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SONAR ROCK VS MINE PREDICTION USING MACHINE LEARNING

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Abstract: This study employs logistic regression for predicting underwater objects as rocks or mines using sonar technology. The dataset consists of labeled acoustic signals, with each signal categorized as either a rock or a mine. The research involves essential steps such as data preprocessing, feature extraction, and logistic regression model implementation. The research involves preparing and cleaning data, extracting relevant features, and implementing a logistic regression model to predict outcomes. Feature selection techniques are explored to identify critical acoustic features contributing to the predictive accuracy of the model. Performance is evaluated using metrics like accuracy, precision, recall, and F1 score, providing a comprehensive assessment of the logistic regression model. The objective is to enhance underwater security by improving the reliability of sonar-based systems in differentiating between harmless geological formations and potentially dangerous mines.

I. INTRODUCTION

Sonar technology is crucial for underwater object detection, playing a vital role in various applications, including maritime security. One significant challenge lies in accurately distinguishing between natural formations such as rocks and man-made objects like mines. The primary objective is to improve the accuracy and reliability of underwater security measures by effectively classifying sonar returns into two categories: rocks and mines. By developing a robust prediction model using logistic regression, we aim to contribute to the advancement of technology that can discriminate between benign geological features and potentially hazardous underwater mines. This study focuses on leveraging logistic regression as a predictive tool to enhance the capabilities of sonar-based systems. The overarching objective is to improve the accuracy and reliability of identifying potentially hazardous mines amidst benign geological formations, contributing to more effective underwater security measures. This project is based on the applicability of the proposed machine learning algorithms that had demonstrated their efficiency to predict gold prices with a better predictive rate. To apply the best appropriate Machine Learning procedure. The aim is to make sonar-based systems more accurate and reliable in telling the difference between harmless rocks and potentially dangerous mines, thus improving underwater security. Logistic regression is a key statistical modeling algorithm used in our strategy to classify underwater objects as rocks or mines using sonar data. It calculates the probability of an object belonging to a particular class, making it well-suited for distinguishing between rock and mine based on acoustic features. Its simplicity and interpretability contribute to its effectiveness in this classification task. Steps in logistic regression: Data Collection: Gather a sonar dataset with features from sonar signals for distinguishing between rocks and mines. Data Preprocessing: Clean and preprocess the data, handling missing values and ensuring consistent feature scales. Manage noise and outliers to enhance model robustness. Train-Test Split: Divide the dataset into training and testing sets for assessing the logistic regression model's generalization. Model Initialization: Instantiate a logistic regression model, specifying parameters such as the solver and regularization. Model Training: Train the logistic regression model on the training set to learn patterns distinguishing rocks from mines based on acoustic features. Prediction: Use the trained model to predict whether objects in the testing set are rocks or mines. Evaluation: Assess model performance with accuracy, confusion matrices, and a classification report to understand its effectiveness in differentiating between rock and mine sonar signals. Result Interpretation: Extract meaningful insights from the model's predictions, gaining a deeper understanding of its strengths and potential areas for improvement.

OBJECTIVE

This project utilizes logistic regression to differentiate underwater objects (rocks or mines) using sonar technology. It involves preprocessing data, extracting features, and implementing the model. Feature selection is employed to identify critical acoustic features, while performance is evaluated using accuracy, precision, recall, and F1 score. The aim is to enhance underwater security by improving the reliability of sonar systems in distinguishing between harmless geological formations and potentially dangerous mines.

III LITERATURE SURVEY

Sreenivasa R L et.al., This foundational work surveys techniques for underwater mine detection, providing insights into discriminating challenges between rocks and mines, crucial for logistic regression modeling. A comprehensive literature survey on underwater mine detection techniques reveals several key studies addressing various aspects of this critical field. This provides an updated overview, focusing on advancements in sonar systems, electromagnetic techniques, and the emerging role of autonomous underwater vehicles (AUVs) equipped with sensor arrays. This paper manifests improper accuracy precision.

