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SONOVAULT_X

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ABSTRACT

The Sonovault X project presents a machine learning-based approach for classifying underwater objects as either Rocks or Mines using SONAR signal data. Traditional methods for underwater detection often rely on manual interpretation, which is time-consuming and error-prone.

To overcome these challenges, this project leverages logistic regression—a simple, interpretable, and efficient binary classification algorithm. The system processes acoustic signals, applies data preprocessing techniques, and trains a logistic regression model to distinguish between natural formations and potential naval threats. With a focus on enhancingmaritime safety, reducing human error, and enabling real-time implementation, Sonovault X offers a lightweight and effective solution for underwater object classification.

Future developments may include integration with embedded systems and expansion to more advanced hybrid models for improved accuracy and scalability.

INTRODUCTION

Underwater object detection plays a crucial role in maritime safety, naval defense, and underwater exploration. Traditional methods rely on manual interpretation of SONAR data, which can be time-consuming and error-prone. To improve accuracy and efficiency, this project introduces a machine learning-based approach to classify underwater objects as either Rocks or Mines using SONAR data.

The system uses Logistic Regression, a fundamental machine learning algorithm for binary classification, to analyze acoustic signal reflections captured by SONAR devices. The dataset consists of numerical features extracted from SONAR signals, which undergo data preprocessing and feature selection before training the model.

2.EXISTING SYSTEM

The existing systems for underwater object detection primarily depend on advanced deep learning techniques and image processing tools that work on SONAR images or acoustic signals. These systems include:

 YOLO (You Only Look Once) and SSD (Single Shot Detector): These models detect and classify objects using synthetic SONAR and drone images. Though accurate, they are computationally heavy.

 Convolutional Neural Networks (CNNs): Commonly used for classifying seabed structures and detecting underwater mines. These models require large datasets and advanced noise reduction.

 Autoencoders: Used for feature extraction in SONAR data. While powerful, they demand extensive tuning and are often prone to overfitting.

These methods, while effective in many cases, are typically "black-box" systems lacking interpretability and demanding high computational resources, making them impractical for lightweight or real-time applications. This creates the need for simpler, more interpretable solutions like the one proposed in Sonovault X.

3.PROPOSED SYSTEM

The proposed system in Sonovault X uses a logistic regression model to classify underwater objects as either Rocks or Mines based on SONAR data. Unlike complex deep learning models, it is lightweight, easy to implement, and highly interpretable. The system includes data preprocessing steps like normalization and feature selection to improve accuracy. Its simplicity allows for fast execution, making it suitable for real-time applications and integration into underwater devices. This approach reduces manual effort and enhances safety in maritime operations

4. METHODOLOGY

1.Data Collection

- **SONAR signal dataset is obtained from the UCI Machine Learning Repository.**
- **Each data point contains 60 numeric features and a label: 'R' (Rock) or 'M' (Mine).**

2. Data Preprocessing

- **Label Encoding is applied to convert class labels ('R', 'M') into numerical values (0, 1).**
- **Normalization ensures all features are on a similar scale.**
- **Data is split into training and testing sets (e.g., 80:20 ratio).**

3. Model Training

- **A Logistic Regression model is trained on the processed data.**
- **The model learns the relationship between input features and object types.**

4. Evaluation

- **The model is evaluated using metrics like accuracy, precision, and recall.**
- **Both training and testing accuracy are recorded for performance validation.**

5. Prediction

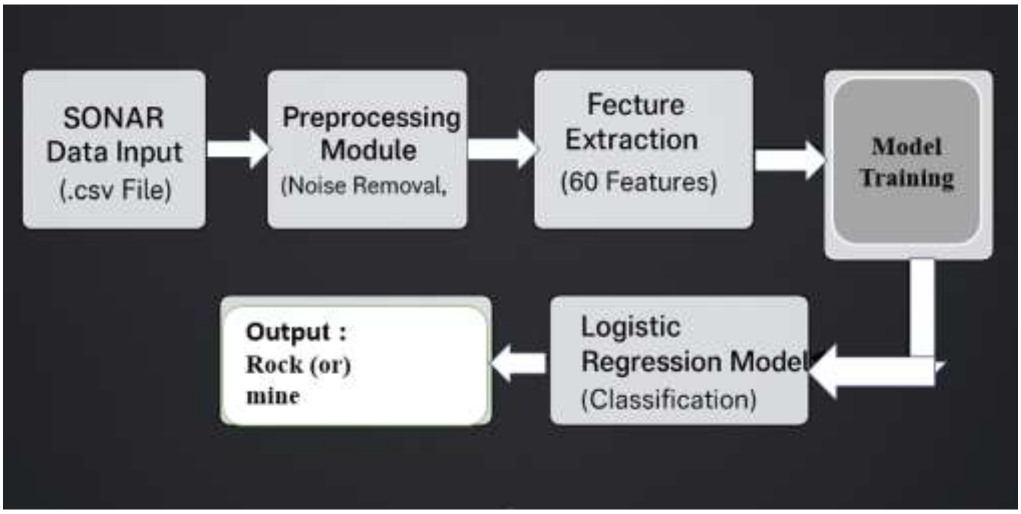
- **Users upload test data via a Streamlit interface.**
- **The trained model predicts the class of each input as either Rock or Mine.**

6. Output & Download

- **Results are shown on-screen in a table format.**
- **Users can download the predictions as a .csv file for further analysis.**

5.SYSTEM ARCHITECTURE

System architecture is a comprehensive blueprint that defines the structure, behavior, and interactions of various components within a system—whether it's a software application, a computer system, or a complex network of systems. It provides a highlevel view of how the system is organized and how different parts such as hardware, software, data storage, processing units, communication protocols, and user interfaces interact to perform specific functions. In software systems, architecture describes how modules or services are divided, how they communicate (e.g., via APIs or message queues), and how data flows through the system. In hardware systems, it includes the design of processors, memory units, input/output devices, and how they are connected. System architecture also includes considerations for scalability (handling growth in users or data), security (protecting data and operations), maintainability (ease of updates and debugging), and performance (speed and efficiency).



