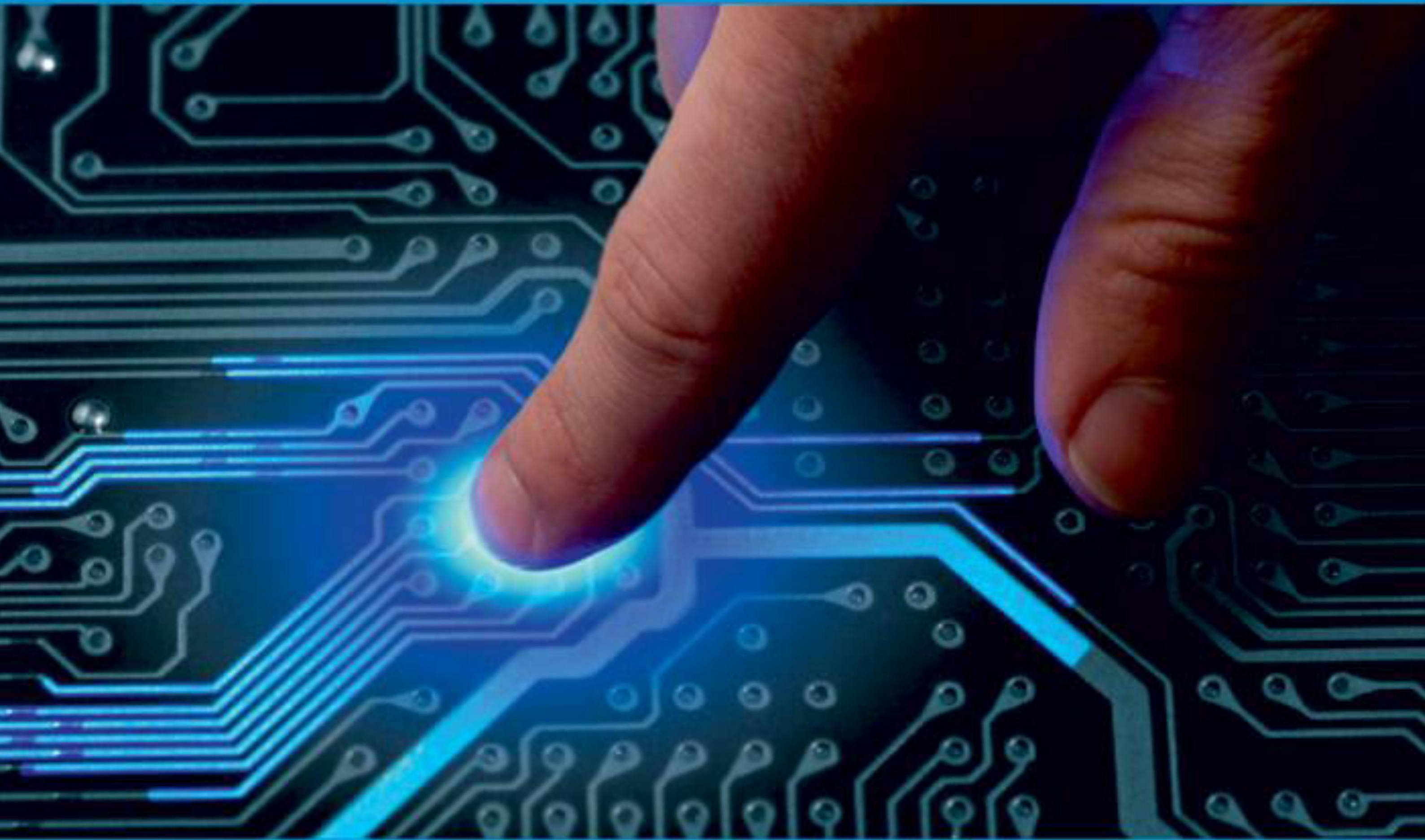
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 3, March 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 3, March 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1203089 |

