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Machine Learning for Road Traffic Accident Improvement and Environmental Resource Management in the Transportation Sector

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Abstract: Despite the measures put in place in different countries, road traffic fatalities are still considered one of the leading causes of death worldwide. Thus, the reduction of traffic fatalities or accidents is one of the contributing factors to attaining sustainability goals. Different factors such as the geometric structure of the road, a non-signalized road network, the mechanical failure of vehicles, inexperienced drivers, a lack of communication skills, distraction and the visual or cognitive impairment of road users have led to this increase in traffic accidents. These factors can be categorized under four headings that are: human, road, vehicle factors and environmental road conditions. The advent of machine learning algorithms is of great importance in analysing the data, extracting hidden patterns, predicting the severity level of accidents and summarizing the information in a useful format. In this study, three machine learning algorithms for classification, such as Decision Tree, LightGBM and XGBoost, were used to model the accuracy of road traffic accidents in the UK for the year 2020 using their default and hyper-tuning parameters. The results show that the high performance of the Decision Tree algorithm with default parameters can predict traffic accident severity and provide reference to the critical variables that need to be monitored to reduce accidents on the roads. This study suggests that preventative strategies such as regular vehicle technical inspection, traffic policy strengthening and the redesign of vehicle protective equipment be implemented to reduce the severity of road accidents caused by vehicle characteristics.

Keywords: road traffic; accident severity; accident prediction; machine learning algorithms

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1. Introduction

Traffic accident severity results from the complex interaction between one or more of the following factors: human, vehicle, road and environment, with the human factor found to be the most important but also the hardest to change [1–3]. Annually, it is reported globally that around 1.3 million people die in road traffic accidents, with children and young adults mostly affected [4]. Also, road traffic accidents contribute to huge financial losses in term of infrastructure damage, loss of productivity, road accident fund payouts for any country and the individual involved [4–6]. With so many losses, the reduction/prevention of traffic fatalities or accidents is one of the factors in attaining global sustainability goals and becoming a priority in transportation management [7–9]. At any road accident, an accident report is collected; this report covers different accident attributes that can be used to further investigate the possible cause of the accident at that particular road section. However, most of the developing countries and under-developed ones are lagging behind the rest of the world in the availability of reliable accident data [10].

Additionally, from the accident reports, road sections with frequent accidents can be determined and are subjected to an accident study that could involve the professional reconstruction of accident scenes. In the reconstruction of an accident scene, it can be quite expensive and challenging to recreate the actual behaviour of road users and the mechanical performance of the vehicle that contributed to the accident. Thus, the use of existing accident traffic data and using analytical solutions could be of help in predicting and averting a future traffic accident for an existing road or a new road network. Overall, the investigation of the nature of traffic accidents and what causes their severity is crucial to building better and safer transportation systems [11]. Using data on road accidents that occurred in the UK in 2020, this study aims to investigate and pinpoint the primary causes of traffic accidents.

1.1. Current Trends: Road Accident Predictions

Accident predictions have become a necessity in order to identify the main contributing factors to road traffic accidents and in turn help with providing an appropriate solution to minimize their adverse effects [8,11,12]. Building a better and safer transportation system requires a proper understanding of the complex interactions that exist between the different accident attributes. The accident database forms an enormous database that covers different accident attributes under the following categories: road users, vehicles, roadway and environment [1,2]. Methods such as statistical models and artificial intelligence models have been used to determine and understand the interactions between these attributes in relation to the severity of the accident [1,2,8,13,14].

However, artificial intelligence models are currently gaining momentum as these can determine the interactions between variables that would be impossible to establish directly using statistical models and with the capability of handling and processing large datasets [11,13–16]. Machine learning (ML) is a branch of artificial intelligence that makes provision for data analysis, decision making and data preparation for the real-time problem and allows self-learning for computers with limited complex coding [8,11,13]. Machine learning identifies data patterns and makes decisions with minimal human intervention.

1.2. Machine Learning and Road Accidents

Machine learning is a data-driven method and it has found application in many real-world application domains and academic fields [16–19]. In recent years, ML has been applied in the field of transportation engineering [15,16]. Machine learning has been explored in the following traffic engineering areas: the identification of road locations prone to accidents, the determination of the severity of damage/injury from an accident, the role of road users in traffic accidents, the impact of drinking and driving on injury severity and the impact of environmental factors, to mention just a few [13,14,16,17,20–22]. Furthermore, researchers have explored the various models available in ML, which are categorized as supervised, unsupervised and semi-supervised [8,23]. The supervised model is further categorized as regression and classification. Overall, the proper prediction of traffic accident severity will help with adequate provision in terms of timely traffic safety management and strategies [2,6].

Annually, road accidents constitute a significant proportion of the number of serious injuries reported [4,7,9]. However, it is challenging to identify the specific conditions that lead to such an event and, hence, it is difficult for the road authority to properly address the number and severity of road accidents [24,25]. Furthermore, research has shown that human, vehicle, road and environmental factors play vital roles [1–3,5,6,8,10,12,13,16,26]. Human factors include age [14,16,26–29], gender [12,29], driving experience [30,31], the influence of alcohol and psychoactive substances [26], et cetera. On the other hand, vehicle factors include vehicle age, engine capacity, type and model, vehicle towing and articulation [2,12,13,16]. Road factors include road type, the condition of the road, road class, road geometry and speed limit [3,12,13,16]. Also, environmental factors include the day of the week, weather and light conditions [1–3]. Overall, of the aforementioned factors, human factors have been extensively explored and various measures have been put in place to mitigate them [14,16,26–31]; however, other factors need to be explored. Thus, it is difficult to concentrate on one factor and, hence, these questions remain regarding traffic accidents: (i) which factors contribute directly and indirectly to traffic accident fatality and (ii) what are the strategies to avert such incidents in the future? In order to answer these questions and specifically provide impact in the areas of the risk score on the probability of a driver having a fatal/serious accident solely based on inputs gathered from individual and vehicle data, this study incorporated the strength of machine learning and the United Kingdom's road accidents database. Situational information was analysed to estimate the severity of an accident [25].

2. Research Objective and Methodology

This study's main goal is to use analytical methods in ML to analyse traffic accident data in order to identify all the direct and indirect causes that have a significant impact on traffic accidents. To accomplish the objective of this study, a creative model was created using a variety of machine learning approaches, and the accuracy of the model was increased by employing the most recent and carefully structured datasets. The modelling process involves four primary stages that entail investigating and getting the datasets ready for modelling. The process includes attempting to comprehend the tabulated data, coming up with a better method of handling missing values, using statistical techniques to identify the factors most likely to cause traffic accidents, training the model using a machine learning algorithm and then assessing the model's performance using existing classification metrics.

