International Journal of Chemical and Biochemical Sciences
(ISSN 2226-9614)
Journal Home page: www.iscientific.org/Journal.html

An Artificial Intelligence based Method for Evaluating the Safety of a Road for the Transport of Highly Hazardous Materials

Esha Rami[1], Uzma Noor Shah[2], Savita[3], Shambhu Bharadwaj[4], Shubhansh Bansal[5]

[1]Assistant Professor, Department of Biotechnology, Parul University, PO Limda, Vadodara, Gujarat, India
[2]Assistant Professor, Department of Genetics, School of Sciences, JAIN (Deemed-to-be University), Karnataka, India
[3]Assistant Professor, Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh, India
[4]Associate Professor, College of Computing Science and Information Technology, Teerthanker Mahaveer University, Moradabad, Uttar Pradesh, India
[5]Centre of Research Impact and Outcome, Chitkara University, Rajpura, Punjab, India

Abstract

Road safety is a multidimensional strategy to preventing transportation-related accidents, injuries, and deaths that includes infrastructure design, vehicle safety features, traffic rules, and public awareness initiatives. The safety evaluation of a road for moving extremely hazardous commodities entails a detailed examination of aspects including road infrastructure, traffic circumstances, weather patterns, and the nature of materials transported. The aim of this study is to detect possible safety issues and execute actions to provide safe and dependable transportation, lowering accident risks and improving road safety. AI based road safety evaluation for extremely hazardous products using machine learning algorithms to forecast and identify possible dangers, hence improving overall transportation safety. In this study, we use the novel method called Modified Cat Swarm Optimized Scalable Naive Bayes Algorithm (MCSO-SNBA) to develop a technique for assessing road safety, with a special focus on incidents involving the transportation of dangerous substances on roads. The first step consists of dataset collection, followed by preprocessing using Min-Max normalization. Independent Component Analysis (ICA) is used to extract features that contribute to a comprehensive assessment of road safety in the context of moving extremely hazardous commodities. The metrics like precision (94.73%), F1 score (93.53%), recall (95.64%), and accuracy (91.54%), that describe the findings of the road safety evaluation. The MCSO-SNBA is strengthened by its flexibility to the particular issues created by incidents involving hazardous material transportation on highways. These findings offer a theoretical framework for future research on the problems and tasks of safe transportation of hazardous chemicals.

Keywords: Road safety, hazardous material, transport, accidents, MCSO-SNBA

Full length article *Corresponding Author, e-mail: esha.rami82036@paruluniversity.ac.in

1. Introduction

The modern society has smoothly integrated roads and transportation into everyday life. For the most part, everyone uses the roads in various capacities. Although the current transportation system has been effective in reducing physical distances, it has also increased the hazards to human life [1]. Every year, traffic accidents cause millions of people to suffer serious injuries and tragically lose thousands of lives. The increasing cost of traffic accidents in terms of lost lives and injuries sustained highlights the urgent need for an equitable and secure transportation system [2]. A wide variety of data on the road transport environment is used to determine the main risks associated with the transportation of hazardous products by road [3]. Similar to hazard assessment, there are possible outcomes with estimating the frequency of specific disaster scenarios. Some good road safety practices include wearing seat belts, using vehicle mirrors properly, utilizing road lights, avoiding over speeding, maintaining proper distance between vehicles, driving defensively in accordance with the weather and road conditions, and having a basic awareness of vehicles [4].

