Rock vs Mine Prediction and Detection for Aquatic Systems: A Comparative Analysis of Different Machine Learning and Deep Learning Algorithms

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***Abstract*— Deep machine learning approaches can enhance the forecasting and detection of rocks and minerals in water defense systems. This research focused on applying deep machine learning techniques to increase accuracy and efficiency in rock and mineral prediction. The researchers employed a series of watermarks that appeared and then utilized a convolutional neural network (CNN) to extract significant characteristics. Using transfer learning approaches and state-of-the-art optimization algorithms, researchers suggested a multi-class solution to identify between rocks and minerals. The suggested technique accurately predicted and recognized rocks and mines in underwater imagery, even in complicated settings with complicated against and illumination circumstances. The finding was essential for water protection and maritime safety systems, as it can assist in the automatic identification of rocks and minerals, decreasing the time and effort necessary for manual inspection**

Keywords*— Aquatic Defense, Neural Networks, Rock, Mine, Deep Learning, Prediction

I. Introduction

This work attempted to handle the challenge of differentiating rocks and mines in underwater settings for water defense systems. Timely detection and identification of possible hazards, such as mines, was necessary to assure the safety and security of water-based operations such as marine defense, maritime transit, and undersea infrastructure support. In recent years, fast progress in machine vision techniques, notably computer vision, has demonstrated promising outcomes in numerous object-detecting challenges. The research took use of these breakthroughs and offered a novel strategy that employed deep machine learning techniques to predict and detect underwater rocks and minerals. The major objective of this research was to construct an accurate and efficient system that can automatically recognize and distinguish stones and minerals in real-time. By applying deep learning models, the suggested system hoped to overcome the limits of current approaches and deliver dependable and automated solutions for water defense systems. Evaluation of the suggested system was done on a different test database by assessing performance indicators such as accuracy, precision, recall, and F1 scores. The findings of the experiment illustrate the usefulness and potential of deep machine learning algorithms in the prediction of rocks and mines and the identification of water defence systems. The study reported in this paper adds to the development of intelligent water protection systems employing the capabilities of deep machine learning techniques. Advanced technologies demonstrate the potential to considerably enhance the speed, precision, and reliability of underwater rock and mineral identification, hence boosting the safety and security of water-based enterprises and maintaining necessary resources such as water

II. Problem Identification

This work focused on the difficulty of discriminating between rocks and mines in aquatic circumstances using sophisticated machine-learning techniques. The purpose of the research was to build an effective prediction and detection system that may help improve water defense systems and lessen the potential risks connected with underwater mines. This research recognized many major challenges regarding submarine defense and mine-detecting systems:

A. Classification between rocks and minerals

Distinguishing submerged natural rocks from man-made minerals was a key challenge. Conventional methods of optical search or sonar-based identification sometimes struggle to effectively identify and classify things due to the complexity of submerged environments.

B. Limited availability of precise data

Collecting appropriate data to train machine learning models may be difficult, especially in underwater circumstances. The paucity of descriptive datasets, notably for the distinction of rocks and minerals, hampered the creation of accurate and trustworthy models for forecasting.

C. Complex underwater environment

The underwater habitat provided various obstacles such as variable water conditions, illumination, and confined vistas. These characteristics make it impossible to extract the features and patterns essential for trustworthy identification and classification.

D. Real-time performance

Real-time performance in water defence systems was important to detect and repel potential attacks. The study solves the difficulty of getting efficient and rapid results while keeping a high degree of accuracy in locating minerals and separating them from rocks.

E. Generalization to varied underwater situations

A trustworthy system should be able to generalize effectively to different underwater locations, depths, and environmental conditions. The research studied gets closer to ensuring that trained models can perform successfully in a range of real-life situations. Overall, this research article tackled the aforementioned issues by applying deep machine learning approaches to increase the accuracy and efficiency of anti-stone mine prediction and detection methods in water defence applications. By overcoming these difficulties, research helped to increase the safety and efficiency of water defence systems, hence decreasing potential threats and conserving key infrastructure.

