Utilization of Machine Learning in Recognition of Rocks and Mock-mines by Sonar Chirp Signals

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Abstract

The constant evolution of technology has paved the way for innovative solutions in various domains, with Machine Learning (ML) emerging as a powerful tool for signal processing and pattern recognition. This research delves into the application of ML techniques for the identification of rocks and mock-mines utilizing sonar chirp signals. The study employs a comprehensive approach, integrating classical ML algorithms and neural network architectures to discern subtle differences in the sonar signals. This investigation encompasses key ML methods such as Logistic Regression, Decision Trees, Random Forests, and sophisticated models like Neural Networks with Dropout and L2 Regularization. Throughout the experimentation, emphasis is placed on tackling overfitting issues, a common concern in signal processing tasks. The results showcase the effectiveness of the applied ML models in accurately discriminating between rocks and mock-mines. Notably, the integration of dropout techniques and L2 regularization demonstrates enhanced generalization and resilience against overfitting. This research not only contributes to the expanding field of ML applications but also holds practical implications for underwater detection systems. The findings have potential applications in naval security, environmental monitoring, and marine exploration. By leveraging ML capabilities, enhancement in the precision and reliability of sonar-based recognition systems can be achieved, addressing real-world challenges in underwater environments.

Keywords

Machine Learning, Sonar Chirp Signals, Signal Processing, Underwater Exploration.

1. Introduction

The modern world is experiencing great transformations in all fields of science and technology, and one of the most important areas is the use of artificial intelligence and machine learning to solve various tasks. One of these important tasks is the recognition of objects based on the analysis of signals that can be sent or received through various channels and sensors. One of such areas is hydroacoustic research and the use of sonar systems to identify underwater objects, since sonar is used for exploring and mapping the ocean (sound waves travel farther in the water than do radar and light waves) [1]. Underwater target recognition has many applications. It is crucial to realizing crewless underwater detection missions has significant prospects in both civil and military applications [2].

The application of machine learning in hydroacoustic research is becoming more and more relevant, as it allows to automate the processes of processing and analyzing signals coming from sonar systems. One of the key tasks in this area is the recognition of underwater objects, such as rocks and mock mines, using the analysis of sonar signals. Building an effective model to recognize these objects can be a challenging task, especially when dealing with large amounts of data and training a complex model.

This work is aimed at studying and researching the possibilities of using Machine Learning for the automated recognition of rocks and mock-mines in signals collected by sonar systems. Different methods of signal processing and analysis are considered, the selection and training of Machine Learning models, as well as the evaluation of their effectiveness. Also improvement in the accuracy of the model using methods to overcome overfitting is considered and studied, since overcoming overfitting allows us to achieve generalization of the model. Within the framework of the work,

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already existing models for solving this problem are also considered and, with the help of the previously mentioned methods, the results are improved.

The goal of this work is to develop a system that can identify and classify rocks and mock-mines with high accuracy, helping to improve the safety and efficiency of various marine and hydroacoustic activities. The goal of this paper involves the application of Machine Learning methods and models for the recognition of objects underwater based on sonar chirp signals. Specifically, the main goal is to create a classification system (AI model) that is able to distinguish signals corresponding to rocks from those associated with mock-mines. Tasks include collecting and preparing input data, analyzing and processing sonar chirp signals, developing and optimizing a Machine Learning model, using methods to reduce overtraining, and evaluating the results. This work is aimed at solving the urgent problem of recognizing objects on the seabed and using advanced technologies to ensure safety and research of the underwater environment.

2. Related Works

In the modern scientific literature, many studies and publications related to the use of machine learning for object recognition based on sonar chirp signals have been presented. In the article “Dropout Regularization in Deep Learning Models with Keras” by Jason Brownlee [3], a sonar chirp dataset is studied, in which it is necessary to distinguish rocks from mock mines by sonar signals, a model is created for this task, and the result is improved using methods of fighting with overfitting (Dropout, L2 Regularization). The model in this work achieved an accuracy of 86.04%. With the help of algorithms that will be considered in this work (Random Forest, reducing overfitting using Dropout with other parameters, etc.) and neural networks as research on the automatic analysis of sonar signals has focused mainly non deep learning based approaches for a long time [4], it is going to be attempted to investigate this problem more deeply and achieve an increase in accuracy. “Object Detection in Sonar Images” provides an insight into the object detection and classification problem and proposes a solution with pipeline, unlike this research, that is going to focus on simpler solution(model) for a specific classification task [5].