Every goods carriage transporting hazardous or dangerous items is equipped with a spark arrestor, a tachograph and an instrument to track the amount of time that the motor vehicle gets operated, including speed maintenance, acceleration, and declaration [5]. The hazards involved in the transportation of hazardous materials known as dangerous products. Despite the industry's stellar safety record, mishaps are possible with the cargo [6]. There are several approaches to lowering the dangers associated with the transportation of hazardous materials such as Explosives, toxic gases, and Biological Hazards [7]. While most of these risk reduction strategies like driver education and routine auto maintenance have a bearing on operations research (OR), a few present fascinating difficulties for the field. Materials classified as hazardous are endangered for the environment, human health, and the lives of organisms. Chemicals that react to produce harmful exterior effects, including fire, poisonous clouds, or explosions, are frequently classified as hazardous materials like Corrosive Substances and Flammable Liquids [8]. In this study, we propose the MCSO-SNBA framework to create a road safety analysis method for analyzing accidents involving hazardous material transportation on roadways. To evaluate road safety in the transportation of hazardous commodities, it is essential to gather datasets and perform preprocessing using Min-Max normalization and Feature extraction using Independent Component Analysis (ICA). To indicate specific recommendations and remedies to address road transport issues and it highlights the regional variances in factors impacting the severity of hazardous material in road transport incidents. To highlight geographical differences in accident severity, MCSO-SNBA offers a secure road for the sustainable transportation of hazardous chemicals. The research [9] addressed the risk assessment of the railway hazardous goods transportation system (RDGTS) by applying and comparing two historical data-driven weight calculation techniques: the Scatter Degree Method (SDM) and the Entropy Weight Method (EWM). The risk was defined as the product of occurrence possibilities and their accompanying weights. The paper [10] created a better transport process model with reduced event risks to raise the safety of passenger road transportation. The study of the passenger road transportation process from six different perspectives time, resource, control, output, prerequisites, and input led to the development of the Functional Resonance Analysis Method (FRAM) that was employed to identify the factors impacting transportation reliability. The research [11] examined the three-machine learning-based models and a statistical model was created: support vector machines (SVM), multilayer perceptron (MLP), decision trees C5.0 (C5.0), and random parameters logit models (RPLM). The estimation dataset was utilized to train and estimate the four models, with the optimal model employed to simulate incidents with varying degrees of severity. The paper [12] evaluated a transportation experiment was designed to increase road safety through an analysis of transport shocks that have a major impact on the vehicle, driver, load, and various parts of the system of securing the vehicle. It has been demonstrated that there were significant differences in individual rides of probability distributions for the shock values, in terms of their shape and median value. The research [13] examined the integration of deep learning with the visualization node was shown to improve road safety, servicing quality, and traffic flow forecasts. The method is used for real-time assessment and choice-making by managing and monitoring roads. The paper [14] examined 4 popular subsidiary trunk roads, branch highways, and trunks, to determine the PM2.5 level, traffic circulation, humidity, wind speed, and wind direction. Utilized main component regression and least squares analysis, they were able to identify a similar trend in the traffic pollution data levels of pollutants were gradually declining on roadways, primary radial roads, regional roads, and bypass routes. Interestingly, in spite of this drop, the underlying factors affecting traffic pollution showed consistency over the course of the evaluation. The research [15] evaluated the legal documentation about the operation and safety evaluation of fully autonomous vehicles. Key factors were studied and integrated security components of highly autonomous cars were shown. It also substantiates the value of employing this technology to monitor the safety of highly automated cars throughout their life cycle. The paper [16] reduced the amount of accidents in logistics transportation that result from a driver's error by using an autonomous system. To identify and categorize the many postures that lead to traffic accidents, they suggest architecture based on CNN. The study [17] offered an approach that uses the CNN algorithm and OpenCV image processing to extract the similarity of images and locate images of damaged roads. To train a CNN model with 280 training and 70 test datasheets using the 350 image data points.

2. Materials and Methods

The study assesses road safety using the MCSO-SNBA, which concentrates on events involving the transfer of harmful substances. Independent Component Analysis (ICA) is used to extract features from the data as it has been gathered and preprocessed using Min-Max normalization techniques. This method offers an extensive understanding of the dynamics of safety while transporting hazardous chemicals on roadways as shown in Fig.1.

2.1. Dataset

A sample of 72 automobiles with a variety of dimensions, ages, engine types, and fuel types including diesel, liquefied petroleum gas (LPG), gasoline, and compressed natural gas (CNG) had their tailpipe emissions examined. Between March 2017 and October 2018, sampling was done at Chandigarh and Mohali (30.660–30.750oN, 76.700–76.840oE). The vehicles selected for sampling were based on popular automobiles in India. After the engine had warmed up during the idle period, while emissions were unlikely to be overestimated, tailpipe emissions were recorded [18].

2.2. Preprocessing using Min-Max normalization

The data is scaled using the Min-Max normalization technique to fall into a certain range. That ensures it each property is dominated by those with higher values and that characteristics have a consistent scale. To enhance the assessment of road safety for the transportation of hazardous products, the study used Min-Max normalization during the preprocessing stage. To assure uniformity and lessen the influence of varying scales and magnitudes, this approach scales the input characteristics.

$$B_{new} = \frac{B - \min(B)}{\max(B) - \min(B)} \quad (1)$$

B_{new} = The updated result was produced using the normalized data related to road safety. B= Preceding worth. max (B) = The greatest value found in the dataset. min (B) = The lowest value in the dataset.

2.3. Feature extraction using Independent Component Analysis (ICA)

The ICA is an important approach for improving road safety in the transportation of hazardous commodities. It separates observable signals into statistically independent components, exposing patterns and unique data. This technique assists in discovering essential characteristics and facilitates accurate safety evaluations. The vector model of the detected signals, represented by P, is explained in relation to road safety.

$$P = N_{JDB}T \quad (2)$$

The variables P, N_{JDB}, and T represent the observed signals, source signals, and mixing matrix, respectively. The N_{JDB} determined every element of the matrix N_{JDB} based on these broad presumptions, and it is then computed the separation matrix X as the matrix N_{JDB}inverse. The associated source signal established and calculated using$T$.

$$T = XP \quad (3)$$

A number of pre-treatments were done to the observed signal X to extract the predicted sources and the mixing matrix needed to ensure a road's safety while transporting very hazardous commodities.

$$Z = X^S O \quad (4)$$

Based on the sprung mass acceleration, Equation (4) the vector of the observed signal Z is created.

