2026 International Conference on Power, Energy and Control Conference for the Industrial and Intelligent systems (PECCII)
17–18 June 2026, PUST, Pabna, Bangladesh

Road Accident Severity Prediction in Bangladesh Using Explainable LightGBM

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***Abstract*—Road traffic accidents remain a significant public safety issue in Bangladesh, causing high mortality rates and economic losses.With high death and economic tolls. While measures have been taken to make roads safer, the rise in the number of cars on the road coupled with the lack of proper infrastructure is aiding accidents.The aim of this study is to predict the severity of road traffic accident based on machine learning methods namely LightGBM and SHAP in Bangladesh. The purpose of this study is to find out the number and type of factors which different low and normal severity incidents from fatal incidents have, and to find out how the identified factors can be used for traffic safety improvement. This study has employed a data set on the occurrence of road traffic accidents using FIR data from three districts of Rajshahi, Natore and Pabna in Bangladesh. Data were carefully preprocessed, with missing values addressed and data normalized. The LightGBM model was applied to classify the severity of accidents and SHAP was applied to understand how the individual features contributed to the model's prediction. The LightGBM model shows great performance, with an AUC of 0.87 for fatal and low/normal severity classes. Type of collision, vehicle type, vulnerable road users and environmental conditions turned out to be the most prominent factors affecting the severity.Overall, the study highlights the potential of machine learning in predictive modeling for improving road safety. These findings can help policy makers prioritize the interventions that are needed for safety, by focusing on the factors that are most likely to lead to death, thus minimizing the number of lives lost on the roads in Bangladesh.**

***Index Terms*—Road Traffic Accidents; Traffic Safety; Predictive Modeling; LightGBM Model; SHAP**

I. Introduction

Road traffic accidents are one of the greatest concerns for public health and development worldwide, claiming more than one million lives every year, and affecting low to middle income countries disproportionately [1]. World Health Organization (WHO) reports that high death rates are due to speeding up of motorization, poor roadway infrastructure, unfriendly roadway environment for driving, and weak enforcement practices [2]. The fact that there have been constantly high rates of death and injury due to accidents in Bangladesh.High rate of deaths and injuries occurring due to accidents in Bangladesh has made it essential to accurately predict the severity of accidents for effective transportation system planning and interventions for accident safety in the country.

In addition to the health effects, road traffic injuries also have a negative effect on sustainable development by lowering the country's economic productivity and worsening inequality. The existing road network is a key barrier to achieving the some of the most vital Sustainable Development Goals (SDGs) including Target 3.6 (safe and sustainable transport) and Target 11.2 (road safety) [3]. Data-driven road safety analysis is thus gaining greater significance for evidence-based road safety policies in developing countries.

The severity of the accidents is related to many of the factors such as vehicle properties and accident mechanisms, road conditions and temporal conditions. These relationships are difficult to be captured by the traditional statistical models, which is why the machine learning approach was chosen. Studies in recent years indicate that ensemble and boosting models are superior to traditional models for severity prediction (among others, [4]).

To address this challenge, recent years have seen the introduction of explainable artificial intelligence (XAI) methods, and in particular SHapley Additive exPlanations (SHAP), that help to interpret a model both from a global and local perspective and thus help to identify their factors contributing to the occurrence of severe crashes [5] and [6].

In this study, a framework for predicting road accidents severity using real-world road accident data has been proposed, which uses explainable machine learning.The present study suggests a framework to predict severity of road accidents using real world road accident data in Bangladesh.

II. Related Works

Recent research has increasingly focused on the application of machine learning and deep learning techniques for traffic accident severity prediction. Due to the complex and nonlinear interactions among vehicle characteristics, road conditions, collision types, and temporal factors, traditional statistical models often fail to achieve satisfactory predictive performance. Consequently, a range of data-driven approaches, including Random Forest, Gradient Boosting, Support Vector Machines, and deep neural networks, have been proposed to improve severity classification accuracy. Several studies report that ensemble and boosting-based models outperform conventional methods, particularly when handling heterogeneous accident datasets [15], [16]. More recently, explainable artificial intelligence techniques, such as SHapley Additive exPlanations (SHAP), have been applied to enhance model transparency and interpretability.