Traffic Crash Data: UK 2020

The tabular dataset used in this study's model development was obtained from the UK's Department of Transport and covered the year 2020. It is worth noting that the traffic accident data for year 2020 were impacted by the COVID-19 virus and the relative social gathering restrictions [32]. However, rather than seeing this as a limitation, it is an open window to explore other factors rather than human factors, which have been greatly explored [26–31]. Also, the use of a year's worth of data in this study is an attempt to take into account the fact that most developing and undeveloped nations are only getting started with accident databases [33,34].

At the scene of the accidents in the UK, full information was gathered for each report, including environmental characteristics such as weather, road type and light conditions, driver factors such as gender and age, accident descriptors such as severity and police presence and vehicle descriptors such as age, power, type, model and the number of vehicles involved [16,35]. Furthermore, the accident data points are unique to the place on the road network and are used to explain certain aspects of the traffic and road conditions [16,36].

The original dataset contains a total of 135 453 data points with 60 attributes. Each variable in the dataset was classified as categorical or numerical based on its nature. Because training time increases exponentially with the number of features, dealing with a lot of features may, for example, have an impact on how well the model performs. It may also increase the risk of over-fitting. To simplify the problem and enhance the functionality of the model, certain highly pointless or unnecessary features were removed [13,16]. The selected feature variables consisted of the junction control, day of the week, road type, road surface conditions, sex of driver, age of the driver, age of the vehicles, light conditions, weather conditions, special conditions at site, speed limit, number of vehicles, vehicle type and vehicle manoeuvre. Table 1 shows the descriptive statistics for the utilized data. The justification of these selections is based on previous studies [2,14,16,19]; these variables have featured as the important variables that contribute to traffic accidents. The accident severity was the target variable, which was divided into three categories based on the severity of the resulting personal damage, namely fatalities, serious injuries and slight injuries. As a result, this study explores the data in order to determine how the chosen feature variables affect the accident severity.

Table 1. Descriptive statistics data related to traffic accident.

Variable	Fatal		Serious		Slight		Total	
	N	%	N	%	N	%	N	%
Sex of driver								
Male	1394	2	17,121	20	67,028	78	85,543	63.2
Female	288	1	5099	16	27,290	84	32,677	24.1
Not traced	74	0	2211	13	14,947	87	17,219	12.7
Age of driver								
<24	337	1	6603	16	34,594	83	41,534	30.7
25–34	373	1	5194	17	24,567	82	30,134	22.2
35–44	294	1	4022	18	18,298	81	22,614	16.7
45–54	274	1	3679	19	15,194	79	19,147	14.1
55–64	249	2	2787	22	9877	76	12,913	9.5
65–74	124	2	1343	24	4084	74	5551	4.1
>75	105	3	803	23	2651	74	3559	2.6
Road type								
Roundabout	24	0	1175	14	7370	86	8569	6.3
One way street	5	0	418	13	2753	87	3176	2.3
Dual carriageway	343	2	3680	17	17,928	82	21,951	16.2
Single carriageway	1362	1	18,581	19	76,028	79	95,971	70.8
Slip Road	20	1	346	14	2141	85	2507	1.8
Unknown	2	0	231	7	3046	93	3279	2.4
Speed limit								
20	63	0	2348	13	15,073	86	17,484	12.9
30	584	1	13,440	17	65,219	82	79,243	58.5
40	182	2	2451	20	9418	78	12,051	8.9
50	143	2	1163	20	4574	78	5880	4.3
60	574	4	3530	27	8981	69	13,085	9.7
70	210	3	1496	19	5990	78	7696	5.7
Missing	0	0	3	21	11	79	14	0.0
Junction control								
Authorized person	3	1	92	17	446	82	541	0.4
Automatic traffic signal	96	1	2286	13	14,845	86	17,227	12.7
Stop sign	3	0	157	17	761	83	921	0.7
Give way or uncontrolled	508	1	10,950	18	49,536	81	60,994	45.0
Not at junction or within 20 m	1146	2	10,804	20	41,041	77	52,991	39.1
Missing	0	0	142	5	2637	95	2779	2.1
Special conditions at site								
None	1707	1	23,549	18	104,026	80	129,282	95.4
Roadworks	33	2	310	17	1508	81	1851	1.4
Others	12	4	325	138	1216	457	1366	1
Unknown	4	0	247	8	2703	92	2954	2.2
Number of vehicles								
1	496	2	5309	27	14,194	71	19,999	14.8
2	772	1	15,156	16	78,282	83	94,210	69.6
3–5	421	2	3787	19	16,136	79	20,344	15.0
>5	67	7	179	20	654	73	900	0.7
Age of vehicle								
0–10	901	1	11,296	17	54,830	82	67,027	49.5
11–20 years	465	1	5678	18	25,929	81	32,072	23.7
21–30 years	34	3	354	28	856	69	1244	0.9
31–40 years	3	3	39	35	71	63	113	0.1
Above 40 years	1	1	28	31	62	68	91	0.1
Missing	352	1	7036	20	27,517	79	34,905	25.8
Vehicle type								
Pedal cycle	119	1	3227	23	10,498	76	13,844	10.2
Motorcycle < 500 cc	75	3	2079	76	6698	221	8852	6.5
Motorcycle > 500 cc	147	5	1161	41	1504	53	2812	2.1
Car	1056	2	14,921	28	78,018	170	93,995	69.4
Bus	27	3	351	33	1668	164	2046	2
Truck	275	12	1992	57	8797	231	11,064	8.2
Others	57	15	700	229	2083	556	2840	2.1

Table 1. *Cont.*

Variable	Fatal		Serious		Slight		Total	
	N	%	N	%	N	%	N	%
Vehicle manoeuvre								
Going ahead	1338	9	14,560	75	53,389	217	69,287	51
Turning left/right/U	127	2	3519	59	13,890	239	17,536	13
Reversing	14	1	238	15	1383	85	1635	1.2
Parked	98	2	1184	20	4581	78	5863	4.3
Slowing/stopping/waiting	65	1	1715	46	13,167	352	14,947	11
Overtaking	66	4	1056	66	3489	231	4611	3
Others	46	2	1336	46	6728	252	8110	6
Missing	2	0	823	19	12,639	181	13,464	10
Day of the week								
Monday	267	2	2998	20	11,785	78	15,050	11.1
Tuesday	239	1	3333	18	15,451	81	19,023	14.0
Wednesday	222	1	3403	17	16,018	82	19,643	14.5
Thursday	242	1	3533	17	16,642	82	20,417	15.1
Friday	258	1	3843	18	16,920	80	21,021	15.5
Saturday	250	1	3900	18	17,910	81	22,060	16.3
Sunday	278	2	3421	19	14,540	80	18,239	13.5
Light condition								
Daylight: streetlights present	1064	1	16,960	18	78,068	81	96,092	70.9
Darkness: streetlights present and lit	359	1	5528	19	23,773	80	29,660	21.9
Darkness: streetlights present but unlit	11	1	176	19	756	80	943	0.7
Darkness: no street lighting	293	5	1377	26	3679	69	5349	3.9
Darkness: street lighting unknown	29	1	390	11	2990	88	3409	2.5
Weather conditions								
Fine without high winds	1473	1	19,760	19	85,416	80	106,649	78.7
Raining without high winds	141	1	2718	17	13,531	83	16,390	12.1
Snowing without high winds	0	0	37	16	189	84	226	0.2
Fine with high winds	37	2	426	22	1470	76	1933	1.4
Raining with high winds	31	2	354	19	1497	80	1882	1.4
Snowing with high winds	0	0	20	29	48	71	68	0.1
Fog or mist—if hazard	30	4	147	20	554	76	731	0.5
Other	33	1	548	13	3536	86	4117	3.0
Unknown	11	0	421	12	3025	88	3457	2.6
Road surface conditions								
Dry	1215	1	17,475	18	76,887	80	95,577	70.6
Wet/Damp	522	1	6552	18	29,596	81	36,670	27.1
Snow	0	0	25	15	141	85	166	0.1
Frost/Ice	12	1	171	20	662	78	845	0.6

