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Impact of Wind Turbine Distraction on Crash Severity: Assessment and Prediction Study

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Abstract

Wind turbines are increasingly installed near highways, yet their potential role as external distractions impacting traffic crashes remains underexplored. This study investigates the effect of wind turbines on crash severity and frequency along Jordan's King's Highway, analyzing data through a mixed-effect logit model and machine learning techniques. Key factors, including driver demographics, road geometry, and environmental conditions, were incorporated to provide a comprehensive analysis. The findings indicate a 117.4% increase in severe injury crashes (KAB) and a 25.7% rise in property damage only near wind turbines. Using MK models such as Bagged Tree classifiers and SMOT-balanced datasets, the study achieved a high prediction accuracy of 89.6% for crash severity. Shapley value analysis identified crash type and wind turbine proximity as critical predictors, while other influential factors included younger drivers, poorly separated roads, and higher speed limits. By integrating statistical and ML approaches, this research provides actionable insights into the relationship between wind turbines and road safety. The results underscore the need for regulatory policies to optimize wind turbine placement and reduce their potential as driver distractions. This study also demonstrated the potential of ML techniques to enhance traffic safety analysis, paving the way for future research to address multi-class crash severity predictions and other external roadside distractions.

Keywords: Wind Turbines; Driver Distractions; Mixed-Effects Logit Model; Machine Learning in Traffic Analysis; Bagged Tree Classifier; Crash Severity.

1. Introduction

Traffic accidents are one of the leading causes of death worldwide, and this issue continues to grow as a public health concern. The World Health Organization [1] reports that approximately 1.3 million people die each year in traffic accidents. Road crashes have now become the eighth leading cause of death globally, surpassing diseases like HIV/AIDS and tuberculosis. Beyond the human toll, these accidents also cost countries up to 3% of their GDP, making road safety an urgent priority for governments worldwide. Many factors contribute to traffic accidents, such as the environment around the road, the behavior of drivers, and the condition of the vehicles. How other road users behave, driving speed, and the road and vehicle conditions all play essential roles in determining the likelihood of a crash. Research shows that young drivers, especially in regions like Africa and the Eastern Mediterranean, are particularly at risk of fatal accidents [2-5]. Traffic crashes are caused by human, vehicle, and environmental factors. Understanding these causes and how often they happen is key to finding ways to prevent them [6, 7]. Studies have shown that human error is the primary cause of most crashes, with road users being the leading cause or contributing factor in almost every case [8, 9]. As a result, efforts to prevent accidents have mainly focused on changing driver behavior rather than modifying road designs or vehicle features.

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One of the biggest problems on the road is driver distraction, which can take many forms and vary in severity. The National Highway Traffic Safety Administration (NHTSA) [10] defines distracted driving as any activity that takes attention away from the road. According to the NHTSA, 80% of car accidents and 65% of near-misses are linked to distractions within three seconds of the incident. Whereas prior estimates had been 25% [11]. This is a vast increase compared to previous estimates. When drivers look away from the road for more than 2.0 seconds, the chance of an accident doubles [12]. Other factors, like driving experience, can also affect how dangerous these distractions are. According to Khattak et al. (2021) [13], about 93% of crashes are caused by human errors, and the most common type of error is recognition, which includes distractions.

In Jordan, traffic accidents have risen alongside the growing population and the number of vehicles on the road. The country's population was about 11 million in 2021 [14], with over 2.9 million licensed drivers and nearly 1.8 million registered vehicles [15]. Despite these numbers, Jordan still has relatively low road safety compared to developed nations, leading to severe social and economic costs. In 2021, there were 160,600 traffic accidents in Jordan, including 11,241 injuries and 589 fatalities, costing an estimated JOD 320 million. Furthermore, 39.4% of these injuries and deaths were due to driver negligence, such as not taking necessary precautions.

Distracted driving is the second most common cause of crashes on rural and suburban roads in Jordan and contributes to many of the fatalities and injuries [16]. To reduce these risks, it's crucial to understand how different road factors influence distraction, especially under varying weather, road types, and seasonal conditions.

While most research on distracted driving has focused on in-vehicle distractions—like adjusting the radio, using a mobile phone, interacting with passengers, or eating [17-19]—it's also important to consider external distractions. Two American studies found that 29% [20] and 35% [21] of drivers involved in crashes were distracted by something outside the vehicle. A study with 3,265 drivers showed that 32.7% of drivers were distracted, and 20.4% of those distractions came from external sources [22]. Stutts et al. (2005) [23] also noted that external distractions significantly cause crashes, with drivers looking outside the vehicle 97.2% of the time. While some studies have looked at distractions like billboards [24], there's been little research on other roadside elements, such as wind turbines, and how they might affect driving behavior. Antonson et al. (2014) [25] suggested that objects near the road, like wind turbines, can impact drivers' behavior.

