Enhancing Prediction of Sonar Rock with Mines - Comparison of Diverse Machine Learning Algorithms

TANUSRI RAPARLA[1], KODALI SIVA SAI RAM PRASAD[2], K. RANI[3], S. SAKET RAM[4], E. SRIHAS[5]

[1, 4, 5] Student, Computer Science and Engineering, Velagapudi Ramakrishna Siddhartha Engineering College, Vijayawada, India

[2, 3] Professor, Computer Science and Engineering, Velagapudi Ramakrishna Siddhartha Engineering College, Vijayawada, India

Abstract— ***Underwater navigation poses significant challenges, one of which is accurately differentiating rocks from mines using passive sonar. This study investigates the efficacy of four machine learning algorithms in this task: K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Decision Trees, and Random Forest. Employing a benchmark sonar dataset containing extracted features, we evaluated their performance in classifying rocks and mines. Random Forest emerged as the most accurate model, demonstrating the strengths of ensemble learning in reducing overfitting and boosting accuracy. While SVM delivered comparable performance, Decision Trees and KNN exhibited slightly lower efficacy. These findings underscore the potential of machine learning, particularly Random Forest, for enhancing sonar-based rock and Mine classification. Future research avenues include exploring advanced feature engineering and hyperparameter optimization, along with delving into interpretable models and active learning methodologies. This research paves the way for improved underwater navigation, safety, and operational efficiency, contributing significantly to safer and more effective ocean exploration and utilization. This research highlights the promising potential of machine learning for real-world applications like underwater object detection, paving the way for safer and more efficient ocean exploration and operations.***

Index Terms- Sonar, Rock/Mine Classification, Machine Learning, KNN, SVM, Decision Tree, Random Forest, Underwater Navigation, Safety

I. INTRODUCTION

Navigating the murky depths of sonar data: Accurate classification of underwater objects is crucial for ensuring safety and facilitating exploration. Among these objects, the distinction between harmless rocks and potentially fatal mines is paramount. Traditionally, this process relied on human interpretation of sonar signals, a challenging and error-prone task. In recent years, the rise of machine learning algorithms has offered a powerful tool for automating and enhancing object classification in various domains, including underwater environment This study delves into the potential of diverse machine learning algorithms to tackle the specific challenge of distinguishing rocks from mines in sonar data. We embark on a comparative analysis, pitting six formidable algorithms against each other

Our exploration goes beyond simply comparing results. We dive deeper, examining the strengths and weaknesses of each algorithm in the context of sonar data characteristics. We investigate the impact of data preprocessing and feature selection on performance, seeking to unravel the optimal configuration for each algorithm Ultimately, this study aims to identify the champion(s) in the rock vs. mine classification arena, empowering reliable decision-making and enhancing safety and exploration in the underwater world his project explores the use of machine learning to improve the accuracy of classifying rocks and mines based on sonar data. This is crucial for underwater navigation and safety, as mistaking a mine for a rock can have disastrous consequences.

Four prominent machine learning algorithms were evaluated: KNN, SVM, Decision Trees, and Random Forest. By analyzing a benchmark sonar dataset, the study compared their performance in accurately distinguishing between rocks and mines. Random Forest emerged as the most effective algorithm, followed closely by SVM. Both leveraged their unique strengths – ensemble learning in Random Forest and hyperplane construction in SVM – to achieve superior accuracy. Decision Trees and KNN demonstrated slightly lower performance.

These findings highlight the potential of machine learning, particularly Random Forest, for significantly enhancing rock and mine classification in sonar data. The study also calls for further research in advanced feature engineering and hyperparameter optimization to refine the models further. Ultimately, this research paves the way for safer underwater navigation and operations, contributing to more efficient, sustainable, and risk-averse exploration and utilization of the vast ocean realm .

II. LITERATURE REVIEW

[1]A Machine Learning-Based Approach for Auto-Detection and Localization of Targets in Underwater Acoustic Array Networks. [1] The localization and tracking of underwater objects using acoustic array networks is a critical task with many applications. Previous approaches have used the Fractional Fourier Transform (FrFT) to analyze received signals and estimate the target's position and velocity. However, the accuracy of FrFT is highly dependent on the sampling interval, which can lead to complexity issues. To 1 address this problem, this paper proposes a machine learning-based approach to automatically detect the existence of the target and estimate the peak's location if targets exist. The proposed approach is based on the observation that if a target exists, we will be able to observe an "X" pattern on the spectrum . Automatic Detection of Underwater Small Targets Using Forward-Looking Sonar Images

