IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 28, 2021, accepted September 6, 2021, date of publication September 14, 2021, date of current version September 23, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3112546

RFCNN: Traffic Accident Severity Prediction Based on Decision Level Fusion of Machine and Deep Learning Model

MUBARIZ MANZOOR[1], MUHAMMAD UMER[2,3], SAIMA SADIQ[2], ABID ISHAQ[2], SALEEM ULLAH[2], HAMZA AHMAD MADNI[4], AND CARMEN BISOGNI[5], (Member, IEEE)

[1]Department of Information Security, Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Rahim Yar Khan 64200, Pakistan
[2]Department of Computer Science, Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Rahim Yar Khan 64200, Pakistan
[3]Department of Computer Science and Information Technology, The Islamia University of Bahawalpur, Bahawalpur 63100, Pakistan
[4]Department of Computer Engineering, Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Rahim Yar Khan 64200, Pakistan
[5]Department of Computer Science, University of Salerno, 84084 Fisciano, Italy

Corresponding authors: Hamza Ahmad Madni (101101770@seu.edu.cn) and Carmen Bisogni (cbisogni@unisa.it)

This work was supported by the Department of Computer Science in collaboration with Fareed Computing and Research Center, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan, Pakistan.

ABSTRACT Traffic accidents on highways are a leading cause of death despite the development of traffic safety measures. The burden of casualties and damage caused by road accidents is very high for developing countries. Many factors are associated with traffic accidents, some of which are more significant than others in determining the severity of accidents. Data mining techniques can help in predicting influential factors related to crash severity. In this study, significant factors that are strongly correlated with the accident severity on highways are identified by Random Forest. Top features affecting accidental severity include distance, temperature, wind_Chill, humidity, visibility, and wind direction. This study presents an ensemble of machine learning and deep learning models by combining Random Forest and Convolutional Neural Network called RFCNN for the prediction of road accident severity. The performance of the proposed approach is compared with several base learner classifiers. The data used in the analysis include accident records of the USA from February 2016 to June 2020. Obtained results demonstrate that the RFCNN enhanced the decision-making process and outperformed other models with 0.991 accuracy, 0.974 precision, 0.986 recall, and 0.980 F-score using the 20 most significant features in predicting the severity of accidents.

INDEX TERMS Road accidents severity, random forest, convolutional neural network, feature importance, ensemble learning.

I. INTRODUCTION

Road traffic accidents are a major cause of injuries, deaths, permanent disabilities and property loss. It not only affects the economy it also affects the health care system because it puts a burden on the hospitals. Statistics shown by the ministry of public security of china from the years 2009 and 2011, traffic accidents caused an average of 65123 people to lose their life and 255540 got injuries annually [1]. Identification of primary factors affecting road accident severity is required to minimize the level of accidental severity. Accidental Severity does not happen by chance; there are patterns that can be predicted and prevented. Accidental events can be analyzed and avoided [2]. Being one of the major issues of accident management, accident severity prediction plays an important role to the rescuers in evaluating the level of severity in traffic accidents, their potential impact, and in implementing efficient accident management procedures.

Accidental severity analysis involves three factors that are number of injuries, number of casualties, and destruction of property. Authors take severity level independent and consider four options like light injury, severe injury, fatal, and property damage [3]. The accidental severity level is defined as injury, possible injury, and property damage [4], [5]. In the last two decades, accidental severity is one of the popular research areas. Researchers were applying different statistical approaches for road accident classification. These techniques help in analyzing the cause of road accidents. The mixed logit

The associate editor coordinating the review of this manuscript and approving it for publication was Jinjia Zhou.

modeling approach [6], logit model [7] and ordered Probit model [8], are few of the traditional statistical-based studies. But these approaches lack the capability to handle multidimensional datasets [9]. At present, due to a large number of available datasets machine learning surpasses the traditional statistical approaches in prediction [10]. In the recent past, many researchers have focused on the work related to the severity prediction of traffic accidents. The focus of the many researchers' work is to find out the main factors that have an impact on the severity of traffic accidents. Nonparametric models, linear models like data mining techniques have been widely utilized to conduct such analysis. To describe the literature about severity prediction of the traffic accidents researches, their techniques and adopted methods have been discussed.

A. ROAD TRAFFIC INJURIES AND SOCIO-ECONOMIC COST

Road traffic accidents cost about 1% annually of the Gross National Product(GNP) in undeveloped countries about 1.5% in underdeveloped countries, and about 2% in the developed countries [11]. Traffic road accidents cost about US$518 billion which is a huge economic cost. The share of the undeveloped countries is about US$68 billion which is a lot and this amount is much more than the amount that is received in terms of removing poverty in the country. Additionally, the estimated cost in the undeveloped and underdeveloped countries are possibly significant underestimate using detailed information and measuring methods, the annual estimated cost of road traffic accidents in Europe alone, which is 5% of the world's total death toll and exceeded about €180 billion [12], [13]. In the US, the road traffic accidents cost is much high in 2000. The cost of road traffic accidents is about US$230 billion [14].

If made a comparison in the undeveloped and underdeveloped countries cost of road traffic accidents, the total cost all around the world is exceeded the current estimation which is US$518 billion. Not only the national and regional economy is disturbed by the road accidents also the households affected by it. For example, in countries like Kenya, more the 75% of the road traffic accidents are from economically productive young people [15]. In spite of that, the road traffic accidents effects not only socially and economically there is little importance not given to this problem as compared to the other problems in which people lose their lives.

Some countries are investing a lot in road traffic safety. The purpose of all this research doing by these countries is simple and clear cut to reduce the fatalities in traffic accidents [16], [17]. Road traffic paid a vital role in the country's economy, but the price paying by society is very high.

B. ROAD TRAFFIC ACCIDENT INJURY PREVENTABILITY AND PREDICTABILITY

One of the common concepts that laying in our society is, it is an event that can happen anywhere and anyone could be the victim of this that's why road traffic accidents are being neglected in society [18], [19]. Road traffic accidents are foreseeable and can be foreseeable results of road traffic. The chance of road traffic accidents is very low for most of the individual's journeys, as people travel many times in a day, month and a year. But the addition of these chances is considerable in countries like the US, UK Canada, etc. The attention to road fatalities during the 1960s to 1970s results in a considerable reduction in road accident fatalities. This response was stimulated by the activists and researchers. Social experiments show that with the political will and commitment of the government to deploy a safe traffic management plan, a quick and effective traffic plan with a low fatality rate can be deployed.

C. SCIENTIFIC APPROACH AND THE NEED FOR RELIABLE DATA

Prevention from a road traffic accident is a highly discussable issue. Every researcher has their own opinion on what could be the important feature that plays a role in traffic accidents. Authentic data, social media and journalism reporting highlight this issue that requires immediate actions, which in turn put the policymaker to make some policies to combat it. Policies that are going to be implemented are based on the data which is reliable and authentic. First of all, data related to severe accidents are needed. After that, a comprehensive understanding of the circumstances that are the cause of the accidents is required to guide the traffic safety policy. After that, how accidents and injuries have happened and what type is a valuable tool for the recognition interventions and the checking of the effectiveness of the interventions. Systematic efforts have not been done by the undeveloped and underdeveloped countries to collect the road traffic data that why there is some unreported cases remain. The health sector has the revocability to establish a good data collecting system and share the data with multiple audiences. Only reliable and authentic data can help to reduce traffic accidents and also helps to find the severity level of the accidents.

A variety of approaches has been utilized to observe the influential factors affecting traffic incidents over the last decade. Generally, there are two main approaches for the said purpose that are statistical approaches and machine learning methods. Statistical methods find relationships between dependant and independent variables based on mathematical formulas. Statistical methods involve regression analysis and hazard-based models that are being used in the analysis of road incidents. The authors applied the Bayesian Averaging Model called BMA for the analysis of incidence clearance time and they also explored the significant factors affecting the duration of clearance of traffic incidents [20]. BMA performed well as compared to classical methods in predicting the time of clearance for traffic. In general, hazard-based models and tree-based models are used for traffic data analysis. Reference [21] compared statistical and machine learning models for traffic incident prediction and found Random Forest as the best performing model. Sometimes, machine learning models are not capable to interpret the explanatory and estimator variables. Therefore, we combine

Random Forest with a deep learning model to overcome these limitations.

There are lots of requirements for funds needed every year to handle this problem. After the construction of infrastructure, we also need more funds to maintain this. From all of the above discussion, we have now a clear concept by improving road traffic safety not only benefits the health system also increases the economy of the countries.

