Transportation Engineering 17 (2024) 100261

Contents lists available at ScienceDirect

Transportation Engineering

journal homepage: www.sciencedirect.com/journal/transportation-engineering

Full Length Article

Factors affecting crash severity in Roundabouts: A comprehensive analysis in the Jordanian context

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ARTICLE INFO

Keywords:
Rule-based model
CN2
Random forest
Property damages only
Injury crashes

ABSTRACT

Roundabouts are widely embraced for their perceived safety advantages over other types of unsignalized intersections. However, there has been an observed increase in crash rates at roundabouts over time in Jordan. This paper delves into modeling traffic crash severity at roundabouts, considering various factors such as weather, lighting, vehicle characteristics, geometric features, and driver age and gender. To comprehensively analyze roundabout crashes in Jordan, we constructed rule-based classifiers and Random Forest models after balancing the dataset. Rule-based models offer interpretability, albeit with some simplicity trade-off, while Random Forest models provide deeper analysis but require additional explanation. Presenting both outputs to subject matter experts and policymakers facilitates a holistic understanding of factors contributing to roundabout crashes in Jordan. Subsequently, CN2 results revealed that injury severity crashes are influenced by the time of the day, driver age, day of the week, speed, and number of vehicles involved. On the other hand, property damage-only crashes are affected by the number of lanes, time of the day, type of driver fault, lighting conditions, speed, and day of the week. The RF model analysis unveiled crucial factors influencing crash severity in roundabouts, notably the varying impact of driver age, time of day, the number of vehicles involved, seasonality, and vehicle speed. This proposed approach is promising, comprehensive, and not only enhances the understanding of roundabout crashes but also informs the development of effective, localized safety interventions.

Introduction

As traffic control systems, roundabouts are generally considered safer than traditional intersections, primarily due to their circular design and reduced potential for high-speed, angle, and head-on collisions [1,2]. Their geometric configuration promotes slower vehicle speeds and facilitates a continuous flow of traffic, minimizing the severity of crashes. However, roundabouts are not immune to crashes, and their safety performance can vary depending on multiple factors [3,4]. The frequency and severity of crashes at roundabouts are influenced by a complex interplay of elements such as geometric design, traffic volume, driver behavior, vehicle characteristics, weather conditions, and lighting [5–8]. Understanding these factors and their interactions is crucial in effectively managing and improving roundabout safety, as it enables the implementation of targeted measures and engineering solutions to reduce the likelihood and severity of crashes, ultimately enhancing road safety for all users [9–11].

Roundabouts have emerged as a popular intersection design worldwide due to their potential to enhance traffic flow efficiency and reduce the frequency of severe crashes. In the context of Jordan, where urbanization and population growth have led to increased vehicular traffic, the adoption of roundabouts as a safer alternative to conventional intersections has gained significant attention [12–14]. However, despite their proven safety advantages, roundabouts in Jordan still witness a considerable number of traffic crashes, raising concerns about their overall effectiveness in mitigating crash severity [13]. This study investigates the complex realm of roundabout safety in Jordan by examining the multifaceted factors influencing crash severity within these traffic control systems. Road traffic crashes, particularly their severity, constitute a critical public health concern globally and in Jordan, with implications for human well-being and the national economy [15,16].

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https://doi.org/10.1016/j.treng.2024.100261
Received 15 March 2024; Received in revised form 22 July 2024; Accepted 22 July 2024
Available online 23 July 2024

In year 2020 in Jordan, there were a total of 122,970 crashes reported during this period. Among these crashes, about 8451 crashes led to injuries and about 461 led to fatalities. Additionally, 558 people suffered major injuries, while 4788 individuals sustained moderate injuries. A further 7344 people experienced minor injuries. The estimated financial cost of these crashes amounted to about 420 million United States dollars yearly. During the same year, the population of Jordan stood at about 10.806 million people, and there were approximately 1729,343 registered vehicles.

This study aims to shed light on the intricate relationship between these factors and crash severity in roundabouts. The findings are expected to provide valuable insights for policymakers, traffic engineers, and safety practitioners in Jordan, ultimately facilitating the development of targeted interventions to reduce the severity of roundabout crashes and enhance the overall safety of road users. By delving into the factors influencing crash severity in roundabouts within the unique context of Jordan, this research seeks to contribute significantly to the ongoing discourse on road safety and provide a foundation for evidence-based decision-making to minimize the societal impact of traffic crashes in the country.

Literature review

Using different modeling techniques, machine learning has been done on various elements of transportation network encompassing roadway, intersection, and freeway segments. Few studies have focused on roundabouts crashes. We will discuss the methods that were used previously on different road infrastructure, and we will then relate the discussion to our study. A study compared the performance of univariate and bivariate negative binomial regression models for predicting crash frequencies and severity. The analysis includes property-damage only (PDO) and fatal plus injury (FI) crashes, as well as single-vehicle (SV) and multi-vehicle (MV) collisions in a specific engineering district in Pennsylvania. The results show that the bivariate negative binomial models, including copula-based models, outperform the univariate models in predicting crash occurrences and severity [17]. Using crash data from 221 signalized intersections in Queensland from 2012 to 2018, hierarchical Multinomial Logit models are employed to account for the hierarchical structure of the data. The results show that the severity of injuries increases with the number of conflicting lanes but decreases with the number of cars in the conflicting lane [18].

Another study utilized a logistic regression model to evaluate the relationship between hit-and-run crashes for different drivers' status distraction in Cook County, Illinois. It was found that there were 17 variables that showed a significant increase in the likelihood of a hit-and-run crash. Additionally, 10 variables were identified that showed a significant decrease in the probability of such crashes. The variables associated with hit-and-run crashes exhibit variation based on the distraction status of the driver [19]. In 2019, research was conducted in Bangladesh that used multiple machine-learning algorithms to predict the severity of crashes. Results showed that adaboost and Naive Bayes have the highest accuracy [20] . Using data from 2018, a study modeled the severity of crashes that occurred on freeways in the Chinese province of Hebei. The gradient boosting algorithm was applied to determine which of the 23 variables that were gathered represented the most useful feature for classifying the severity of traffic crashes [21]. Several studies have conducted to model traffic crashes in Jordan [22–24]. In their studies they used various machine learning were implemented using Bayesian Network, KNN, SVM and CART [25–30]. However, they used different modeling techniques to identify the most contributing factors for identifying the severity of traffic crashes, but urban roundabouts were neglected. Some factors including driver age and gender were not used. Moreover, the effect of the contribution factors was not comprehensively explained. In this study, we explore the crashes near urban roundabouts, and we incorporate new explanatory variables as well as new modeling techniques to model severity of traffic crashes at roundabouts.

To Summarize, the application of machine learning techniques across various elements of the transportation network has provided substantial insights into traffic crash dynamics but lacked investigating roundabout crashes, underscoring the importance of addressing roundabout crashes. Studies using advanced models, such as bivariate negative binomial regression in rural Pennsylvania and hierarchical Multinomial Logit models in Queensland, have shown the effectiveness of complex modeling techniques in predicting crash frequencies and severities. These approaches revealed critical insights, such as the increased severity associated with specific signal strategies and the impact of road alignments on crash likelihood, which are pertinent to roundabout safety. Research on driver distraction in Cook County highlighted the significant role of distraction-related variables in hit-and-run crashes, a factor highly relevant in the visually and cognitively demanding environment of roundabouts. Additionally, studies employing machine learning algorithms like Decision Tree, K-Nearest Neighbors, Naive Bayes, AdaBoost, and gradient boosting have demonstrated high prediction accuracy for crash severity, emphasizing the need for incorporating these advanced techniques to improve roundabout safety analysis. These findings collectively suggest that roundabouts, with their unique traffic dynamics, require focused research utilizing advanced modeling and machine learning techniques to identify and mitigate crash risks effectively.

Despite the extensive use of machine learning in traffic crash modeling, there remains a gap in the literature regarding the specific context of urban roundabouts. This study aims to address this gap by incorporating new explanatory variables and modeling techniques to analyze crash severity at roundabouts, thus improving upon existing practices and providing a more comprehensive understanding of the contributing factors to traffic crashes in these unique settings. This study can significantly improve existing practices through several innovative approaches. By focusing specifically on roundabouts in Jordan, it fills a critical gap in global traffic safety studies, which often overlook this region. This localized insight allows for the development of targeted interventions that are more effective and relevant to the unique traffic conditions and cultural context of Jordan. Second, we utilized a balanced datasets technique to ensure that the analysis is not skewed towards more frequent but less severe crashes. This balanced approach provides a more accurate representation of all crash types, including those that are less common but potentially more severe. This is crucial for developing comprehensive safety strategies that address the full spectrum of crash scenarios. Third, the combination of rule-based classifiers and Random Forest model used in our study offers a dual advantage. Rule-based models provide interpretability, making it easier for policymakers to understand and act on the findings. In contrast, Random Forest model offers deeper analysis and can capture complex interactions between variables. Presenting the outputs of both models to subject matter experts and policymakers ensures a holistic understanding of the factors contributing to roundabout crashes in Jordan. This dual approach facilitates better-informed policy decisions and the design of effective safety interventions. Fourth, the detailed analysis of factors influencing crash severity—such as time of day, driver age, number of vehicles involved, and vehicle speed—yields actionable insights. These specific factors can be directly targeted in educational campaigns, enforcement strategies, and infrastructure improvements to reduce both the frequency and severity of crashes. Lastly, identification of seasonal variations in crash severity in roundabouts suggests that traffic management and enforcement practices should be adjusted seasonally. To the best of our knowledge, this is the first study the delve into safety measures that are tailored to address the increased risks during specific times of the year, further enhancing road safety in roundabouts.

Dataset

In this research, crash data from the Jordanian Traffic Institute (JTI) is requested for the most critical roundabouts (i.e., black spots roundabouts) in the capital of Jordan, Amman. The dataset involves traffic crashes from 2017 to 2021, with 30,486 crashes from 16 roundabouts collected. The collected data have 23 variables describing roadway characteristics and conditions, weather conditions, vehicle, driver, and crash type with the number of casualties. Data was carefully screened and processed to avoid misleading results based on data completeness, and irrelevant or redundant variables were disregarded. The initial screening of the data shows that there is 98.37 % Property Damage Only (PD), 1.5 % slight to intermediate injured, and the rest were fatal. This percentage distribution is highly imbalanced. The preprocessing of the data followed the methodology according to Fig. 1.

Moreover, researchers showed that crashes on vacation are more severe than crashes on regular dates [24]. As such, in this study, we improve the previous models by incorporating driver age and gender in the analysis. Specifically, the original dataset was reduced to 12,971 data points out of 30,486 were validated. This reduction was done according to the previous stat-of-art, as follows:

1. Any missing value in driver age was removed as driver age is a significant attribute in crash severity prediction, according to [28]. The total missing values in driver age are 3770 points.
2. Only driver-at-fault records were included in this work; according to [28], 13,201 data points were deleted using this condition.
3. An error in recording driver age, for instance, it is not allowed to drive before 15 years old in Jordan, nor the age can be a negative value a total of 922 data points were deleted.

The reduced dataset can be adequately analyzed for the causes of crashes, provided that the data cleaning and reduction steps have been conducted systematically and based on established methodologies [31, 28]. The dataset is suitable for meaningful analysis for several reasons. Removing records with missing driver age values ensures that the dataset retains only those records with complete information on this critical attribute. Since driver age is a significant predictor of crash severity, having complete data on this variable enhances the reliability of the analysis. Moreover, including only driver-at-fault records aligns the dataset with the focus of many crash severity studies, which aim to understand the behavior and characteristics of drivers responsible for crashes. This filtering helps in isolating the effects of driver-related factors on crash outcomes, providing clearer insights into causality. Additionally, excluding records with erroneous driver age values, such as ages below the legal driving age or negative ages, ensures the integrity and accuracy of the dataset. This step removes outliers and potential errors that could distort the analysis, leading to more robust and reliable results. Despite the reduction, the dataset still comprises 12,971 data points, which is a substantial sample size for statistical and machine learning analyses. This volume is sufficient to uncover meaningful patterns and relationships within the data. By focusing on significant attributes and ensuring data quality, the dataset is tailored for analyzing crash severity and understanding the underlying causes. This targeted approach helps in deriving actionable insights that can inform policy, and interventions aimed at improving road safety.