Despite these advances, the literature still reveals notable limitations, including reliance on region-specific datasets,. Recent efforts addressing class imbalance through ensemble learning further emphasize the need for robust and generalizable severity prediction models [17]. The comparative summary of recent machine learning–based traffic accident severity prediction studies is presented in Table I.

TABLE I
SUMMARY OF MACHINE LEARNING-BASED TRAFFIC ACCIDENT SEVERITY STUDIES

Ref.	**Study**	**Objective**	**Methodology**	**Key Findings**	**Limitation**
[7]	ML-Based Traffic Accident Severity Forecasting	Forecast accident severity	NB, RF, LR, ANN	RF and LR achieved ∼87% accuracy	No casualty-level features
[8]	Explainable ML for Road Accident Severity	Predict injury severity	RF, XGB, AdaBoost, LGBM, CatBoost + SHAP	RF achieved 81.45% accuracy	High-dimensional data
[9]	ML Approaches for Accident Severity: A Review	Review ML-based severity prediction	RF, XGB, hybrid ML models	Ensembles performed best	Limited cross-regional validity
[10]	The Key Determinants of Road Accidents Analysis	Identify major accident factors	Ridge Classifier, PyCaret	Time and vehicle factors dominant	Imbalanced and small dataset
[11]	Comparing Prediction for Severity using ML Methods	Compare ML and statistical models	KNN, DT, RF, SVM, OP, MNL	ML models outperformed statistics	Overfitting risk
[12]	Predicting Crash Injury Severity with Machine Learning Algorithm	Improve severity prediction accuracy	SVM, FNN with FCM	SVM–FCM performed best	Dataset dependency
[13]	Boosting-Based Severity Prediction with SHAP	Compare boosting ensemble models	NGBoost, CatBoost, LGBM, AdaBoost	LightGBM best (73.63%)	SHAP sensitivity
[14]	CNN-Based Traffic Accident Severity Prediction	Predict accident severity using DL	CNN with FM2GI	TASP-CNN best performance	High computational cost

III. METHODOLOGY

This workflow is designed to provide a machine learning model to predict the severity outcomes of an accident, based on police reports, surveys and traffic data.The process begins with data collection where a variety of data sources, representative dataset. For data preprocessing, data should be very well cleaned then, and normalisation to improve uniformity and uniformity. Exploratory Data Analysis gets the

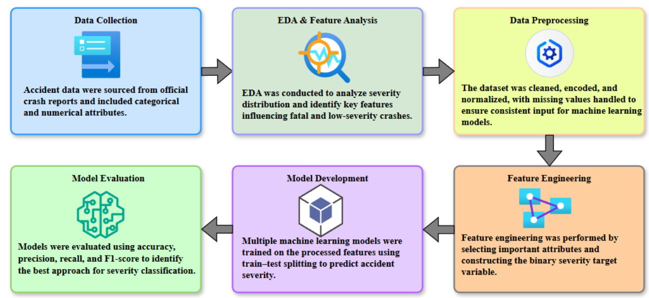

Fig. 1. Proposed machine learning workflow for accident severity detection.

most influential attributes to improve model efficiency. During model development, advanced machine learning techniques, such as Sikitlearn, They are used in conjunction with systemic split between train and test to provide strong training. The evaluation stage thoroughly analyzes the performance of the models with regard to Significant metrics such as accuracy, precision, recall and the AUC score. The key factors associated with the severity of accidents are then uncovered by using a SHAP analysis. Lastly, the model can be implemented for actual time monitoring and can be used to provide data-driven recommendations for improving safety, and reducing serious crashes on the road.