A pre-processing step was performed before each model development to improve the model's prediction capabilities. The noise was reduced by removing the outliers [37]. The data were cleaned and pre-processed to look for missing values that could disrupt the learning process. A machine learning feature selection method such as the Scikit-learn Random Forest library (RRID:SCR 002577) was used to identify the most relevant and correlated attributes influencing the learning process. These datasets were investigated using supervised learning to predict the class label based on driver and vehicle characteristics, weather conditions and road properties [14,19,35].

Since there are often more serious and minor injuries in accidents than fatal ones, the accident dataset is unbalanced. To overcome this problem, many researchers utilized the oversampling or undersampling technique on unbalanced data. In this study, to overcome this problem, SMOTE (Synthetic Minority Oversampling Technique) oversampling for imbalanced multi-class classification was used to synthesize new examples of the minority classes so that the number of examples in the minority class more closely resembled or matched the number of examples in the majority of classes. This is a very effective type of data augmentation for tabular data [19].

3. Model Development

A supervised machine learning technique that excels at analysing predictive data is prediction. It is based on the learning of fresh feature variables recorded into particular target variables based on relevant feature variable values through training data. It is crucial to employ cutting-edge prediction algorithms to ensure the best accuracy because of their capacity for handling complex related factors and their efficacy in handling connected variables. Multi-class classification algorithms with Sklearn (RRID: SCR 019053) were utilized in this study, including Decision Tree (DT), Light Gradient Boosting Machine (LightGBM) and Extreme Gradient Boosting (XGBoost). The justification for the selection of these algorithms is based on obtained good classification accuracy and noting that Decision Tree requires less effort for data preparation during pre-processing. Additionally, both LightGBM and XGBoost enable parallel arithmetic, but LightGBM is more potent than the XGBoost model due to a faster training speed and occupying less memory, which lowers the communication cost of parallel learning [14,19]. However, the XGBoost classifier is one of the newest and most effective machine learning-based prediction algorithms [19,21]. Following a thorough examination of various machine learning multi-class classification algorithms reported in the literature, the scalable, flexible, accurate and relatively fast XGBoost algorithm for classification was chosen to provide more regularized model formalization and better over-fitting control [14,19,21].

4. Model Evaluation

The goal of developing a predictive model is to create a model that is accurate on previously unseen data. This can be accomplished by employing statistical methods in which the training dataset is carefully selected in order to estimate the model's performance on new and unexplored data. The most basic technique of model validation is to split off a portion of the labelled data and reserve them for evaluating the model's final performance. It is critical to preserve the statistical properties of the available data when splitting them. This implies that in order to prevent bias in the trained model, the data in the training and test datasets must share similar statistical characteristics with the original data. The labelled dataset in the current study was divided into 80% training and 20% testing. The effectiveness of each model was evaluated in turn in order to compare their performance in terms of confusion matrix, sensitivity, specificity and area under the curve (AUC) of the receiver operating characteristic (ROC) for the severity of the accident. The model's performance was evaluated using a variety of criteria provided by the confusion matrix. From this particular matrix, it can infer a set of evaluation metrics. One of these is the accuracy, which is basically the proportion of correct prediction, and it is calculated as follows [19,37]:

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

where TP stands for True Positives, TN stands for True Negatives, FP stands for False Positives and FN stands for False Negatives, followed by the precision, which is the proportion of the positive cases that were correctly identified, and it is computed as follows [19,37]:

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

and the recall/sensitivity, which is the proportion of the actual positive cases that were correctly identified and calculated as follows [19,37]:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

and the specificity, which is the proportion of the actual negative cases that were correctly identified and calculated as follows [19,37]:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

and lastly, the F1 score, which is measuring the balance between precision and sensitivity and can be computed as follows [37]:

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

The sensitivity and specificity can indicate whether the algorithm with default or tuning parameters is best for our data. If correctly identifying positives is more important in relation to the data, then the algorithm with the higher sensitivity is the best. If correctly identifying negatives is more important in relation to the data, then the algorithm with higher specificity is the best.

Using charts is also an easy way to gain a quick level of understanding when evaluating a classification model. The receiver operating characteristic (ROC) chart (RRID: SCR 008551), which is simply a graph of the true positive rate against the false positive rate, was also carried out in order to provide further evidence. Both macro-average and micro-average ROC curves were produced. As opposed to a micro-average ROC curve, which aggregates class participation to determine the average metric, a macro-average ROC curve measures the metric freely for each class before taking the average. Another metric derived from this is the area under the curve (AUC), which is the area of the applied surface under the ROC curve.

5. Results and Discussion

In this work, a total of 135,453 records of UK traffic accidents in the year 2020 were examined. Fifteen attributes selected using feature selection with ranking were used with the class variable of the severity of injury to predict the degree of injury severity in traffic accidents. The statistical analysis results show that male (63.2%) and young drivers (<24 years old) (30.7%) contribute the most to accidents. Also, the result shows that cars (67.70%) contributed the most under vehicle type, followed by the pedal cycle (10%). Additionally, under vehicle manoeuvres, going ahead of others (46%), turning left (18.32%) and slowing or stopping (5.24%), contributed the most to traffic accident severity. The number of vehicles at the scene of the accident further contributes to accident severity, with two vehicles (70%) on the scene taking the lead. The aspect of vehicle age highlighted that vehicles between 0 and 10 years old contribute more to traffic accidents. Furthermore, it was observed that accident numbers could depend on the amount of traffic on a particular day, and most of the accidents occurred on roads where the speed limit was 30 mph (48 km/h). Thus, more accidents could be expected on highways or major roadways. It was also noted that most of the accidents occurred during weekends and during daylight hours with streetlights present, with weather conditions that did not have an adverse effect on driving (dry road conditions) [2,16,19]. In order to build the prediction models, three different classification algorithms, such as Decision Tree, LightGBM and XGBoost, were applied to the dataset. Additionally, 10-fold cross-validation techniques were used to evaluate the prediction performance, a number of hyper-parameter settings were evaluated for each model, and the setting yielding the best performing model was chosen [6].

