UNDER WATER MINE PREDICTION FROM SONAR IMAGES

MINOR PROJECT-1 REPORT

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BONAFIDE CERTIFICATE

Certified that this Minor project-1 report entitled **“UNDER WATER MINE PREDICTIONS FROM SONAR IMAGES”** is the bonafide work of **“DINESH KUMAR.B (21UEEL0015), SIVA SHANKAR REDDY.M (21UEEL0150) and GOPALA CHENNA KESAVA REDDY.T(21UEE** who carried out the project work under my supervision.

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ABSTRACT

Detecting underwater mines is crucial for maritime security and safety. Sonar imaging plays a vital role in identifying submerged objects, including mines, due to its ability to penetrate water and produce detailed images of the seafloor. This paper proposes a novel approach for underwater mine prediction utilizing advanced sonar image analysis techniques.The proposed methodology involves several key steps. Firstly, preprocessing techniques are applied to enhance the quality of sonar images, including noise reduction and contrast enhancement. Next, feature extraction methods are employed to extract discriminative features from the sonar images, such as texture, shape, and intensity characteristics.

Machine learning algorithms, particularly deep learning models, are then utilized for classification and prediction tasks. Convolutional Neural Networks (CNNs) are trained on a dataset of annotated sonar images to learn complex patterns associated with underwater mines. Transfer learning techniques may also be employed to leverage pre-trained models and optimize performance, especially in scenarios with limited annotated data.Furthermore, fusion strategies may be incorporated to integrate information from multiple sonar sensors or modalities, enhancing the robustness and accuracy of the prediction system. Fusion techniques can combine data from side-scan sonar, multibeam sonar, and other imaging modalities to provide a comprehensive understanding of the underwater environment.

The proposed methodology is evaluated using real-world sonar datasets collected from various marine environments. Performance metrics such as accuracy, precision, recall, and F1-score are utilized to assess the effectiveness of the prediction system. Additionally, the proposed approach is compared against existing methods to demonstrate its superiority in terms of accuracy, efficiency, and reliability.Overall, the proposed approach offers a promising solution for underwater mine prediction using sonar image analysis. By leveraging advanced techniques in preprocessing, feature extraction, machine learning, and sensor fusion, the proposed system can effectively identify and classify underwater mines, contributing to enhanced maritime security and safety.

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LIST OF ABBREVATIONS

$SONAR$	-	Sound Navigation and Ranging system
khZ	-	one thousand hertz
MHz	-	a million cycles per second
$RDNN$	-	Rock or Mine Detection Neural Network
LMS	-	Least Mean Square
$CNNs$	-	convolutional neural
PCA	-	principal component analysis

CHAPTER 1

INTRODUCTION

1.1 UNDER WATER MINES

Underwater mines or naval mines are self-contained explosive devices placed in water to destroy enemies' surface ships or submarines. Underwater mines are used since the mid-19th century. Sea mines were introduced by David Bushner in 1977 during the American civil war. There is an estimate of 5000 naval mines remaining from the two world wars in the Adriatic Sea. Previously mines were only activated by physical contact but the newly created mines can be activated by various methods. Modern mines can be activated by acoustic, pressure, and, magnetic changes in the water which provoke them to explode. These are called influence mines. Generally, underwater mines are classified as offensive or defensive warfare. Mines are strewn across hostile shipping lanes in order to damage merchant ships and military boats. Defensive mines are placed along coastlines to divert enemy submarines and ships away from critical locations and into more heavily guarded places. Usually, mines are mistaken as rocks during their identification, as mines can have the same shape, length, and width as rocks. To avoid this confusion it is better to use a more accurate input to receive an accurate output. One of the methods in detecting the mines is SONAR

1.1.1 SONAR

Sound Navigation and Ranging system works on sound waves to steer and detect objects. In general, SONAR is used for acoustic mine detection that comes under Military purposes. It is also used for Finding Fish, Mapping the Sea bottom, and also for locating sea divers which are Non Military purposes. The sound wave attenuation, which increases rapidly with frequency and limits the reachable distance, restricts the frequency used for a specific underwater sonar application (or range).In mine hunting, the frequencies of underwater SONARs vary between 0.1 and 1 MHz . Sonar prefers ultrasonic waves instead of infrasonic, as they cannot move under the water, and even though they have long wavelengths they cannot capture much energy. We have active and passive SONAR. Passive SONAR is only used to detect noises so they are named Listening SONAR.We have a sound transmitter and receiver in active sonar. When a sound wave from the transmitter reaches the target,