A. Dataset Collection

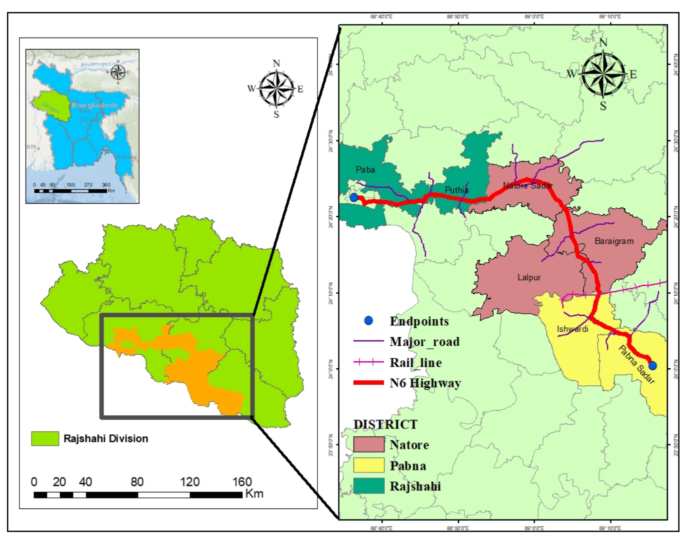

Fig. 2. Study Area Map for road traffic accident analysis.

The data for this study was obtained from the FIR reports at highway police stations in FIR reports in the Rajshahi, Natore district and Pabna district of the north western parts of Bangladesh. The analysis is important for these areas as they are thought to have a higher number of severe accidents. Key geographical and environmental information is gathered, such as season, environmental factors and time of the accident, in addition to essential information about the accident itself.

TABLE II
DESCRIPTIVE STATISTICS OF THE STUDY VARIABLES

Category	**Measure**	**Valid/Missing**	**Values (%)**
Season	Nominal	199 / 0	Monsoon (19.6), Summer (30.7), Winter (49.7)
Time range	Nominal	199 / 0	12–4am (4.0), 12–5pm (28.6), 5–7am (14.6), 6–7pm (18.1), 8–11am (22.1), 8–11pm (12.6)
Time of day	Nominal	199 / 0	Morning (37.2), Afternoon (35.7), Evening (6.5), Night (20.1), Late night (0.5)
Location	Nominal	199 / 0	Natore (44.7), Rajshahi (35.7), Pabna (15.6)
Collision type	Nominal	199 / 0	Head-on (38.2), Pedestrian hit (13.1), Loss control (5.5)
Cause of accident	Nominal	199 / 0	Overspeed & rash driving (63.8), Overtaking (15.6), Lane change (11.1), Loss control (4.0), Others ($\leq$2.5)
Affected vehicle	Nominal	199 / 0	Motorcycle (25.6), 3-wheeler (13.6), Truck (6.0), Bus (3.5), Car (2.0), Pickup (2.5), Others ($\leq$1), Unknown (21.1)
Responsible vehicle	Nominal	199 / 0	Truck (36.2), Bus (20.6), Motorcycle (6.0), Car (4.0), Pickup (4.0), Microbus (4.5), Unknown (7.5)
Death count	Scale	199 / 0	Mean 1.19, SD 0.92, Min 0, Max 7

In this research work, we have created a dataset for road accidents with 199 data entries, where each data entry represents an instance of an accident.

B. Exploratory Data Analysis

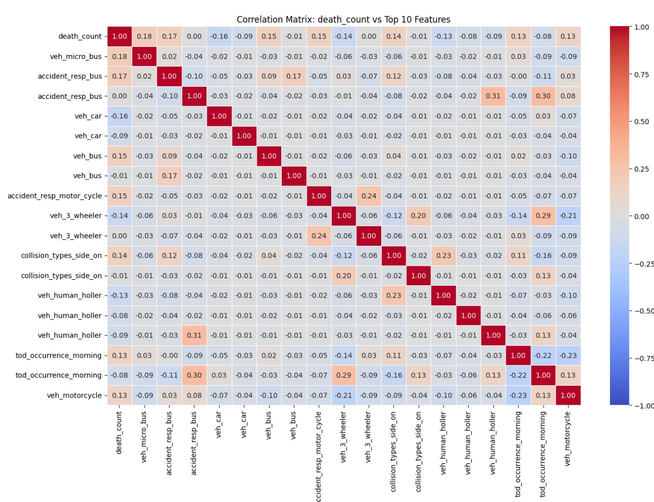

Fig. 3. Correlation matrix illustrating the linear association between accident severity (death count) and the top ten categorical features.

