sustainability

MDPI

Article

A Multi-Model Machine Learning Framework for Predicting and Ranking High-Risk Urban Intersections in Riyadh

Saleh Altwaijri [1], Saleh Alotaibi [2,*], Faisal Alosaimi [3,4], Adel Almutairi [3] and Abdulaziz Alauany [3]

[1] Department of Urban Planning, King Saud University, Riyadh 11543, Saudi Arabia; saltwaijri@ksu.edu.sa
[2] Civil and Environmental Engineering Department, Faculty of Engineering, Rabigh Branch, King Abdulaziz University, Jeddah 21911, Saudi Arabia
[3] Department of Infrastructure Projects, Riyadh Municipality, Riyadh 12611, Saudi Arabia; fsalosaimi@alriyadh.gov.sa or falosaimy@ksu.edu.sa (F.A.); almezaniadel@gmail.com (A.A.); aalauony@alriyadh.gov.sa (A.A.)
[4] Collage of Architecture and Planning, King Saud University, Riyadh 11543, Saudi Arabia
* Correspondence: salnufiae@kau.edu.sa

Abstract

Road traffic accidents at intersections pose a persistent challenge in Riyadh, Saudi Arabia, contributing significantly to public health burdens and economic losses. Traditional statistical approaches often fail to capture the complex, non-linear interactions among geometric design, traffic parameters, and accident severity. This study develops a multi-methodological machine learning framework to predict intersection accident severity using the Equivalent Property Damage Only (EPDO) metric. Historical data (2017–2023) from Riyadh Municipality for 150 high-risk intersections were analyzed, incorporating predictors such as service road distance (SRD), U-turn distance (UTD), median width (MW), peak hour volume (PHV), heavy vehicle percentage (HV%), and injury/frequency counts. Six algorithms, i.e., Decision Tree, Random Forest, Gradient Boosting, Support Vector Machine, Linear Regression, and Artificial Neural Network, were compared using a 70/30 train–test split and k-fold cross-validation in this study. The Gradient Boosting model achieved superior performance (R^2 = 0.89 with MSE = 63.43 and RMSE = 7.96) and was selected for final deployment. SHAP feature importance analysis revealed minor injuries (MIs), serious injuries (SRIs), and fatalities (FAs) as the most important dominant predictors, with geometric factors (UTD, MW) and traffic composition (HV%) providing actionable infrastructure insights. The model ranked intersections and identified the "Jeddah Road with Taif Road" (predicted EPDO = 137.22) as the highest-risk location. Evidence-based recommendations include enforcing the minimum 300 m U-turn buffers with staggering service road exits $\geq$150 m and restricting heavy vehicles during peak hours. The scalable framework developed in this study supports the data-driven prioritization of safety interventions and aligns with sustainable urban mobility goals and offers transferability to other metropolitan contexts worldwide.

Keywords: road traffic accidents; intersection safety; machine learning; Gradient Boosting; EPDO; accident severity prediction; urban planning; Riyadh

Academic Editor: Juneyoung Park

Received: 31 January 2026
Revised: 27 March 2026
Accepted: 28 March 2026
Published: 8 April 2026

1. Introduction

Rapid urbanization and motorization in emerging economies have elevated road traffic accidents (RTAs) to a major public health and socioeconomic challenge in recent decades [1–3], particularly in the Kingdom of Saudi Arabia (KSA), where RTAs have historically ranked among the highest globally and contribute to approximately 4.7% of all mortalities and annual economic losses exceeding $16 billion [4,5]. Transformative interventions under Vision 2030 include the Saher automated enforcement system with infrastructure enhancements and awareness campaigns and have driven a substantial decline in fatality rates from 28.8 per 100,000 population in 2016 to around 13 in 2023, with continued improvements observed in 2025 [6–9].

Riyadh is a rapidly growing megacity that is experiencing exponential growth, which has led to an increase in traffic density at intersections. These intersections have consistently contributed to over 50% of urban accidents. However, to provide a solution to these safety issues, a comprehensive approach is needed that considers the intricate relationship between several important parameters, such as driving behavior, road surface condition, vehicle condition, and road infrastructure design. Although driving behavior is responsible for accidents, the road infrastructure design status is equally important in defining the level of functionality of a road. This study aims to address the unexplored importance of micro-level geometric design parameters in this context [10–12]. The early literature predominantly attributes 80–90% of crashes to human factors, speeding (>35%), red-light running, young male/expatriate drivers, and low seatbelt compliance, often overshadowing infrastructural contributors [13–16]. Macro-level analyses highlight Riyadh's disproportionate national accident share and severe pedestrian outcomes at trauma centers, yet granular examinations of geometric design elements remain limited [17–19].

An increasing number of recent studies have begun integrating machine learning (ML) for severity prediction with XGBoost and ensemble methods; these methods outperform traditional regression on highway and provincial datasets. Explainable AI (XAI) has also been incorporated via SHapley Additive exPlanations (SHAP) to reveal feature contributions [20–23]. In urban KSA contexts in Jeddah and Riyadh, boosted trees have demonstrated superiority for crash forecasting, emphasizing non-linear relationships. Internationally and regionally, the Equivalent Property Damage Only (EPDO) metric, which is a weighted composite of frequency and severity, has proven effective for hotspot prioritization, though its ML-driven application at micro-level intersections incorporating detailed geometric features (e.g., U-turn proximity, median width, service road spacing) and traffic composition (e.g., heavy vehicle percentage) remains underexplored [24–28]. Traditional statistical models frequently fail to capture these complex and non-linear interactions because they constrain proactive and evidence-based planning [29]. Ensemble ML approaches include Gradient Boosting with SHAP interpretability that offer a superior framework for modeling multifaceted risks and deriving actionable insights [30–34].

This study aims to explore the non-linear relationships between geometric design, traffic parameters, and accident severity in high-risk urban intersections in Riyadh as well as similar intersection types across the globe. The main objective of this study is to design a machine learning workflow, based on Gradient Boosting and SHAP values, to predict accident severity based on the Equivalent Property Damage Only (EPDO) measure. To ensure that the present study is in line with the latest developments in traffic safety modeling, several recent high-impact studies have also been incorporated. For example, a systematic review and meta-analysis stresses that ensemble approaches like XGBoost and Random Forest, which form the basis of the proposed framework, have shown consistent superiority over conventional approaches in accident severity predictions, based on data from all over the world from 2014 to 2025 [35], where the importance of interpretability in safety predictions has also been stressed, where XAI approaches like SHAP have shown promise in converting 'black-box' predictions into useful safety insights, thereby providing a crucial urban setting for the application of data-driven approaches to strategic safety goals, as set out in Saudi Vision 2030. Also, the framework presented in this study helps in

https://doi.org/10.3390/su18083651

sustainable urban mobility by providing a cost-effective approach for prioritizing safety interventions. Although the framework has been tested using the Riyadh data, the proposed multi-model pipeline and its approach are highly transferable to other metropolitan settings around the world that are experiencing similar pressures of rapid urbanization.

The main contributions of this study are summarized as follows:

1. Methodological Framework: A sound machine learning framework was formulated to assess intersection safety, comparing and ranking six different algorithms to determine the best approach to model accident severity in high-density urban areas.
2. Geometric Risk Factors: The effects of targeted geometric factors, including U-turn lengths, median sizes, and service road designs, on accident severity at hotspots were identified.
3. Model Generalization: The ability to generalize complex accident safety patterns using advanced ensemble learning techniques (Gradient Boosting) has been demonstrated, making it unnecessary to develop separate models for different regions of a city.
4. Alignment with Strategic Vision: A data-driven solution that aligns with the Saudi Vision 2030 and the Quality-of-Life Program is offered by providing city authorities with recommendations for proactive infrastructure safety measures.

2. Materials and Methods

2.1. Research Workflow

The research flowchart is included, as shown in Figure 1, to provide a general overview of the entire methodology used in this study. The flowchart indicates the process of data collection from Riyadh Municipality, data preprocessing (including missing value handling and feature scaling), as well as the parallel implementation of six machine learning algorithms. The proposed approach also includes the interpretation step using SHAP and the final ranking of high-risk intersections.

