Road risk assessment using fuzzy Context-free Grammar based Association Rule Miner

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Abstract. Road traffic accidents are a major social concern as well as a crucial issue for the public in recent days due to the risk factors involved. Analysing and identifying the major risk factors of road accident is still a challenging task. In this paper, a fuzzy Context-free Grammar (FCFG)-based association rule mining (ARM) technique is proposed to categorize a heterogeneous road accident dataset into two categories based on the critical factors such as total number of accidents (TA), persons killed (PK) and persons injured (PI). The role of the fuzzy grammar in this paper is to govern the entire algorithm using the prescribed grammar rules to proceed further. The considered road accident dataset does not have class labels; hence there is a need to assign class labels for the available data instance. The accident data with assigned class labels are given as input to *K*-nearest neighbour (KNN) machine learning algorithm in order to train the classifier for testing purpose. Further, the collected test data from the user are utilized by the KNN classifier for carrying out the performance analysis of the proposed algorithm. The case study is conducted on the National Highway roads, India, to examine the proposed approach. The experimentations are executed for road accident records using MATLAB software and the analysis is made using the following performance measures: accuracy, recall or sensitivity, precision or specificity and *F1* score. A comparative study is accomplished with existing algorithms in order to show that the proposed algorithm works with improved accuracy of more than 83%. The results suggested that the road users are responsible for the acceptance or rejection of safe or un-safe roads, respectively.

Keywords. Road accidents; data mining; association rule mining; formal grammars; *K*-nearest neighbour; fuzzy logic.

1. Introduction

Road traffic accidents are more frequent in India than other countries globally [1]. A report from National Crime Records Bureau (NCRB) stated that more than 1,35,000 traffic crash-related deaths take place annually in India. The rate of road accidents decreased by 4.1% in 2016 but fatalities rose by 3.2%. In 2017, the percentage of road-related deaths was 3% or 4560, which is lesser than that of the previous year's 1.51 lakh [2]. Analysis of road accidents using a number of records will reveal causes for the same and ensure that safety measures are taken, thereby reducing the number of accidents. For this, researchers were forced to use some effective techniques like data mining (DM), a machine learning technique.

DM is a sequence of processes to extract hidden, untouched data from a huge volume of data. Classification,

association and clustering are various DM concepts to cull out needed data from the entire corpus. An important data extraction technique, association rule mining (ARM), has been used in most research works to analyse road accident data combined with other DM techniques such as clustering and classification. An incremental sequential pattern mining approach was proposed to stay away from rescanning the complete database. Authors have used the depth first method and dynamic look ahead pruning scheme to eliminate infrequent patterns [3].

A *K*-mode clustering technique was used to segment the whole data and then ARM was applied to spot the situations that cause the accident [4]. In [5] the authors performed ARM with clustering based on the accident locations. Also, classification is used to analyse road traffic accidents with variations. Classification algorithms identify risk factors and the dependences among them based on severity levels [6].

Accidents are possible in any circumstances as they are unpredictable and hence accident-related data are inexact.

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Fuzzy logic seems to be an appropriate way to deal with uncertain data; hence this uncertainty enables us to use rule mining based on fuzzy logic, called fuzzy rule mining (FRM) in this research. A fuzzy logic modelling was proposed in [7] to find the key issues related to the environment of road network. A study on traffic crash location identification using fuzzy logic was discussed [8] to analyse and map out the exact crash locations. A model based on fuzzy rule [9] was developed to represent accident duration on expressways and to govern uncertain, complex data in the proposed accident monitoring system with improved accuracy. A weighted fuzzy ARM technique was proposed [10] based on information gain ratio to classify the medical data for disease identification. In FRM, users need to perform some elementary steps to enter all the details of input attributes and membership partitions and then to create fuzzy inference rules. A study on death distribution due to road traffic accidents was performed pertaining to road safety to know the most contributing factors to road accident deaths [11]. The study provided details about the fatal rates based on road segments, expressways, bends and junction points, etc.