Exploratory Data Analysis (EDA) was conducted to identify influential attributes and guide subsequent feature engineering and model development. A correlation-based analysis (including a correlation matrix using severity proxies such as death count) was used to identify features most associated with accident severity and to support subsequent rule design and feature selection. Although individual linear correlations are modest, this analysis provides preliminary insight into potentially influential factors and motivates the use of non-linear ensemble models to capture complex interactions.

C. Data Preprocessing (Cleaning and Normalization)

To ensure consistent learning and reduce noise, the dataset was cleaned and normalized before modeling. Text-based categorical fields were standardized by converting to lowercase, trimming extra whitespace, and replacing missing/empty values with a common “unknown” token. Duplicate or inconsistent formatting in categorical labels was minimized using string normalization. This preprocessing step improves feature consistency and reduces sparsity after encoding.

D. Feature Engineering and Target Construction

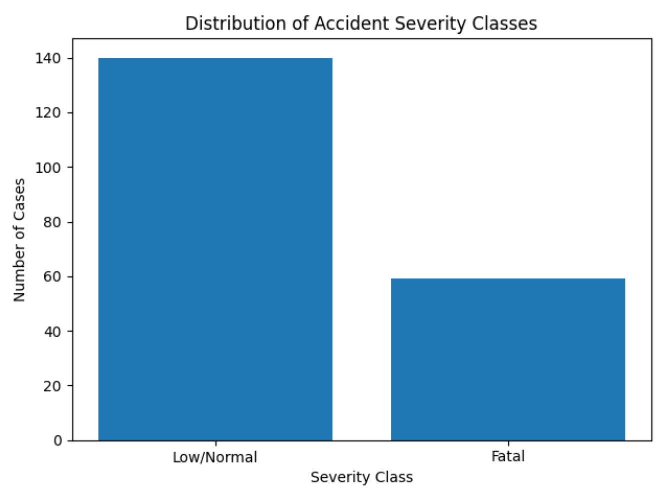

Fig. 4. Distribution of constructed accident severity classes based on rule-based risk scoring.

The dataset did not contain a consistent binary severity label, so we created a rule-based severity scoring scheme to create an operational ”low/normal” vs. ”fatal” target. Accident descriptors, often associated with severe accidents, were used to define the rules and exploratory feature analysis was used to inform the development of the rules. Using the variables associated with the context of the accident, a composite risk_score was calculated that had more severe scores associated with more severe potential.Composite risk_score was computed from the accident context variables (e.g., collision type and involvement of vulnerable road users, time condition, responsible vehicle type, and cause-related indicators) and higher scores were associated with increasing severity potential. To get a binary label for severity, a threshold was created at 0.8

of the quantiles and the records with risk scores in the upper 20All the variables included in the score (including risk_score) and any direct outcome proxy (e.g. death related variables) were not included in the model training predictive feature set to avoid label leakage and post-event bias. This will guarantee that the classifier learns the severity patterns from predictors that are independent in nature, without re-using the signals of label generation.

E. Model Development (Supervised Binary Classification)

Scikit-learn is not only used to handle the classification problem, it can also be used to handle some other data pre-processing problems like handling missing values, feature Encoding, Feature Scaling. Different machine learning models such as decision trees, gradient boosting machines, or support vector machines can be used with different algorithms for their selection, using accuracy, F1 measure and AUROC scores. Even optimization of the model can be done by optimization with grid search.

A supervised learning Pipeline was employed using the Library 'scikit-learn'. After stratified splitting process, the ratio of fatal/low remained in the split process for the dataset, where 70% of data is kept as the training set and 30% as the test set. Categorical variable(s) were one-hotted and numerical variable(s) were standardized.

TABLE III
SUMMARY OF EXPERIMENTAL SETUP

Description	Value
Target Variable	severity_bin
Target Encoding	Binary (fatal = 1, low = 0)
Train–Test Split	70% Train, 30% Test
Random State	42
Sampling Strategy	Stratified Train–Test Split
Categorical Encoding	One-Hot Encoding
Numerical Feature Scaling	StandardScaler
Preprocessing Framework	ColumnTransformer
Feature Leakage Handling	Leakage-prone features removed
Class Imbalance Handling	scale_pos_weight (LightGBM)
Classifier	LightGBM (LGBMClassifier)
Number of Trees	500
Learning Rate	0.05
Number of Leaves	31

All experiments were conducted using a stratified 70/30 train–test split with a fixed random seed. Multiple classifiers were evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC, and the best-performing model was selected.