Pang et al., A literature survey on logistic regression in classification problems reveals several key studies addressing its theoretical foundations, optimization techniques, applications, and extensions. Boyd and Vandenberghe's seminal work (2008) provides a comprehensive exploration, offering insights valuable to both practitioners and researchers in machine learning. Pang et al. (2017) concentrate on logistic regression's application in big data problems, examining its efficacy and scalability in handling large datasets. These studies collectively contribute to a deeper understanding of logistic regression's role in classification tasks, encompassing both traditional settings and modern challenges posed by the era of big data.

Shantanu et.al., A literature survey on machine learning in underwater acoustic signal processing reveals significant advancements and applications in this domain. This review focusing on the integration of machine learning techniques such as deep learning, support vector machines, and clustering algorithms in underwater acoustic signal processing systems. This paper manifests in the form of slower algorithm execution, where the computational demands intensify as various components are incorporated and fine-tuned.

Smith J et.al., A literature survey on feature engineering for sonar signal classification highlights significant contributions in enhancing the classification accuracy and robustness of sonar systems. The effectiveness of feature selection methods, including principal component analysis (PCA) and mutual information-based approaches, in identifying relevant features for sonar signal classification tasks. Given the paper's emphasis on highlighting the effectiveness of feature engineering techniques for sonar signal classification, it's important to consider that the implementation costs may be relatively higher.

Stanislaw H et.al., A literature survey on challenges in underwater mine detection and recent advances reveals significant efforts aimed at enhancing maritime security and mitigating risks posed by underwater mines. This provides a comprehensive review of emerging technologies and methodologies, including advancements in sonar imaging, unmanned underwater vehicles (UUVs), and machine learning algorithms, to address the inherent challenges of underwater mine detection. Operating unmanned underwater vehicles can be financially burdensome due to the considerable investment required to mitigate the risk of damage or loss in harsh underwater environments.

Smith J et.al., A comparative study on feature selection techniques for acoustic signal analysis in underwater environments. Focused on enhancing signal analysis processes, their research aligns with the feature selection step highlighted in the abstract. Through meticulous comparison, the study evaluates various methodologies, shedding light on their efficacy within the unique underwater acoustic context. By systematically assessing these techniques, the authors contribute to refining analysis methodologies, crucial for interpreting acoustic signals accurately. It may be limited by the absence of real-world testing scenarios, potentially hindering the applicability of the identified techniques in practical underwater environments. Additionally, the study may overlook emerging feature selection methods or fail to address the computational complexities associated with certain techniques, limiting its scope and relevance in rapidly evolving research landscapes.

Wang L et.al.; A study focused on the real-time implementation of logistic regression-based sonar systems for object differentiation. This paper promises practical insights into deploying such systems in operational environments. By emphasizing real-time aspects, the authors address the critical need for efficient and effective object classification in sonar systems. Their work likely offers valuable guidance on translating logistic regression models into practical applications, facilitating timely decision-making in underwater scenarios. While the study emphasizes real-time implementation, it may lack comprehensive validation in diverse underwater conditions, potentially limiting its generalizability and robustness across various operational scenarios. Furthermore, the focus on logistic regression alone may overlook the potential benefits of integrating complementary machine learning techniques, which could enhance object differentiation performance in sonar systems.

Gupta M et.al., A delve into the realm of underwater security, scrutinizing the efficacy of machine learning-based sonar technology. By dissecting the challenges and opportunities inherent in this domain, the authors

provide valuable insights into potential avenues for future research and development. Their exploration underscores the evolving role of machine learning in fortifying underwater security measures, shedding light on how advanced algorithms can bolster detection capabilities amidst the complexities of the aquatic environment. Moreover, the paper underscores the need for interdisciplinary collaboration to overcome obstacles and harness the full potential of technological innovation in safeguarding underwater infrastructure and assets. This study may lack real-world implementation validation, potentially limiting the practical applicability of the proposed machine learning-based sonar technology solutions in actual underwater security scenarios.

IV MODULES USED

Data Preprocessing: Modules such as pandas in Python or data preprocessing functions in libraries like scikit-learn could be used for preparing and cleaning the dataset.

