Systematic Approach Towards Prediction of Land Mine Using Support Vectors

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***Abstract* – Before the invention of the SONAR technique, which depends on specific criteria to be able to recognize the obstruction or the surface is a rock or a mine, it would have been exceedingly difficult to discover rocks and minerals. By demonstrating improvements in predictive analytics, machine learning has captured the interest of the majority of technology-related and -based industries. The major objective is to produce a capable prediction representation that is united by the machine learning algorithmic characteristics and can determine whether the target of the sound wave is a rock, a mine, or any other organism or type of other body. This attempt is a straightforward case study that develops a machine learning strategy for classifying rocks and minerals using an enormous, extremely complicated, and spatially distributed SONAR dataset.**

The attempts, which were conducted on a highly spatial SONAR dataset, resulted in an accuracy of 83.17% and an AUC of 0.92. With the random forest technique, the outcomes are further enhanced by feature selection to achieve 90% accuracy. Results that are reliable are obtained when the created framework is put up against industry-standard classifiers like SVM, random forest, etc. using various assessment criteria like accuracy, sensitivity, etc. Machine learning is playing a major role in improving the quality of detection of underwater natural resources, and will tend be better in the near future.

Keywords—machine learning; prediction; feature selection; data analytics; rocks and mines; SONAR.

I. INTRODUCTION

Rocks and mines are two of the important natural resources that can be found beneath the deep waters (of the seas and oceans), and it would have been very challenging to find them before the development of the SONAR technique, which stands for Sound Navigation and Ranging and is used to measure the depth of the sea or the ocean or the distances in the water, according to Dura et al. (2015). After the preprocessing of the input, several machine learning classifiers are trained to test the success of categorisation in a manner similar to how these sounds are used in this inquiry.

The best classifier was evaluated in contrast to some well-known modern classifiers, like Random Forest, SVM, C4.5, Adabag, etc. Advantageous outcomes are obtained when we compare the performance of the classifiers in the framework, including common classifiers like SVM, random forest, adabag, neural networks, etc., using different evaluation measures like accuracy, area under the curve, sensitivity, specificity, etc. Rocks, mines, and underwater surfaces can all be predicted using waves [3]. Machine learning findings are being used by researchers to create prediction models across a variety of fields [4, 5]. In this inquiry, various machine learning classifiers are developed to test the success of classification after the input has been pre-processed.

Additionally, this paper is divided into the following sections: The classification techniques used in the desired design are briefly described in Section 2. The data, its characteristics, and the experimental setup are discussed in Section 3. The experimental results and their comparisons of success are covered in Section 4. Section 5 concludes the research with a conclusion and discusses the potential applications of this prediction model in the future.

The process of choosing a subset of features to be used in model creation in a learning and statistics system is known as feature selection. Three considerations led to the use of feature selection techniques: To improve generalisation, shorten training times, and simplify the models. Data dimensionality has frequently been decreased through feature selection. The classification performance, approximation function, and pattern recognition systems are all improved by data reduction in terms of efficiency, precision, and ease of use. The use of sequential search algorithms can help local search algorithms reduce the amount of features[1]. Because of its capacity to capture and depict intricate correlations between data's input and output, artificial neural networks [2,3] are one of the most widely utilised artificial intelligence systems.

A neural network is made up of straightforward components that operate concurrently. The biological nerve systems are the inspiration for these elements. Like in nature, connections between pieces mostly define how well a network functions. Pattern recognition, identification, voice, vision, classification, and control systems are just a few of the application areas where it was released. The fuzzy inference system's ability to handle language expressions is an advantage, yet a neural network's ability to be trained and then self-learn and improve is an advantage. In order to create the Adaptive Neuro-Fuzzy Inference System (ANFIS), Jang combined the two systems in 1993, utilizing both of their advantages.

The idea behind combining neural networks and fuzzy inference is to create a system that uses a fuzzy system to represent knowledge in an understandable way and has the learning ability derived from a neural network that can adjust the membership function parameters and linguistic rules directly from data to improve the system performance[4].

Although it may also be used for estimate and prediction, the k-Nearest Neighbor (kNN) classification approach is one of the most basic and straightforward classification techniques. It was created out of the requirement to do discriminant analysis when it was difficult or impossible to obtain accurate parametric estimates of probability densities. For k's ideal values, it performs admirably.[5,6] The format of this essay is as follows: The fundamental ideas of neural networks, an adaptive neuro-fuzzy inference system, and kNN are reviewed in section 2. The sequential forward feature selection method is explained in Section 3. Section 4 provides a description of the dataset, whereas Section 5 provides a description of this work.