Light Gradient Boosting Machine (LightGBM) is an ensemble classifier based on gradient boosted decision trees. The final prediction is obtained by an additive combination of multiple weak learners:

$$\hat{y}_i = \sum_{m=1}^{M} f_m(x_i), \tag{1}$$

where f_m denotes the m-th decision tree and M is the total number of boosting iterations.

The model is trained by minimizing an objective function consisting of a loss term and a regularization component:

$$\mathcal{L} = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \sum_{m=1}^{M} \Omega(f_m). \tag{2}$$

For binary accident severity prediction, the probability of a fatal outcome is computed as:

$$P(y = 1|x) = \frac{1}{1 + e^{-\hat{y}}}, \tag{3}$$

where $y = 1$ represents the fatal class.

Evaluation Metrics: To quantitatively assess the classification performance of the proposed model, precision and recall are defined as follows:

$$\text{Precision} = \frac{TP}{TP + FP}, \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN}. \tag{5}$$

Model Interpretability: To ensure transparency and interpretability of the trained LightGBM model, SHapley Additive exPlanations (SHAP) were employed to explain individual predictions. The SHAP formulation is expressed as:

$$f(x) = \phi_0 + \sum_{i=1}^{n} \phi_i, \tag{6}$$

where ϕ_i represents the contribution of the i-th feature to the final model output.

IV. RESULTS AND PERFORMANCE ANALYSIS

The following classifiers were implemented, compared, and evaluated (Top candidates):

TABLE IV
PERFORMANCE COMPARISON OF CANDIDATE MODELS

Model	Accuracy	AUC	Recall	Precision
LightGBM	0.8000	0.8628	0.9200	0.5872
GBC	0.7298	0.5483	0.7698	0.6939
Decision Tree	0.7098	0.5476	0.7698	0.6939
AdaBoost	0.6098	0.5430	0.7698	0.6939
XGBoost	0.5048	0.5415	0.5048	0.5824

This study classified the causes of traffic accidents using different machine learning techniques. Data preprocessing handled missing values, outliers, and categorical variables. ROC curves, feature importance, and confusion matrices are some of the metrics that was used to evaluate the trained models with sikitlearn. Such models were LightGBM, Decision Tree Classifier, Gradiant Boosting, Ada Boost, Extreme Gradient Boosting Classifier etc.