D. CONTRIBUTIONS OF THE STUDY

This paper makes use of an ensemble learning model that combines machine learning and deep learning models to accurately predict the severity of road accidents. The proposed ensemble combines Random Forest (RF) and Convolutional Neural Network (CNN) model called RFCNN. The base learning models used in this experiment are AdaBoost Classifier(AB), Gradient Boosting Machine (GBM), Random Forest(RF), Extra Tree(ET), and Voting Classifier of machine learning models. The voting classifier of machine learning models used in this experiment is an ensemble of two regression-based models (Logistic Regression and Stochastic Gradient Descent). The proposed model RFCNN is applied to the US road accident dataset in two phases. In the first phase, all 48 features of the dataset are used to predict the severity of the accident. In the first experimental phase, we also calculate the feature importance value of all features using the RF classifier. In the second phase of the experiment, the top 20 features that are calculated using RF classifier feature importance are used to train all models to predict the severity of road accidents. This research serves the following key contributions:

- A novel ensemble of machine learning and deep learning model (RFCNN) has been proposed for accidental severity prediction. RFCNN combines RF and CNN through soft voting.
- Comparative analysis of tree-based and regression-based Ensemble learning classifiers such as AB, GBM, RF, ET, and Voting Classifier(LR+SGD).
- Influence of significant variable on evaluation measures such as accuracy, precision and recall is analyzed.
- Most suitable methods and suitable input parameters are explored for the classification of road accidents' severity.
- As a decrease of input variables improves the performance, it will also reduce the cost of data collection.

The rest of the paper is organized as follows. Section III presents an overview of the methodology adopted for the current research as well as a detailed description of the US road accident dataset used for the experiment. Results are discussed in Section IV and discussion in section V. The conclusion and future work are discussed in Section VI.

II. LITERATURE REVIEW

Data mining is immensely used in different fields like deep learning has been utilized by many researchers for image classification [22], text mining [23], Fake news detection [24], and text classification [25], [26]. Traffic accident data analysis using different data mining approaches has been considered by many researchers. Many works in the literature explored road accident severity in different countries [27]–[29]. Authors utilized the ANN to model injury severity of traffic accidents using classifying the injury severity into five different categories (no injury, possible injury, minor non-incapacitating injury, incapacitating and fatality). There were 150 parameters out of which they have selected the most significant 16 parameters using some parameter selection algorithms that affect the injury level of the drivers. ANN was deployed to classify the injury severity level. They have achieved the accuracy of 40.71% which is quite low [30].

For any kind of data analysis regression models are the basic components with the relationship between explanatory variable and response variable. In [31], authors worked on the severity of traffic accidents in the United States using logistic regression. At probability cut-point 0.20 they obtained the model sensitivity and specificity were 40% and 98% respectively. Their research finding also shows that velocity, seat belt use, and crash direction are important parameters for the prediction of the severity of traffic accidents. Authors proposed fuzzy rule mining for the analysis of quality accidents [32]. Authors used accident data to predict the requirement of emergency vehicle [33].

A classification and regression models tree (CART) is an important data mining technique. It is a non parametric technique. Many researchers used CART as a tool for classification and for prediction in research related to traffic accidents. Reference [34] utilized CART to analyze the rural traffic accidents in Iran. CART is utilized to find the most important variable that affects the severity of the accidents. In the analysis process, three classes were predicted in the form of a group of binary prediction models that assists to achieve the higher accuracy for the predicted model, and obtained accuracy is 60.94%.and the important variable which affects the severity of the accidents is improper overtaking and not fasting the seat belt.

Sharma *et al.* [35] used a Support Vector Machine and multi-layer perception to analyze road accidents. They experimented on a limited number of data samples. They explored only two variables that are speed and alcohol as a key contributor to road accidents. SVM outperformed with 94% accuracy. They claimed high-speed driving after drinking is the reason for the incident. Tiwari *et al.* [36] used machine learning models like Decision Tree (DT), Naive Bayes(NB) and Support Vector Machine (SVM) for classification and SOM and K-modes for clustering. They achieved better results with the cluster dataset.

AlMamlook *et al.* [37] used NB, AdaBoost, Random Forest (RF) and Logistic Regression (LR) to find highways with a high risk of accident for traffic agencies. They evaluated their models using AUC, ROC, Recall, Precision and F- measure. RF outperformed with 75% accuracy. In another work, Beshah and Hill [38] experimented to analyze important roadway-related variables that can affect road accident severity. They used DT, NB and KNN to make decision rules for road safety measures. They mainly focus on drivers and pedestrians without giving importance to any other factor such as whether, time or speed. They even did not focus on the influence of machine learning model accuracy for better identification of accidental severity risk.

Many researchers employed improved machine learning models by using decision level fusion for road traffic analysis. Ma *et al.* [39] proposed an improved model known as gradient boosting decision tree (GBDT) for analysis of traffic clearance in terms of time. Their proposed model significantly performed well in short clearance time as well as long clearance time. Zou *et al.* [40] analyzed incident clearance time and got better prediction results using copula model. Authors in [21] compared statistical methods and machine learning models in predicting time for incident clearance. Deep learning models have also been employed by researchers in predicting the duration of road incidents. Yu *et al.* [41] proved the superiority of the artificial neural network model in predicting longer duration and compared results with SVM.

However, the severity prediction of road accidents is still under development. In the past work we have seen room to improve classification accuracy using machine learning models for road safety. There is a dearth of comparing state-of-the-art machine learning models with hybrid models. Obtaining an appropriate approach will improve prediction accuracy. Finding the best paradigm also helps in identifying factors affecting road accidents. Furthermore factors that are more specific to the target can help machine learning models to improve in prediction results that were not identified previously. The aim of the researches related to the traffic accident data govern on data mining can be divided into two categories:

- Prediction of traffic accidents severity
- The important factors that affect the severity of an accident

III. MATERIAL & METHODS

In this section we will discuss classifiers and dataset utilized for Road Severity Prediction. Figure 1 demonstrates the proposed methodology of data and workflow of this research work.

A. MODELING METHODS

In this research, road accident severity analysis is performed by using an ensemble learning model by combining machine learning and a deep learning model called RFCNN. Base learning models include in this study are RF, ADC, ETC, GBM and a Voting Classifier (LR+SGD).

In the past, many ensemble techniques have been proposed by researchers but the most common are bagging [42] and boosting [43]. Random forest (RF) was first developed by Breiman [44]. In the RF algorithm if N number of trees are built by RF then four steps are involved in N iteration. Step 1 involves training of data using the bootstrap dataset, bootstrap dataset is a subset of the original dataset. Step 2 involves tree generation and at step 3 attributes are selected randomly. Finally in step 4 final prediction is based on the tree result selected on the basis of majority voting [45]. The working of RF is shown as follows.

$$p = mode\,\{T_1(y), T_2(y), \ldots, T_m(y)\} \tag{1}$$

$$p = mode\left\{\sum_{m=1}^{m} T_m(y)\right\} \tag{2}$$

Here p is the final prediction, calculate by majority votes of trees T_1, T_2 and T_m [46].

AdaBoost is a short form of adaptive boosting. It is also an ensemble model based on decision trees. AdaBoost Classifier (AC) is popular for being the first algorithm in the adoption of weak learners [47]. AC trains weak learners recursively on duplication of the original dataset where weak learners focus on outliers [48]. It is a meta classifier and trains weak learners on the same feature set but with different weights. AC outperformed in many classification tasks [49], [50].

Extra Tree Classifier (ETC) also uses a random subset of features to split nodes of trees. But it builds trees using a complete sample unlike RF and randomly selects a cut point to split a node. ETC utilizes multi-linear approximation instead of piecewise constant for RF. Extra randomization of ETC makes it superior in terms of performance than RF and base learners' mistakes are less correlated with each other. ETC showed better performance than RF in terms of accuracy in [51].

Gradient Boosting Machine (GBM) is based on boosting and a powerful ensemble model to perform classification. It uses an ensemble of weak learners specifically decision trees for prediction [52], [53]. Weak learners are converted to strong ones in boosting technique and every new tree is fit on a modified form of trees. GBM uses gradient in the loss function, which measures how efficiently the model coefficient fits the data.

Convolutional Neural Network (CNN) [54] is a deep neural network model that handles data complexity during computation. CNN model consists of convolutional layers, pooling layers, activation layer, dropout layer, and flatten layer. The convolutional layer is the main layer and is used to extract features, the pooling layer reduces the size of extracted features, the dropout layer is used to reduce overfitting, and flatten layer is used to convert data into an array. In this study, RELU is used as an activation function and 0.2 is used as a dropout rate.