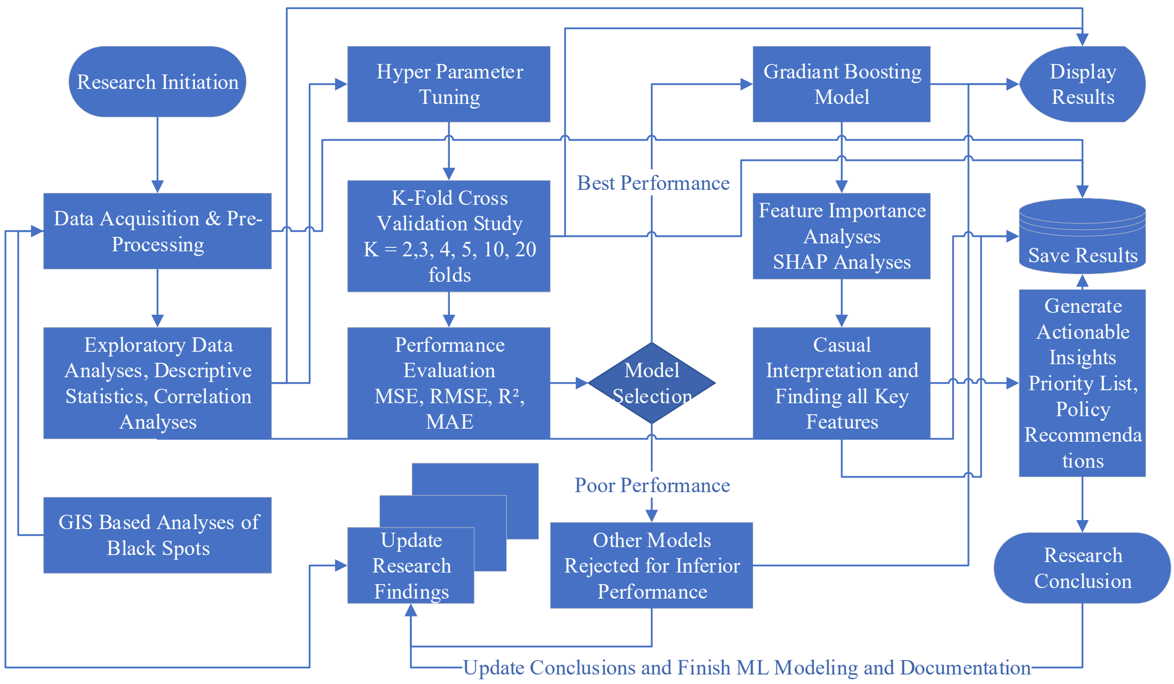

Figure 1. Research workflow illustrating data collection from Riyadh Municipality, preprocessing steps, parallel application of machine learning models, SHAP-based analysis, and identification of high-risk intersections.

2.2. Data Collection

For this study, historical traffic accident data from 2017 to 2023 were collected from the Riyadh Municipality's Accident Monitoring Center. This dataset included 150 high-risk intersections, which were identified as "blackspots" according to their accumulated Equivalent Property Damage Only (EPDO) values (refer to Equation (1)). The criteria for selecting the dataset included the application of weighting coefficients. The blackspots that were identified showed a wide range of severity, with EPDO values, representing the most severe nodes of the urban network. The geographical location of the blackspots is shown in Figure 2. The five clusters that have been identified in Figure 2 are the different geographical areas of Riyadh, from the high-density Central Business District (CBD) to the growing suburbs. The five clusters also reflect the different land use patterns and traffic flow conditions that affect the number and severity of accidents.

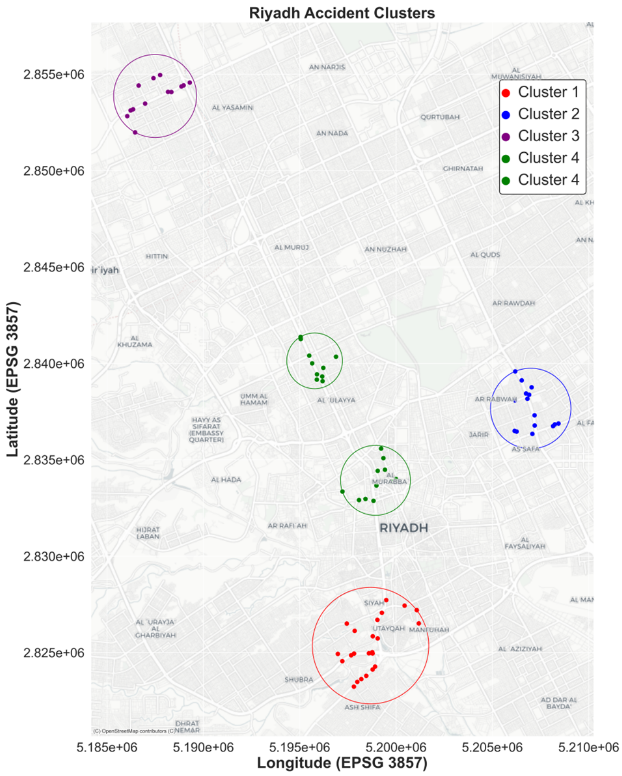

Figure 2. The locations of the 150 selected high-risk intersections (blackspots) across Riyadh.

Predictor variables and the target variable were selected based on the established engineering relevance and data availability, provided by the authorities (summarized in Table 1).

Table 1. The description of predictor and target variables.

Variable	Description	Unit/Type
SRD	Service Road Distance	meters
PHV	Peak Hour Volume	vehicles/hour
AF	Accident Frequency	count
SI	Stable Injuries	count
MI	Minor Injuries	count
SRI	Serious Injuries	count
FA	Fatalities	count

Table 1. *Cont.*

Variable	Description	Unit/Type
INT	Intersection Type	categorical
NLANE	Number of Lanes	count
UTD	U-Turn Distance	meters
MW	Median Width	meters
HV%	Heavy Vehicle Percentage	percentage
EPDO	Equivalent Property Damage Only	score

The dataset was classified into various categories, including the numerical and categorical, with the categorical variable intersection type (INT) being label-encoded to facilitate machine learning compatibility, as detailed in Table 2.

Table 2. Label encoding for intersection type (INT).

Intersection Type	Encoded Label
Right In/Out	1
Right In/Out Bridge	2
Four-Leg Intersection	3
Three-Leg Intersection	4
Interchange	5
U-Turn	6
Roundabout	7
On-Street	8
Elevated Intersection	9

The target variable was the Equivalent Property Damage Only (EPDO) score, a composite metric widely used in traffic safety analysis to integrate both accident frequency and severity [36]. It was computed using the standard form given in Equation (1).

$$EPDO = w_f F_i + w_s S_i + w_m M_i + w_p P_i \quad (1)$$

Fi, Si, Mi, and Pi in Equation (1) denote the number of fatalities, serious injuries, minor injuries, and property damage only accidents, respectively, at each site, and w_f, w_s, w_m, w_p denote the weighting coefficients (12, 9, 5, and 1) and are based on the established severity scaling practices in KSA traffic safety studies (as prescribed by the Saudi Highway Code (SHC 603) for road safety management in the Kingdom) that assign progressively higher values to more severe outcomes and have missing values in the dataset, which are minimal and imputed using tree-based iterative imputation (e.g., via Decision Tree surrogates). This method was chosen for its effectiveness in capturing the non-linear relationships and handling mixed data types, thereby maintaining data integrity and preserving distributional patterns before model training and working on machine learning.

2.3. Exploratory Data Analysis

Exploratory Data Analysis (EDA) was performed to understand the distribution of variables, correlations between predictor variables, and potential problems like multicollinearity before applying machine learning models. Descriptive statistics for the 150 intersections are shown in Table 3. These results show high variability, especially in traffic variables. For instance, peak hour volume (PHV) varied between 0 and 25,181 vehicles per hour (SD = 5156), while U-turn distance (UTD) varied between 0 and 8100 m (SD = 1080). However, severe consequences had very low means (fatalities, FAs = 0.25; serious injuries, SRIs = 0.52), which is not surprising given their low frequency of occurrence despite their severity. The target EPDO score showed considerable heterogeneity (mean = 32.37, SD = 24.94, range 9–154), underscoring diverse severity levels across sites.

Table 3. The descriptive statistics of predictor and target variables (n = 150).

Data	Count	Mean	Standard Deviation	Sum	Minimum
SRD	150	138.01	431.97	20,702.00	0.00
PHV	150	4035.65	5156.43	60,5348.00	0.00
AF	150	10.77	7.65	1615.00	3.00
SI	150	10.21	7.66	1532.00	0.00
MI	150	2.89	2.48	433.00	0.00
SRI	150	0.52	0.91	78.00	0.00
FA	150	0.25	0.67	38.00	0.00
INT	150	4.88	2.35	731.57	1.00
NLANE	150	3.67	0.97	550.59	1.00
UTD	150	585.63	1079.96	87,845.15	0.00
MW	150	13.41	24.19	2011.19	0.00
HV%	150	2.80	4.11	419.49	0.10
EPDON	150	32.37	24.94	4855.00	9.00

The Pearson correlation coefficients were calculated to assess linear relationships (Table 4). The EPDO score exhibited strong positive correlations with injury and frequency components (e.g., MI r = 0.79, AF r = 0.77, SI r = 0.72), thus validating its role as a comprehensive severity metric, and the inter-predictor correlations were generally weak ($|r| < 0.3$), indicating minimal multicollinearity among geometric and traffic features.

Table 4. Pearson correlation matrix for selected variables.