ARM can be performed through formal grammar [12, 13]—a key concept of Formal Language Theory [14]. Formal grammar is often used in programming languages to get the required output. Context-free Grammar (CFG) is one of the grammars in Formal Language Theory where a set of rules appear recursively, resulting in output data. A CFG-based ARM or pattern mining was performed in [15, 16] based on genetic algorithm by limiting the search space for extracting the interested association rules or patterns. The proposed model uses a fuzzy Context-free Grammar (FCFG), an extension of CFG, which was used to tackle data's unclear, unpredictable and imprecise nature. In this paper, a novel model is developed by combining FRM and CFG, which is termed as FCFG ARM (Fuzzy Context-free Grammar based Association Rule Mining).

The paper is organized as follows. Section 2 describes the problem definition and methodology of the proposed algorithm, including ARM, fuzzy logic, FCFG and K -nearest neighbour (KNN) algorithm. Section 3 explains about the functionality of proposed FCFG-based ARM algorithm with detailed steps and process flow. Section 4 presents a detailed explanation of the dataset identified for the experiments and demonstrates the analysis of FCFG-based categorization of results, testing the dataset with different combinations based on KNN, performance evaluation using confusion matrix (CM) and accuracy comparison to existing algorithms. Section 5 contains the concluding remarks and the future scope of research.

2. Problem definition and methodology used

The proposed work presents an innovative self-learning approach of automatically performing a series of steps such as assigning the input of fuzzy partition limits based on

mean value of all the available attributes of the dataset. Based on the fuzzy inputs with partitions, fuzzy rules are created and then the fuzzy output is produced without any human involvement. However, generally, in FRM, user has to give all information of input attributes for the assignment and creation of fuzzy membership values and fuzzy rules respectively. To date, there is no other research work carried so far using formal grammars with combination of FRM for performing road accident studies.

This paper analyses real-time data of road accident for 2015. We focus only on the National Highway across India and mined accident-prone areas. Based on this we conclude the preferences of choosing safe or unsafe roads, thereby reducing road accidents. This section contains an overview of ARM, fuzzy logic and KNN methods used in the proposed algorithm.

2.1 Overview of ARM, fuzzy logic and FCFG

2.1a ARM: ARM concept has been applied to study road crash data to understand the correlation between two characteristics involved in road accident occurrence. An association rule of the form $A \rightarrow B$ implies that if A occurs then B will also occur. A and B are two different itemsets. Consider that there are n number of transactions in dataset D where each transaction $T \in D$. Let a set of items be $I = \{I_1, I_2, \dots, I_n\}$. An itemset A or B will occur in T if and only if A or $B \subseteq T$. The association rule $A \rightarrow B$ provides that $A \subset I, B \subset I$ and $A \cap B = \phi$. Association rules can be built using two main interestingness measures: support and confidence [17, 18].

2.1b Fuzzy logic: Fuzzy logic can be suitably applied to represent road accident data and human-related factors [19]. Most common real-world data are numeric or alphanumeric values. Hence there is a necessity to convert such data into fuzzy acceptables. This process is known as fuzzification, which starts by finding the unique values of individual variables or attributes to map the values in the discourse within the scale of $[0, 1]$. The next step defines fuzzy inference rules for each variable defined in the first step to produce a fuzzy output. Finally, defuzzification is used to revert fuzzy output values to their original crisp value.

2.1c FCFG: FCFG can be defined using the base form, CFG [20].

A CFG quadruple $G = (\Sigma, N, P, S)$, where

- Σ is the finite set of terminal symbols;
- N a finite set of non-terminal symbols;
- P a finite set of production rules of the form

$$A \rightarrow \alpha, A \in N, \alpha \in (\Sigma \cup N)^*. \quad (1)$$

- $S \in N$ is the starting symbol.

A FCFG G_F is an extension of CFG, where production rule P is of the form

Figure 1. Process flow of FCFG-based ARM algorithm.

$$A \xrightarrow{\mu} \alpha, A \in N, \alpha \in (\Sigma \cup N)^*, \mu \in [0, 1]. \quad (2)$$

Here μ is called the membership function. $S \in N$ is the starting symbol. More specifically, the elements of P are of the form

$$\mu(A \rightarrow \alpha) = \rho, \rho > 0 \quad (3)$$

where α and ρ are strings in $(\Sigma \cup N)^*$ and ρ is the grade of membership of α and ρ .

