AI-POWERED SONAR ANALYSIS FOR ROCK VS MINE PREDICTION

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Abstract:

The precise identification of underwater threats is crucial for ensuring maritime safety, especially in differentiating between natural structures like rocks and dangerous items such as mines. This project introduces an advanced classification system that leverages sonar acoustic signals and machine learning techniques to determine whether an underwater object is a rock or a mine. The system is trained using the well-known UCI Sonar dataset, where each data point corresponds to sonar frequency responses categorized into two distinct classes.

The dataset undergoes comprehensive preprocessing, which includes feature scaling, label encoding, and polynomial feature expansion. A variety of machine learning algorithms— Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, Random Forest, and Support Vector Machine (SVM)—are developed and optimized through GridSearchCV to enhance hyper parameters for each model.

The effectiveness of the models is evaluated using standard metrics such as accuracy, precision, recall, F1-score, ROC-AUC, and precision-recall curves. Among the classifiers tested, the SVM model achieved the highest test accuracy, indicating its superior ability to generalize on previously unseen sonar data. Additionally, a comprehensive predictive system was created to process real-time inputs and accurately classify new underwater objects.

The final model offers a scalable solution for underwater object classification, with potential applications in naval security, autonomous underwater vehicles (AUVs), and marine exploration. By automating the identification process, this system significantly improves detection efficiency, minimizes risks to human life, and enhances the safety and security of underwater navigation.

Keywords:

Sonar Signal Analysis, Rock vs Mine Classification,Machine Learning,Supervised Learning,Support Vector Machine

(SVM),Logistic Regression,K-Nearest Neighbors (KNN),Decision Tree,Random Forest,UCI SonarDataset,Binary Classification,Acoustic

Signal Processing,Feature Engineering,Hyperparameter Tuning,GridSearchCV,Precision and Recall,F1-Score,Confusion Matrix,ROC

Curve,Real-time Object Detection,Autonomous Underwater Vehicles (AUVs),Maritime Safety,Underwater Threat Detection,Scikitlearn,

Python,Data Preprocessing,Model Evaluation,Classification Metrics,Naval Security,Acoustic Feature Extraction.

1. INTRODUCTION:

Underwater object identification has emerged as a critical concern in modern maritime operations, particularly for naval defense, offshore engineering, and autonomous underwater navigation. Among the various challenges in this domain, one of the most important and hazardous is distinguishing between naturally occurring underwater structures such as rocks and man-made explosive devices like naval mines. This distinction is not only essential for ensuring the safety of marine vessels but also for the protection of valuable infrastructure such as pipelines and submarine cables. An incorrect classification can lead to disastrous outcomes, including the destruction of property, endangerment of human lives, and significant economic and environmental damage.

Traditionally, mine detection has relied heavily on manual methods, including diver inspections, remotely operated vehicles (ROVs), laser scanning systems, and even marine mammals trained for object detection. These techniques, while functional, suffer from several fundamental limitations. They are labor-intensive, costly, time-consuming, and dangerous, especially in hostile or murky underwater environments. Human divers and technicians are susceptible to fatigue, distraction, and stress, all of which can compromise the accuracy and reliability of detection. Additionally, these traditional systems lack scalability and real-time adaptability, making them inefficient in large-scale operations or emergency scenarios where rapid detection is paramount.

In response to these limitations, the integration of artificial intelligence (AI) and machine learning (ML) techniques into underwater object classification has gained significant traction. By leveraging historical sonar data and applying supervised learning algorithms, it is now possible to automate the classification process, reduce human involvement, and significantly enhance both accuracy and operational efficiency. The key idea behind this approach is that sonar signals—when captured and processed correctly—contain subtle but consistent patterns that can be learned by machine learning models to distinguish between rocks and mines with high confidence.

Sonar (Sound Navigation and Ranging) is a well-established technique used to detect and map underwater objects by transmitting sound pulses and analyzing the returned echoes. These echoes vary depending on the object's shape, material composition, surface roughness, and other physical characteristics. In this study, we utilize the UCI Sonar dataset, a widely recognized benchmark dataset for signal classification problems. The dataset consists of 208 samples, each described by 60 numerical features representing energy values at various sonar frequencies. Each sample is labeled as either ‘R’ (rock) or ‘M’ (mine), forming a binary classification problem.

