithms

This research employs two distinct machine learning algorithms, chosen for their proven effectiveness in classification tasks. These algorithms were meticulously selected based on a comprehensive review of the research background. The implemented algorithms are as follows:

3.8.1. Decision tree

Decision trees (DT) are used to approximate discrete-valued objective functions by creating a tree-like model of decisions based on feature values. The main challenge is selecting the optimal feature for classification at each node, typically addressed using statistical measures like information gain, Gini index, chi-square, and entropy. Bashah and Hill [27] employed DT to model the severity of crash injuries in Ethiopia by examining 18,288 crash incidents. Their approach achieved an accuracy rate of approximately 80%, highlighting the effectiveness of DT methods in predicting crash severity outcomes. In a different study, Wahab and Jiang [28] utilized a variety of machine learning algorithms—including the DT classifier to examine injury severity in motorcycle accidents. Their study analyzed all motorcycle crashes that occurred in Ghana between 2011 and 2015. The machine learning algorithms were validated using 10-fold cross-validation, and the results indicated that these machine learning models outperformed the multinomial logit model in terms of both accuracy and effectiveness in predicting injury severity.

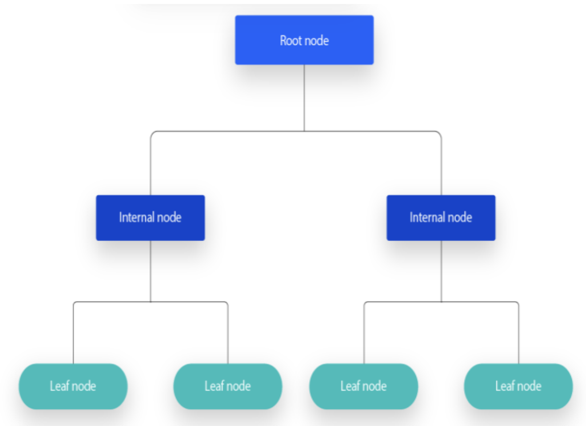

Figure 10. Decision tree.

3.8.2. Random Forest

Random forest is a supervised learning algorithm that efficiently handles high-dimensional datasets and mitigates the risk of overfitting. It leverages ensemble learning by combining multiple decision trees. The algorithm's performance hinges on three key meta-parameters: the number of trees, node size, and the number of sample features. Random forest enhances prediction accuracy by averaging the predictions from multiple trees.

A study by Malik et al. [29] demonstrated that random forest provided superior accuracy in predicting road crash severity compared to other machine learning algorithms. Similarly, Zhang et al. [4] examined crash severity prediction using both statistical and machine learning approaches, concluding that machine learning models outperformed statistical methods. Among the four techniques evaluated—RF, DT, SVM, and k-NN—RF achieved the highest accuracy. This method used as a modeler in the metaheuristic optimizer algorithm.

Classifier	Class	Precision	Recall	F1-Score	Overal Accuracy	Overal Score
DT	Fatal	12%	14%	13%	54%	24%
	Suspected Serious	7%	12%	8%		
	Incapacitating	8%	10%	9%		
	Suspected Minor	25%	30%	27%		
	Non Incapacitating	23%	27%	25%		
	Possible injury	20%	22%	21%		
	No injury	71%	65%	68%		
ANN	Fatal	4%	12%	6%	42%	23%
	Suspected Serious	5%	18%	8%		
	Incapacitating	3%	15%	6%		
	Suspected Minor	22%	60%	33%		
	Non Incapacitating	23%	53%	32%		
	Possible injury	20%	13%	16%		
	No injury	77%	50%	61%		

Table 2. Comparison of the results of the Model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{5}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{6}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{7}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{8}$$

$$F1\text{ score} = 2\times\frac{\text{Precision * Recall}}{\text{Precision + Recall}} \tag{9}$$

3.8.3. Artificial Neural Network

Artificial neural networks (ANNs) have been extensively used in transportation due to their ability to mimic the human brain and their strong learning capabilities. They handle many variables well, with irrelevant variables typically obtaining negligible weight values, while significant variables receive substantial weights. Unlike parametric methods, ANNs do not require assumptions about the functional form of the relationship between predictor and response variables. This study utilizes various types of Artificial Neural Networks (ANNs) to determine the most effective model for predicting crash severity. The typical architecture of an ANN includes an input layer, an output layer, and one or more hidden layers. For this research, the input layer contains 10 neurons, each representing explanatory variables derived from previously identified risk factors and available data.