III. Literature Review

Lots of experiments and investigations have been carried out in this ambit of the studies. In the sonar signals utilization, and the machine learning technique, classification and detection of mines and rocks have been made. [BTP1] The key purpose of this project, therefore, involves examining the group of binary classifier models that are built in Python and in the supervised machine learning format in a quest for accurate detection as the main target. [2] The predictive system described in detail in this module is more closely associated with the elements of machine learning supervised techniques which accounts for the record that includes 61 features and 209 samples. [3] the sensitivity analysis, which is a rock fall failure with computer training, is 80 blocks that fails each other. [4] when the SVM algorithm train the model on data set of the underwater objects the algorithm much appropriately. In the 5th part of this project, the RDNN classifier model with an accuracy level of 92.85% is developed. [6] she advocates the variety of methods such as LDA, SVM, KNN, CART and NB, but the result indicates that KNN classifier is better with an accuracy level of 95.24%. [7] the research work using cross-solod boost classifier for the overall classification accuracy having been no less than 88%. [8] Network Analogy (ANFIS), and kNN, the kNN is ranked one as the best of the three in terms of efficiency. Hence, the AI is a large framework that contains the classical image processing algorithms as well as the neural network which facilitates the construction of the automatic system. [10] go into the way of applying deep neural nets in sonoar target recognition, including CNNs, RNNs, and autoencoders. At present SONAR imagery is the most suitable functionality like real-time monitoring that is implemented in the non-supervised mode. [12] The good dynamic object segmentation in precision sonar imaging algorithm proposed by the investigate was the right one. [13] such system is important for architecture of neural networks, which were built for object detection with side scan sonar images faciliation is faced. [14] is supported with Random Forest, SVM, and Decision Tree technique that are different from each other compared to our rock and mine scaled models with significant improvements. [15] include the Gorman's et al. Networks for the classification of SONAR returns. [16] employs KNN, SVM, RF, and the Decision tree frameworks on the UCI dataset. RF, as a classifier, gives the best results with 90.2% accuracy. [17] is based on the working model of the Deep CNNs and its detection is performed in underwater images that have exceptional performance. [26] is compared the results over multiple deep learning architectures to find the most accurate results. [27] help in efficient feature selection (FS) plays an ornamental role in improving the overall performance of machine learning (ML) frameworks. [28] Helps in ML and DL methods for holes in these security solutions that demand strategies are then highlighted. [29] Machine learning (ML) techniques can uncover hidden patterns and other important facts from the huge amount of health data that traditional analytics can't find in a reasonable length of time.

IV. Methodology

The data source for this project is Kaggle (which a publicly available statistical project database) and preprocessing with data cleaning is executed. Later after the training and test split of the dataset in the ratio of 7:3, four proposed algorithms such as Logistic regression, Random Forest, Support Vector machine, Recurrent Deep neural network are chosen to be compared on the grounds of model performance, model interpretability, data dimension reducer, non-linear boundaries and deep learning capability with availability of resources needed to provide an efficient and economical model.

Ensemble of the decision trees makes more than one decision tree during the training and, thus, the finalized model by this method serves as the foundation for future classification differentiation. At the backside it is able to come out with the final prediction by means of either averaging the predictions made by various trees or by taking the mean of the final result as a whole. The logistic regression in line with linear model, the logistic function which is produced as a result of input features is mapped to the binary outcomes. The SVM process is a classification machine which has the capacity to identify the optimal hyperplane which imposes the largest distance between two classes that can be divided by it. For a mathematical tool, SVM always purports to make any optimization problem convex in order to make out the exact decision boundary. RDNN is a deep neural network variant which special in RBF hidden units that are advanced on the basis on radial basis function. It uses the notion of RBFs in transforming the input data into a high-dimensional space that is then used in the method of a linear classifying layer.

V. DATASET AND ALGORITHMS DISCUSSED

The dataset used here is publicly available in Kaggle (https:The data set //www.kaggle.com/code/sugamkhetrapal/project-3-sonar-mines-vs-rocks/input) as sonar.all-data.csv. Here in the dataset, the pattern's representation is given as a set of numbers in the range of 0.0 to 1.0 that constitute up to 60 numbers. This resonance is formed by the number that is produced at a particular frequency band. This number represents the energy that is produced in a certain time interval. Label attached to every individual record can show character R when this record is about rock or indicate M for a metal object (a mine). The numbers that are shown in the labels are arranged in a sequence of aspect orientation with the lowest angles on the right. However, the digits do not contain the angle itself.

A. Logistic Regression

Logistic regression is among the most popular modeling methods for classification-type problems. This is based on the logic of fitting a logistic function to the data, which is to say that the input features depend on the given chance class of belonging as in Eq [1.1]. For the scenario, we receive "rock" and "mine" classes as the input attributes.

$$\ln\left(\frac{P}{1-P}\right) = a + bX$$

$$\frac{P}{1-P} = e^{a+bX}$$

$$P = \frac{e^{a+bX}}{1+e^{a+bX}}$$

Eq. 1.1: Basic Equation for the Logistic Regression

Logistic regression explored the weights and biases that diminish the discrepancy between projected probability and actual grade scores. The learning model may then be used to forecast whether specific sonar findings can be regarded as acceptable for rock or metal.