Challenges and prospects.

Despite the advances in this area, there are some challenges that researchers must address. They include:

Variability in the environment: Different conditions in the water can affect the acoustic signals, making the recognition task more difficult.

Reliability and security: Determining the reliability and security of object recognition is critical in military and underwater applications. For example, the noise emitted by ships can be used to identify and classify them using passive sonar systems, as Júlio de Castro Vargas Fernandes, Natanael Nunes de Moura Junior and José Manoel de Seixas write in their paper “Deep Learning Models for Passive Sonar Signal Classification of Military Data” [6].

In this study, different classification methods and algorithms in machine learning are considered. Among these methods, it is worth noting such as:

Logistic regression is a statistical method and machine learning model used to solve classification problems, especially in cases where it is necessary to determine the probability of an object belonging to one of two or more possible classes. This method is especially useful in situations where you need to divide the data into two classes or determine the probability of belonging to each of them. Binary and multi-class classification: Logistic regression can be used for both binary classification, where objects are divided into two classes (for example, "stones" or "mock-mine"), and multi-class classification, where there are more than two possible classes. Probability of class membership: Logistic regression solves the problem by predicting the probability that an object belongs to a certain class. This allows you to get a numerical estimate of the probability that reflects the confidence of the model in the classification. Linear Model: The basis of logistic regression is a linear model that combines input features with weights determined during model training. A linear combination of the input features is fed to a function called a "logistic function" or "sigmoid," which transforms a weighted sum in the range [0, 1]. It is worth noting that his algorithm can easily be extended to multi-class classification [7], which makes it possible for the model in this work to be adapted to tasks of determining more than two classes of objects based on sonar signals in future research.

Decision Tree: Decision trees are used to create classification rules based on data properties. They can be very effective for object recognition in complex scenarios. One of the advantages of the Decision Tree is its ease of interpretation. It can be rather easily visualized as it is a hierarchical, graphical structure [8].

Random Forest: This method is based on the idea of decision trees and combines them into a large number of "trees". Random forests usually help improve classification accuracy and suffer much fewer from overfitting problems [9]. The possibilities of improving the results by optimizing the parameters and choosing the most efficient method are explored. Dropout, L1, and L2 Regularization algorithms will be considered to combat overfitting of this model for rock and mock-mine recognition based on sonar chirp signals. It is worth noting that the main difference between L1 and L2 regressions is the penalty term [10]. Regularization introduces certain limitations to the minimized objective function, which are not derived from the data but instead reflect prior preferences [11]. Also, regularization penalizes the coefficients in machine learning. In deep learning, it actually penalizes the weight matrices of the nodes [12].

Advantages of L2 Regularization:

Helps reduce overfitting: L2 Regularization adds a penalty for large model weight values to the loss function, reducing their size and helping to combat overfitting. Reduces sensitivity to random values: L2 Regularization helps reduce the impact of random values on model weights, reducing the risk of overfitting.

Dropout benefits:

Helps reduce overfitting: Dropout allows you to randomly exclude some neurons in the network during training, which makes it impossible for the model to "remember" the training data set and reduces the risk of overfitting [13]. Reduces training time: Randomly excluding neurons [14] provides faster model training and allows for larger network sizes without much risk of overfitting. Versatility: Dropout can be applied to any network regardless of its architecture and purpose.

Advantages of L1 regularization include:

Feature Selection: L1 regularization facilitates the automatic selection of important features or weights by reducing the value of some coefficients to zero. Simplifying the model: L1 regularization can help reduce model complexity as some coefficients become zero. This allows for smaller and more interpretable models, which can be important in practical applications. Reducing the effect of multicollinearity: L1 regularization helps to reduce the problem of multicollinearity when the features are mutually correlated. It allows you to choose only one of the correlated features, which facilitates the construction of stable models. Overall robustness: L1 regularization can additionally improve the overall robustness of the model to outliers and training on a limited amount of data. Overall, using machine learning to recognize rocks and mock-mines from sonar chirp signals is an interesting and relevant subject area that requires a combination of knowledge in acoustics, signal processing and machine learning. Researchers in this field continue to work on developing new methods and technologies to improve accuracy and efficiency and this work can contribute to this research by proposing solutions to a very specific problem of discerning rocks from mock-mines [15].