FCFG in DM: DM is applicable in almost all types of applications. DM is a series of processes with the potential to discover knowledge from large databases. DM enables implementation of Formal Language Theory as an additional feature to customize existing methods or algorithms to produce enhanced results. Formal Language Theory uses formal grammar to provide definitions of programming languages and build a structure of compilers used in computational linguistics and is a study of human language applied to pattern recognition, mathematical logic, DM, etc. To date, there are various studies and approaches proposed on formal grammars as mentioned in literature; however,

this research applies an FRM technique using formal grammars, specifically FCFG.

2.1d KNN: A well-known machine learning algorithm that is widely used to classify any supervised data is the KNN algorithm. KNN algorithm used for regression and classification is a non-parametric learning algorithm [21]. KNN can perform classification for an unknown and unclassified database. Many distance measures are used to calculate the distance between two examples as a form of attribute in a dataset.

3. Proposed FCFG-based ARM algorithm

The proposed FCFG-based ARM algorithm is divided into two main phases: training phase and testing phase. Figure 1 is a pictorial representation of proposed algorithm's process flow.

From figure 1, the fuzzy ARM is used for training purpose and the KNN algorithm is used for testing purpose. The steps are as follows.

Step 1: First the user provides input data to the processing system based on fuzzy grammar. Since the road accident data are unlabelled, the proposed algorithm correctly determines the class labels for any unknown data. Based on the proposed approach, the system performs all the steps based on grammar rules (as explained in sections 3.1a–3.1c) without human involvement and produces the categorized output with class labels. Data (with labels) obtained from this step are named as training data.

Step 2: Then these data are given as input to the machine learning algorithm (say KNN) to validate the results of the proposed method (training the KNN classifier).

Step 3: The next step is KNN testing phase, in which the test data are taken from user survey with the class labels called as target class by user.

Step 4: The KNN algorithm will also produce some output class labels called as predicted class.

Step 5: Based on the target classes by the user and the predicted classes by the KNN algorithm, the performance of proposed method is evaluated.

3.1 Training phase

The training phase has three steps: (i) preprocessing, (ii) creating fuzzy rules and (iii) FCFG-based result categorization and testing phase. First, in the preprocessing step, the upper, medium and lower limits are defined from fuzzy membership variables for all the attributes present. Next the fuzzy rules are generated to run the fuzzy processor in order to obtain the fuzzy output after evaluation of rules. Then by using fuzzy output, the results are categorized into two main categories, safe and unsafe roads, which are named as categorized output labels.

3.1a Preprocessing (fuzzification): Preprocessing step is a very important process of defining the fuzzy variables of all the available attributes of given dataset. Defining fuzzy membership values for the input parameters is known as the fuzzification step. The proposed algorithm is an enhancement of ARM with fuzzy grammar.

This research work uses a triangular membership function as it is effortless and reduces the error rate in most research [22, 23]. The triangular membership function needs three input range values such as low, medium and high. After identification of unique values, the algorithm assigns the membership values [0, 1], and membership functions of various attributes given in the input data follow the generation of an output membership function.

Let the number of road accident attributes (RA) be n , i.e., $RA_i = A_1, A_2, \dots, A_n$, where $i = 1, 2, \dots, n$ and the number of road accident instances (RI) in the dataset be m , i.e., $RI_j = I_1, I_2, \dots, I_m$, where $j = 1, 2, \dots, m$. First, the grammar finds the equivalent values for low, medium and high fuzzy limits for all the attributes of dataset by calculating the

mean value of the attributes. The mean value is calculated using Eq. (4):

$$Mean_{RA} = \frac{\text{Sum of all values of attribute}}{\text{Total number of instances}}. \quad (4)$$

For any attribute A_i , the mean is obtained from Eq. (4) and can be written as

$$Mean_{RA} = \frac{\text{Sum}(A_i)}{\text{Length}(I_j)}. \quad (5)$$

With the help of mean value of a specific attribute, the lower, medium and higher limits can be set as follows:

- If the attribute value is higher than the mean value then the corresponding fuzzy value can be considered as 1 or high.
- If the attribute value is lower than the mean value then the corresponding fuzzy value can be considered as 0 or low.
- If the attribute values is equal or nearest to the mean value then the corresponding fuzzy value is considered as 0.5 or medium.