Akin and Ekbas [30] designed an ANN to predict intersection crashes in Macomb, Michigan. They analyzed the relationship between crash types and variables such as time, weather, lighting conditions, surface conditions, and driver and vehicle attributes using a dataset of 16,000 crash records. Their findings showed that intersections were the most probable crash sites, with crashes most likely to occur on the last working day of the week.

4. Result

4.1. Evaluation of classification algorithms and selection of optimal algorithm

4.1.1. Evaluation criteria

The models' performance was assessed using several fundamental metrics, including accuracy, recall, precision and the F1 score. These metrics can be computed from the confusion matrix. In this context, true positives (TP) indicate instances where both the predicted and actual labels are positive, while true negatives (TN) refer to instances where both labels are negative. A FN occurs when a true positive label is mistakenly predicted as a false negative. A FP is generated when a true negative tag is mistakenly predicted as a positive. Understanding these definitions is critical to calculating various performance metrics and ensuring accurate model evaluation [31]. In this section, we perform an in-depth evaluation and comparison of the statistical analysis model and machine learning models used in our study. First, we compare the overall performance of different models and clarify their respective strengths and weaknesses. Finally, we examine the importance of different features in the decision-making process of the model using permutation features. Through this approach, we aim to provide a comprehensive understanding of the performance of our best model, thus uncovering the complexities of machine learning-based crash severity prediction. According to the evaluation criteria of the model as well as the comparison of the overall accuracy of the used models, the DT algorithm was recognized as the best model for predicting the severity of crashes.

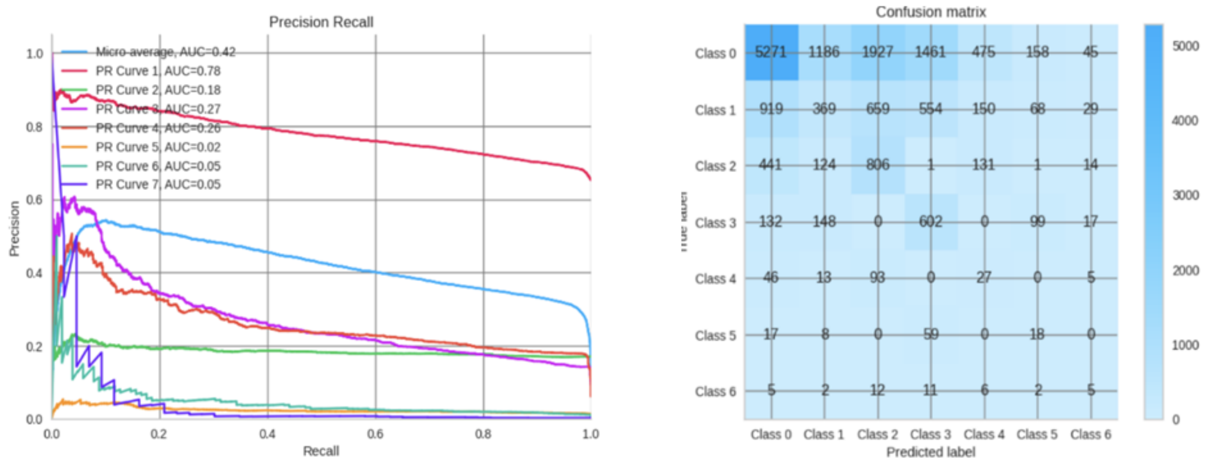

Figure 11. The confusion matrix and the precsion and recall diagram of the decision tree model.