Landmines are explosive devices that must be detonated by a victim, usually a person or a moving object. A mine is made up of a certain amount of explosive that is often contained in some kind of casing (typically made of metal, plastic, or wood), together with a fusing mechanism that sets off the primary explosive charge. Some are buried in the ground, while others are fixed to poles, posts, or other structures that are elevated above the surface. A variety of methods, such as pressure, trip wires, electrical commands, or magnetic influences, can trigger them. Even other kinds of electronic sensors can be used to start some modern mines. Landmines pose serious risks since they require a lot of time, resources, labor, equipment, and transportation to create and remove.

If left in place, landmines can hinder friendly mobility and result in losses to friendly forces and noncombatants. Robotic mine detection reduces costs and poses little risk to human life because they can be controlled wirelessly from a distance. Landmine Classification - Anti-vehicle and anti-personnel landmines are the two broad categories into which they are typically divided. Although the anti-vehicle or anti-tank mines are pressure actuated, they are normally made so that a person's foot cannot set them off. The majority of anti-tank mines require between 348.33 pounds (158 kg) and 745.16 pounds (338 kg) of pressure to detonate.

That amount of weight can be applied by the majority of tanks and other military vehicles. Anti-personnel landmines are primarily designed to divert or expel foot infantry from a certain region. These antipersonnel mines, which are typically detonated by pressure, tripwires—wires stretched close to the ground—or remote detonation—can even kill their victims.

In essence, landmines are explosive devices that are intended to detonate when pressure or a tripwire is applied. The normal location of these objects is on or just below the ground's surface. Armed forces deploy mines to cripple any person or vehicle that comes into contact with them through explosion or by releasing fragments at a high rate of speed. Landmines are simple to create, inexpensive, and efficient weapons that may be quickly placed over vast areas to hinder enemy movement. Although mechanical minelayers that can plow the ground and drop and bury mines at predetermined intervals are more uncommon than human minelayers, they do exist. In order to stop the enemy from going through a specific area or occasionally to push the enemy through a specific area, mines are frequently planted in clusters, also known as mine fields.

II. Literature Review

Antipersonnel Land Mine (APL) detection is a difficult process that involves trying to learn about the properties of the soil and of the objects buried in it. It has been investigated how to find landmines that are buried using various techniques. None of these techniques satisfies the requirements that organizations like the United Nations and the US Army have established. Therefore, the development of new and better techniques is urgently needed, especially in light of the danger that abandoned landmines represent to civilian populations.

Thermography was found to be an effective way to find objects that are only shallowly buried in the several studies analyzed in this paper. The only way to greatly enhance the de-mining process is using detection technologies that can locate buried land mines fast and precisely. The interpretation of sensor data for land mine detection is a difficult problem because of the low signal-to-noise ratio, fluctuating measurement environment circumstances, and presence of other natural or man-made items that provide sensor signals identical to the land mine.

The land mine's fundamental idea has been used throughout military history. According to some sources, Zhuge Liang of the Chinese Kingdom of Shu devised a weapon like a land mine in the third century. Roman soldiers occasionally excavated tiny, foot-sized holes that were covered with a sharp spike and used as weapons. To stop an enemy's march, small, four-pronged spiked objects known as caltrops or crows' feet might be dispersed throughout the ground during the Middle Ages in Europe. The Ming Dynasty began to create some early modern mines with powder, which was in the form of stone, pottery, or pig iron, around the 14th or 15th century[41].

During the Battle of Yorktown in 1862, Brigadier General Gabriel J. Raines' Confederate army developed the first mechanically fused high explosive anti-personnel field mines. (Earlier in his career as a Captain, Raines had used explosive booby traps in Florida's Seminole Wars in 1840[42]. Both mechanically and electrically fuzed "land torpedoes" were used, but by the conclusion of the war it had been established that mechanical fuzes were more consistently reliable. Nearly 2,000 standard-pattern "Raines mines" had been placed by the end of the war, many of which were made on the spot, mainly from explosive shells.

Around 1912, Imperial Germany developed improved mine designs, which all the key players in the First World War copied and produced. Land mines were prominently utilized in World War One at the beginning of the Passchendale campaign. The British were producing field mines using poison gas as opposed to explosives well before the war was done. The Soviet Union produced poison gas mines at least into the 1980s. According to Dany (1998), the notion was at least tested in the 1950s in the US.