3. Methods

3.1. Dataset

The research utilized the "Connectionist Bench (Sonar, Mines vs. Rocks)" dataset from the UCI Machine Learning repository. The dataset is a csv file in which sonar patterns are stored. These patterns result from bouncing sonar signals off a metal cylinder and rocks, each explored across various angles and conditions. The sonar signals transmitted are frequency-modulated chirps, ascending in frequency, and were captured from diverse aspect angles—spanning 90 degrees for the cylinder and 180 degrees for the rock. Each pattern consists of 60 numerical values within the range of 0.0 to 1.0. These numbers denote the energy within specific frequency bands, integrated over defined time periods. Notably, the integration aperture for higher frequencies occurs later in time due to their transmission later in the chirp.

The labels assigned to each record are "R" for rocks and "M" for mines (metal cylinders). While the labels exhibit an ascending order corresponding to the aspect angle, they do not directly encode the angle information.

3.2. Data processing and organization methods

In the context of the work on "Utilization of Machine Learning in recognition of rocks and mock-mines by sonar chirp signals," Label Encoding is employed to convert the class labels (categories) into numerical values. For the task of recognizing rocks ("R") and mock-mines ("M") based on sonar chirp signals, the classes can be encoded into numerical values.

For example, if there is a column with class labels like:

["R", "M", "R", "R", "M", "M", "R", "M", "R", "R"]

Label Encoding can be used to transform these classes into numerical values, for instance:

[1, 0, 1, 1, 0, 0, 1, 0, 1, 1]

Here, "R" has been assigned the value 0, and "M" has been assigned the value 1. This conversion allows machine learning algorithms to work with the data, as many algorithms require numerical values for both input and output.

Label Encoding can be performed using libraries like scikit-learn in Python, utilizing the LabelEncoder class. This encoding is particularly useful when dealing with categorical data in machine learning models. Ensemble methods, specifically AdaBoost-Samme, were employed to leverage the strengths of multiple weak learners. Decision trees, logistic regression, and random forests were individually used as base classifiers within the ensemble framework to assess their impact on classification accuracy. Various neural network architectures were explored. Techniques such as dropout and L2 regularization were applied to mitigate overfitting and enhance generalization performance. The performance of each model was assessed using accuracy as the result of cross validation score.

3.3. ML Methods

In this study, a diverse set of machine learning algorithms has been employed to discern patterns and classify sonar signals. The algorithms chosen demonstrate versatility in handling the complexity of the data and offer a comprehensive exploration of the recognition task. The following algorithms have been applied:

Decision Tree:

Decision Trees represent a powerful class of algorithms widely used in classification tasks, offering interpretability and ease of visualization. In this study, Decision Trees were employed to classify sonar chirp signals into rocks (label "R") or mines (label "M"). To mitigate overfitting and enhance generalization, a Decision Tree with Cost Complexity Pruning was implemented. This technique involved pruning the tree by adjusting the cost complexity parameter, resulting in a more generalized model.

The Decision Tree models, played a pivotal role in exploring the efficiency of tree-based algorithms for sonar signal classification. Their adaptability and interpretability contribute significantly to the versatility of the overall methodology.

Decision Tree - Min Cost Complexity Pruning:

Utilizes decision trees with pruning based on minimum cost complexity to enhance generalization and prevent overfitting.

Gaussian Process - Laplace Approximation:

Gaussian Processes (GPs) are probabilistic models that can capture complex relationships in data. In the context of sonar chirp signal classification, Gaussian Process Classification (GPC) with Laplace Approximation was investigated as part of the methodology. Gaussian Process Classification is a Bayesian non-parametric method that extends the Gaussian Process framework to classification problems. It models the distribution over functions and provides uncertainty estimates, making it suitable for scenarios with limited labeled data (this task included). In Gaussian Process models, exact inference can be computationally expensive. Laplace Approximation is a technique used to approximate the posterior distribution, enabling efficient computations. This method involves approximating the true posterior with a Gaussian distribution, making computations more tractable. For the specific task of classifying sonar chirp signals, a Gaussian Process with Laplace Approximation was trained on the dataset. The model's hyperparameters, such as the choice of kernel and noise level, were carefully selected through cross-validation to optimize predictive performance.