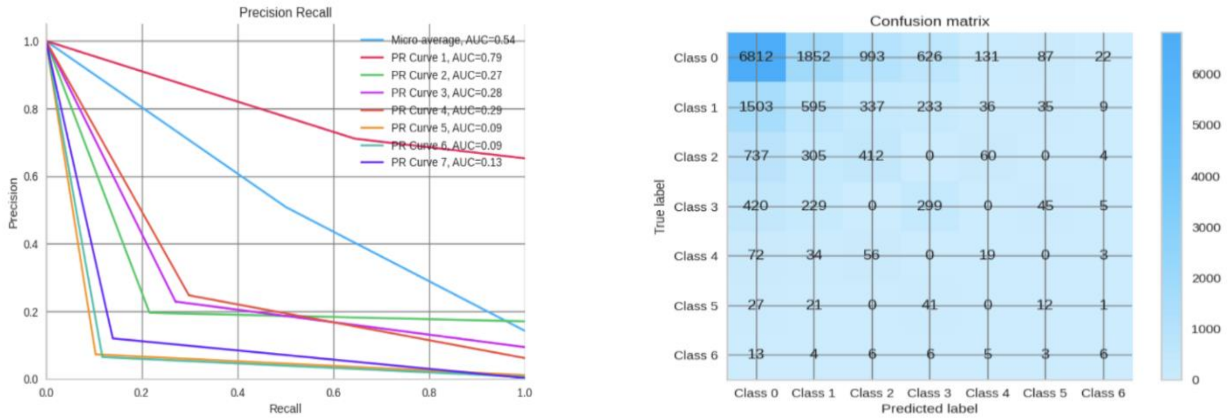

Figure 12. The confusion matrix and the precsion and recall agram of the ANN model.

Among these models, although there are no significant differences in the accuracy measure, DT achieved the highest overall accuracy, reaching 54%. The following models were obtained with overall accuracy values of 42% corresponding to ANN. Also, in the F1 score criterion, we are faced with exactly the same ranking, that the DT algorithm is the best, and then ANN is in the next ranks. Table 2 shows the comparison of models.
hould be noted that the performance evaluation of the selected machine learning models was performed focusing on balanced data and therefore, the results are very close to reality.

4.1.2. Analysis of confusion matrix and precision-recall graph

As you can see in the figures 111 and 12 in left, the horizontal axis of this graph indicates the correct positive rate (Sensitivity), and the vertical axis indicates the value of the false positive rate. Different classification results indicate different points on this graph and finally form a curve. According to the figures, in the best case and assuming 100% correct classification in both categories, the corresponding point is the upper left corner point, i.e. point (0,1) and assuming random classification, the corresponding point in the curve, one of the points on the line connecting the point (0,0) and the point (1,1) will be.

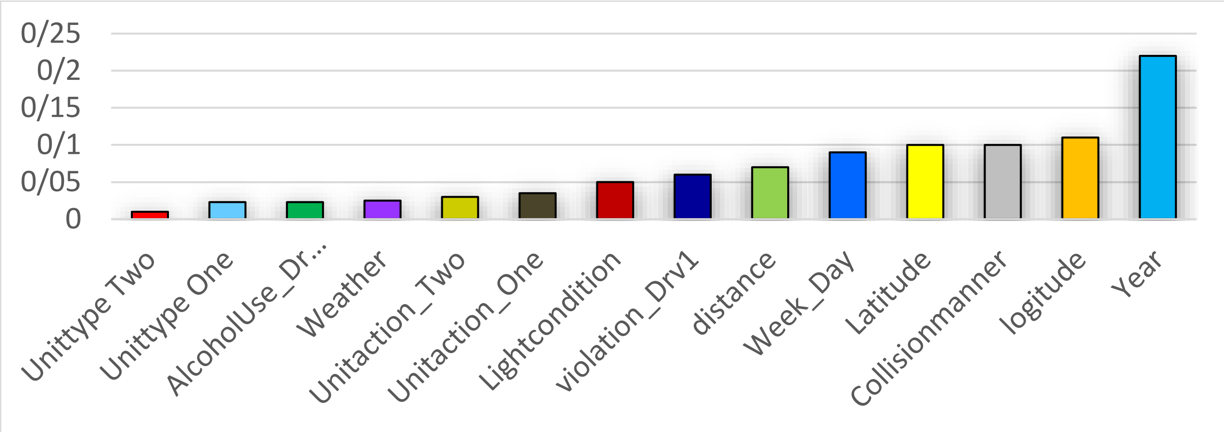

Figure 13. The importance of features in the superior model.

Regarding the confusion matrix, the numbers along the main diagonal represent the correctly classified instances. If all the off-diagonal values are zero, it means the algorithm has achieved maximum accuracy. To calculate the accuracy of a classifier, you simply divide the sum of the diagonal elements (correct classifications) by the total number of elements in the matrix (the total number of classifications). This ratio provides a straightforward measure of the classifier's overall performance.

