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Studying Traffic Accidents Utilizing a Machine Learning Approach: Case Study of Jordan

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Abstract

Traffic accidents continue to be a significant public safety concern in Jordan, largely due to the many interaction of human, vehicle, road, and environmental factors. The research presented here is based on a data-driven analysis of fatal traffic crashes in Jordan with a comprehensive dataset using a national dataset covering all recorded crashes between 2018 and 2022. Within this dataset, there is detailed information about driver demographics, vehicle characteristics, conditions of the road, environmental factors and accident attributes, providing the necessary information to perform a complete machine learning analysis. Statistical analyses were conducted using the selected features to identify and quantify the relationships most strongly associated with death resulting from traffic accidents. Machine learning models were developed to predict whether an accident would result in a fatal outcome. The most accurate machine learning models were Random Forest and XGBoost, both of which achieved an accuracy of approximately 0.96 overall, while further evaluation using class-sensitive metrics highlighted differences in their ability to identify fatal cases. The analysis used explainable artificial intelligence methods to enhance interpretability. SHAP was used to identify the implications of the different factors leading to fatal accidents on a global basis while LIME was used for local predictions for any given accident. The combination of machine learning and explainable models are highly valuable to improve understanding of the mechanisms of fatal traffic accidents. The findings of this investigation support evidence-based policy actions in Jordan, including targeted enforcement efforts, infrastructure changes, and interventions that address behaviours linked with high-risk driving to minimise fatalities and serious injuries from traffic accidents.

Keywords: *Traffic Accidents, Machine Learning, death prediction, Random Forest, XGBoost, XAI, SHAP, LIME.*

1 Introduction

Accidents are a major problem for public safety throughout the world and result in serious human and economic consequences. An estimated 1.35 million people die each year as a result of road traffic crashes globally, and they are the leading cause of death among people aged 5–29 years, according to the World Health Organization (WHO) [1]. Injuring between

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20-50 million people suffer non-fatal injuries annually, making road traffic injuries one of the leading causes of death and disability across all age groups [2], [3], [4]. In addition, road traffic accidents also create a significant number of economic costs for each country around the world, including money spent on health care for accident victims, repairs/replacement of damaged infrastructure, loss of work productivity, etc., with an estimated worldwide cost of $518 billion per year, up to 3% of the gross domestic product (GDP) of many countries [2].

The published literature shows that there is a serious disparity in road traffic related deaths around the world, with approximately 93% of all road traffic fatalities occurring in low and middle-income countries even though those countries represent about 60% of the total global vehicle fleet [5]. The majority of this extreme inequality in road traffic fatalities is due to the high rate of population growth, increased motorization of low to mid-income countries, and lack of investment in safe transportation systems and infrastructure development and building institutional support [4], [5]. As a result, through more advanced analytical and predictive models and methods used, it has been discovered by researchers that data-driven road safety research is well-suited for examining and optimizing traffic safety interventions and improving predictive accuracy in developing country contexts [3], [5].

Jordan is a significant case in this global framework. Traffic accidents became a significant public issue during the late 1980s to mid-1990s, and became the second leading cause of death in 2007 [6], [7]. The accident records show a sharp rise in the number of accidents from approximately 15,000 per year in the late 1980s to more than 110,000 in 2007, with the number of accidents growing at a disproportionate rate compared with vehicle ownership growth [5]. Statistics recently reported for 2021 indicate an annual cost of traffic accidents to Jordan of approximately 4% of the Jordanian economy; this figure is higher than the average reported across the world. Jordan experienced 160,000 traffic accidents in 2021, of these accidents resulted in 589 deaths and more than 320 million Jordanian Dinar in losses due to financial impacts [7].

The occurrence and severity of traffic injuries/accidents can be attributed to the complex relationships between infrastructure and environmental condition, vehicle characteristics, such as, make and model, and human behavior [8], [9]. However, human behavior is the primary cause of traffic-related deaths and injuries. Statistics show that 90% of all traffic fatalities were caused by human behaviors, including speeding, distracted driving and violation of traffic rules and law [2]. Many fatal traffic accidents within Jordan are attributable to the violation of traffic laws and the act of tailgating or not yielding the right of way in addition, environmental conditions, such as, temperature, light, and moisture, contribute significantly to risk while operating a vehicle, primarily in relation to the ability to see the roadway and control a vehicle. Many studies have been conducted that show the increase in severe accidents experienced during the winter months compared to the summer months. In Jordan, empirical data indicates that winter months have an increased incidence of serious accidents by 23%, due primarily to reduced traction and visibility [5].

Despite the severity and persistence of traffic accidents in Jordan, existing studies remain limited in their ability to model the complex, non-linear interactions among human, vehicle, roadway, and environmental factors using large-scale disaggregated accident data. Past analyses typically depend upon descriptive statistics or traditional regression methods, which do not sufficiently leverage the rich structure of national accident databases nor do they accurately predict serious or fatal crashes. As such, there is strong motivation for data-driven tools that can better analyse the relationships among the various variables in order to enhance predictive accuracy.

To fill this need, this study employs machine learning techniques applied to a comprehensive national traffic accident dataset from 2018 to 2022 in order to identify factors related to crash risk, as well as improve the prediction of crash severity in Jordan. The integration of exploratory data analysis, feature engineering, and advanced classification modelling will further provide a solid basis for targeted enforcement efforts, infrastructure improvements, and behaviour-based interventions to reduce the likelihood of fatalities and serious injuries related to traffic accidents.

In this work, a model for death prediction caused by accidents was implemented using ML algorithms, and XAI SHAPE, and LIME were used to figure out which inputs mattered most among the input features in the data set.

The following sections of this paper will be as follows: related work, the proposed framework, experimentation, results and discussions, and conclusion.

2 Related Work

Instead of viewing accidents as discrete events, recent research suggests that the interactions of the behavioral, engineered systems and environmental factors interact as a socio-technical system and produce the results associated with road safety [5], [6], [7]. This point of view acknowledges the complexity of accident causation as an intricate system of multiple non-linear relationships between variables, thereby highlighting the importance of computational methods that can model this complexity [6]. Specifically, within this context, there is a clear analytical distinction between the number of accidents and the level of severity associated with those accidents. In other words, Accident frequency indicates the sum total number of accidents that occur within an explicitly defined temporal and spatial context, accident severity represents the amount of physical damage inflicted during that accident to the individual involved, defined into four categories: fatal, severe, moderate, and slight [7]. Based upon the body of studies produced through research conducted in Jordan, there is a clear inverse relationship that exists between these two accident metrics, urban areas have high frequencies of accidents, but lower average severities associated with those accidents, urban areas have high frequencies of accidents, but lower average severities associated with those accidents, whereas rural highways and roadways experience lower frequencies, yet substantially greater severity of accidents due to factors related to higher travel speeds and impaired emergency response times associated with these types of roads [5].

The traffic safety research conducted in Jordan has relied primarily upon descriptive/statistical means to investigate accident patterns, accident types and vulnerable road users [5], [10], [11]. The various trends associated with Jordan's traffic accidents in relation to critical periods for traffic accidents, types of accidents, etc. and pedestrian involvement in fatal roadway traffic accidents have been investigated [12]. At the city level, [11] investigated pedestrian accidents in Irbid and found that the majority of pedestrian accidents had occurred at points of mid-block locations during periods of clear weather with male drivers found to be accountable in most cases .[13] Using spatiotemporal clustering of the accidents dataset, showed how traffic management interventions produce evolving hotspots of accidents. Additional studies have examined spatial and temporal accident patterns, identifying seasonal peaks during winter months and elevated severity during late-night hours [5].

Other studies in Jordan have focused on predictive modeling. [14] adopted a macro-level approach by predicting traffic accidents using artificial neural networks (ANN) based on aggregated indicators such as registered vehicles, population, and GDP. Nonetheless, their model was based on aggregation at the country level, which restricts it for generalization in real-time prediction of accident severity. [15] Used neural networks as part of their accident analysis and were limited by only examining temporal trends, making their analysis less interpretable. On the other hand, the study conducted by [16] was limited because it only examined the use of one independent variable (cost) using regression analysis, which does not provide a comprehensive view of the relationships of all other variables.

Additionally, several studies have also investigated traffic safety policies and countermeasures. For example, [14] examined traffic safety policies and interventions through both quantitative analysis (regression) and qualitative analysis (questionnaires) to assess the effectiveness of potential safety improvements such as improved sidewalks, more public transportation options, etc. In examining fatal accidents through evidence obtained from forensics, [10] found that approximately 25% of fatal crashes were attributable to alcohol or psychotropic substances. This indicates that researchers should consider how human behavior affects risks associated with crashes that are not reflected in traditional crash data sources. Investigating public and professional attitudes toward traffic safety, [17] found there were significant differences in perceptions of risk and priority of remedial measures between the general public and professional traffic.