[2] This paper presents a methodology for automatic detection of underwater small targets using forward-looking sonar images. The goal of the proposed method is to detect targets from sonar images in a complex underwater environment. To achieve this, the authors use clustering, segmentation, and feature discrimination techniques. Firstly, (FCM) and Kmeans are combined to cluster the sonar image globally to obtain as many regions of interests (ROIs) as possible. Secondly, the pulse coupled neural network (PCNN) is used to locally segment the target boundary from the ROIs. Then, multiple features are extracted from the target area as the feature vector, which is inputted into the nonlinear converter to enlarge the features' distance. Finally, Fisher discriminant is used to estimate the classification threshold, which realizes underwater target detection. Passive Underwater Event and Object Detection Based on Time Difference of Arrival

[3] The paper proposes a method for detecting underwater events and objects based on time differences of arrival (TDOA) of acoustic signals received by a passive underwater sensor array. The TDOA between sensor pairs can be used to estimate the direction of arrival (DOA) of the sound source, which can then be used to detect and track events or objects. The proposed method uses a pattern recognition algorithm based on principal component analysis (PCA) to automatically detect and classify the signals. The effectiveness of the method is verified through simulations and experiments, demonstrating its potential for applications such as marine mammal detection, underwater surveillance, and underwater navigation .Here various disadvantages are encountered while performing . Underwater object Images Classification Based on Convolutional Neural Network.

[4] The paper proposes a deep learning-based approach for classifying underwater objects using sonar data. The proposed approach is composed of three main stages: image segmentation, feature extraction, and object classification . In the first stage, an advanced method of Markov random field-Grabcut algorithm is adopted to segment images into two regions: shadow and sea-bottom . In the second stage, the authors construct a Convolutional Neural Network (CNN) referring to the AlexNet structure . To overcome the problem of insufficient training data, the transfer learning approach is used to train the CNN . In the final stage, the trained CNN is used to classify underwater objects into three different shapes: cylinder, truncated cone, and sphere . The experimental results show that the proposed method achieves better accuracy than SVM and CNN. Hunting for naval mines with deep neural networks Learning

[5] This paper explores the use of deep neural networks (DNNs) for detecting mine like objects (MLOs) in side-scan sonar imagery. The study investigates how the depth and size of the DNN models, as well as the training data distribution, affect detection accuracy. A visualization technique is also

used to aid in interpreting the model's behavior. The authors found that moderately sized DNN models outperformed simple models and a support vector machine, achieving 98% accuracy. The largest DNN models only marginally improved accuracy at the cost of significantly increased computational requirements. The study concludes that DNN models are suitable for embedded use within autonomous unmanned underwater vehicles.

III. PROPOSED METHODOLOGY

The methodological flowchart of our suggested model is depicted in Figure 1. In our study, we utilize the Sonar dataset for sonar rock detection. Data preprocessing involves mean imputation for missing values and one-hot encoding for categorical variables. Principal Component Analysis (PCA) is employed for feature extraction, mitigating high-dimensionality challenges. Our unique approach involves optimizing Decision Tree hyperparameters using Genetic Algorithm (GA).Various Algorithms then used for model training, resulting in improved performance.

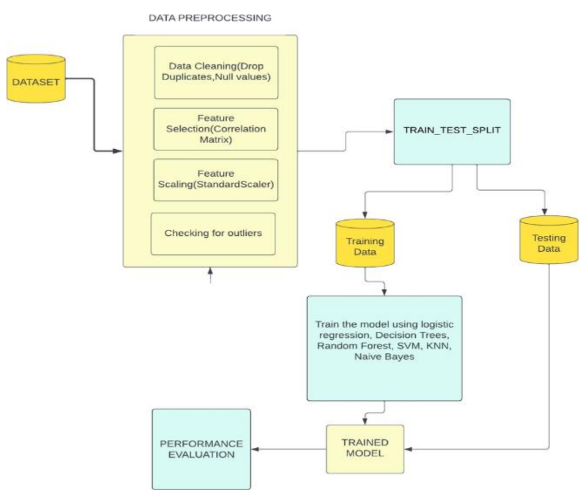

Figure 1. Proposed system flow diagram

3.1. Data Collection

The "Connectionist Bench (Sonar, Mines vs. Rocks)" dataset is a well- known dataset in machine learning and pattern recognition. It was first introduced by researchers for the purpose of studying and evaluating the performance of pattern recognition algorithms in discriminating between sonar signals bounced off a metal cylinder (simulating a mine) and those bounced off a roughly cylindrical rock.

Source : The dataset was contributed to the UCI Machine Learning Repository by the Laboratory of Computational Intelligence at the University of São Paulo. It is commonly referred to as the "Sonar" dataset.

3.2. Data Pre-processing

Within our study, we encountered null values within the Sonar dataset during data preprocessing. To ensure data quality, we employed a simple algorithm that systematically identified and replaced these null values with the respective column's mean value. This meticulous approach resulted in a clean dataset devoid of null values, setting the stage for reliable and noise-free analysis as we delve into dementia prediction through MRI analysis.