Despite the growing number of wind turbines along highways in many countries, their impact on driver distraction has not been well studied. Most research on this topic has only emerged in the last 15 years. George (2007) [26] was one of the first to examine whether wind farms along roads contribute to driver distraction. His study compared crash rates before and after installing wind farms but found no significant differences. However, more research is needed to understand wind turbines' role in driver distraction fully and whether they increase crash risk.

Milloy & Caird (2011) [27] used driving simulations to investigate whether external distractions, such as wind farms and video billboards, impact driving performance. Their study found that while small wind farms had little effect, larger wind turbines (over 100 meters tall) caused drivers to slow down as they passed. However, the study also showed that drivers reduced their following distance when passing these wind farms, which could potentially reduce safety. More research is needed to explore the long-term effects of wind turbines on driver attention and road safety. Alferdinck et al. (2012) [28] studied how wind turbines in the Netherlands affect driver behavior. Their findings showed that when wind turbines were placed closer to the road (26 meters instead of the recommended 55 meters), driving speed became more variable, and drivers tended to change lanes more. This suggests that wind turbines could lead to unsafe driving behavior, although the overall impact on crash rates is still uncertain. Other studies that looked at crash rates before and after the installation of wind turbines found that while driving speed decreased, increased variability in speed and lane position could be a safety concern [29].

Despite these studies, there is no consistent evidence on how wind turbines affect crash rates, and the existing research is limited in terms of sample size and long-term observation. In Jordan, there are no specific regulations for placing wind turbines along nonurban roads, and many drivers have complained about increased crashes after these turbines were installed. This indicates a need for further research to understand the connection between wind turbines and road safety.

2. Research Methodology

In this study, we combine two powerful approaches—mixed-effects logit models and machine learning techniques—to better understand and predict how wind turbines along King's Highway in Jordan might affect the severity of traffic crashes. Mixed-Effects Logit Model is a beneficial model for analyzing crash severity because it helps us account for different factors that could vary from one crash to another. By including fixed and random effects, we can capture the unique differences in the data, such as road conditions, the characteristics of the drivers, and the surrounding environment. In simple terms, this model allows us to estimate how the presence of wind turbines influences crash severity in different situations, shedding light on how these factors interact unpredictably. To complement the mixed-effects logit model, we also use several machine learning algorithms like decision trees, support vector machines (SVM), and Bagged tree classifiers. These tools help us analyze large amounts of data and uncover complex patterns that are not always obvious. By applying these techniques, we're not just looking for statistical relationships but also aiming to predict crash outcomes with high accuracy.

Together, these methods give us a complete picture of the problem, helping us identify key factors contributing to crashes and offering practical solutions to improve road safety. Focus on Wind Turbines as External Distractions: One of the main contributions of this research is its focus on wind turbines as potential distractions for drivers. While much of the existing research has looked at in-car distractions, little attention has been paid to how things outside the vehicle, like wind turbines, might impact driver behavior. This study proposes that large wind turbines, with their striking visual presence, might distract drivers and cause them to behave differently on the road, potentially increasing the risk of severe crashes.

This study aimed to examine the impact of installing wind turbines along Kings Highway on crash severity and occurrences, considering both pre- and post-installation phases. The study defined two periods of wind turbine presence: Period 0, before installation or absence, and Period 1, when wind turbines were operational. The aim was to evaluate the effects of wind turbine installation by analyzing changes in crash occurrences and severity between Period 1 and Period 0. The analysis time frame was as follows: Period 0, January 2015 to December 2017, and Period 1, September 2018 to December 2021. The period from January 2018 to August 2018 was excluded from consideration due to the construction of the wind turbines.

The road network served as the foundational framework for our analysis. As of the conclusion of 2023, the King Highway spanned approximately 115 kilometers, a two-lane highway stretching from Busira in Tafileh to Ras Alanaqab in Aqaba. On any given day, 2840 vehicles traversed this thoroughfare in both directions. Given the variations in traffic volumes, environmental surroundings, geometric attributes, and the inclusion of wind turbines along its length, the highway was segmented into distinct subsections, as depicted in Figure 1. It also shows the extent of the presence of wind turbines along Kings Highway, based on field surveys by the study team in 2015 and 2019. It was supported by contacting the wind turbine operating company to confirm the locations and the construction date. The study areas encompass sections C-D and I-K, as illustrated in Figure 1. The wind turbines differ in height and blade diameter along the road section: heights range from 80 to 112 m, and blade diameters range from 114 to 136 m.