B. Recurrent Deep Neural Networks(RDNN)

A deep recurrent neural network is a form of neural network architecture designed to analyze structured input such as sequences or trees. In our example, sonar data may be characterized as a sequence of measurements.

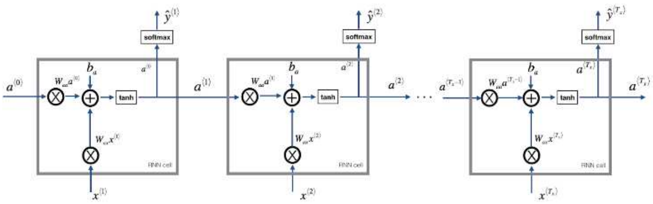

Fig 1.2: Basic RNN Model

R-DNN analyzed input sequences by capturing local and global dependencies as shown in Fig [1.2] in the basic RNN model. This design enables the model to investigate complicated patterns and relationships in the data. By training R-DNN on sonar data and related rock and mineral records, we may construct algorithms that can foresee new classes of sonar readings. A basic RNN cell can be seen in Fig. [1.3].

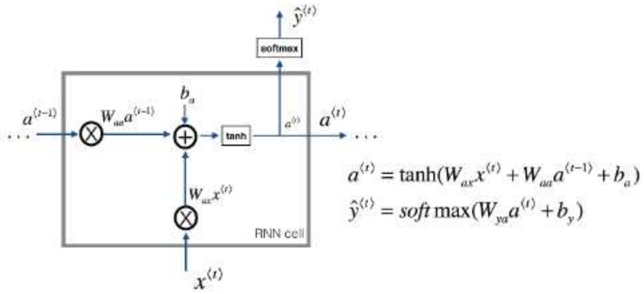

Fig. 1.3: Basic RNN Cell.

C. Support Vector Machines (SVM)

Support vector machines are sophisticated supervised learning models that may be utilized in classification and regression situations. SVMs try to discover the hyper-plane that separates data points from distinct classes by the highest margin as shown in Eq. [1.4].

$$\textit{Primal Form for non} - \textit{perfect seperation}$$

$$\min_{w,b,\{\beta_n\}} \frac{1}{2}||w||_2 + C\sum_n \beta_n$$

$$s.t.\ \ y_n\left[w^T\phi(x_n) + b\right] \geq 1 - \beta_n\ ;\ \forall n$$

$$\beta_n \geq 0\ ,\ \forall n$$

$$\frac{\partial L}{\partial w} = w - \sum_n \alpha_n y_n \phi(x_n) = 0 \Rightarrow w = \sum_n \alpha_n y_n \phi(x_n)$$

$$\frac{\partial L}{\partial b} = \sum_n \alpha_n y_n = 0 \Rightarrow \sum_n \alpha_n y_n = 0$$

$$\frac{\partial L}{\partial \beta_n} = C - \alpha_n - \lambda_n = 0 \Rightarrow C - \alpha_n - \lambda_n = 0$$

$$max_{\{\alpha_i\}}\, g(\{\lambda_n\},\{\alpha_n\}) = \sum_n \alpha_n + \frac{1}{2}\sum_n \alpha_m\alpha_n y_m y_n \phi^T(x_m)\phi(x_n)$$

$$\alpha_n, \lambda_n \geq 0\ ,\ \forall n\ ;\ \sum_n \alpha_n y_n = 0\ ;\ C - \alpha_n - \lambda_n = 0$$

Eq. 1.4: Derivation of the final dual form equation for Support Vector Machines starting from Primal and Lagrangian form

In terms of rock vs mine prediction, SVM learned the decision boundary that maximized the distance between rock and mine in the feature space. SVMs can employ different kernel functions to address nonlinear connections in the data. By training an SVM on sonar data, the model can be developed that can predict if a given sonar reading may be regarded as good for rock or ore.