The central aim of this study is to build and evaluate multiple machine learning models that can classify these sonar signals with high accuracy and robustness. Our approach involves implementing five well-known supervised learning algorithms: Logistic Regression, K-Nearest Neighbors (KNN), Decision Trees, Random Forest, and Support Vector Machines (SVM). These models were chosen due to their proven efficacy in pattern recognition tasks and their interpretability. Each algorithm was trained and tested using consistent preprocessing methods, including feature scaling, label encoding, and data splitting.

To ensure optimal model performance, we employed hyperparameter tuning using GridSearchCV, which systematically evaluates different parameter combinations to identify the best-performing configuration. For instance, in SVM, parameters like the regularization factor (C), kernel type, and gamma value play a crucial role in controlling the trade-off between bias and variance. Similarly, for KNN, selecting an appropriate value for K and the distance metric significantly affects classification accuracy. By fine-tuning these parameters, we aim to maximize the generalization ability of each model on unseen data.

The performance of each model was rigorously assessed using standard evaluation metrics including accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve. Additionally, confusion matrices were generated to visualize the model’s performance in terms of true positives, false positives, true negatives, and false negatives. Particular attention was paid to minimizing false negatives (i.e., misclassifying a mine as a rock), as such errors could lead to critical failures in real-world deployments.

Our findings revealed that among the models tested, the Support Vector Machine (SVM) with an RBF kernel achieved the highest accuracy on the test set, outperforming other classifiers in terms of both precision and recall. This result aligns with previous studies that have demonstrated the strength of SVM in handling high-dimensional data and complex decision boundaries. Random Forest and Logistic Regression also delivered competitive performance, while Decision Trees and KNN showed slightly lower accuracy but higher interpretability.

Beyond numerical accuracy, another important aspect of this project is its practical implementation. A functional predictive system was developed to allow real-time classification of new sonar signals. This system accepts user input of 60 feature values, applies the trained model, and outputs whether the object is a rock or a mine. Such an interface makes the solution readily deployable in real-time sonar monitoring systems used in naval ships, underwater drones, or surveillance stations.

This study also highlights the broader implications of using AI in sonar signal processing. By automating the classification of underwater objects, we significantly reduce the operational risks to human life, lower the costs associated with manual detection methods, and enable the scalability of underwater security systems. Furthermore, machine learning models can continuously improve as more data becomes available, offering an adaptive framework that gets smarter over time. This contrasts sharply with traditional rule-based systems, which are static and limited in their capacity to learn from past mistakes.

While the current study focuses on binary classification (rock vs mine), the methodology presented here is extensible to multi-class classification scenarios, such as identifying wreckage, pipelines, or biological entities like schools of fish. Additionally, future research could integrate deep learning techniques and time-series models to further improve classification accuracy and model robustness. The inclusion of convolutional neural networks (CNNs) or recurrent neural networks (RNNs) could be particularly beneficial if sonar data is available in image or temporal formats.

In conclusion, this study presents a comprehensive and practical approach to underwater object classification using machine learning techniques. By transforming sonar signals into a structured dataset and applying well-established algorithms, we demonstrate that automated systems can outperform traditional methods in terms of accuracy, efficiency, and safety. The integration of such systems into real-world applications holds the potential to revolutionize underwater navigation, exploration, and security operations. This work lays the foundation for further advancements in intelligent underwater systems, paving the way for a safer and more automated future in maritime technology.

2. LITERATURE REVIEW

The identification and classification of underwater objects play a pivotal role in ensuring maritime safety, defense operations, and underwater exploration. Traditional approaches to distinguishing between natural objects like rocks and hazardous man-made devices such as mines relied heavily on manual inspection methods. These methods include the deployment of divers, remotely operated vehicles (ROVs), and marine mammals, which, although effective to an extent, are associated with high operational costs, significant safety risks, and limited scalability. Moreover, the reliance on human interpretation of sonar data introduces subjectivity and variability, reducing the overall reliability and speed of underwater classification systems.