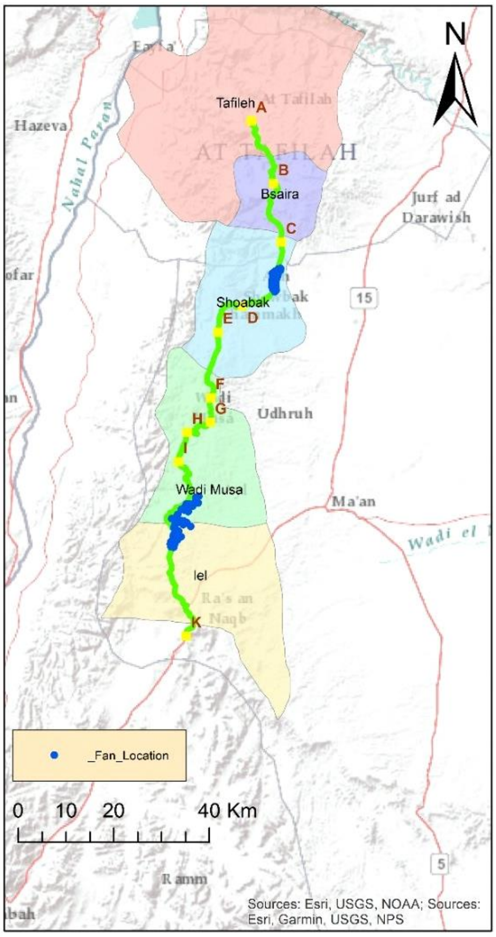


Figure 1. King's Highway with allocated wind turbine locations

Given the differences in road characteristics and the presence of wind turbines alongside Kings Highway, the study's evaluation framework included two analyses with different compositions of treatment sites (with wind turbines) and control group sites (without wind turbines).

2.1. Crash Data

Road crash data for the analyses were extracted from the Public Security Directorate (Traffic Department), including records on all traffic crashes on Kings Highway. The research group received all crash data reported on Kings Highway by the police department between 2015 and the end of 2021. The records were classified by the Kings Highway structure of all crash types (from run-off roads and multiple vehicle crashes) and all severities (fatal, incapacitating, capacitating, minor injury, and damage-only). Fatal crashes were included in injury crash counts because of the rareness of the King's Highway.

Table 1 shows the statistics summary of the variables used for the crash severity model. Between 2015 and 2021, 1646 crashes were recorded on highway segments with and without wind turbines. The variables could be categorized into demographic and behavioral characteristics of the drivers (age, gender, and violation type), road geometric and operational characteristics (grade, speed limit, ADT, and light condition), vehicle characteristics, and crash severity and type.

Table 1. Statistic's summary of the model variables

Variable	Min	Max	Mean	Std. Dev.	Variable	Min	Max	Mean	Std. Dev.
Driver > 18 years old	0	1	0.022	0.148	Uphill straight	0	1	0.102	0.303
Young (18-24)	0	1	0.131	0.338	Level Road	0	1	0.661	0.474
Adult (25-64)	0	1	0.696	0.460	Downhill straight	0	1	0.047	0.213
Seniors 65 and above	0	1	0.053	0.225	Uphill Curvature	0	1	0.029	0.167
Gender (1=Male, 0=Female)	0	1	0.894	0.308	Downhill Curvature	0	1	0.047	0.213
Before and After Wind Turbine Installation	0	1	0.518	0.500	**Driver Fault**				
Average Daily Traffic (ADT)	615	18194	2823.829	1371.479	Wrong way driving	0	1	0.038	0.192
Speed Limit	10	110	49.105	12.704	Improper passing turn backing	0	1	0.168	0.374
Property Damage Only (PDO)	0	1	0.762	0.426	Tailgating	0	1	0.085	0.278
Fatal Crashes K	0	1	0.020	0.141	Skid due to tire-related issues	0	1	0.128	0.334
Non-incapacitating Injury B	0	1	0.026	0.160	District Maan=1, Tafilah=0	0	1	0.632	0.482
Private Vehicle Driver license	0	1	0.783	0.413	Mini Bus and Pickup Trucks	0	1	0.358	0.480
Professional Driver license	0	1	0.288	0.453	Passenger Cars	0	1	0.757	0.429
Type of surfaces asphalt =1, other=0	0	1	0.974	0.159	Construction and Agriculture	0	1	0.027	0.162
Light Condition					Motorcycle	0	1	0.003	0.055
Night Time	0	1	0.088	0.284	Runoff Crashes =1, Multiple Crashes =0	0	1	0.068	0.252
Artificial Light Night Time	0	1	0.131	0.337	Two lane highways (Separated =1 Unseparated =0)	0	1	0.706	0.456
Clear weather =1, Other =0	0	1	0.929	0.258	Road condition (dry=1, wet =0)	0	1	0.936	0.244

2.2. Mixed Effect Logit Model

The mixed logit model extends the traditional multinomial logit model by allowing the parameter vector β to vary across observations. This means it can account for differences (heterogeneity) within the crash dataset by letting the elements of β change. The constants related to the outcomes and the parameters (β) can be fixed or randomly distributed. A "mixing distribution" is introduced, which helps calculate the probabilities of different crash severity outcomes. The probability for a specific outcome j given parameters ϕ is represented as [30].

$$Porb(j|\varphi) = \int \frac{EXP\ [\beta X_{ij}]}{\sum EXP\ [\beta X_{IJ}]}\ f(\beta|\varphi)d\beta \tag{1}$$

In this equation, X_{ij} represents the measurable characteristics (like crash, road, environment, driver, or vehicle factors) that influence the injury outcome j for crash i, and $f(\beta \mid \phi)$ is the probability distribution of β, with ϕ describing its parameters (like mean and variance).