To rank the attributes in this study, Random Forest classification feature importance was used to highlight the most relevant feature at predicting the target variable, resulting in improved model performance. The feature selection method revealed that the vehicle characteristics, such as the vehicle type [16], vehicle manoeuvre "actions immediately before the accident" [16], the number of vehicles and age of the vehicle [16], had the greatest impact on accident severity out of the 15 features as depicted in Figure 1. Also, the age of drivers [12,16] under human characteristics, and speed limit under road characteristics [16,19], top the chart. The results show that vehicle characteristics play a major role in the accidents reported in the UK for the year 2020.

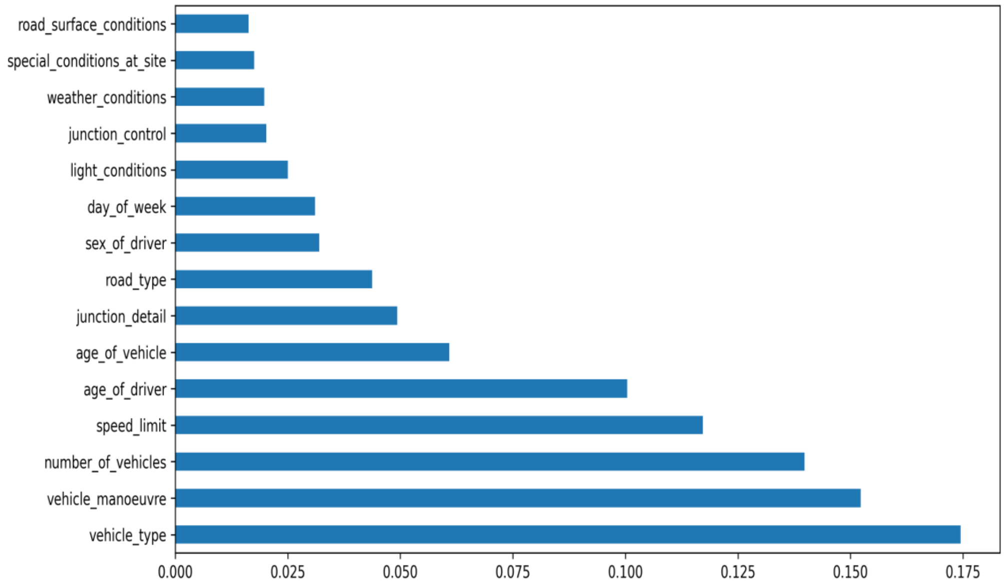

Figure 1. The Random Forest Classifier's bar chart for feature importance scores, displayed in ascending order.

Generally, vehicle characteristics include vehicle dimensions, weight, power, minimum turning radius, speed, acceleration and braking characteristics; however, the vehicle dimensions in vehicle type stood out. This implies that the width, length and height of vehicles significantly affects safe overtaking distance. Picking up also on the number of vehicles, after the understanding of the vehicle type, it is critical to know the number of vehicles involved in the accident (for example, a head-on collision will be two vehicles involved), as this will determine the extent of the accident severity. Although various studies [12,16,38,39] have highlighted human characteristics as the most critical, the results placed the spotlight on vehicle characteristics as a major factor contributing to traffic accident severity [16]. This is worth noting as the data used in the study were during the period with COVID-19 travel restrictions with a limited number of people travelling and the majority of vehicles not serviced as a result of the restrictions. Nevertheless, it is critical to point out that human characteristics such as drivers' years of experience and the details on drivers' licences (eligibility to drive) were not documented and this might have changed the dynamics.

5.1. Decision Tree Classification Algorithm Analysis Result

The outcome of the Decision Tree classification algorithm, which aids in looking at all possible predictions for each class, is presented and discussed in this paragraph. The result of the Decision Tree algorithm using its default parameters (DT-D) will be compared with the one using hyper-parameter settings (DT-H). As seen in Table 2, the Decision Tree classifier with default parameters was able to predict three classes of accident severity out of three with an overall accuracy of 84.61%. With hyper parameter tuning, the algorithm was able to predict the three classes of accident severity with 84.35% overall accuracy, as shown in Table 3. The slight difference in accuracy score shows that some algorithms perform better with default parameters. Precision, recall, specificity, F1 score and a false positive rate with default and hyper tuning parameters were also measured for each class of accident severity as shown in Tables 2 and 3.

Table 2. The Decision Tree algorithm analysis result with default parameters includes a summary of precision, recall, per-class F1-Score, specificity and the false positive rate (FPR) measurements for the three classes. The overall accuracy of the model was also measured.

	Accuracy			**84.61%**	
			Predicted Values		
Value	**Precision**	**Recall**	**F1-Score**	**Specificity**	**FPR**
Fatal	0.932518	0.957956	0.945066	0.962942	0.037058
Serious	0.779072	0.785760	0.782402	0.889107	0.110893
Slight	0.824731	0.795534	0.809869	0.859503	0.140497

Table 3. The Decision Tree algorithm analysis result with hyper-tuning parameters includes a summary of precision, recall, per-class F1-Score, specificity and the false positive rate (FPR) measurements of the three classes. The overall accuracy of the model was also measured.

	Accuracy			**84.35%**	
			Predicted Values		
Value	**Precision**	**Recall**	**F1-Score**	**specificity**	**FPR**
Fatal	0.932267	0.954782	0.943390	0.965584	0.034416
Serious	0.776561	0.778094	0.777327	0.888581	0.111418
Slight	0.819520	0.798393	0.808819	0.853590	0.146409

Additionally, for further analysis the confusion matrix with three rows and three columns was created to summarize the classification with three classes such as Fatal, Serious and Slight injury as shown in Tables 4 and 5. As shown, the diagonal with values (20,825, 17,117, 17,528) represents the correct predictions and the other values on the table indicate incorrect predictions. The algorithm with default parameters correctly predicted more fatal and serious accident severity than the one with tuned parameters (20,756, 16,950, 17,591), which correctly predicted more slight injuries as depicted in Table 5. Looking carefully at the 3×3 confusion matrices displayed in Tables 4 and 5, it is worth noting that the Decision Tree algorithm with default parameters performed significantly better. It predicted more fatal and serious injuries as true positives. After filling out the confusion matrix table, two useful metrics, such as sensitivity and specificity, were evaluated. Referring to Table 2, sensitivity for fatal injury indicates that 95.80% of fatal injuries were correctly identified positives and specificity for fatal injury indicates that 96.30% of fatal injuries were correctly identified negatives. On the other hand, sensitivity for serious injury indicates that 78.60% of serious injuries were correctly identified positives and specificity for serious injuries indicates that 88.91% of serious injuries were correctly identified negatives. Finally, sensitivity for slight injury indicates that 79.55% of slight injuries were correctly identified positives and specificity for slight injuries indicates that 85.95% of slight injuries were correctly identified negatives.