A system for landmine detection employing robotics, communication, and data processing was proposed by Majd Ghareeb and colleagues. The Raspberry Pi, camera board, metal detector circuit, and GPS shield make up the bulk of the system. A mobile unit powered by a raspberry pi for detection, data gathering, and transmission to the central unit that will later analyze the collected data. Metal detection is accomplished using a metal detector circuit. The precise location of the identified object is discovered using GPS shield. To enhance system performance, the type of detector and camera resolution capacity must be taken into account.

A multi-purpose landmine-detecting robotic vehicle with a metal detector as a supplemental tool was proposed by S. Sasikumar et al. The system is made up of an ATmega328 microprocessor, a metal detector, and GPS. With the use of IOT, a GPS system locates the landmine and transmits its location to a web server. The ATmega328P microcontroller is used to create a metal detector with driver circuit and control the entire process. The primary benefit of this project is that it uses a GPS module to precisely measure latitude and longitude location, making it simple to identify where a landmine is located. Additionally, this prototype offers a less complicated structure and lower construction costs for a landmine detection robot.

A robot that can detect landmines was developed by V. Abilash and J. Paul Chandra Kumar and is run by an Arduino. The system is made up of a GPS, metal detector, buzzer, and Arduino UNO microcontroller. Robot actuation is carried out with a powerful DC motor supported by a H bridge circuit that enables robot to move in any direction, a metal detector for mine detection, a buzzer for warning alert, the robot is controlled with assistance from computers using the zigbee module, an ultrasonic sensor fixed to it in order to locate and avoid the obstacle, and a GPS sensor for latitude and longitude detection. The proposed wheeled robot has the advantages of being more affordable, durable, and useful in the military for surveying and monitoring tasks.

J. Bharath described a robot design that can locate hidden land mines and identify them while being wirelessly controlled from a distance. This method searches for land mines using the robot's built-in metal detector circuit. To find metallic components utilized in landmine manufacture, a robot-interfaced metal detector circuit is left on the search area. It alerts the user when there are landmines that are unevenly distributed beneath the surface and can then move the landmine safely from one location to another without risk of exploding.

A surveillance drone was used to locate landmines by Yuvaraj Ganesh and others. A quadcopter, a metal detector circuit, an IR camera, an RF transmitter and receiver, an Ardunio Uno, a GPS module, and a GSM module make up the system. The latitude and longitude of the mine that was discovered are provided by the GPS module. The user receives the location through text message thanks to the GSM module. RF Transmitter and Receiver are used to establish wireless communication. The algorithm was processed on the Ardunio Uno, which was also used to interface with the GPS, GSM, metal detector, and IR camera. The drone's operational range and the cost of implementation are disadvantages.

A robot capable of autonomously locating and mapping landmines was proposed by Kishan Malaviya et al. A metal detector circuit, servo motor, gas sensor, GPS, and GSM module make up the system. According to the output, metal may be found 2 cm beneath the soil with a 90% accuracy rate, 5 cm with a 60% accuracy rate, and 10 cm with a 50% accuracy rate.

A robot structure developed by Mohammad A. Jaradat and colleagues was given powerful capabilities that let it move freely over minefields without being constrained in any way. The stability, simplicity, and reduced control effort of the robot's wheeled locomotion type, along with the Bogie suspension's superior reaction to other suspension types, give it an edge over others. The robot controller is also configured with the force angle measure of tip-over stability margin to warn it before any tip-over.

A concept for robot navigation control based on monocular pictures employing image processing algorithms was put out by William Benn and Stanislao Lauria. The implementation of colour segmentation against a chosen floor plane to clearly distinguish barriers from traversable space is then enhanced with clever edge detection to distinguish similarly colored boundaries from the floor plane. The resulting binary map shows a white area where there are no obstacles and a black area where there are. Fuzzy logic was then applied to this to determine the robot's subsequent motions. This image processing system, according to the output, performed well on solid-colored carpets, timber floors, and concrete floors but struggled to distinguish between colors in multicolored floor types like patterned or ornamental carpets.

Particle Swarm Optimization (PSO), Discrete Particle Swarm Optimization (DPSO), and Fractional Order are a few optimization strategies that Safia et al. [7] mentioned. The best or most ideal characteristics of the driver's face can be chosen using discrete particle swarm optimization (FODPSO) techniques to indicate his tiredness.