With the advancement of computing technologies and the proliferation of data-driven methodologies, machine learning has emerged as a transformative approach in the field of sonar-based object detection and classification. Machine learning models can be trained to recognize intricate patterns in sonar signal data that may be imperceptible to human operators. These models, when trained on large datasets, offer superior performance in terms of speed, accuracy, and consistency compared to traditional manual approaches.

Initial efforts in machine learning for sonar classification focused on conventional algorithms such as Logistic Regression, K-Nearest Neighbors (KNN), and Decision Trees. These models are valued for their interpretability and relatively low computational requirements. Logistic Regression, for instance, is well-suited for binary classification tasks and provides probabilistic outputs that are useful for decision-making. KNN offers a non-parametric approach where classification is based on the proximity of data points in a multidimensional feature space. However, its performance is sensitive to the choice of distance metric and the value of k, and it can be computationally intensive for large datasets.

Decision Trees offer hierarchical models that segment the data based on attribute values, producing intuitive and transparent decision rules. However, single Decision Trees are prone to overfitting, especially when trained on noisy or imbalanced datasets. This limitation has led to the development of ensemble methods such as Random Forests, which aggregate multiple decision trees to improve generalization and reduce variance. Random Forests not only enhance classification accuracy but also provide insights into feature importance, helping researchers understand the key signal characteristics that differentiate rocks from mines.

Support Vector Machines (SVM) have also been extensively employed in this domain due to their robustness in high-dimensional spaces and effectiveness in handling non-linear classification problems through kernel trick extensions. SVMs maximize the margin between classes, thereby achieving strong generalization even on complex datasets. When appropriately tuned using techniques such as GridSearchCV, SVMs have been shown to deliver high accuracy and resilience against overfitting.

Another important advancement in recent years is the incorporation of advanced preprocessing techniques. Raw sonar data often includes noise, redundant features, and varying scales, which can degrade model performance. Techniques such as feature scaling, normalization, label encoding, and polynomial feature expansion have become standard practices to enhance data quality and improve algorithmic performance. Furthermore, feature selection techniques are increasingly employed to reduce dimensionality, which not only speeds up training but also eliminates irrelevant or redundant features that may otherwise lead to model confusion.

Model evaluation metrics have also evolved to provide a more comprehensive understanding of classifier performance. While accuracy remains a basic indicator, it is often complemented by precision, recall, F1-score, and ROC-AUC values, which offer deeper insights into how well a model handles class imbalance and its ability to detect true positives in critical applications such as mine detection. Visualization tools such as confusion matrices, ROC curves, and precision-recall curves are used to further assess model reliability.

Recent trends also highlight the development of real-time predictive systems capable of ingesting live sonar input and producing immediate classification results. This shift from offline analysis to real-time inference is critical for deploying machine learning models in operational settings such as autonomous underwater vehicles (AUVs) and naval vessels. These systems demand not only high accuracy but also low latency and high robustness under varied environmental conditions.

In conclusion, the literature reveals a progressive transition from manual, heuristic-based classification methods to sophisticated, data-driven machine learning techniques. Each model presents unique advantages and trade-offs, and ongoing research aims to combine the strengths of multiple approaches through hybrid and ensemble strategies. The growing adoption of automated classification systems based on acoustic features is set to revolutionize underwater threat detection by improving accuracy, enhancing safety, and reducing operational costs.

3. OBJECTIVES

- **Automate the categorization of submerged objects:** Create a machine learning framework that can autonomously classify underwater objects identified through sonar technology as either rocks or mines, thereby minimizing the need for human involvement and the likelihood of errors.