4.2. Explanation of features

4.2.1. The importance of the permutation feature

We assess the significance of a feature by determining how much the model's prediction error increases when the feature's values are altered. A feature is deemed "important" if changing its values causes a notable rise in the model's error, indicating that the model depends on this feature for making accurate predictions. Conversely, a feature is considered "insignificant" if shuffling its values has no effect on the model's error, suggesting that the model disregards the feature in its predictions. This approach to measuring feature importance was first introduced by Breiman [32] for random forests. Building on this concept, Fisher, Rudin, and Dominici [33] developed a more general, model-independent version of this metric, which they termed model reliance. Finally, by using the permutation feature importance method, the effect of different parameters in predicting the severity of crashes has been quantified and finally, by using the permutation feature importance method, the effect of different parameters in predicting the severity of crashes has been quantified. Therefore, based on Figure 13, it is clear that the variables of year, spatial characteristics, distance, year, collision manner, week day, distance have a great impact on the prediction model and then violation, lighting and weather conditions, unit action, alcohol use and unit type are next.

5. Conclusion

The comprehensive model proposed in this study is a model that predicts the severity of crashes based on the analysis of multiple variables such as individual characteristics, weather conditions, road conditions, driver's condition and temporal and spatial variables using machine learning methods. 12-year accident data from the state of Arizona and the city of Tempe were used. According to the large volume of data, the necessary pre-processing was done and due to the serious imbalance in accident severity data, the SMOTE Technique is applied. The features selection is done using the grey wolf metaheuristic optimizer algorithm and RF as modeler that 16 features were selected. Then the selected features enter the next stage, which is pattern prediction, in which 2 different algorithms of machine learning classification include DT and ANN are used for classification, and then model evaluation is done. According to the evaluation criteria of the model as well as the comparison of the overall accuracy of the used models, the DT algorithm was recognized as the best model for predicting the severity of crashes with overall accuracy of the 54% and the following models were obtained with overall accuracy values of 42% corresponding to ANN. In order to explain the effective data in the model and quantify their effect in the model, the permutation feature importance method is used, and the analysis of the important effects between the features is done. variables of year, spatial characteristics, distance, year, collision manner, week day, distance have a great impact on the prediction model and then violation, lighting and weather conditions, unit action, alcohol use and unit type are next. Similar results have been obtained in previous [17, 34, 35].

6. Limitations and suggestions

However, several limitations of this study should be noted. The traffic accident data set used may not fully represent different traffic scenarios around the world. This is a common issue in traffic accident datasets, which often lack comprehensiveness and consistency due to differences in data collection and reporting standards across countries. Such limitations in the dataset can affect the robustness and generalizability of predictive models.

Furthermore, while DT showed superior performance in this study, comparisons were made with a limited number of machine learning models. Other complex models exist and their relative performance can vary based on the nature and quality of the data set.

In addition, it is expected that the results of this study can help other researchers in building accident severity prediction models with higher accuracy and by including more important features.

References

[1] WHO (World Health Organization). "Road Traffic Injuries, Retrieved from WHO, Fact Sheets." https://www.who.int/news-oom (accessed.

[2] G. Singh, S. Sachdeva, and M. Pal, "Comparison of three parametric and machine learning approaches for modeling accident severity on non-urban sections of Indian highways," *Advances in transportation studies,* vol. 45, 2018.

[3] W. D. Fan, L. Gong, E. M. Washing, M. Yu, and E. Haile, "Identifying and quantifying factors affecting vehicle crash severity at highway-rail grade crossings: Models and their comparison," 2016.

[4] J. Zhang, Z. Li, Z. Pu, and C. Xu, "Comparing prediction performance for crash injury severity among various machine learning and statistical methods," *IEEE Access,* vol. 6, pp. 60079-60087, 2018.

[5] K. Santos, J. P. Dias, and C. Amado, "A literature review of machine learning algorithms for crash injury severity prediction," *Journal of safety research,* vol. 80, pp. 254-269, 2022.

[6] W.-H. Chen and P. P. Jovanis, "Method for identifying factors contributing to driver-injury severity in traffic crashes," *Transportation Research Record,* vol. 1717, no. 1, pp. 1-9, 2000.

[7] M. T. Kashifi, M. Al-Turki, and A. W. Sharify, "Deep hybrid learning framework for spatiotemporal crash prediction using big traffic data," *International journal of transportation science and technology,* vol. 12, no. 3, pp. 793-808, 2023.