Safia et al.'s [8] recommendation to capture the region of interest and inspect it thoroughly in terms of pixel values, assessing the amount of noise present, analyzing the position of boundaries to study the region of interest, analyzing the fluctuating intensities across the forehead region of the face, and taking into account the edge effects of the eyes was also suggested.

The landmine detection mobile robot goes forward and utilizes a landmine detector to discover landmines and a GPS module to track the location. Kuo-Lan Su, et al., designed a multi robot-based landmine-detection system that also includes a following mobile robot. It logs the coordinates and sends them wirelessly through an RF link to the next mobile robot. The next robot logs the coordinates of the landmines in the area as well as the position and orientation of the landmine detection robot. The robot that follows moves in close proximity to the landmine and plans a path that will automatically avoid obstructions. [9]

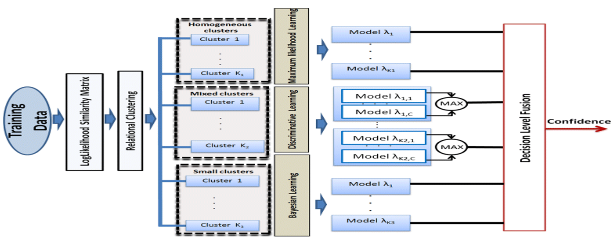
A road map for using robotics for humanitarian demining was put forth by Pedro F. Santana et al. A low cost four-wheel steering robot with biological locomotion control is employed as part of a portable demining kit to tackle emergency situations in outlying areas. The benefit of this effort was the creation of a low-cost robot employing locally accessible components, including bicycle wheels, minimal mechanical and energetic stress, simple sensory and computational equipment, and virtual components. [10]

III. Material and Methods

The material and methods used for proposing the prediction model is discussed in this section.

3.1 Block Diagram

Land Mine



A land mine is an explosive device that is hidden beneath or on the ground and is intended to kill or disable enemy targets when they move over, close to, or encircle it, including soldiers, vehicles, and tanks.

i) Clustering

A machine learning approach called clustering or cluster analysis groups the unlabeled dataset. It is described as *"A method of clustering the data points into various groups, each grouping data points that are similar to one another. The items with potential resemblances continue to be in a group that shares little to no characteristics with another group"*.

ii) Relational Clustering

The items with potential resemblances continue to be in a group that shares little to no characteristics with another group.It accomplishes this by identifying comparable patterns in the unlabeled dataset, such as shape, size, color, behavior, etc., then classifying the data according to the presence or absence of these patterns. It uses an unsupervised learning approach, which means the algorithm receives no supervision, and it works with an unlabeled dataset.Each cluster or group is given a cluster-ID after using this clustering technique, which ML systems can employ to streamline the processing of big and complicated datasets.

iii) Homogeneous Clustering

In homogeneous clusters, it is thought that every machine is the same; however, in heterogeneous clusters, each machine has a unique computation and consuming capacity. An energy management framework in Map is called the All-in Strategy (AIS).By shutting down each node in a cluster during a time of low utilization, clusters can be reduced.

4.2 Training Dataset

The data was gathered via the UCI Repository. It consists of 209 such examples and includes 61 characteristics that distinguish and classify rocks and mines.

4.3 Experimental Setting

The various feature selection and model building processes have been implemented using the WEKA tool. The primary goal is to determine the classifier's predictive accuracy while it is operational and then classify additional samples without the benefit of understanding the true class of the data. A 10-fold cross validation trial will be implemented by the comparators. Ten equally distributed subsets are created from the dataset. The nine-subset layer is taught using the most precise machine learning classifier as a base classifier, which is then examined on the final subset layer. The process is repeated to assess the groundwork's resilience. Seven different criteria, including F measure, accuracy, MCC, error rate, True and False Positive rates, and area under curve (AUC), are utilized to evaluate the performance of the framework under consideration.