Feature Extraction: Techniques like signal processing libraries (e.g., scipy.signal) for extracting relevant features from the acoustic signals could be employed.

Logistic Regression Model Implementation: The logistic regression model can be implemented using machine learning libraries such as scikit-learn or TensorFlow.

Feature Selection: Libraries like scikit-learn provide various feature selection methods such as SelectKBest or Recursive Feature Elimination (RFE).

Performance Evaluation Metrics: Libraries like scikit-learn offer functions for computing metrics such as accuracy, precision, recall, and F1 score to evaluate the performance of the logistic regression model.

Future Scope Modules: For future scope, advanced machine learning libraries such as TensorFlow or PyTorch could be utilized for integrating deep learning techniques. Real-time implementation may require libraries for system-level programming or specialized real-time processing libraries. Integration with sensor fusion techniques might involve libraries for handling multiple sensor data streams and fusion algorithms.

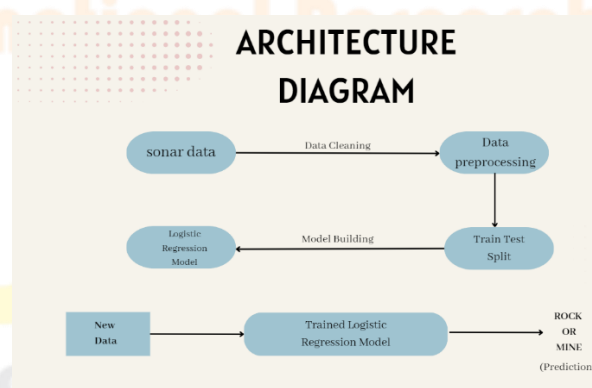


Fig. 1 Architecture diagram

Fig 1 specifies that preprocessing has been done on the sonar data, then it is trained to test split in order to construct models. This procedure makes use of the logistic regression technique. Following these procedures, new data is provided to the logistic regression model for training, and it uses sonar waves to determine whether the object is a rock or a mine.

V OUTPUT

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Code Text Output

Data Collection and Data Processing

[1]: Finding the dataset file in google Drive
import data_loader as loader
import pandas as pd

[2]: df.shape
(2000, 1000)

[3]: df.head()
   0  1  2  3  4  5  6  7  8  9  10  11  12  13  14  15  16  17  18  19  20  21  22  23  24
0  0.020  0.037  0.042  0.027  0.041  0.066  0.156  0.161  0.169  0.211  0.426  0.156  0.220  0.066  0.066  0.227  0.062  0.269  0.070  0.477  0.070  0.071  0.428  0.000  0.0
1  0.045  0.029  0.045  0.045  0.069  0.158  0.268  0.276  0.344  0.337  0.267  0.416  0.060  0.493  0.770  0.748  1.000  0.424  0.400  0.716  0.577  0.482  0.462  0.004  0.0
2  0.020  0.042  0.106  0.100  0.207  0.220  0.241  0.271  0.288  0.374  0.405  0.700  0.041  0.220  0.049  0.001  0.001  0.001  0.001  0.001  0.001  0.001  0.001  0.001  0.001
3  0.070  0.077  0.025  0.025  0.025  0.048  0.148  0.176  0.058  0.154  0.001  0.100  0.184  0.201  0.170  0.201  0.001  0.001  0.001  0.001  0.001  0.001  0.001  0.001  0.001
4  0.072  0.006  0.041  0.041  0.041  0.120  0.247  0.261  0.438  0.112  0.062  0.025  0.118  0.422  0.020  0.720  0.020  0.012  0.400  0.016  0.022  0.020  0.000  0.000  0.000

