# Utilization of Machine Learning in recognition of rocks and mock-mines by sonar chirp signals in real time

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**Abstract**

The rapid development of modern technologies has created new opportunities in many areas, including signal processing. Machine learning has become a useful tool for automatically recognizing objects based on collected data. This paper studies the use of machine learning methods for identifying rocks and mock-mines using sonar chirp signals in real time.

Unlike many previous studies that mainly focused on achieving high classification accuracy, this work also considers the computational speed of the models. This aspect is especially important for real-time systems. Several machine learning models are tested and compared, including Logistic Regression, Decision Trees, Random Forest, Support Vector Machines, Naïve Bayes, Gradient Boosting, and Neural Networks with Dropout and L2 regularization.

Special attention is paid to the problem of overfitting, which often occurs in sonar signal classification tasks. The results show that there is a trade-off between accuracy and processing time. More complex models, such as ensemble methods and neural networks, usually provide better accuracy but require more computation time. Simpler models, such as Naïve Bayes and Support Vector Machines, work faster but achieve slightly lower accuracy.

The results of this study can be useful for the development of real-time underwater detection systems, including applications in security, environmental monitoring, and marine research. This work shows that finding a balance between accuracy and computational efficiency is important for the practical use of sonar-based recognition systems.

**Keywords**

Machine Learning, Sonar Chirp Signals, Object Classification, Real-Time Processing, Computational Efficiency, Underwater Detection.

## 1. Introduction

During the early development of underwater exploration technologies, sonar systems became the primary tool for detecting objects beneath the water surface. In the initial stages, sonar signal analysis was largely based on manual interpretation and simple rule-based methods, which limited both accuracy and processing speed. As computational capabilities improved, more advanced techniques were introduced, creating the foundation for automated approaches to underwater object recognition.

The rapid development of artificial intelligence and machine learning has further transformed this field, enabling new solutions for signal analysis and pattern recognition [2]. These technologies allow the automated processing of large volumes of data obtained from various sensors and communication systems, reducing reliance on human operators.

Hydroacoustic research is one of the key areas where these advances are particularly valuable. Sonar systems are widely used for detecting and classifying underwater objects because sound waves propagate much farther in water than light or radar signals [1]. As a result, sonar technology plays an essential role in ocean exploration, seabed mapping, and autonomous underwater operations.

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In recent years, machine learning methods have been increasingly applied to sonar signal analysis, offering improved accuracy and robustness compared to traditional approaches. However, a major challenge remains the real-time identification of underwater objects, such as rocks and mock-mines, using sonar chirp signals. This task requires not only reliable classification performance but also high computational efficiency to ensure fast processing.

## 2. Analysis of recent publications

Recent scientific publications show growing interest in using machine learning for recognizing underwater objects from sonar chirp signals. Most studies focus on improving classification accuracy by applying different learning models to sonar data.

In the work "Dropout Regularization in Deep Learning Models with Keras" by Jason Brownlee [3], neural networks are used to classify rocks and mock-mines based on sonar chirp signals. These results confirm that deep learning approaches can be effective for sonar signal classification. However, the study mainly focuses on accuracy and gives little attention to execution speed or computational cost. This is an important limitation for real-time systems, as neural networks usually require more processing time than simpler models.

Other studies, such as "Object Detection in Sonar Images" [5], analyze object detection and classification using structured processing pipelines for sonar data. These works show that machine learning can successfully extract useful information from sonar signals. At the same time, most evaluations are performed offline, and real-time performance is not discussed in detail.

Earlier approaches to sonar signal analysis often relied on traditional, non-deep learning methods [4]. These methods are usually fast and computationally efficient, but they may provide lower accuracy in complex underwater conditions. This has led researchers to explore machine learning techniques as a way to improve recognition performance.

Despite noticeable progress, several challenges remain. Underwater conditions can change due to temperature, salinity, and water movement, which affects signal quality and classification results. In addition, real-time applications require models that are not only accurate but also fast. Reliability is especially important in safety-related areas such as underwater navigation and security, as noted in studies on military sonar data classification [6].

In summary, existing publications show that machine learning improves sonar-based object recognition, but most studies prioritize accuracy over execution speed. This indicates a gap in the literature regarding the analysis of computational efficiency, especially for real-time underwater applications.