At present, the methods used for assessing the severity of road accidents are regression-based approaches (e.g., logistic regression and ordered probit), which are the most interpretable and provide a strong statistical rationale [2]. However, most of these models only assume linear relationships between predictors and outcomes, and the large volume of accident data makes it difficult for them to accurately capture the high dimensionality, non-linear nature, and diversity of data [3], [4], [6]. accident severity prediction is typically framed as a multi-class classification problem with imbalanced data, where fatal and severe crashes occur less frequently than minor crashes but have much more serious consequences when misclassified [18], [19]. This imbalance presents significant challenges for model training and evaluation, as accuracy-based assessments tend to favor majority classes and underestimate model performance on critical outcomes.

To overcome this drawback while maintaining the ability of a model to provide understandable results, researchers have begun to adopt Explainable Artificial Intelligence (XAI) methodologies [20]. XAI is a relatively new research area that has become a focus of much attention in recent years as a new way of optimizing the prediction capabilities of Machine Learning algorithms [21] for many real-world applications, particularly when predictive accuracy is not satisfactory without transparency or accountability [22], [23]. XAI defines a variety of methods used to maintain high-quality predictive performance while allowing for people to understand, trust and control how the model behaves, distinguishing between interpretability as the passive comprehensibility of a model and explainability as the active procedural clarification of its internal functions [22]. For example, non-linear models commonly used in traffic safety research, such as ensemble or deep learning models, post-hoc explainability techniques are especially relevant [24]. Among these, feature attribution methods such as SHapley Additive exPlanations (SHAP) have become widely adopted due to their ability to quantify the contribution of individual variables to specific predictions in a theoretically consistent manner. Within accident severity predictions, XAI methods will be critical in identifying the dominant contributing risk factors in the development of policy decisions that affect accident severity [24], [25].

Internationally, researchers have applied XAI methodologies as an alternative to traditional regression methods when attempting to predict the occurrence of fatal traffic accidents [22], [24], [26]. These studies have further established that transportation safety systems are of critical concern and due to their inherent complexity lack the level of interpretive safeguards needed to be ensure proper protection of the public and continuity of safe transportation practices [26]. Recent research has therefore employed explainable deep learning and ensemble models to analyze crash severity under severe class imbalance, where fatal crashes constitute a small yet socially critical proportion of the data. Using XAI techniques, [24] had identified the combination of vehicle speed, lighting conditions and vehicle type as the leading predictors of fatal and severe crash instances and, thus show, how through intervention methodologies that were based on traditional statistics of crash severity were not able to uncover non-linear risk interactions.

In Jordan, a series of recent studies have adopted machine learning techniques to national-scale datasets on accidents, with growing emphasis on explainability for safety-critical decision-making. The work by [5] utilized XGBoost to predict accident severity with 87.1% accuracy, identifying the most important predictor to be weather, Using the JO-Traffic-Accidents Dataset (JO-TAD). Using multiple classifiers, [27] evaluated various classifiers and found that Multinomial Logistic Regression was the most accurate method, achieving 98.1% accuracy, highlighting vehicle speed, road geometry, and lighting conditions as key severity determinants. In order to address the severe class imbalance in pedestrian data, a modified version of XGBoost known as the Balancing Loss Function − XGBoost was developed by [24] that resulted in 95% true positive rate across all injury categories. In addition, according to [24], high speeds, heavy vehicles, and poor lighting conditions represent the greatest levels of risk through the use of XAI Tools, employed by SHAP and LIME. The results of the temporal analyses indicate that Risk Severity has decreased after 2020, indicating that the increased stringent laws that have been implemented.

While all of the studies and investigations add significantly to the existing body of knowledge regarding accident prediction through the use of machine learning in Jordan, however, no single cohesive framework exists to use ML based XAI models to effectively facilitate evidence-based interventions for roadway safety. Current studies are constrained by the use of aggregated data, linear modeling assumptions, and a lack of machine learning applications that can identify non-linear interactions between risk factors. The purpose of this study is to address these gaps by providing a method to improve the accuracy and interpretability of accident severity predictions in Jordan through the application of Machine Learning techniques. A summary of the studies that have previously published results related to accident predictions in Jordan is provided in Table 1.

Table 1. Comparison of ML Models in Accident Death and Severity Prediction

Ref.	Study Scope	Methodology	Severity / Fatality Focus	Main Findings Related to Death or Severity
[5]	Jordan (national)	XGBoost, statistical analysis	Accident severity	Urban areas have higher frequency but lower severity; rural/highways show higher severity. Winter months have 23% higher severe crash rates; weather is a dominant predictor. XGBoost showed 87.1% accuracy while Random Forest (85.3%).
[6],[7]	Conceptual / international	Socio-technical, computational models	Severity vs. frequency	Severity arises from non-linear interactions between behavioral, engineering, and environmental factors.
[10]	Jordan (forensic)	Forensic analysis	Fatal accidents	About 25% of fatal crashes involved alcohol or psychotropic substances.
[11]	Irbid city	Descriptive statistics	Pedestrian severity	Most pedestrian accidents occurred mid-block; male drivers frequently responsible.
[12]	Jordan	Trend analysis	Fatal accidents	Pedestrians account for a significant share of fatal accidents; critical periods identified.
[13]	Jordan	Spatiotemporal clustering	Severity hotspots	Traffic interventions shift spatial and temporal severity hotspots.
[14]	Jordan (macro-level)	ANN, regression	Severity (indirect)	Aggregated models predict trends but lack real-time or severity-level fatality prediction.
[15]	Jordan	Neural networks (temporal)	Severity trends	Limited interpretability; severity analyzed only temporally.
[16]	Jordan	Regression (single variable)	Accident severity	Use of one variable limits understanding of fatal and severe crash factors.
[17]	Jordan	Survey-based	Perceived severity	Public and professionals differ significantly in perceived risk and priorities.
[23]	Jordan & international	XGBoost + XAI	Fatal and severe injuries	95% TPR for fatal/severe injuries; speed, heavy vehicles, and poor lighting are key risk factors.
[26]	Jordan (national)	Multinomial Logistic Regression	Accident severity	98.1% accuracy; speed, road geometry, and lighting strongly influence severe and fatal crashes.

In comparison to existing researches, the present research uses a nationwide dataset of all recorded traffic accidents across a four-year period for all cities in Jordan, with a rich set of explanatory features. The included data set has a very broad set of predictor variables to enable reliable and accurate predictions of the number of fatalities.

3 The Proposed Framework

Accident severity is assessed in a system framework based on a systematic approach illustrated in Figure 1. The first step is data preprocessing to examine the trends/relationships among between critical accident variables: such as demographic characteristics of the driver, vehicle characteristics, roadways, environment, and accident aspects. The integrity of the dataset is maintained the imputation of missing and inconsistent values.

In addition, for compatibility with machine learning models, categorical variables are encoded, while numerical features are normalized to improve model performance and interpretability. Once data is preprocessed, feature engineering and feature selection is done, where data is processed prior to modeling, and not all predictors are used in the modeling.

We derive the most significant relationships between independent variables and accident severity using correlation analysis and feature importance ranking techniques. Hence, extracting the relevant variables, which can be a wildcard for reducing redundancy, is crucial.

Second, machine learning models are created and deployed to classify the severity of the accident. Our MLR is used as the baseline model, which is simple and interpretable, meaning that it provides probabilistic relationships between the predictor variables and the four possible categories for accident severity (i.e., fatal, severe injury, moderate injury, and slight injury) up to October 2023. However, as MLR has limitations from the assumption of linear relationships, a random forest (RF) model is also applied to the dataset. Since RF shows very high performance for freeform associations and deals very well with high-dimensional data, it effectively models complex relationships within the traffic system. In addition, the feature importance ranking by RF is employed to find out about the specific risk factors and resultant behaviors that contribute to the severity of such events. This methodological approach has already been successfully applied in different contexts. For example, Wang et al. (2013) analyzed road traffic accident severity in the UK based on multinomial logistic regression (MLR) and random forest (RF). The predictive capabilities of RF methods were superior to those of multiple linear regression (MLR) models when tested using accident data from the Department for Transport, United Kingdom; MLR models could still provide an easily interpretable probabilistic representation of the relationship between the risk factors of accident severity provided by the RF models. The authors demonstrated that the major risk factors for accidents included lighting conditions, speed limits, and age of the driver; thus, it is likely that these models will provide good generalizations when applied to other data sets to predict accident severity.

Finally, the analysis also integrates driver fault classification. Thus, this approach allows for both understanding of what is going on interpretively and also provides an opportunity for actionable insights and the creation of practical solutions in terms of policies. We present a multi-level taxonomy that partitions driver faults into four categories: recognition error, decision error, performance error, and violation of law. The study provides methods for identifying driver's behaviors showing severe risk-taking that may result in accidents. Additionally, the analysis includes classification of the risk of accidents and establishes a ratio of a driver fault ratio and a risk ratio. In addition to creating the predictive model, the logged data is an input for the design and implementation of a targeted intervention plan to reduce driver error, increasing the level of safety on public roadways.