In the mixed logit model, β can account for unobserved variations in how X affects crash severity outcomes. The density function $f(\beta|\phi)$ helps determine β. The mixed logit probabilities are then a weighted average of different values of β across crashes, where some elements of β may be fixed while others are randomly distributed. If all parameters are fixed, the model simplifies to the standard multinomial logit model.

3. Modeling Results and Discussion

The findings from the mixed-effects logit model utilizing the maximum likelihood estimation method in STATA software version 14 [31] are summarized in Table 2. The regression coefficients, incident rate ratio (IRR), and P-values are delineated for each variable. The IRR value exceeding the value of one signifies a correlation in the increase of that variable with the crash occurrence. In contrast, an IRR that falls below the value of one indicates an inverse association between the variable and the crash. The P-value for each variable shows the significance of the variable at a 95% confidence level. Distinct Models were formulated for KAB, KABC, and property damage-only crashes. The wind turbine indicator reflects the existence of wind turbines at the crash location.

Table 2. Mixed effect logit model results for KAB, KABC, O related crashes

	KAB			KABC			O (Property Damage Only)		
	Coef.	**IRR**	**P>z**	**Coef.**	**IRR**	**P>z**	**Coef.**	**IRR**	**P>z**
Intercept	-2.375	0.093	0.000	-2.375	0.093	0.000	3.120	22.661	0.000
Wind Turbine Indicator	0.777	2.174	0.000	-0.214	0.807	0.085	0.229	1.257	0.023
Speed Limit	0.031	1.032	0.000	0.025	1.025	0.000	-0.026	0.974	0.000
Runoff Crashes	0.866	2.377	0.001	1.468	4.341	0.002	-1.324	0.266	0.000
Profession License	-0.889	0.411	0.000			0.019	0.528	1.695	0.000
Skid	-1.877	0.153	-	-1.332	0.264	0.024	1.081	2.948	0.000
Minibus And	-1.097	0.334	0.029			-	0.238	1.269	0.097
Passenger	-1.343	0.261	0.063			0.010	0.470	1.600	0.001
Young Driver (18-24)	-	-	0.000	0.372	1.451	0.033	-	-	-
Undivided Roads	-	-	0.042	0.260	1.297	0.089	-0.329	0.720	0.031
Improper Passing	-	-	0.014	-1.291	0.275	0.064	-	-	-
	-	-	-	0.187	1.206	0.003	-	-	-
No fault							0.975	2.650	0.012
Random effect	**Variance**		**S. D**	**Variance**		**S. D**	**Variance**		**S.D**
Segment ID	**0.001**		**0.028**	**0.069**		**0.05**	**0.063**		**0.05**
Likelihood-ratio test vs. Logistical:	Wald Chi2 (2) =116.46: Prob> chibar2=0.487			Wald Chi2 (2) = 138.48: Prob> chbari2=0			Wald Chi2 (2) = 139.43: Prob> chbari2=0		
Dispersion parameter, α	0.05			0.005			0.001		
95 % CI for α	2.22e-29-3.92e+22			0.0164-0.287			0.0146-0.268		
Log-likelihood	-469.967			-809.75			-818.44		

Other models, such as negative binomial and logistic models, were used for crash severity analysis compared to the mixed-effect logit model based on Akaike's Information Criterion (AIC). The mixed-effect logit models perform better than others in terms of KABC, KAB, and O crash analysis.

A mixed-effects logit model was applied to analyze total O, KABC, and KAB crashes, with findings showing a more substantial impact, as illustrated in Table 2. This model indicates a 117.4 % and 25.7 % rise in KAB and O crashes, respectively, along the King Highway due to the existence of wind turbines at the time of the analyzed crashes. In contrast, the wind turbine indicator shows a 19.3% decrease in KABC crashes. The results show that wind turbine distraction significantly contributes to the rise of medium to significant injuries and fatalities compared to those crashes with minor injuries (C).

Various factors, such as speed limit, crash type, driver age, fault type, and median type, were analyzed in this model. The speed limit variable shows a positive association with crash types KAB and KABC, with a rise of 3.1% and 2.5%, respectively. These findings are consistent with previous research that has shown a positive relationship between speeding and the occurrence and severity of crashes [32-35]. This implies that higher speed limits are increasing the likelihood of severe crashes. Crash type (run-off) significantly correlates with KAB and KABC, leading to 137.7 % and 334.1% increments, respectively. This finding is consistent with other studies that have identified a significant relationship between run-off crashes and crash severity [36, 37]. KABC crashes were observed to be 45.1% more likely to occur based on driver age from 18 to 24 years. Young drivers were identified as the leading cause of crashes, as confirmed by several previous studies [38], due to their lack of experience and risk-taking behaviors while driving, such as speeding and distracted driving [39]. The results show that poorly separated roads yield a 29.7% rise in KABC crashes. Khattak et al. found similar results when studying the impact of road infrastructure on crash frequency [40].