[8] W. Shunshun, Y. Changshun, and S. Yong, "A review of road traffic accident prediction methods," *American Journal of Management Science and Engineering,* vol. 8, no. 3, pp. 73-77, 2023.

[9] X. Wen, Y. Xie, L. Wu, and L. Jiang, "Quantifying and comparing the effects of key risk factors on various types of roadway segment crashes with LightGBM and SHAP," *Accident Analysis & Prevention,* vol. 159, p. 106261, 2021.

[10] I. Ahmad, M. Basheri, M. J. Iqbal, and A. Rahim, "Performance comparison of support vector machine, random forest, and extreme learning machine for intrusion detection," *IEEE access,* vol. 6, pp. 33789-33795, 2018.

[11] H. Nassiri, S. I. Mohammadpour, and M. Dahaghin, "Forecasting time trends of fatal motor vehicle crashes in Iran using an ensemble learning algorithm," *Traffic injury prevention,* vol. 24, no. 1, pp. 44-49, 2023.

[12] M.-M. Chen and M.-C. Chen, "Modeling road accident severity with comparisons of logistic regression, decision tree and random forest," *Information,* vol. 11, no. 5, p. 270, 2020.

[13] Q. Cai, M. Abdel-Aty, Y. Sun, J. Lee, and J. Yuan, "Applying a deep learning approach for transportation safety planning by using high-resolution transportation and land use data," *Transportation research part A: policy and practice,* vol. 127, pp. 71-85, 2019. [Online]. Available: https://doi.org/10.1016/j.tra.2019.07.010.

[14] X. Shi, Y. D. Wong, M. Z.-F. Li, C. Palanisamy, and C. Chai, "A feature learning approach based on XGBoost for driving assessment and risk prediction," *Accident Analysis & Prevention,* vol. 129, pp. 170-179, 2019. [Online]. Available: https://doi.org/10.1016/j.aap.2019.05.005.

[15] J. Bao, P. Liu, and S. V. Ukkusuri, "A spatiotemporal deep learning approach for citywide short-term crash risk prediction with multi-source data," *Accident Analysis & Prevention,* vol. 122, pp. 239-254, 2019. [Online]. Available: https://doi.org/10.1016/j.aap.2018.10.015.

[16] H. A. Abd Rahman and B. W. Yap, "Imbalance effects on classification using binary logistic regression," in *Soft Computing in Data Science: Second International Conference, SCDS 2016, Kuala Lumpur, Malaysia, September 21-22, 2016, Proceedings 2,* 2016: Springer, pp. 136-147.

[17] M. Yahaya, W. Fan, C. Fu, X. Li, Y. Su, and X. Jiang, "A machine-learning method for improving crash injury severity analysis: a case study of work zone crashes in Cairo, Egypt," *International journal of injury control and safety promotion,* vol. 27, no. 3, pp. 266-275, 2020.

[18] D. Liu, P. Yan, Z. Pu, Y. Wang, and E. I. Kaisar, "Hybrid artificial immune algorithm for optimizing a Van-Robot E-grocery delivery system," *Transportation Research Part E: Logistics and Transportation Review,* vol. 154, p. 102466, 2021.

[19] K. Yang, X. Wang, and R. Yu, "A Bayesian dynamic updating approach for urban expressway real-time crash risk evaluation," *Transportation research part C: emerging technologies,* vol. 96, pp. 192-207, 2018.

[20] X. Wang and S. H. Kim, "Prediction and factor identification for crash severity: comparison of discrete choice and tree-based models," *Transportation research record,* vol. 2673, no. 9, pp. 640-653, 2019.

[21] Z. E. Abou Elassad, H. Mousannif, and H. Al Moatassime, "A real-time crash prediction fusion framework: An imbalance-aware strategy for collision avoidance systems," *Transportation research part C: emerging technologies,* vol. 118, p. 102708, 2020.

[22] Y. Peng, C. Li, K. Wang, Z. Gao, and R. Yu, "Examining imbalanced classification algorithms in predicting real-time traffic crash risk," *Accident Analysis & Prevention,* vol. 144, p. 105610, 2020.

[23] X. Shi, Y. D. Wong, C. Chai, and M. Z.-F. Li, "An automated machine learning (AutoML) method of risk prediction for decision-making of autonomous vehicles," *IEEE Transactions on Intelligent Transportation Systems,* vol. 22, no. 11, pp. 7145-7154, 2020. [Online]. Available: https://doi.org/10.1109/TITS.2020.3002419.