LR uses logit, which is the natural logarithm to measure the likelihood ratio of the dependent variable as 1 in case of a serious accident and 0 for the opposite case of a minor accident. The probability of accident is represented by p and given by:

$$Y = logit = \ln \frac{P}{1-P} = \beta X \tag{3}$$

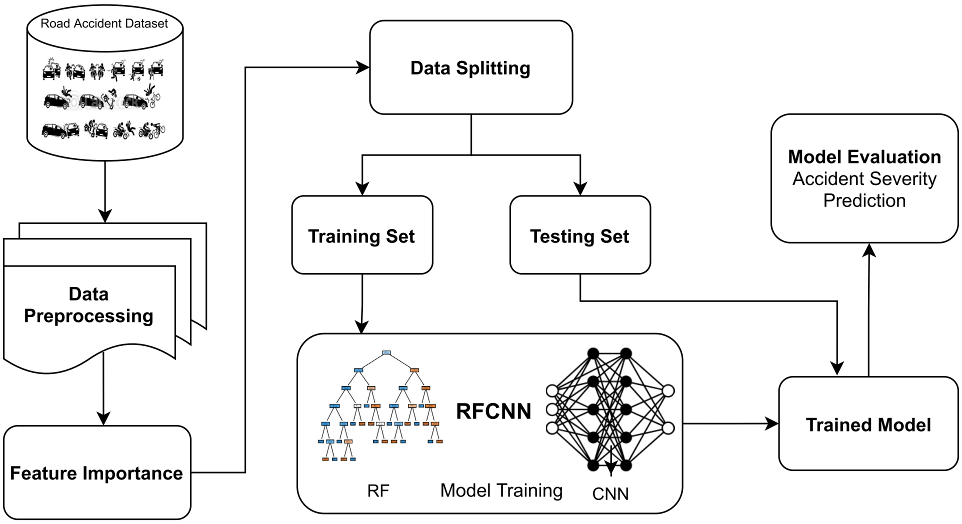


FIGURE 1. **Proposed methodology diagram.**

where Y is the variable measuring severity of the accident. If accidental severity is serious y will be 1 and if the severity is minor y will be 0. X represents independent variables and β is to be estimated [55]. Stochastic gradient descent (SGD) is an iterative approach and optimizes objective function by selecting smoothness in terms of properties [56]. The actual gradient obtained from the dataset is replaced by an estimate which is calculated from the subset of the dataset. It achieves faster iteration by low convergence trade-off and reduces the computational burden. It has been extensively used in machine learning and deep learning problems. A voting classifier is an ensemble combination of individual classifiers and combines prediction results of classifiers and could achieve better results than single classifiers [47]. This research utilizes the voting ensemble of two machine learning models that are LR and SGD to predict road accident severity.

An ensemble model is a machine learning model that works on the merging of two or more models and gets better performance than individual classifier [47]. It predicts the output on the basis of high probability. This study utilizes two ensemble models, first is an ensemble of two machine learning models (LR and SGD) and the second is an ensemble of a tree-based machine learning model and a deep learning model (RF and CNN). Hyperparameters values are presented in Table 1.

B. PERFORMANCE EVALUATION PARAMETERS

The evaluation of models is an important task in classification, and different parameters have been represented in this regard. This study makes use of accuracy, precision, recall, and F-score, which are among the most commonly applied evaluation metrics. Formally, accuracy is used as the correctness of prediction, and is calculated as:

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \tag{4}$$

whereas for binary classification, accuracy can also be calculated in terms of positives and negatives, as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

where TP, TN, FP, and FN represent true positive, true negative, false positive and false negative and are defined as follows [57].

True Positive (TP): TP shows the positive predictions of a class that are correctly predicted by the classifier.

True Negative (TN): These are the negative predilections of a class that are correctly labeled by the classifier.

False Positive (FP): FP shows the negative predictions of a class that are incorrectly labeled as positive by the classifier.

False Negative (FN): These are positive predictions of a class that are incorrectly labeled as negative by the classifier.

Precision is referred to as the exactness of a classifier and tells what percentage of all tuples are labeled positive which are actually positive. It is calculated as:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall on the other hand often called as the measure of completeness and it presents the percentage of true positive tuples which are labeled correctly. It is calculated as:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

F-score is a statistical analysis measure of classification, which considers both precision and recall of the classifier and computes a score between 0 and 1 [24]. It shows the effect of both precision and recall and is calculated as:

$$Fscore = 2\frac{precision.recall}{precision + recall} \tag{8}$$

C. DATASET

1) SELECTION OF ACCIDENT DATASET

This is a countrywide car accident dataset, which covers 49 states of the USA. The accident data contains records from February 2016 to June 2020 [58]. There are about 4.2 million accident records in this dataset. The dataset contains 49 columns which are 'ID', 'Source', 'TMC', 'Severity', 'Start_Time', 'End_Time', 'Start_Lat', 'Start_Lng', 'End_Lat', 'End_Lng', 'Distance(mi)', 'Description', 'Number', 'Street', 'Side', 'City', 'County', 'State', 'Zipcode', 'Country', 'Timezone', 'Airport_Code','Weather_Timestamp', 'Temperature(F)', 'Wind_Chill(F)', 'Humidity(%)', 'Pressure(in)', 'Visibility(mi)', 'Wind_Direction', 'Wind_Speed(mph)', 'Precipitation(in)', 'Weather_Condition', 'Amenity', 'Bump', 'Crossing','Give_Way','Junction', 'No_Exit', 'Railway', 'Roundabout', 'Station', 'Stop', 'Traffic_Calming', 'Traffic_Signal', 'Turning_Loop', 'Sunrise_Sunset', 'Civil_Twilight', 'Nautical_Twilight', and 'Astronomical_Twilight'. The number of records against each target class is shown in Figure 2. The value '1' indicates the least severity while the value '4' tell us the accident is severe.

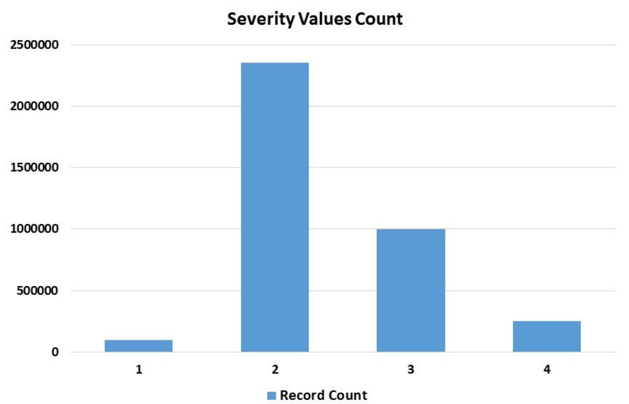


FIGURE 2. Countplot showing class-wise data distribution.

2) DATA VISUALIZATION

Data Visualization helps to understand the hidden patterns lying inside the dataset. It helps to get more details about the dataset by visualizing the characteristics of the attributes. Figure 3 shows the ratio of missing values of each column in the dataset. Figure 5 presents the significant features identified by RF and top features affecting accidental severity include distance, temperature, wind_Chill, humidity, visibility, and wind direction.

3) DATA PREPROCESSING

Datasets contain unnecessary data in raw form that can be unstructured or semistructured. That unnecessary raw data increases the time of training the model but decreases the performance of the model. Preprocessing plays a significant role in improving the performance of machine learning models and saving computational resources. Text preprocessing boosts the prediction accuracy of the model [59]. We performed the following steps in preprocessing; missing values removal, partial records removal.

D. PROPOSED METHODOLOGY

Ensemble models have been widely used to improve the accuracy and efficiency of classification results. Merging of classifiers can exhibit better performance as compared to the separate models. In order to achieve better results, this study employs two ensemble models to predict road accident severity. One is the ensemble of two machine learning models and the other is the ensemble of one machine learning and one deep learning model.

The proposed approach is called RFCNN voting classifier that combines RF and CNN using criteria of soft voting. The class with high probability will be considered as the final output. Algorithm 1 explains the working of the proposed ensemble model that can be expressed as:

$$\widehat{p} = argmax \left\{ \sum_{i}^{n} RF_i, \sum_{i}^{n} CNN_i \right\}. \tag{9}$$

Here $\sum_{i}^{n} RF_i$ and $\sum_{i}^{n} CNN_i$ both will give prediction probabilities against each test sample. After that, the probabilities for each test example by both RF and CNN pass through the soft voting criteria as shown in Figure 4.