2.4. Evaluate the road safety using Modified cat swarm optimized scalable naive Bayes algorithm (MCSO-SNBA)

The MCSO-SNBA allows for systematic analysis and evaluation of parameters such as accident-prone zones, driver behavior patterns and environmental conditions. This improved knowledge allows authorities to adopt targeted interventions and preventative measures, ultimately contributing to overall road safety improvements and lowering the number of incidents on roads. To enhance the $z_{new}(j)$ mapping function, substitute the random variable and (0, 1). Equation 5 describes the modified expression.

$$z_{new}(j) = \begin{cases} 2z_{old(j)} + rand(0,1) \times \frac{1}{M} \; 0 \leq z_{old(j)} < \frac{1}{2} \\ 2\left(1 - z_{old\,(j)}\right) + rand\,(0,1) \times \frac{1}{M} . \frac{1}{2} \leq z_{old(j)} \leq 1 \end{cases} \quad (5)$$

Where $z_{old(j)}$ is the original solution following random generation, $rand(0,1)$ that is a random integer among 0and 1, and M is the total amount of particles in the Tent sequence, $z_{new}(j)$.To find people in a group, use reverse mappings on the $w_j$projections evenly dispersed chaotic sequence (Equation 6).

$$w_j = z_{new(j)}(va - ka) + ka \quad (6)$$

In Equation (5) generates the disordered sequencesw_j, where z_j is the localized MCSO-SNBA individual. The upper and lower boundaries of the exploratory space are represented by ka and va. In accuracy balances the algorithm with a resolution of efficacy and complexity. $w_{new\,(j)}$ Indicates the stage that uses a mathematical method to prevent road safety, as outlined in Equation (7).

$$w_{new\,(j)} = q_2 \,.\left(z_{best(s)} + rand(0,1). w_{old(j)}\right) \quad (7)$$

Throughout the MCSO-SNBA algorithm of the exploitation phase, safety refers to the gap between the optimal and current positions. This enables the safety to investigate alternative, possibly better prey spots. Equation (8) represents the formula for updating the location during this period.

$$\begin{cases} O = |rand(0,1). |w_{best(j)} - w_{old(j)} \\ w_{new(j)} = w_{best(s)} - q_2 . O. cos(\theta) \end{cases} \quad (8)$$

In this equation, O represents the update factor, $rand(0,1)$. is a random number between 0 and 1, $w_{old(j)}$ represents the individual to be updated, $w_{best(j)}$ represents the best individual in the current iteration, and $w_{new(j)}$ represents a new individual. Equation (9) demonstrates that $q_H$is calculated.

$$q_H = t_N - \left(\frac{2 \times t_M \times s}{2 \times S}\right) \quad (9)$$

Wheret_N denotes the present iteration count and t_M indicates the highest iteration count. The MCSO-SNBA algorithm relies on S to govern the transition between the discovery and extraction stages. S is determined as shown in Equation (10).

$$Q = 2 \times q_H \times rand(0,1) - q_H \quad (10)$$

The Equation (10) states that the controlling variable q_H drops linearly from 2 to O as iterations advance, $rand(0,1)$ is a random integer between $O$and 1. Equation (11) determines the different sensitivity ranges for each safeguard.

$$q_2 = t_H \times rand(0,1) \quad (11)$$

Whereq_2 represents the range of sensitivity levels for every road safety. The ESCSO algorithm either exploits or is forced into exploration. Equation (12) illustrates $w_{new(j)}$ is the aforementioned preventative techniques.

$$w_{new(j)} = \begin{cases} w_{best(j)} - q_2.O.cos(\theta), if\ |Q| \leq 1, exploitation \\ q_2.\left(w_{best(s)} + rand(0,1)w_{old(j)}, else, exploration\right) \end{cases} \quad (12)$$

Equation (13) defines the inverse solution while an elite individual represents the extreme point of the current demographic.

$$w_{new(j)} = \delta(ka_s + va_s) - w_{old(j)} \quad (13)$$

In this equation, δ is an estimate based on the range,ka_s and va_s are the highest and lowest values in the current iteration, which change with the number of iterations. $w_{new(j)}$ represents the new person, while$w_{old(j)}$ represents the individual that requires updating. Equation (14) and (15) illustrates the calculation for the technique.

$$e(w) = \frac{1}{\pi} \times \frac{1}{1+w^2} \quad (14)$$

$$w_{new(j)} = cauchy(0,1) + \left(w_{best(j)} - w_{old(j)}\right) \quad (15)$$

Segmentation is an essential part of predictive modeling and data mining. The fundamental purpose of classification is to create a classifier from a set of prepared data that has a matching division label, every instance that is specified by a pair of values for attributes $(v_1, v_2, \ldots, v_n)$. The category of factor, E is utilized and its particular value is denoted by the initial C. A NB Rule-based classifier algorithm is designed to provide a class label to a given example by calculating the chance connected with the example. Where E=$(v_1, v_2, \ldots, v_m)$ VM belongs to a group $p(e)$is established.