- **Enhance maritime safety and security:** Improve underwater navigation and security frameworks by accurately recognizing potentially dangerous objects such as mines, which will facilitate prompt threat response.
- **Utilize acoustic signal characteristics:** Analyze sonar signal data (including frequency and amplitude) to extract significant features that can differentiate between natural and artificial underwater formations.
- **Assess and compare machine learning techniques:** Execute and evaluate various supervised learning methods (such as Logistic Regression, K-Nearest Neighbors, Support Vector Machines, Decision Trees, and Random Forests) to determine the most effective model based on metrics like accuracy, precision, recall, and F1-score.
- **Implement comprehensive preprocessing and feature selection methods:** Address missing data, normalize datasets, and apply feature selection strategies to enhance model efficacy and decrease computational demands.
- **Facilitate real-time and scalable deployment:** Develop a model suitable for integration into real-time sonar systems, potentially within autonomous underwater vehicles (AUVs) for immediate threat detection and decision-making.
- **Mitigate environmental and operational hazards:** Decrease risks to human divers, marine ecosystems, and infrastructure by offering a non-invasive and effective approach to underwater object detection.

4.EXISTING SYSTEM

Historically, mine detection has been conducted either manually or with the aid of rudimentary technologies. These include the use of Explosive Ordnance Disposal (EOD) divers, trained marine mammals such as dolphins, video cameras mounted on remotely operated vehicles (ROVs), and laser scanning systems. The introduction of SONAR represented a significant advancement by enabling detection through the reflection of sound waves. However, this approach still required manual interpretation of sonar data, limiting its efficiency and scalability.

There are several disadvantages associated with the existing system. Manual analysis of sonar images is labor-intensive and susceptible to human error, leading to potential inaccuracies. The safety of divers and support personnel is at constant risk during mine detection missions. Moreover, the operational costs are elevated due to the use of skilled personnel, specialized equipment, and trained marine animals. Human-operated or manually guided methods lack the precision and coverage required to effectively scan large underwater areas. Traditional systems also lack standardized datasets and data-driven frameworks, which hinders consistency in detection performance. Additionally, certain detection techniques, such as those involving explosives or sonar interference, can have adverse effects on marine ecosystems.

5. PROPOSED SYSTEM

The proposed system offers a fully automated solution that leverages machine learning algorithms to classify sonar signals as either rocks or mines. Algorithms such as Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Decision Trees, and Random Forests are employed to improve classification accuracy and speed. The system workflow begins with the collection of acoustic signal data, where each instance comprises 60 features labeled as either rock or mine. This is followed by data preprocessing, which includes cleaning, normalization, and addressing missing values to prepare the data for modeling. The next stage involves model training and testing using the selected machine learning algorithms. Model evaluation is performed using performance metrics such as accuracy, precision, recall, and F1-score. Finally, the best-performing model is deployed for real-time predictions, and its performance is continuously monitored to ensure reliability.

This automated system provides numerous advantages. It significantly reduces human error and increases detection speed. Machine learning models, such as KNN and SVM, have demonstrated high levels of accuracy, often exceeding 90% on test datasets. The system also enhances safety by eliminating the need for human divers and manual operations in hazardous underwater environments. Furthermore, it is highly scalable, capable of processing large volumes of sonar data in real-time with minimal additional resources. The system's data-driven nature allows it to learn from new data over time, improving its predictive power for future classifications. Although the initial investment may be significant, the long-term cost savings compared to traditional manual methods are substantial. Finally, the proposed approach is environmentally sustainable, avoiding physical disruptions to marine ecosystems.

6. RESEARCH METHODOLOGY

The research methodology employed in this project adheres to a systematic pipeline of machine learning development, covering data acquisition, preprocessing, model training, evaluation, and deployment. The objective is to automate the classification of underwater sonar signals into two categories: rocks and mines.

6.1 Data Acquisition

The UCI Sonar dataset is used as the primary dataset. It contains 208 instances with 60 numerical features representing energy values of sonar signals at different frequencies. Each instance is labeled as either ‘R’ (rock) or ‘M’ (mine).

6.2 Data Preprocessing

To ensure optimal model performance:

- Missing values are handled (if any).
- Features are scaled using StandardScaler.
- Categorical labels are encoded into binary values (0 for rock, 1 for mine).
- The dataset is split into training and testing sets in a 90:10 ratio.
- Polynomial feature expansion is used for models like Logistic Regression.