Sonar Rock Vs Mine Prediction

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ABSTRACT: Naval mines, serving as self-contained explosive devices deployed in water to target surface ships or submarines, pose a significant challenge in identification due to their resemblance to rocks in shape and dimensions. To discern between these mines and natural formations, SONAR technology is employed. SONAR, or Sound Navigation and Ranging, operates by emitting sound waves from a transmitter and analyzing the echoes received by a receiver. By examining the frequencies of these echoes, the system determines whether the object is a mine or a rock. This project employs Python and a supervised machine learning algorithm, specifically the Extra Trees Classifier, renowned for its effectiveness in handling imbalanced datasets. This classifier proves advantageous, particularly in scenarios where one class has significantly fewer samples than the other. The objective is to enhance the performance, reliability, and generalization ability of the machine learning model. The dataset utilized, sourced from Kaggle, comprises 60 attributes and 208 records. Among these, 111 patterns derived from bouncing SONAR signals off a metal cylinder under different conditions and angles, along with 97 patterns associated with rocks analyzed under similar circumstances. The overarching aim of this endeavor is to improve the dependability, effectiveness, and adaptability of machine learning models used in underwater mine detection scenarios, consequently strengthening maritime security and safety.

KEYWORDS: Extra Trees Classifier, SONAR, Underwater mines, Classification Algorithm, Supervised Machine Learning

I. INTRODUCTION

A submarine is a naval vessel that can dive deep under ocean water and also travel on the surface of the water. Research scientists and explorers generally use smaller subs. Researchers or civilians carry cameras and mechanical weapons in submarines. In order to patrol the ocean during the war, the military used submarines and, in general, it is enormous.

A submarine crew uses sonar to find the enemy's way in the dark deep ocean. Sonar equipment locates objects by picking up sound waves. Light does not penetrate long distances in the ocean, so it is required to travel in the water blind. On the surface to travel, the submarine takes the help of a Global Positioning System (GPS) that determines latitude and longitude. But GPS cannot work when the submarine is sunk into the water. It uses SONAR (Sound navigation and ranging) to locate any target that emits sound waves to travel in water. Based on the travel speed to the target and reflection, the computing device calculates the distance between the submarine and the target. Dolphins use a similar type of concept to whales to locate their prey. Submarine uses the Doppler effect, similar to an ambulance or police car driving with a siren on the pitch changes. The siren pitch will be very high when it comes closer, and as it moves forward, it reduces. The same is observed in the sonar sub marine. Using machine learning techniques and considering the frequencies obtained from the sonar process, we design a Machine Learning model to predict whether the underwater object detected is a rock or a mine.

Working of SONAR

Sonar, which stands for Sound Navigation and Ranging, is a technology that uses sound waves to detect and locate objects underwater. It works on the principle of sending out sound pulses into the water and then listening for the echoes that bounce back from objects in the water. The time it takes for the sound waves to bounce back and the characteristics of the returning echo provide information about the distance, size, shape, and composition of the objects in the water. When it comes to underwater rock versus mine prediction, sonar can be used in various ways depending on the specific application and the equipment being used. Here's a generalized process:

1. Transmitting Sound Pulses: The sonar system sends out a series of sound pulses, typically in the form of high-frequency sound waves, into the water. These sound waves propagate through the water until they encounter an object.

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2. Interaction with Objects: When the sound waves encounter an object, such as a rock or a mine, they are partially reflected back towards the sonar receiver. The amount of energy reflected depends on the size, shape, and composition of the object.
3. Receiving Echoes: The sonar system listens for the echoes of the transmitted sound waves. It measures the time it takes for the echoes to return to the sonar receiver. By analyzing the time delay and the characteristics of the echoes, the sonar system can determine the distance to the object.
4. Signal Processing and Analysis: The received echoes are processed and analyzed to extract information about the objects in the water. Advanced signal processing techniques can be employed to filter out noise and enhance the detection of objects. The characteristics of the echoes, such as frequency can provide clues about the nature of the objects, such as whether they are solid rocks or man-made mines

II. RELATED WORK

In [1] authors focus on employing deep learning-based neural networks for the critical task of discerning between objects resembling mines or pebbles in SONAR datasets specific to underwater acoustics. Their investigation aims to enhance classification accuracy and efficiency by introducing a novel neural network architecture termed RDNN. The authors rigorously assess the performance of RDNN against established deep learning models, utilizing metrics such as accuracy and loss to gauge effectiveness. This comparative analysis contributes valuable insights into the advancement of underwater target discrimination techniques, thereby enhancing the capabilities of mine detection systems and bolstering maritime security measures.