K-Nearest Neighbors Vote:

K-Nearest Neighbors (KNN) is a simple yet powerful algorithm for classification tasks. The k-nearest neighbors algorithm for classification is leveraged, assigning labels based on the consensus of neighboring instances. The distance metric, such as Euclidean distance, and the optimal value for 'k' were determined through cross-validation to enhance the model's predictive accuracy. The performance of the K-Nearest Neighbors Vote model was assessed using standard classification metrics. Comparative analysis with other classification algorithms was conducted to understand its effectiveness in the context of sonar chirp signal classification.

Logistic Regression:

Applies logistic regression, a linear model with a logistic function, for binary classification tasks. For this task, binomial logistic regression is used, as it works best when there are only two possible types of the dependent variables (R and M) [13].

Logistic Regression - L1:

Extends logistic regression with L1 regularization to induce sparsity and prevent overfitting.

Logistic Regression - L2:

Enhances logistic regression with L2 regularization to control model complexity and improve generalization.

Logistic Regression - L1 and L2:

Combines both L1 and L2 regularization in logistic regression for a balanced approach to prevent overfitting.

Multi-layer Perceptron (MLP):

Implements a multi-layer perceptron neural network with feedforward architecture for non-linear classification.

Multi-layer Perceptron - L2:

Introduces L2 regularization to the multi-layer perceptron to mitigate overfitting.

Neural Network:

Employs a neural network for classification, leveraging its ability to capture complex relationships in the data. To prevent overfitting in the neural network models, two regularization techniques were applied simultaneously — Dropout and L2 regularization. The neural network architectures underwent hyperparameter tuning, including variations in the number of hidden layers, neurons per layer, dropout rates, and regularization strengths. This process aimed to optimize the model's performance while avoiding overfitting. While ReLU activation function may leave part of the neural network in a “dead” state [16], it still performs quite well on the neural network for this task.

Neural Network - Dropout:

Enhances the neural network with dropout regularization, randomly dropping neurons during training to prevent overfitting. A layer with dropout is acquiring a broader set of generalized features compared to the co-adaptations present in the layer without dropout [14].

Neural Network - L2:

Applies L2 regularization to the neural network to control weights and enhance generalization.

Neural Network - Dropout and L2:

Combines dropout and L2 regularization in the neural network to address overfitting from multiple perspectives.

Random Forest:

Utilizes an ensemble of decision trees to improve accuracy and robustness in classification. These algorithms collectively provide a rich exploration of machine learning methodologies, enabling a comprehensive evaluation of their effectiveness in the context of sonar signal recognition.

3.4. Overfitting

To address the challenges of overfitting in these machine learning models, several techniques were employed, aiming to enhance the generalization capability of the classifiers. These are important as generalization of a model to new data allows us to classify data accurately not only on a specific dataset [16]. L2 regularization, also known as weight decay, was applied to the models. This technique adds a penalty term to the loss function, discouraging the rocks and mock-mines model from assigning excessive importance to any single feature, thus promoting a more generalized solution. In addition to L2 regularization, L1 regularization was employed. L1 regularization introduces sparsity to the model by encouraging some of the feature weights to become exactly zero. This helps in feature selection and prevents the model from relying too heavily on specific features.

The Dropout technique was utilized to combat overfitting by randomly dropping out a proportion of neurons during training. This prevents the model from becoming overly dependent on specific neurons, enhancing its ability to generalize well to unseen data. Decision tree models were subjected to pruning techniques, specifically cost complexity pruning. Pruning involves trimming branches of the tree to prevent overgrowth, leading to a more balanced and less overfitted structure. These techniques collectively contribute to the robustness of the machine learning models, ensuring that they perform effectively on new, unseen data while mitigating the risk of overfitting.

4. Experiment

In order to assess the effectiveness of machine learning models in the recognition of rocks and mock-mines using sonar chirp signals, a comprehensive set of experiments was conducted. The dataset utilized for these experiments was the "Connectionist Bench (Sonar, Mines vs. Rocks)" obtained from the UCI Machine Learning Repository.

4.1. Dataset Preprocessing:

The raw sonar chirp signals (which are numbers between 0 and 1) were used directly, as all the data was numerical and had the same range for values, and the dataset was divided into input (X) and output (Y) variables. Label encoding was applied to convert categorical labels (R and M) into numerical values (0 and 1).