The variables used in this research were collected from the JTI and were decomposed as needed. For instance, crash hour was categorized as 'morning', 'midday', 'evening', and 'night'. The month of crash occurrence was decomposed into seasons, and vehicle type was decomposed into four categories. Vehicle categories were classified into five main types, namely automobile, bike, light truck, medium truck, and heavy truck.

After pre-processing the data, the first step in data analysis was to check variables counts and percentages of the total dataset size. A summary of data descriptive statistics is presented in Table 1. It shows that more than 97.5 % of the total crashes were property damages (PD), 2.14 % were injury, 0.05 % were seriously injured, and about 0.04 % fatal crashes. Most of crashes occurred at a flat dry roadway surface during midday. Moreover, about 95 % of the total crashes occurred in clear weather conditions. Interestingly, more than 75 % of the crashes caused by male drivers with age less than 40 years old. Nonetheless, it is worth mentioning that the variables were categorized by the Jordanian Traffic Institute.

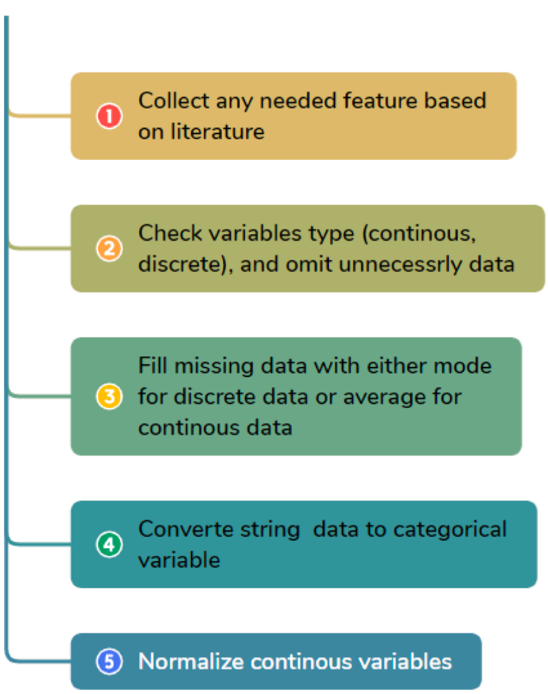

Fig. 1. Flowchart of the data collection and preprocessing.

Method

Problem statement

The crash dataset exhibits a significant imbalance, as highlighted in Table 1. This dataset encompasses four distinct classes: Property Damage (PD), Minor, Major, and Fatal, with corresponding counts of 12,740, 223, 5, and 3, respectively. To address this imbalance, we made the decision to transform this multiclass problem into a binary classification challenge. This entailed merging the three minority classes into a single category called "Injury". Despite this transformation, the dataset remained imbalanced, now featuring 12,740 instances in the majority class and 231 instances in the minority class. This imbalance posed challenges in generating meaningful rules from the data.

To tackle these challenges, we adopted a two-fold approach as shown in Fig. 2. We started by equalizing class imbalances through random down-sampling of the majority class to match the minority class's size [32,33]. To create 200 distinct down-sampled datasets, we employed a systematic approach to ensure balanced and representative samples for model training and validation. Initially, the original dataset comprised 12,740 instances of the majority class (Property Damage) and 231 instances of the minority class (Injury), which combined Minor, Major, and Fatal classes. We addressed the class imbalance by randomly down-sampling the majority class to match the minority class's size. Specifically, for each of the 200 datasets, 231 instances were randomly selected from the majority class. This random selection process was repeated 200 times, resulting in 200 distinct balanced datasets, each containing 462 instances. This approach allowed for a diverse representation of the majority class across multiple datasets, facilitating

Table 1
The count and percentage of each selected variable in the processed dataset.

Variable	Categories	Count	Percentage
Crash			
Crash Type	Collision (Hundredth)	12894	99.40 %
	Pedestrian (Run Over)	53	0.41 %
	Run Off Road (Deterioration)	24	0.19 %
Day Of Week	Weekday	9985	76.98 %
	Weekend	2986	23.02 %
Hour Group	Morning	1666	12.84 %
	Midday	5070	39.09 %
	Evening	4200	32.38 %
	Night	2035	15.69 %
Holiday	Yes	371	2.86 %
	No	12,600	97.14 %
Season	Summer	3385	26.10 %
	Fall	3205	24.71 %
	Winter	3175	24.48 %
	Spring	3206	24.71 %
Driver			
Driver Gender	Male	10635	82 %
	Female	2336	18 %
Driver Age	Less Than 25 Years	2262	17.44 %
	25–30 Years	2471	19.05 %
	30–40 Years	3629	27.98 %
	40–50 Years	2270	17.5 %
	50–60 Years	1332	10.27 %
	>60 Years	1007	7.76 %
Speed	≤30 km/hr	416	3.21 %
	40 km/hr	5339	41.16 %
	50 km/hr	3607	27.81 %
	60 km/hr	3153	24.31 %
	70 km/hr	393	3.03 %
	≥80 km/hr	63	0.49 %
Roadway			
Direction and Location of Occurrence	Two Directions Separated by a Middle Island	9205	70.97 %
	Two Directions Not Separated by a Median	2439	18.80 %
	One-Way	1084	8.36 %
	Inside a Bus Stop	212	1.63 %
	Public Squares	31	0.24 %
Alignments (Horizontal and Vertical)	Uphill Curve	4	0.03 %
	Uphill Straight	305	2.35 %
	Downhill Curve	7	0.05 %
	Flat	12558	96.82 %
	Curve	18	0.14 %
	Downhill	79	0.61 %
Vehicle			
Vehicle Classification	Passenger Car	11569	89.19 %
	Light Truck	1061	8.18 %
	Medium Riding	243	1.87 %
	Heavy Truck	71	0.55 %
	Bike	21	0.16 %
Vehicle Involved in the Crash	1	441	3.40 %
	2	11782	90.83 %
	3	664	5.12 %
	≥4	84	0.65 %
Environmental Factors			
Surface Condition	Dry	12317	94.96 %
	Wet	639	4.93 %
	Snow	9	0.07 %
	Oil	6	0.05 %
Lightening	Day	9217	71.06 %
	Night and Road with Sufficient Lighting	2930	22.59 %
	Insufficient Night Lighting	520	4.01 %
	Sunset	282	2.17 %
	Sunrise	15	0.12 %
	Darkness	7	0.05 %
Weather Condition	Clear	12390	95.52 %
	Rain	545	4.20 %
	Fog	17	0.13 %
	Snow	10	0.08 %
	Storm Wind	9	0.07 %
Severity	Property Damages	12682	97.77 %
	Minor Injured	277	2.14 %
	Serious Injured	7	0.05 %
	Death	5	0.04 %

robust and unbiased model training and validation. By utilizing these balanced datasets, we were able to construct and evaluate both rule-based classifiers and Random Forest models, ensuring that the models were trained on data that accurately reflected the distribution of the minority class, thereby enhancing their predictive performance and reliability in identifying patterns related to roundabout crashes. The resulting balanced dataset was then employed to construct two distinct types of classifiers: rule-based classifiers and Random Forest models. This approach was deliberate; rule-based classifiers inherently yield interpretable models at the expense of some accuracy, while Random Forest models provide deeper analysis but are complex and challenging to interpret, often requiring additional steps for explanation. In the final stage, we integrate and present the outputs of both classifier types to the subject matter experts and policymakers. This allows them to leverage both sets of explanations, thus facilitating a more comprehensive understanding of the contributing factors in roundabout crashes in the context of Jordan.

The choice to employ a combined approach that integrates rule-based classifiers and Random Forest models for the analysis of factors affecting crash severity in roundabouts offers a balanced and comprehensive strategy. Rule-based classifiers inherently provide easily interpretable and transparent models, making them invaluable for understanding the explicit decision criteria behind crash severity classifications. This approach is particularly user-friendly and is well-suited for non-technical stakeholders. On the other hand, Random Forest models, while highly accurate, can be complex and challenging to interpret. By combining these two methodologies, we strike a thoughtful balance between deeper analysis and interpretability, ensuring the model remains accessible to a wide range of users. Moreover, the rule-based models serve as a valuable tool for validating and explaining the predictions of the Random Forest models, enhancing the overall trustworthiness of the results. This combined approach ultimately facilitates a comprehensive understanding of the factors influencing crash severity in roundabouts, supporting evidence-based decision-making and safety interventions.

Training two models, CN2 and Random Forest, is necessary due to their complementary strengths and the diverse insights they can provide. CN2, a rule-based classifier, is valued for its interpretability. It generates straightforward, easy-to-understand rules that can be readily comprehended by non-technical stakeholders such as policymakers and traffic safety experts. These rules can illuminate specific conditions or combinations of factors that lead to higher crash severity, making it easier to identify and communicate actionable insights. For instance, CN2 might reveal simple rules such as "if the crash occurs at night and involves a young driver, the severity is likely to be higher." This level of clarity is crucial for making informed decisions quickly and effectively.

On the other hand, Random Forest models excel in handling complex data interactions and providing deeper analysis. They are ensemble learning methods that combine the predictions of multiple decision trees to improve overall performance and robustness. Random Forest models can manage large datasets with numerous variables, capturing the intricate relationships between factors that contribute to crashes. For example, they might identify complex patterns such as "a combination of high speed, poor lighting, and driver age significantly increases crash severity." Although these models are more challenging to interpret, their predictive power is essential for developing precise and effective safety interventions.

Integrating the outputs of these two models can significantly enhance both the understanding of roundabout crashes and the development of effective policies. First, our method offers complementary insights. The interpretability of CN2 rules can highlight key risk factors in a manner that is accessible to policymakers, who can then use this information to prioritize interventions. This can be used for day-to-day measures and with small datasets on specified areas. The clear rules generated by CN2 can be directly translated into straightforward policy recommendations. Meanwhile, the detailed and nuanced predictions

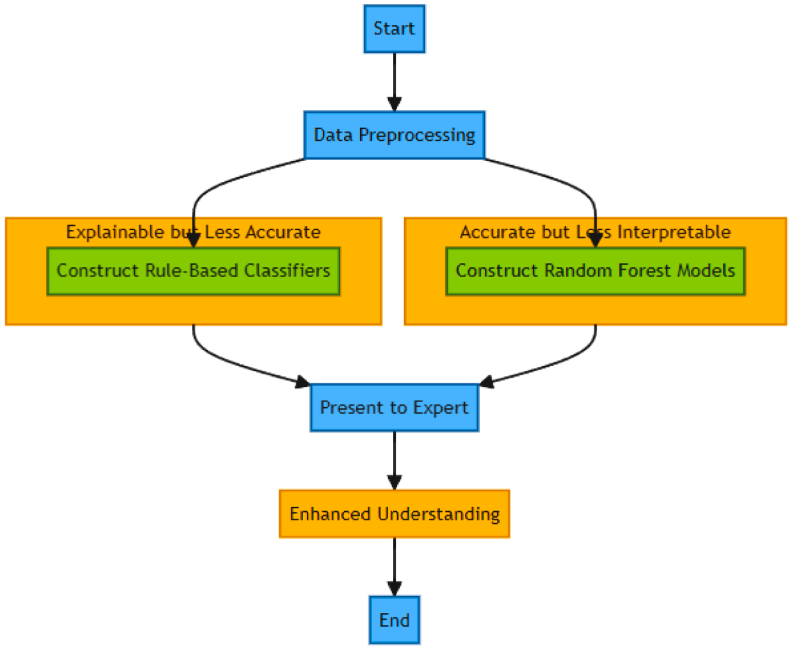

Fig. 2. The conceptual flowchart of the problem statement, which balances between level of analysis and interpretability.

from Random Forest models can validate and refine these priorities by providing a deeper understanding of the underlying data patterns. This can be used for deeper analysis and long-term projects that needs large datasets with multiple factors involved. Random Forest predictions can support these policies by providing evidence of their expected effectiveness based on historical data. Together, these insights create a more comprehensive picture of the factors influencing crash severity. This approach ensures that policies are not only based on clear and simple rules but are also backed by comprehensive statistical analysis, leading to more effective and justified interventions. Second, it provides iterative refinement of the models. The integration of both models allows for an iterative approach to policymaking. Initial rules and insights from CN2 can be tested and validated using the predictions from Random Forest models. If the Random Forest model suggests additional factors or interactions not captured by CN2, policies can be adjusted accordingly. This iterative process ensures continuous improvement and refinement of safety interventions. Experts can appreciate the detailed analysis of the Random Forest model while valuing the simplicity and clarity of CN2 rules. This dual presentation enhances stakeholder engagement, fostering collaboration and consensus on the best strategies to reduce roundabout crashes.