$$p(f|E) = \frac{p(e|c)p(c)}{p(E)} \quad (16)$$

Class C assigns an instance E to be favorable provided for safety using the MCSO-SNBA method.

$$f_b(E) = \frac{p(C=+|E)}{p(C=-|E)} \geq \quad (17)$$

This approach uses a Bayesian classifier designated$f_b(E)$. It assumes that all attributes are conditionally free given the group variable's value.

$$p(c|E) = p(v_1, v_2, \ldots, v_n|c) = \prod_{i=1}^{n} p\ (v_i|c) \quad (18)$$

The system that was created is as follows:

$$f_{nb}(E) = \frac{p(C=+|E)}{p(C=-|E)} \prod_{i=1}^{n} \frac{p(v_i|C=+)}{p(v_i|C=-)} \quad (19)$$

It demonstrates MCSO-SNBA operates, with each attribute node independent of the others save the group node.

$$pG(v_1, \ldots, v_m, C) = p(c) \prod_{i=1}^{n} p\ (v_i|pa(v_i), e) \quad (20)$$

Where $pa(v_i)$ refers to assigning values to the parents of v_i. where $pa(v_i)$ denotes v_i safety. MCSO-SNBA is a distinct Bayesian network version in which no node is designated as a division node. MCSO-SNBA reflects any Bayesian network for road safety. The MCSO-SNBA better responds to the intricacies of road safety data, enabling more accurate evaluation and forecasting of possible dangers. Its portability ensures that it is capable of handling big datasets used in road safety assessments are defined as algorithm 1.

Algorithm 1: MCSO-SNBA

Enter Data: M_{pop}, s, α
In support of j=1: $Mpop$
Create a specific safety$w_j$with chaotic mapping
Determine the safety value$j$'
End for $s = 1$
While $s \leq S$
For $j = 1$: $Npop$
Decide on a position at randomnessθamong 0 and 360 degrees to prevent an accident
If$Q \leq 1$
Change the value currently in place.
Else
Used to modify the current individual
End if
Upload valuesq_2, q_H and Q
End for
Calculateoq
For$j = 1$: $Npop$
If$o_q rand$
Update$o_q s = s + 1$
End while

3. Results and discussion

The experiment used the Windows 10, 64-bit operating system; 200 GB of C drive storage, and 8 GB of RAM. Throughout the testing process, Python was utilized. The MCSO-SNBA is to create a system for measuring road safety, with a specific focus on occurrences involving the transportation of hazardous chemicals on highways, that is compared with the other existing methods like Random forest (RF) [19], Extreme Gradient Boosting (XGBoost) [19], and Adaptive Boosting (AdaBoost) [19]. To assess a model trained with appropriate emotion classification, measurements like accuracy, precision, recall, and F1-score are necessary.

3.1. Accuracy

Accuracy is essential in anticipating road safety while moving extremely hazardous items. It identifies and categorizes possible dangers, allowing authorities to reduce them, establish safety standards, and improve route planning. Accuracy protects humans and the environment against possible harm.

$$Accuracy = (Tp + TN)/(Tp + Tn + Fp + Fn) \quad (21)$$

Table 1. Numerical Outcomes of Accuracy

Accuracy (%)	
Methods	**Percentage**
RF [19]	86.64
XGBoost [19]	81.63
AdaBoost [19]	73.15
MCSO-SNBA [Proposed]	91.54

Table 2. Numerical Outcomes of Precision

Precision (%)	
Methods	**Percentage**
RF [19]	86.82
XGBoost [19]	81.74
AdaBoost [19]	73.19
MCSO-SNBA [Proposed]	94.73

Table 3. Numerical Outcomes of Recall

Recall (%)	
Methods	**Percentage**
RF [19]	86.61
XGBoost [19]	81.59
AdaBoost [19]	73.12
MCSO-SNBA [Proposed]	95.64