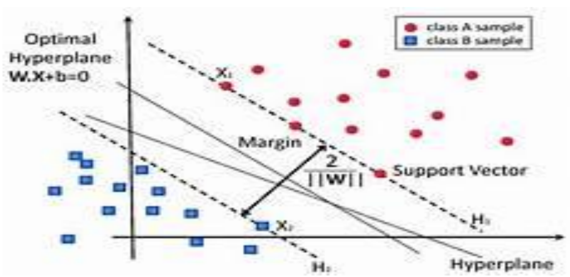
4.4 Machine Learning Classifiers

i.Random Forest: Under the category of tree-type classifiers, Random Forest examines each dataset value independently using the same distribution as all of the forest's trees. Internal valuation keeps track of the strength, mistakes, and correlations that are put into place to show the reaction to the expanding set of features that have been used in splitting.

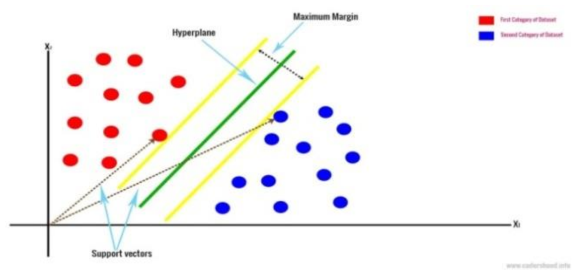
*ii. Neural Network:*Perceptrons are a group of connected nodes in an artificial neural network that resembles the vast network of neurons in the human brain. In this case, the machine was trained using the perceptron technique. It is for the controlled learning of two-fold classifiers that can determine whether or not an input belongs to a particular category.

iii. Support Vector Machine: (Super visional learning techniques called SVM)networks determine the data needed for classification and backsliding analysis. A visible gap divides the categories in the SVM model's representation of the instances as points in space. Then, based on which side of the chasm the new samples fall, they are mapped into that same area and assigned to a category.

3.2 *Support Vector 1*



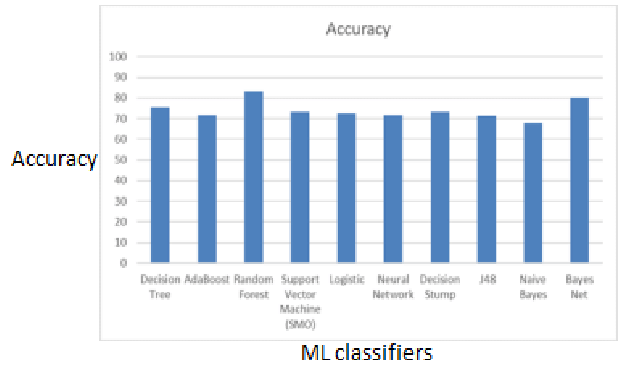
3.3 *Support Vector 2*



iv.Adaboost can perform better when used with a range of different classifiers. Adaboost is generally mentioned as the finest pre-built classifier. The Adaboostalgorithm's data for each training sample is jammed into the tree-viable algorithm in such a way that later trees prefer to focus on samples that are harder to categorize.

v. The aim of *logistic regression-bayesian networks* is to create acyclic graphs with nodes that represent variables in a bayesian sense. Each node is connected to a probability function that outputs the probability distribution of the variable each node represents based on a particular set of values for the node's parent variables as input.

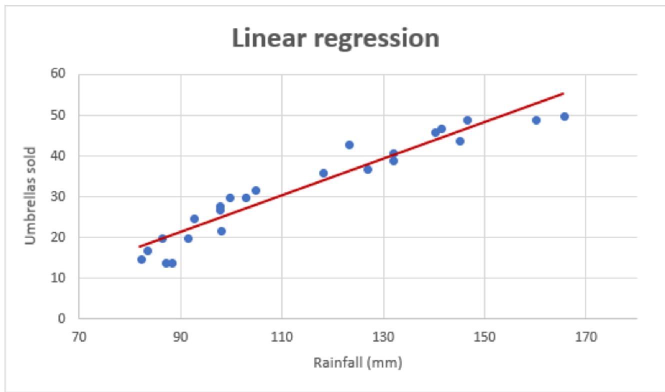
3.4 *Accuracy Graph*



Accuracy in percentage for classifiers

In order to determine how accurately a particular classifier will categorize future data—that is, data on which the classifier has not yet been trained—evaluating and assessing the accuracy of classifiers is vital.

3.5 *Linear Regression*



The relationship between two variables and how a change in one variable affects the other are displayed by the linear regression procedure. The algorithm demonstrates the effects of modifying the independent variable on the dependent variable. Explanatory variables are those independent variables that explain the influences on the dependent variable. It's common to refer to the dependent variable as the factor of interest or predictor. Real continuous values are estimated using linear regression.