The functionality of the RFCNN can be discussed with an example. When a given sample passes through the RF and CNN, a probability score is assigned to each class. Let RF's probability score be 0.6, 0.2,0.7 and 0.4 for Class-1, 2, 3 and 4 respectively. CNN's probability score be 0.5, 0.4, 0.8 and 0.5 for class-1, 2, 3 and 4 respectively. Let P(x) is the probability score of x and domain of x is limited to the 4 classes of the dataset Then the probability for the four classes can be calculated as

$$\begin{aligned} P(1) &= (0.6 + 0.5)/2 = 0.55 \\ P(2) &= (0.2 + 0.4)/2 = 0.35 \\ P(3) &= (0.7 + 0.8)/2 = 0.75 \\ P(4) &= (0.4 + 0.5)/2 = 0.45 \end{aligned}$$

Final prediction will be 3 whose probability score is the largest as shown below:

$$RFCNN = argmax(g(x)) \tag{10}$$

The proposed RFCNN makes the final decision by combining the predicted probabilities of both classifiers and decides the final class based on the maximum average probability of a class. The proposed framework for severity prediction of road accidents is presented in Figure 4. The proposed RFCNN is an ensemble of machine learning and deep learning model. US road accident dataset used in this experiment is scrapped from the Kaggle repository. First the dataset is preprocessed by removing unwanted data. The proposed models are applied to the US road accident dataset in two phases. In the first phase, all 48 features of the dataset are used

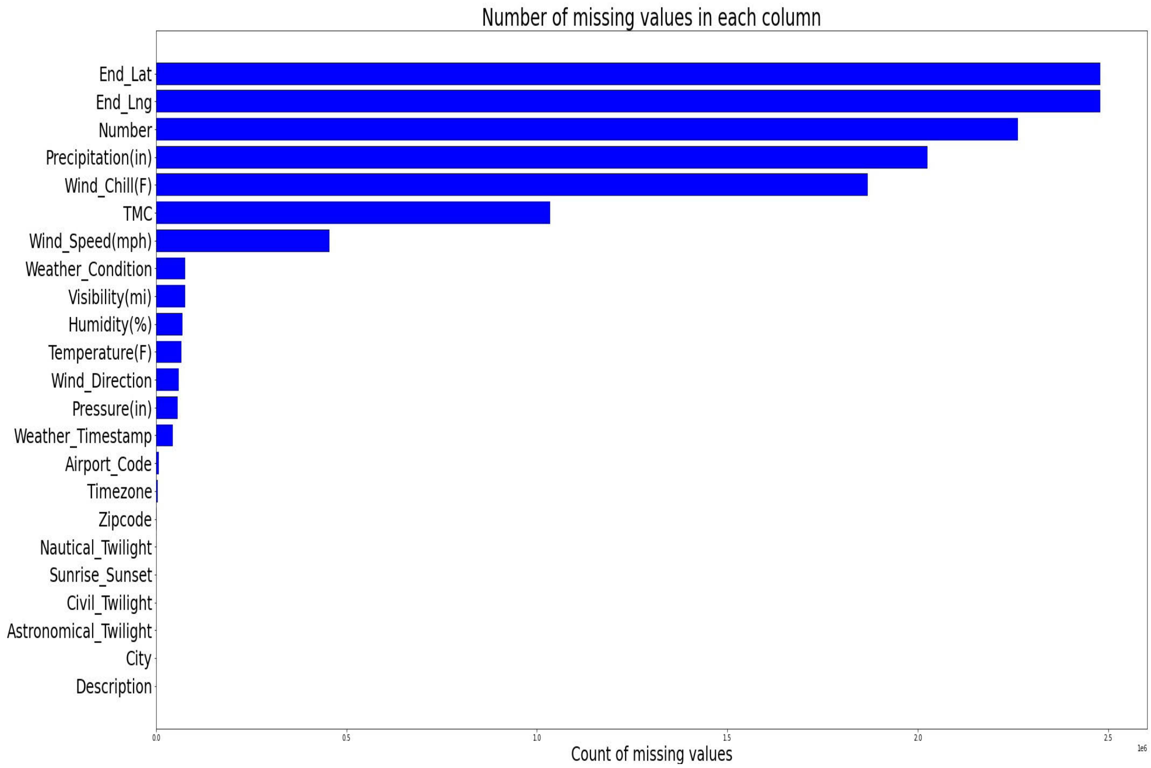


FIGURE 3. Countplot of missing values of each column.

TABLE 1. Hyper parameter settings of learning models.

Classifiers	Parameters
RF	n_estimator=200, max_depth=20, random_state=50
AB	n_estimator=200, max_depth=20, random_state=50
ETC	n_estimator=200, max_depth=20, random_state=50
GBM	n_estimator=200, learning_rate=0.1, max_depth=20, random_state=50
CNN	num_filters, 7, activation='relu', padding='same'
VC(LR+SG)	voting='soft'
RFCNN	voting='soft'

to predict the severity of the accident. In the first experimental phase, we also calculate the feature importance value of all features using the random forest classifier. In the second phase of the experiment, the top 20 features that are calculated using random forest classifier feature importance are used to train all machine learning models and to predict the severity of road accidents. Then the data was split into two parts, training dataset and testing data. The training data was given the percentage of 70% while testing data was of 30%. The evaluation parameters used in this experiment are: (a) Accuracy (b) Precision (c) Recall (d) F-score.

IV. RESULTS

All the experiments are executed on a $2GB$ Dell PowerEdge $T430$ graphical processing unit on $2x$ Intel Xeon 8 Cores $2.4Ghz$ machine which is equipped with 32 GB $DDR4$ Random Access Memory (RAM). We have utilized Jupyter notebook environment to perform experiments in Python programming language by Anaconda. Machine Learning models and deep learning models are implemented using sklearn, Keras and Tensorflow.

This section presents results after executing the ensemble RFCNN model and other base learner models such as RF, AC, ETC, GBM, and Voting Classifier (LR+SGD) on the US road accident dataset. Significant variables identified by RF are illustrated in section IV-A. In this study from 48 original feature set variables, 20 important feature sets are identified by RF. Section IV-B presents the comparison of accuracy by both sets of variables (original in section IV-B1 and important in section IV-B2) by comparing results of ensemble models.

A. SIGNIFICANT FEATURES

In this step, RF with the input of all 48 feature variables of the whole dataset identified the top 20 significant features. Identified important features are presented in the Figure 5.

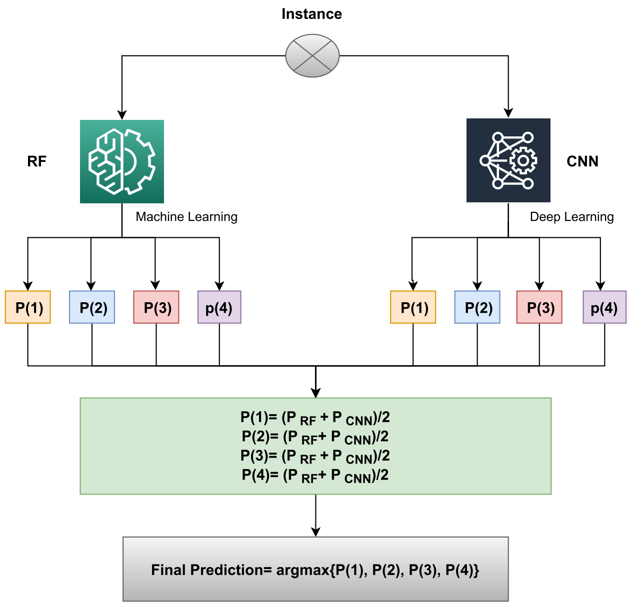


FIGURE 4. Architecture of the proposed RFCNN.