The rule-based model

The rule-based model method is a well-established approach within the realm of crash analysis and road safety assessment [34–36]. This method relies on constructing an ordered list or unordered set of rules and a criterion to systematically classify and evaluate traffic crashes based on various contributing factors and circumstances. Unlike purely statistical or machine learning-based models, which derive patterns from large datasets, the rule-based model method explicitly incorporates expert knowledge and domain-specific guidelines to interpret crash data [34–36]. In the context of crash analysis, these rules typically encompass a wide range of factors, including road geometry, traffic control devices, weather conditions, driver behaviors, and vehicle characteristics, among others [8,37,38]. By applying these rules to the details of individual crashes, the rule-based model method allows for a structured and comprehensive understanding of the contributing factors of each crash.

Furthermore, this approach is particularly valuable in identifying recurring patterns and trends in crash data, which can inform targeted interventions and safety improvements. Rule-based models also serve as valuable tools for traffic engineers, policymakers, and safety practitioners to develop evidence-based strategies and countermeasures aimed at reducing the frequency and severity of crashes in specific contexts or on road segments [34–36]. In essence, the rule-based model method represents a systematic and knowledge-driven approach to crash analysis, offering a valuable complement to data-driven techniques and contributing to the broader goal of enhancing road safety by identifying and addressing the root causes of traffic crashes.

Fig. 3(a) shows the flowchart of the rule-based method that was used in our study.

The CN2 algorithm is a covering algorithm used for rule-based classification, particularly in the context of data mining and knowledge discovery [39]. Developed by Peter Clark and Tim Niblett in the early 1980s [39], CN2 is designed to discover symbolic classification rules from labeled datasets. CN2 is particularly useful for problems involving symbolic or categorical data, and it excels at producing human-interpretable classification rules. It has been used in various domains. Here's a brief pseudocode of how the CN2 algorithm works:

1. Initialization: CN2 starts with an empty rule list and a dataset containing instances with associated class labels.
2. Rule Generation: The algorithm iteratively generates rules to classify instances. It selects a condition (a conjunction of attribute-value pairs) that maximizes the information gain or another relevant measure. This condition becomes part of a rule.
3. Rule Evaluation: The algorithm evaluates the rule's performance by measuring its accuracy on the training data. It considers how well the rule correctly classifies instances of the target class.
4. Pruning: If a rule doesn't significantly improve classification accuracy or if it overfits the data, it may be pruned or removed.
5. Iteration: Steps 2–4 are repeated until no further improvement in classification accuracy can be achieved or until a predefined stopping criterion is met.
6. Final Rule list: The CN2 algorithm produces a list of rules, each with conditions that, when satisfied, predict the class label of an instance.

Subsequently, we employed the CN2 algorithm to generate a

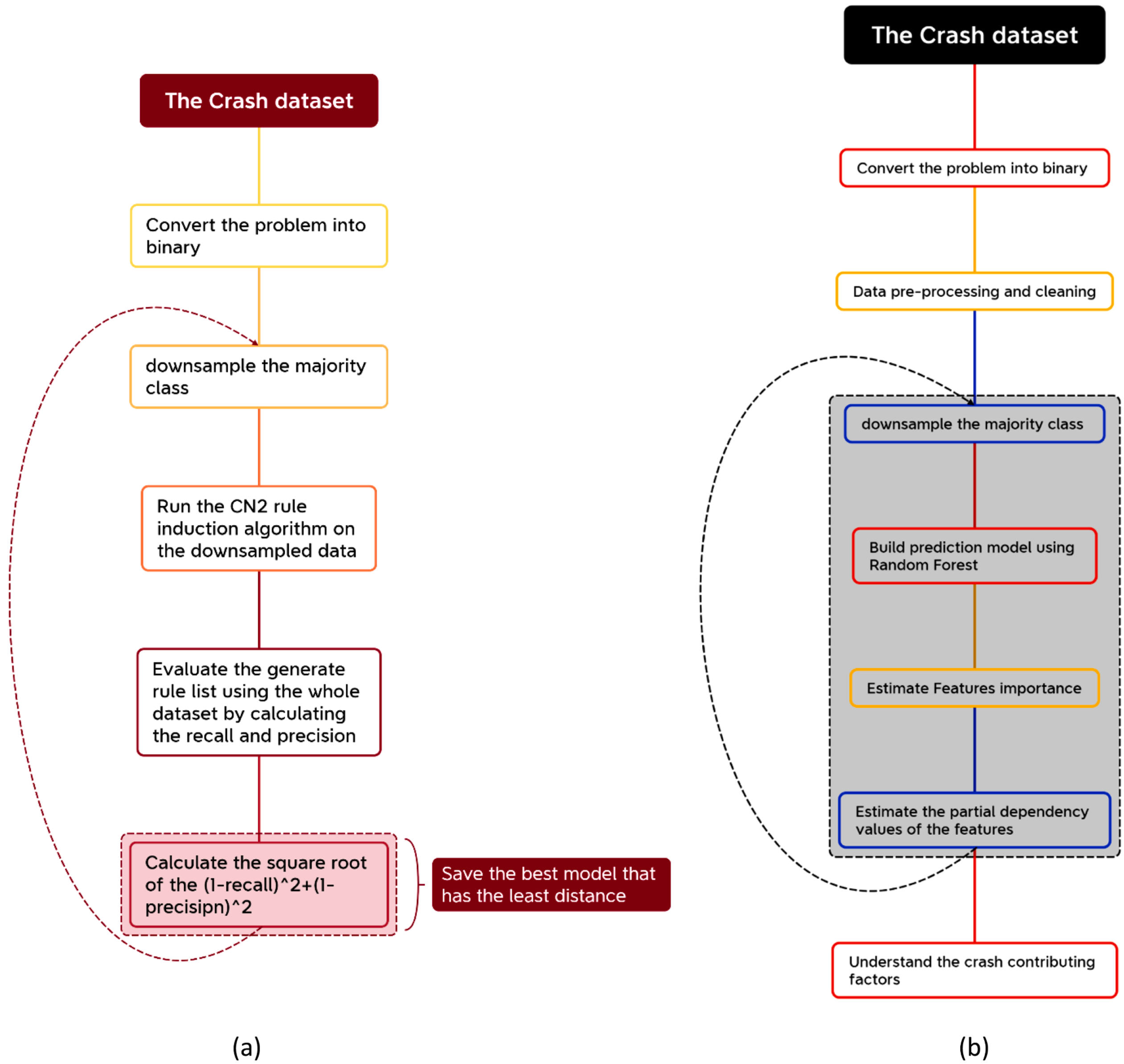

Fig. 3. Flowchart of the (a) rule-based and (b) ML-based methods.

comprehensive rule list capable of classifying the down-sampled dataset effectively. This rule list was then subjected to evaluation using the entire dataset, with the precision and recall metrics estimated under the assumption that the positive class pertains to the Injury class (i.e., the minority class). Furthermore, we gauged the distance from this rule list to the optimal operating point within the precision-recall domain. This distance measurement, as depicted by Eq. (1), captures the trade-off between precision and recall, revealing the proximity of the rule list's performance to the optimal balance between these two metrics.

$$Distance = \sqrt{(1 - recall)^2 + (1 - precision)^2} \tag{1}$$

This multifaceted procedure was iterated a substantial number of times, exemplified by 100 iterations in our analysis. Ultimately, the rule list that yielded the smallest distance measurement was selected as the optimal one. This selection was pivotal in extracting insights into the contributing factors behind injuries and property damage occurrences, thus offering valuable understanding and guidance for future prevention strategies.

The machine learning (ML) model

ML-based approaches have revolutionized the field of crash analysis by providing powerful tools to predict, understand, and mitigate traffic crashes [39–41]. Among these methods, Random Forest stands out as a versatile and widely applied algorithm for crash analysis [40,42,43]. Random Forest is an ensemble learning technique that combines multiple decision trees to improve predictive accuracy and generalizability. In the context of crash analysis, Random Forest (RF) excels at identifying complex relationships among various contributing factors, making it a valuable tool for both research and practical applications in road safety.

Fig. 3(b) shows the flowchart of the ML-based method that was used in our study. The key steps in using Random Forest for crash analysis are as follows.

1. Data Collection and Preprocessing: The first step involves gathering comprehensive data on past traffic crashes, including factors such as road conditions, weather, driver behavior, vehicle attributes, and crash severity. This data is then cleaned, processed, and formatted for machine learning input.

2. Feature Selection using Importance: Feature selection is crucial for identifying the most relevant variables that contribute to crash severity. Random Forest can handle a large number of features, but feature selection helps improve model efficiency and interpretability.
3. Training the Model: In the training phase, the Random Forest algorithm builds a multitude of decision trees using bootstrapped subsets of the data. Each tree is constructed by considering a random subset of features at each node. This randomness and diversity among the trees help mitigate overfitting.
4. Ensemble Learning: Random Forest combines the predictions of individual decision trees to produce a more robust and accurate overall prediction. The ensemble nature of the model enhances its generalization to unseen data.
5. Prediction and Evaluation: Once the model is trained, it can be used to predict crash severity for new or unseen data. Evaluation metrics such as accuracy, precision, recall, and F1 score are used to assess the model's performance.
6. Interpretability: One of the advantages of Random Forest is its interpretability. Researchers and practitioners can analyze the importance of each feature in the model's predictions, gaining insights into the factors that contribute most to crash severity.
7. Model Deployment and Recommendations: The insights gained from the Random Forest model can inform safety interventions and recommendations. For example, if the model highlights the significance of certain road conditions or driver behaviors in predicting severe crashes, targeted safety measures can be implemented to address these factors.

Analysis and results

The rule-based model

In our study, we applied a rule-based model to systematically analyze and uncover the key factors influencing crash severity in roundabouts across Jordan. We used the CN2 algorithm to derive a list of induced rules. These rules encapsulated the complex relationships between various contributing factors, including geometric design, driver behavior, weather conditions, and vehicle attributes. By iteratively generating, evaluating, and refining rules, the CN2 algorithm allowed us to discern patterns within the data, shedding light on the factors that most significantly impact crash severity in the unique context of Jordanian roundabouts. We employed robust assessment techniques to gage the efficacy of the rule-based model's performance in predicting crash severity within Jordanian roundabouts. The Receiver Operating Characteristic (ROC) curve, shown in Fig. 4, demonstrated a substantial area under the curve (AUC) of about 0.85, indicating a strong ability of the model to discriminate between different levels of crash severity. This curve illustrated the trade-off between true positive rates (sensitivity) and false positive rates (1-specificity) across varying classification thresholds, highlighting the model's ability to identify the induced rules resulted from the model. With these outcomes, the ROC curve reinforced our confidence in the rule-based approach as a valuable tool for effective crash severity prediction. However, we also found the precision, recall, and F1-score equal 9 %, 72 %, and 15 %, respectively.

Table 2 shows the condition, corresponding severity class, the distribution (i.e., the number of cases for each severity class), and the length of each rule. These induced rules serve as invaluable insights for policymakers, traffic engineers, and safety practitioners, providing a structured framework to inform evidence-based interventions and strategies to enhance roundabout safety and reduce the severity of traffic crashes in the region. As shown in Table 2, out of the twenty-seven resulted induced rules, eleven rules corresponded to the injury severity class and the rest were for the PD class. For the rules where injury class was dominant, hour group, driver age, day of week, speed, and number of vehicles seemed to be the most factors that led to injury severity crashes. Some notable rules that resulted from the injury class include if the type of the crash was running off the road (Rule 1); if the crash occurred while the roadway surface was not dry, and the lighting of the street is dark (Rule 9); and if the crash occurred in a morning during the spring season and the driver age is greater than 30 (Rule 14).