## 3. The purpose and objectives of the research

The purpose of this research is to analyze the application of machine learning methods for the real-time recognition of rocks and mock-mines using sonar chirp signals, with a particular focus on balancing classification accuracy and computational efficiency.

The main objectives of the study are:

- To review and analyze existing machine learning approaches used for sonar-based object recognition.
- To investigate the suitability of different machine learning models for real-time classification tasks.
- To evaluate the trade-off between classification accuracy and execution speed of the considered models.
- To analyze the impact of regularization techniques on model performance and generalization.

- To identify machine learning solutions that are efficient and practical for real-time underwater applications.

# 4. Methods

## 4.1. Dataset

The dataset used in this research is the Connectionist Bench (Sonar, Mines vs. Rocks) dataset from the UCI Machine Learning Repository. It contains sonar signals obtained by sending sonar chirp pulses toward two types of objects: metal cylinders that represent mock-mines and natural rocks.
The sonar signals were collected under different conditions and from various angles, which makes the dataset closer to real-world scenarios. Each signal is represented by 60 numerical features with values between 0.0 and 1.0. These values describe the energy of the signal in different frequency bands over a fixed time interval.
The sonar chirps used in the dataset increase in frequency over time. Higher frequency components are recorded later in the signal, which reflects the physical properties of sonar wave propagation.
Each sample in the dataset is labeled as "R" (rock) or "M" (mine). Although the data were collected at different aspect angles, the angle information is not directly included in the labels.
This dataset is well suited for training machine learning models for real-time object recognition, where both classification accuracy and processing speed are important. It provides a reliable basis for evaluating different models in the task of distinguishing between rocks and mock-mines using sonar chirp signals.

## 4.2. Data processing and organization methods

In this work, Label Encoding was used to convert class labels into numerical values for machine learning processing [16]. The task focuses on distinguishing between rocks ("R") and mock-mines ("M") using sonar chirp signals. The labels were encoded as 0 for rocks and 1 for mock-mines, since most machine learning models require numerical inputs and outputs.To improve classification performance for real-time applications, ensemble methods were applied, with AdaBoost-SAMME used to combine multiple base learners such as decision trees, logistic regression, and random forests [9]. This approach helped increase accuracy while maintaining fast prediction times. Neural networks were also tested, with dropout and L2 regularization applied to reduce overfitting and improve generalization [10-14, 18]. Model performance was evaluated using classification accuracy with cross-validation, while also considering computational efficiency to ensure suitability for real-time processing.

## 4.3. ML Methods

In this work, sonar chirp signals were analyzed using several machine learning algorithms to distinguish between rocks ("R") and mock-mines ("M"). Special attention was given to methods that provide a good balance between classification accuracy and computational efficiency, which is essential for real-time applications.
Among the tested approaches, Decision Trees were selected for their simple structure and fast inference [8]. To avoid overfitting, cost complexity pruning was applied, which reduces unnecessary branches and simplifies the model. This pruning step also lowers computational cost, making the algorithm more suitable for real-time processing [19].
A probabilistic approach based on Gaussian Process Classification (GPC) was also investigated [11]. To reduce the high computational cost of exact inference, the Laplace approximation was used. This allowed faster predictions while preserving the ability of the model to capture complex data patterns. Model parameters were optimized using cross-validation.

The K-Nearest Neighbors (KNN) algorithm was included as a distance-based classification method [16]. Classification was performed using a voting mechanism among the nearest neighbors, with the number of neighbors and distance metric selected through cross-validation. This approach provided a useful comparison with other models in terms of speed and accuracy.

As a baseline solution, Logistic Regression was applied due to its simplicity and high computational efficiency [7, 16]. To improve generalization, L1, L2, and combined L1–L2 regularization techniques were used, helping to control model complexity and reduce overfitting.

In addition, several widely used machine learning models, such as Support Vector Machines, Naive Bayes, Gradient Boosting, and Random Forests, were evaluated to broaden the comparison across different algorithm families [9].