VARIABLE	SRD	PHV	AF	SI	MI	SRI	FA	INT	NLANE	UTD	MW	HV%	EPDON
SRD	1.00	0.08	0.16	0.13	0.29	0.06	0.13	0.14	0.05	0.30	−0.03	0.02	0.25
PHV	0.08	1.00	0.21	0.22	0.15	0.12	0.07	−0.12	−0.08	−0.06	−0.04	0.10	0.20
AF	0.16	0.21	1.00	0.95	0.59	0.31	0.27	−0.02	0.00	−0.03	0.05	0.58	0.77
SI	0.13	0.22	0.95	1.00	0.46	0.32	0.25	−0.02	−0.01	−0.02	0.02	0.54	0.72
MI	0.29	0.15	0.59	0.46	1.00	0.36	0.11	0.06	0.06	0.13	−0.04	0.28	0.79
SRI	0.06	0.12	0.31	0.32	0.36	1.00	0.19	−0.07	0.09	0.05	−0.10	0.22	0.67
FA	0.13	0.07	0.27	0.25	0.11	0.19	1.00	−0.03	0.17	0.13	−0.12	0.12	0.52
INT	0.14	−0.12	−0.02	−0.02	0.06	−0.07	−0.03	1.00	−0.01	0.16	0.08	−0.11	−0.01
NLANE	0.05	−0.08	0.00	−0.01	0.06	0.09	0.17	−0.01	1.00	0.04	−0.19	0.12	0.11
UTD	0.30	−0.06	−0.03	−0.02	0.13	0.05	0.13	0.16	0.04	1.00	−0.08	−0.01	0.12
MW	−0.03	−0.04	0.05	0.02	−0.04	−0.10	−0.12	0.08	−0.19	−0.08	1.00	−0.12	−0.08
HV%	0.02	0.10	0.58	0.54	0.28	0.22	0.12	−0.11	0.12	−0.01	−0.12	1.00	0.41
EPDON	0.25	0.20	0.77	0.72	0.79	0.67	0.52	−0.01	0.11	0.12	−0.08	0.41	1.00

The preliminary multivariate ordinary least squares (OLS) regression further quantified associations (Table 5) in which the injury-related predictors (MI, SRI, FA, SI) and certain geometric features (SRD, UTD) emerged as highly significant ($p < 0.001$) and reinforced dataset suitability for non-linear ML modeling.

These descriptive, correlational, and multivariate analyses provided initial insights into variable behavior and confirmed the absence of severe multicollinearity. While informative, the linear approaches are limited in capturing non-linear interactions; thus, the subsequent machine learning framework addresses this issue by leveraging ensemble methods for enhanced predictive accuracy and feature interpretation in detail.

https://doi.org/10.3390/su18083651

Table 5. Multivariate OLS analyses (linear regression coefficients, standard errors, t-values, and *p*-values for predictor variables in the intersection accident severity model).

Variables	$\hat{\beta}_i$	$SE\ (\hat{\beta}_i)$	t	p
β_0	-1.4×10^{-13}	5.4×10^{-13}	-2.6×10^{-1}	7.9×10^{-1}
SRD	-3.1×10^{-15}	2.7×10^{-16}	-1.1×10^{1}	5.9×10^{-21}
PHV	4.2×10^{-17}	2.2×10^{-17}	1.9×10^{0}	5.8×10^{-2}
AF	-4.9×10^{-15}	5.8×10^{-14}	-8.3×10^{-2}	9.3×10^{-1}
SI	1.0×10^{0}	5.0×10^{-14}	2.0×10^{13}	0.0×10^{0}
MI	5.0×10^{0}	6.7×10^{-14}	7.5×10^{13}	0.0×10^{0}
SRI	9.0×10^{0}	1.3×10^{-13}	6.7×10^{13}	0.0×10^{0}
FA	1.2×10^{1}	1.8×10^{-13}	6.7×10^{13}	0.0×10^{0}
INT	1.0×10^{-14}	4.8×10^{-14}	2.1×10^{-1}	8.3×10^{-1}
NLANE	1.1×10^{-14}	1.2×10^{-13}	9.4×10^{-2}	9.3×10^{-1}
UTD	4.7×10^{-16}	1.1×10^{-16}	4.3×10^{0}	3.0×10^{-5}
MW	1.5×10^{-15}	4.7×10^{-15}	3.1×10^{-1}	7.6×10^{-1}
PHV	3.7×10^{-16}	3.4×10^{-14}	1.1×10^{-2}	9.9×10^{-1}

2.4. Machine Learning Modeling and Evaluation

In this study, a supervised regression framework was developed to predict the EPDO score using six machine learning algorithms, as illustrated in Figure 1. The architecture of the models employs a hybrid set of features. Although the addition of injury variables (MIs, SRIs, FAs, SIs) is consistent with the mathematical formulation of the target variable (EPDO), the value of the model lies in its capacity to combine these variables with non-structural features like median width, U-turn distance, and traffic mix. The entire process and modeling were performed in the software Orange Data Mining (Version: Orange 3.40.0 as of 1 April 2026), which integrates scikit-learn libraries for efficient implementation, hyperparameter tuning, and evaluation. The dataset was divided into training (70%) and test (30%) sets, thus ensuring that the balanced representation of the target variable and hyperparameter optimization was conducted via a grid search combined with 5-fold cross-validation on the training data with the model stability further verified across different cross-validation folds (k = 2, 3, 5, 10, 20). The variable logic formulation particularly distinguishes the predictors into structural parts (injury counts) and causal predictors (geometric/traffic factors). Although the structural parts guarantee that the model is focused on the mathematical definition of EPDON, a sensitivity analysis was performed to guarantee that the model's explanatory capability is not entirely reliant on these elements. The findings show that the geometric predictors have maintained significant values for feature importance scores, validating that the model can identify risk mechanisms based on infrastructure regardless of the injury-weighting structure. The target variable for the classification models was created using a rigorous two-step process. In the first step, a weighted Equivalent Property Damage Only (EPDO) score was determined for each intersection based on past crash data. In the second step, the EPDO scores were grouped into distinct categories of risks. The processed dataset, with the derived targets and the independent geometric and traffic variables, was created. This order ensures that the machine learning models are trained on an objective, pre-computed safety target while investigating the predictive role of urban infrastructure design. The injury severity variables such as fatalities, serious injuries, minor injuries, and stable injuries are used to compute the EPDO outcome. However, it is important to note that the overall objective of the machine learning framework is not to replicate the EPDO equation. EPDO is a simplified severity metric based on injury counts only. The machine learning framework has extended the EPDO outcome to include additional injury variables related to roadway geometries and traffic exposures, such as U-turn distance, median width, service road spacing, number of lanes, peak hour volume, and heavy vehicle percent. These injury variables are not included in the EPDO outcome (Table 6).

Table 6. Role of injury severity variables and infrastructure predictors in the EPDO formulation and machine-learning analysis.

Variable Group	Variables	Role in Study	Included in EPDO Equation
Injury Severity Components	FA, SRI, MI, SI	Observed crash severity outcomes used to compute EPDO	Yes
Accident Frequency	AF	Exposure indicator representing crash occurrence	No
Infrastructure Variables	UTD, MW, SRD, NLANE, INT	Geometric design characteristics influencing intersection safety	No
Traffic Variables	PHV, HV%	Traffic composition and exposure characteristics	No

The compared models cover a wide range of approaches to capture both linear and non-linear relationships, in which the Decision Tree regression employed a binary tree structure with a maximum depth of 100 and required at least five instances to split a node and two instances to form a leaf. Furthermore, Random Forest consisted of an ensemble of 10 trees and Gradient Boosting utilized 100 sequential trees with a learning rate of 0.1 and a maximum depth of 3. The Support Vector Machine regression adopted a Radial Basis Function kernel, with tuning focused on the regularization parameter C and kernel coefficient γ. A baseline Linear Regression model was fitted without regularization in this study, and an Artificial Neural Network featured a single hidden layer with 100 ReLU-activated neurons, trained using the Adam optimizer, L2 regularization (α = 0.0001), and a maximum of 200 iterations. All these parameters were chosen based on the best performance and outcome.

Performance on the hold-out test set is summarized in Table 7. The Gradient Boosting model demonstrated superior predictive accuracy, achieving an R^2 of 0.89, MSE of 63.43, RMSE of 7.96, and MAE of 4.01. Random Forest followed closely with an R^2 of 0.81. The perfect score observed for Linear Regression (R^2 = 1.00) was identified as anomalous, resulting from partial feature leakage due to injury counts contributing directly to the EPDO calculation; consequently, this model was excluded from further consideration. Although RMSE allowed the estimation of the relative magnitude of the error, R^2 was used as the main criterion for ranking models. This was performed because R^2 directly captures the model's capacity to explain the variance of accident severity, which is of prime importance for determining the importance of geometric risk factors.

Cross-validation results across varying fold numbers confirmed the robustness of Gradient Boosting, which maintained R^2 values between 0.89 and 0.92 (Figure 3).

Table 8 shows the results of hyperparameter tuning, which helped set the final model settings. For Gradient Boosting, a moderate tree depth and learning rate gave the best balance between model complexity and performance.

Table 7. The comparative performance metrics of machine learning models on the test set.