Algorithm 1 Ensembling of RF and CNN (RFCNN)

Input: input data $(x, y)_{i=1}^{N}$
M_{RF} = Trained_ RF
M_{CNN} = Trained_ CNN

for $i = 1$ *to* M **do**
  if $M_{RF} \neq 0$ & $M_{CNN} \neq 0$ & $training\_set \neq 0$ **then**
    $ProbCNN - 1 = M_{CNN}.probability(1 - class)$
    $ProbCNN - 2 = M_{CNN}.probability(2 - class)$
    $ProbCNN - 3 = M_{CNN}.probability(3 - class)$
    $ProbCNN - 4 = M_{CNN}.probability(4 - class)$
    $ProbRF - 1 = M_{RF}.probability(1 - class)$
    $ProbRF - 2 = M_{RF}.probability(2 - class)$
    $ProbRF - 3 = M_{RF}.probability(3 - class)$
    $ProbRF - 4 = M_{RF}.probability(4 - class)$
    Decision function = $max(\frac{1}{N_{classifier}} \sum_{classifier} (Avg_{(ProbCNN-1, ProbRF-1)}, (Avg_{(ProbCNN-2, ProbRF-2)}, (Avg_{(ProbCNN-3, ProbRF-3)}, Avg_{(ProbCNN-4, ProbRF-4)}))$
  end if
  Return final label $\widehat{p}$
end for

It can be seen that the top features that have significant impact on accident are: distance, temperature, wind_Chill, humidity, visibility and Wind direction. Then, the performance of the proposed RFCNN model and the other five base learner models is compared using full features and top 20 features.

B. COMPARISON OF PREDICTIVE PERFORMANCE OF MODELS

1) CLASSIFICATION RESULTS WITH INPUT OF ORIGINAL 48 VARIABLES

Classification results of the proposed RFCNN and other base learner models like RF, AC,ETC, GBM and VC(LR+SGD) using all 48 features is presented in Table 2. It can be clearly observed that RF achieved 0.744 accuracy value, 0.784 precision and 0.790 recall, which are the highest values among all other individual machine learning models. In addition, ETC produces 0.728% accuracy, 0.698 precision which is the second highest values after RF among machine learning models. While VC(LR+SGD) achieved 0.789 recall which is the second highest and 0.740 f-score value which is highest among all individual models. RFCNN outperforms all other models in terms of accuracy, recall, precision and F-score. Using all features, RFCNN achieves 0.812 value of accuracy, 0.842 value of precision, 0.864 value of recall and 0.853 value of F-Score and performs comparatively better than all other models.

TABLE 2. Classification result of all machine learning models using all features.

Models	Accuracy	Precision	Recall	F-Score
RF	0.744	0.784	0.790	0.722
AC	0.704	0.682	0.711	0.696
ETC	0.728	0.698	0.754	0.726
GBM	0.714	0.672	0.741	0.706
CNN	0.712	0.674	0.770	0.722
VC(LR+SGD)	0.722	0.692	0.789	0.740
RFCNN	**0.812**	**0.842**	**0.864**	**0.853**

2) CLASSIFICATION RESULTS WITH INPUT OF MOST SIGNIFICANT 20 VARIABLES

Table 3 shows the accuracy, precision, recall and F-score of classification with significant features calculated using RF's features importance. It can be seen clearly that the classification result of all models improved in this case. This means that utilizing significant features helps in reducing extra noise from variables which increases the classification results as shown in table 3. On the other side, it also reduces the extra cost of collection of accident data. Instead of collecting data of 48 features, there is a need to collect only 20 features. In addition it can be observed clearly that the proposed RFCNN outperformed all other models with 0.991 value of accuracy, 0.974 value of precision, 0.986 value of recall and 0.980 value of F-score. Random Forest classifier achieved the second-highest accuracy value 0.974, precision value with 0.954. recall is 0.93, and 0.942 F-score. Performance of voting classifier(LR+SGD) also improved after using significant features identified by RF and it achieves 0.962 accuracy value which is third highest after RF. ETC achieved the highest precision and highest f-score value with 0.928 and 0.916 respectively after RF among machine learning models. GBM achieved the highest recall with 0.921 value

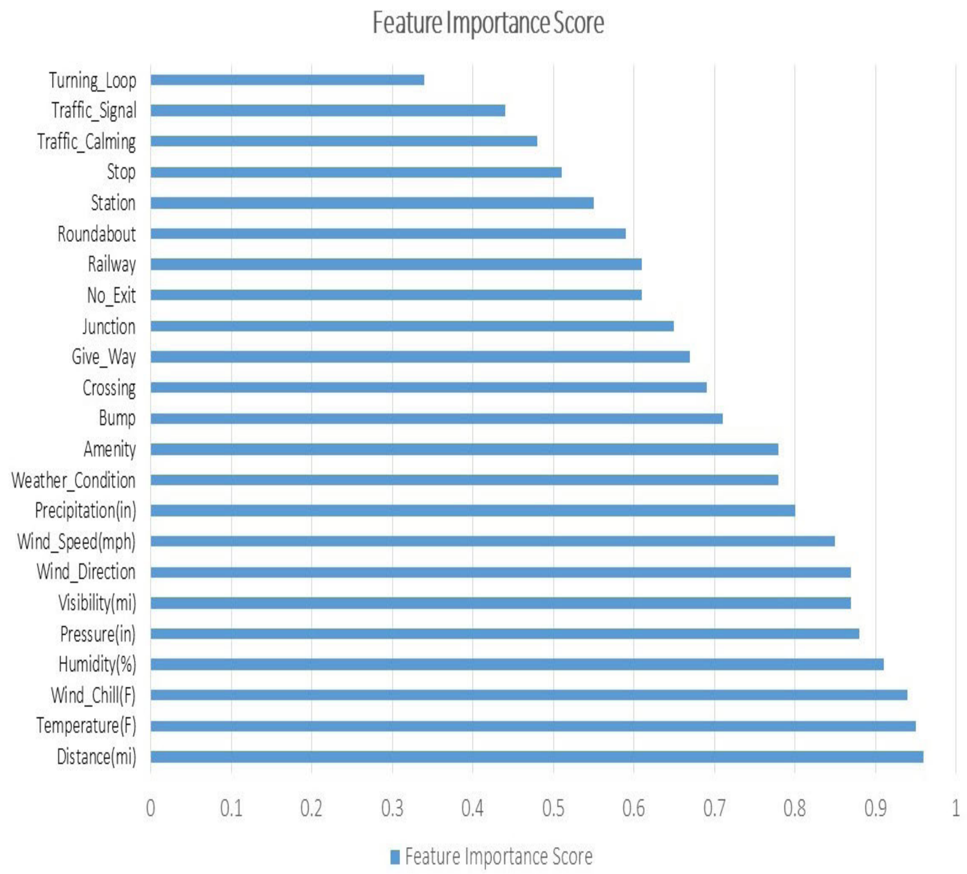


FIGURE 5. Feature importance calculated using random forest.

among machine learning models using important features. The deep learning model, CNN did not perform better than machine learning models but its results still improved after using significant features.

Considering all the results, it is clear that RFCNN shows the highest performance results using 20 significant features to predict accident severity.

TABLE 3. Classification result of all machine learning models using significant features.

Models	Accuracy	Precision	Recall	F-Score
RF	0.974	0.954	0.930	0.942
AC	0.944	0.922	0.901	0.911
ETC	0.917	0.928	0.904	0.916
GBM	0.921	0.902	0.921	0.911
CNN	0.923	0.904	0.911	0.907
VC(LR+SGD)	0.962	0.912	0.919	0.915
RFCNN	**0.991**	**0.974**	**0.986**	**0.980**

V. DISCUSSIONS

In this study, road accident severity prediction has been performed by an ensemble model. Accidental severity involves many factors and needs to be identified. We conducted the comparison of the proposed RFCNN model with the base learner models that are tree-based ensemble models (RF, AC, ETC, and GBM) and an ensemble of regression algorithms (Voting classifier (LR+SGD)) to measure the severity of road accidents. We also identified 20 significant features by Random forest which are almost half of the all available features of the dataset. In our experiment, we used all available features of the dataset as input for all ensemble models in the first phase. While in the second phase of the experiment, we used the most significant features identified by RF as input for all ensemble models.

Empirical results for accidental severity prediction are summarized in four main findings. First, in terms of accuracy RFCNN outperformed among all above-mentioned ensemble learning models to predict accident severity. The accuracy of RF (0.991), using 20 significant features as input, is the highest in this study. Accuracy results of all ensemble models using all available features and significant features are presented in Figure 6. Using all features as input in Voting Classifier (LR+SGD) achieved 0.722 accuracy value, while by using significant features it also improved with 0.962 accuracy value. It can be noticed that by utilizing significant features identified by tree based model RF performance of ensemble of regression models has also improved. However, CNN model achieved 0.712 value of accuracy using all features which is lower than most of the machine learning models. It can be observed clearly from Figure 6 that accuracy of all machine learning, deep learning, and ensemble models have been improved more than 20% using significant features as input rather than using all features as input.