Neural network-based models were also considered, including Multi-layer Perceptrons (MLP) and deeper neural networks. During training, Dropout and L2 regularization were applied to improve generalization and prevent overfitting. These techniques helped ensure stable performance on unseen sonar data while keeping prediction times acceptable for real-time use [3, 12-14].

Overall, the evaluated methods provide a structured comparison of machine learning approaches for real-time sonar chirp signal classification, emphasizing both performance and efficiency.

### 4.4. Overfitting

To reduce overfitting and ensure real-time performance, several regularization and optimization techniques were applied to the machine learning models used for sonar chirp signal classification. These methods were selected to improve model generalization while maintaining low computational cost, which is essential for time-sensitive real-time applications. L2 regularization was used to limit model complexity by penalizing large weights, while L1 regularization was applied to introduce sparsity by removing less important features [10, 11]. Together, these techniques help prevent overfitting and reduce the number of computations required during classification.

For neural network models, Dropout was employed to improve robustness by randomly deactivating neurons during training, encouraging the learning of more generalized features [12-14]. In addition, cost complexity pruning was applied to decision tree models to simplify tree structures and remove branches with low predictive value [19]. These approaches reduce overfitting and improve prediction speed, ensuring accurate and efficient real-time classification of sonar chirp signals.

## 5. Experiments and Results.

To evaluate the performance of machine learning models for real-time sonar signal recognition, a series of experiments was conducted under conditions close to practical application. The main objective was to determine whether the models can accurately classify rocks and mock-mines while maintaining prediction speed suitable for real-time systems.

The Connectionist Bench (Sonar, Mines vs. Rocks) dataset from the UCI Machine Learning Repository was used as a benchmark. Since all feature values are already scaled between 0 and 1, no additional normalization was required. Class labels (“R” and “M”) were converted into numerical form using Label Encoding.

Each model was evaluated according to two key criteria: classification accuracy and execution time. This allowed analysis of the trade-off between predictive performance and computational efficiency. To reduce overfitting and improve generalization, regularization techniques such as Dropout, L2 regularization, and pruning were applied where appropriate.

Stratified k-fold cross-validation was used to ensure stable and reliable evaluation results. Final performance metrics were calculated as average accuracy and average inference time across validation folds.

The experimental results provide a structured comparison of the evaluated machine learning models in terms of both classification accuracy and computational efficiency. Since real-time sonar recognition systems require a balance between reliable detection and fast processing, the obtained results help identify models that offer the most practical compromise between performance and speed.

The classification accuracy results obtained for the evaluated machine learning models are presented in Table 1. The table summarizes the performance of each algorithm in distinguishing between rocks and mock-mines using sonar chirp signals.
As shown in Table 1, more complex models generally achieve higher classification accuracy. The best result (88.45%) was obtained by the Neural Network with Dropout and L2 regularization. Ensemble methods and neural network-based approaches demonstrate strong predictive performance, while simpler models such as Decision Tree and Naive Bayes show lower accuracy but remain computationally efficient.

**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 - 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 |
| SVM | 77.75 |
| Naive Bayes - Gaussian NB | 67.76 |
| Gradient Boosting | 83.62 |

The execution time required for prediction by each evaluated model is presented in Table 2. This metric reflects the computational efficiency of the algorithms and their suitability for real-time applications.

As shown in Table 2, lightweight models such as Decision Tree, Logistic Regression, and Naive Bayes demonstrate extremely low inference time. In contrast, neural network-based models require significantly more computation time, especially when additional regularization is applied. These results clearly illustrate the trade-off between classification accuracy and execution speed in real-time sonar recognition tasks.

**Table 2**

Execution time of estimator evaluation on test dataset

| Algorithm | Time (seconds) |
|---|---|
| AdaBoost-Samme - decision tree | 0.00086 |
| AdaBoost-Samme - logistic regression | 0.01945 |
| AdaBoost-Samme - random forest | 0.00639 |
| Decision Tree | 0.00013 |
| Decision Tree - min cost complexity pruning | 0.00020 |
| Gaussian process -Laplace approximation | 0.00091 |
| K-nearest neighbors vote | 0.00365 |
| Logistic Regression | 0.00020 |
| Logistic Regression – L1 | 0.00020 |
| Logistic Regression - L2 | 0.00039 |
| Logistic Regression L1 and L2 | 0.00097 |
| Multi-layer Perceptron | 0.00525 |
| Multi-layer Perceptron - L2 | 0.00110 |
| Neural Network | 0.08094 |
| Neural Network - dropout | 0.07665 |
| Neural Network - L2 | 0.08430 |
| Neural Network - dropout and L2 | 0.11481 |
| Random Forest | 0.00782 |
| SVM | 0.00059 |
| Naive Bayes - Gaussian NB | 0.00016 |
| Gradient Boosting | 0.00206 |

To provide a clearer comparison of representative algorithms, their classification accuracy is illustrated in Figure 1.