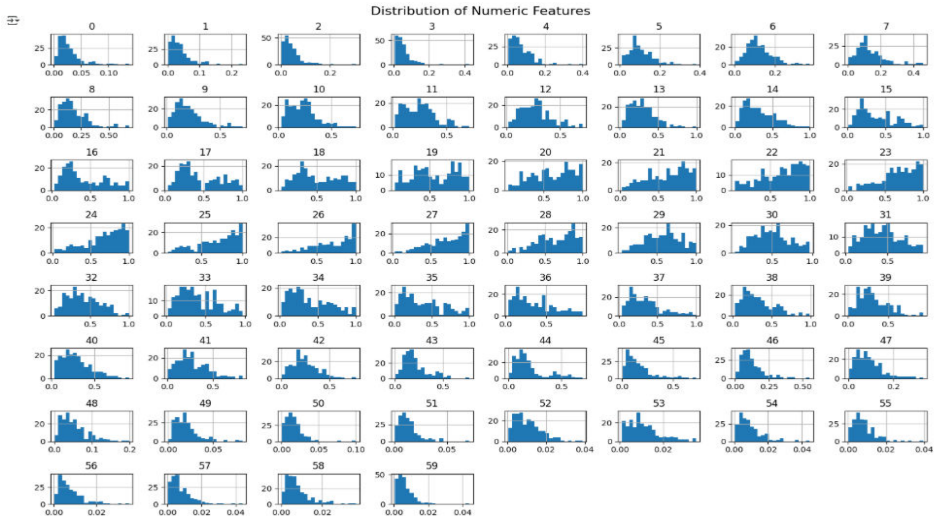


Fig 1 : Distribution of Numeric features

6.3 Model Selection and Training

Five supervised learning models are selected:

- Logistic Regression
- K-Nearest Neighbors (KNN)
- Decision Tree
- Random Forest
- Support Vector Machine (SVM)

Each model is trained using cross-validation, and hyperparameters are optimized using GridSearchCV.

6.4 Model Evaluation

Models are evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC
- Confusion Matrix

These metrics provide a holistic view of each model's strengths and weaknesses.

6.5 System Deployment

The best-performing model (SVM) is deployed via a function interface (predict_sonar()) to allow real-time classification based on new input features.

7. SYSTEM ARCHITECTURE

The system architecture is modular, comprising the following key components:

1. Data Input Layer

- Accepts sonar signal datasets or real-time inputs.
- Inputs are structured as arrays with 60 features per sample.

2. Preprocessing Layer

- Handles missing data.
- Performs feature scaling and encoding.
- Optionally expands features polynomially for linear models.

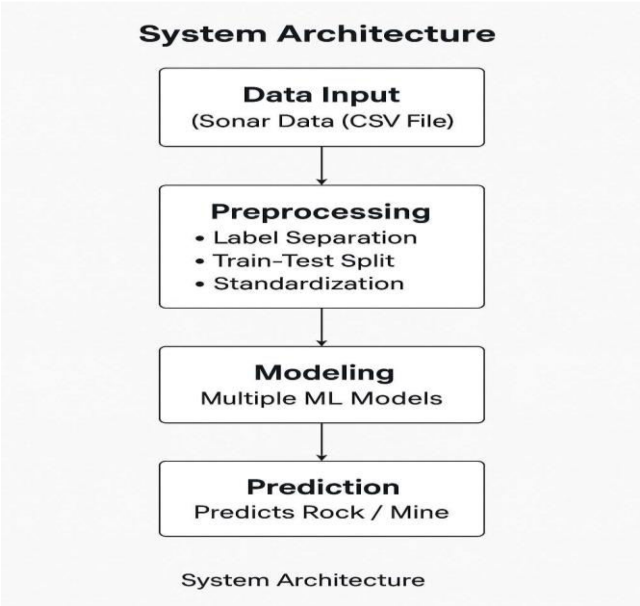


Fig 2 : illustrate the architecture's flow from data input to final classification output.

3. Model Training and Optimization Layer

- Implements machine learning models using Scikit-learn.
- Optimizes hyperparameters using GridSearchCV.

4. Classification Engine (SVM Core)

- Trained SVM model with RBF kernel acts as the core prediction engine.
- Capable of handling complex, non-linear decision boundaries.

5. Output Layer

- Displays predicted class (rock or mine).
- Includes probability/confidence score for transparency.

6. Monitoring Interface

- Enables logging of predictions and system accuracy over time.