Therefore, this method is appropriate for designing a multifaceted, evidence-based framework to identify contributing factors to crash severity and ultimately support the development and implementation of effective traffic safety policies and interventions based on both infrastructure and driver behavior in Jordan. The following figure 1. Shows the methodological framework for death prediction of traffic accidents in Jordan.

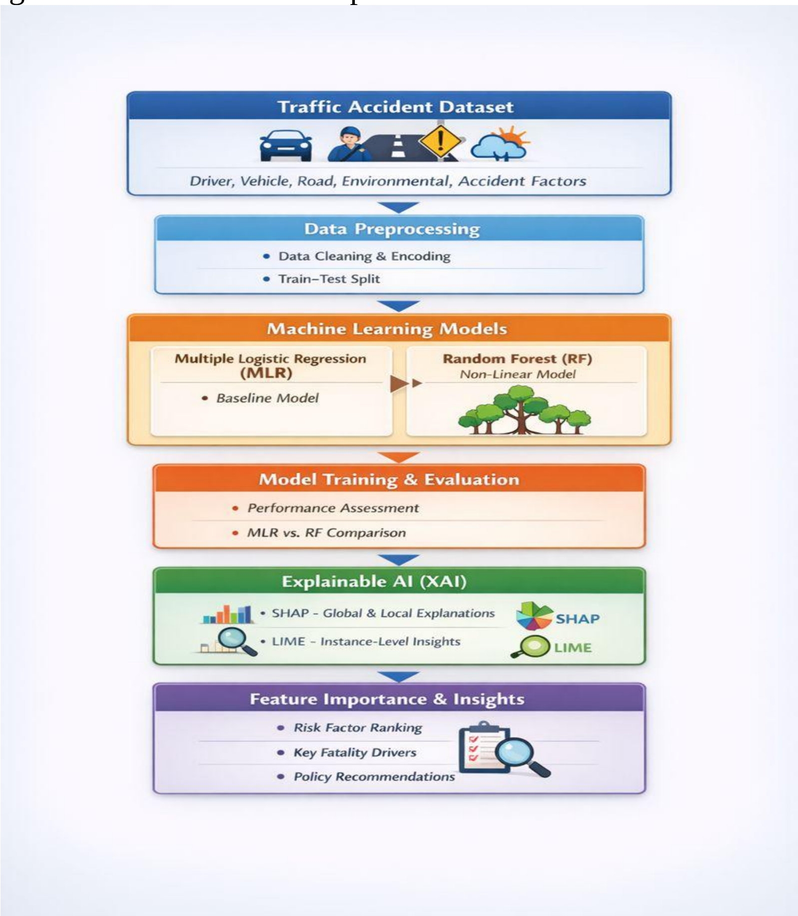


Figure 1: A Methodological Framework for Predicting Traffic Accident Fatalities

4 Experimentation

The analysis is based on a nationwide dataset, which aggregates records of all traffic crashes from 2018 to 2022, collected through the Memorandum of Understanding between Al-Balqa Applied University and the Jordanian Public Security Directorate. In addition, ongoing communication was established with the Traffic Force, Vehicle Licensing Agency and the Information Technology departments within the Jordanian Public Security Directorate. The data includes driver demographic (age, sex, licence type, fault classification); Vehicle characteristics (type and year of manufacture); Road characteristics (number of lanes, layout of lanes, road surface type, nighttime light and speed limit). Environmental factors such as: weather conditions, and time of the day; accident conditions include: gravity, classification, and the number of vehicles involved. the dataset used in this research project consists of all road traffic accidents in Jordan between 2018-2022. A comprehensive preprocessing of the dataset helped maintain quality and reliability. While many attributes were originally documented in Arabic, they were translated into English in order to facilitate their inclusion into the various data analytic software tools. To enable training of models using various techniques, categorical data was converted to numerical representations.

During the cleaning process, missing and incomplete entries were identified, including absent demographic information such as driver gender, as well as missing vehicle and driver-related fields such as license issue and expiration dates. In addition, erroneous entries were detected in some date fields (e.g., default values such as the year 1900), which were removed to prevent distortion of the analysis. Inconsistent and ambiguous string values such as road lighting conditions were standardized and encoded numerically.

All data cleaning, transformation, and encoding procedures were performed with the objective of improving data consistency and maximizing the predictive performance of the proposed traffic accident fatality prediction model. Table 2. Shows all items in the collected data and their category description as follows:

Table 2. List of all features and their categories.

Variable	**Description**
ID	Unique ID for each accident
Date	Date and time
Speed	The posted speed limit of the roadway at the location where the accident occurred in km/h.
Fatalitites	The total number of fatalities resulting from the accident.
Severe_Injuries	The total number of severe injuries resulting from the accident. .
Moderate_Injuries	The total number of moderate injuries resulting from the accident.
Slight_Injuries	The total number of slight injuries arising from the accident.
Roadway_Lanes	"One-way"; "Two directions not separated by a central island"; "Two directions separated by a central island"; "Inside a garage"; "Public squares".
Roadway_Surface	"Snowy"; "Dry"; "Icy"; "Sandy"; "Oily"; "Wet"; "Clay"
Vehicle_Nationality	The origin or registration of vehicles.
Driver_License_Type	1: "Unknown Driver"; 2:"Category 1-Motorcycle"; 3: "Category 2A-Construction Vehicle"; 4: "Category 2B-Agricultural or Construction Vehicle"; 5: "Category 3A: Private Passenger Car with Manual Gearbox"; 6: "Category 3B: Private Passenger Car with Automatic Gearbox"; 7:"Category 4: Public Passenger Car"; 8: "Category 5: Medium Bus"; 9: "Category 6A: Locomotive and Trailer or Head of Locomotive and Semi-Trailer"; 10: "Category 6B: Bus"; 11: "Categories 6A and 6B"; 12:"Category 7: Accessible Vehicle"; 13: "Trainee".
Governorate	1: "Irbid", 2: "Balqaa", 3: "Zarqa", 4: "Tafeelah", 5: "Amman", 6: "Aqaba", 7: "Karak", 8: "Mafraq", 9: "Jarash", 10: "Ajloun", 11: "Madaba", 12: "Maan".
Vehicle_Type	1: "Bus", 2: "Motorcycle", 3: "Tractor Unit ", 4: "Medium Bus", 5: "Passenger Car", 6: "Cargo Vehicle", 7: "Cargo Tractor and Trailer", 8: "Cargo Tractor and Semi-Trailer", 9: "Construction Vehicle", 10: "Special Use Vehicle", 11: "Agriculture Vehicle", 12: "Trailer", 13: "Semi-Trailer", 14: "Public Transport Vehicle".
Roadway_Type	0: "Wood", 1: "Asphalt", 2: "Cement", 3: "Soil", 4: "Gravel", and 5: "Metal".
Lighting_Condition	1: "Dawn", 2: "Darkness", 3: "Sunset", 4: "Night with Insufficient Lighting", 5: "Night with Sufficient Lighting", and 6: "Daytime".
Weather	1: "Snow", 2: "Stormy Winds", 3: "Clear", 4: "Fog", 5: "Dust", and 6: "Rain".
Roadway_Characteristics	1: "Straight and Uphill", 2: "Straight and Level", 3: "Straight and Sloping", 4: "Curved and Uphill", 5: "Curved and Level", and 6: "Curved and Sloping".

Accident_Type	1: "Rollover", 2: "Runover", and 3: "Collision".
Driver_Gender	1: "Male" and 2: "Female"
Driver_License_Year	The year in which the driver first obtained their driver's license.
Vehicle_Make_Year	The year in which the vehicle was manufactured.
Number_Vehicles	The number of vehicles involved in the accident.
Day	1: "Sunday", 2: "Monday", 3: "Tuesday", 4: "Wednesday", 5: "Thursday", 6: "Friday", and 7: "Saturday".
Year	The year of accident occurrence
Driver Age	The age of the driver in years

4.1 Dataset Statistics

The following subsection shows different statistics that have been extracted from the data. These statistics have been grouped according to the feature types. The figures presented in this section are structured into six analytical categories that collectively support a systematic transition from descriptive characterization to outcome-oriented assessment as follows:

Table 3. Analytical Categories of the statistical analyses

Category Number	Category Name	Figures represented
1	Driver and vehicle characteristics	Fig 2, 3, 4.
2	Roadway characteristics	Fig 5.
3	Accident severity and demographic interactions	Fig 6.
4	Fatality risk and outcome-oriented patterns	Fig 7,8.
5	Accident Configuration and Exposure Characteristics	Fig. 9.
6	Spatial and temporal distributions of accidents	Fig 10, 11, 12.

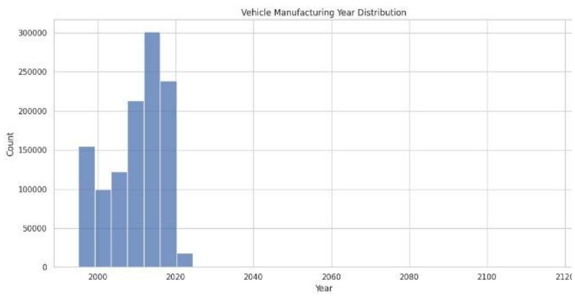
The following are the disruption of the figures presented based on the analytical categories.