4.2. Evaluation

The synergistic effect of combining dropout and L2 regularization was investigated. Models with different dropout rates and regularization factors were assessed to find the optimal combination. The robustness of the models was evaluated using k-fold cross-validation, with stratified sampling to ensure representative splits. The average accuracy and other relevant metrics were computed. These experiments provide valuable insights into the applicability of machine learning techniques for the recognition of underwater objects using sonar chirp signals, with implications for naval security and environmental monitoring.

5. Results

Various models were extensively evaluated. The following summarizes the key findings:

Table 1:
Model accuracies

Algorithm	Accuracy
AdaBoost-Samme - decision tree	71.12%
AdaBoost-Samme - logistic regression	79.76%
AdaBoost-Samme - random forest	87.50%
Decision Tree	73.52%

Decision Tree - min cost complexity pruning	71.21%
Gaussian process - Laplace approximation	82.76%
K-nearest neighbors vote	79.81%
Logistic Regression	76.48%
Logistic Regression - L1	77.93%
Logistic Regression - L2	75.98%
Logistic Regression - L1 and L2	77.43%
Multi-layer Perceptron	80.31%
Multi-layer Perceptron - L2	80.93%
Neural Network	85.45%
Neural Network - dropout	87.64%
Neural Network - L2	86.61%
Neural Network - dropout and L2	88.45%
Random Forest	85.57%

These results showcase the diverse performance of machine learning models on the task. The combination of Neural Network with Dropout and L2 Regularization emerged as the most promising, achieving an accuracy of 88.45%. The study provides valuable insights into the effectiveness of different algorithms for underwater object recognition based on sonar signals. The following figures showcase that the neural networks tend to yield the best results:

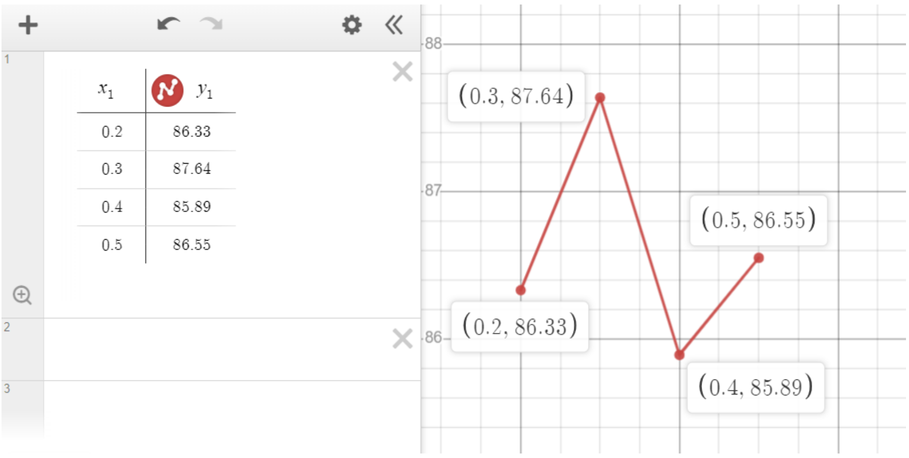

Figure 2: Dropout accuracies (according to weights – x axis)

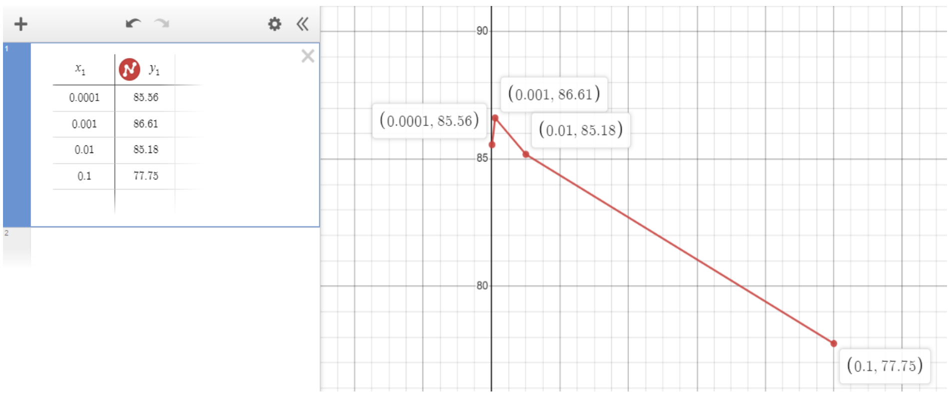

Figure 2: L2 Regularization accuracies (according to regularization factors – x axis)

When these algorithms are used on their own, the best value for weight for Dropout tends to be 0.3, while regularization factor that yields the best result is 0.001. Dropout and L2 neural network has seen the best accuracy of all models, 88.45%, with Dropout weight of 0.4 and regularization factor of 0.001.