Table 4. Confusion matrix for multi-class classification of Decision Tree algorithm analysis results with default parameters.

		Confusion Matrix	
	Fatal	**Serious**	**Slight**
Fatal	20,825	690	224
Serious	1166	17,117	3501
Slight	341	4164	17,528

Table 5. Confusion matrix for multi-class classification of Decision Tree algorithm analysis result with hyper-tuning parameters.

Confusion Matrix			
	Fatal	**Serious**	**Slight**
Fatal	20,756	749	234
Serious	1194	16,950	3640
Slight	314	4128	17,591

With the help of the ROC curve shown in Figure 2, it further examines how well the Decision Tree with default settings will predict the three classes of accident severity considering different thresholds. Additionally, the AUC gives a single value metric that makes it easy to comprehend how well the classification model performs in predicting each class. For the perfect unrealistic curve (a point at the upper left corner of the chart), the area under the curve will be 100%, while for the completely random class (the diagonal line on the chart) the area under the curve will be 50%. A class that performs worse than a random class will have an area below 50%. Here, class-1(fatal) is more accurate in this case than class-2(serious) and class-3(slight), as class-1 has a larger area under the curve than classes 2 and 3.

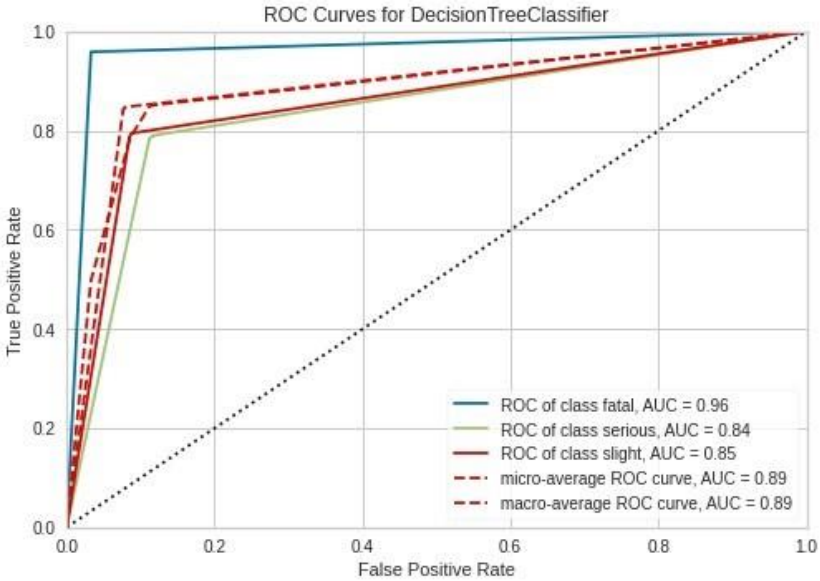

Figure 2. Receiver Operating Characteristic (ROC) curves for each accident severity class of Decision Tree algorithm analysis result with default parameters. The area under the ROC curve is reported in the legend.

Regarding the Decision Tree algorithm with hyper-tuning parameters as shown in Table 3, sensitivity for fatal injury show that only 95.47% of fatal injuries were correctly identified positives and specificity for fatal injury shows that 96.55% of fatal injuries were correctly identified negatives. Additionally, sensitivity for serious injuries shows that 77.80% of serious injuries were correctly identified positives and specificity for serious injuries indicates that 88.85% of serious injuries were correctly identified negatives. Finally, sensitivity for slight injuries shows that 79.83% of slight injuries were correctly identified positives and specificity for slight injuries shows that 85.35% of slight injuries were correctly identified negatives.

Figure 3 shows the resulting ROC chart of Decision Tree with hyper-tuning settings. The blue curve of the Fatal class is closer to the y-axis than the Serious and Slight classes and has a more moderate AUC of 0.96 than other classes. Overall, tuning the parameters slightly improves the AUC of the Decision Tree results in predicting the Slight class of accident severity. Both macro-average and micro-average ROC curves were also produced. Macro-averaged ROC curve, AUC: to be calculated.

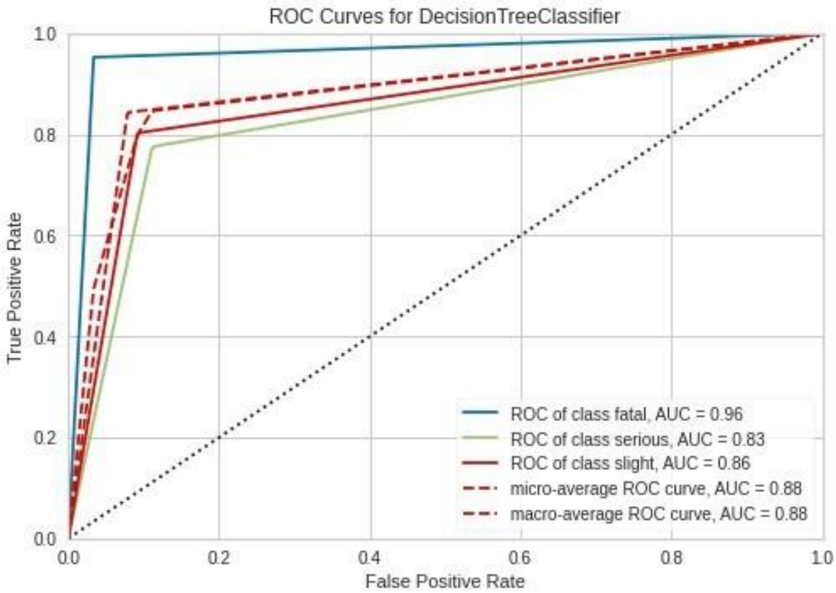

Figure 3. Receiver Operating Characteristic (ROC) curves for each accident severity class of Decision Tree algorithm analysis result with hyper-tuning parameters. The area under the ROC curve is reported in the legend.

Calculate the AUC for each class separately, then average them out. For the AUC, micro-averaged ROC curve: calculate true positive and false positive rates for each class and then use that to calculate the overall AUC. The micro- and macro-average ROC curve values obtained with hyper-tuning parameters are lower than those obtained with default parameters, i.e., AUC (dec.tree tuning) micro, macro = 0.88, 0.88, while AUC (dec.tree default) micro, macro = 0.89, 0.89 as shown in Figures 2 and 3.

5.2. LightGBM Classification Algorithm Analysis Result

Tables 6 and 7 provide an overview of the metrics defined for a multi-class confusion matrix and, in particular, the overall accuracy of the model, recall, precision and F1-score, specificity and false positive rate (FPR) in order to compare the performance of the LightGBM algorithm with the default (LGBM-D) and hyper-tuning parameters (LGBM-H). The algorithm with default parameters was able to predict three classes of accident severity out of three with an overall accuracy of 81.00%. With the hyper-tuning parameters there was a significant improvement in the model accuracy of the accident severity. It jumped from 81.00% for default parameters to 84.72% for tuned parameters as depicted in Tables 6 and 7.