1. Driver and Vehicle Characteristics

This section highlights two of the most commonly referenced driver and vehicle attributes related to traffic accidents (the year the vehicle was manufactured, the driver's age) that are frequently referred to in the literature as contributing factors in the occurrence and severity of the accident. The accident data is illustrated in Figure 2 is the number of accidents according to the year the vehicle was manufactured. The results typically show a higher involvement of relatively older vehicles compared to newer ones. Figure 3 illustrates the number of accidents based by age group of the driver(s) that were involved. The greatest portion of accidents is commonly within the young/middle-aged groups of drivers, who usually drive more frequently and require greater mobility. Young drivers are also over-represented statistically in crash statistics due to their inexperience as drivers, willingness to engage in risky behaviors, and lower levels of hazard perception skills.

Figure 4 disaggregates driver age groups by accident severity. The figure indicates that severe and fatal outcomes tend to be more pronounced at the extremes of the age spectrum, namely younger and older drivers. Younger drivers generally engage in dangerous driving behaviors (e.g., aggressive driving, speeding) which increases their risk for high-severity accidents, while older drivers infrequently and typically sustain more severe injuries due to their higher level of physical vulnerability and reduced capabilities to respond to danger. This dual effect is being used as an inclusion of driver age as a key explanatory variable in severity prediction models. The general pattern of distribution of driver Age corresponds to the higher likelihood that the accident will occur for the economically active Age group(s), therefore, highlights the importance of driver exposure in regards to accidents. The continuous formulation of the age variable permits the representation of non-linear processes that exist across the age of an individual and the probability of being injured in a crash. Thus, the continuous representation of the variable is expected to facilitate better modeling of the relationship between age and accident severity than could coarse grouping of age categories

Finally, the data patterns depicted in Figures 2–4 demonstrate that both the age of the driver and the year in which the vehicle was manufactured are both significant contributing factors to the outcome of a traffic accident and have strong theoretical and empirical support for inclusion in predictive models and corresponding explainable AI.



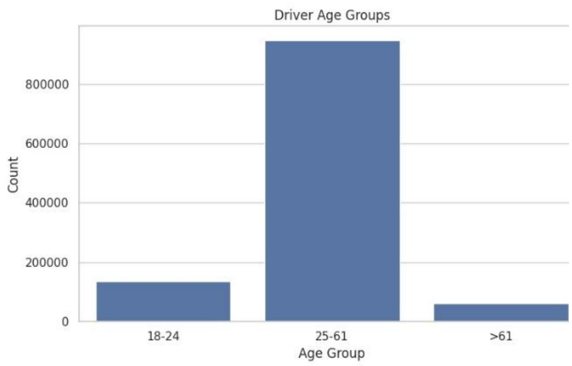


Figure 2. Vehicle Manufacturing Year Distribution

Figure 3. Driver Age Groups

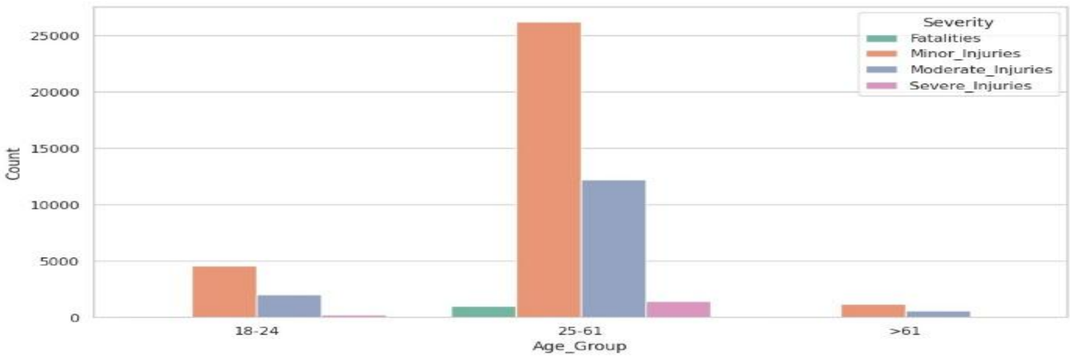


Figure 4. Driver Age Groups divided by Severity

2. Road Characteristics

This section is focused on the road condition associated with a traffic accident with a specific focus on the road surface conditions. The physical and contextual characteristics of the environment in which the accident occurs will continue to be significant contributors to both crash frequency and crash severity in both traditional methods (i.e., statistical models) and machine learning methods. Accidents are predominately found on urban roads and arterial roads, which are characterized by high volumes of traffic and repeated interaction between vehicles, pedestrians and roadside activities, as indicated in Figure 5. In contrast, crashes on highways and rural roads, although fewer in number, tend to be more severe due to higher operating speeds and longer emergency response times.

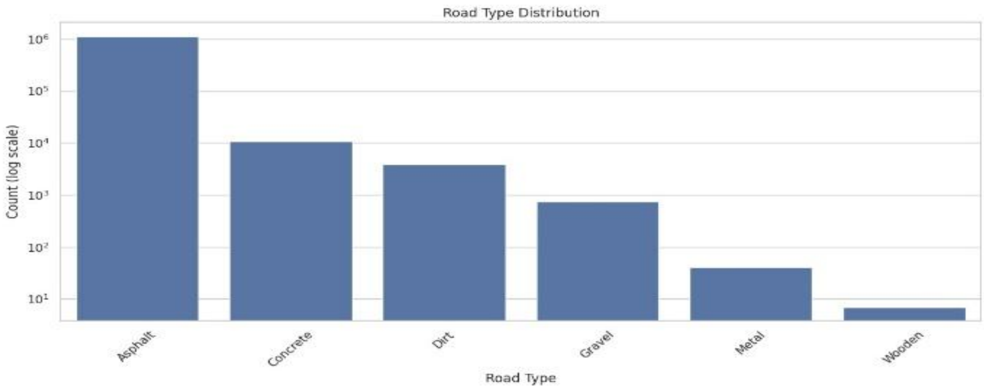


Figure 5. Road Type Distribution

3. Accident Severity and Demographic Interaction

Figure 6 shows Severity of Accidents by Age Group of Driver, Gender Segregated. The results indicate significant differences in severity between demographic groups. Within Gender/Sex, Male Drivers generally have a higher percentage with Severe & Fatal Accidents across the majority of Driver Age Groups. This higher participation rate within Male Drivers is generally attributed to the greater Percentage of Exposure, more frequent Speeding Events, Greater Aggressive Driving Behaviors, and a Greater Tendency to take Risks as compared to Female Drivers. Also, there are significant differences related to Age. Younger Drivers (Male/Female) Highest Severity Outcomes are greater when compared to older Drivers, as the Younger Drivers have Lower Experience Levels and tend to Overestimate their Driving Skill Level. The Older Driver Age Groups have higher levels of injury severity but lower crash rates, indicating that older Drivers are more physically fragile and have a lower tolerance to the forces of crashes. The Age by Gender interactions indicate that demographic factors do not work independently but in tandem to determine the severity of an accident, thus providing further justification for the use of interaction aware modeling approaches.

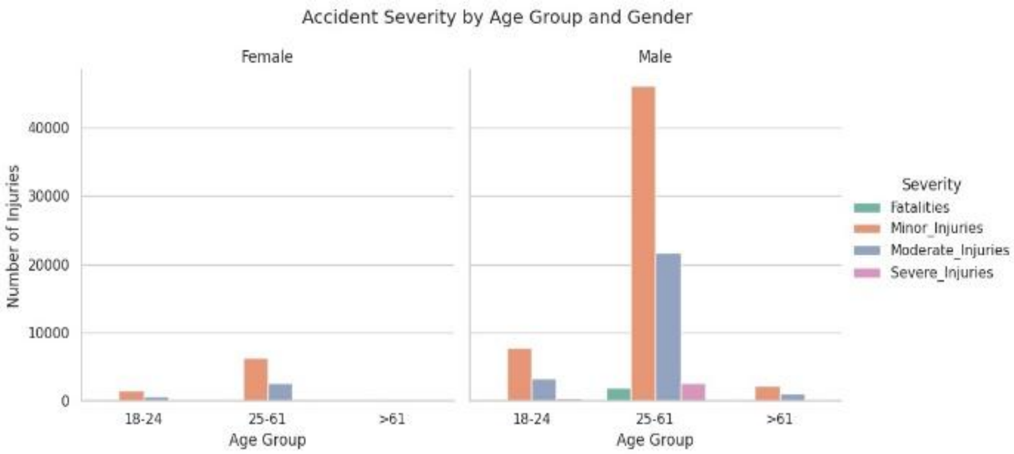


Figure 6. Accident Severity by Age Group and Gender

4. Fatality Risk and Outcome-Oriented Analysis

Furthermore, Figure 7 clearly illustrates the massively different number of fatal injuries that occur to drivers at different times of the day. When the accident occurs under dark conditions and without the benefit of street lighting, those drivers have the highest rates of fatality from that crash. The next most frequent types of accidents to have a fatal outcome are those that occur under dark conditions with inadequate amounts of available lighting. Accidents that occur during daylight generally have far fewer deaths than those that take place at night. This is consistent with the results found in the literature on road safety, which indicates that being able to see your surroundings clearly increases your chances of responding more quickly in case of a crash, thereby reducing the amount of injury sustained by that individual involved in the accident.