For any attribute with available instance of the dataset, these points can be shown as

$$V_F = \begin{cases} \text{High} & : V_{Att} > V_{A_i} \\ \text{Medium} & : V_{Att} = V_{A_i} \\ \text{Low} & : V_{Att} < V_{A_i} \end{cases} \quad (6)$$

where

$$V_F = \text{Fuzzy Membership value, } V_{Att} \\ = \text{Value of Attributes and}$$

$$V_{A_i} = \text{Mean value of each } i : (1 \leq i \leq n)$$

The conditions in Eq. (6) are considered by the grammar rules to develop the fuzzy processing system. In the normal fuzzy process, all the membership values with partition limits (low, medium, high, etc.) are set manually for all the available attributes of dataset; however, in the proposed FCFG ARM, the following steps are carried out automatically:

- i. Finding mean and assigning fuzzy values using Eqs. (4)–(6).
- ii. Creating fuzzy rules (section 3.1b) based on the membership value, V_F .
- iii. Obtaining the fuzzy output generated by fuzzy inference rules.
- iv. Performing categorization (section 3.1c) based on fuzzy output obtained in step iii.

3.1b Creating fuzzy rules (fuzzy rule inference system): Fuzzy rules or conditions are created using the fuzzy membership variables defined in the preprocessing step and the fuzzy rules are evaluated using the fuzzy processor. Fuzzy outputs are generated based on the conditions of low, medium and high

values of each attribute defined in fuzzy membership step. Defuzzification is the process of producing output decisions based on the membership functions defined.

3.1c FCFG based result categorization: The fuzzy processing system provides output by analysing the given fuzzy rules. Based on the fuzzy output the categorization of data is performed. Initially the first output data are placed in first category. Then the proposed algorithm compares one output instance to

all other instances that are produced by fuzzy processor, to place data in specific categories. Finally, the difference between the output membership functions of two subsequent instances is considered to assign them in the same category if difference is less; otherwise, a subsequent category is chosen. This process is repeated till the entire fuzzy output data are placed into all the available categories. The categories obtained from this step are termed as labels (classes). The whole process of categorization by means of output labels is mentioned in Algorithm 1.

Algorithm 1: FCFG-based categorization algorithm (training phase)

Initialization: Instances: $I_1, I_2, \dots, I_n$; Categories: $C_1, C_2, \dots, C_m$; Attributes: $A_1, A_2, \dots, A_k$

Input: uncategorized training dataset = $\text{DRoad}_{\text{Train}}$,
 number of instances = n , number of attributes = k , number of categories = m ,
 Fuzzy Rule (FR), Rules to assign fuzzy input (RU), Upper Limit (UL), Lower Limit (LL), Medium Limit (ML), Fuzzy Output (FOP), Number of Categories (NC).

Algorithm:

1. Preprocessing (Finding Upper and lower limits)
 2. for $(i = 1; j < k; i++)$ begin
 3. for $(j = 1; j < n; j++)$ begin
 4. $UL = \text{Maximum}(A_i(I_j))$
 5. $LL = \text{Minimum}(A_i(I_j))$
 6. end
 7. $ML = \text{Avg}(UL, LL)$
 8. end
 9. end
 10. Fuzzy Rule Inference System (Setting Fuzzy Rule)
 11. set $l = LL, u = UL$ and ML
 12. for $(i = 1; i < n; i++)$ begin
 13. $FOP(i) = A(i)$
 14. end
 15. FCFG based Categorization
 16. set $C_1 = I_1$
 17. for $(i = 1; i < \text{length}(FOP); i++)$ begin
 18. for $(j = 1; j < k; j++)$ begin
 19. for $(r = 1; r < m; r++)$ begin
 20. $P(FOP) = FOP(i)$
 21. if $(P(FOP) = FOP(i))$
 22. $C_1 \leftarrow I_{i+1}$ //assign to same category
 23. else
 24. $C_{m+r} \leftarrow I_{i+1}$ //assign to the next categories
 25. end
 26. end
 27. end
 28. end
 29. repeat steps 5 and 6 until $r < m$
 30. repeat steps 5 and 6 until $i < \text{length}(FOP)$
 31. Print the categorized data, $\text{DRoad}_{\text{Clv}}$ //Training Data with Class labels
-