In [2] authors delve into the crucial task of classifying underwater SONAR returns to detect potential sea mines, which pose significant threats to ships and submarines. Their research utilizes the 'Connectionist Bench (Sonar, Mines vs. Rocks) Data Set' obtained from the UCI machine learning repository. This dataset comprises 60 attributes and 208 records, with 111 patterns originating from bouncing SONAR signals off a metal cylinder and 97 patterns from rocks under similar conditions. The authors employ standardization preprocessing techniques, utilizing the StandardScaler utility class to generate scaled data. Subsequently, they employ the k-Nearest Neighbour and Support Vector Classifier classification algorithms to train and evaluate the model's performance, calculating accuracy in each case. Additionally, Principal Component Analysis is conducted for feature selection, and optimal hyperparameters are tuned to enhance accuracy.

In [3] authors address the pressing need for accurate prediction systems to distinguish between underwater mines and rocks, crucial for naval defense systems. The potential misidentification of mines as rocks poses significant threats to marine life and submarine vessels. To tackle this challenge, the authors leverage machine learning algorithms, utilizing a dataset provided by Gorman, R. P., and Sejnowski, T. J. (1988), to train models for accurate prediction. They employ sonar signals to capture the diverse frequencies of underwater objects from 60 different angles, constructing three binary classifier models based on their respective accuracies. These prediction models are then utilized to categorize objects into mines and rocks. The authors implement Python and supervised machine learning classification algorithms to develop these prediction models, contributing to the advancement of underwater mine detection technology.

In [4] authors address the challenges faced by submarines in distinguishing between rocks and mines, crucial for naval defense and maritime security. Mistaking rocks for mines or vice versa poses significant threats to marine vessels. Leveraging the SONAR technique, the authors utilize high-resolution images to detect underwater objects, recording frequencies from 60 different angles. They employ machine learning algorithms, including standalone classifiers, cross-validation techniques, and bagging classifiers, to construct predictive models based on the dataset. The study emphasizes the limitations of standalone algorithms, such as overfitting and feature selection issues, and highlights the efficacy of bagging with cross-validation in overcoming these challenges. The primary objective is to enhance the performance, reliability, and generalization ability of machine learning models. Among the algorithms evaluated, random forest demonstrates superior performance across all categories, indicating its effectiveness in underwater mine and rock prediction.

In [5] authors explore the application of Meta-Cognitive Neural Network (MCNN) and Extreme Learning Machine (ELM) classifiers for distinguishing between SONAR targets, specifically rocks and mines. The paper highlights the strategies employed by MCNN, such as the sample delete strategy and neuron growth strategy, to enhance classification efficiency. Additionally, it emphasizes the advantages of ELM, particularly its ability to achieve efficient classification without requiring tuning for the hidden layer. Through performance analysis, the study reveals that MCNN achieves a training efficiency of 81.7% and testing efficiency of 87.5%, while ELM demonstrates slightly higher training efficiency at 88% but slightly lower testing efficiency at 84%. This research contributes valuable

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insights into the effectiveness of advanced neural network classifiers for SONAR target classification, aiding in the development of efficient underwater mine detection systems.

III. PROPOSED ALGORITHM

The proposed Machine Learning algorithm used for the Sonar Rock vs Mine Prediction is Extra Trees Classifier. The ensemble machine learning algorithm selected for the proposed system will be chosen based on its balance between predictive performance and interpretability. While maintaining high accuracy, preference will be given to algorithm that offer insights into the decision-making process, facilitating better understanding and trust from stakeholders.

A) Workflow of System

The proposed system for our project involves several key steps:

1. Data Collection: The system collects sonar data from sonar devices. This data includes information about the frequency at 60 different angles of sonar signals, as well as corresponding labels indicating whether each object is a rock or a mine.
2. Data Processing: The collected data undergoes preprocessing to handle any missing values, outliers, or inconsistencies.
3. Test-Train Split: Split the data into training and testing sets using the train_test_split() function from sklearn. The features (X) are stored in X_train and X_test, and the target variable (Y) is stored in Y_train and Y_test .
4. Model Training and Evaluation:
   a) Initialize an Extra Trees Classifier model (etc) with specified parameters such as the number of estimators, maximum features, and criterion.
   b) Fit the model to the training data using the fit() method.
   c) Calculate feature importances and plot the top 20 important features.

   d) Make predictions on the training and testing data and calculate the accuracy scores.