Figure 8 presents the interaction between vehicle type and accident type in shaping fatality risk. The results demonstrate that fatal crashes involving large vehicles (trucks and buses) are substantially higher than fatal crashes involving only passenger cars, particularly when the crashes are head-on or when they involve non-motorized road users (pedestrians). The greater mass and momentum of large vehicles creates greater forces on collision and causes more severe injuries than passenger vehicles. Conversely, passenger car–to–passenger car accidents are typically less likely to cause fatalities, especially in non-frontal or side-swipe crash configurations. However, there are much greater rates of fatalities in pedestrian crashes or motorcycle crashes involving passenger vehicles than in crashes involving only passenger vehicles, therefore indicating that unprotected road users are at a significantly greater risk of fatality.

From a policy and planning standpoint, this figure reinforces the importance of vehicle-specific and collision-type–specific interventions, such as traffic calming in mixed-traffic environments, separation of heavy vehicles from vulnerable road users, and targeted enforcement on corridors with high heavy-vehicle traffic. In the context of the machine learning and XAI framework adopted in this study, the strong interaction effects observed here explain why vehicle type and accident configuration consistently emerge as dominant predictors of fatal outcomes in SHAP and LIME analyses.

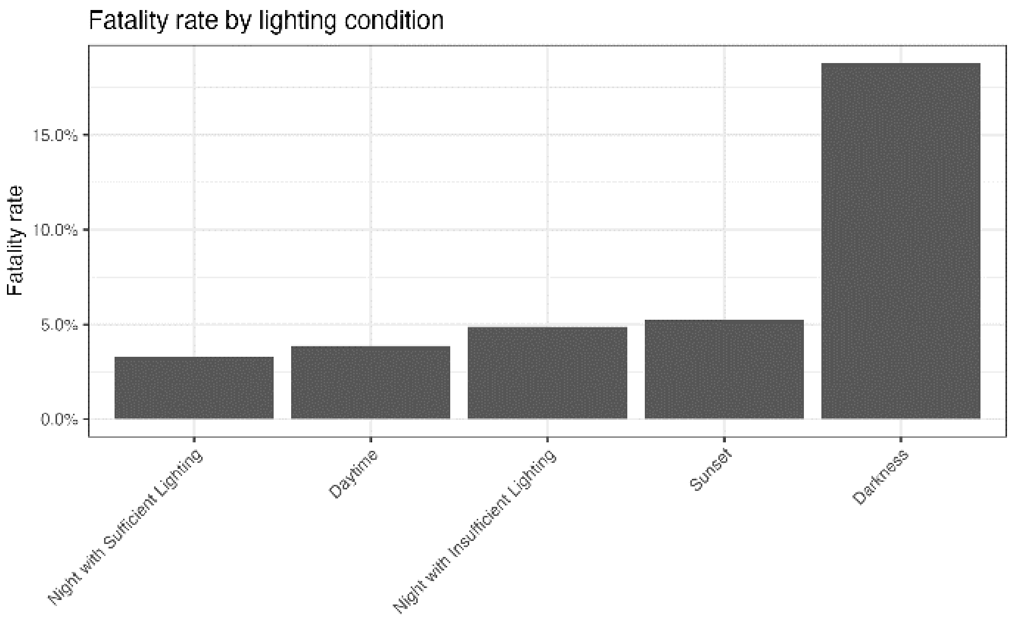


Figure 7. Fatality rate by lighting condition

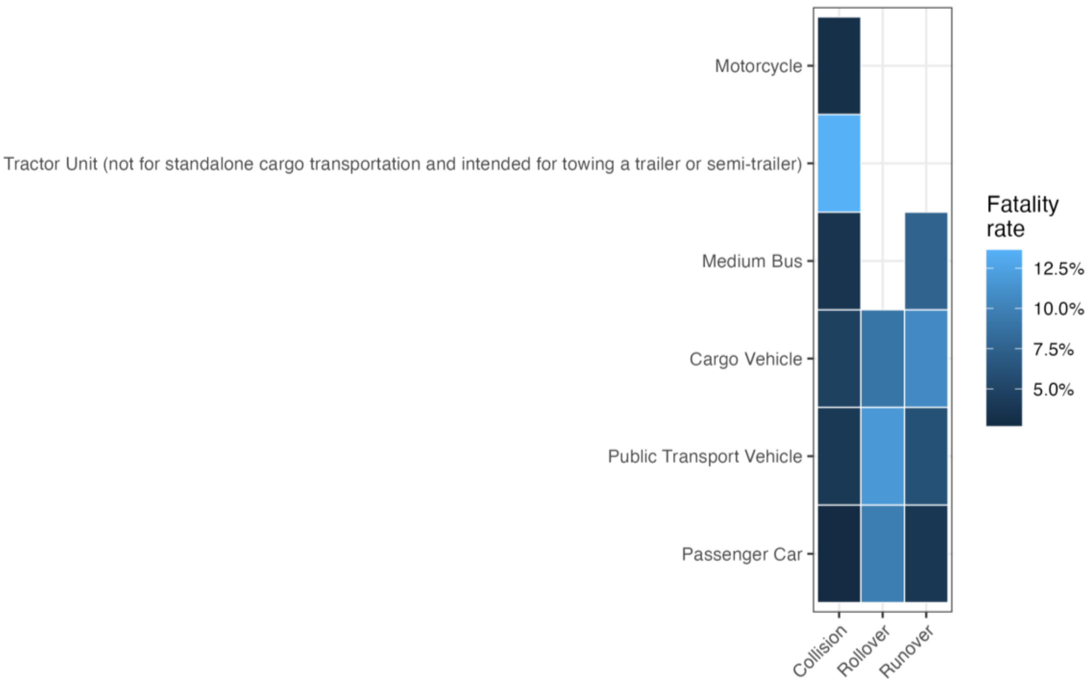


Figure 8. Fatality risk by vehicle type and accident type

5. Accident Configuration and Exposure Characteristics

The distribution of accident types based on number of vehicles involved Figure 9, shows the important characteristics of exposure and configuration that are associated with the outcome of traffic accidents. The findings show that single-vehicle crashes have the highest proportion of total crashes. Single-vehicle crashes are typically the result of loss of control due to excessive speed, driver fatigue, or due to environmental or roadway-related factors. These crashes are frequently found in rural areas or at times when the environment is not conducive to safe driving conditions. Single-vehicle accidents are generally considered to have a higher probability of severity and fatality than other types of vehicle accidents, as single-vehicle accidents often include the collision with fixed objects, rollover events, or high-speed departures from the roadway. For example, two-vehicle crashes represent the majority of multi-vehicle accidents; typically associated with interaction-based conflict types (e.g., rear-end, side-impact, and head-on collisions). The three main factors that have the greatest effect on the severity of two-vehicle crashes include traffic volume, intersection density, and driver behaviour, although the severity will vary greatly depending on the speed of the vehicles involved, types of vehicles, and collision angles. Three or more vehicle crashes happen less frequently; however, when they occur, they usually represent very complex exposure conditions such as heavy vehicle traffic congestion, reduced headway, and/or adverse visibility conditions. Although such crashes may individually exhibit lower fatality probabilities compared to single-vehicle crashes, their cumulative impact is significant due to the higher number of road users exposed and the potential for secondary collisions.

From an analytical perspective and focus on outcomes, the total number of vehicles in an accident acts as an incredibly valuable measurement tool for both traffic exposure and complexity of vehicle-to-vehicle interaction. This study's machine learning methodology has demonstrated that this variable provides valuable contextual data that will help accurately differentiate between high-risk isolated-event crashes and high-risk crashes that occur as a result of an interaction between two or more road users through the use of explainer-based analyses of machine learning-based crash models.