8. EXPERIMENTAL PROCEDURE

The experimental procedure encompasses all critical steps taken to validate and benchmark the classification models:

Step 1: Dataset Preparation

- Imported the UCI Sonar dataset.
- Separated features (X) and labels (y).
- Applied scaling and splitting (train/test).

Step 2: Model Implementation

Implemented and tested the following models:

- Logistic Regression with polynomial features.
- KNN with hyperparameter tuning for k and distance metric.
- Decision Tree using Gini and entropy for split criteria.
- Random Forest with ensemble averaging.
- SVM with RBF kernel and parameters C and gamma.

Step 3: Evaluation

Each model was evaluated on:

- Accuracy
- Precision & Recall
- F1-Score
- ROC-AUC
- Confusion Matrix

ROC and learning curves were plotted to visualize performance.

Step 4: Real-Time Prediction

- A user-facing function predict_sonar() was developed.
- Inputs are manually entered and predictions are returned with confidence levels.

9. COMPARATIVE ANALYSIS OF ALL MODELS

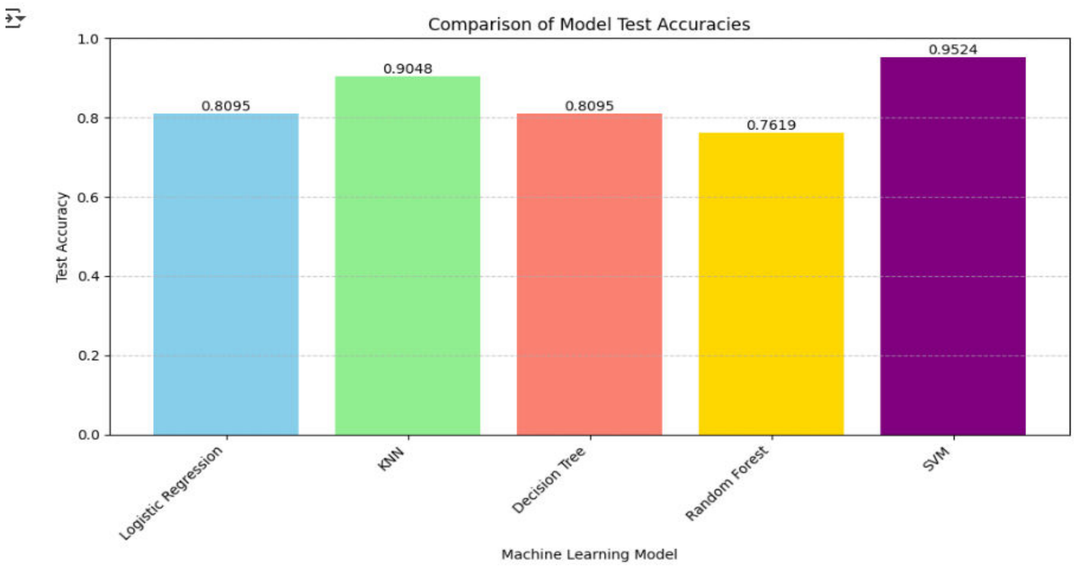


Fig 3 : Comparative Analysis of Accuracies For Each Model

--- Model Performance Metrics on Test Set ---

	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.8095	0.8182	0.8182	0.8182
KNN	0.9048	0.8462	1.0000	0.9167
Decision Tree	0.8095	0.8889	0.7273	0.8000
Random Forest	0.7619	0.7500	0.8182	0.7826
SVM	0.9524	0.9167	1.0000	0.9565