The random effect model in Table 2 accounts for unobserved variability influencing road segment crash frequency due to unobserved factors. One of the objectives of this study was to examine the variation between segment and crash frequencies. A mixed-effect logit model was employed to capture unobserved factors contributing to crash frequency among segments along the King Highway. The observed variance in KABC, KAB, and O crashes due to random effects was 6.9%, 0.1%, and 6.3%, respectively. Additionally, the observed variance in wind turbine indicators for KABC, KAB, and O crashes was 0.5%, 5%, and 0.1%, respectively.

4. Crash Severity Level Prediction

In this section, the severity level of a traffic accident will be the target class. It was sorted into two classes: 1 (no injury) and 2 (injury). The data set shows that 75.91 % of total instances were class (1), and only 24.09 % were class (2). It can be concluded that the dataset is imbalanced, with an imbalanced ratio greater than 1.5. Thus, two data-balancing approaches were selected to test the effectiveness of a balanced data set in predicting the target classes:

The random under-sampling technique (RUS) eliminates instances from the major class to rebalance the dataset between minor and major classes at a ratio of 1:1 [41].

The synthetic minority oversampling technique (SMOTE): This method creates synthetic input for the minor classes instead of duplication using the K-nearest neighbor algorithm, which could be estimated depending on the required amount of oversampling to balance the dataset [42].

4.1. Study Design and Model Evaluation

Five different ML classifiers were selected to develop a crash severity rate prediction: Decision Tree, Naïve Bayes, Support Vector Machine (SVM), Kernel, and Ensemble. The data set contains 17 different independent variables. The datasets, including the original, under-sampled, and oversampled datasets, will be divided into training and validation sets with 10-fold for cross-validation (70% of the instances) and test set (30% of the total instances).

The prediction models for the severity level will be evaluated based on the total accuracy of the test set, confusion matrices of the classifiers to explain the test accuracy results, and Receiver operator characteristics (ROC) for a comprehensive assessment of the selected classifier from each dataset.

4.2. Results and Discussion

Figure 2 shows the accuracy of the test set using the selected classifiers for the original data set, under-balanced dataset, and over-balanced dataset. Figure 2 shows that a coarse tree classifier (Tree) has the highest test accuracy among all classifiers using the original data set with an average accuracy of 85.6%; the SVM kernel (Kernel) uses an under-sampled data set with an average test accuracy of 74.2%; and the Bagged tree (Ensemble) uses an over-sampled data set with an average accuracy of 89.6%. It is evident from Figure 2 that the over-sampled data set has higher accuracy among all datasets, followed by the original data set and the under-sampled data set, with a significant drop in accuracy compared with other datasets because the RUS technique could eliminate significant instances for target class prediction.