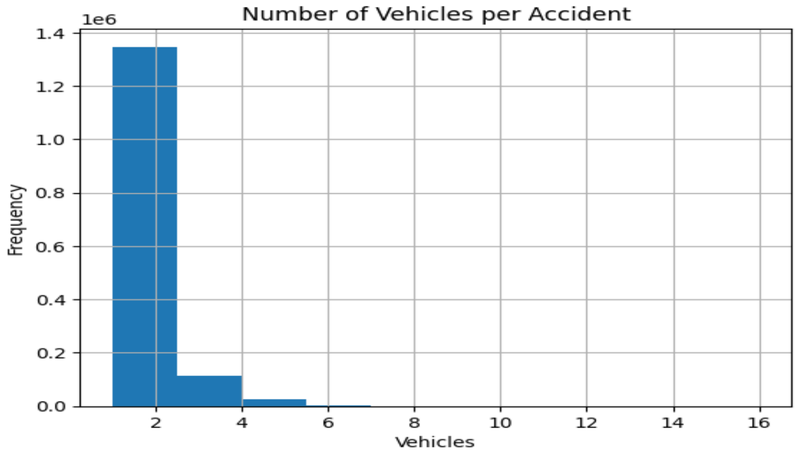


Figure 9. Number of Vehicles Involved per Accident

6. Spatial and Temporal Distribution of Accidents

In the following section, the analysis of the temporal evolution and spatial concentration of the traffic accident statistics in Jordan, based on the annual trends and governorate-based distributions, has been conducted. The examination of these accidents by both time and space helps to provide necessary context in relation to fatality risk, as well as exposure patterns and regional variability, enabling an evidence-based approach to targeting safety intervention efforts. The annual distribution of traffic accidents in the specified time period is shown in Figure 10. The temporal trend generally follows year-to-year fluctuations due to changes in traffic volume, enforcement intensity, socio-economic conditions, and catastrophic events.

The temporal trend and spatial clustering of traffic accidents in Jordan are explored in this section, through annual rates as well as governorates. Analysis of fatal accident rates, exposure patterns, and regional differences over time is fundamental for interpretation of fatality risk; it allows a safety intervention targeting based on evidence. Figure 10 demonstrates the distribution of traffic accidents by year throughout the period covered in the analysis.

Accidents in Jordan, like those in most other countries, continue to increase resulting from increases in population and vehicle ownership. Short-term decreases in the total number of accidents may occur during periods of reduced mobility or increased enforcement. As a safety analysis tool, annual trends are useful in separating much of what might appear to be trends of structural change from random variation. Conversely, long-term trends can help to determine the success of national road safety strategies, vehicle safety improvements, and/or improvements to infrastructure, while variations from these long term patterns may serve as indicators of extreme external shocks or changes to public policies.

Several studies emphasize the need for temporal aggregation when identifying whether the changes in traffic crash outcomes are persistent or transient. Accordingly, within predictive modeling, year and temporal indicators often capture latent factors related to system-wide changes that are not directly observed in other variables. Figure 11 presents the spatial distribution of traffic crashes across Jordanian governorates. As shown in the figure, crashes are concentrated mainly in highly urbanized and populated governorates with many of these locations hosting major metropolitan areas and regional transportation corridors.

This spatial pattern is largely driven by exposure. The density of people, traffic volume, and intensity of land use all contribute significantly to the amount of interaction between vehicles and the potential points of conflict between them. While regions with higher densities tend to have a greater number of crashes, there is no direct correlation between the geographical concentration of accidents and the risk of having a fatal accident per crash. The findings of many research projects support the fact that most motor vehicle accidents happen in urban areas, while more people die from accidents in rural areas or locales that have low population densities because of increased speed limits, lack of access control, and greater amount of time elapsing before emergency services respond. Therefore, governorate-level analysis is essential for differentiating between accident frequency and accident severity.

From an analytic perspective, a machine learning-based approach using spatial variables is particularly useful since they represent the regional variation in quality of infrastructure, enforcement strategies, and driving cultures. When they are combined with explainable AI techniques such as SHAP and LIME. This governorate-level approach will also provide insight into how specific localities contribute to the overall number of fatal motor vehicle accidents and, therefore enable the development of more targeted road safety interventions through geographically based policies.

Figures 10,11,12 illustrate how traffic accidents occur both temporally and spatially within Jordan, indicating that including time and geography into fatality prediction modelling will help to predict the fatality's causes and ultimately to implement effective geographical interventions to reduce traffic accidents. By including both the temporal and spatial elements in the prediction models will not only improve their explanatory strength but will also lead to more effective and better targeted interventions away from the location of the fatality.

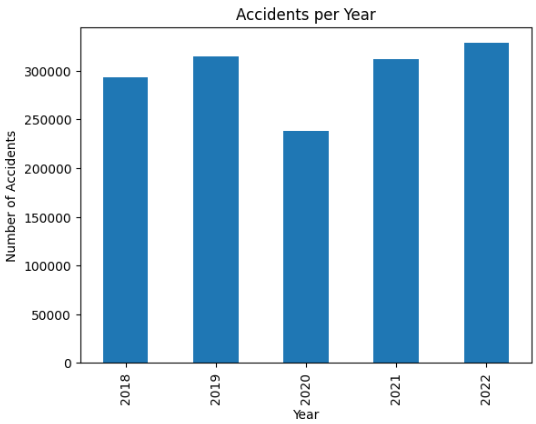


Figure 10. Annual distribution of traffic accidents in Jordan

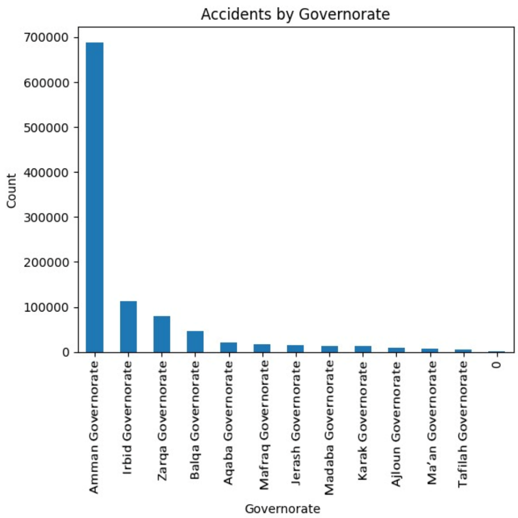


Fig 11. Traffic Accidents by Governorate

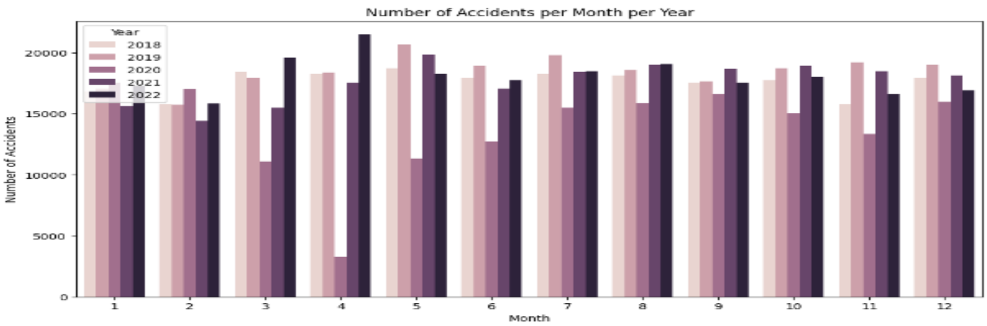


Figure 12. Monthly Distribution of Traffic Accidents by Year

5 Results and Discussions

In this section, results from the classification models will be summarized and discussed. For reference, Table 4 contains performance metrics for both the Random Forest and XGBoost models as defined by their accuracy, precision, recall, and F1-score; this provides an overall view of both model types and how they handle class imbalance in terms of making predictions.

Table 4. Performance Comparison of the Classification Models

	Accuracy	Precision	Recall	F1
Random Forest	0.960078	0.509259	0.379310	0.434783
XGBoost	0.960078	0.508197	0.427586	0.464419

Both Random Forest and XGBoost were found to have high accuracy of 0.960, therefore, they both performed equally when evaluated with regards to aggregate accuracy. However, this metric alone provides limited insight into model behavior, particularly in datasets where class imbalance is present. For instance, even if both models had high accuracy values, this does not mean that either would accurately identify the minority class if they had an imbalance present within their dataset.

When looking at precision and recall metrics, the differences between both approaches become more apparent. The precision metrics for both Random Forest and XGBoost are nearly the same suggesting that they make nearly the same amount of positive predictions that are actually correct. However, XGBoost has a significantly higher recall metric than Random Forest; this suggests that XGBoost will capture more instances of true positives than Random Forest will. The improvements in recall for XGBoost directly result in a higher F1-score than Random Forest; which means that XGBoost has an improved balance between false positives and false negatives.

The differences observed between the two model types are directly linked to the underlying learning strategies of the models. For example, XGBoost learns using a boosting mechanism that means progressively emphasizes misclassified observations in order to adapt more effectively to complex patterns and underrepresented classes. In contrast, Random Forest reduces the variability of the model’s predictions through ensemble averaging; thus, Random Forest is typically less sensitive to minority results than XGBoost.