Model	MSE	RMSE	MAE	MAPE	R^2
Tree	185.85	13.63	7.66	0.20	0.68
Random Forest	107.75	10.38	5.58	0.15	0.81
Gradient Boosting	63.43	7.96	4.01	0.10	0.89
SVM	427.20	20.67	11.13	0.29	0.26
Linear Regression	0.00	0.00	0.00	0.00	1.00 (invalid due to leakage)
Neural Network	487.56	22.08	18.45	0.61	0.16

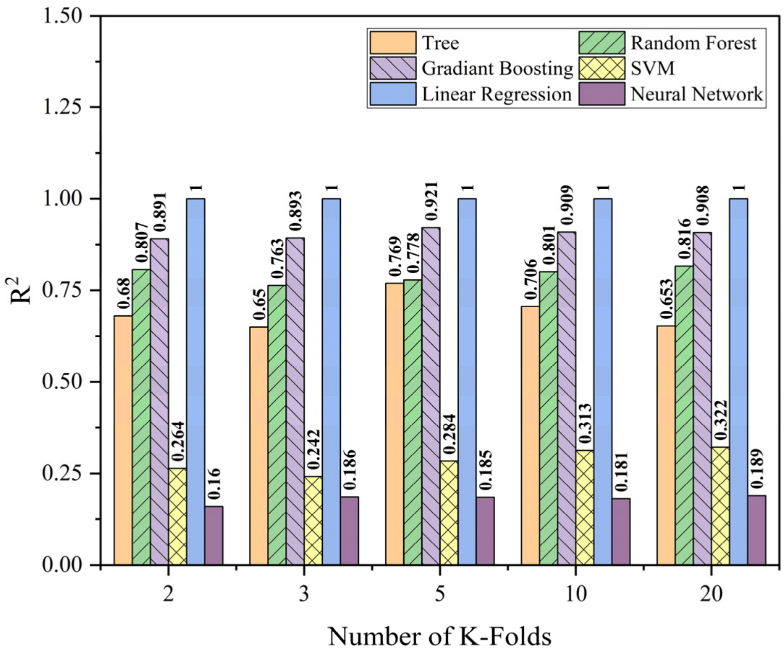

Figure 3. Model performance stability assessed via k-fold cross-validation, shows the R^2 scores for the evaluated machine learning algorithms across different fold configurations.

Table 8. The selected hyperparameter tuning results and final model configurations.

Model	Key Parameter	Tested Values	Final Selection	Best R^2
Decision Tree	Maximum depth/minimum leaf instances	Various (2–100)	Depth 100, leaf 2	0.72
Random Forest	Number of trees	10, 15, 20	10	0.85
Gradient Boosting	Number of trees/learning rate/maximum depth	100–500/0.01–0.1/3–10	100/0.1/3	0.92
SVM	Kernel/regularization (C)	Linear/poly/RBF/0.1–25	RBF/C = 1	0.77
ANN	Neurons in hidden layer/activation	50–200/ReLU, Tanh, logistic	100/ReLU	0.84

3. Results

The Gradient Boosting model, which was identified as the optimal algorithm using comparative evaluation, was deployed on the full dataset to generate predictions and facilitate detailed interpretation.

3.1. Feature Importance Analysis

The SHAP analysis quantified the contribution of each predictor to the model's EPDO predictions, with the feature importance ranking, from the highest to the lowest, being minor injuries (MIs), serious injuries (SRIs), fatalities (FAs), accident frequency (AF), stable injuries (SIs), median width (MW), U-turn distance (UTD), number of lanes (NLANE), intersection type (INT), and heavy vehicle percentage (HV%). The injury-related variables collectively dominated the model's decision-making process, and the geometric and traffic features exerted a secondary but notable influence. Also, the SHAP evaluation verifies that, even when the model "knows" the injury outcomes, the geometric design features are statistically significant predictors. This suggests that the infrastructure features are not simply noise, but are, in fact, inherently tied to the severity mechanisms that the ML model is identifying. This whole SHAP summary plot (Figure 4) illustrates both global importance and the direction of impact for each feature in this machine learning process.

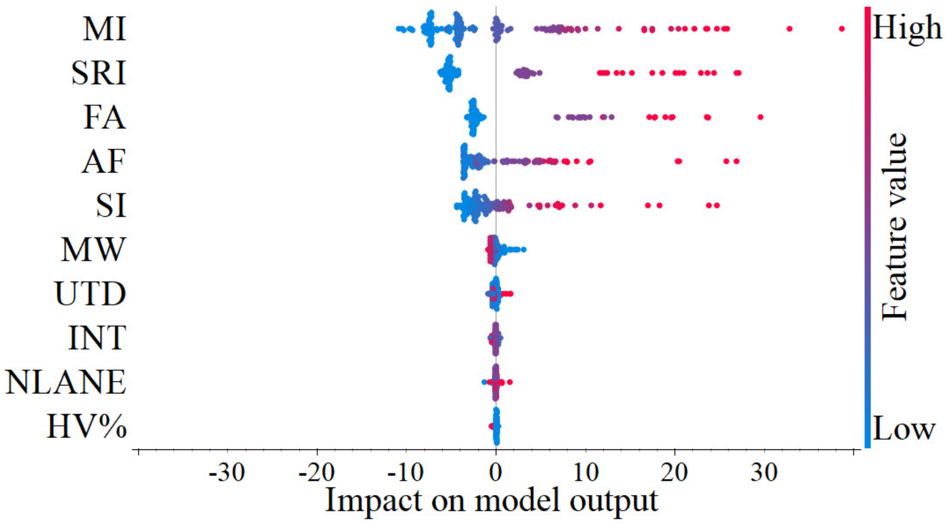

Figure 4. The SHAP summary plot displaying feature importance and individual impact directions for the Gradient Boosting model in predicting EPDO scores.

The prominence of injury-related variables (MI, SRI, FA, and SI) in the SHAP values' ranking confirms the model's validity, since EPDO is a direct function of these results, ensuring that the algorithms are able to identify the mathematical structure underlying the dataset. Nevertheless, these variables are more closely related to the severity of risk rather than its causes. In terms of safety measures, geometric and traffic variables become more prominent, with median width (MW) and U-turn distance (UTD) being the most important design variables.

3.2. Model Predictive Performance on Hold-Out Test Set

The application of the final Gradient Boosting model to the unseen test set yielded a strong alignment between the predicted and actual EPDO values. The bar chart (Figure 5) shows most points clustered closely around the line of equality, with representative examples including an accurate prediction of 67.82 against an actual value of 65 and a near-perfect agreement at 11.10 versus 11. Minor deviations were observed, such as an under-prediction of 31.95 for an actual value of 54 and an over-prediction of 52.54 for an actual value of 43. Overall, the distribution confirms high predictive fidelity across the severity spectrum.

https://doi.org/10.3390/su18083651

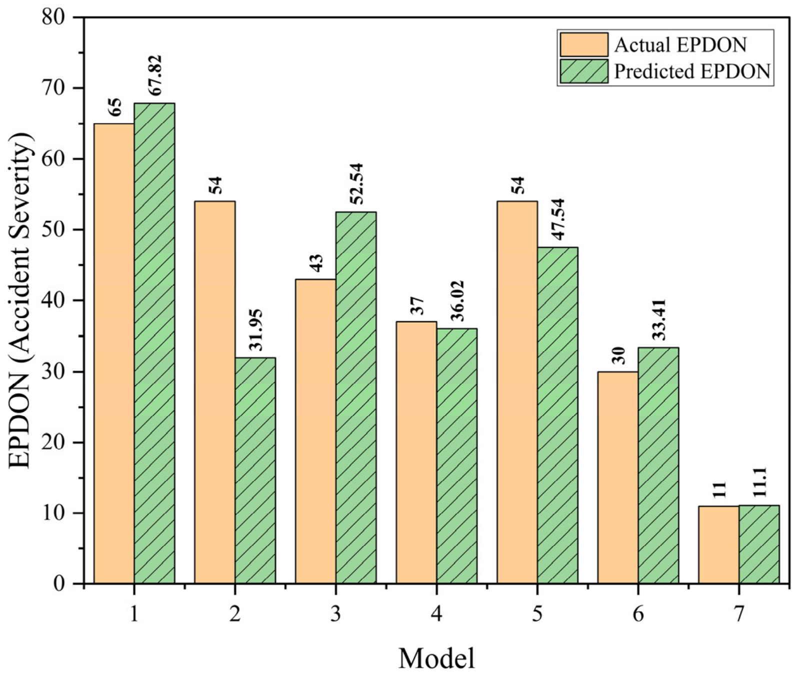

Figure 5. The bar chart of actual versus predicted EPDO scores on the hold-out test set using the Gradient Boosting model.

3.3. Intersection Risk Ranking

The trained Gradient Boosting model was used to compute predicted EPDO scores for all 150 intersections. The resulting ranking identified distinct high-risk locations, with the top 10 locations presented in Table 9, in which the intersection of Jeddah Road with Taif Road emerged as the most hazardous, with a predicted EPDO score of 137.22, closely followed by Makkah Al-Mukarramah Road before Wadi Laban towards the Western Ring Road at 130.40. The multiple entries from the Second Ring Road and Western Ring Road corridors underscore the concentrated risk along these arterial routes.

Table 9. Top 10 high-risk intersections ranked by EPDO scores predicted by Gradient Boosting.

Rank	Intersection Name	Predicted EPDO
1	Jeddah Road with Taif Road	137.22
2	Makkah Al-Mukarramah Road before Wadi Laban towards Western Ring Road	130.4
3	Second Ring Road exit before Southern Ring Road	99.7
4	Second Ring Road with Prince Ahmed bin Salman Street	86.59
5	Khurais Road with Hassan Bin Thabet Street	84.72
6	University Road exit meeting Airport Road	81.82
7	Abu Bakr Al-Siddiq Road with Mount Uhud	81.06
8	Hamza Ibn Abdul Muttalib with Al-Matari	80.09
9	Othman Bin Affan Road with Anas Bin Malik Street	75.4
10	From Western Ring Road towards Makkah Al-Mukarramah Road	72.28

Along with the tabulated ranking in Table 9, the distribution of predicted EPDO scores for these top-ranked sites is visualized in Figure 6.