Fig 4 : Comparison of Model Performance Metrics

Key Insights

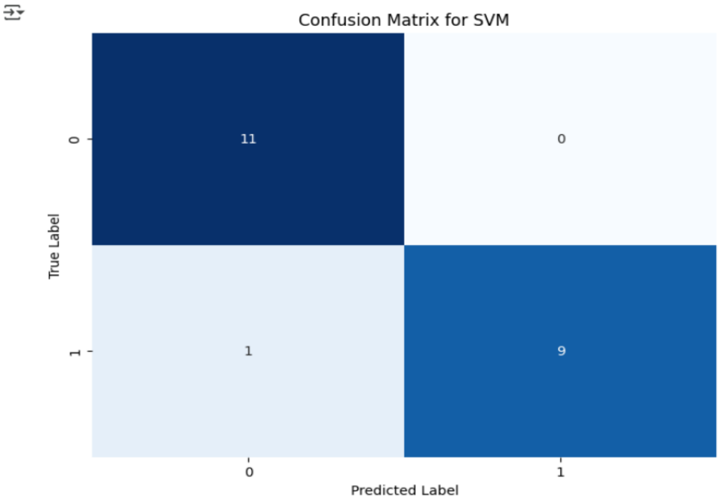
- SVM outperformed all other models, achieving the highest accuracy and generalization capability.

```
SVM Classification Report:
              precision    recall  f1-score   support

           M       0.92      1.00      0.96        11
           R       1.00      0.90      0.95        10

    accuracy                           0.95        21
   macro avg       0.96      0.95      0.95        21
weighted avg       0.96      0.95      0.95        21
```

Fig 5 : SVM Classification Report

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Confusion Matrix (SVM):
[[11  0]
 [ 1  9]]