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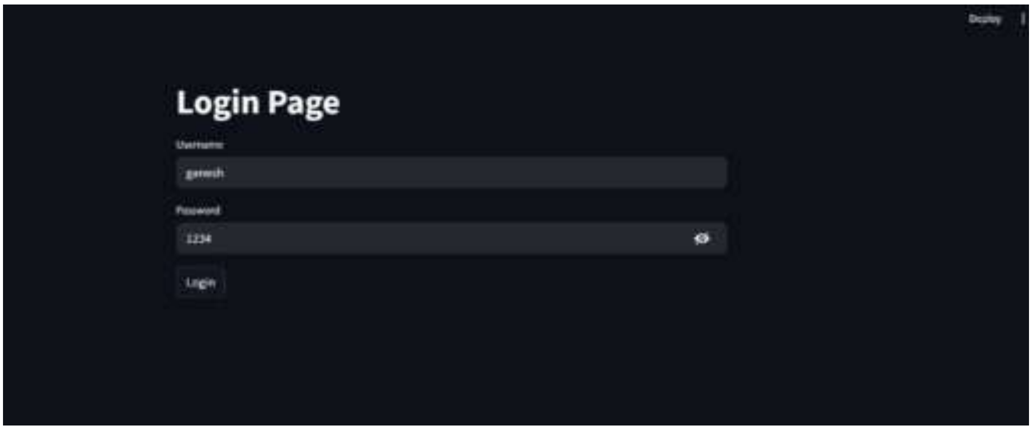
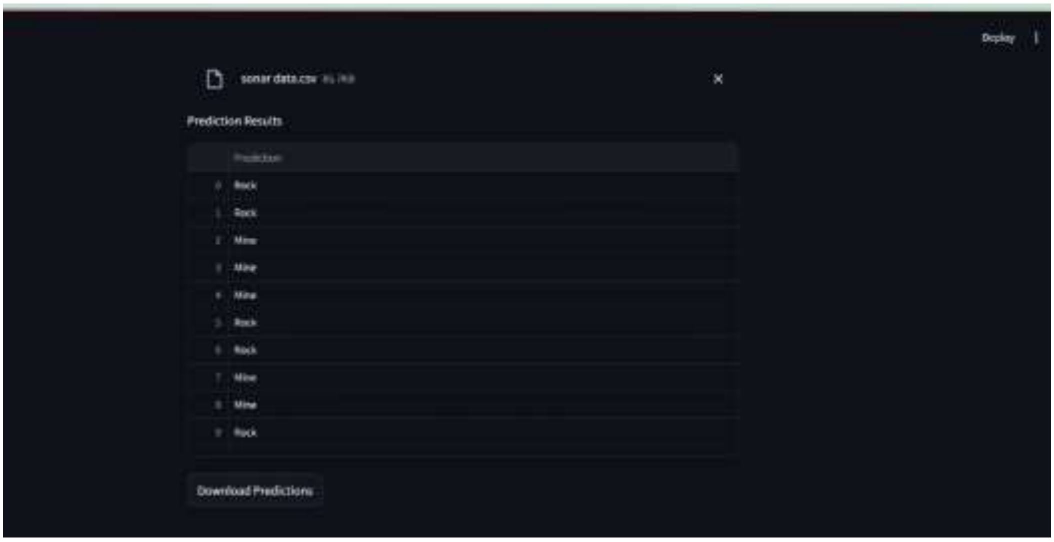
6. RESULTS AND OUTPUT





7. CONCLUSION

The **Sonovault X** project successfully addresses the need for a simple, interpretable, and effective solution to underwater object classification using SONAR data. Unlike complex deep learning models, the use of logistic regression provides transparency, fast computation, and ease of deployment. The model was trained on real-world SONAR data and achieved high accuracy in classifying objects as either Rocks or Mines.

Data preprocessing steps such as normalization and label encoding played a key role in enhancing model performance. The integration of a user-friendly Streamlit interface allows users to upload data, generate predictions, and download results effortlessly. This makes the system accessible to both technical and non-technical users.

The architecture is lightweight, modular, and well-suited for real-time and embedded applications. It demonstrates that simple models, when combined with proper preprocessing and clean interfaces, can deliver practical solutions in real- world environments. The project lays the groundwork for future enhancements like live SONAR integration, multi-class detection, and AI-powered underwater navigation

8.FUTURE SCOPE

The Sonovault X system demonstrates the effectiveness of logistic regression in classifying underwater objects using SONAR data. While the current implementation is efficient and interpretable, there are several potential areas for future enhancement:Sonovault X

Integration with Real-Time SONAR Devices:

The system can be adapted to work with live SONAR feeds from underwater drones or autonomous vehicles for continuous monitoring.

Deployment on Embedded Systems:

The lightweight nature of the model makes it suitable for deployment on low-power hardware like Raspberry Pi or edge AI devices.

Extension to Multi-Class Classification:

Future versions can be extended to classify more than just Rocks and Mines — such as metal debris, vegetation, or wreckage.

Model Upgradation:

Advanced algorithms like ensemble models or deep learning (with proper explainability) could be tested to improve classification accuracy further.

Visualization and Alert Systems: Integration with visualization dashboards and automated alert systems can improve usability in operational marine environments

9. REFERENCES

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