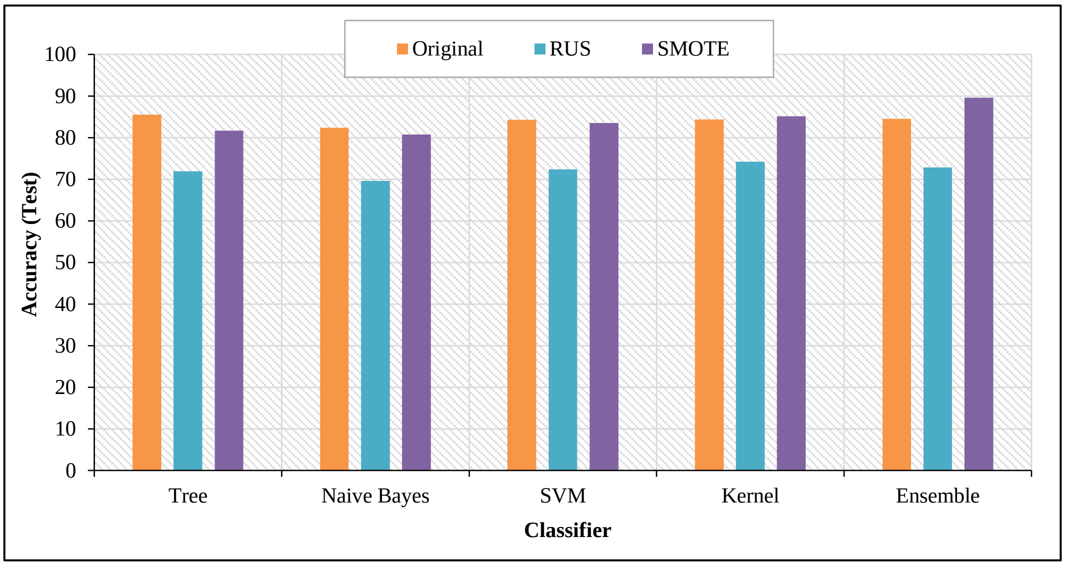
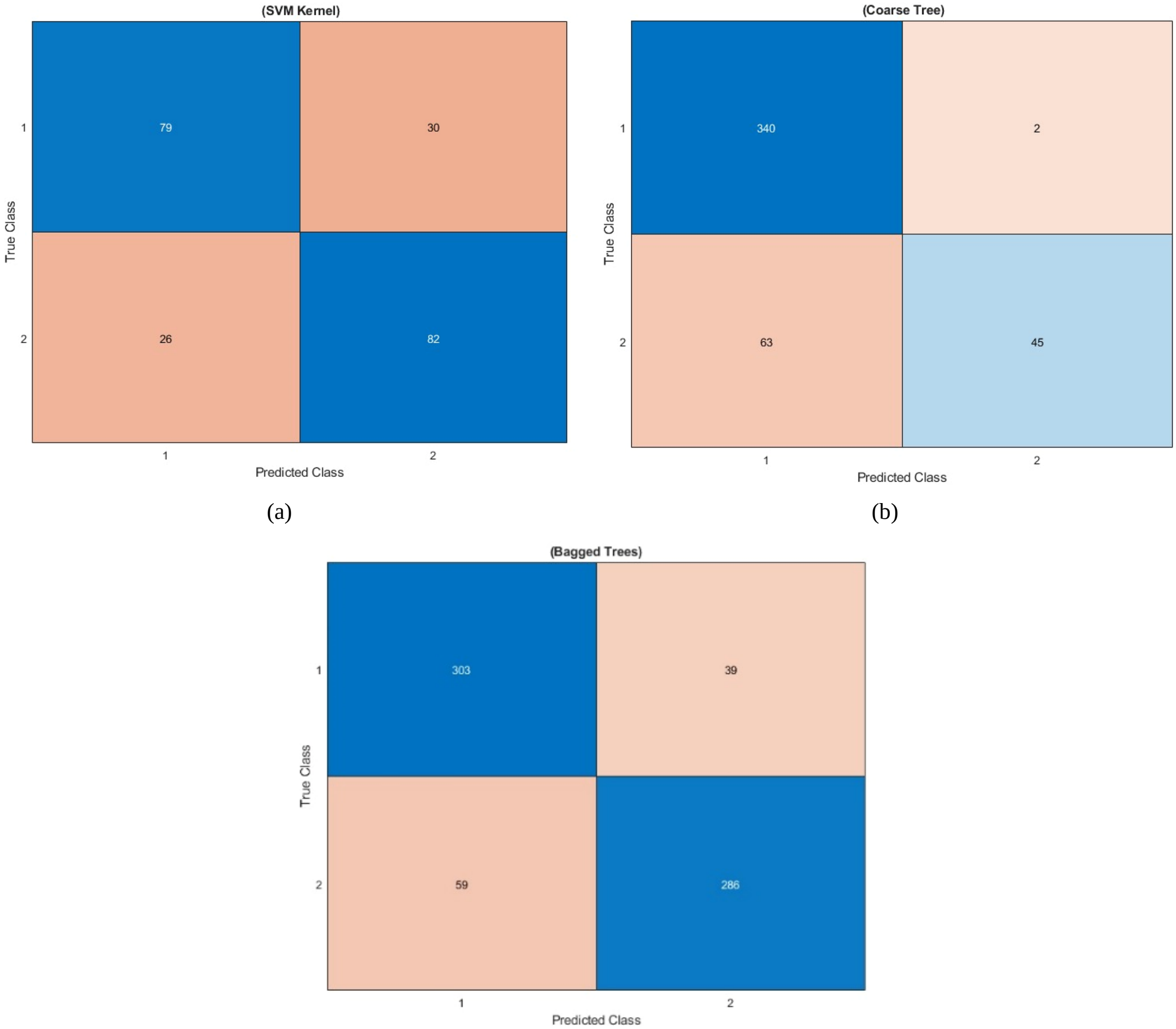


Figure 2. Test accuracy using original, underbalanced, and overbalanced data sets

The accuracy of the test set might be misleading when the dataset is imbalanced from the original dataset. The confusion matrices and ROC-AUC for the best classifiers for the three datasets will be compared to assess the prediction model more comprehensively. Figures 3-a, 3-b, and 3-c show the confusion matrices for the coarse tree classifier using the original dataset, the SVM kernel using an underbalanced dataset, and the Bagged tree using an overbalanced dataset, respectively.