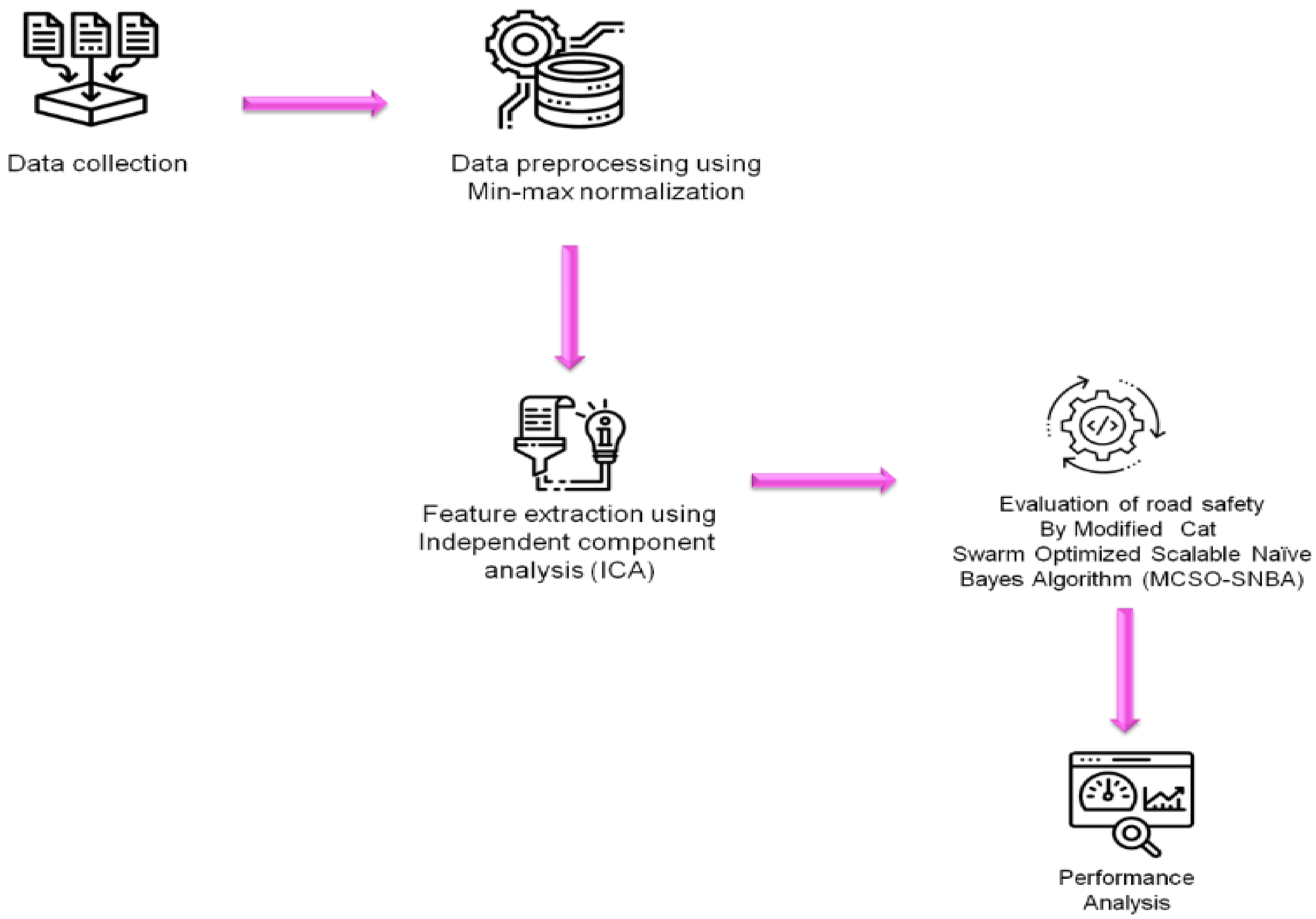

Figure 1. Graphical representation of a proposed method

Table 4. Numerical outcomes of F1-score

F1-score (%)	
Methods	**Percentage**
RF [19]	86.62
XGBoost [19]	81.6
AdaBoost [19]	73.12
MCSO-SNBA [Proposed]	93.53