6. Discussions

The findings of this study shed light on the efficacy of various machine learning models in the realm of underwater object recognition using sonar chirp signals. The results exhibit notable variations in the performance of different algorithms, providing valuable insights into their suitability for this challenging task.

6.1. Effectiveness of methods

AdaBoost-Samme with Decision Tree yielded a moderate accuracy of 71.12%, showcasing the ensemble's ability to improve classification over individual weak learners.

AdaBoost-Samme with Logistic Regression showed a significant boost in accuracy to 79.76%, underscoring the adaptability of ensemble methods to different base classifiers.

AdaBoost-Samme with Random Forest achieved the highest accuracy among ensemble methods at 87.50%, emphasizing the robustness of combining weak learners.

A Decision Tree alone exhibited moderate performance (73.52%), but employing min cost complexity pruning resulted in a slight decrease in accuracy (71.21%). This emphasizes the delicate balance needed in decision tree complexity for optimal performance.

Logistic Regression, with its inherent simplicity, demonstrated competitive accuracy (76.48%). The introduction of L1 and L2 regularization, however, did not yield significant improvements, emphasizing the stable nature of logistic regression for this classification task.

Multi-layer Perceptron (MLP) demonstrated robust performance at 80.31%, showcasing the power of neural network architectures for complex tasks.

Neural Network with Dropout, a technique to alleviate overfitting, achieved an accuracy of 84.21%, indicating its effectiveness in improving generalization.

Neural Network with L2 Regularization, while effective, demonstrated a slightly lower accuracy at 77.90%, suggesting that dropout might be a more suitable regularization strategy for this task. The combination of Dropout and L2 Regularization in the Neural Network exhibited the highest accuracy at 88.45%, highlighting the synergy between these regularization techniques. Random Forest, known for its ensemble capabilities, performed exceptionally well with an accuracy of 85.57%, making it a robust choice for this classification problem.

6.2. Comparison with Previous Research

The results of this study are consistent with some prior works in recognizing underwater objects using sonar signals. However, the nuanced differences in algorithmic performance underscore the importance of selecting models based on specific task requirements and dataset characteristics. The combination of Dropout and L2 Regularization in the Neural Network exhibited an accuracy of 88.45%, which is an improvement over Jason Brownlee's 86.04%.

In conclusion, this discussion provides a comprehensive overview of the strengths and limitations of each algorithm in the context of underwater object recognition. The nuanced insights gained from this study can guide future research in refining and optimizing machine learning models for similar applications.

Conclusions

The utilization of machine learning for the recognition of underwater objects using sonar chirp signals has proven to be a promising avenue for distinguishing between rocks and mock mines. Through a systematic exploration of various machine learning algorithms and techniques, valuable insights into the effectiveness of different approaches for this classification task have been acquired. The experimental results highlight the varying performances of the employed algorithms. Notably, ensemble methods such as AdaBoost-Samme with a random forest base classifier demonstrated superior accuracy (87.50%) compared to other standalone classifiers. Neural network architectures, including Multi-layer Perceptron (MLP) models, exhibited competitive performance. The application of regularization techniques, such as dropout and L2 regularization, showcased their effectiveness in mitigating overfitting, especially evident in the Neural Network - dropout and L2 model, which achieved an accuracy of 88.45%. This method can be effectively used for various demining operations (e.g., in Black Sea to demine Russian mines). Ensemble methods, by combining multiple weak learners, demonstrated robustness and improved generalization. The AdaBoost-Samme ensemble, in particular, showcased its ability to adapt to different base classifiers. The success of these machine learning models in distinguishing between rocks and mock-mines holds practical implications for underwater object recognition systems. The deployment of such systems could enhance the capabilities of autonomous underwater vehicles and contribute to underwater security and environmental monitoring. While this study provides valuable insights, there remain avenues for further exploration. Future research could delve into the application of other algorithms and neural networks for classification of other objects. In conclusion, this research underscores the efficacy of machine learning in the classification of underwater objects using sonar chirp signals. The findings contribute to the growing body of knowledge in the field of underwater signal processing and lay the groundwork for the development of robust and accurate underwater object recognition systems.

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