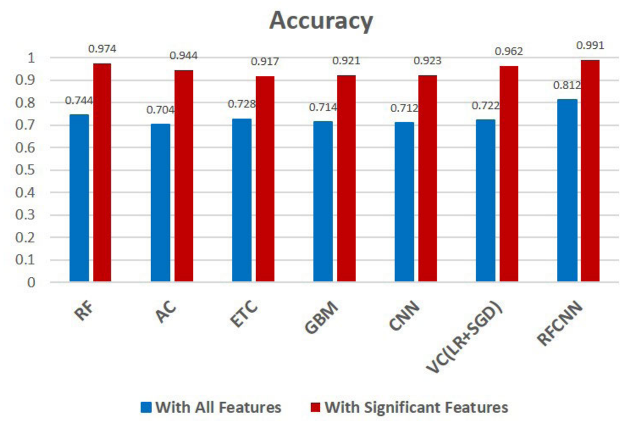


FIGURE 6. Accuracy of all ensemble learning models.

Second, in terms of precision RF achieved better result with significant difference as compared to the voting classifier(LR+SGD) among machine learning models as shown in Figure 7. However, RFCNN achieved higher values with 0.842 precision value using all features as well as with 0.974 precision value using significant features identified by RF. The Voting classifier achieved 0.692 precision value using all features as input and 0.912 precision value using significant features which are less than the RF precision score which is 0.954. Tree ensemble models RF, AC, ETC are achieving high precision scores (0.954,0.922 and 0.928 respectively) using significant features as compared to the voting classifier(LR+SGD) (0.912). But precision scores of GBM and CNN are lower than voting classifier using all features (0.672 and 0.674 respectively) and using significant features (0.902 and 0.904 respectively).

Third, in terms of recall (sensitivity) RFCNN achieves a 0.986 recall score using significant features, which is the highest recall value for predicting accident severity. AC and ETC achieved almost similar recall values using significant features which are 0.901 and 0.904 respectively but lower than RF which shows 0.93. GBM achieved less recall score with 0.741 than voting classifier (LR+SGD) with 0.789 using all features. But GBM also achieved a higher recall value with 0.921 than a regression-based model with a 0.919 score using significant features. The recall value of the CNN model is 0.770 using all features and 0.911 using significant features which is higher than individual machine learning models and lower than their ensemble model. When ensemble models are input with significant variables identified by RF improved their recall score. Recall score is presented in Figure 8.

Fourth, in terms of F-score which is another important evaluation measure and provides a balance between precision and recall scores, RFCNN outperformed other aforementioned

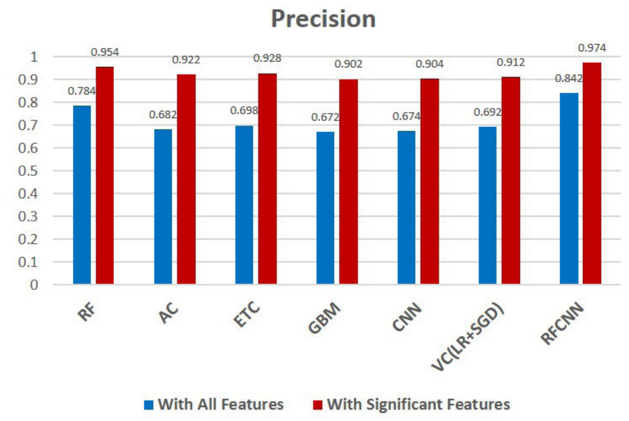


FIGURE 7. Precision of all ensemble learning models.

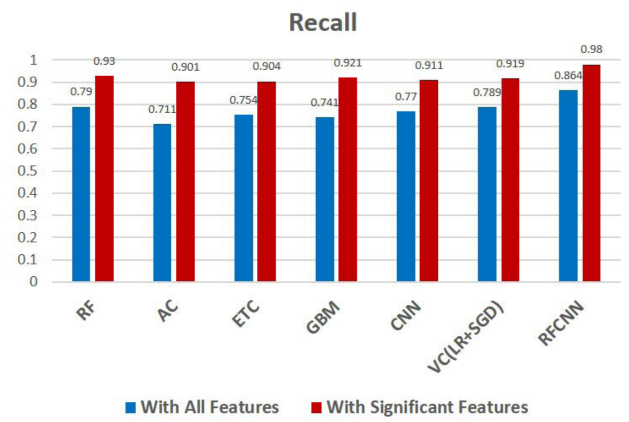


FIGURE 8. Recall of all ensemble learning models.

ensemble models. From Figure 9, it can be seen that F-score or RF (0.853) is highest than all other models using all features. But by using significant features as input RFCNN achieves the highest F-score with a 0.980 value.

In general, based on the summary of the results, if the primary focus is the overall performance of the models in predicting road accident severity, RFCNN achieved the highest results using significant features. Significant features, that are a subset of the original feature set, are identified by RF. By using significant features as input by ensemble models not only significantly improve accuracy but also improved precision, recall and f-score. RF in combination with significant features not only improving prediction performance but also reduce the cost of the data collection. There are 48 features regarding the road accident dataset to measure the severity of the accident. Considering 20 important variables identified by RF significantly improve the prediction process of accident severity. The performance of ensemble models is also compared using all features and using important features as input. Tree-based ensembles showed the better performance to predict accidental severity due to their ability to learn non-linear solutions and these models scale well on

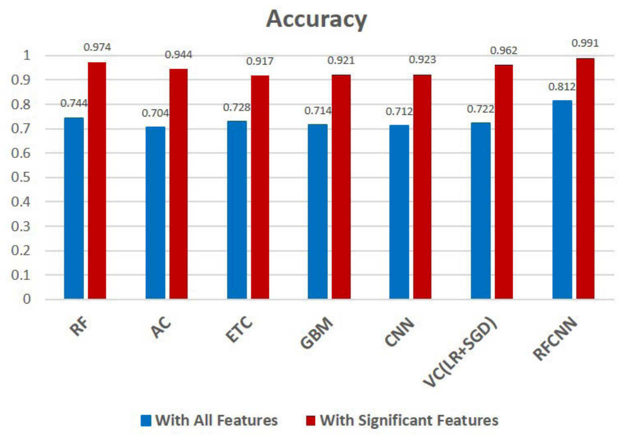


FIGURE 9. F-Score of all ensemble learning models.

large datasets. Finding the probability for the target class using machine learning and deep learning models separately and then computing the target class with maximum probability to make the final prediction boosts its performance as compared to the individual models. The deep architecture of RFCNN makes it more efficient and accurate. RFCNN surpassed every other model used in the experiment using significant features. Management should pay more attention to the 20 most important features affecting accident severity.

VI. CONCLUSION

Traffic accidents are the root cause of injuries, casualties, and destruction of property and became a critical issue of public health and safety. Accidents also create congestion and delay of traffic. To improve the efficiency of the transport system, there is a need to manage accidents by investigating related factors. In this paper, road accident severity level is predicted by combining machine learning and deep learning model namely RFCNN. In this paper, experimental results explained that classification results of RFCNN are higher than RF,AC, ETC, GBM, and voting classifier (LR+SGD). Significant features are identified by RF and top features include top features affecting accidental severity include distance, temperature, wind_Chill, humidity, visibility, and wind direction. Most significant features identified by RF are also used as input to the ensemble models and also promote accuracy, precision, recall and f-score of all ensemble models but RF again outperformed with a significant difference. Therefore it can be said that RF is the most efficient and effective model among all ensemble models and showed consistent results in predicting accident severity.

On the other hand, the identification of significant features from overall features was focused to measure their correlation with road accidents. The influence of significant variables on prediction performance results of ensemble models is also evaluated in this study. In the first phase, experiment is performed by using all features, while in the second phase experiment is performed by using significant variables identified by RF. Important variables improved accuracy, precision, recall and f-score of all ensemble models. Therefore it can be said that important features identified by RF can help in boosting the prediction performance of the models and also reduce the cost of data collection. The result shows that distance between vehicles is the most important feature affecting the severity of the accident so road authorities can take preventive measures by focusing on important features identified by RF. The performance comparison of the models reveals that the proposed RFCNN shows superiority in predicting accidental severity. Despite the superiority of the proposed ensemble of machine learning and deep learning approach, it also increased the complexity as compared to individual models which will be addressed in future work. we also plan to apply the proposed model on the multi-domain dataset to prove its effectiveness and generalizability.

REFERENCES

[1] World Health Organization, *Global Status Report on Road Safety 2015*, World Health Org., Geneva, Switzerland, 2015.

[2] W. Gissane, "Accidents—A modern epidemic," *J. Inst. Health Educ.*, vol. 3, no. 1, pp. 16–18, 1965.