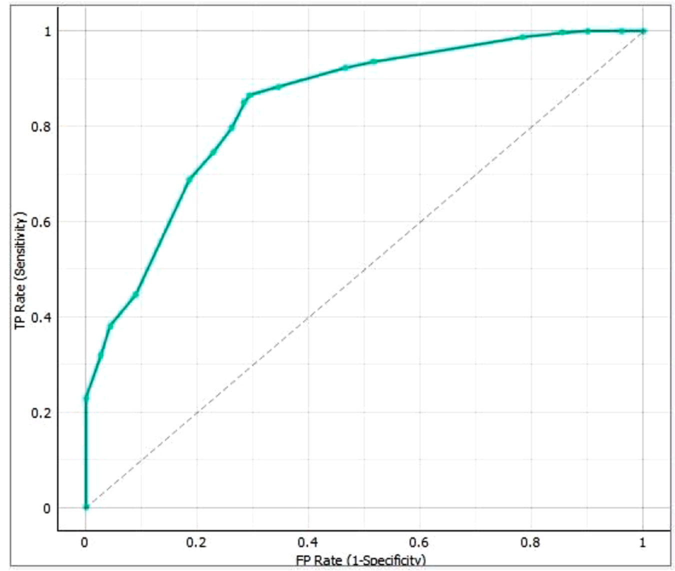

Fig. 4. The ROC curve of the rule-based model.

On the other hand, where the PD class was leading, the number of lanes, hour group, the type of driver fault, lighting, speed, and day of week seemed to be the most factors that led to PD-severity crashes. Some notable rules that resulted from the PD class include if the crash occurred in a midday of Sunday during the Winter season (Rule 5); if the driver did not leave the safe relay distance in a two-lane not separated by a median and during the midday (Rule 6); if the driver does not leave the safe relay distance as well but the vehicle speed is greater than 50 and the crash occurred during the night with sufficient road lighting (Rule 8); and if the crash occurred during the Fall season and a driver of age greater than 24 violated traffic rules and priorities (Rule 22).

The machine learning model

In the Method section, we emphasized the significant challenge posed by imbalanced data in our crash analysis study. To tackle this issue effectively, we implemented a strategic approach by consolidating the minority classes, thereby simplifying the problem into a binary classification setup. Our methodology involved the creation of 200 distinct down-sampled datasets, each meticulously crafted for training, testing, and evaluating partial dependencies and feature importance. This iterative process allowed us to gain invaluable insights into the behavior of individual features and their relative significance across different model runs. By aggregating the results of partial dependency and feature importance analyses from all models, we not only obtained a comprehensive understanding of feature importance but also unveiled the collective partial dependency patterns that underlie the entire dataset. This rigorous approach not only addressed the imbalanced data challenge but also enriched our exploration of the intricate relationships between features and crash severity within roundabouts in Jordan.

In Fig. 5, we present a detailed visualization of the RF results, providing values for precision, recall, and F1-score achieved by models individually applied to each of the 200 generated down-sampled datasets. This approach resulted in the creation of a distinct model for each dataset. To ensure the reliability of our assessments, we rigorously evaluated these models using a 5-fold cross-validation approach, yielding robust performance metrics across various scenarios. The

Table 2
The induced rules list resulted from the rule-based model.

#	Condition	Severity Class	Distribution [# of Injury, # of PD]	Length
1	Type = Run Over	Injury	[53, 0]	1
2	Lanes = One-way *AND* Driver Age ≤ 45.0 *AND* Holiday = False	PD	[0, 17]	3
3	Driver Fault = Reversing the vehicle leading to a crash *AND* License Type ≠ Fourth Class *AND* Number of vehicles ≥ 2.0	PD	[1, 15]	3
4	Number of vehicles ≥ 3.0 *AND* Hour Group ≠ Morning	Injury	[21, 1]	3
5	Hour Group = Midday *AND* Day of Week = Sunday *AND* Season Group ≠ Winter	PD	[0, 18]	3
6	Driver Fault = The driver does not leave the safe relay distance *AND* Hour Group = Midday *AND* Lanes ≠ Two directions not separated by a median	PD	[2, 17]	3
7	Driver Age ≥ 81.0 *AND* Day of Week ≠ Monday *AND* License Type ≠ Third Class Automatic	Injury	[14, 2]	3
8	Driver Fault = The driver does not leave the safe relay distance *AND* Speed ≥ 50.0 *AND* Lighting = Night and road with sufficient lighting	PD	[2, 13]	3
9	Roadway Surface ≠ Dry AND Lighting ≠ Sunset	Injury	[12, 3]	2
10	Hour Group = Night *AND* Driver Age ≤ 33.0 *AND* Lighting ≠ Night and road with sufficient lighting	Injury	[14, 1]	3
11	Day of Week = Tuesday *AND* Driver Age ≥ 40.0	PD	[2, 13]	2
12	Hour Group = Midday *AND* Season Group = Winter *AND* Lanes ≠ Two directions not separated by a median	PD	[2, 13]	3
13	Driver Fault = The driver does not leave the safe relay distance *AND* Speed ≥ 50.0 *AND* Day of Week ≠ Thursday	PD	[3, 16]	3
14	Hour Group = Morning *AND* Driver Age ≥ 30.0 *AND* Season Group ≠ Spring	Injury	[15, 2]	3
15	Vehicle Type ≠ Small ride car *AND* Vehicle Type ≠ Shipping *AND* Lighting ≠ Insufficient night lighting	Injury	[13, 3]	3
16	Day of Week = Sunday *AND* Season Group ≠ Summer *AND* Speed ≤ 60.0	PD	[3, 12]	3
17	Hour Group = Evening *AND* Season Group = Winter *AND* License Type ≠ Fifth Class	PD	[3, 12]	3
18	Day of Week = Wednesday *AND* Lanes ≠ Two directions not separated by a median *AND* Driver Age ≥ 31.0	PD	[3, 12]	3
19	Driver Age ≤ 29.0 *AND* Hour Group = Night *AND* License Type ≠ Third class automatic	Injury	[12, 4]	3
20	Day Group ≠ Weekday *AND* Season Group ≠ Fall *AND* Driver Fault ≠ Sudden change of lane	PD	[2, 13]	3
21	License Type ≠ Third Category *AND* Speed ≥ 50.0 *AND* Day of Week ≠ Thursday	Injury	[14, 2]	3
22	Season Group = Fall *AND* Driver Fault ≠ Violations of traffic rules and priorities *AND* Driver Age ≥ 24.0	PD	[2, 13]	3
23	Lanes ≠ Two directions separated by a middle island *AND* Day of Week ≠ Monday *AND* Driver Fault ≠ Driving a vehicle without taking the necessary traffic safety precautions	Injury	[14, 2]	3
24	Driver Fault ≠ Driving a vehicle without taking the necessary traffic safety precautions *AND* Driver Age ≥ 37.0 *AND* License Type ≠ Fifth Class	PD	[2, 13]	3
25	Driver Age ≥ 32.0 *AND* Lanes ≠ Two directions not separated by a median *AND* License Type ≠ Sixth Category (A)	Injury	[14, 2]	3
26	Driver Fault ≠ The driver does not leave the safe relay distance *AND* Day of Week ≠ Saturday *AND* Driver Fault ≠ Driver taking the wrong lane	PD	[4, 12]	3
27	True	PD	[231, 231]	0

precision values, averaging at 0.74 and 0.72 for injury and PD, respectively, demonstrate the models' high accuracy in correctly classifying crash severity. With an average recall of 0.70 for injury and 0.76 for PD, the models displayed a commendable ability to identify the most relevant instances of severe crashes. The F1-score, averaging at 0.72 and 0.73 for injury and PD, respectively, encapsulated an overall measure of model effectiveness, striking a balance between precision and recall. By examining these metrics across multiple dataset iterations, we gained a nuanced understanding of how the RF models consistently performed under varying conditions, further reinforcing the robustness of our crash analysis.

In Fig. 6, we present a histogram that illustrates the importance of each of the different features, as quantified by the RF models applied individually to each of the 200 crafted down-sampled datasets, resulting in a dedicated model for every dataset. To ensure the robustness of our analysis, we meticulously employed a 5-fold cross-validation methodology. This rigorous approach allowed us to precisely gage the significance of each feature within our crash analysis. Among these features, driver age emerged as the most influential, with an average importance score of about 0.21. Number of vehicles followed behind, with an average importance score of about 0.15. Furthermore, hour group and season group contributed with average importance scores of about 0.09 and 0.08, respectively. The speed then followed by average importance score of about 0.08. For this study, we will focus our analysis on the five most important features, and we will further analyze them using the marginal impact to the Precision-Recall (PR) for the PD class; knowing that the marginal impact to the PR for the injury class equals one minus the former. We will add the resulted analysis of the marginal impact to the RP to the remaining features in the Appendix.

To that extent, the marginal impact to PR typically refers to the change in Precision-Recall metrics when a specific factor or feature is modified or introduced into a model or dataset. Precision and Recall are two fundamental evaluation metrics used to assess the performance of classification models, especially in cases where class imbalance is present. The marginal impact to PR quantifies how much the Precision and Recall metrics are affected when a particular change is made. It helps measure the contribution of a specific variable, factor, or modification to the overall model performance, particularly in terms of correctly identifying positive instances (True Positives) and minimizing false positives and false negatives. Calculating the marginal impact to PR involves comparing the PR metrics before and after the change or modification. This concept is valuable in model development and feature engineering

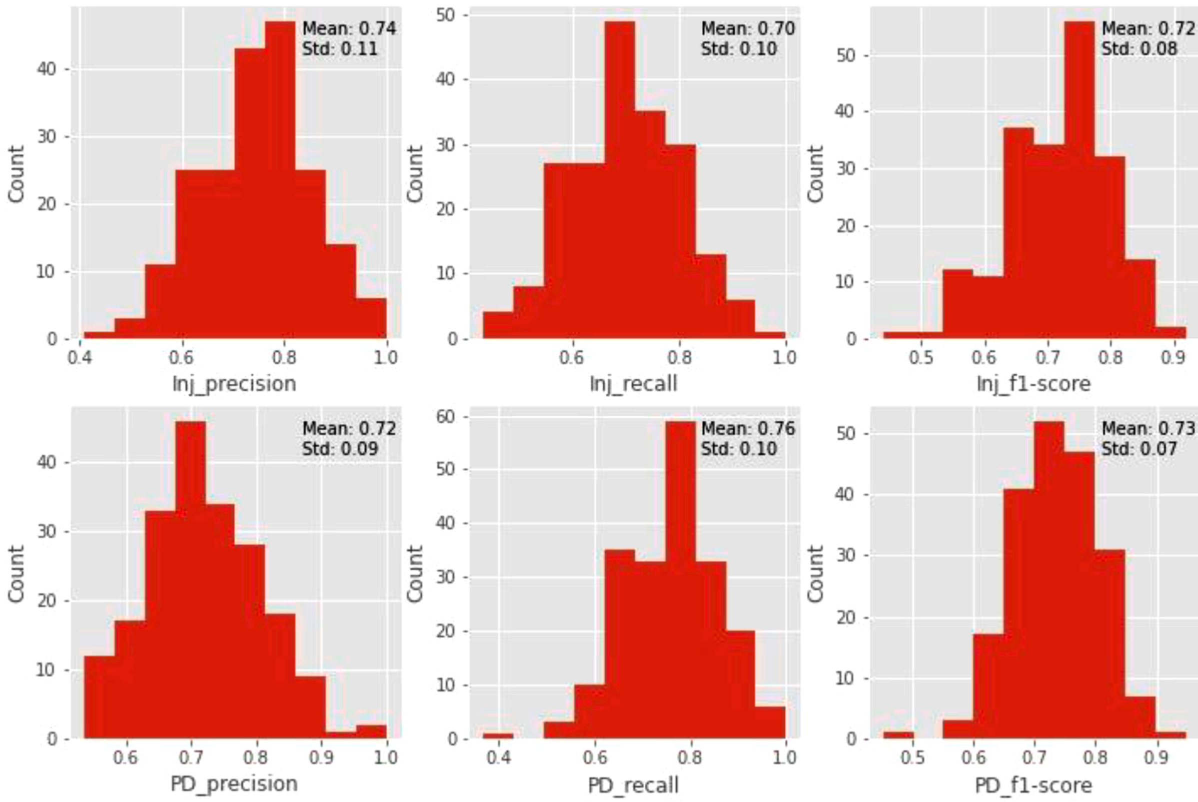

Fig. 5. The precision, recall, and F1-score of the Random Forest models for the two classes.

to understand which factors have the most significant influence on a model's performance, and it helps in making informed decisions about which changes or features to prioritize for improving Precision and Recall. This detailed feature importance analysis offered a nuanced understanding of the key factors driving crash severity in Jordanian roundabouts, providing valuable insights for safety interventions and policy decisions.