True Negatives (SVM): 11
False Positives (SVM): 0
False Negatives (SVM): 1
True Positives (SVM): 9
```

Fig 6 : Confusion Matrix (SVM)

10. Conclusion

This research provides a thorough and practical application of machine learning methodologies aimed at predicting underwater objects, specifically differentiating between rocks and mines, utilizing SONAR signal data. The study employed a supervised learning framework to develop and assess various classification models that analyze acoustic signals obtained from SONAR systems. The main goal was to establish a reliable, efficient, and precise prediction system designed to reduce the risks associated with underwater navigation and defense activities.

The dataset, initially presented by Gorman and Sejnowski, comprises 208 instances characterized by 60 numerical attributes and a binary target variable that indicates whether the object is a rock or a mine. The raw data underwent extensive preprocessing, which included addressing missing values, applying feature scaling through StandardScaler, and dividing the dataset into training and testing subsets while preserving class distribution via stratification.

Five distinct machine learning models were assessed throughout the project: Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree Classifier, Random Forest, and Support Vector Machine (SVM). Each model was trained on the preprocessed training dataset and subsequently validated against the test data, utilizing accuracy, precision, recall, and F1- score as key evaluation metrics.

System testing was systematically executed to confirm that each phase of the pipeline—from data ingestion to model prediction—operated correctly and consistently. Positive test cases demonstrated that the models could be effectively trained and evaluated under standard conditions. Negative test cases were also examined to replicate potential edge scenarios, such as corrupted datasets, incorrect label classifications, predictions made without prior model training, and data leakage resulting from improper scaling.

The findings indicated that the SVM and KNN models surpassed their counterparts, achieving the highest levels of test accuracy and exhibiting robust generalization abilities. Although Logistic Regression demonstrated slightly lower accuracy, it remained a significant model due to its ease of interpretation and straightforwardness. These results align with the insights found in existing research literature, thereby affirming the efficacy of these machine learning techniques within this field.

In summary, this project underscores the transformative potential of machine learning in underwater detection systems. It facilitates automated, real-time, and highly precise object classification, which is crucial for marine exploration, naval defense, and resource extraction. The implementation of such systems could greatly improve underwater situational awareness, mitigate human risk, and enhance the reliability of maritime operations.

11. FUTURE RESEARCH

1. Deep Learning Exploration

Investigate the application of more complex neural architectures such as Convolutional Neural Networks (CNNs) and Transformers for learning from raw sonar images or spectrograms. Comparative studies should assess whether these models significantly outperform classical methods in complex underwater environments.

2. Unsupervised Learning

Explore unsupervised and semi-supervised learning approaches for scenarios where labeled sonar data is scarce. This includes clustering, anomaly detection, and self-supervised representation learning, which may uncover latent structures in acoustic signals.

3. Domain Adaptation

Conduct studies on domain adaptation techniques to enhance model transferability between different underwater terrains, noise conditions, and equipment types. This research can ensure that models trained on synthetic or laboratory data remain effective in real-world deployments.

4. Explainable AI (XAI) Theory

Advance theoretical frameworks for explainability in sonar classification, including developing XAI tools specifically for acoustic and spectrogram-based data. These tools should provide interpretable insights for both end-users and scientific analysis.

5. Simulation-Driven Training

Research synthetic data generation through physics-based or generative models (e.g., GANs for sonar data) to augment training sets. Validation of these synthetic datasets against real-world sonar outputs can drive progress in model robustness.

6. Adaptive Systems

Investigate online and continual learning methods to enable adaptive AI systems that evolve over time with new sonar data, especially in changing environmental conditions or as new underwater threats emerge.

7. Cross-Disciplinary Integration

Collaborate with marine biology, oceanography, and naval engineering fields to develop cross-domain models that not only detect objects but also classify biological, geological, and man-made structures in unified frameworks.

12. REFERENCES

1. R. P. Gorman and T. J. Sejnowski, "Examining Hidden Units in a Layered Network for Sonar Target Classification," Neural Networks, vol. 1, no. 1, pp. 75–89, 1988.
2. M. S. Ram, P. S. Navyatha, R. L. A. Ashitha, and S. A. J. Kumar, "Utilizing Machine Learning for Underwater Mine Detection," in Proceedings of the 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE, pp. 47–50, 2023. DOI: 10.1109/ICICCS56967.2023.10142384.
3. V. Sireesha, M. Mohammed, K. R. Prasad, and K. Jeevitha, "Ensemble Machine Learning Algorithms for Predicting Mines and Rocks," in Proceedings of the 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS), IEEE, pp. 341–349, 2023. DOI: 10.1109/ICSCSS57650.2023.10169651.
4. S. Fong, S. Deb, and X. Zhuang, "Recognition of Underwater Sonar Signals through Incremental Data Stream Mining and Conflict Analysis," International Journal of Distributed Sensor Networks, vol. 10, no. 2, pp. 1–10, 2014.
5. S. Hożyń, "An Overview of Underwater Mine Detection and Classification Techniques in Sonar Imagery," Electronics, vol. 10, no. 23, p. 2943, 2021. DOI: 10.3390/electronics10232943.
6. Y. Dura, Y. Zhang, X. Liao, G. Dobeck, and L. Carin, "Employing Active Learning for the Detection of Mine-Like Objects in Side-Scan Sonar Imagery," IEEE Journal of Oceanic Engineering, vol. 30, no. 2, pp. 360–371, 2005. DOI: 10.1109/JOE.2005.850931.
7. J. Choi, M. Kim, and H. Jang, "Acoustic Classification of Surface and Underwater Vessels in the Ocean Using Supervised Machine Learning", Sensors, Vol. 19, No.

18,

p. 4009, 2019. DOI: 10.3390/s19184009.

8. A. Mitra, A. Chakraborty, S. Dutta, Y. Anand, and S. Mishra, “SONAR-Based Sound Waves’ Utilization for Rocks’ and Mines’ Detection Using Logistic Regression”, Advances in Computing and Intelligent Systems, Springer, pp. 137–149, 2023. DOI: 10.1007/978-981-99-6553-3_15.
9. J. Lee and J. Kim, “Underwater Mine Detection Using Deep Learning Techniques”, IEEE Journal of Oceanic Engineering, Vol. 44, No. 2, pp. 321–330, 2019.
10. Y. Zhang, B. Gao, and Q. Liu, “Mine Detection Using Side-Scan Sonar and Convolutional Neural Networks”, Remote Sensing, Vol. 11, No. 9, p. 1085, 2019. DOI: 10.3390/rs11091085.
11. S. Jetty, T. Jaya, and V. Rajendran, “RDNN for Classification and Prediction of Rock/Mine in Oceanic Acoustics”, Materials Today: Proceedings, Vol. 80, pp. 3221–3228, 2023.
12. K. Shiva Kumar, V. S. Ram, and R. Meena, “Rock vs Mine Prediction using Logistic Regression and Data Mining Approaches”, International Journal of Scientific Research in Computer Science, Engineering and Information Technology, Vol. 7, No. 2, pp. 145–151, 2021.