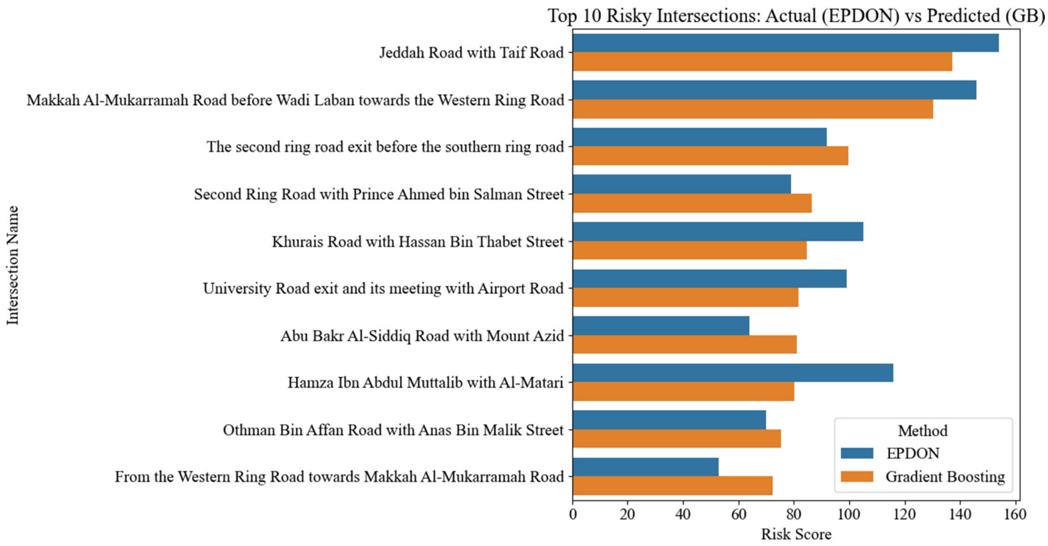

Figure 6. The ranking of intersections based on ML predictions.

4. Discussion

4.1. Superiority of Gradient Boosting in Capturing Complex Severity Patterns

The results in Table 7 show a clear hierarchy among the evaluated algorithms, with Gradient Boosting achieving an R^2 of 0.89, MSE of 63.43, and RMSE of 7.96 on the test set and metrics that substantially outperform Random Forest (R^2 = 0.81, MSE = 107.75) and leave Decision Tree (R^2 = 0.68), SVM (R^2 = 0.26), and ANN (R^2 = 0.16) far behind, due to which this advantage stems from Gradient Boosting's sequential ensemble structure, which iteratively corrects residuals and excels at modeling the non-linear interactions inherent in traffic safety data, where variables such as peak hour volume (ranging from 0 to 25,181 vehicles/h; Table 3) and U-turn distance (SD = 1079.96 m) exhibit pronounced heteroscedasticity. The model's robustness is further evidenced by its consistent performance across k-fold cross-validation configurations (R^2 = 0.89–0.92; Table 8), demonstrating resilience to variations in training subsample composition. The hyperparameter optimization (Table 8) played a critical role, with the selected configuration of 100 trees, learning rate of 0.1, and maximum depth of 3 striking an optimal balance between bias and variance, avoiding the overfitting observed in deeper trees or higher learning rates.

In contrast, the anomalous perfect fit of Linear Regression with an R^2 of 1.00 highlights the perils of feature leakage when injury counts contribute directly to the EPDO target (Equation (1)), underscoring the necessity of non-linear approaches for valid generalization. Gradient Boosting's success aligns with broader trends in transportation research where ensemble methods increasingly dominate severity modeling due to their ability to handle mixed data types and interaction effects without explicit specification, and these characteristics make the model particularly suitable for Riyadh's intersection environment and characterized by high variability in exposure and design features and provide a reliable foundation for the interpretability and ranking analyses that follow. The chosen Gradient Boosting models have a strong generalization capability and can capture the dynamic safety patterns of both high-density urban areas and high-speed suburban peripheries without the need for stratification.

4.2. Dominance of Injury-Related Predictors in Severity Modeling

The SHAP values (Figure 4) unequivocally position injury outcomes and minor injuries (MIs) and serious injuries (SRIs), as well as fatalities (FAs), as the primary drivers of EPDO predictions and a pattern corroborated by Pearson correlations (MI r = 0.79, SRI r = 0.67, FA r = 0.52; Table 4) and multivariate OLS coefficients (MI = 5.00, SRI = 9.00, FA = 12.00; Table 5). This dominance reflects the weighted structure of the EPDO metric (Equation (1)), yet it extends beyond mere mathematical aspects to reveal a fundamental characteristic of intersection risk in which the severity is predominantly determined by the propensity for conflicts to produce human harm rather than their raw frequency (AF r = 0.77). Stable injuries (SIs) also contribute meaningfully (r = 0.72), which reinforces that even non-fatal outcomes carry substantial predictive weight in composite severity indices. The prominent ranking of injury-related variables is acknowledged as a structural effect of the EPDON weighting scheme and mainly functions as a functional verification of the model's internal consistency. By filtering out these mathematically caused effects, it is possible to identify the independent empirical effect of geometric and traffic variables. In particular, the SHAP values of median width (MW) and U-turn distance (UTD) offer meaningful information about the infrastructure mechanisms related to intersection risk, irrespective of the target variable definition.

The relevance of U-turn distance (UTD) and median width (MW) in the SHAP values is based on the physics of energy dissipation and conflict point management. Small UTD values decrease the "weaving" distance available to vehicles, increasing the speed differential that multiplies kinetic energy in a collision, while inadequate MW does not offer a recovery area for out-of-control vehicles, resulting in head-on or high-angle collisions. Likewise, the service road distance (SRD) is a vital buffer zone, and its reduction enhances "friction" between arterial and local traffic, multiplying the complexity of the environment and hence the likelihood of a high-severity conflict.

The close alignment between actual and predicted EPDO scores (Figure 6) validates this injury-centric focus, with residual errors generally being small across the severity spectrum (mean EPDO = 32.37, SD = 24.94; Table 3), which resonates with Riyadh's documented trauma burden where the intersections generate a disproportionate share of severe cases requiring intensive care. More importantly, it shifts analytical emphasis from counting crashes to understanding escalation mechanisms and offering a more nuanced lens for safety planning in high-motorization settings where behavioral compliance remains challenging.

4.3. Secondary but Actionable Influence of Geometric Design Elements

Although injury-related variables rightfully command primary attention in SHAP rankings (Figure 4), the geometric design features consistently occupy a robust secondary tier, with median width (MW), U-turn distance (UTD), and service road distance (SRD) emerging as meaningful contributors despite their modest individual Pearson correlations (generally $|r| < 0.3$; Table 4). This positioning reveals that these parameters do not drive severity independently but exert substantial influence through interactions with exposure levels and conflict probability. In high-volume settings (PHV often exceeding 10,000 vehicles/h; Table 3), short U-turn distances create constrained weaving segments that elevate collision energy and inadequate median widths diminish the separation between opposing flows, heightening the risks of head-on and sideswipe crashes. Service road exits placed too close to the main intersections similarly force abrupt merging maneuvers, amplifying outcomes when human errors, such as distraction or speeding, occur. Notwithstanding the mathematical superiority of the injury terms, geometric variables such as median width (MW) and U-turn distance (UTD) had a statistically significant impact on the model's predictions. This suggests that although the injuries set the scale of the risk, it is the infrastructure variables that the model recognizes as being associated with severe outcomes.

The number of lanes (NLANE) and intersection type (INT) follow closely in importance, reflecting how increased complexity and specific configurations multiply conflict points within the intersection footprint; thus, these findings directly challenge the predominant behavioral explanations that have long dominated the regional traffic safety literature, demonstrating instead that infrastructural choices systematically amplify or mitigate severity escalation. In Riyadh's distinctive context, where U-turns serve as widespread alternatives to protected left turns, relocating openings beyond empirically derived thresholds (e.g., >300 m) represents a highly feasible engineering intervention capable of yielding substantial severity reductions, even in the absence of perfect driver compliance. Such modifications, informed by the model's isolation of geometric effects after accounting for historical injury patterns, offer municipal authorities practical, cost-effective levers for enhancing intersection safety within the existing urban constraints.

4.4. Role of Heavy Vehicles as Severity Amplifiers

Heavy vehicle percentage (HV%) occupies a lower position in the global SHAP importance ranking (Figure 4), yet its range across the dataset, from 0.1% to 12% (Table 3), and moderate Pearson correlation with EPDO (r = 0.41; Table 4), highlighting its importance. Trucks and buses, by the virtue of their greater masses, longer braking distances, and higher centers of gravity, introduce kinetic energy profiles that fundamentally alter collision dynamics. Thus, a moderate-impact event between passenger vehicles frequently escalates into a high-severity outcome when heavy vehicles are involved, particularly in mixed-flow conditions characteristic of Riyadh's major arterial roads where peak hour volumes routinely exceed 10,000 vehicles/h; thus, this amplification becomes especially pronounced in corridors combining high exposure with geometric constraints, such as short weaving sections or narrow medians, where the model's predicted EPDO scores rise disproportionately even at modest HV% levels.