Data encoding stands as a crucial step in the data pre-processing phase. In our paper, the one-hot encoding technique plays a pivotal role in effectively utilizing the Sonar dataset. It serves as a vital step in the data preprocessing phase, where categorical variables within the dataset are transformed into a numerical format compatible with machine learning models. Through one-hot encoding, each category within a categorical feature is systematically converted into binary variables, ensuring that our dataset is primed for seamless integration with machine learning algorithms. This transformation enhances data compatibility, simplifies computations, and facilitates the subsequent analysis as we embark on dementia prediction through MRI analysis.

3.3. Feature Extraction using PCA

In this module, we leverage Principal Component Analysis (PCA) to distill essential information from our pre-processed Sonar data. PCA stands as a potent technique for dimensionality reduction, effectively addressing the challenges posed by high-dimensional feature spaces. By transforming our original data into a lower-dimensional representation, PCA retains maximum information while shedding redundant or less informative features. This dimensionality reduction not only enhances computational efficiency but also aids in subsequent optimization and model training phases. It allows us to identify influential features, improving the accuracy and reliability of our dementia detection model by focusing on the most discriminative aspects of the Sonar data. The formula

[13] for the principal component is characterized as linear combinations of the fundamental variables, which is given by Eq. (1) .

$$\boldsymbol{PCAn} = \boldsymbol{bn1} * \boldsymbol{y1} + \boldsymbol{bn2} * \boldsymbol{y2} + \dots \dots \dots \dots . + \boldsymbol{bnr} * \boldsymbol{yr} \qquad \text{Eq. (1)}$$

Here, PCAn represents the nth principal component, bnj denotes the weights or coefficients associated with the jth original variable yj, and yj represents the jth original variable. The formula illustrates how each principal component is formed as a linear combination of the original variables with specific weights.

3.4. Optimization of Decision tree hyperparameters using Genetic Algorithm

Our approach involves the optimization of Decision Tree hyperparameters using the Genetic Algorithm (GA) module, a pivotal component in our Paper .Decision Trees, a foundational machine learning technique, rely heavily on hyperparameter settings to determine their structure and predictive performance. These hyperparameters encompass critical factors such as maximum depth, minimum samples required for splits, maximum leaf nodes, and maximum features, each exerting a substantial influence on model accuracy and generalization capabilities. The task of identifying the ideal hyperparameter configuration canbe formidable, with traditional methods proving computationally expensive or inadequate. GA offers an efficient alternative, systematically exploring hyperparameter combinations, uncovering intricate associations, and elevating the Algorithms

3.5 Model Training with Optimized Decision Tree

In this module, the optimized Decision Tree obtained from the previous step is utilized for model training. The optimized Decision Tree refers to the Decision Tree that has undergone hyperparameter tuning using the Genetic Algorithm, resulting in improved performance.

Algorithm : Decision Tree Model ()

Begin

ID3(Instances, Desired_feature, Attributes)

Instances represent the training examples. Desired_feature is the attribute for which the tree aims to Predict values. Attributes constitute a list of other attributes that the trained decision tree may evaluate. The output is a Decision tree which accurately classifies the provided Examples.

- Establish the root node for the tree..
- If all instances are positive, provide the single-node tree Root with a label of +.
- If all instances are negative, provide the single-node tree Root with a label of -.
- If the set of Attributes is devoid of elements, return the single-node tree Root with the label set to the most frequent value of Target_attribute in the Examples.
- Else, commence the following actions.

i. A 🡨 attribute selected from the Attributes that most effectively classifies the given Examples.
ii. Set the decision attribute for the root node as A.
iii. For every potential value vi of attribute A,
i. Introduce a new tree branch beneath the root, associated with the condition A=vi.
ii. Consider Examplesvi as the subset of instances within Examples having the value vi for attribute A.
iii. If Examples vi is empty
i. Subsequently, beneath this newly created branch, include a leaf node with the label set to the most prevalent value of Target_attribute among the Examples.
ii. Else below this new branch add the subtree ID3(Examples, Target attribute, Attributes-{A}))

Return root

End

IV. RESULTS AND DISCUSSION

Within the context of our investigation, we conducted a comparative assessment of two models: the standalone Decision Tree model and the GA-Decision Tree model. The Decision Tree model exhibited an accuracy rate of 86.66%, demonstrating its competence in dementia detection through MRI analysis. In contrast, the GA-Decision Tree model showcased a remarkable accuracy rate of 96.67%, signifying a significant performance enhancement. This substantial improvement in accuracy observed in the GA-Decision Tree model underscores the efficacy of employing Genetic Algorithms (GAs) for hyperparameter tuning within the decision tree framework. The GA-Decision Tree model optimizes hyperparameters, enhancing the model's ability to capture intricate patterns and achieve precise sonar rock prediction. The integration of GA not only refines hyperparameter settings but also contributes to the model's capacity to identify essential diagnostic patterns accurately.