In our comprehensive analysis of crash severity prediction within roundabouts, we investigated the marginal impact to PR graph while considering the PD class as a reference, given that the marginal impact to the PR for the injury class equals one minus the PD class. Specifically, we thoroughly examined the top five important features as shown in Fig. 6 including driver age, number of vehicles, hour group, season group, and speed. In Fig. 7, which illustrates the relationship between driver age and PD crash severity, we conducted a thorough analysis to understand how the marginal impact of age varied across different age groups. We observed that for young drivers, typically within the age range of 18 to 25, the marginal impact ranged from 0.3 to 0.6. This means that small changes in age within this group had a moderate effect on the measured metric. As driver age increased, reaching the range of 26 to 60 years old, the marginal impact relatively decreased, hovering between 0.4 to 0.6. In this age range, the impact of age on the metric was less pronounced, suggesting that changes in age had a slightly smaller influence. However, the situation changed notably for drivers older than 60 years. In this age group, the range of the marginal impact started to dramatically increase. This indicates that for relatively older drivers, even small changes in age had a substantial effect on the metric being measured. In essence, this analysis highlights that the marginal impact of relatively older drivers was the highest, followed by that of young drivers, in the context of PD crash severity.

In Fig. 8, which presents the marginal impact to PR analysis categorized by hour groups, we meticulously examined how variations in the time of day influenced the PR metrics, specifically for the PD class crash severity. To facilitate our analysis, we partitioned the time of day into four distinct groups: night, evening, midday, and morning. Our observations revealed intriguing trends. When crashes occurred during the night hours, the marginal impact on PR for the PD class spanned a range from approximately 0.15 to 0.4. This indicated that slight variations in the time of night had a relatively modest effect on the model's capability to predict PD-class incidents. As we transitioned to the evening and midday hours, the impact notably increased, with the marginal impact ranging from about 0.5 to 0.6. This suggests that changes in the time of day during these periods had a more pronounced influence on the model's PR metrics for PD-class incidents. Additionally, it's noteworthy that crashes during the morning exhibited a Marginal Impact within the range of approximately 0.35 to 0.6. Overall, our analysis underscores the significant impact of hour groups on the model's performance, with the Marginal Impact being particularly prominent during the evening, midday, and morning periods in relation to PD-class incident prediction, compared to the night hours.

In Fig. 9, which presents the marginal impact to PR analysis categorized by number of vehicles involved in crashes concerning the PD crash severity, we delved into how variations in the number of vehicles involved influenced the PR metrics. Our investigation categorized crashes into single-vehicle, two-vehicles, and multiple-vehicle types. When dealing with single-vehicle crashes, the marginal impact on PR for the PD class ranged from approximately 0.1 to 0.4. This signified that small changes in the number of vehicles in these types of crashes had a relatively modest impact on the model's ability to predict PD-class incidents. However, as we shifted our focus to multiple-vehicle crashes, the marginal impact expanded, ranging from about 0.2 to 0.5. This indicated that alterations in the number of vehicles in these incidents had a more noticeable influence on PR metrics. Intriguingly, the most significant change was observed in two-vehicle crashes, where the marginal impact dramatically increased, spanning a range from about 0.55 to 0.6. This highlighted the substantial impact that variations in the number of vehicles had on the model's PD-class incident prediction, particularly in the context of two-vehicle crashes.

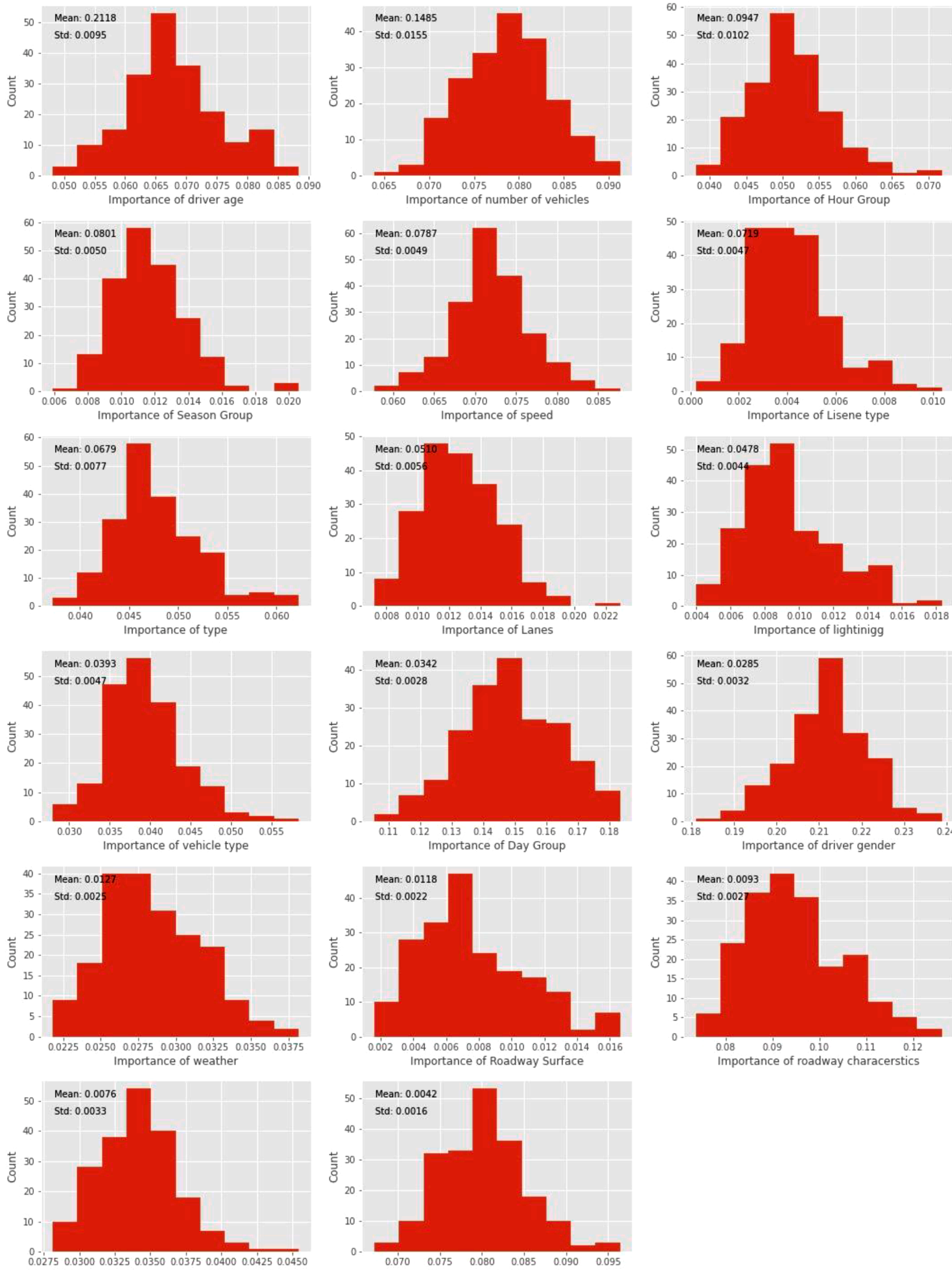

Fig. 6. Features' importance resulted from RF models.

In our analysis of the marginal impact to PR concerning the PD crash severity and its relationship with different seasons shown in Fig. 10, we examined how changes in the season group influenced the PR metrics. Our study encompassed all four seasons: spring, summer, fall, and winter. Our findings revealed a consistent trend across all seasons. The marginal impact on PR for the PD class ranged from approximately 0.42 to 0.56 regardless of the season. This indicates that small variations in the season had a relatively consistent impact on the model's ability to predict PD-class incidents throughout the year. The stability of the marginal impact suggests that seasonality, in terms of its influence on PD-class incident prediction, remained relatively constant, with only minor fluctuations observed across the different seasons.

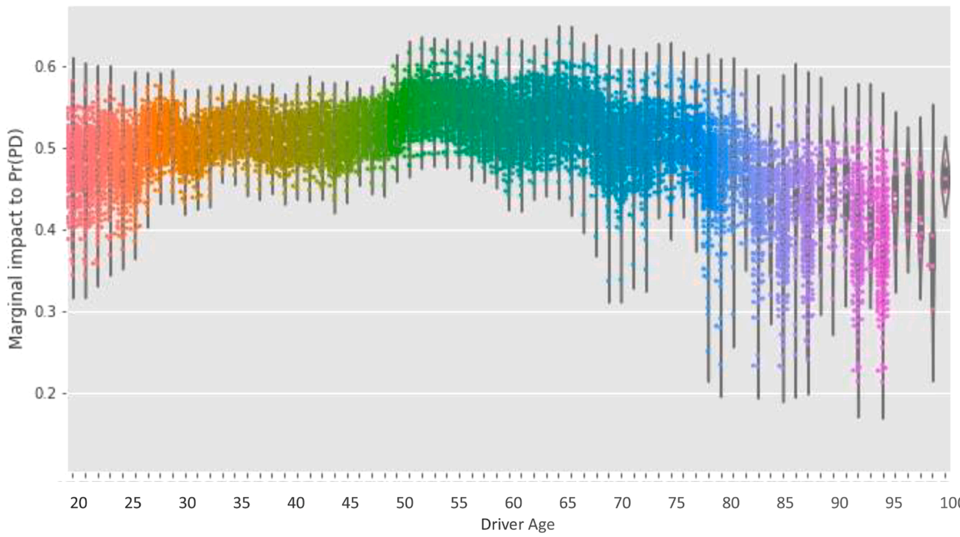

Fig. 7. Marginal impact to PR for the driver age on the PD class.

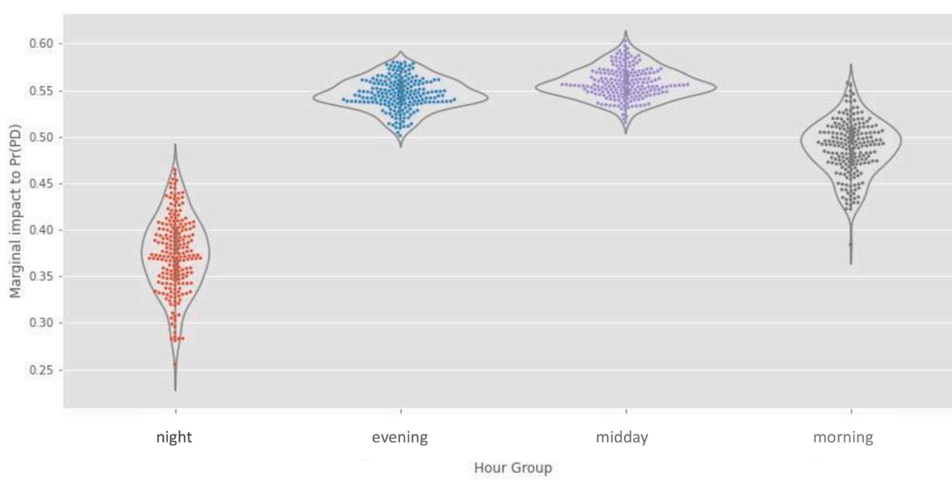

Fig. 8. Marginal impact to PR for the hour group on the PD class.

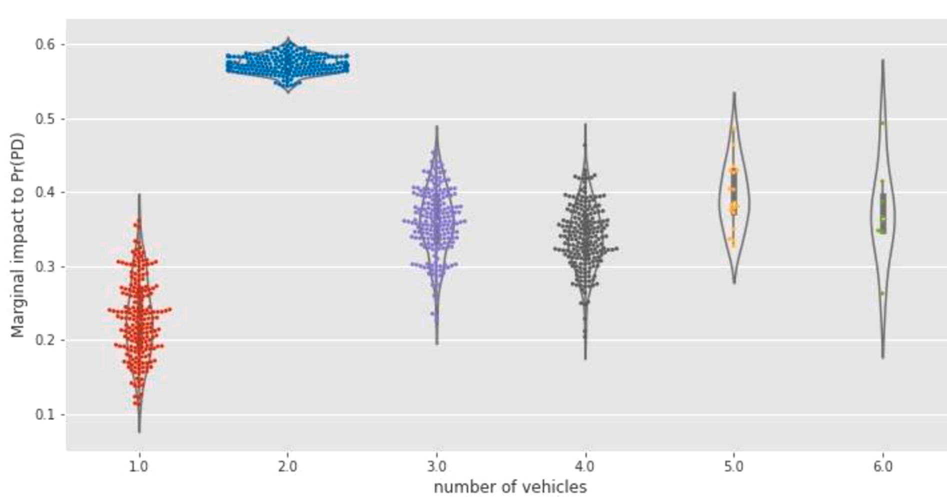

Fig. 9. Marginal impact to PR for the number of vehicles on the PD class.