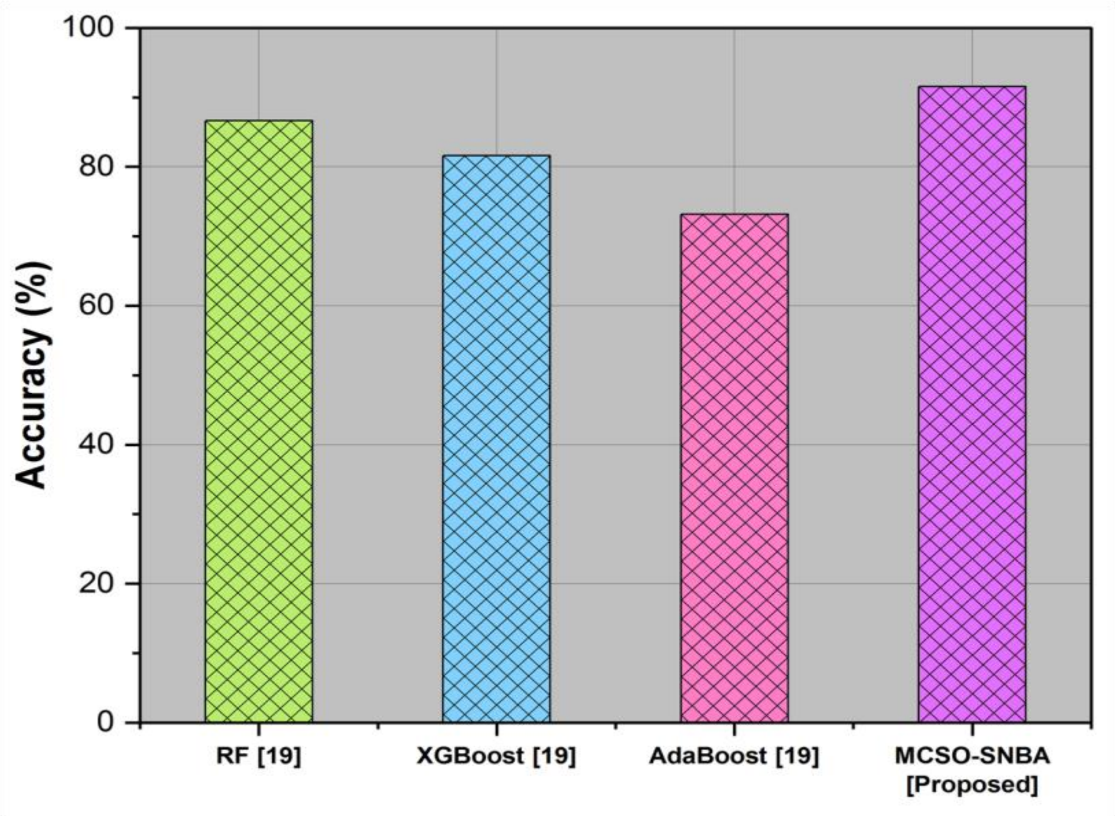

Figure 2. Graphical representation of Accuracy

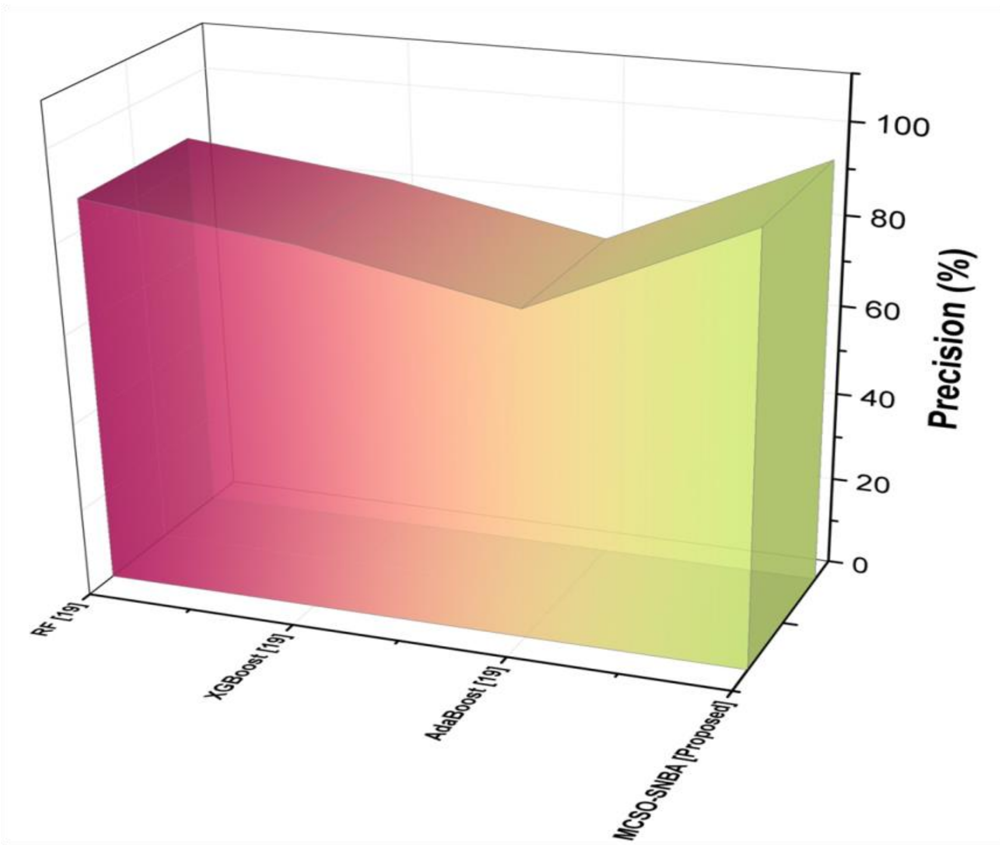

Figure 3. Graphical representation of Precision

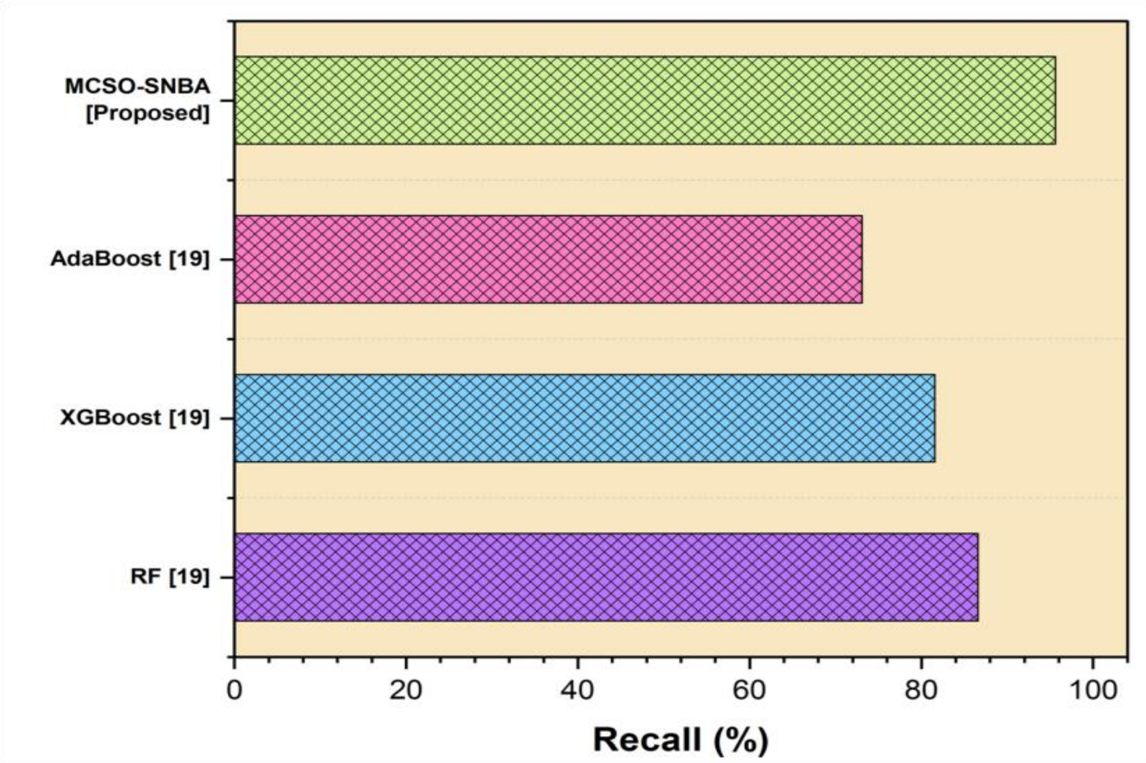

Figure 4. Graphical representation of Recall

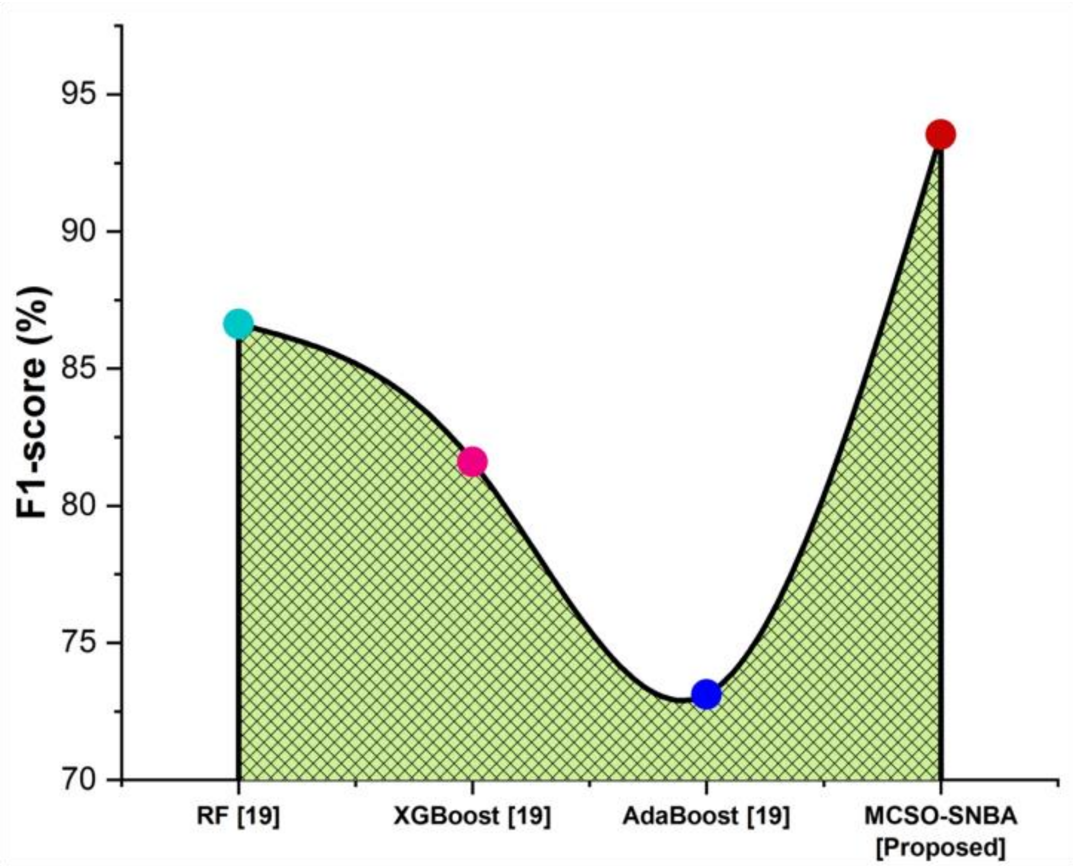

Figure 5. Graphical representation of F1-score

Where Tp is true positive, TN is True negative, Fp is false positive, and FN is false negative. Table 1 and Fig. 2 presents the accuracy of the proposed and existing method. The MCSO-SNBA achieved 91.54% that is compared with the existing methods of RF attained 86.64%, AdaBoost attained 73.15%, and XGBoost attained 81.63%. It demonstrates that the suggested process achieves higher rates than existing methods.