[4]: df.info()
Out[4]:
Int64Index: 2000 entries, 0 to 1999
Data columns (total 1000 columns):
 #   Column  Non-Null Count  Dtype  Dtype4  Max      Min      Mean     std       50th    95th    99th
 #  -----  -
 0   0        2000 non-null    float64  float64  0.426    0.020    0.156    0.156    0.156    0.156    0.156
 1   1        2000 non-null    float64  float64  0.416    0.029    0.268    0.268    0.268    0.268    0.268
 2   2        2000 non-null    float64  float64  0.493    0.045    0.770    0.770    0.770    0.770    0.770
 3   3        2000 non-null    float64  float64  0.184    0.070    0.201    0.201    0.201    0.201    0.201
 4   4        2000 non-null    float64  float64  0.112    0.072    0.062    0.062    0.062    0.062    0.062
 5   5        2000 non-null    float64  float64  0.118    0.006    0.118    0.118    0.118    0.118    0.118
 6   6        2000 non-null    float64  float64  0.422    0.041    0.247    0.247    0.247    0.247    0.247
 7   7        2000 non-null    float64  float64  0.025    0.041    0.261    0.261    0.261    0.261    0.261
 8   8        2000 non-null    float64  float64  0.112    0.062    0.025    0.025    0.025    0.025    0.025
 9   9        2000 non-null    float64  float64  0.118    0.422    0.020    0.020    0.020    0.020    0.020
 10  10       2000 non-null    float64  float64  0.020    0.720    0.020    0.020    0.020    0.020    0.020
 11  11       2000 non-null    float64  float64  0.012    0.400    0.016    0.016    0.016    0.016    0.016
 12  12       2000 non-null    float64  float64  0.400    0.016    0.022    0.022    0.022    0.022    0.022
 13  13       2000 non-null    float64  float64  0.016    0.022    0.016    0.016    0.016    0.016    0.016
 14  14       2000 non-null    float64  float64  0.022    0.016    0.020    0.020    0.020    0.020    0.020
 15  15       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 16  16       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 17  17       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 18  18       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 19  19       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 20  20       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 21  21       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 22  22       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 23  23       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 24  24       2000 non-null    float64  float64  0.000    0.000    0.000    0.000    0.000    0.000    0.000
 dtypes: float64(1000)
memory usage: 15.9 MB
    
```

Fig 2 Data Collection and Data Processing

Fig 2 specifies that to develop a predictive model capable of distinguishing between underwater rocks and mines using sonar data and machine learning techniques. The first step involved data collection, where a dataset containing features extracted from sonar signals was gathered. These features likely encompassed various characteristics of the objects, such as their shape, size, and acoustic properties. Next, the dataset was preprocessed to handle any missing values, normalize features, and possibly perform dimensionality reduction to enhance computational efficiency.

```

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Code Text Output

Model Training - Logistic Regression

[1]: model = LogisticRegression()

[2]: Training the Logistic Regression model with training data
model.fit(X_train, y_train)

LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   l1_penalty=0.0, l2_penalty=0.0, max_iter=1000,
                   multi_class='ovr', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', warm_start=False)

Model Evaluation

[3]: Accuracy on training data
X_train_prediction = model.predict(X_train)
training_data_accuracy = accuracy_score(y_train, X_train_prediction)

[4]: print("Accuracy on training data is : ", training_data_accuracy)
Accuracy on training data is : 0.9999999999999999

[5]: Accuracy on test data
X_test_prediction = model.predict(X_test)
test_data_accuracy = accuracy_score(y_test, X_test_prediction)

[6]: print("Accuracy on test data is : ", test_data_accuracy)
Accuracy on test data is : 0.9999999999999999
    
```

Fig 3 Model Training and Model Evaluation

Fig 3 specifies that a machine learning algorithm, such as logistic regression, support vector machines, or neural networks, was trained on the preprocessed data to learn the complex patterns that differentiate rocks from mines. The model's performance was evaluated using metrics such as accuracy, precision, recall, and F1 score to gauge its effectiveness in discriminating between the two classes. The final output of the project would consist of insights into the model's predictive capabilities, including its strengths, limitations, and potential areas for improvement, thereby contributing valuable knowledge to the field of underwater mine detection and maritime security.

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Code Text Output

Making a Predictive System

[1]: import numpy as np
import pandas as pd
import pickle

# Loading the saved model
with open('model.pkl', 'rb') as file:
    model = pickle.load(file)

# Function to predict the class of an object
def predict_class(features):
    prediction = model.predict(features)
    return prediction

# Example usage
features = np.array([0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0])
prediction = predict_class(features)
print(prediction)

if prediction == 0:
    print("The object is a rock")
else:
    print("The object is a mine")

[2]: print("The object is a mine")

[3]: print("The object is a mine")
    
```