[3] H. Manner and L. Wünsch-Ziegler, "Analyzing the severity of accidents on the German autobahn," *Accident Anal. Prevention*, vol. 57, pp. 40–48, Aug. 2013.

[4] J. C. Milton, V. N. Shankar, and F. L. Mannering, "Highway accident severities and the mixed logit model: An exploratory empirical analysis," *Accident Anal. Prevention*, vol. 40, no. 1, pp. 260–266, 2008.

[5] N. V. Malyshkina and F. L. Mannering, "Markov switching multinomial logit model: An application to accident-injury severities," *Accident Anal. Prevention*, vol. 41, no. 4, pp. 829–838, Jul. 2009.

[6] K. Haleem, P. Alluri, and A. Gan, "Analyzing pedestrian crash injury severity at signalized and non-signalized locations," *Accident Anal. Prevention*, vol. 81, pp. 14–23, Aug. 2015.

[7] M. Bedard, G. H. Guyatt, M. J. Stones, and J. P. Hirdes, "The independent contribution of driver, crash, and vehicle characteristics to driver fatalities," *Accid Anal. Prevention*, vol. 34, no. 6, pp. 717–727, 2002.

[8] S. S. Zajac and J. N. Ivan, "Factors influencing injury severity of motor vehicle–crossing pedestrian crashes in rural connecticut," *Accident Anal. Prevention*, vol. 35, no. 3, pp. 369–379, May 2003.

[9] W.-H. Chen and P. P. Jovanis, "Method for identifying factors contributing to driver-injury severity in traffic crashes," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1717, no. 1, pp. 1–9, Jan. 2000.

[10] S. Sarkar, S. Vinay, R. Raj, J. Maiti, and P. Mitra, "Application of optimized machine learning techniques for prediction of occupational accidents," *Comput. Oper. Res.*, vol. 106, pp. 210–224, Jun. 2019.

[11] K. Rumar, "Transport safety visions, targets and strategies: Beyond 2000," *First Eur. Transp. Saf. Lecture, Brussels, Eur. Transp. Saf. Council*, pp. 6–8, 1999.

[12] T. Hummel, "Land use planning in safer transportation network planning," *Leidschendam, Inst. Road Saf. Res.*, Citeseer, 2001.

[13] A. S. Edlin, *Per-Mile Premiums for Auto Insurance*. Cambridge, MA, USA: National Bureau of Economic Research, Dec. 1998. [Online]. Available: https://ssrn.com/abstract=142667, doi: 10.2139/ssrn.142667.

[14] R. Wittink, "Promotion of mobility and safety of vulnerable road users: Final report of the European research project promising (promotion of measures for vulnerable road users)," Inst. Road Saf. Res., Tech. Rep., 2001.

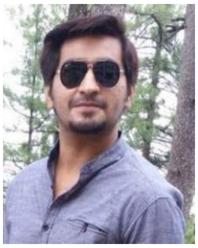
[15] D. Mohan and G. Tiwari, "Traffic safety in low-income countries: Issues and concerns regarding technology transfer from high-income countries," in *Reflections of the Transfer of Traffic Safety Knowledge to Motorising Nations*, vol. 56. Melbourne, Global Traffic Safety Trust, 1998.

[16] S. Ameratunga, M. Hijar, and R. Norton, "Road-traffic injuries: Confronting disparities to address a global-health problem," *Lancet*, vol. 367, no. 9521, pp. 1533–1540, May 2006.

[17] M. N. Ghani, A. Zainuddin, R. R. Umar, and H. Hussain, "Use of exposure control methods to tackle motorcycle accidents in Malaysia research report 3/98," Road Saf. Res. Centre, Serdang, Malaysia, Tech. Rep., 1998.