D. Random Forest

Random forest is one of the types of ensemble learning that employs decision trees. It is diverse, meaning that it settles an issue by employing various decision trees at a time and that is how predictions are obtained. Each tree is constructed on a randomly falling portion of the data, and the final forecast is derived by totalling predictions from all separate trees. We can do it by mentioning the kernel function equation which can be written as Eq. (1).[1.5].

$$K_k^{cc}(\mathbf{x},\mathbf{z}) = \sum_{k_1,\ldots,k_d,\sum_{j=1}^d k_j = k} \frac{k!}{k_1!\cdots k_d!}\left(\frac{1}{d}\right)^k \prod_{j=1}^d \mathbf{1}_{\lceil 2^{k_j}x_j\rceil = \lceil 2^{k_j}z_j\rceil},$$

$$\text{for all } \mathbf{x},\mathbf{z} \in [0,1]^d.$$

Eq. 1.5: Corresponding kernel function, or connection function for Random Forest

Random forests can manage complicated relationships between features and are resilient to redundancy. By training a random forest on sonar data, we constructed a model that leveraged the collective knowledge of many trees to categorize fresh sonar signals as rocks or mines.

VI. PROPOSED SYSTEM DESIGN

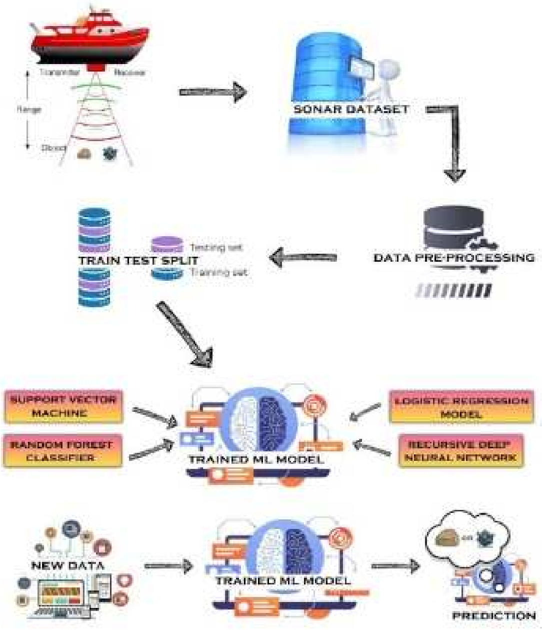

Fig 2: Graphical Abstract for the proposed system design

Fig [2] described the detailed methodology proposed in the system of this extensive research work.

VII. RESULTS AND DISCUSSIONS

The system on which the deep neural networks were implemented and the dependencies used for the successful training and implementation of the model:

Processor: 11th Gen Intel(R) Core (TM) i5-11400H @ 2.70GHz 2.69 GHz
Memory: 24.0 GB (23.7 GB usable)
Disk: NVMe Micron_2450_SSD (512GB)
Network: MediaTek Wi-Fi 6 MT7921 Wireless LAN Card (100Mbps up and down)
GPU 1: Intel® UHD Graphics 6000
GPU 2: Nvidia GeForce RTX 3050 Ti Laptop GPU
Dependencies and packages: TensorFlow, Keras, CUDA Toolkit, matplotlib, and cuDNN libraries should be configured as per the GPU available. In my case, I used TensorFlow version 2.10.0 with CUDA version 11.2 and cuDNN library 8.1.

In this research work, a comparative examination of multiple machine-learning methods for predicting and detecting rocks and minerals in water defense systems was done. Specifically, the performance of Logistic Regression, Recurrent Deep Neural Networks, Support Vector Machine, and Random Forest algorithms were evaluated.