Furthermore, the confusion matrix with three rows and three columns was created to summarize the classification with three classes such as Fatal, Serious and Slight injury as shown in Tables 8 and 9. As shown, the diagonal with default values (18,882, 12,492, 21,729) and tuning values (19,875, 13,920, 21,747) represent correct predictions and the other values on the tables indicate incorrect predictions. The algorithm with hyper-tuning parameters correctly predicted more fatal, serious and slight accident severity than the one with default parameters as depicted in Tables 8 and 9. Looking carefully at the 3×3 confusion matrices displayed in Tables 8 and 9, it is worth noting that the LightGBM classification algorithm with hyper-tuning parameters did much better. It predicted more fatal, serious and slight injuries as true positive. After filling out the confusion matrix table, two useful metrics such as sensitivity and specificity were evaluated. Referring to Table 6, sensitivity for fatal injury indicates that 86.85% of fatal injuries were correctly identified positives and specificity for fatal injury indicates that 90.80% of fatal injuries were correctly identified negatives. On the other hand, sensitivity for serious injuries indicates that 57.34% of serious injuries were correctly identified positives and specificity for serious injuries indicates that 94.35% of serious injuries were correctly identified negatives. Finally, sensitivity for slight injuries shows that 98.62% of slight injuries were correctly identified positives and specificity for slight injuries shows that 73.76% of slight injuries were correctly identified negatives.

Table 6. The LightGBM algorithm analysis with default parameters includes a summary of precision, recall, per-class F1-Score, specificity and the false positive rate (FPR) measurements of the three classes. The overall accuracy of the model was also measured.

	Accuracy			**81.00%**	
			Predicted Values		
Value	**Precision**	**Recall**	**F1-Score**	**Specificity**	**FPR**
Fatal	0.824038	0.868577	0.845721	0.907980	0.092019
Serious	0.834748	0.573448	0.679855	0.943503	0.056497
Slight	0.785092	0.986203	0.874231	0.737649	0.262350

Table 7. The LightGBM algorithm analysis with hyper-tuning parameters includes a summary of precision, recall, per-class F1-Score, specificity and the false positive rate (FPR) measurements of the three classes. The overall accuracy of the model was also measured.

	Accuracy			**84.72%**	
			Predicted Values		
Value	**Precision**	**Recall**	**F1-Score**	**Specificity**	**FPR**
Fatal	0.869423	0.914255	0.891276	0.981875	0.068124
Serious	0.890026	0.639001	0.743908	0.960705	0.039294
Slight	0.803777	0.987019	0.886023	0.763637	0.236362

Table 8. Confusion matrix for multi-class classification of LightGBM algorithm analysis result with default parameters.

		Confusion Matrix	
	Fatal	**Serious**	**Slight**
Fatal	18,882	2273	584
Serious	3928	12,492	5364
Slight	104	200	21,729

Table 9. Confusion matrix for multi-class classification of LightGBM algorithm analysis result with hyper-tuning parameters.

		Confusion Matrix	
	Fatal	**Serious**	**Slight**
Fatal	19,875	1476	388
Serious	2943	13,920	4921
Slight	42	244	21,747

According to Table 7, sensitivity for fatal injury indicates that 91.42% of fatal injuries were correctly identified positives and specificity for fatal injury indicates that 98.20%

of fatal injuries were correctly identified negatives. On the other hand, sensitivity for serious injuries indicates that 63.90% of serious injuries were correctly identified positives and specificity for serious injuries indicates that 96.07% of serious injuries were correctly identified negatives. Finally, sensitivity for slight injuries indicates that 98.70% of slight injuries were correctly identified positives and specificity for slight injuries indicates that 76.36% of slight injuries were correctly identified negatives.

Figure 4 shows the resulting ROC chart of the LightGBM model with default settings of every type of injury. The AUC of fatal injury was 0.96, for serious injury it was 0.86 and for slight injury it was 0.96, all of which show that the model has a decent ability to predict outcomes/different classes. Figure 5 shows that the LightGBM model with hyper-tuning settings performed marginally better in predicting the AUC of the three classes. Both macro-average and micro-average ROC curves were also produced. The micro- and macro-average ROC curves values obtained with hyper-tuning parameters are slightly different to those obtained with default parameters, i.e., AUC (LightGBM tuning) micro, macro = 0.96, 0.95 while AUC (LightGBM default) micro, macro = 0.94, 0.92 as shown in Figures 4 and 5.

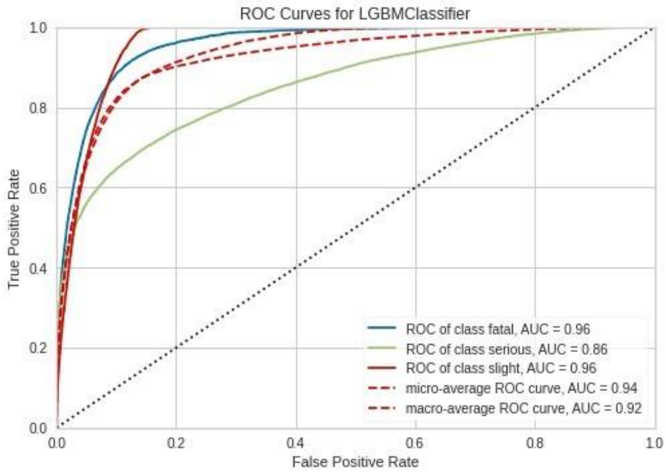

Figure 4. Receiver Operating Characteristic (ROC) curves for each accident severity class of LightGBM algorithm analysis result with default parameters. The area under the ROC curve is reported in the legend.

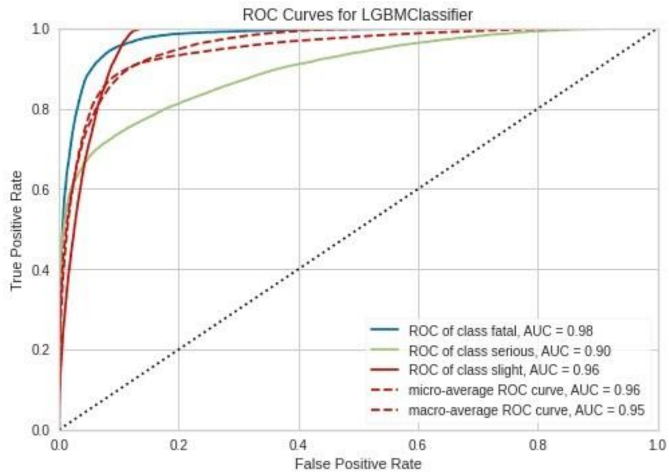

Figure 5. Receiver Operating Characteristic (ROC) curves for each accident severity class of LightGBM algorithm analysis result with hyper-tuning parameters. The area under the ROC curve is reported in the legend.