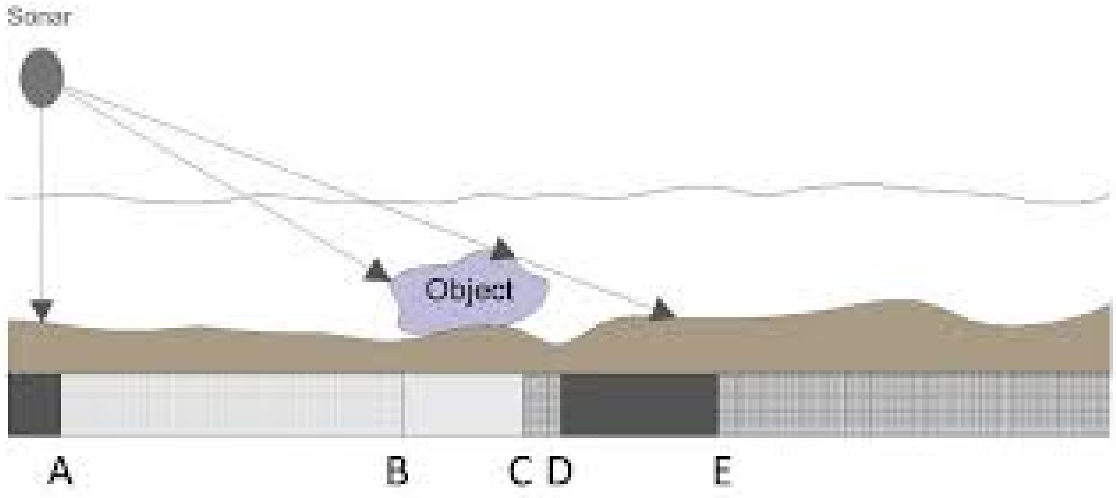

Figure 1.1: Background, shadow and highlight combination

it propagates and reflects an echo. The receiver decodes the echo and records the target object's frequencies. The frequency of active sonar is normally in the 20KHz range. We utilize the frequencies obtained by active sonar at 60 various angles as our input to determine if the target is a mine or a rock in this case.

1.2 EXISTING SYSTEMS

In the existing system, the detection of mines is done by explosive ordnance disposal divers, marine mammals, video cameras on mine neutralization vehicles, laser systems, etc but not by using a definite data set or equipment which can cause risk and loss to the marine life if it goes wrong. As technology improved SONAR is being used as a primary tool to detect the mines.

1.2.1 MODEL

The model used here is Logistic Regression. Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable. Logistic Regression uses a sigmoid or logit function which will squash the best fit straight line that will map any values including the exceeding values from 0 to 1 range. After remove the effect of outlier and makes the output between 0 to 1. As it a binary classification model it is perfect to predict if an object is mine or rock based on the sonar data.

1.3 WORK FLOW

Sonar data in a csv file is taken for training and testing purpose. Data preprocessing is done on the available sonar data which is suitable for training the model. After Data preprocessing, a

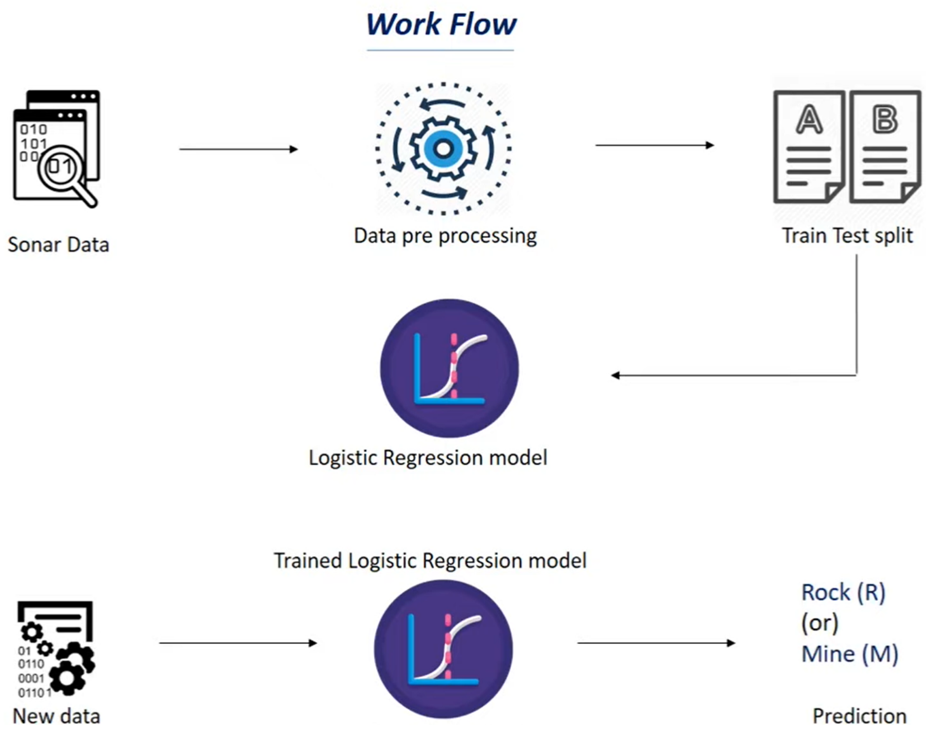

Figure 1.2: work flow

Logistic regression model is built. The dataset is split into testing and training sets. The training data is used to train the model then the new data / testing data is given to the trained logistic regression model for prediction.