Also, a proof of Logistic regression model accuracy on the test data was made, and 0.7619 exactness has been reached. The testing of the regression logistic model is undertaken for both the training and test data sets and the ROC curve is plotted at [Fig 2.1] as shown. Nevertheless, the precision-recall curve could be an intended benefit from the stepwise investigation of the model's outcomes as it represented in [Fig 2.2.] An accuracy level of 90.47% was achieved for the deviated detector neural network algorithm, meaning that almost 90.5% of the test set samples were classified correctly. The accuracy of the model for both predictive values and mineral discrimination can be witnessed as is presented in Fig. 2.3. RDNN (Rocks and Minerals Detector Network) algorithm showed a great performance with an F1 score of 0.875, and this score demonstrates the balance between the accuracy and recall, which indicates the usefulness depth of this algorithm in detecting the proper rocks and mines [Fig 2.4]. The ROC AUC value of 0.899 was achieved by the RDNN algorithm during classification; this means that the algorithm was efficient and could correctly point out rocks from the minerals as depicted in the graph as shown in [Fig 2.5]. If people are able to remember more about these systems it means that the fence identification is becoming better, which is not less critical when it comes to water defense as it reduces the possibility of the threat not being recognized. It was discovered that with an F1 score being combination of precision and recall, SVM method scored as a 0.667. F1 score index was a benchmark of balancing precision and recall as shown in [fig 2.7]. The performance of Bagging Vegetable Classification SVM model was represented by confusion matrix that indicated the number of true positives (20), true negatives (11), false positives (7), and false negatives (4) as the results of classification. It appeared that the SVM algorithm demonstrated a better performance, i.e., the algorithm made fewer errors (false positives and false negatives) versus the number of correct predictions (true positives and true negatives) shown in the Fig 2.8. In a random forest approach, 78.57% of data was successfully categorised. The performance report of the model has given a detailed overview by computing the accuracy, recall, and F1-score for the each class (mine and rock) individually as illustrated in the ROC step shown in [Fig.2.9]. The M class was the highest for random forest algorithm , the score is 0.81; and as for the R class, the score is 0.71. The concept of the points where the tradeoff ranges between precision and recall for various thresholds can be drawn from the Fig 2.10 In the case of metrics of accuracy, recall and F1 scores, they were also close to 100%, which indicates the highest efficiency of random forest algorithm in identifying mines and rocks. The modeling often misses a few objects and vice versa, which is also demonstrated in the figure below, as seen in Figure [2.11].