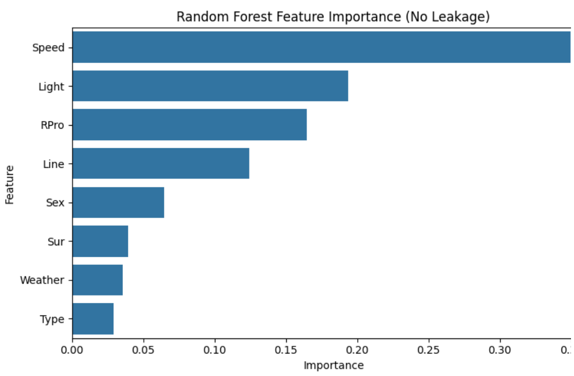
Overall, both models are capable of predicting accident-related fatalities to a high level; however, based on additional metrics beyond simple accuracy, XGBoost has been shown to produce a more balanced classification of accident-related fatalities than Random Forest, making it better suited for use when the primary goal is to correctly identify positive cases rather than to correctly identify all cases.

Tables 4 and 5 compare and evaluate the ability of XGBoost and Random Forest to predict accident-related fatalities in Jordan, both before and after removing combined severity features. Both models produced similar high levels of accuracy (96.01%) with moderate precision and recall values when severity information was included (Table 3), which indicates their ability to identify fatal cases reasonably effectively, despite the class imbalance. Notably, XGBoost slightly outperformed Random Forest in terms of recall (0.43 vs. 0.38) and F1-score (0.46 vs. 0.43), suggesting a better balance between sensitivity and precision when severity characteristics were available. When the severity-related features were removed from both models (Table 5), overall levels of accuracy remained high (≈95.9%), but there was a substantial decline in recall and F1-score for both models, with the recall for Random Forest dropping to 0.048 and XGBoost dropping to 0.034. These results indicate that neither model has much ability to correctly predict fatal accidents once severity-related features are removed. Therefore, this degradation of the performance provides a strong evidence of the role of using severity-related features to determine the underlying causes of fatal accidents. Additionally, using SHAP and LIME to perform an explainability analysis supports this observation, as severity-related features were among the most significant contributors to models' predictions. Overall, these findings demonstrate that while accuracy alone may suggest stable model performance, severity-related features are essential for meaningful and reliable fatality prediction, particularly in safety-critical applications such as road accident analysis.

Table 5. Performance Comparison of the Classification Models

	Accuracy	Precision	Recall	F1
Random Forest	0.958961	0.437500	0.048276	0.086957
XGBoost	0.958961	0.416667	0.034483	0.063694

The purpose of this section is to present the visual results of the model evaluations, which are used to support the quantitative findings. The figures that are provided show the performance of the classification models statistically and provide a convenient format for comparing the differences in predictive behavior, error distribution, and performance by class. By providing a visual representation of the tabulated results, the images of the model predicted class labels provide patterns and contrasts between the different classification methods that may not be easily observed from the tabular results alone.



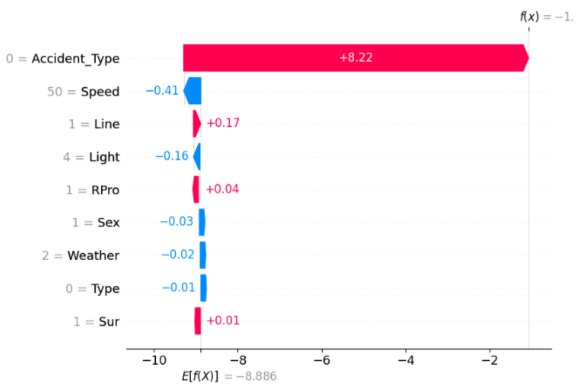


Figure 13 Random Forest Feature Importance for Fatality

Figure 14 Local SHAP Explanation for Fatality Prediction

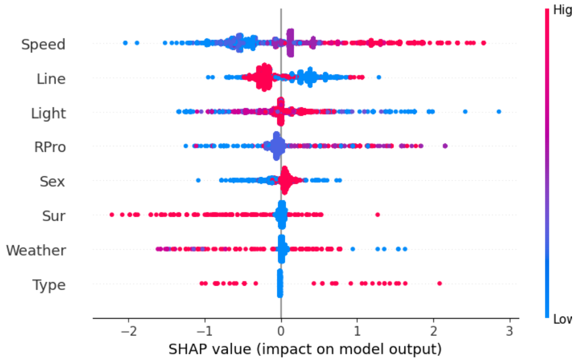


Figure 15 Global SHAP Summary for Fatality Prediction

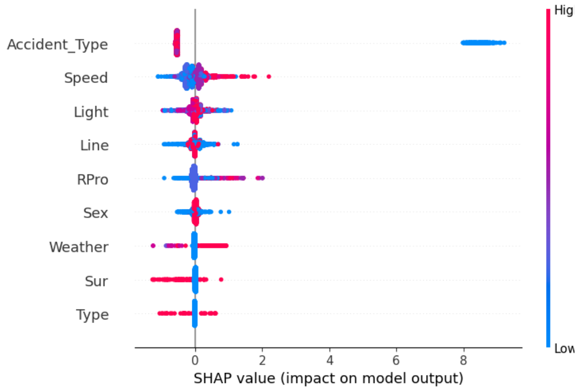


Figure 16 SHAP Summary Including Accident Type for Fatality Prediction

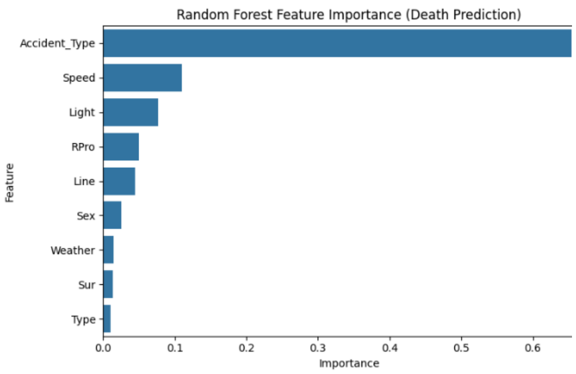


Figure 17 Random Forest Feature Importance for Death Prediction

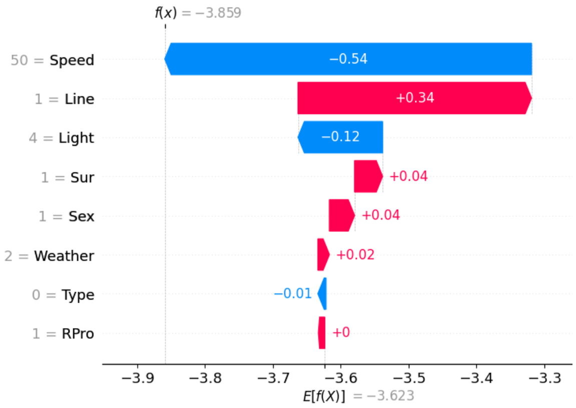


Figure 18 Local SHAP Explanation for a Non-Fatal Prediction

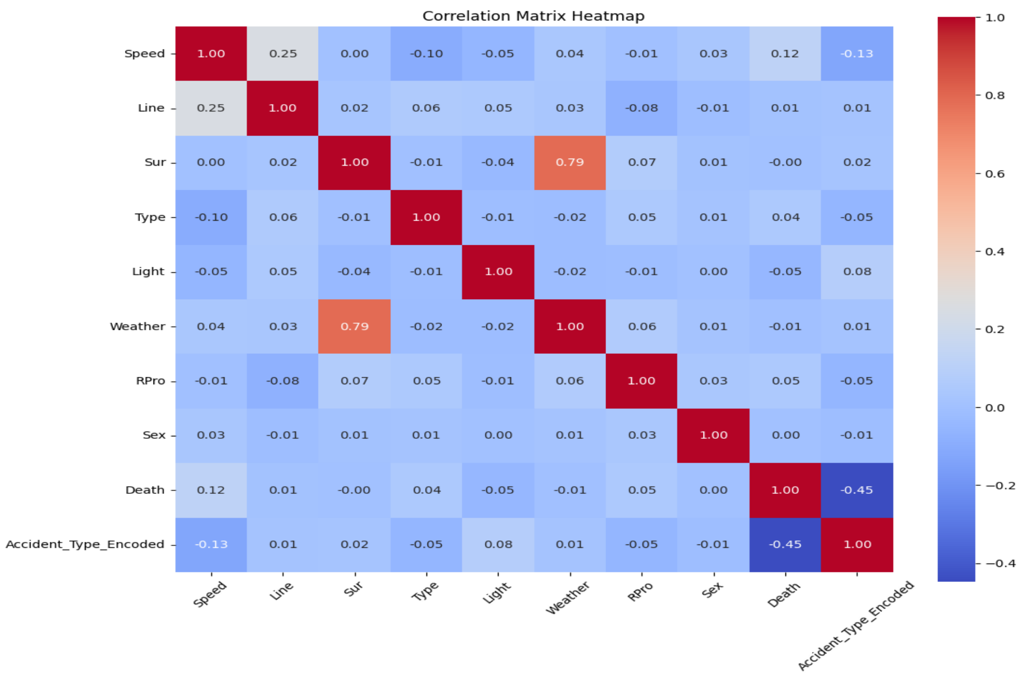


Figure 19 Correlation Structure of Variables Used in Fatality Prediction

The results of the Random Forest model identifying the factors behind traffic fatalities in Jordan, shown in Figure 13, allowed for data leakage to be avoided. Overall, it is apparent that speed is the most significant contributor to death among all the variables. This finding is consistent with the large body of evidence showing that the higher the speed, the more likely it is that a vehicle will cause a serious crash and/or result in death.