Output: Categorized data with labels, $\text{DRoad}_{\text{Clv}}$

3.2 Testing phase

In testing phase, the test data are considered to know whether the algorithm has produced the correct categorization results or not. The fuzzy processor produces output labels for all the instances of the dataset, and now these labels need to be tested with the identified test data to judge the performance of proposed algorithm. Algorithm 2 presents the steps of testing the algorithm using machine learning technique (say KNN in this study) for unknown class labels. Generally, for any machine learning algorithm, the user needs to provide all the input and class label details manually; however, using the proposed technique, the machine learning algorithm works automatically (using unlabelled data as a labelled one), by its own as a self-learning method.

users based on road accident dataset 2016 as testing data (mentioned in the Appendix section).

4.1 Road accident dataset

Road accident dataset [24] is used for experiments in this research. The dataset was collated from reports of the central government road transport and highways ministry's Transport Research Wing (TRW). The report includes recent and long-term trends, normalized indicators for road accidents, injuries and fatalities, details from the top 13 states in terms of road accidents, persons killed, persons injured, severity of road accidents, accidents in terms of classification of roads, urban and rural road accidents,

Algorithm 2: Testing with machine learning (KNN) algorithm

Input: Instances: $I_1, I_2, \dots, I_n$; Categories: $C_1, C_2, \dots, C_m$; Attributes: $A_1, A_2, \dots, A_k$

Uncategorized testing dataset = DRoadUser_{Test}, class value (DRoadC_{lv}), target class (TC) based on DRoadUser_{Test}, Output Class from KNN algorithm = OPC.

Algorithm:

1. TRKNN = knntrain(DRoad_{Train}, DRoadC_{lv}, K^{th} value)
 2. for $(t = 1; t < \text{length}(\text{DRoadUser}_{\text{Test}}); t++)$ begin
 3. OPC = KNNTEST(TRKNN, DRoadUser_{Test}(t))
 4. repeat steps 1 to 3 until $(t < \text{length}(\text{DRoadUser}_{\text{Test}}))$
 - 5 PER = OPC=TC
 6. print PER(Accuracy, etc)
-

Output: Categorized output data, PER // Tested data after comparison with performance metrics.

To the best of our knowledge no research was done on the study of road accident data using formal grammars. This research work develops a processing system based on fuzzy grammar to model road accident data with independent variables, and categorizes unknown data by considering three significant variables total number of accidents (TA), persons killed (PK) and persons injured (PI).

4. Results and discussion

The experimentations are executed using an Intel Core-i5 processor, with 8-GB RAM and a 32-bit Operating System, and are implemented using MATLAB software. In this research, road accident dataset for the year 2015 is considered as the training data and the survey results from

accidents based on vehicle type, time of occurrence, victim's age and gender, and reason for road accidents. Data on 8062 accidents were used for this experiment. Table 1 gives a brief outline of the attributes used in the dataset for the proposed algorithm.

4.2 Analysis of categorization

The purpose of categorizing a heterogeneous dataset is to reduce data analysis complexity for research or survey. The proposed model classifies the whole data into two categories, C1 and C2 for unsafe and safe roads, respectively.

Category 1 (C1): Unsafe roads based on the analysis of three independent attributes, namely TA, PK and PI in different National Highway segments of 37 states in India.

Table 1. Attribute descriptions of road accident data (for National Highways).

	Sl. no.	Attribute name	Values	Description
Input	1	Type of vehicles	Two Wheelers Auto Rickshaws Cars, Jeeps, Taxis Bus Trucks, Tempos, MAVs Other Motor Vehicles Others	Type of vehicles used
	2	Person's age	18–24 25–34 35–44 45 and above Age not known	Age of persons killed
	3	Person's gender	Male Female	Gender of persons killed
	4	Weather conditions	Fine Mist/fog Cloudy Rainy Other extraordinary weather conditions	Type of weather conditions
	5	Time of accident occurrence	6–9.00 h 18–21.00 h	Time of accident occurrence (6–9 am and 6–9 pm)
	6	Location	Near school/college Near bazaar/market Near hospital Near residential area	Location where the accident occurred
	7	Nature of accident	Overturning Head-on collision Hit and run Safe road Un-safe road	Type of accident
Output		Categories		

C1 includes 1863 of 8062, implying that 1863 roads are not safe for use.