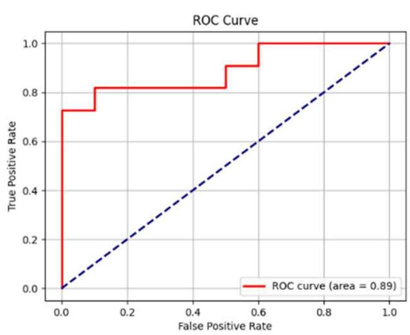

Fig 2.1: ROC Curve for Logistic Regression analysis

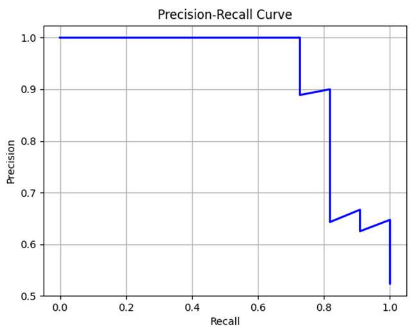

Fig 2.2: Precision-Recall Curve for Logistic Regression

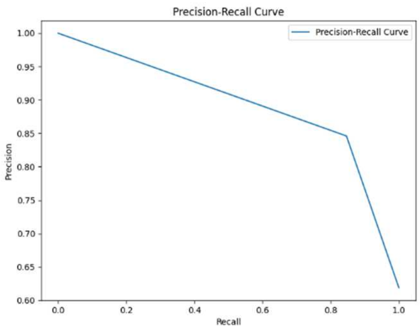

Fig 2.3: Precision-Recall Curve for RDNN

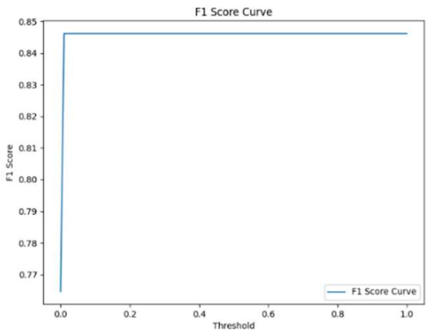

Fig 2.4: F1 Score Curve for RDNN

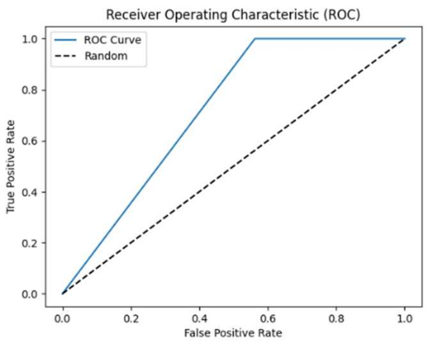

Fig 2.5: Receiver Operating Characteristic Curve for RDNN

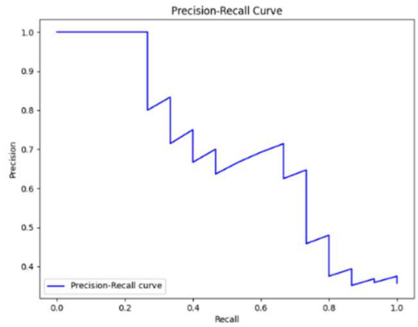

Fig 2.6: Precision-Recall Curve for SVM

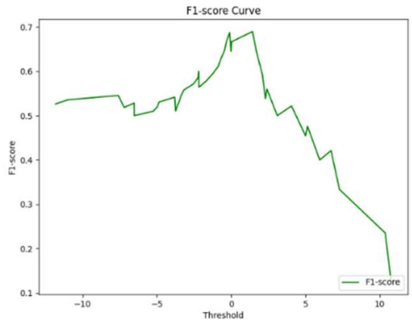

Fig 2.7: F1-Score Curve for SVM

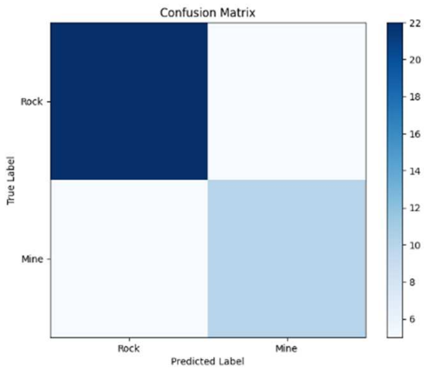

Fig 2.8: Confusion Matrix of proposed SVM model

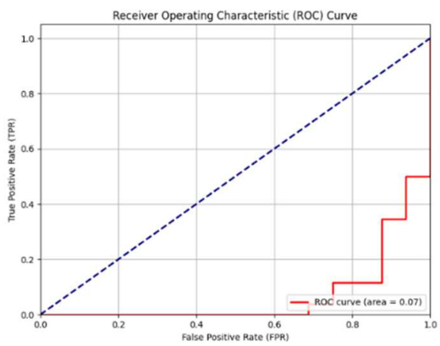

Fig 2.9: ROC Curve for proposed Random Forest model

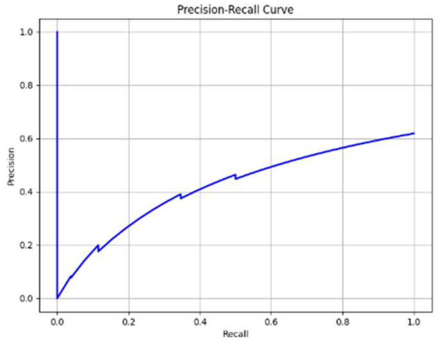

Fig 2.10: Precision-Recall curve for Random Forest

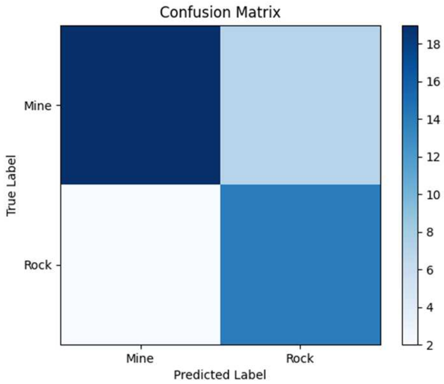

Fig 2.11: Confusion Matrix for Random Forest

VIII. Comparative study

In summary, the comparison research demonstrates that all four algorithms have strengths and drawbacks in predicting and identifying rocks and minerals in the water defence system. RDNN and random forest algorithms offer improved performance with high accuracy, precision, recall, F1 score, and ROC AUC score compared to Logistic Regression and SVM. However, more investigation and assessment may be necessary to establish the most effective algorithm for specific applications in water defence systems.

A graph is well presented below to demonstrate a comparative analysis of the various outputs of different algorithms as shown in Fig [3].

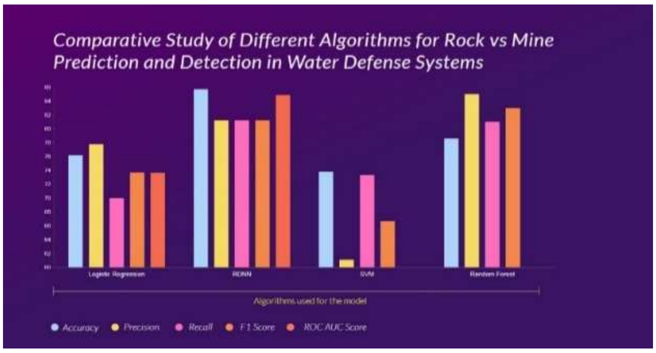

Fig 3: Comparative study of different algorithms for Rock vs Mine Prediction

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