The Gradient Boosting framework's sensitivity to HV% underscores an often-underappreciated dimension of intersection risk in logistics-intensive urban environments like Riyadh, where construction and commercial transport sustain elevated heavy traffic shares. Temporal separation measures, restricting heavy vehicles during peak hours, or spatial strategies, such as dedicated freight lanes on high-risk ring-road segments (evident in seven top-10-ranked sites; Table 9), could yield disproportionate severity reductions without necessitating the complete elimination of essential goods movement; thus, these interventions complement the traditional behavioral campaigns targeting passenger vehicle drivers, offering a multifaceted approach that addresses both the initiator (human error) and the escalator (vehicle mass) of severe outcomes, thereby enhancing the overall system resilience in high-motorization settings.

4.5. Interplay Between Driver Behavior and Infrastructural Context

Driver behavior continues to serve as the immediate trigger for most intersection conflicts in Riyadh, with speeding, red-light violations, distraction, and low seatbelt use repeatedly identified as the leading contributors in regional analyses, and these behavioral factors account for the initiation of most crashes, reflecting a complex mix of young driver demographics, diverse expatriate populations, and cultural attitudes towards road rules. However, the study findings, particularly the secondary but consistent influence of geometric variables such as U-turn distance, median width, and service road spacing on SHAP rankings (Table 9), reveal that infrastructure plays a decisive role in determining whether these behavioral lapses result in minor property damage or catastrophic injury. Short weaving segments induced by closely spaced U-turns (often <300 m), inadequate median separations, and abrupt service road exits create environments where recovery from human error is severely constrained, transforming routine mistakes into high-severity events.

This critical interplay offers a more complete explanation for the persistence of severe outcomes despite national declines in the overall crash frequency. Enforcement initiatives and public awareness campaigns effectively target behavioral triggers, yet their impact on severity remains limited when the physical road environment amplifies consequences and the model's capacity to isolate geometric contributions, evident in their ranking being above the intersection type and heavy vehicle percentage (Table 9). Despite modest individual correlations (Table 4), this study provides robust empirical evidence for integrated Safe System strategies in high-motorization contexts. By demonstrating that infrastructural modifications can mitigate escalation independently of perfect behavioral compliance, these results advocate for balanced interventions that combine traditional driver-focused measures with design enhancements capable of absorbing inevitable human error, ultimately advancing sustainable urban safety objectives.

4.6. Practical Implications of Severity-Based Risk Ranking

The severity-based ranking generated by the Gradient Boosting model (Table 9; Figure 6) directly translates predictive insights into clear operational priorities for Riyadh Municipality. Jeddah Road with Taif Road emerges as the most critical site with a predicted EPDO of 137.22, closely followed by Makkah Al-Mukarramah Road before Wadi Laban at 130.40 and the Second Ring Road exit before Southern Ring Road at 99.70, and the clustering of seven top-10 intersections along ring-road corridors, collectively accounting for predicted EPDO scores ranging from 72.28 to 137.22, exposes systemic vulnerabilities where high design speeds on peripheral arterial roads increasingly conflict with proliferating access points driven by urban expansion; thus, this spatial pattern underscores the need for targeted interventions on these corridors rather than dispersed efforts across the network.

In contrast to traditional frequency-based hotspot identification, which often overlooks sites with moderate crash volumes but high injury potential, severity-weighted ranking (EPDO metric; Equation (1)) optimizes resource allocation by focusing on locations offering the greatest marginal reduction in societal harm per intervention, and with municipal budgets being inevitably constrained, this approach maximizes return on investment, directing upgrades such as signal enhancements, lane channelization, and access restrictions to intersections where the predicted severity is the highest. This multi-model machine learning technique is directly in line with the Saudi Vision 2030 strategic plan of improving the livability and safety of cities. This study, through its data-driven approach to the identification of "blackspots," aims to support the National Transformation Program's goal of lowering road traffic deaths and improving the position of the Kingdom of Saudi Arabia in the Global Competitiveness Index for road quality. More specifically, our model provides a proactive approach for city planners to make informed decisions about U-turn distances and median sizes, which is critical to the achievement of the Quality-of-Life Program's aim of providing safer and smarter cities.

4.7. Alignment with International Traffic Safety Research

The patterns uncovered in Riyadh's intersections find striking parallels in megacities across the globe, where similar infrastructural legacies intersect with rapid motorization. The elevated severity associated with short weaving segments from closely spaced U-turns mirrors high-risk median openings extensively documented in Asian urban networks, where comparable design strategies have been linked to disproportionate crash costs despite moderate frequency. Likewise, the concentration of hotspots along ring-road corridors (Table 9; Figure 6) echoes peripheral highway challenges. Gradient Boosting's decisive performance ($R^2 = 0.89$; Table 7) and stability (Figure 5) align with its burgeoning adoption in international transportation research.

This convergence extends to conceptual frameworks: the emphasis on geometric modulators of severity, evident in the secondary yet robust SHAP contributions of U-turn distance, median width, and service road spacing (Figure 4), directly contributes to Safe System and Vision Zero discourses and the interpretable nature of the present framework, achieved through the SHAP visualization and explicit handling of non-linear interactions, and offers a transferable methodology particularly suited to rapidly urbanizing regions confronting the analogous pressures of motorization, diverse driver populations, and evolving land use patterns. By bridging local empirical findings with global safety principles, this study underscores the universal relevance of integrated, evidence-based strategies for achieving sustainable reductions in road trauma.

4.8. Methodological Contributions and Robustness

The systematic evaluation of six distinct algorithms, ranging from baseline Linear Regression to advanced ensembles (Table 7), combined with exhaustive k-fold cross-validation across configurations from k = 2 to k = 20 (Figure 3) and detailed SHAP-based interpretation (Figure 4), establishes a level of methodological rigor that exceeds typical regional traffic safety studies. The explicit identification and exclusion of Linear Regression due to feature leakage, alongside comprehensive hyperparameter documentation (Table 8), ensure transparency and reproducibility, critical attributes in applied machine learning where opaque processes often undermine practical adoption and these choices not only validate the superiority of Gradient Boosting (R^2 = 0.89, MSE = 63.43, RMSE = 7.96) but also provide a clear audit trail for practitioners seeking to replicate or extend the approach.

Utilizing municipality-sourced micro-level data for 150 precisely identified intersections advances substantially beyond the aggregate provincial or national datasets common in prior KSA research, delivering site-specific granularity that translates directly into operational priorities (Table 9); thus, this fine-scale focus, paired with the careful handling of mixed data types and non-linear relationships through tree-based imputation and ensemble modeling, positions the framework as a practical benchmark for future ML applications in traffic safety, particularly in data-constrained or rapidly evolving urban environments. The combination of predictive accuracy, interpretability, and real-world applicability offers a replicable template capable of supporting evidence-based decision making across comparable high-motorization settings worldwide.

It is worth noting that the results of the current research are consistent with previous studies on road safety. The significant impact of proximity to U-turns is also consistent with findings from [37], which emphasized conflict points related to U-turns. The impact of median width is also consistent with findings from [38], which showed the impact of median width on severe crashes. The impact of intersection types and volume is also consistent with findings from [38], which emphasized exposure and environmental factors related to intersections and volume.

4.9. Critical Limitations and Sources of Uncertainty

The inclusion of injury counts, minor injuries (MIs), serious injuries (SRIs), and fatalities (FAs) as predictors, alongside their direct incorporation in the EPDO target (Equation (1)), inevitably introduces an element of circularity. The coefficients in multivariate OLS (Table 5) mirror the EPDO weighting (MIs = 5.00, SRIs = 9.00, FAs = 12.00), and strong correlations with the target (MI r = 0.79, FA r = 0.52; Table 4) reflect this overlap. However, the emergence of geometric variables, such as median width, U-turn distance, and service road distance, as consistent secondary contributors in SHAP rankings (Figure 4) substantially mitigates concerns of triviality; thus, these design features exert influence

https://doi.org/10.3390/su18083651

independently of historical injury patterns, indicating that the model captures meaningful infrastructural modulators of risk rather than merely reproducing the target composition.

The static nature of the 2017–2023 dataset (Table 3) further constrains temporal resolution, excluding diurnal fluctuations, peak hour surges, seasonal variations, and environmental factors such as rain or extreme heat that are known to alter driver behavior and collision dynamics. Spatial aggregation at the intersection level masks finer-grained lane-specific or turning-movement conflicts, potentially underestimating the heterogeneity within sites. Although predictive fidelity appears robust (Figure 6), the observational design precludes causal inference; changes in predicted EPDO following interventions remain hypothetical until validated through controlled before–after studies or quasi-experimental evaluations; thus, these limitations highlight opportunities for refinement while underscoring the framework's value as a diagnostic and prioritization tool in its current form.

Since the current model has been trained only on 150 high-risk intersections in Riyadh, its main application is to detect risk drivers in high-severity urban areas. Although the internal validation has shown that the model has a high predictive accuracy in this particular setting, its ability to be generalized to low-risk intersections or other geographical locations is yet to be determined using external validation. Therefore, the model should be considered as a specialized tool for blackspot mitigation in urban settings common in the Middle East.