The second most prominent factor identified by the Random Forest model was lighting, which indicates how visibility and nighttime driving conditions are important elements associated with traffic fatalities. Also, lane and roadway profile characteristics also have been identified as significant contributing factors for crashes. Lane and roadway are reflective of how the geometric configuration and roadway infrastructure influence/dynamics with respect to crashes. The sex of the driver is of moderate importance; while surface condition, weather, and type of vehicle are less important, indicating their effect is typically indirect or dependent on a specific context. From the standpoint of explanation, the results obtained provide a global perspective of how the model prioritized inputs when predicting death. The model's ability to capture the predominant patterns associated with speed being the most critical and then lighting conditions and roadway characteristics is an indication that it is in agreement with established traffic safety theories pertaining to fatal outcomes in Jordan.

A SHAP force plot, as shown in Figure 14, explain an individual accident case's fatality prediction. The results indicate that accident type is the main factor driving the prediction toward a fatal outcome, while other variables contribute only marginally.

In the current case, the speed had a negative contribution. Therefore, the actual speed of the accident lowers the predicted fatality risk of the model from the baseline predictions. This is due to the fact that the effects of features on SHAP values are dependent upon both the actual values of features and their interaction with other variables in a given case, rather than its overall importance in the model.

Overall, the figure illustrates how the model combines multiple inputs to reach a case-level death prediction and highlights the role of SHAP in providing transparent and interpretable explanations for individual accident outcomes.

A SHAP summary plot, as shown in Figure 15 in, shows the global influence of the model's variables used for predicting the deaths in traffic accidents. The results support that speed is the most significant predictor, with model predictions toward an increased likelihood of a fatality when predicting at a higher rate of speed. This pattern illustrates what has been well established regarding the nonlinear relationship between impact speed and crash severity.

Lighting and road profile characteristics make notable contributions**,** as certain feature categories can both increase or decrease the probability of fatality based upon their respective values. These results show significant interaction effects for the SHAP value spread of these two feature categories rather than a uniform impact across all cases. In addition, driver sex, road surface, weather, and vehicle/accident type each have much smaller but still valuable contributions to the fatality prediction model and largely affect predictions of certain subsets of cases rather than all cases in the dataset.

Overall, the SHAP distribution shows that fatalities result from the interplay of multiple behavioral, environmental and infrastructural factors. No single variable is sufficient to predict a fatality. The wide dispersion of SHAP values supports the use of explainable machine learning, as it reveals how feature effects vary across individual accidents as it remains consistent with existing knowledge regarding traffic safety.

As shown in Figure 16, the model summary SHAP plot represents accident types as well as the behavioral, environmental and roadway features of the fatality prediction model. The results show that accident type has the widest spread of SHAP values, indicating that crash configuration plays a major role in distinguishing fatal from non-fatal outcomes. Certain accident types strongly push the model toward a fatal prediction, while others are associated with substantially lower risk.

As previous findings indicate, speed continues to be an important indicator. Greater speeds will increase the probability of death. Lane characteristics and lighting conditions also appear to have a moderate impact on crash prediction, although the extent of such varies from case to case indicating some level of interaction with other features. Other features that have a smaller and more localized influence when predicting fatalities for specific cases but not across the entire dataset include road profile, driver gender, weather, surface conditions and vehicle type.

Overall, the figure reinforces the importance of using explainable machine learning methods. The SHAP summary provides both a representation of the magnitude and direction of feature effects, thus providing insight into how the interaction of various features impacts fatality predictions. In addition, the SHAP summary allows for clear and transparent interpretation of the model's behavior when predicting fatalities for traffic accidents in Jordan.

Figure 17 contains the feature importance results for the random forest model created specifically for predicting fatalities as a result of traffic accidents in Jordan. It is apparent that the type of accident plays the most significant role as the primary feature impacting prediction; in other words, it is a more important contributing factor than any other variable. This indicates the significant value of crash configuration regarding the ability to differentiate fatal versus non-fatal outcomes; each type of accident represents a unique impact mechanism and level of exposure.

Accordingly, Speed ranks as the second most important feature, reinforcing its well-established association with fatal injury risk. Lighting conditions, road profile, and lane-related characteristics also contribute to the prediction, though to a lesser extent, indicating that roadway and visibility conditions help shape fatal outcomes in combination with crash type and speed. Variables such as driver sex, weather, road surface, and vehicle type show relatively low importance, suggesting that their influence on death prediction is more indirect or context-specific.

Based on these results, fatality predictions in this database are associated with crash mechanics and operating conditions and not with demographic or environmental factors alone. Furthermore, the significant role that crash type plays, in addition to the model utilizing explainable AI techniques, demonstrates transparency in terms of how crash characteristics drive the model's fatality predictions and how they can be verified and validated with existing traffic safety knowledge.

Graph 18 depicts a SHAP force plot on an individual accident that was predicted to be non-fatal. The figure illustrates the model's change from the baseline outcome toward a lower probability of a fatal outcome as a result of the impact of all the input features combined together.

In this case, speed is the dominant factor pushing the prediction away from a fatal outcome, indicating that the observed speed level substantially reduces the estimated death risk relative to the dataset average. In contrast, lane characteristics contribute positively, partially increasing the predicted risk, while lighting conditions have a smaller negative effect. Road Surface Condition, Driver sex, Weather, Vehicle Type, and Road Profile have either minimal contribution or are limited in the final prediction for this case.

As a whole, this figure provides evidence of how SHAP provides insights and understanding of the reasons behind the low Mortality Probability assigned by SHAP to this accident. Additionally, it highlights that the effects of features are dependent upon the specific values of the features and the interactions therewith. For example, depending upon other influencing features, the value of speed could either be a positive or negative contributor to the likelihood of a fatality.

Results from the correlation matrix for primary variables of the fatality prediction model as presented in figure 19 have generally low to moderate correlations with each other. These results suggest that many of the predictors in the dataset are not highly correlated with each other, which indicates that multicollinearity is not likely to be problematic when using tree-based machine-learning prediction models to estimate fatalities.

A notable exception to this is the strong positive correlation found between road surface condition and weather, reflecting their natural co-occurrence in real driving environments. This relationship is expected and does not necessarily imply redundancy, as these variables capture different aspects of road and environmental conditions. There is a moderate correlation between speed and lane attributes. This suggests a moderate relationship between speed and the configuration of the roadway.

With respect to the target variable, fatal injury (death) has weak linear relationships with most predictor variables. This indicates that they have a complicated and non-linear relationship with many fatal crashes, and therefore cannot be easily explained using single variables alone. In particular, the greater negative correlation between death and accident type indicates that the way in which a crash occurs is important in determining whether or not an individual sustains a fatal injury or dies as a result of a crash, and this relationship will be further explored with machine learning and explainable AI methods.

Overall, the correlation results justify the adoption of non-linear models and XAI techniques in this study, as they are better suited to capture interaction effects and complex relationships underlying traffic accident fatalities.

6 Conclusion

The present study contributes knowledge in the area of traffic safety research by showing machine learning combined with an explainable Artificial Intelligence (XAI) can both improve both prediction and explainability of Fatal Highway Crash Prediction Models. In the prediction results, as shown in the tables and figures, point out that while the model's overall accuracy is similar through all models, yet there are important differences based on class-sensitive metrics. XGBoost consistently produces better Recall and F1 scores compared with the other two models. This indicates that XGBoost is more capable of correctly identifying fatal crashes than the other two models; thus, the use of XGBoost in safety-related applications has considerable benefits due to the high consequences associated with missed crash detections.

This study is primarily focused on the predictive accuracy of models used to predict accident severity, also emphasizes the importance of model interpretability achieved via the use of Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME. SHAP analysis provides a global considerate of feature significance by quantifying each variable’s influence to fatal accident results crosswise the dataset, while LIME provides a localized view of how each individual predictions are formed. Both analyses complement each other by providing system-level and case-specific insights into risk factors associated with severe motor vehicle accidents. This dual form of explanation increases trust in the predicted outcomes from the models, and supports the concept that complicated machine learning output continues to be meaningful to individuals who do not have technical backgrounds.

There results support previously existing research showing that fatal car accidents originate from socio-technical systems and not just from individual driver relationships. The combined evidence derived from the predictive model and the XAI processes show that a combination of factors (human factors, roadway characteristics, vehicle characteristics, and environmental characteristics) lead to the formation of the crash severity.

By using both nonlinear and interdependent relations, a proper model has been created to represent the actual dynamics of road safety. Finally, through analysis performed through the SHAP and LIME analyses, information obtained through the above may be utilized for policymaking in Jordan based on empirical evidence to enforce actions towards upgrading critical infrastructure or implementing other regulatory measures to reduce or avoid fatal roadway accidents.

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