[24] M. Becerra-Rozas *et al.,* "Continuous metaheuristics for binary optimization problems: An updated systematic literature review," *Mathematics,* vol. 11, no. 1, p. 129, 2022.

[25] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *Journal of machine learning research,* vol. 3, no. Mar, pp. 1157-1182, 2003. [Online]. Available: https://doi.org/10.1016/j.aca.2011.07.027.

[26] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "SMOTE: synthetic minority over-sampling technique," *Journal of artificial intelligence research,* vol. 16, pp. 321-357, 2002.

[27] T. Beshah and S. Hill, "Mining road traffic accident data to improve safety: role of road-related factors on accident severity in Ethiopia," in *2010 AAAI Spring symposium series*, 2010.

[28] L. Wahab and H. Jiang, "A comparative study on machine learning based algorithms for prediction of motorcycle crash severity," *PLoS one,* vol. 14, no. 4, p. e0214966, 2019.

[29] S. Malik, H. El Sayed, M. A. Khan, and M. J. Khan, "Road accident severity prediction—a comparative analysis of machine learning algorithms," in *2021 IEEE Global Conference on Artificial Intelligence and Internet of Things (GCAIoT),* 2021: IEEE, pp. 69-74.

[30] M. U. Abdulazeez, W. Khan, and K. A. Abdullah, "Predicting child occupant crash injury severity in the United Arab Emirates using machine learning models for imbalanced dataset," *IATSS research,* vol. 47, no. 2, pp. 134-159, 2023.

[31] A. Fisher, C. Rudin, and F. Dominici, "All models are wrong, but many are useful: Learning a variable's importance by studying an entire class of prediction models simultaneously," *Journal of Machine Learning Research,* vol. 20, no. 177, pp. 1-81, 2019.

[32] H. T. Abdelwahab and M. A. Abdel-Aty, "Development of artificial neural network models to predict driver injury severity in traffic accidents at signalized intersections," *Transportation research record,* vol. 1746, no. 1, pp. 6-13, 2001.

[33] X. Wen, Y. Xie, L. Jiang, Z. Pu, and T. Ge, "Applications of machine learning methods in traffic crash severity modelling: current status and future directions," *Transport reviews,* vol. 41, no. 6, pp. 855-879, 2021.

[34] S. Ahmed, M. A. Hossain, S. K. Ray, M. M. I. Bhuiyan, and S. R. Sabuj, "A study on road accident prediction and contributing factors using explainable machine learning models: analysis and performance," *Transportation research interdisciplinary perspectives,* vol. 19, p. 100814, 2023.

[35] S. Sun, B. Zhou, and S. Zhang, "Analysis of factors affecting injury severity in motorcycle involved crashes," in *CICTP 2020,* 2020, pp. 4207-4219.

استفاده از یادگیری ماشین و الگوریتم بهینه ساز فراابتکاری برای پیش بینی شدت تصادف در شبکه معابر شهری

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چکیده:

این مقاله شدت تصادفات را بر اساس تحلیل متغیرهای متعدد و با استفاده از روش‌های یادگیری ماشینی پیش‌بینی می‌کند. برای این منظور از داده‌های مربوط به سال‌های ۲۰۱۲ تا ۲۰۲۴ شهر تمپ در ایالت آریزونا آمریکا استفاده شد. ویژگی‌ها با استفاده از روش فرا ابتکاری انتخاب شدند. سپس با استفاده از درخت تصمیم و شبکه عصبی مصنوعی طبقه بندی شدت تصادفات انجام شد. بر اساس معیارها، درخت تصمیم با دقت کلی ۵۴ درصد از شبکه عصبی مصنوعی عملکرد بهتری داشت. در نهایت با استفاده از روش اهمیت ویژگی جایگشت، مدل بهینه تفسیر شد. نتایج نشان می‌دهد که ویژگی‌های سال با ۰,۲۲ و ویژگی‌های مکانی با ۰,۱۱ و نوع تصادف با ۰,۱ اهمیت بیشتری در پیش‌بینی شدت تصادفات در جاده‌های شهری دارند.

کلمات کلیدی: شدت تصادفات، تحلیل‌های مکانی زمانی، یادگیری ماشین، الگوریتم فرا ابتکاری، جنگل تصادفی.