4.10. Future Directions and Broader Applicability

The current static framework, while effective, invites extensions that could enhance its operational value. Incorporating real-time data streams, such as traffic volumes, congestion levels, and weather conditions, would enable dynamic, time-varying severity forecasts, capturing fluctuations absent in the historical 2017–2023 dataset (Table 3). Explicit interaction terms, for instance, combining short U-turn distances with high heavy vehicle percentages (HV% up to 12%), would clarify compounding effects beyond individual SHAP contributions (Figure 4), and coupling the model with traffic simulation or digital twin tools would allow the virtual evaluation of interventions, such as extending U-turn buffers to 300 m or staggering service road exits $\geq$150 m, quantifying the expected EPDO reductions before implementation.

Applying the methodology to other GCC cities would rigorously test transferability and facilitate region-wide standards, while broader adoption in similar high-motorization contexts could advance global Safe System goals. Ultimately, this interpretable Gradient Boosting approach (R^2 = 0.89; Table 7) shifts traffic safety from reactive to proactive management, demonstrating machine learning's potential to guide evidence-based infrastructure prioritization for sustainable urban mobility in Riyadh and comparable cities worldwide.

Future research should also investigate the creation of stratified models for individual geographic clusters. As mentioned in this study, the intersection of central urban areas tends to have high frequencies of crashes with lower severity because of congestion, whereas suburban intersections tend to have higher severity because of higher operating speeds. The models could be further stratified based on their accuracy of safety predictions.

Although the current study concentrates on motorized traffic dynamics, the future versions of the model may include data from non-motorized vehicles. As Riyadh's urban development strategy changes to become more pedestrian-friendly, it will be essential to include these variables in a future Vulnerable Road User (VRU) safety analysis.

Although this study has highlighted important geometric factors that influence intersection risk, it is also necessary to recognize the impact of driving environment factors that were not considered in the present dataset. These factors include sight distance, visual openness, and the clarity of pavement markings, which are very important for driver perception and reaction time. The lack of consideration of these factors could result in the underestimation of the "human factor" in the model's explanatory power. For example, a good U-turn design (high UTD) could still be risky if the sign placement is suboptimal. Future research should therefore seek to incorporate high-resolution street view images or LiDAR (Light Detection and Ranging) data to measure these factors, further improving the strength of the EPDON predictive model.

4.11. Scientific Interpretation of Model Behavior and Nonlinearity

Outside of the direct performance benefits, the advantage of using a Gradient Boosting approach is that it leverages the inherently non-linear and interaction-rich nature of intersection safety systems. As statistical methods rely on additive and independent effects among predictors, the results of this study demonstrate that intersection safety is actually a function of compounding relationships among exposure factors, infrastructure features, and traffic composition. For example, the effect of various geometric factors such as U-turn distance or median width is significantly enhanced in specific traffic environments (i.e., high volumes during peak hours or mixed traffic compositions). Therefore, this study's findings demonstrate that intersection safety cannot be evaluated in a vacuum as a function of specific predictors but rather as a complex system in which threshold effects play a critical role in defining severity outcomes. The ability of the algorithm to account for these complex interactions more realistically mirrors real-world traffic environments.

4.12. Implications for Causality and Mechanistic Understanding

Although the model indicates a good predictive ability, the structure of the model also provides evidence for the underlying mechanisms for the escalation of crash severity. The distinction between primary (injury-based) and secondary (geometric and operational) predictors indicates that the process starts with the occurrence of a conflict event and continues with the escalation of that event into a severe crash. From this perspective, the infrastructure does not simply relate to the escalation of crash severity but rather acts as a moderating factor that determines the dissipation of energy, conflict angles, and opportunities for recovery. This perspective is consistent with physical models of crashes, in which the severity of a crash is a function of the conditions of the impacts rather than the occurrence of the impacts per se. Thus, the results provide evidence for a mechanistic perspective in which the roadway design directly affects the underlying probability distribution of the injury outcomes and in which it is essential to move beyond statistical associations and toward a more causally based approach to safety interventions.

5. Conclusions

This study has developed and validated an interpretable machine learning framework that advances the understanding and management of intersection accident severity in Riyadh. Using Gradient Boosting and SHAP analysis on municipality-sourced micro-level data, this study provides clear evidence of the dominant role of injury escalation while identifying actionable geometric and traffic-related modulators of risk. The resulting severity-based prioritization offers municipal authorities a practical tool for targeted interventions in a resource-constrained environment. The main conclusions drawn from this study are as follows:

- This study successfully developed a robust machine learning framework using Gradient Boosting to predict intersection accident severity (EPDO metric) in Riyadh, achieving superior performance with an R^2 of 0.89, MSE of 63.43, and RMSE of 7.96 on the test set (Table 7).

- Gradient Boosting outperformed five alternative algorithms and demonstrated consistent stability across k-fold cross-validation (R^2 = 0.89–0.92; Figure 3), confirming its suitability for non-linear traffic safety modeling.
- SHAP feature importance analysis (Figure 4) revealed that injury outcomes, minor injuries, serious injuries, and fatalities dominate predictions, highlighting escalation from conflicts to harm as the core driver of severity.
- Geometric design elements such as U-turn distance, median width, and service road distance were identified as the important and practical factors that contribute to intersection safety. These results illustrate the key opportunities for design changes to actively reduce risks.
- Heavy vehicle percentage exerts a meaningful amplifying effect on severity, particularly in high-volume corridors, supporting targeted temporal or spatial separation strategies.
- The model generated a credible severity-based risk ranking (Table 9; Figure 6), identifying Jeddah Road with Taif Road (predicted EPDO = 137.22) as the highest-priority site and revealing systemic vulnerabilities along ring-road corridors.
- A close alignment of actual and predicted EPDO scores (Figure 5) validates the framework's predictive fidelity across the observed severity spectrum (range 9–154).
- The study results confirm that the infrastructural context is a crucial factor in traffic safety, namely, design decisions determine whether inevitable human errors cause minor incidents or catastrophic consequences.
- Evidence-based recommendations, enforcing U-turn buffers $\geq$ 300 m, staggering service road exits $\geq$ 150 m, and restricting heavy vehicles during peaks, offer practical, cost-effective pathways for accident severity reduction.
- This interpretable, data-driven approach provides a scalable template for proactive traffic safety management in Riyadh and comparable high-motorization cities worldwide, aligning with sustainable urban mobility and Vision 2030 objectives.

Author Contributions: Conceptualization: S.A. (Saleh Altwaijri) and A.A. (Abdulaziz Alauany); Methodology: S.A. (Saleh Altwaijri) and S.A. (Saleh Alotaibi); Software: S.A. (Saleh Alotaibi); Validation: S.A. (Saleh Alotaibi) and F.A.; Formal Analysis: S.A. (Saleh Altwaijri) and S.A. (Saleh Alotaibi); Investigation: S.A. (Saleh Altwaijri), F.A., A.A. (Adel Almutairi) and A.A. (Abdulaziz Alauany); Resources: F.A., A.A. (Adel Almutairi) and A.A. (Abdulaziz Alauany); Data Curation: F.A., A.A. (Adel Almutairi) and A.A. (Abdulaziz Alauany); Writing—Original Draft Preparation: S.A. (Saleh Altwaijri); Writing—Review and Editing: S.A. (Saleh Altwaijri), S.A. (Saleh Alotaibi) and A.A. (Abdulaziz Alauany); Visualization: S.A. (Saleh Alotaibi); Supervision: A.A. (Abdulaziz Alauany); Project Administration: A.A. (Abdulaziz Alauany). All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Riyadh Municipality: RM-22354.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions imposed by Riyadh Municipality on sensitive traffic accident records and intersection-specific details.

Acknowledgments: The authors express sincere gratitude to Riyadh Municipality and its Accident Monitoring Center for generously providing the historical traffic accident data essential to this study, as well as for their continued support and collaboration throughout the research process.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Full Form
AF	Accident Frequency
AI	Artificial Intelligence
ANN	Artificial Neural Network
C	Regularization Parameter (in SVM)
EDA	Exploratory Data Analysis
EPDO	Equivalent Property Damage Only
EPDON	Equivalent Property Damage Only (Normalized/Index)
FAs	Fatalities
GCC	Gulf Cooperation Council
HV%	Heavy Vehicle Percentage
INT	Intersection Type
KSA	Kingdom of Saudi Arabia
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MIs	Minor Injuries
ML	Machine Learning
MSE	Mean Squared Error
MW	Median Width
NLANE	Number of Lanes
OLS	Ordinary Least Squares
PHV	Peak Hour Volume
R^2	Coefficient of Determination
ReLU	Rectified Linear Unit
RMSE	Root Mean Square Error
RTA	Road Traffic Accident
SD	Standard Deviation
SHAP	SHapley Additive exPlanations
SIs	Stable Injuries
SRD	Service Road Distance
SRIs	Serious Injuries
SVM	Support Vector Machine
UTD	U-Turn Distance
XAI	eXplainable Artificial Intelligence