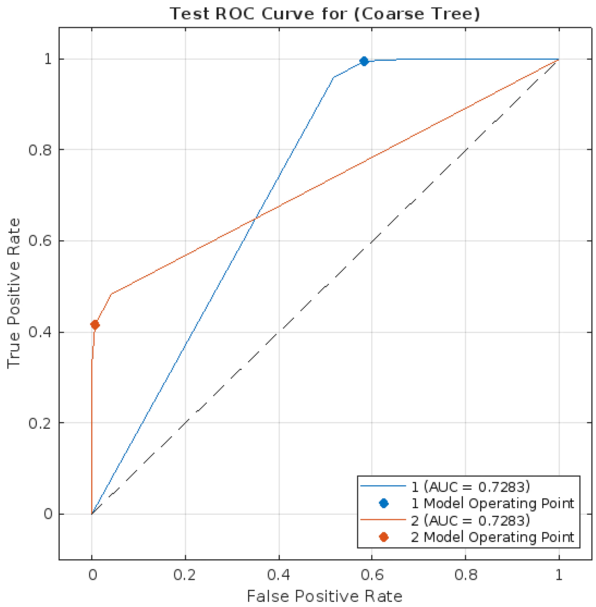


(a) (b) (c)

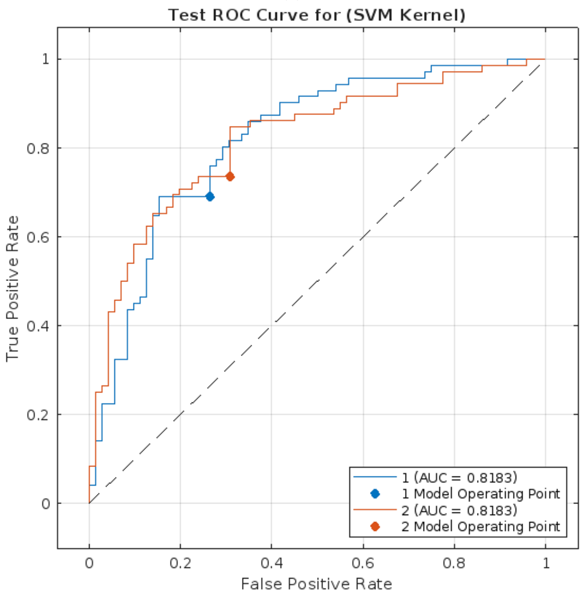
Figure 3. Confusion matrix for (a) Coarse tree, (b) SVM kernel, and (c) Bagged tree

Figure 3-a shows that the coarse tree classifier successfully predicts the primary class (1) with False Negative Rates (FNR) of 0.6 % but fails in minor class prediction (FBR = 58.3%), showing that the test accuracy is meaningless when using an imbalanced dataset. The FNR for predicting class 2 becomes 24.1% using an underbalanced dataset, even though it has less test accuracy than the classifier using the original dataset, as shown in Figure 3b. The least false negative rate for predicting class 2 is 17.1% using an overbalanced dataset, as shown in Figure 3c. Figures 3a, b, and c show that the overbalanced data set enhanced the model performance regarding accuracy and error distribution among target classes (FNR and TPR).

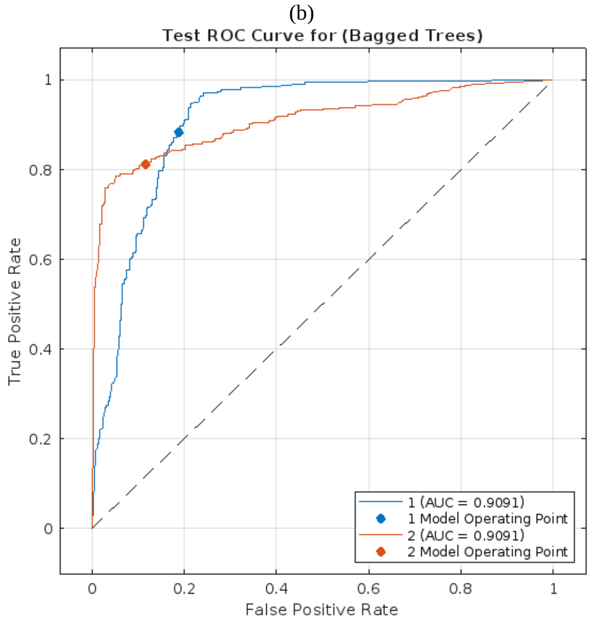
Figures 4-a, 4-b, and 4-c show the ROC curve for target classes using the original, under-sampled, and oversampled datasets. Figure 4-c shows that the ROC-AUC value using the Bagged tree classifier applied on the overbalanced dataset has the best performance (0.9241), followed by the SVM kernel applied on the underbalanced dataset (0.8218), followed by the coarse tree classifier applied on the original dataset (0.7283). These results are consistent with the findings based on the confusion matrices, as shown in Figure 3.



(a)



(b)



(c)

Figure 4. ROC curves for (a) Coarse tree, (b) SVM kernel, and (c) Bagged tree

From the above results, the overbalanced dataset using the SMOTE technique has shown the best results applying the Bagged tree classifier in terms of accuracy and FNR distribution for target classes compared to other datasets. Therefore, the overbalanced dataset will be chosen to interpret the importance of independent variables in contributing to severity level prediction since one of the primary objectives of this study is to investigate the impact of the accident location based on the installed wind turbines. To achieve that, Shapley values based on the test set query points using the Bagged tree classifier will be used to establish a better evaluation of the contribution of model attributes to the prediction model. Shapley values have been utilized in meta-feature evaluation to accurately evaluate the feature's importance to the prediction model [43], making it a practical solution for real applications [44]. Figure 5 shows the Shapley importance for the Bagged tree; it's evident that the crash type feature has the highest impact on the prediction models, followed by the number of involved vehicles in an accident and license type. Some features have a moderate impact relatively, including vehicle speed, accident fault type, vehicle type, location of the accident, and driver's age.