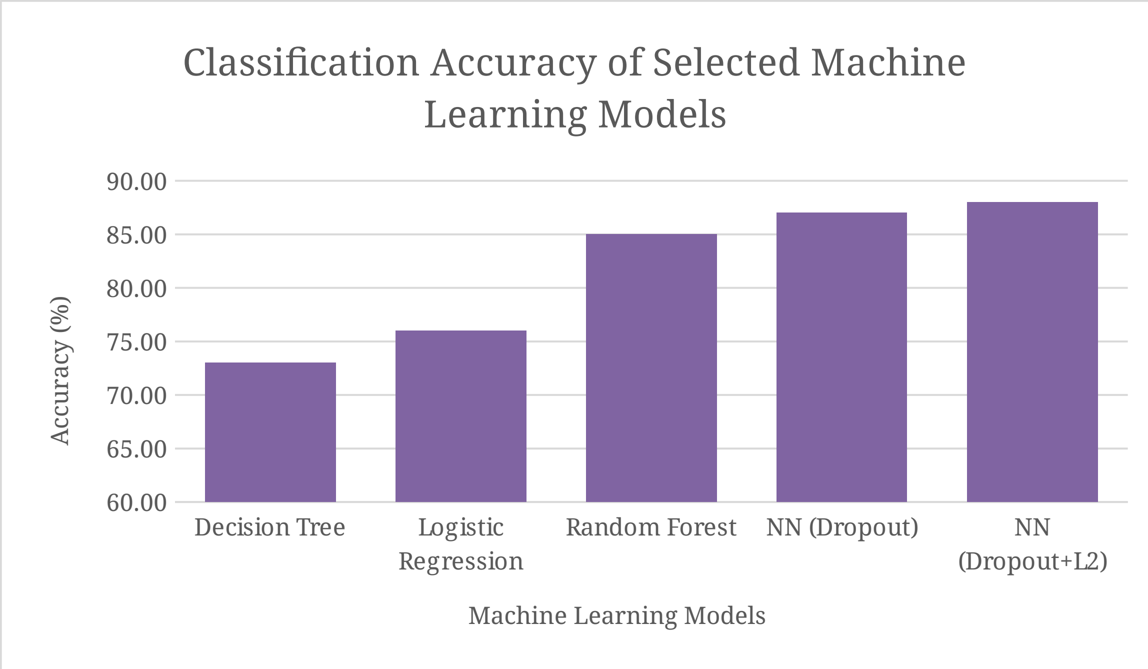


Figure 1. Classification accuracy of selected machine learning models

As shown in Figure 1, ensemble and neural network-based models achieve higher predictive performance compared to simpler approaches. The highest accuracy (88.45%) was obtained by the Neural Network with Dropout and L2 regularization.

## Conclusions

This work shows that machine learning can be effectively used for real-time underwater object recognition based on sonar chirp signals. Different models were tested with respect to accuracy and processing speed, which are both important for real-time use.

The results indicate a clear trade-off between accuracy and efficiency. More complex models, such as ensemble methods and neural networks, achieved higher accuracy but required more computation. Simpler models, including Logistic Regression and Decision Trees, provided faster predictions and are better suited for real-time applications with limited resources.

Overall, the findings confirm that machine learning methods are a practical solution for real-time sonar-based classification of rocks and mock-mines, especially when the balance between accuracy and speed is carefully considered.

## Declaration on Generative AI

The authors have not employed any Generative AI tools. All experimental procedures, calculations, results, interpretations, and conclusions were produced by the authors, who take full responsibility for the content of this publication.

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