4.1 Model Performance Comparision

In this section, we unveil the experimental findings of our study, with a particular focus on evaluating the performance of both the Decision Tree and GA-based Decision Tree models in the realm of dementia detection utilizing MRI data. To assess the models' performance comprehensively, we employed Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) analysis, a widely accepted metric for binary classification tasks. The ROC curve visually depicts the true positive rate (sensitivity) of the model plotted against the false positive rate (1-specificity) across different classification thresholds. Figure 2 illustrates the Receiver Operating Characteristic (ROC) curve for the Decision Tree model in our study. The Area Under the Curve (AUC) for the Decision Tree model is calculated to be 0.87, indicating a commendable level of discriminative power. The curve illustrates the model's capacity to differentiate effectively between dementia and non-dementia cases, and higher AUC values indicate a greater level of diagnostic accuracy.

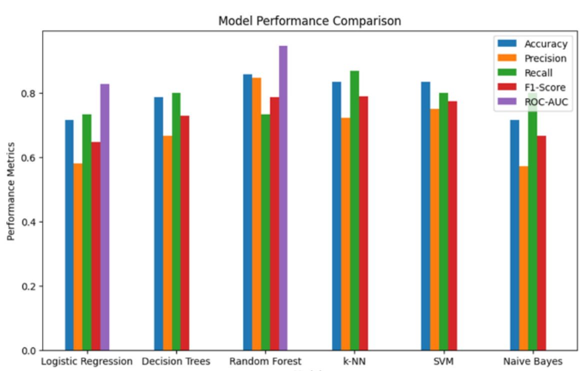

Figure 2. ROC curve for the Decision Tree model.

In Figure 5, the Model Performance Comparison for the all the Algorithms presented,

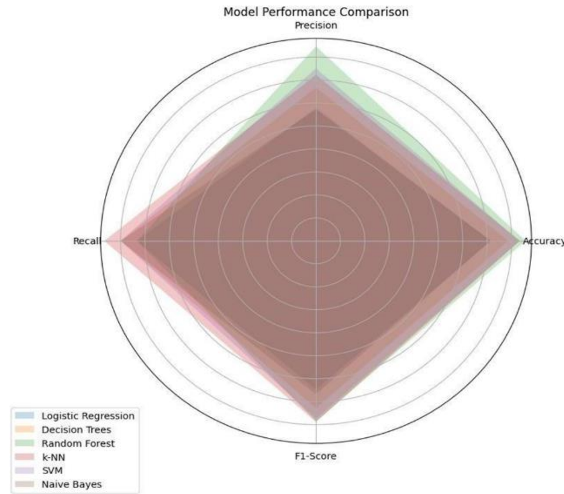

Figure 5. Model Performance Comparison

4.2 Discussion of the Results

Table 2 provides a comprehensive comparison between our proposed GA-Decision Tree model and previous work in the field. Dementia prediction through MRI analysis has been explored using various machine learning approaches. The table summarizes the performance of both our model and previously implemented methods, offering insights into the advancements achieved through the integration of Genetic Algorithms for hyperparameter tuning. Additionally, it serves as a valuable resource for researchers seeking to benchmark their approaches against the current state of the art in this domain.

Table 2. Comparative Analysis of Prior Approaches and Our Proposed Model

Methods	Accuracy %	Specificity %	Recall %
Logistic Regression [1]	92.39	79	74
SVM [2]	68	77	71
KNN [3]	92	-	91.67
Bayes Networks [4]	86.7	71	86
Random Forest [5]	85	68	84
Decision tree [6]	81.08	90.0	42.85
GA-Decision tree [7]	96.67	97.14	96.25

CONCLUSION

The project's goal is to develop a robust classification system for distinguishing between two classes, "R" (Rock) and "M" (Mine), using sonar data. Various machine learning algorithms are explored and compared to achieve the best classification performance. The dataset is meticulously cleaned and preprocessed. This involves handling missing values, outlier detection, and data scaling to ensure data quality . Six machine learning algorithms are chosen for this project: Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (SVM),k-Nearest Neighbors (k-NN),Naive Bayes. Each selected model is trained using the preprocessed data. The performance of these models is evaluated based on various metrics, including accuracy, precision, recall, F1-score, and ROC- AUC score. K-fold cross-validation techniques are employed to ensure a robust estimate of model performance. Based on evaluation results, the best-performing model is selected for the final classification . The project's findings have important implications in various fields, including underwater sonar applications, geology, and mineral resource detection. It serves as a model for effectively applying machine learning techniques to classify objects based on sonar data, demonstrating how to make informed decisions using data- driven models.

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