   Accuracy=(TP+TN)/(TP+TN+FP+FN)
5. Visualization: Visualize the confusion matrix using Seaborn's heatmap() function.
6. Create Streamlit App: Start building Streamlit app with required design and then create a button that triggers the predictions.

B) Extra Tree Classifier

The Extra Trees Classifier, known as Extremely Randomized Trees Classifier, is an ensemble learning method based on decision trees. It belongs to the family of tree-based models along with Random Forests and Gradient Boosted Trees. It aggregates the results of multiple de-correlated decision trees collected in a “forest” to output its classification result. In concept, it is very similar to a Random Forest Classifier and only differs from it in the manner of construction of the decision trees in the forest. Each Decision Tree in the Extra Trees Forest is constructed from the original training sample. Then, at each test node, ach tree is provided with a random sample of k features from the feature-set from which each decision tree must select the best feature to split the data based on some mathematical criteria (typically the Entropy).
This random sample of features leads to the creation of multiple de-correlated decision trees. To perform feature selection using the above forest structure, during the construction of the forest, for each feature, the normalized total reduction in the mathematical criteria used in the decision of feature of split is computed. This value is called the Gini Importance of the feature. To perform feature selection, each feature is ordered in descending order according to the Gini Importance of each feature and the user selects the top k features.

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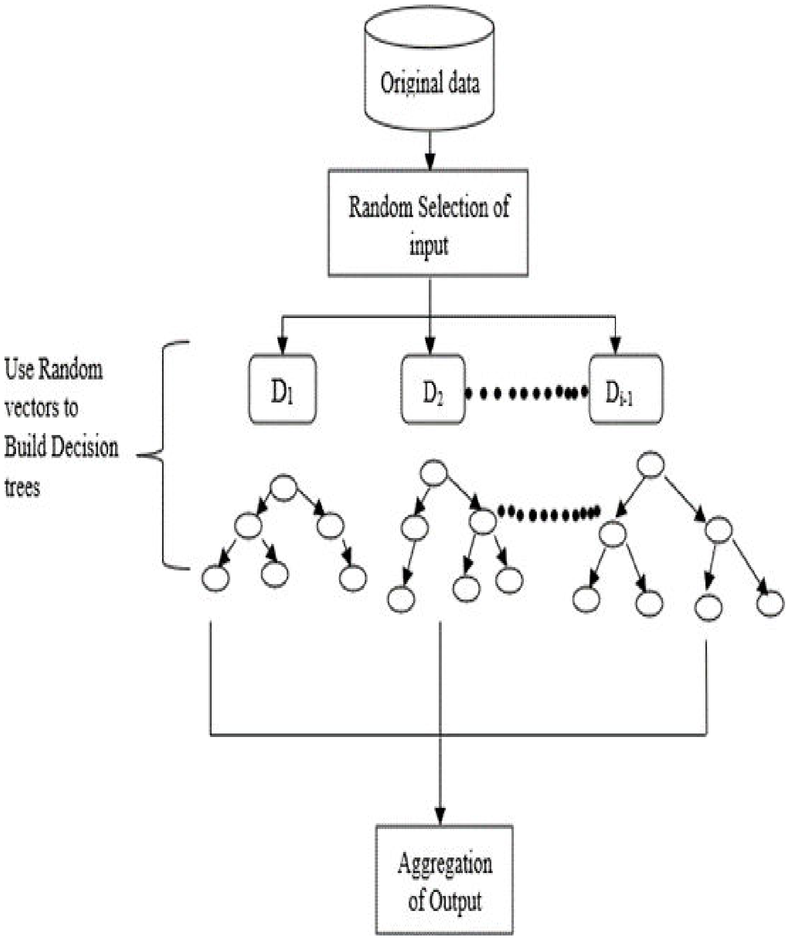
- **Workflow of Extra tree Classifier**



IV. PREREQUISITES

To follow along the reader will need the following:
1. Ensure Python installed on your system. You can download and install Python from the official Python website.
2. Ensure required libraries (numpy, sklearn, pandas, matplotlib, streamlit) are installed and imported.
3. Ensure a dataset available in the form of a CSV file.