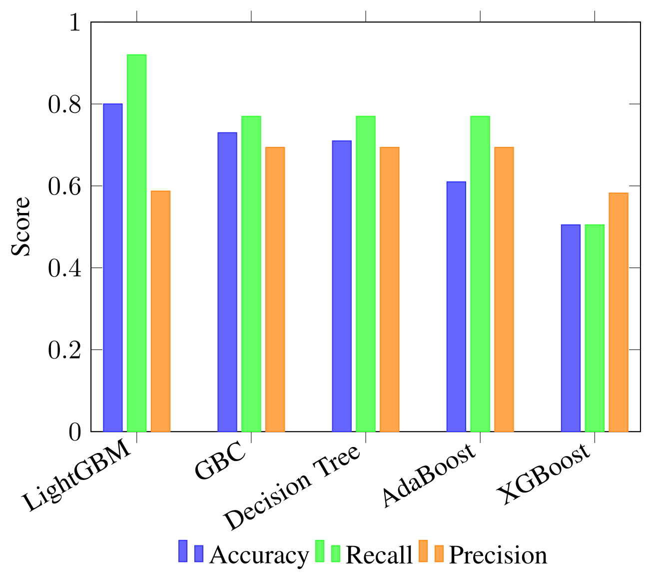

Fig. 5. Comparison of accuracy, recall, and precision across different models

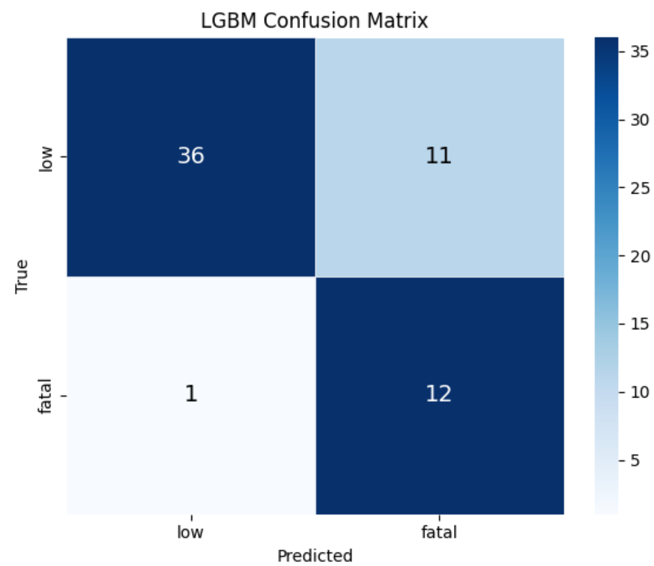

Fig. 7. Confusion matrix of the LGBMClassifier.

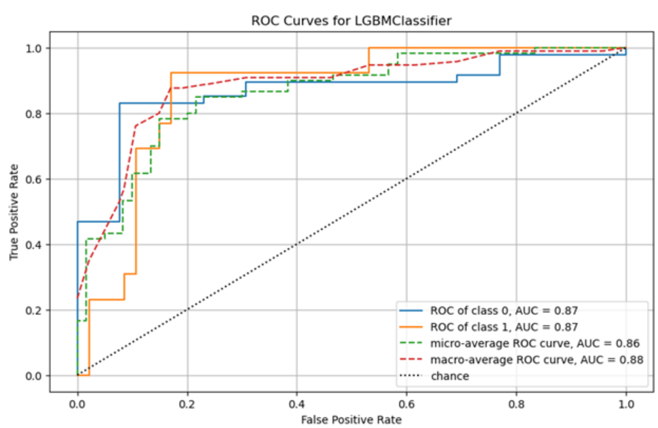

Fig. 6. ROC curve for LGBM classifier.

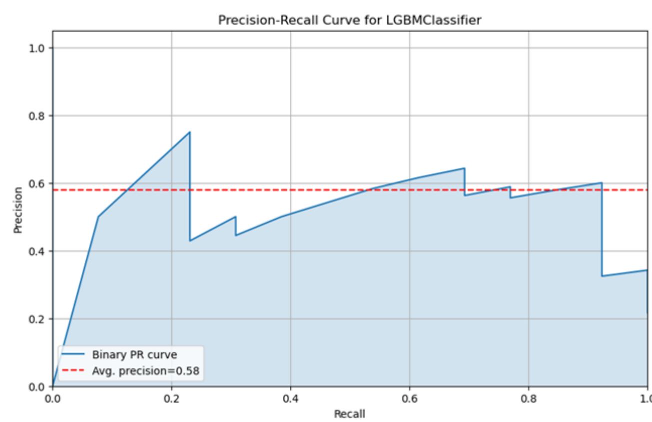

Fig. 8. Precision Recall Curve of LGBMClassifier.

The ROC curves in Fig. 6 indicate that the proposed LightGBM model achieves strong separation between the two severity classes. The ROC analysis shows balanced discrimination for both severity classes. with AUC = 0.87 for both. In addition, the overall discrimination remains high as reflected by the aggregated AUC scores: the micro-average AUC is 0.86 and the macro-average AUC is 0.88.

Fig. 7 shows the confusion matrix of the proposed LGBMClassifier for binary accident severity prediction (low/normal vs. fatal). The model correctly classifies 36 low/normal cases and 12 fatal cases. Only one fatal accident is misclassified as low severity, indicating strong sensitivity toward fatal detection. However, 11 low/normal cases are predicted as fatal, suggesting the model generates some false alarms. Overall, the confusion matrix confirms that the classifier prioritizes detecting fatal accidents with a low false-negative rate, which is desirable for safety-critical severity screening.