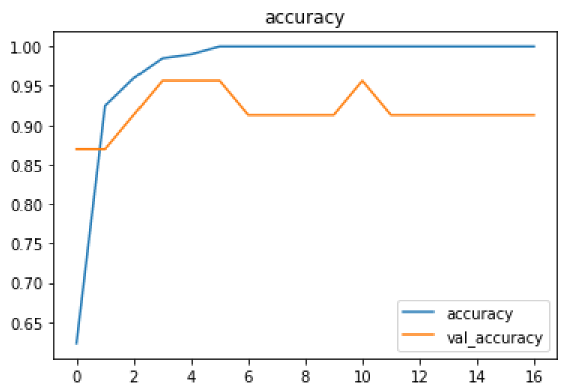
V. PROPOSED FRAMEWORK

The primary goal of analysis in the field of machine learning is to create a planned computer system for classifying predictions of objects based on available data.The output of the proposed framework aids in predicting which surface will cause the triggered sound waves to reflect back: A mine or a rock.

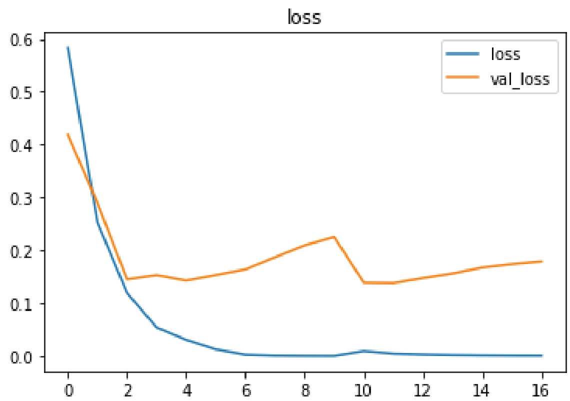
5.1 Steps of Proposed Framework

Generally speaking, there is no restriction on the sorts of data while dealing with real-world problems. Pre-processing steps like missing value removal, feature selection, etc. are always necessary. Machine learning is focused on adopting cutting-edge methods to process massive amounts of complex data more cheaply. Figure 1 illustrates the suggested framework's abstract view. Based on around 61 features or parameters, processed by 10 separate classifier models, and producing outputs with a respectable accuracy and precision percentage, the prediction model in Figure 1 was developed to assess whether the surface was a rock or a mine.

3.6 *The Plot of Accuracies*



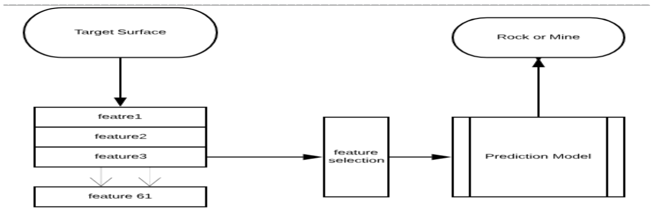
3.7 *The Plot of Losses*



*i Pre processing:*Mean value imputation is used to eliminate missing values in their place.

ii Feature Selection: The importance of each trait is ranked using the mean Gini index. The prediction model is supplied with the top 50 features as determined by mean gini index.

iii Prediction Model: To discover the most effective approach, many ML classifiers are investigated and used.The ensemble model with the highest performance, Random Forest, has an accuracy rate of 83.17%. The accuracy of the results was improved further to 90.20 percent by using the feature selection technique to feed the prediction model with the best features. This framework's results aid in determining if the targeted surface is a rock or a mine.



3.8. Proposed Prediction Framework

The proposed prediction framework is illustrated visually in the figure. A block diagram of the framework is used to show the linkages and order of the various steps of the prediction process.

The signal-to-clutter ratio (SCR) for landmine identification using ground-penetrating radar is estimated in real time using a regression model. Artificial neural networks are used to represent SCR in relation to the characteristics of the soil, the depth of the target, and the pulse's central frequency. Using the finite-difference time-domain method, the SCR is synthetically evaluated over a large range of diverse and controlled scenarios. Both the surface roughness and the geometry of the heterogeneities in the soil are described by fractals. The standard soil metrics of sand fraction, clay fraction, water fraction, bulk density, and particle density are employed to express the soil's dispersive dielectric properties. A training set that is coherent and evenly distributed is produced using this method. Using cases not covered during training, the overall performance of the generated nonlinear function is assessed. The recommended framework's generalizability and validity are demonstrated by the calculated and anticipated SCR's strong agreement.