[18] T. Litman, "Integrating public health objectives in transportation decision-making," *Amer. J. Health Promotion*, vol. 18, no. 1, pp. 103–108, Sep. 2003.
[19] P. F. Waller, "The genesis of GDL," *J. Saf. Res.*, vol. 34, no. 1, pp. 17–23, Jan. 2003.
[20] Y. Zou, B. Lin, X. Yang, L. Wu, M. M. Abid, and J. Tang, "Application of the Bayesian model averaging in analyzing freeway traffic incident clearance time for emergency management," *J. Adv. Transp.*, vol. 2021, pp. 1–9, Mar. 2021.
[21] J. Tang, L. Zheng, C. Han, W. Yin, Y. Zhang, Y. Zou, and H. Huang, "Statistical and machine-learning methods for clearance time prediction of road incidents: A methodology review," *Anal. Methods Accident Res.*, vol. 27, Sep. 2020, Art. no. 100123.
[22] M. Umer, S. Sadiq, M. Ahmad, S. Ullah, G. S. Choi, and A. Mehmood, "A novel stacked CNN for malarial parasite detection in thin blood smear images," *IEEE Access*, vol. 8, pp. 93782–93792, 2020.
[23] M. Umer, I. Ashraf, A. Mehmood, S. Ullah, and G. S. Choi, "Predicting numeric ratings for Google apps using text features and ensemble learning," *ETRI J.*, vol. 43, no. 1, pp. 95–108, Feb. 2021.
[24] M. Umer, Z. Imtiaz, S. Ullah, A. Mehmood, G. S. Choi, and B.-W. On, "Fake news stance detection using deep learning architecture (CNN-LSTM)," *IEEE Access*, vol. 8, pp. 156695–156706, 2020.
[25] S. Sadiq, A. Mehmood, S. Ullah, M. Ahmad, G. S. Choi, and B.-W. On, "Aggression detection through deep neural model on Twitter," *Future Gener. Comput. Syst.*, vol. 114, pp. 120–129, Jan. 2021.
[26] Z. Imtiaz, M. Umer, M. Ahmad, S. Ullah, G. S. Choi, and A. Mehmood, "Duplicate questions pair detection using Siamese MaLSTM," *IEEE Access*, vol. 8, pp. 21932–21942, 2020.
[27] M. I. Sameen and B. Pradhan, "Severity prediction of traffic accidents with recurrent neural networks," *Appl. Sci.*, vol. 7, no. 6, p. 476, 2017.
[28] S. Seid and Pooja, "Road accident data analysis: Data preprocessing for better model building," *J. Comput. Theor. Nanosci.*, vol. 16, no. 9, pp. 4019–4027, Sep. 2019.
[29] S. K. Singh, "Road traffic accidents in India: Issues and challenges," *Transp. Res. Proc.*, vol. 25, no. 5, pp. 4708–4719, Dec. 2017.
[30] D. Delen, R. Sharda, and M. Bessonov, "Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks," *Accident Anal. Prevention*, vol. 38, no. 3, pp. 434–444, May 2006.
[31] D. W. Kononen, C. A. C. Flannagan, and S. C. Wang, "Identification and validation of a logistic regression model for predicting serious injuries associated with motor vehicle crashes," *Accident Anal. Prevention*, vol. 43, no. 1, pp. 112–122, 2011.
[32] P. Duan, Z. He, Y. He, F. Liu, A. Zhang, and D. Zhou, "Root cause analysis approach based on reverse cascading decomposition in QFD and fuzzy weight ARM for quality accidents," *Comput. Ind. Eng.*, vol. 147, Sep. 2020, Art. no. 106643.
[33] H. M. Alnami, I. Mahgoub, and H. Al-Najada, "Highway accident severity prediction for optimal resource allocation of emergency vehicles and personnel," in *Proc. IEEE 11th Annu. Comput. Commun. Workshop Conf. (CCWC)*, Jan. 2021, pp. 1231–1238.
[34] A. T. Kashani and A. S. Mohaymany, "Analysis of the traffic injury severity on two-lane, two-way rural roads based on classification tree models," *Saf. Sci.*, vol. 49, no. 10, pp. 1314–1320, 2011.
[35] B. Sharma, V. K. Katiyar, and K. Kumar, "Traffic accident prediction model using support vector machines with Gaussian kernel," in *Proc. 5th Int. Conf. Soft Comput. Problem Solving*. New York, NY, USA: Springer, 2016, pp. 1–10.
[36] P. Tiwari, S. Kumar, and D. Kalitin, "Road-user specific analysis of traffic accident using data mining techniques," in *Proc. Int. Conf. Comput. Intell., Commun., Bus. Anal.* New York, NY, USA: Springer, 2017, pp. 398–410.
[37] R. E. AlMamlook, K. M. Kwayu, M. R. Alkasisbeh, and A. A. Frefer, "Comparison of machine learning algorithms for predicting traffic accident severity," in *Proc. IEEE Jordan Int. Joint Conf. Electr. Eng. Inf. Technol. (JEEIT)*, Apr. 2019, pp. 272–276.
[38] T. Beshah and S. Hill, "Mining road traffic accident data to improve safety: Role of road-related factors on accident severity in Ethiopia," in *Proc. AAAI Spring Symp., Artif. Intell. Develop.*, vol. 24. Princeton, NJ, USA: Citeseer, 2010, pp. 1173–1181.
[39] X. Ma, C. Ding, S. Luan, Y. Wang, and Y. Wang, "Prioritizing influential factors for freeway incident clearance time prediction using the gradient boosting decision trees method," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 9, pp. 2303–2310, Sep. 2017.
[40] Y. Zou, X. Ye, K. Henrickson, J. Tang, and Y. Wang, "Jointly analyzing freeway traffic incident clearance and response time using a copula-based approach," *Transp. Res. C, Emerg. Technol.*, vol. 86, pp. 171–182, Jan. 2018.
[41] B. Yu, Y. T. Wang, J. B. Yao, and J. Y. Wang, "A comparison of the performance of ANN and SVM for the prediction of traffic accident duration," *Neural Netw. World*, vol. 26, no. 3, p. 271, 2016.
[42] L. Breiman, "Bagging predictors," *Mach. Learn.*, vol. 24, no. 2, pp. 123–140, 1996.
[43] R. E. Schapire, "A brief introduction to boosting," in *Proc. IJCAI*, vol. 99, 1999, pp. 1401–1406.
[44] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.
[45] C. R. Sekhar, S. Minal, and E. Madhu, "Mode choice analysis using random Forrest decision trees," *Transp. Res. Proc.*, vol. 17, pp. 644–652, Jan. 2016.
[46] G. Biau and E. Scornet, "A random forest guided tour," *Test*, vol. 25, no. 2, pp. 197–227, 2016.
[47] Y. Zhang, H. Zhang, J. Cai, and B. Yang, "A weighted voting classifier based on differential evolution," *Abstract Appl. Anal.*, vol. 2014, May 2014, Art. no. 376950.
[48] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *J. Comput. Syst. Sci.*, vol. 55, no. 1, pp. 119–139, 1997.
[49] I. Sevilla-Noarbe and P. Etayo-Sotos, "Effect of training characteristics on object classification: An application using boosted decision trees," *Astron. Comput.*, vol. 11, pp. 64–72, Jun. 2015.
[50] R. Zitlau, B. Hoyle, K. Paech, J. Weller, M. M. Rau, and S. Seitz, "Stacking for machine learning redshifts applied to SDSS galaxies," *Monthly Notices Roy. Astron. Soc.*, vol. 460, no. 3, pp. 3152–3162, Aug. 2016.
[51] P. Geurts, D. Ernst, and L. Wehenkel, "Extremely randomized trees," *Mach. Learn.*, vol. 63, no. 1, pp. 3–42, 2006.
[52] A. Natekin and A. Knoll, "Gradient boosting machines, a tutorial," *Frontiers Neurorobot.*, vol. 7, p. 21, Dec. 2013.
[53] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *Ann. Statist.*, vol. 29, no. 5, pp. 1189–1232, Oct. 2001.
[54] K. O'Shea and R. Nash, "An introduction to convolutional neural networks," 2015, *arXiv:1511.08458*. [Online]. Available: http://arxiv.org/abs/1511.08458
[55] R. Tay, S. M. Rifaat, and H. C. Chin, "A logistic model of the effects of roadway, environmental, vehicle, crash and driver characteristics on hit-and-run crashes," *Accident Anal. Prevention*, vol. 40, no. 4, pp. 1330–1336, Jul. 2008.
[56] L. Bottou, "Large-scale machine learning with stochastic gradient descent," in *Proceedings of COMPSTAT'2010*. New York, NY, USA: Springer, 2010, pp. 177–186.
[57] M. Umer, I. Ashraf, A. Mehmood, S. Kumari, S. Ullah, and G. S. Choi, "Sentiment analysis of tweets using a unified convolutional neural network-long short-term memory network model," *Comput. Intell.*, vol. 37, no. 1, pp. 409–434, Feb. 2021.
[58] S. Moosavi, M. H. Samavatian, S. Parthasarathy, and R. Ramnath, "A countrywide traffic accident dataset," 2019, *arXiv:1906.05409*. [Online]. Available: https://arxiv.org/abs/1906.05409
[59] S. Sadiq, M. Umer, S. Ullah, S. Mirjalili, V. Rupapara, and M. Nappi, "Discrepancy detection between actual user reviews and numeric ratings of Google app store using deep learning," *Expert Syst. Appl.*, vol. 181, Nov. 2021, Art. no. 115111.

MUBARIZ MANZOOR received the B.S. degree from the Department of Computer Science, The Islamia University of Bahawalpur, Pakistan. He is currently pursuing the Ph.D. degree in computer science with KFUEIT. His recent research interests include data mining, mainly working on natural language processing-based problems.



MUHAMMAD UMER received the B.S. degree from the Department of Computer Science, Khwaja Fareed University of Engineering & Information Technology (KFUEIT), Pakistan, from October 2014 to October 2018. He is currently pursuing the Ph.D. degree in computer science with KFUEIT. He is also serving as a Research Assistant for Fareed Computing Research Center, KFUEIT. His recent research interests include data mining, mainly working on machine learning and deep learning-based IoT, text mining, and computer vision tasks.

SAIMA SADIQ is currently pursuing the Ph.D. degree in computer science with Khwaja Fareed University of Engineering & Information Technology (KFUEIT). She is also working as an Assistant Professor with the Department of Computer Science, Government Degree College for Women. Her recent research interests include data mining, machine learning, and deep learning-based text mining.

ABID ISHAQ received the M.Sc. degree in telecommunication from the Government College University, Lahore, in 2009. He is currently pursuing the master's degree in computer science with KFUEIT. His recent research interests include data mining, mainly working on AI and deep learning-based text mining, and data science management technologies.

SALEEM ULLAH was born in Ahmedpur East, Pakistan, in 1983. He received the B.Sc. degree in computer science from The Islamia University of Bahawalpur, Pakistan, in 2003, the M.I.T. degree in computer science from Bahauddin Zakariya University, Multan, in 2005, and the Ph.D. degree from Chongqing University, China, in 2012. He has almost 14 years of industry experience in field of IT. From 2006 to 2009, he worked as a Network/IT Administrator in different companies. From August 2012 to February 2016, he worked as an Assistant Professor with The Islamia University of Bahawalpur. He has been working as an Associate Dean with Khwaja Fareed University of Engineering & Information Technology, Rahim Yar Khan, since February 2016. He is an Active Researcher in the field of *adhoc* networks, the IoTs, congestion control, data science, and network security.

HAMZA AHMAD MADNI received the B.S. degree in computer system engineering from NFCIET (BZU), Multan, Pakistan, in 2010, the M.S. degree in electrical and electronic engineering from the University of Bradford, U.K., in 2012, and the Ph.D. degree in electromagnetic field and microwave technology from Zhejiang University, China, in June 2017. He became an Assistant Professor with Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan, Pakistan. In December 2017, he was nominated for a postdoctoral position at Southeast University (SEU), Nanjing, China, and completed it, in September 2019. His current research interests include transformation optics, coding metamaterials, antennas, invisibility cloaking, and theoretical and numerical methods of electromagnetics, sensors, and controllers.

CARMEN BISOGNI (Member, IEEE) received the B.S. and M.S. degrees *(cum laude)* in mathematics from the University of Salerno, Italy, in 2015 and 2017, respectively, and the Ph.D. degree in computer science from the University of Salerno, in 2021, with excellent evaluation. She is currently with the Biometrics and Image Processing Laboratory (BIPLAB), University of Salerno, as a Postdoctoral Researcher. Her research interests include applied mathematics for machine learning, biometrics, image processing, statistical analysis, and human–robot interactions. She has been/is in the Program Committee and the Technical Program Committee of various international conferences, such as IEEE ICC 2021, and IEEE iSCI 2019 and 2020. She is a Topic Editor of the journal *Electronics* (MDPI) and has been an Associate Editor of the IEEE Biometrics Council Newsletter, since April 2020. She serves as a Reviewer for reputed journals, like *Pattern Recognition*, *Pattern Recognition Letters*, *Multimedia Tools and Applications*, and IEEE Access.