3.2. Precision

Precision is an important criterion in forecasting road safety for extremely hazardous material delivery. It demonstrates the prediction models of accuracy in predicting prospective risks and hazards, ensuring focused responses and effective resource allocation. High accuracy enables regulatory authorities to reduce hazards and improve safety.

$$Precision = Tp/Tp + Fp \qquad (22)$$

Table 2 and Fig.3 present the comparison of precision between the proposed and existing method. The MCSO-SNBA achieved 94.73% that is compared with the existing methods of RF attained 86.82%, AdaBoost attained 73.19%, and XGBoost attained 81.74%. It demonstrates that the suggested process achieves higher rates than existing methods.

3.3. Recall

Recall is an important metric in forecasting road safety while moving extremely hazardous items. It evaluates a predictive model's capacity to detect all relevant occurrences of dangers. A high recall value guarantees that major safety issues are identified, raising safety standards and reducing accidents.

$$Recall = TP/TP + FN \qquad (23)$$

Table 3 and Fig.4 present the comparison of recall between the proposed and existing methods. The MCSO-SNBA achieved 95.64% that is compared with the existing methods of RF attained 86.61%, AdaBoost attained 73.12%, and XGBoost attained 81.59%. It demonstrates that the suggested process achieves higher rates than existing methods.

3.4. F1-score

The F1-score is an important measure in forecasting road safety for extremely hazardous material transport since it evaluates the model's performance by balancing accuracy and recall. A high F1 score implies that the model efficiently recognizes both positive and negative episodes, offering a comprehensive indicator for risk management.

$$\text{F1-score}=2 \text{ x } [(\text{Precision x Recall}) / (\text{Precision + Recall})] \qquad (24)$$

Table 4 and Fig.5 present the comparison of the F1-score between the proposed and existing methods. The MCSO-SNBA achieved 93.53% that is compared with the existing methods of RF attained 86.62%, AdaBoost attained 73.12%, and XGBoost attained 81.6%. It demonstrates that the suggested process achieves higher rates than existing methods. The study assesses road safety using the MCSO-SNBA, concentrating on accidents involving the transportation of hazardous materials. It is used to assess factors impacting accident severity across different geographies and demonstrates improved prediction accuracy. The RF [19] algorithms are useful for predicting tasks such as road safety analysis have limits for carrying extremely dangerous chemicals. XGBoost [19] has limits for predicting road safety for extremely hazardous cargo transportation. These constraints need thorough examination and the use of additional methodologies to provide accurate and trustworthy forecasts. AdaBoost [19] is a predictive modeling approach for forecasting road safety for extremely hazardous compounds, but its applicability is limited because of its sensitivity to noisy data, dependency on base learners, and possible concerns with unbalanced data. The data showed regional variations in the dissemination of incidents involving highway transportation of dangerous substances, and MCSO-SNBA performed best in the locations with the most data. As a consequence, it is obvious that information is required to get useful results. The findings of the accident study indicated that according to the area, many factors affected serious dangerous substance road transport incidents. By area, the same elements' relative relevance in assessing the seriousness of incidents differed. Additionally, there were some geographical variations in the reasons that the same component influenced the severity of incidents.

4. Conclusions

Road safety requires a comprehensive strategy that includes public awareness campaigns, traffic laws, infrastructure design, and improvements to vehicle safety. To reduce hazards and safeguard public safety, routes for the transportation of hazardous goods must be assessed, taking into account factors such as traffic patterns, meteorological dynamics, and material properties. This paper presents the MCSO-SNBA method for creating a ternary classification model that differentiates between accidents that result in merely property damage, injuries, and fatalities. In comparison to other models, the results show that MCSO-SNBA has better prediction accuracy (91.54%), precision (94.73%), recall (95.64%), and f1 score (93.53%). The method is used to look at the significance of different elements that influence the severity of hazardous material road transport incidents in different areas. There is notable regional variation in the distribution of hazardous material road transport accidents; nonetheless, MCSO-SNBA typically performs well, especially in regions with large data quantities. This highlights the need for thorough data to provide significant results in this study. It is difficult to predict road safety for the transportation of extremely hazardous materials because of complexity, unpredictability, a lack of data, legal restrictions, and security issues. Future studies will concentrate on creating sophisticated prediction models and algorithms that forecast road safety when moving hazardous chemicals. It should also use machine learning techniques and real-time data to reduce the likelihood of accidents.

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