V. RESULTS

After selecting the top 20 features based on feature importance, the model harnesses the sonar frequencies emitted and received during underwater exploration as input variables. These frequencies, representing various acoustic signals, capture essential characteristics of the objects encountered in the marine environment. Leveraging advanced algorithms, the model processes this data to discern intricate patterns and correlations indicative of distinguishing features between rocks and mines. By analyzing these features, such as signal strength, frequency variation, and echo patterns, the model can effectively discriminate between rocks and mines, enabling accurate classification. This predictive capability holds significant implications for naval operations, underwater resource management, and

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maritime safety, empowering decision-makers with timely insights to mitigate risks and optimize resource allocation in marine environments.

The figure showed in Fig. 1 is the top 20 features that are extracted based on feature importance using entropy criterion and the Fig. 2 represents the confusion matrix of the proposed model.

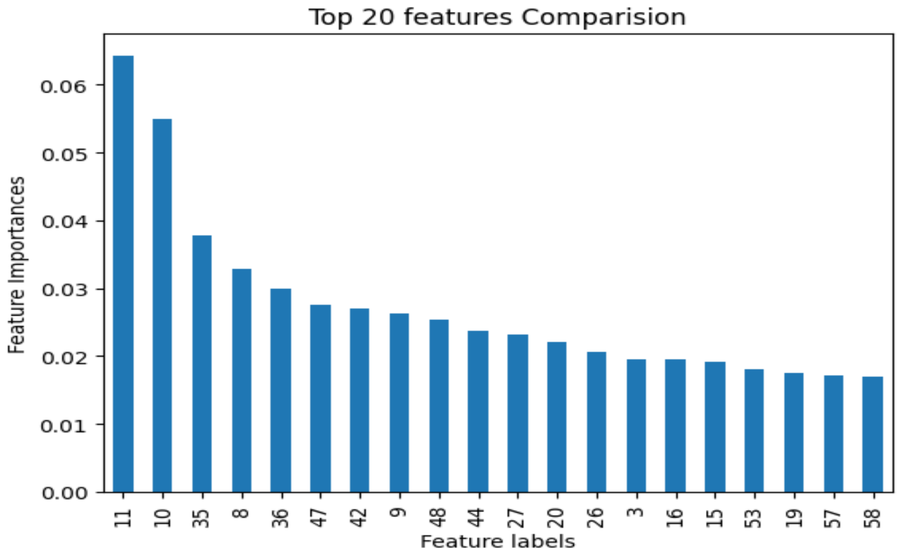

Fig.1. The top 20 important Features extracted

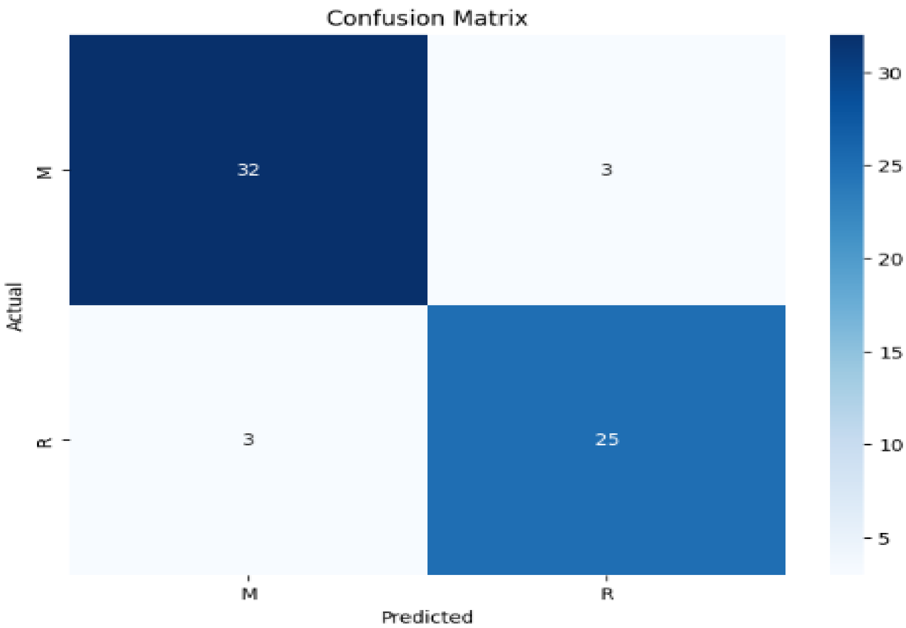

Fig. 2. Confusion matrix

VI. CONCLUSION

The project successfully implemented a predictive model using the Extra Trees Classifier to distinguish between underwater objects such as rocks and mines based on sonar signals. Through rigorous data preprocessing, model training, and evaluation, the classifier demonstrated high accuracy in differentiating between the two classes. Feature importance analysis provided insights into the key characteristics of sonar signals contributing to the classification task. The developed model holds significant implications for real-world applications, including underwater navigation,

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marine exploration, and defense, where accurate classification of sonar targets is crucial for safety and threat detection. Continuous monitoring and potential model refinement will be essential for ensuring its reliability and effectiveness in various underwater environments.

REFERENCES

[1] Jetty Bangaru Siddhartha, T. Jaya, V. Rajendran, RDNN for classification and prediction of Rock/Mine in underwater acoustics, Materials Today: Proceedings, www.elsevier.com/locate/matpr.