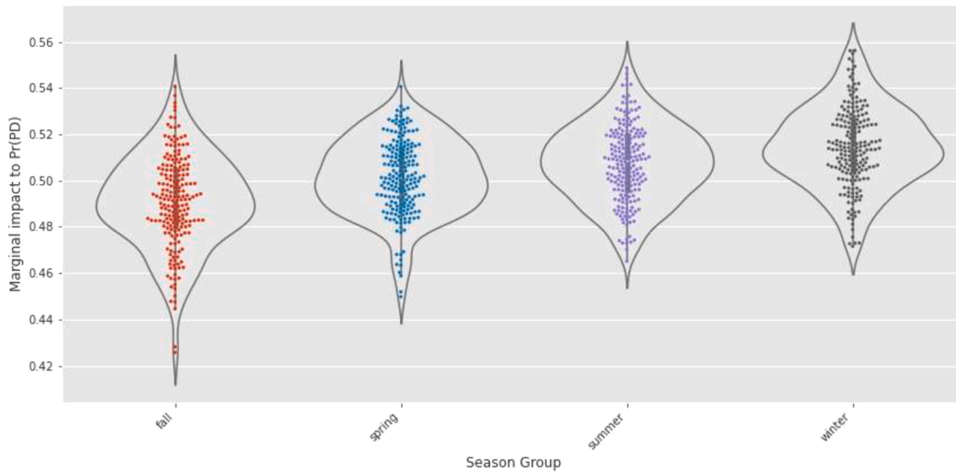

Fig. 10. Marginal impact to PR for the season group on the PD class.

Fig. 10 shows the marginal impact to PR for the PD crash severity in terms of the speed of the vehicle before crash. The marginal impact ranged between about 0.4 to 0.65 when the speed is relatively low (i.e., less than 30 km/hr). However, it ranged from about 0.42 to 0.55 as the speed increased until it reaches 70 km/hr and then the marginal impact increased again to become from 0.35 to 0.6.

In Fig. 10, which presents the marginal impact to PR analysis for the PD crash severity concerning the speed of the vehicle before a crash, we explored how variations in vehicle speed influenced the PR metrics. Our analysis revealed intriguing insights. When examining relatively low speeds, specifically less than 30 km/hr, the marginal impact on PR ranged from about 0.4 to 0.65. This suggests that small changes in vehicle speed within this lower range had a noticeable impact on the model's ability to predict PD-class incidents. As we transitioned to higher speeds, ranging up to 70 km/hr, the marginal impact narrowed its range, spanning from about 0.42 to 0.55. This indicates that variations in vehicle speed within this middle range had a slightly smaller effect on PR metrics. However, what's particularly noteworthy is that as the vehicle speed exceeded 70 km/hr, the marginal impact once again increased. In this higher speed range, the impact ranged from about 0.35 to 0.6. This suggests that changes in vehicle speed at higher velocities had a more significant influence on PR metrics. Our analysis underscores the dynamic relationship between vehicle speed and PD-class incident prediction, with the marginal impact varying based on the speed range, emphasizing the importance of considering speed as a factor in crash severity assessment.

Discussion

In this work, we used CN2 and RF to classify crashes severity at roundabouts in Jordan. In CN2 model, we derived 27 list of rules that incorporate the different contribution factors. While eleven rules out of 27 were related to predict injury, the rest are related to predict PD-class. According to the results, traffic crashes that has a type of run off the road are always associated with injury severity. Run-off crashes in roundabouts, consistently linked to injury severity, can be explained by a combination of factors. These incidents often occur when a vehicle exits the roundabout at an excessive speed, potentially due to driver error or misjudgment. The design of roundabouts is intended to gradually slow down vehicles as they navigate the circular path, but if drivers fail to adjust their speed when exiting, the vehicle may continue a straight trajectory into a run-off area. The higher velocity, coupled with the limited space for deceleration and the potential for oblique or head-on impacts with barriers or roadside objects, significantly elevate the risk of injury severity. Additionally, the absence of protective features in run-off areas, such as crash barriers or forgiving infrastructure, contributes to the increased injury potential in these crashes [44]. Nonetheless, safety measures aimed at mitigating injury severity in run-off crashes within roundabouts encompass a multi-faceted approach. These include design enhancements focused on equipping run-off areas with protective

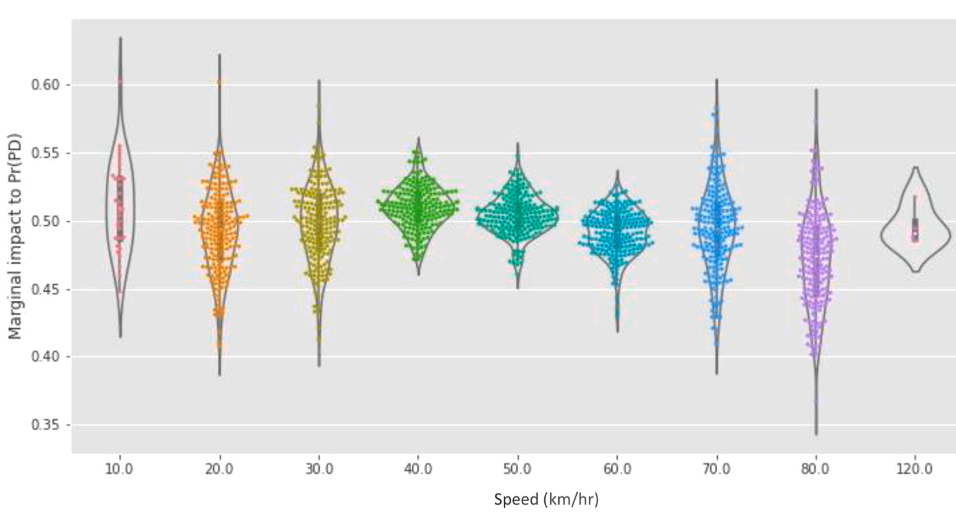

Fig. 11. Marginal impact to PR for the speed on the PD class.

features like crash barriers and clear zones, thus reducing the risk of severe impacts. Managing vehicle speed through proper design, road markings, and speed limit enforcement is crucial in promoting safer exits from roundabouts. Driver education campaigns are instrumental in raising awareness about roundabout-specific driving behaviors and the importance of adhering to posted speed limits. Effective law enforcement ensures compliance with speed limits and safe driving practices within roundabouts. The deployment of advanced warning systems, like flashing lights and dynamic signage, provides real-time alerts to drivers, helping them make informed decisions during exit maneuvers.

Another finding was the road lightening, which affects the crashes severity in roundabouts. Our finding indicated that dark light with non-dry surface always caused injury crashes. This finding meets with previous findings related to weather and lightening conditions studies [29, 45]. To mitigate injury crashes, it is crucial to ensure that roundabouts are well-illuminated, especially during adverse weather conditions and on non-dry road surfaces. Installing and maintaining efficient street lighting systems can significantly enhance visibility and reduce the likelihood of crashes, particularly during dark hours or inclement weather. These safety measures align with previous research in weather and lighting conditions, emphasizing the critical role that proper road lighting plays in minimizing crash severity within roundabouts [29,45].

Furthermore, our study emphasizes that young drivers with private licenses who drive at night particularly in situations involving multiple vehicles have a higher likelihood of experiencing more severe injuries. A sub rule derived from this finding highlights the connection between driver age and light conditions. Specifically, drivers under the age of 33 involved in crashes demonstrated an incidence of injury severity. However, it was discovered that PD class is not only linked to factors like driver age and road conditions but also influenced by a range of driver errors. Various driver errors were identified as significant contributors to the anticipated level of crash severity. To address the higher likelihood of more severe injuries in these scenarios, safety interventions could include enhanced driver education programs, emphasizing safe driving practices at night and under challenging conditions. Additionally, a focus on drivers under the age of 33 can help in reducing injury severity, potentially through graduated licensing systems and stricter enforcement of night driving restrictions for novice drivers. Moreover, addressing a range of driver errors could involve promoting defensive driving strategies, raising awareness about common driver mistakes, and fostering a culture of responsible driving among all age groups.

For results from RF, the marginal impact to PR was analyzed for several features. The analysis revealed that driver age had a varying marginal impact, with the highest impact observed for older drivers. The time of day (hour group) showed a significant impact on the model's PR metrics. The number of vehicles involved in crashes also had a noticeable effect on the model's prediction, with the greatest impact observed in two-vehicle crashes. Additionally, the analysis showed that seasonality had a relatively consistent impact on the model's ability to predict PD-class incidents, with minor fluctuations across different seasons. Finally, the speed of the vehicle before a crash had a varying marginal impact, with the highest impact observed at relatively low speeds and again at higher speeds. Findings of this study meet several previous studies including [19,46–51].

In comparing the CN2 and RF models, the performance metrics—precision, recall, and F1-score—clearly demonstrate that the RF model is significantly more accurate and reliable. The CN2 model, with a precision of 9 %, recall of 72 %, and F1-score of 15 %, indicates a high rate of false positives and an overall low predictive accuracy. The low precision suggests that many of the positive predictions made by the CN2 model are incorrect, while the high recall indicates that it is better at capturing actual positives. However, the very low F1-score, which balances precision and recall, underscores its incapability in providing a dependable classification. In contrast, the RF model achieves a balanced and high performance across all metrics, with precision, recall, and F1-score all equal to 73 %. This uniformity implies that the RF model has a much better trade-off between precision and recall, accurately identifying true positives while minimizing false positives and false negatives. Consequently, the RF model is more accurate and reliable for predicting crash severity at roundabouts, making it the preferred choice for informing safety interventions and policymaking.

The integration of CN2 and Random Forest models provides a comprehensive analysis of roundabout crashes in Jordan, each offering unique insights into crash severity factors. The CN2 model identified 27 rules, highlighting that run-off-the-road crashes are consistently linked to injury severity due to high exit speeds and inadequate deceleration spaces, while factors like inadequate lighting on non-dry surfaces further elevate injury risks. Random Forest model revealed that variables such as driver age, time of day, number of vehicles, seasonality, and speed significantly impact crash severity predictions. Older drivers and nighttime driving were notably influential, with speed variations having a pronounced effect on crash outcomes. These results from the two different approaches allow policymakers to understand the underlying causes of crashes and support the development of targeted safety interventions, such as improved lighting, speed enforcement, and driver education programs, ultimately enhancing roundabout safety in Jordan.

To address the varying impact of driver age on crash severity, safety initiatives could include specialized refresher courses and awareness campaigns tailored for older drivers. Moreover, implementing more frequent and rigorous license renewal processes for senior drivers, encompassing vision tests and cognitive assessments, could help ensure their continued fitness to drive safely. Additionally, promoting the adoption of vehicles equipped with Advanced Driver Assistance Systems (ADAS) may assist older drivers in making safer decisions on the road. Furthermore, recognizing the significant influence of the time of day on crash severity, it is essential to invest in improved road lighting infrastructure, especially during night hours. Additionally, bolstering road signage and launching public awareness campaigns to educate drivers about the specific challenges and precautions needed during nighttime driving can enhance safety. For situations involving multiple vehicles, measures could focus on promoting safe following distances, discouraging aggressive driving, and enhancing the effectiveness of traffic enforcement. Lastly, addressing the consistent impact of seasonality may involve year-round safety initiatives, such as maintenance of road surfaces, anti-icing treatments during winter, and increased monitoring during adverse weather conditions. To mitigate the varying impact of vehicle speed, strict adherence to speed limits, especially within roundabouts, is paramount, supported by speed-monitoring technologies and targeted enforcement.