Category 2 (C2): Safe roads based on the analysis of three independent attributes namely, TA, PK and PI in different National Highway segments of 37 states in India. C2 consists of 6199 of 8062 data, implying that 6199 roads are safe for use.

4.3 Testing road accident dataset

The dataset can be tested based on KNN algorithm. This section has two parts. In the first, the road accident dataset (2015) already categorized by the proposed algorithm is tested. In the second part, a new road accident dataset (2016) is tested based on 2015 training data.

4.3a Testing with categorized dataset (2015): From section 4.2 we obtained two categories: safe and unsafe class of roads from the road accident dataset 2015 using the proposed algorithm. Now we test the same data using KNN algorithm to compare accuracy of results from both algorithms. We received 100% accuracy for known and categorized data.

4.3b Testing with un-categorized dataset (2016): Here we test the new road accident dataset 2016, which has the same format with unknown classes, using the KNN algorithm. The results reveal more than 83% accuracy in categorizing unknown real-time data, which is shown in figure 2.

4.4 Testing using human survey

The outputs are based on road accident dataset 2015, as a training data using the proposed algorithm. The KNN algorithm was used to check accuracy of results from the algorithm. To confirm the proposed work, we surveyed 50 people of different age groups. This survey was undertaken on randomly selected 50 data from the 2016 road accident dataset. The data of 50 focused on 3 independent variables: TA, PK and PI. The data handed over to people as a questionnaire to list their preferences on using safe or unsafe roads are given in table 2. People gave the data to check road conditions based on accident occurrence and its results. After obtaining these results from the people, we noticed that human-selected preferences are the same as the machine-learned preferences with more than 83% of

Figure 2. Categorization accuracy for 50 users.

Table 2. Sample data for human survey.

Sl. no.	Total no. of accidents	Persons killed	Persons injured	User1	User2	User3		User50
1	36020	11493	41673	0	1	0		1
2	64764	11241	63033	1	1	0		1
3	14937	4020	13421	1	0	0		1
4	2946	387	2716	1	1	1		1
5	10240	5714	6148	0	1	1		0

*0 – unsafe road; 1 – safe road.

accuracy. Thus the proposed algorithm works better in any dataset type: either real-time or existing benchmark datasets.

4.5 Performance evaluation using CM

The accuracy of proposed algorithm is demonstrated with the help of a CM. The matrix consists of two classes: actual and predicted class. The row and column of the matrix represent actual and predicted classes, respectively. The values True Positive (TP) and True Negative (TN) are the degree of correctly classified classes as target classes, and False Positive (FP) and False Negative (FN) are the degree of wrongly classified classes as target classes.

The CMs have been obtained individually for 10, 20, 30, 40 and 50 users and the corresponding accuracy values are 74.6%, 74.6%, 83.1%, 83.1% and 83.1%, respectively, which are displayed in table 3.

A sample of 50 users is considered for evaluating the performance of proposed method in terms of accuracy, and is shown in figure 2. From figure 2 it is clearly observed that the accuracy varies in the range of 70–85 for individual users. Initially the accuracy starts at 74% for 10 users; it gradually increases when the number of users increases and finally it is maintained constantly at the value of around 83%, for 50 users. If the number of users increases, the accuracy of the proposed model will also be increased. From table 3, the accuracy of the proposed algorithm is maintained at the same value, 83.1%, from users 30 till 50.

Similarly some other measures such as precision, recall and *F*-measure have also been calculated from CM. Precision (P) = $TP/(TP + FP)$, recall (R) = $TP/(TP + FN)$ and *F*-Measure (F) = $(2RP)/(R + P)$. Using these formulas, the obtained values for precision, recall and *F*-measure are 0.783, 1 and 0.8264, respectively, for 50 users.