References

1. Adedeji, J.A.; Feikie, X. Exploring the informal communication of driver-to-driver on roads: A case study of Durban City, South Africa. *J. Road Traff. Eng.* **2021**, *67*, 1–8. [CrossRef]
2. Bokaba, T.; Doorsamy, W.; Paul, B.S. A comparative study of ensemble models for predicting road traffic congestion. *Appl. Sci.* **2022**, *12*, 1337. [CrossRef]
3. Mohanty, M.; Panda, R.; Gandupalli, S.R.; Sonowal, D.; Muskan, M.; Chakraborty, R.; Dangeti, M.R. Development of crash prediction models by assessing the role of perpetrators and victims: A comparison of ANN & logistic model using historical crash data. *Int. J. Inj. Control Saf. Promot.* **2023**, *30*, 155–171. [CrossRef]
4. Al-Ahmadi, H.M. Analysis of traffic accidents in Saudi Arabia: Safety effectiveness evaluation of SAHER enforcement system. *Arab. J. Sci. Eng.* **2023**, *48*, 5493–5506. [CrossRef]
5. Alogaili, A.; Mannering, F. Unobserved heterogeneity and the effects of driver nationality on crash injury severities in Saudi Arabia. *Accid. Anal. Prev.* **2020**, *144*, 105618. [CrossRef]
6. Alanazi, F.; Umar, I.K.; Yosri, A.M.; Okail, M.A. Comparative evaluation of deep learning and traditional models for predicting traffic accident severity in Saudi Arabia. *Sci. Rep.* **2025**, *15*, 32568. [CrossRef]
7. Bakiş, E.; Erçetin, M.A.; Acar, E.; Gökalp, İ.; Yılmaz, M. Prediction of traffic accidents trend with learning methods: A case study for Batman, Turkey. *Sci. Rep.* **2025**, *15*, 26566. [CrossRef]

8. Shaik, M.E.; Islam, M.M.; Hossain, Q.S. A review on neural network techniques for the prediction of road traffic accident severity. *Asian Transp. Stud.* **2021**, *7*, 100040. [CrossRef]
9. Owais, M.; Alshehri, A.; Gyani, J.; Aljarbou, M.H.; Alsulamy, S. Prioritizing rear-end crash explanatory factors for injury severity level using deep learning and global sensitivity analysis. *Expert Syst. Appl.* **2024**, *245*, 123114. [CrossRef]
10. Srivastava, N.; Gohil, B.N.; Ray, S. Road traffic accident severity prediction using causal inference and machine learning. In Proceedings of the CODS-COMAD 2024—Proceedings of the 8th Joint International Conference on Data Science and Management of Data, Jodhpur, India, 18–21 December 2024; pp. 292–300. [CrossRef]
11. Qian, Y.; Aghaabbasi, M.; Ali, M.; Alqurashi, M.; Salah, B.; Zainol, R.; Moeinaddini, M.; Hussein, E.E. Classification of imbalanced travel mode choice to work data using adjustable SVM model. *Appl. Sci.* **2021**, *11*, 11916. [CrossRef]
12. Gkyrtis, K.; Pomoni, M. Use of Historical Road Incident Data for the Assessment of Road Redesign Potential. *Designs* **2024**, *8*, 88. [CrossRef]
13. Jamal, A.; Zahid, M.; Tauhidur Rahman, M.; Al-Ahmadi, H.M.; Almoshaogeh, M.; Farooq, D.; Ahmad, M. Injury severity prediction of traffic crashes with ensemble machine learning techniques: A comparative study. *Int. J. Inj. Control Saf. Promot.* **2021**, *28*, 408–427. [CrossRef] [PubMed]
14. Santos, K.; Dias, J.P.; Amado, C. A literature review of machine learning algorithms for crash injury severity prediction. *J. Saf. Res.* **2022**, *80*, 254–269. [CrossRef] [PubMed]
15. Gatarić, D.; Ruškić, N.; Aleksić, B.; Đurić, T.; Pezo, L.; Lončar, B.; Pezo, M. Predicting road traffic Accidents—Artificial neural network approach. *Algorithms* **2023**, *16*, 257. [CrossRef]
16. Singh, G.; Pal, M.; Yadav, Y.; Singla, T. Deep neural network-based predictive modeling of road accidents. *Neural Comput. Appl.* **2020**, *32*, 12417–12426. [CrossRef]
17. Theofilatos, A.; Chen, C.; Antoniou, C. Comparing machine learning and deep learning methods for real-time crash prediction. *Transp. Res. Rec. J. Transp. Res. Board* **2019**, *2673*, 169–178. [CrossRef]
18. Pourroostaei Ardakani, S.; Liang, X.; Mengistu, K.T.; So, R.S.; Wei, X.; He, B.; Cheshmehzangi, A. Road Car accident prediction using a Machine-Learning-Enabled data analysis. *Sustainability* **2023**, *15*, 5939. [CrossRef]
19. Al-Ghamdi, A.S. Analysis of traffic accidents at urban intersections in Riyadh. *Accid. Anal. Prev.* **2003**, *35*, 717–724. [CrossRef]
20. Li, P.; Abdel-Aty, M.; Yuan, J. Real-time crash risk prediction on arterials based on LSTM-CNN. *Accid. Anal. Prev.* **2020**, *135*, 105371. [CrossRef]
21. Assi, K.; Rahman, S.M.; Mansoor, U.; Ratrout, N. Predicting crash injury severity with machine learning algorithm synergized with clustering technique: A promising protocol. *Int. J. Environ. Res. Public Health* **2020**, *17*, 5497. [CrossRef]
22. Mannering, F.; Bhat, C.R.; Shankar, V.; Abdel-Aty, M. Big data, traditional data and the tradeoffs between prediction and causality in highway-safety analysis. *Anal. Methods Accid. Res.* **2020**, *25*, 100113. [CrossRef]
23. Hamim, O.F.; Hoque, M.S.; McIlroy, R.C.; Plant, K.L.; Stanton, N.A. A sociotechnical approach to accident analysis in a low-income setting: Using accimaps to guide road safety recommendations in Bangladesh. *Saf. Sci.* **2020**, *124*, 104589. [CrossRef]
24. Alnowaiser, K. A Computational Intelligence GNN–LSTM Framework for Spatiotemporal Prediction of Traffic Accident Severity in Smart Cities Using SHAP XAI. *Int. J. Comput. Intell. Syst.* **2025**, *18*, 271. [CrossRef]
25. Gutierrez-Osorio, C.; Pedraza, C. Modern data sources and techniques for analysis and forecast of road accidents: A review. *J. Traffic Transp. Eng.* **2020**, *7*, 432–446. [CrossRef]
26. Jiang, W.; Luo, J. Graph neural network for traffic forecasting: A survey. *Expert Syst. Appl.* **2022**, *207*, 117921. [CrossRef]
27. Ullah, Z.; Al-Turjman, F.; Mostarda, L.; Gagliardi, R. Applications of artificial intelligence and machine learning in smart cities. *Comput. Commun.* **2020**, *154*, 313–323. [CrossRef]
28. Silva, P.B.; Andrade, M.; Ferreira, S. Machine learning applied to road safety modeling: A systematic literature review. *J. Traffic Transp. Eng.* **2020**, *7*, 775–790. [CrossRef]
29. Asadianfam, S.; Shamsi, M.; Kenari, A.R. Big data platform of traffic violation detection system: Identifying the risky behaviors of vehicle drivers. *Multimed. Tools Appl.* **2020**, *79*, 24645–24684. [CrossRef]
30. Ma, Z.; Mei, G.; Cuomo, S. An analytic framework using deep learning for prediction of traffic accident injury severity based on contributing factors. *Accid. Anal. Prev.* **2021**, *160*, 106322. [CrossRef]
31. Formosa, N.; Quddus, M.; Ison, S.; Abdel-Aty, M.; Yuan, J. Predicting real-time traffic conflicts using deep learning. *Accid. Anal. Prev.* **2020**, *136*, 105429. [CrossRef]
32. Li, K.; Xu, H.; Liu, X. Analysis and visualization of accidents severity based on LightGBM-TPE. *Chaos Solitons Fractals* **2022**, *157*, 111987. [CrossRef]
33. Gilani, V.N.M.; Hosseinian, S.M.; Ghasedi, M.; Nikookar, M. Data-driven urban traffic accident analysis and prediction using logit and machine learning-based pattern recognition models. *Math. Probl. Eng.* **2021**, *2021*, 9974219. [CrossRef]
34. Owais, M.; El Sayed, M.A. Red light crossing violations modelling using deep learning and variance-based sensitivity analysis. *Expert Syst. Appl.* **2025**, *267*, 126258. [CrossRef]

35. Yun, J.; Kim, S.; Kim, D.; Lee, J. Evaluation of Equivalent Property Damage Only (EPDO) weight sets for hotspot identification: A case study on Korean expressways. *Case Stud. Transp. Policy* **2025**, *21*, 101531. [CrossRef]
36. Samadi, H.; Rahmani, O.; Shaaban, K.; Nasiri, A.S.A.; Hasanvand, M. Optimizing Equivalent Property-Damage-Only (EPDO) Prediction Models with Genetic Algorithms: A Case Study on Roundabout Geometric Characteristics. *Infrastructures* **2025**, *10*, 61. [CrossRef]
37. Garner, G.R.; Deen, R.C. *Elements of Median Design in Relation to Accident Occurrence*; Kentucky Department of Highways: Lexington, KY, USA, 1973.
38. Abebe, M.T.; Belayneh, M.Z. Identifying and ranking dangerous road segments: A case of Hawassa–Shashemene–Bulbula two-lane two-way rural highway, Ethiopia. *J. Transp. Technol.* **2018**, *8*, 151–174. [CrossRef]