5.3. XGboost Classification Algorithm Analysis Result

The performance of the hyper-tuned XGboost classification algorithm (XGB-H) was compared to that of the algorithm with default parameters (XGB-D). The performance of several predictions of each class of accident severity was the foundation for the comparison. Tables 10 and 11 show the results of different multi-class metrics based on different measurements such as the overall accuracy of the model, recall, precision and F1-score, specificity and false positive rate (FPR), which helped to analyse the behaviour of the same model by tuning different parameters. The algorithm with both default and hyper tuning parameters has a similar performance in terms of predicting three classes of accident severity out of three with a significant increase in overall accuracy.

Table 10. The XGboost algorithm analysis with default parameters includes a summary of precision, recall, per-class F1-Score, specificity and the false positive rate (FPR) measurements for the three classes. The overall accuracy of the model was also measured.

	Accuracy			**74.50%**	
			Predicted Values		
Value	**Precision**	**Recall**	**F1-Score**	**Specificity**	**FPR**
Fatal	0.732652	0.804269	0.766792	0.854394	0.145605
Serious	0.736050	0.471722	0.574962	0.915814	0.084186
Slight	0.760052	0.956611	0.847078	0.717572	0.282428

Table 11. The XGboost algorithm analysis result with hyper-tuning parameters includes a summary of precision, recall, per-class F1-Score, specificity and the false positive rate (FPR) measurements of the three classes. The overall accuracy of the model was also measured.

	Accuracy			**81.55%**	
			Predicted Values		
Value	**Precision**	**Recall**	**F1-Score**	**Specificity**	**FPR**
Fatal	0.824642	0.872211	0.847760	0.907980	0.092019
Serious	0.835927	0.584466	0.687937	0.942908	0.057091
Slight	0.796466	0.988018	0.881961	0.753249	0.246751

Furthermore, the confusion matrix with three rows and three columns was created to summarize the classification with three classes such as Fatal, Serious and Slight injury as shown in Tables 12 and 13. As shown in the tables, the diagonal with default values of (17,484, 10,276, 21,077) and hyper- tuning values of (18,961, 12,732, 21,769) represents correct predictions and the other values on the tables indicate incorrect predictions. The algorithm with hyper-tuning parameters correctly predicted more fatal, serious and slight accident severity classes than the one with default parameters, which correctly predicted more slight injuries as depicted in Tables 12 and 13. Looking carefully at the two confusion matrix tables, it is worthy of note that the XGboost classification algorithm with hyper-tuning parameters outperformed the one with default parameters. It predicted more fatal, serious and slight injuries as true positives. After filling out the confusion matrix table, two useful metrics such as sensitivity and specificity were evaluated. Referring to Table 10, sensitivity for fatal injury indicates that 80.43% of fatal injuries were correctly identified positives and specificity for fatal injury indicates that 85.44% of fatal injuries were correctly identified negatives. On the other hand, sensitivity for serious injuries indicates that 47.17% of serious injuries were correctly identified positives and specificity for serious injuries indicates that 91.58% of serious injuries were correctly identified negatives. Finally, sensitivity for slight injury shows that 95.66% of slight injuries were correctly identified positives and specificity for slight injuries shows that 71.75% of slight injuries were correctly identified negatives.

Table 12. Confusion matrix for multi-class classification of XGboost algorithm analysis result with default parameters.

Confusion Matrix			
	Fatal	**Serious**	**Slight**
Fatal	17,484	3435	820
Serious	5674	10,276	5834
Slight	706	250	21,077

Table 13. Confusion matrix for multi-class classification of XGboost algorithm analysis result with hyper-tuning parameters.

Confusion Matrix			
	Fatal	**Serious**	**Slight**
Fatal	18,961	2281	497
Serious	3986	12,732	5066
Slight	46	218	21,769

According to Table 11, sensitivity for fatal injury shows that 87.22% of fatal injuries were correctly identified positives and specificity for fatal injury indicates that 90.80% of fatal injuries were correctly identified negatives. On the other hand, sensitivity for serious injuries shows that 58.44% of serious injuries were correctly identified positives and specificity for serious injuries indicates that 94.30% of serious injuries were correctly identified negatives. Finally, sensitivity for slight injuries shows that 98.80% of slight injuries were correctly identified positives and specificity for slight injury indicates that 75.32% of slight injuries were correctly identified negatives.

However, ROC curve analysis was also carried out for additional support. The resulting ROC graph and the area under the curve of the XGboost model with default and hyper-tuning parameters for each type of injury are shown in Figures 6 and 7. It has been demonstrated that the normal setting for fatal injury AUC ROC was 0.91, for serious injury it was 0.78 and for slight injury it was 0.95, whereas the hyper-tuning setting for fatal injury was 0.96, for serious injury it was 0.86 and for slight injury it was 0.96, indicating good predictive power for the model with both default and hyper-tuning parameters for fatal class injury. Both macro-average and micro-average ROC curves were also produced. The micro- and macro-average ROC curve values obtained with hyper-tuning parameters are slightly different to those obtained with default parameters, i.e., AUC (dec.tree tuning) micro, macro = 0.94, 0.93 while AUC (dec.tree default) micro, macro = 0.90, 0.88 as shown in Figures 6 and 7.

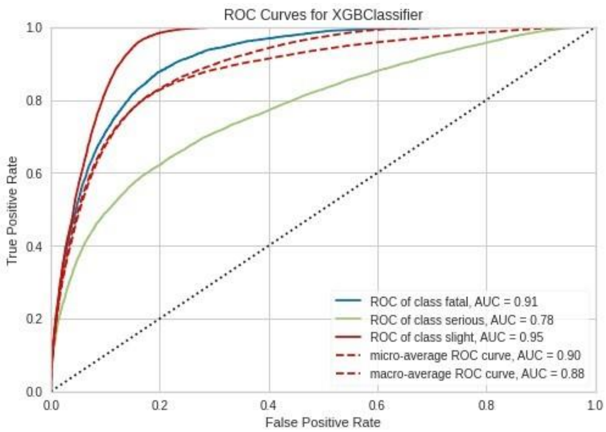

Figure 6. Receiver Operating Characteristic (ROC) curves for each accident severity class of XGboost algorithm analysis result with default parameters. The area under the ROC curve is reported in the legend.