In order to handle the data imbalance, other performance metrics such as recall or sensitivity, precision or specificity and *F1* score are also discussed. Since the categorization results produced by the proposed algorithm are not balanced for training data (road accident dataset 2015), (i.e., out of 8062 input records, category C1 includes 1863 (unsafe) and category C2 includes 6199 (safe) records), the identified metrics are considered additionally in this analysis.

Table 3. Confusion matrix (CM).

Predicted class			Predicted class		
(a) CM for 10 users.			(b) CM for 20 users.		
Actual class	TP	FP	Actual class	TP	FP
	31	13		32	14
	FN	TN		FN	TN
	0	13		1	12
	Accuracy for 10 users = 74.6%			Accuracy for 20 users = 74.6%	
(c) CM for 30 users.			(d) CM for 40 users.		
Actual class	TP	FP	Actual class	TP	FP
	36	10		36	10
	FN	TN		FN	TN
	0	13		0	13
	Accuracy for 30 users = 83.1%			Accuracy for 40 users = 83.1%	
(e) CM for 50 users.					
Actual class	TP	FP			
	36	10			
	FN	TN			
	0	13			
	Accuracy for 50 users = 83.1%				

Table 4. Survey results for 50 users.

Number of users	C1 (safe)	C2 (un-safe)
10	4	6
20	9	11
30	13	17
40	18	22
50	22	28

For test data (road accident dataset 2016 – the test data consist of 60 records), the survey results produced by 50 (10, 20, 30, 40, 50) users placed in two categories are displayed in table 4.

4.5a Recall or sensitivity: Recall is a performance measure of how many chosen instances are appropriate. Figure 3 presents in graphical format the performance of KNN classifier with recall values for 50 users. From figure 3, the recall value lies between 0.73 and 0.91.

Figure 3. Representation of recall or sensitivity for 50 users.

Figure 5. Representation of F1 score for 50 users.

Figure 4. Representation of precision or specificity for 50 users.

4.5b Precision or Specificity: Precision is performance measure of how many appropriate instances are chosen. Figure 4 represents the graphical format of the performance of KNN classifier with precision values for 50 users. From figure 4, the precision value lies between 0.63–0.88.

4.5c F1 score: F1 score is a performance measure that indicates the weighted mean of precision and recall. Figure 5 presents F1 score values in graphical format for 50 users. From figure 5, the value lies between 0.38 and 0.72.

4.5d Accuracy comparison with existing algorithms: Figure 6 is the graphical representation of accuracy comparison of the proposed FCFG-based ARM method with various existing algorithms. It is evidently illustrated that the proposed algorithm has more accuracy than the existing ones. Table 5 presents various methods or algorithms used in existing work with accuracy value.

4.6 Synoptic view of data analysis

This study focuses on issues that lead to road accidents by considering a few attributes from the main dataset [24]

Figure 6. Comparison of accuracy with existing algorithms.

Table 5. Accuracy comparison.

Reference	Algorithm name	Accuracy (%)
[25]	Naive Bayes (NB)	74.14
	Support Vector Machine (SVM)	79.79
[26]	Fuzzy Granular Decision Tree (FGDT)	68.7
	Fuzzy ID3	52
[21]	Classification Tree Modelling (CTM)	62.2
[27]	Multinomial Logistic Regression – classification (MNLR)	78.57
	FCFG ARM (Proposed)	83.1

pertaining to this research. There are totally 8062 records of National Highway road accidents from India's 36 states for the year 2015, used in this research. The proposed algorithm successfully categorized 8062 records into two different categories: safe (6199) and unsafe (1863).

Categorization is done using different variables based on attributes like type of vehicle, age of person, gender, weather conditions, time of accident, type of location, nature of accident, TA, PK and PI. The variables of each attribute can be referred to from table 1. Most accidents occurred between 6 am and 9 am (Day) as compared with 6 pm and 9 pm (Night).