VI. Results and Discussion

The parameter evaluation measures used to assess the effectiveness of different machine learning algorithms are covered in this section. The results of the 10-fold cross validation approach are graphically displayed and thoroughly discussed.

6.1 Performance Evaluation

The effectiveness of the desired strategy is evaluated using various confusion matrix parameters, as given in Table 1.

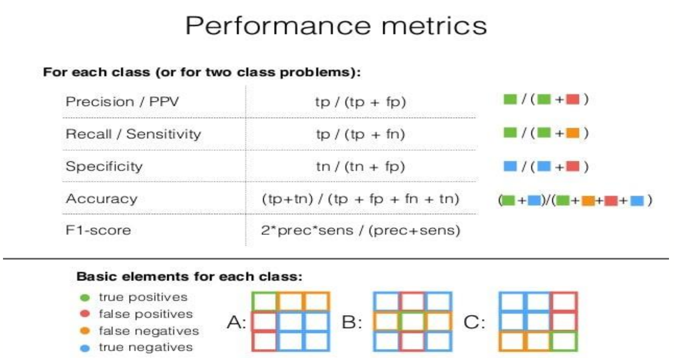
Table 2 displays the many evaluation metrics that were derived using the data in Table 1. The confusion matrixassisted positive and negative conditions for prediction are shown in Table 1.

TABLE 1:CONFUSION MATRIX

	Predicted (0)	Predicted (1)
Actual (0)	True Negatives (TN)	False Positives (FP) Type 1 error
Actual (1)	False Negatives (FN) Type 2 error	True Positives (TP)

The performance of the classification models for a certain set of test data is evaluated using a matrix called the confusion matrix. Only after the true values of the test data are known can it be determined. Although the matrix itself is simple to understand, some of the terminology used in connection with it might be.

TABLE 2:PERFORMANCE METRICS FOR MACHINE LEARNING MODELS



Each machine learning pipeline includes performance indicators. They quantify your progress and let you know if you're making any. All machine learning models require a metric to assess performance, whether they use linear regression or a SOTA method like BERT.

6.2 Experimental Results

Results are covered in this Section in great detail. Table 3 displays the findings of the experiment. The performance of classifiers is compared using a variety of performance indicators, and the results are represented visually in Figures 2 and 3, which compare accuracy and AUC, respectively.

VII. CONCLUSION

An appropriate prediction miniature is proposed that, when combined with machine learning classifying features, can determine whether the target of the sound wave is a rock, a mine, any other organism, or any other form of body. The random forest model, an ensemble tree-based classifier in machine learning with the highest accuracy rate of 83.17% and giving the best ROC-AUC rate 0.93, with least error for better elaboration of this prediction model, is found to be the best at predicting the best outcome for the target to be a rock or a mine. The large data Hadoop architecture will be used to handle increasingly complicated data in future studies. The accuracy of the results obtained with the random forest technique is 91.15% after further feature selection optimization.

VIII. LIMITATIONS AND FUTURE WORK

This study made the case that it is possible to assess the probability risks of land mine contamination using historical de-mining data and ML models. We also evaluated the effectiveness of these models, demonstrating that they are effective at excluding the existence of landmines. We think that the performance of these models can be significantly enhanced with additional research and data.This application faces the problem of unbalanced datasets because of the sparse distribution of mines. We looked into various strategies to address this problem.

In order to optimize parameter selection for both models, a grid search methodology with cross validation was used.We can train a model to favor gain or cost because the models are adaptive in terms of scoring systems. The study's results section compares the SVM and LR approaches, and the findings indicate that SVM typically performs better than LR. The LR algorithm can also deliver trustworthy results with a significantly lower time and memory cost in areas where topographical variance is not as pronounced. The optimal strategy for maximizing performance may be to combine the knowledge from the two models. One significant drawback to our research.

Our pipeline works well when determining the absence of mines but poorly when determining their presence. More data might be useful in addressing this restriction. In our upcoming work, we intend to expand the amount of information we collect from on-site sources and enhance our models. These models' ability to be explained would enable us to comprehend patterns and correlations between geographic and social characteristics and the presence or absence of mines, as well as the hazards of contamination. Millions of people live in post-conflict nations around the world, and with more work, the suggested approach can aid in the efficient planning of de-mining operations and the optimization of resource allocation.

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