[2] Monika S, Shakthi Sagar M, Merin Meleet, "Prediction of Underwater Sonar Targets", International Journal of Advanced Research in Computer and Communication Engineering, Issue 7, July 2022.

[3] Sri Ramya Yaramasu, Uppada Sai Gayatri, Vadlamani Manjusha, Vaishna C Bhanu, Koda Indu. "Underwater Mine & Rock Prediction by Evaluation Of Machine Learning Algorithms". International Research Journal of Modernization in Engineering Technology and Science in Engineering Volume: 04/Issue:04/April-2022.

[4] Mine &Rock Prediction by Ensemble Machine Learning Algorithms, Vedururu Sireesha, Moulana Mohammed, K. Rajendra Prasad, Kypa. Jeevitha, 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)

[5] Elakkiya S, Jincy Francis, Rejina Parvin, Tamilmalar S.N, "Classification of Sonar Targets Using Advanced Neural Classifiers", International Journal of Pure and Applied Mathematics, Volume 114 No. 12, 2017, 627-637.

[6] Venkataraman padmaja, V. Rajendran, P. Vijayalakshmi, "Study on metal mine detection from underwater sonar images using data mining and machine learning techniques", Journal of Ambient Intelligence and Humanized Computing.

[7] P. Vinaya sree1, Ch. Bhavana2, D. Saiteja3, J. Saiteja Predicting Sonar Rocks Against Mines Using Machine Learning, JETIR, R November 2022, Volume 9, Issue 11

[8] K. Sivachandra; Kumudham. R; P Sathish Kumar; V. Rajendran; 978-1-6654-9260-7/23/2023 IEEE G. R. Jothi Lakshmi Rock / Mine Classification Using Supervised Machine Learning Algorithms

[9] Aakash Tiwari, Aditya Prakash, International Journal of Engineering and Technical Research (IJETR) ISSN: 2321-0869, Volume-2, Issue-9, September 2014 Improving classification of J48 algorithm using bagging, boosting and blending ensemble methods on SONAR dataset using WEKA

[10] Goran R. P, Sejnowski T.J, "Learned Classification of Sonar Targets using a Massively Parallel Network", IEEE pp 1135-1140

[11] Simon Fong, Suash Deb, Raymond Wong, and Guangmin Sun, Underwater Sonar Signals Recognition by Incremental Data Stream Mining using conflict analysis, Hindawi Publishing Corporation International Journal of Distributed Sensor Networks, Volume 2014, Article ID 63583.

[12] D. Williams, V. Myers, and M. Silvious, "Mine Classification with Imbalanced Data," IEEE Geoscience and Remote Sensing Letters, Vol. 6, No. 3, pp. 528-532, July 2009.

[13] Ningyi Sun, "Neural Network in Classifying Sonar Targets: Mines and Rocks", presented at the Association for Business Communications Conference, Australia, 2018.

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