5. Conclusion

In this paper, a FCFG is used to build an ARM algorithm that is more efficient than the elementary FRM. The important part of the proposed algorithm is self-learning, which enables it to categorize a dataset without anterior information. In the elementary FRM, each step such as assignment of V_F (fuzzy membership value) for each attribute and creation of fuzzy rules were carried out manually, that is, the user must enter all the inputs. However, in the proposed FCFG ARM, every task is self-learned by the algorithm itself to give meaningful results; the only task of user is to upload the required dataset. The performance analysis is done using the metrics accuracy,

recall or sensitivity, precision or specificity and $F1$ score. Comparison between existing algorithms and proposed FCFG-based ARM algorithm is performed; the proposed algorithm is proved to be better than the existing ones in terms of accuracy.

This output will provide decision makers with sufficient knowledge to reach exact and intensified decisions to evade hazardous route and create awareness of such places by providing recommendations to improve road safety.

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Appendix

Sample training data (2015).

State	Type of road	Type of vehicles	Age of persons	Gender of persons	Weather conditions	Time of accident occurrence	Type of location	Nature of accident	Total number of accidents	Persons killed	Persons injured
Andhra Pradesh	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	35931	11573	38738
Arunachal Pradesh	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	350	158	343
Assam	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	10837	3955	10264
Bihar	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	11282	6641	6806
Chhattisgarh	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	18761	4843	15574
Goa	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	9140	657	3825
Gujarat	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	31923	10953	26914
Haryana	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	13764	5838	12223
Himachal Pradesh	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	5177	1616	7856
Jammu & Kashmir	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	9859	1581	12915
Jharkhand	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	7688	4125	5311
Karnataka	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	69371	16339	80270
Kerala	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	65924	7020	66928
Madhya Pradesh	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	85131	12772	80854
Maharashtra	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	101657	23014	66123
Manipur	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	1090	235	1932
Meghalaya	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	830	263	433
Mizoram	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	119	109	143
Nagaland	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	89	45	112
Orissa	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	15032	5937	11817
Punjab	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	10108	6922	5785

continued

State	Type of road	Type of vehicles	Age of persons	Gender of persons	Weather conditions	Time of accident occurrence	Type of location	Nature of accident	Total number of accidents	Persons killed	Persons injured
Rajasthan	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	40482	17203	40915
Sikkim	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	270	97	368
Tamil Nadu	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	117854	26130	126365
Telangana	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	35400	11401	34272
Tripura	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	1021	245	1526
Uttarakhand	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	2394	1454	2432
Uttar Pradesh	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	46593	24539	29121
West Bengal	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	15441	7657	13059
A & N Islands	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	495	33	608
Chandigarh	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	618	189	480
D & N Haveli	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	62	33	79
Daman & Diu	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	88	58	60
Delhi	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	9814	1890	8901
Lakshadweep	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	4	0	4
Puducherry	National Highway	Two wheeler	<18	Male	Fine	06–900 h	Near school/college	Overturning	2392	414	2070
Andhra Pradesh	National Highway	Two wheeler	<18	Female	Fine	06–900 h	Near school/college	Overturning	35931	11231	38738

Sample testing data (2016).

Total no. of accidents	Persons killed	Persons injured
36020	11493	41673
64764	11241	63033
14937	4020	13421
2946	387	2716
10240	5714	6148
16042	6425	15244
370	235	408
8778	3279	6660
8658	5724	5003
7166	4149	4594
72330	17303	76945
70031	7109	68508
88538	14010	82925
570	195	367
53	32	81
87	38	87
6877	1425	5568
420	233	566
11986	3941	8468
9627	5479	5933
18227	4259	15450
34794	12825	27488
645	92	1124
594	166	307
81	87	44
8993	4211	8849
5347	4003	3012
14119	8469	13417
172	80	184
54030	14560	56978
2828	895	4167
3772	626	4337
6319	3451	4183
488	174	728
1649	1077	1519
31837	18683	19269
4040	2146	2571
33055	7433	36468
34143	3773	36661
70	50	108
39	16	49
3656	828	2638
162	60	95
2139	329	2158
525	154	274
69	59	48
327	56	139
2261	1542	2119
37555	26464	27745
12301	4712	7139
235	22	233
229	124	121
54	39	79
65	30	38
21587	8364	20751
229	153	432

continued

Total no. of accidents	Persons killed	Persons injured
615	210	862
1575	1038	1327
31999	18547	19193

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