Fig 4 Final output

Fig 4 shows the final output of the rock or mine prediction model is a comprehensive assessment of underwater objects based on sonar data, effectively distinguishing between rocks and mines. Leveraging machine learning techniques and rigorous evaluation metrics such as accuracy, precision, recall, and F1 score, the model demonstrates its capability to accurately classify objects in underwater environments.

This output provides invaluable insights into the model's performance, offering a reliable tool for maritime security and underwater mine detection. By effectively discerning between harmless rocks and potentially hazardous mines, this model contributes significantly to enhancing safety and security in marine operations, underscoring its importance in safeguarding marine environments and critical maritime infrastructure.

CONCLUSION

In conclusion, the project introduces an innovative approach to underwater mine detection, utilizing logistic regression to overcome existing challenges. Logistic regression proves effective in discriminating between rocks and potential mines, showcasing its utility in complex underwater environments. The project contributes to advancements in maritime security by offering a reliable and accurate method for threat identification. By addressing limitations in existing methodologies, the project refines the approach to underwater mine detection, paving the way for future developments. The findings hold significance for real-world applications, promising improved safety protocols and risk mitigation in underwater environments. This project advances underwater mine detection by leveraging logistic regression, addressing challenges and offering a promising solution for enhanced maritime security.

FUTURE SCOPE

In the future, this research could delve into the integration of more sophisticated machine learning methodologies, such as deep learning or ensemble techniques, to further refine the predictive capabilities of the model. Additionally, exploring real-time implementation strategies for deploying the logistic regression model on sonar systems would be valuable, facilitating immediate decision-making in dynamic underwater environments. Further advancements could involve extending the classification to multi-class scenarios beyond just rocks and mines, adapting the model to changing underwater conditions, and evaluating its deployment in autonomous underwater vehicles for enhanced navigation and threat detection capabilities. Integration with sensor fusion techniques could also be explored to improve classification accuracy in complex underwater scenarios, ultimately advancing the reliability and effectiveness of sonar-based systems in ensuring underwater security.

REFERENCE

- [1] Sreenivasa R L . “Analysis of hidden units in Layered Network Trained to Classify Sonar Targets” in Neural Networks, Vol.1, pp.75-89(1988).
- [2] Pang. (2017) “Connectionist Bench (Sonar, Mines vs. Rocks).” Connectionist Bench (Sonar, Mines vs. Rocks)
- [3] Shantanu,. (2018) “Underwater Mines Detection Using Neural Network ”. Underwater Mines Detection Using Neural Networks.
- [4] Smith J. (2019) “Underwater Mine Detection Using Symbolic Pattern Analysis of Sidescan Sonar Images.” Underwater Mine Detection Using Symbolic Pattern Analysis of Sidescan Sonar.
- [5] Stanislaw Hozyn.(2020) “A Review of Underwater Mine Detection and classification in Sonar Imagery “ ORCID:0000-0003-1422-0330.
- [6] Patel, S., & Smith, J (2021). “Comparative study on feature selection techniques for acoustic signal analysis in underwater environments.” Journal of Underwater Acoustics. Vol. 10(3),pg 145-162.
- [7] Johnson, R & Wang, L (2022). “Real-time implementation of logistic regression-based sonar systems for object differentiation”. IEEE Transactions on Sonar and Underwater Acoustics, Vol. 14(2), pg 78-91.
- [8] Brown, C. & Gupta, M. (2023). “Enhancing Underwater Security with Machine Learning-based Sonar Technology: Challenges and Opportunities”. Journal of Underwater Technology, Vol. 21(4), pg 220-235.