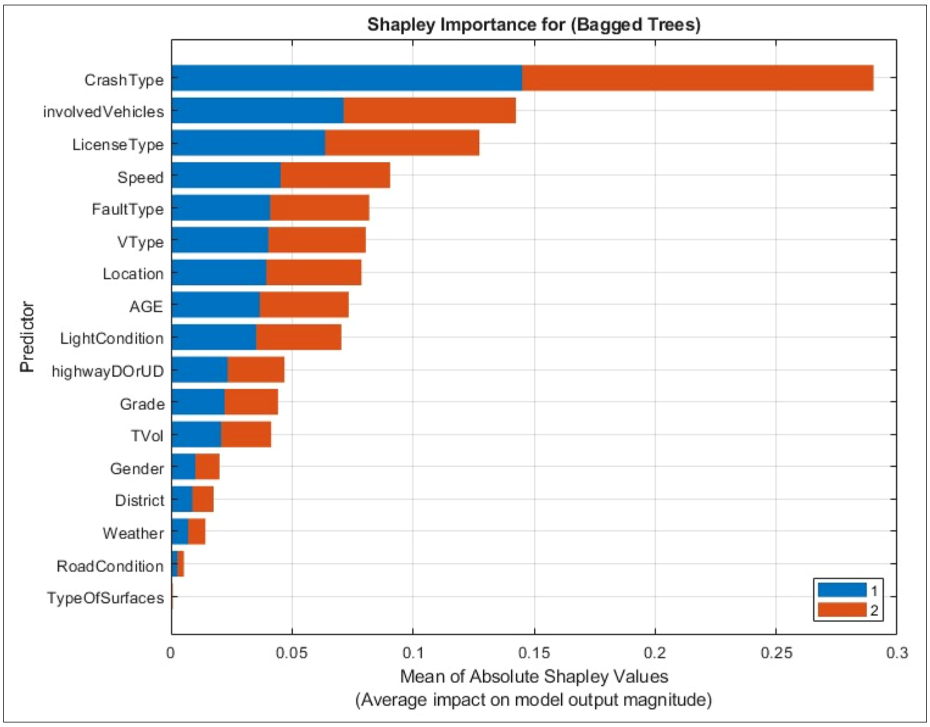


Figure 5. Shapley importance for Bagged tree classifier

5. Conclusions

This study introduces a full assessment of the impact of wind turbines as a distraction on the severity of crashes along King's Highway in Jordan through descriptive and analytical research using a mixed-effect logit model. Also, this work unlocks the ability to predict crash severity levels using multiple ML models. The findings of this study can be concluded as follows:

- The mixed effects logit model performs superiorly to the other models in analyzing the impact of wind turbines on crash severity.
- The KAB and O wind turbine-related crashes increased by 117.4 % and 25.7 %, respectively.
- The mixed-effect logit model successfully analyzes other parameters correlated to crash severity, such as driver age, speed limit, and crash type.
- The use of the SMOTE technique in crash severity prediction performs better than under-sampling techniques.
- Bagged tree classifier performs best among other ML models regarding accuracy and ROC-AUC values for the target classes.
- This study shows how wind turbines can act as external distractions, influencing road safety. Our findings clearly link wind turbine presence and crash severity along King's Highway in Jordan. However, since traffic laws, road designs, and driving habits vary from country to country, these results might not apply everywhere in the same way.
- To get a clearer picture, future research should explore this issue in different regions, using similar methods to see if the patterns hold. Researchers can assess how wind turbines impact crash severity in various settings by applying mixed-effects models and machine-learning techniques. Comparing results across different locations will help us better understand external distractions and shape stronger, more effective road safety policies worldwide.

This study's results can serve as guidelines for policymakers and transport operators to profoundly investigate the proper location where the wind turbines should be installed. In the future, more effort will be applied to investigate the prediction model's capability for more than two target classes, including all crash severity levels. Also, the impact of environmental factors and their interaction with the type of wind turbines on traffic crash severity could be studied in the future.

6. Declarations

6.1. Author Contributions

Conceptualization, F.A. and M.A.; methodology, F.A. and M.A.; software, F.A., M.A., and R.A.; validation, M.A., F.A., and R.A.; formal analysis, F.A. and M.A; data curation, M.A.; writing—original draft preparation, F.A. and M.A.; writing—review and editing, F.A. and M.A; visualization, M.A. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Conflicts of Interest

The authors declare no conflict of interest.

7. References

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