Conclusion

Safety modeling plays a crucial role in shaping national policy. By understanding the factors contributing to crashes and the occurrence of crashes, agencies can implement effective countermeasures to reduce these incidents. We quantified the effect of the different contributing factors pf crash severity on roundabouts in Jordan using the different modeling techniques. The resulting balanced dataset was then employed to construct two distinct types of classifiers: rule-based classifiers and Random Forest models. This approach was deliberate; rule-based classifiers inherently yield interpretable models at the expense of some accuracy, while Random Forest models provide deeper analysis but are complex and challenging to interpret, often requiring additional steps for explanation. In the final stage, we integrate and present the outputs of both classifier types to the subject matter experts and policymakers. This allows them to leverage both sets of explanations, thus facilitating a more comprehensive understanding of the contributing factors in roundabout crashes in the context of Jordan.

The CN2 model analysis yielded 27 rules, with eleven linked to predicting injury severity, highlighting the consistent association between run-off road crashes and injury severity in roundabouts. These crashes typically occur when vehicles exit roundabouts at excessive speeds, often due to driver error or misjudgment. The design of roundabouts, intended to gradually reduce vehicle speeds, can fail to mitigate the risk when drivers neglect to adjust their exit speed, leading to higher velocities and a heightened risk of injury. Safety measures to counter this issue encompass design enhancements, speed management, driver education, law enforcement, and advanced warning systems. The RF model analysis unveiled crucial factors influencing crash severity in roundabouts, notably the varying impact of driver age, time of day, the number of vehicles involved, seasonality, and vehicle speed. To address these factors, a comprehensive set of safety initiatives is recommended. Specialized refresher courses and awareness campaigns tailored for older drivers can help mitigate age-related variations in crash severity. Moreover, implementing more stringent license renewal processes for senior drivers, incorporating vision tests and cognitive assessments, ensures their continued safe driving. The adoption of vehicles equipped with Advanced Driver Assistance Systems (ADAS) offers a technology-driven solution to assist older drivers in making safer choices.

By providing a detailed, context-specific analysis and combining interpretability with the level of analysis through innovative modeling approaches, this study offers valuable insights and practical recommendations for improving road safety around roundabouts in Jordan. This comprehensive approach not only enhances the understanding of roundabout crashes but also informs the development of effective, localized safety interventions. The methodologies and findings can be generalizable and offer valuable insights that may be adapted and tested in different contexts. The use of rule-based classifiers and Random Forest models to analyze crash data provides a robust framework that can be applied to similar studies in other regions. Future research could focus on comparing roundabout crash data from various countries to assess the broader applicability of these findings and refine safety interventions accordingly. While the specific results of this study are most directly applicable to Jordanian roundabouts, the methodological approach and general insights into roundabout safety have the potential to inform roundabout safety improvements in other regions, with appropriate contextual adjustments.

CRediT authorship contribution statement

Huthaifa I. Ashqar: Writing – review & editing, Supervision, Project administration. **Taqwa I. Alhadidi:** Writing – original draft, Investigation, Data curation. **Mohammed Elhenawy:** Validation, Software, Methodology, Investigation, Formal analysis. **Shadi Jaradat:** Writing – original draft.

Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data availability

The authors do not have permission to share data.

Appendix A

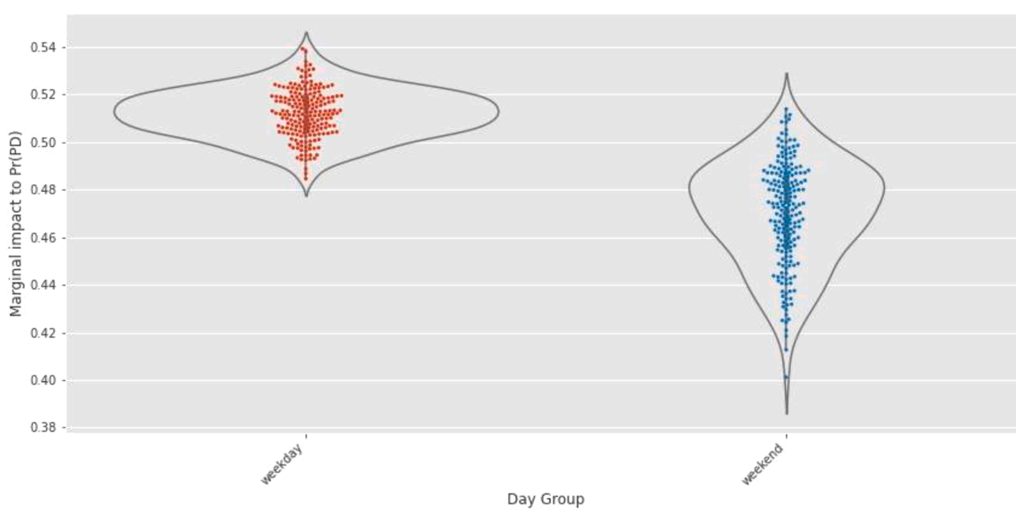

Fig. A.1. Marginal impact to PR for the Day of the Week on the PD class.

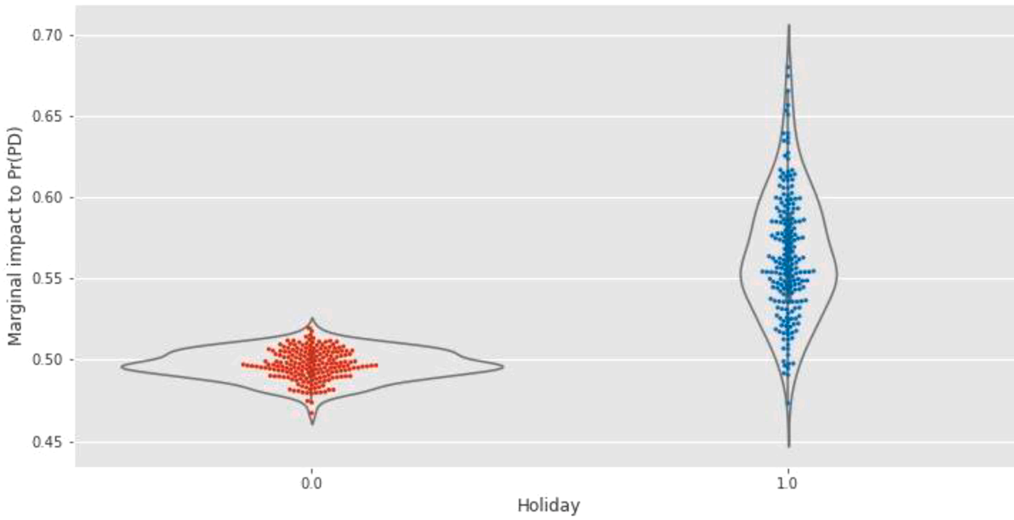

Fig. A.2. Marginal impact to PR for the Holiday on the PD class.

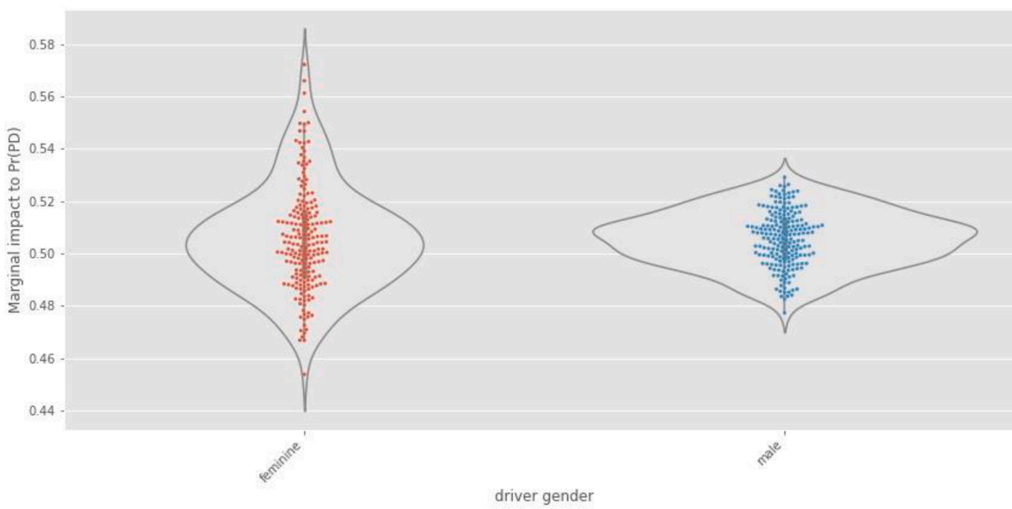

Fig. A.3. Marginal impact to PR for the Driver Age on the PD class.

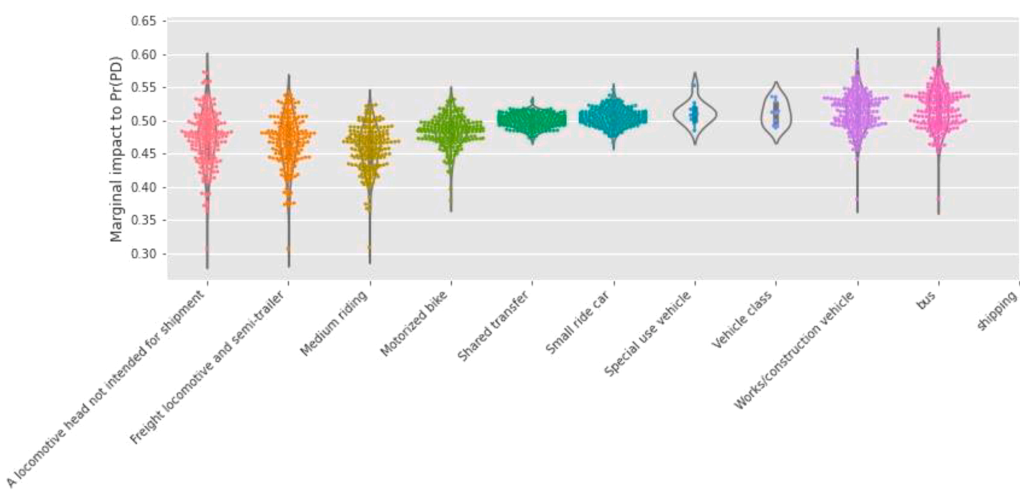

Fig. A.4. Marginal impact to PR for the Vehicle Type on the PD class.

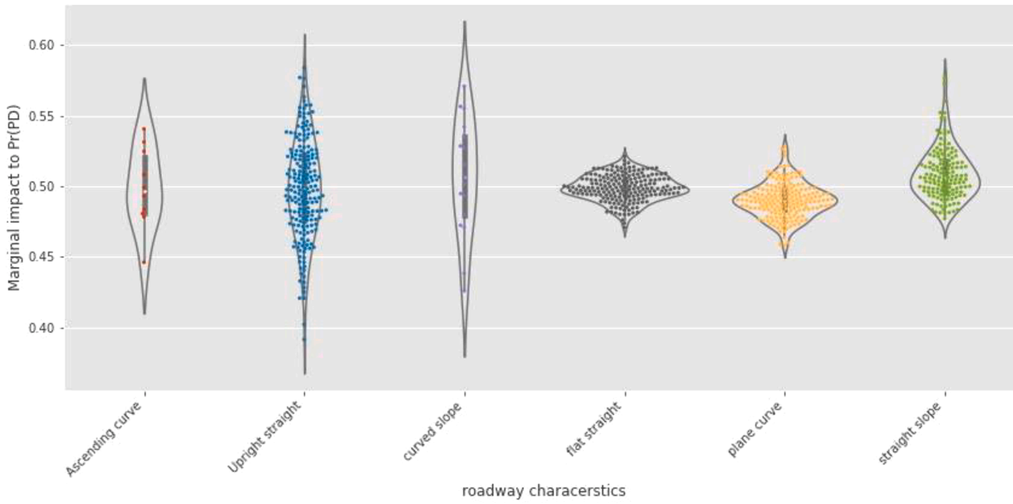

Fig. A.5. Marginal impact to PR for the Roadway Characteristics on the PD class.