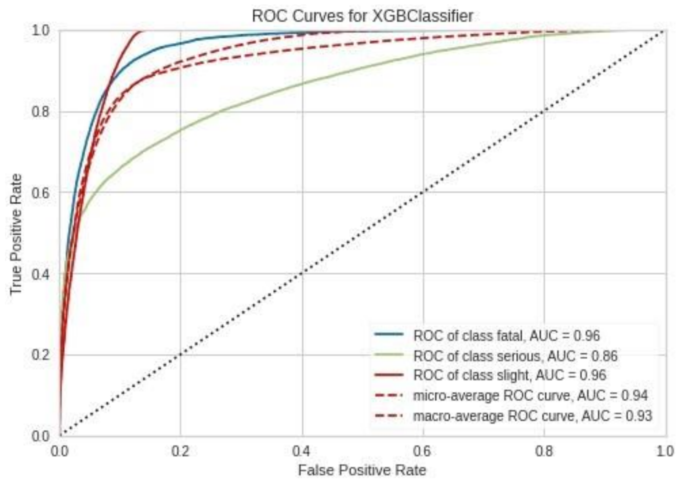

Figure 7. Receiver Operating Characteristic (ROC) curves for each accident severity class of XGboost algorithm analysis result with hyper-tuning parameters. The area under the ROC curve is reported in the legend.

5.4. Comparative Analysis of Machine Learning Techniques

Using the radar chart, a comparative analysis for all machine learning techniques is presented in Figure 8. The result shows that overall the Decision Tree models (default and hyper-turning) performed better than the other developed models based on F1 score, precision, recall, specificity and accuracy value in predicting fatal accidents. However, the LightGBM models performed better in terms of precision and accuracy for serious injuries but not so well on F1 score and recall. It can be observed overall that XGboost had the weakest performance for the fatal and serious injury models. Furthermore, it can be observed that the hyper-tuning parameter enhanced the prediction power of all three models. Overall, the prediction accuracies in the study presented are comparable to the results of those from previous studies on traffic crash severity [13,19].

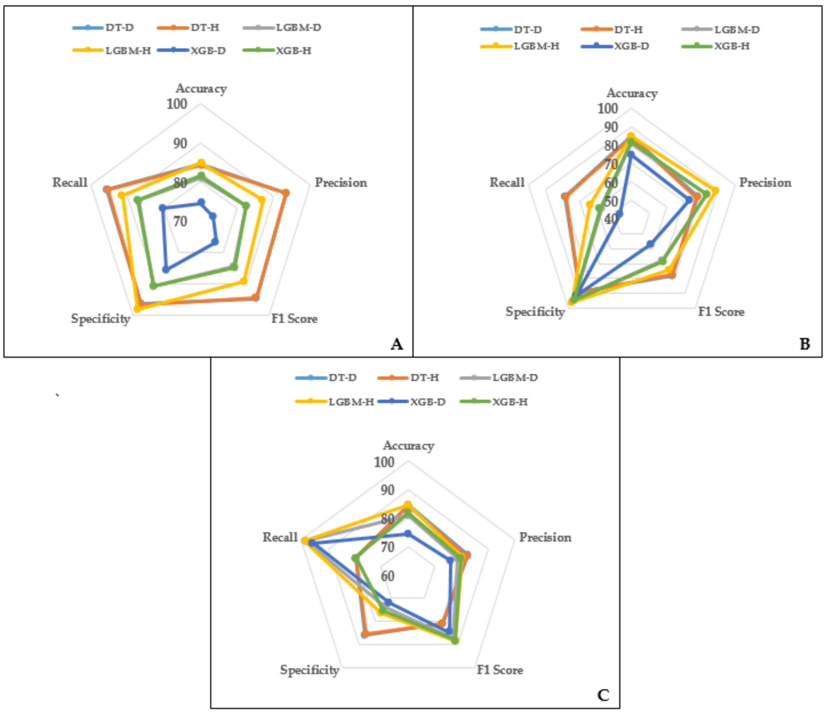

Figure 8. Performance measures of the developed models. (**A**): Fatal, (**B**): Serious injuries and (**C**): Slight injuries.

6. Conclusions

The direct objective of this study was to use three groups of data-driven methodologies to account for the negative effects of traffic accidents on society. It was discovered that Decision Tree models did quite well in terms of number. Also, considering the confusion matrix, it is worth noting that the Decision Tree algorithm did much better. It predicted more fatal and serious injuries as true positives. The accuracy score is lower compared to the LightGBM hyper-tuning algorithm, and it is worth noting that the LightGBM and XGboost algorithms predicted the majority of slight accidents, and those numbers are high overall in the dataset. The confusion matrix helps us to understand which algorithm worked better in terms of looking at all the different predictions of each class. Furthermore, the results further highlight the possibility that the high performance of the Decision Tree algorithm can predict traffic accident severity and also provide reference to the critical variables that need to be monitored in order to reduce accidents on the roads. Overall, it was discovered that vehicle and road user characteristics played a leading role in the severity of accidents in the year 2020 in the UK.

Under vehicle characteristics, the vehicle type is observed to be the highest importance score, thus implying the necessity of furnishing the first accident respondent with information of the vehicle type, as the vehicle type will determine the number of passengers on board and consequently the possible number of accident causalities [16]. Following the vehicle type, the feature importance scores rank vehicle type, vehicle manoeuvre, number of vehicles, age of the vehicle and age of drivers, respectively.

Considering the results of the study, the following can be concluded:

(i) Prediction of Future Traffic Accidents—in the study, 20% of the year 2020 data were used to predict the annual accident data. Although the predictions via the machine learning techniques are a little higher than those of the actual accident data, it is worth noting that the machine learning techniques have excluded the imbalance in data and data with errors. Thus, with the scarcity of traffic accident data for developing and underdeveloped countries [13], the quarterly accident data of the year can be used to establish trends and analyse and make the necessary transportation planning for the whole year in terms of accident prevention strategies. Also, the understanding of the accident trends needs to be carefully monitored to consider the effect of various holidays.

(ii) Machine Learning as Identifier of Significant Traffic Variables—the study also highlighted vehicle characteristics as one of the important variables in the accident severity; however, it is worth noting that the data used for this study were impacted by COVID-19 travel restrictions. Overall, it can be concluded that human and vehicle characteristics play an important role in traffic accidents. The necessity of identifying the significant variables is to assist in strategic planning and sensitizing road users to the causes of road accidents, especially during accident peak season. As a result, this study concludes that more emphasis be placed on vehicle characteristics during the road geometric design phase. To reduce the severity of road accidents caused by vehicle characteristics, preventative strategies such as regular vehicle technical inspection, traffic policy strengthening and the redesign of vehicle protective equipment must be implemented. [40,41].

(iii) Vehicle technical inspection—more emphasis should be placed on the vehicle's roadworthiness, as vehicle characteristics contribute to accident severity while policy strengthening can be ensured by continuously enforcing traffic control laws (such as speed limits and seatbelt/helmet use enforcement) by traffic police. Vehicle protective equipment focuses on the design of different vehicle modes other than cars and protective equipment, which may result in fewer injuries [40,41]. Also, the study emphasizes the need to incorporate more variables in terms of driver characteristics such as years of driving experience and recent involvement in any other traffic accident as this might affect the traffic accident. On a final note, this study concludes that machine learning models can be used to determine traffic accident fatalities under three severity levels such as fatal, serious injuries and minor injuries.

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