Fig. 8 illustrates the Precision–Recall (PR) curve of the proposed LGBMClassifier under class imbalance, where fatal accidents form the minority class.

The curve demonstrates the model achieves strong fatal-case sensitivity with a low false-negative rate, while the Average Precision (AP = 0.58) indicates moderate overall performance in maintaining reliable fatal predictions. This behavior is desirable in safety-critical applications, where prioritizing the detection of fatal cases is more important than minimizing false alarms.

A. SHAP-Based Model Interpretability

SHAP was applied to explain the predictions of the proposed LightGBM model and identify the most influential factors contributing to fatal accident severity.

SHAP can give insight into the predictions by displaying the contribution from particular factors to the prediction. The positive values indicate that there is an increased probability of having a fatal severity compared to the baseline; the negative values indicate that there is a decreased probability of fatal severity compared to the baseline.

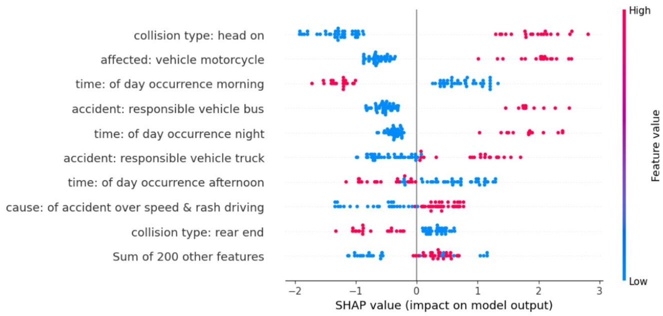

Fig. 9. SHAP summary plot showing feature contributions to fatal severity prediction.

in Fig:9 The Show Plot plot (beeswarm) shows the importance and direction of the effect of each feature on all the accident records. The results show that the type of collision (head-on) has the greatest influence on the prediction of fatal severity of the collision. Likewise, accidents with vulnerable motor vehicles like motorcycles drastically raise the risk of death.

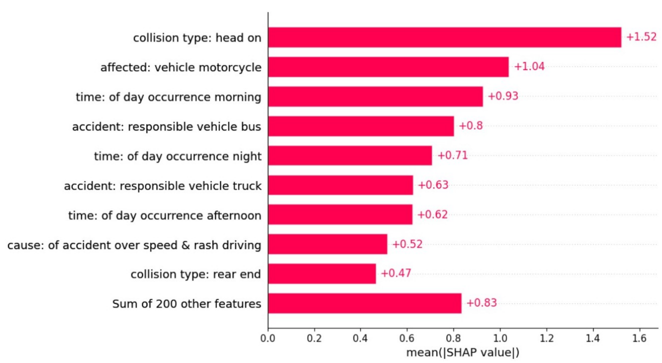

Fig. 10. Mean absolute SHAP values indicating the most influential features in the LightGBM model.

The global SHAP picture of most influential determinants of fatal accident outcomes further validates that collision characteristics, vehicle involvement and overspeed-related factors are some of the most significant factors.

V. Conclusion and Future work

This study proposed an explainable LightGBM-based framework for predicting road accident severity in Bangladesh using FIR-based accident records. Since no distinct severity binary label was available a rule-based approach for a risk scoring mechanism was introduced in order to provide a fatal vs. low/normal severity target without a leak of label in data for model training purposes. Three classifiers were tested: Accuracy values were used as the metric and LightGBM achieved the best results with accuracy of 0.80, and an ROC-AUC score of 0.86. The classifier exhibited low false negative rate with high sensitivity to fatal accidents, which is suitable for using the classifier in safety critical severity classification. Explainability of the SHAP technique was also utilized to promote trust and transparency and it was determined that factors such as head-on collision, vulnerable vehicle (particularly motorcycle), nighttime, overspeed, and others are some of the most important factors which impact the severity of a fatal crash. Further expansion of this dataset (such as geographical/environmental information) and multi-class prediction of severity would be useful for further generalization of this model as future work. In general, the proposed explainable ML pipeline can be a hopeful answer to decrease the death toll in road crashes in the developing world.

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