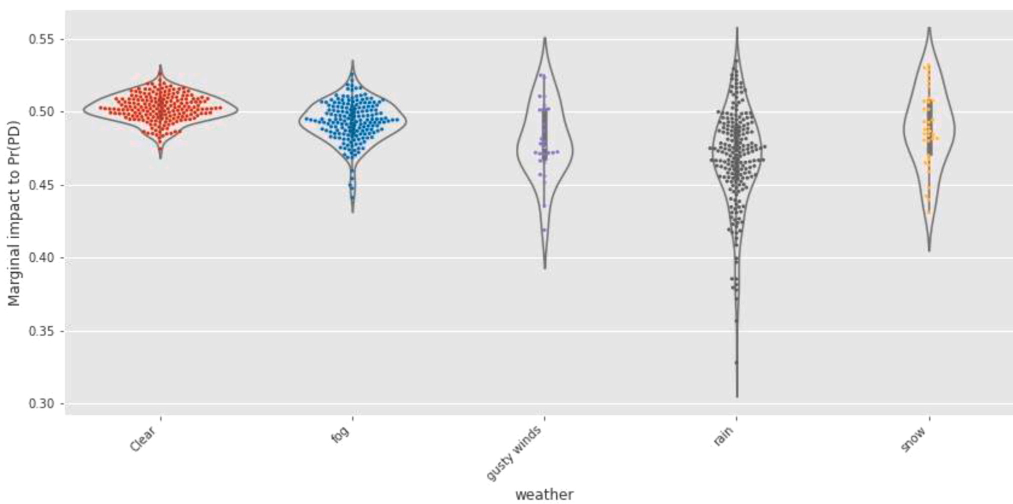

Fig. A.6. Marginal impact to PR for the Weather on the PD class.

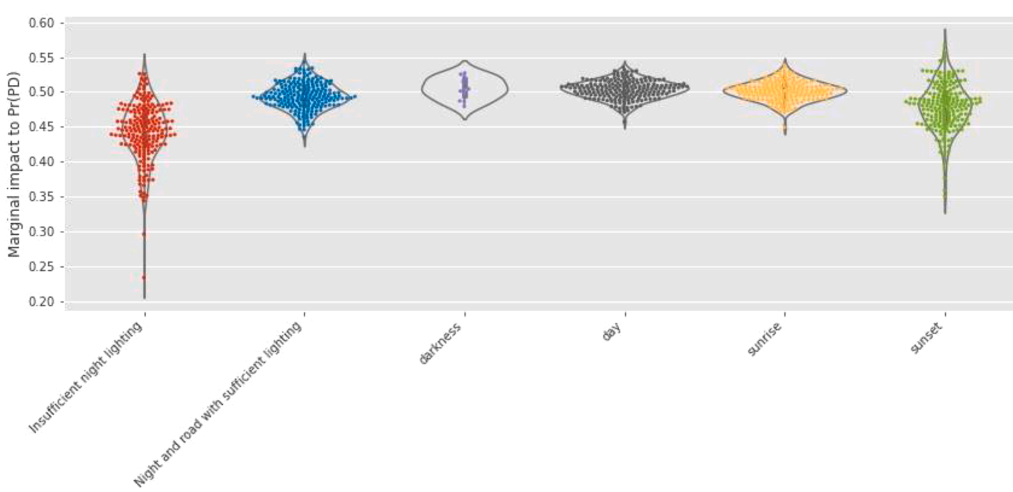

Fig. A.7. Marginal impact to PR for the Lightening on the PD class.

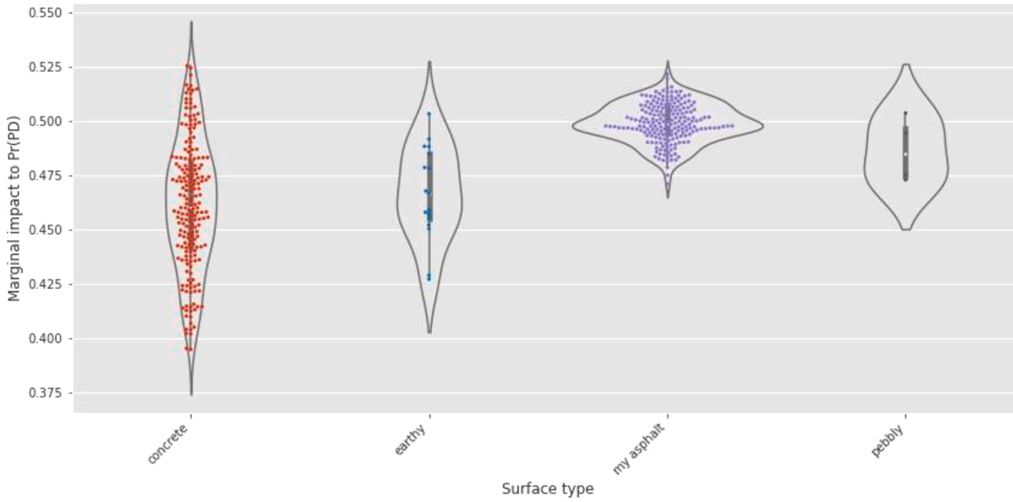

Fig. A.8. Marginal impact to PR for the Surface Type on the PD class.

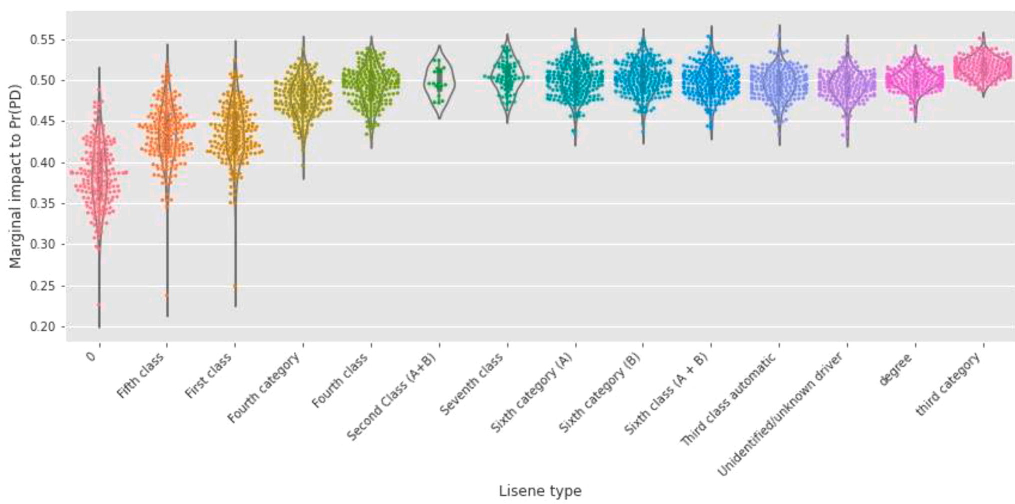

Fig. A.9. Marginal impact to PR for the License Type on the PD class.

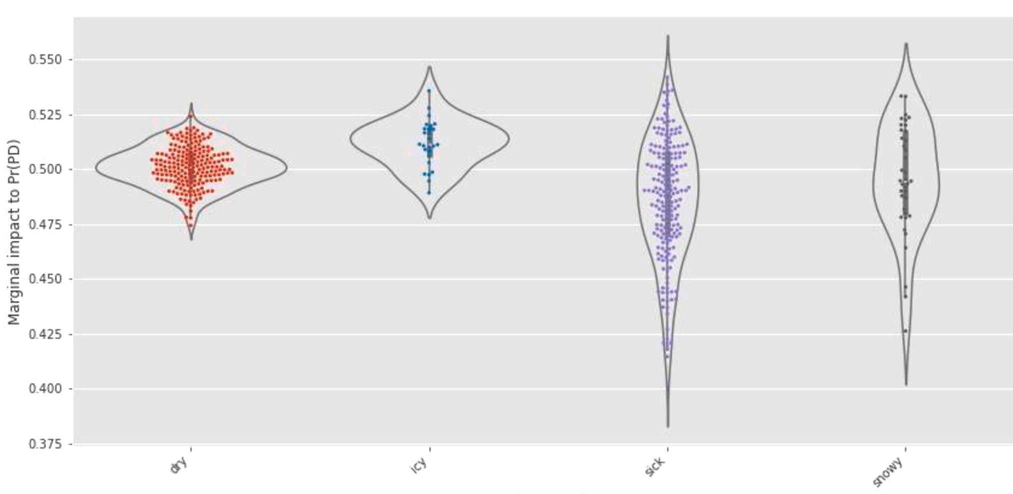

Fig. A.10. Marginal impact to PR for the Roadway Surface on the PD class.

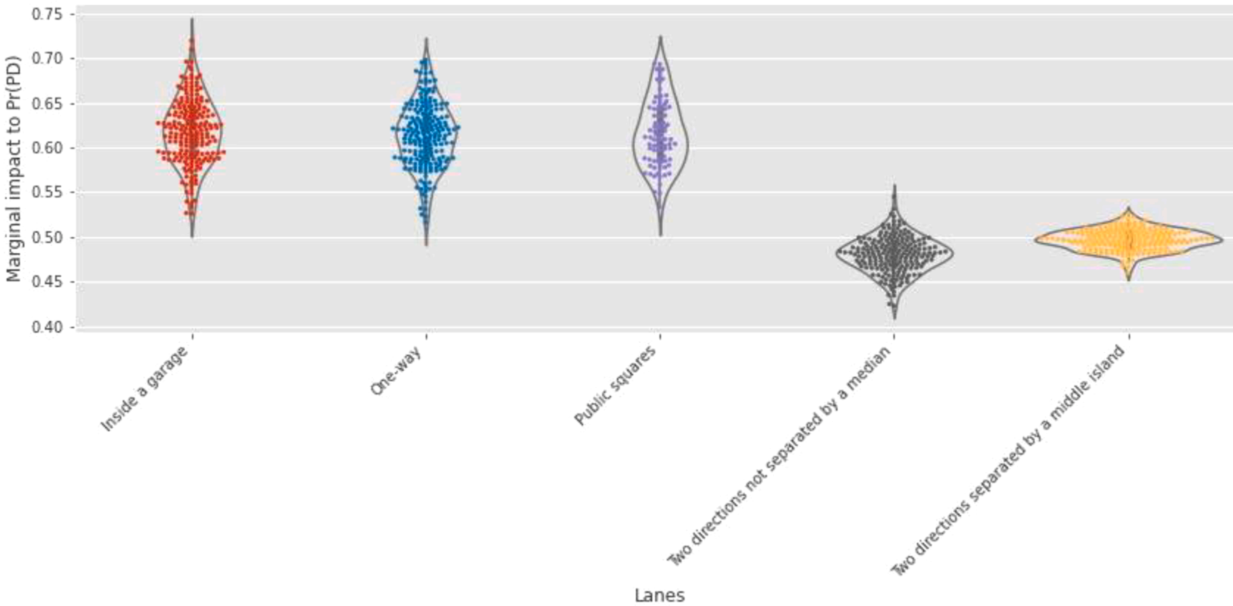

Fig. A.11. Marginal impact to PR for the Lanes Type on the PD class.

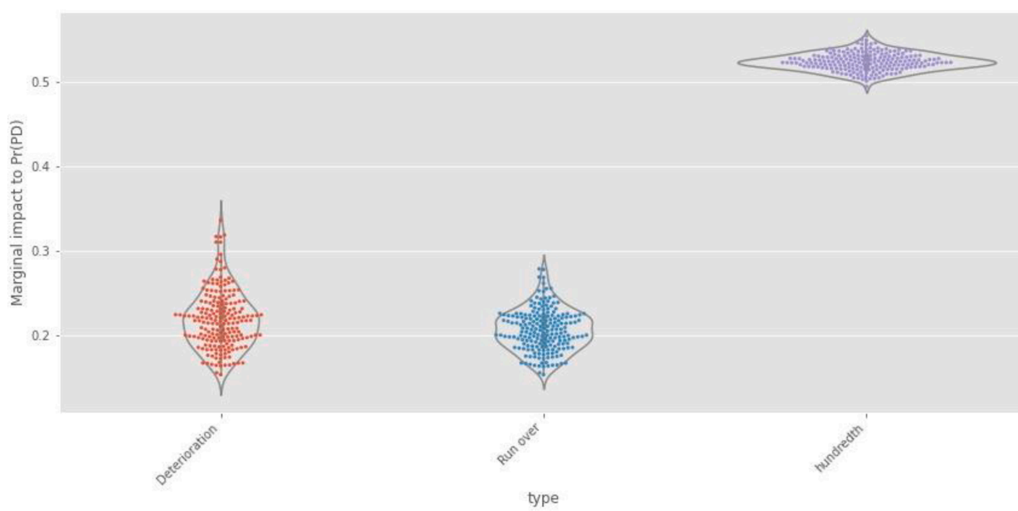

Fig. A.12. Marginal impact to PR for the Crash Type on the PD class.

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