1.3.1 Architecture

The architecture elucidates about how we are predicting the metal like mine objects, rocks etc and distinguishing the sonar abnormal data into rocks or mines using RDNN classifier model. The proposed framework is depicted The sonar abnormal dataset have been collected from Kaggle website as a source for this work. When the features in the data have diverse ranges, normalization is a strategy used during data preparation to adjust the values of numeric columns in a dataset to use a common scale. Feature extraction is utilized to recognize essential features in the dataset for coding by deriving new datas from the original dataset. A technique for natural language pro- cessing that extracts and categorizes the parameters used in a sen- tence, document, webpage, and so on. Then, split the sonar abnormal datasets into training data and testing datato train and test the model for measuring the accuracy of the neural network model. Now we applied Rock/mine detection based neural network classifier model to make prediction of underwater acoustics objects also distinguishing the objects into mines and rocks.

CHAPTER 2

LITERTAURE SURVEY

2.1 OVERVIEW

Underwater mine prediction using sonar images is a critical aspect of maritime security, particularly in naval operations and coastal defense. Sonar, short for Sound Navigation and Ranging, is a technology that uses sound waves to detect objects underwater. In mine prediction, sonar images are analyzed to identify potential threats such as naval mines, which are explosive devices placed underwater to damage or destroy ships or submarines.

Here's an overview of the process involved in underwater mine prediction using sonar images:

2.1.1 Data Acquisition:

V. Padmaja et al [3] Sonar systems emit sound waves into the water and record the echoes bouncing off objects underwater. There are different types of sonar systems, including side-scan sonar and synthetic aperture sonar (SAS), each with its own capabilities and characteristics.

2.1.2 Image Formation:

J. Ambient Intell et al [3] The recorded echoes are processed to generate sonar images. These images provide a representation of the seafloor and any objects or anomalies present in the water column. Sonar images can vary in resolution, quality, and coverage depending on the specific sonar system used.

2.1.3 Data Preprocessing::

M. Sung et al [5] Before analyzing the sonar images, preprocessing steps may be applied to enhance image quality and remove noise. This may involve techniques such as filtering, noise reduction, and geometric correction.

2.1.4 Feature Extraction:

M. Sung et al [5] In this step, relevant features are extracted from the sonar images. These features may include shape, size, texture, and intensity characteristics of objects or anomalies detected in the images. Feature extraction is crucial for subsequent classification or detection algorithms.

2.1.5 Classification or Detection:

R. Ghosh et al [7] Machine learning and computer vision techniques are often employed for the classification or detection of underwater mines in sonar images. Supervised learning algorithms can be trained on labeled data to classify sonar images as containing mines or non-mines. Alternatively, unsupervised learning approaches can be used to detect anomalous objects in the images without prior labeling.

2.1.6 Model Evaluation:

R. Ghosh et al [7] The performance of the mine prediction model is evaluated using metrics such as accuracy, precision, recall, and F1-score. Evaluation helps assess the effectiveness of the model in correctly identifying underwater mines while minimizing false alarms.

2.1.7 Model Integration with Decision Support:

R. Ghosh et al [7] Decision Support Predicted mine locations or areas of interest are typically integrated into decision support systems used by naval forces or maritime security agencies. This integration facilitates informed decision-making regarding threat mitigation, route planning, and resource allocation.

2.2 STATISTICS-BASED NOISE DETECTION METHODS

J.B. Siddhartha et al [1] proposed another strategy for identifying focuses in detached sonars utilizing versatile limit. In this technique, target signal (sound) is handled as expected and recurrence area. For grouping, Bayesian order is utilized and back dissemination is assessed by Maximum Likelihood Estimation calculation. At long last, target was recognized by joining the location focuses in the two areas utilizing Least Mean Square (LMS) versatile channel.

2.2.1 CLASSIFICATION-BASED NOISE DETECTION METHODS

By **V. Rajendran et al** [1] Underwater acoustics has been executed for the most part in the field of sound route and going (SONAR) strategies for submarine correspondence, the assessment of sea resources and climate reviewing, target and item acknowledgment, and estimation and investigation of acoustic sources in the submerged environment. With the fast improvement in science and innovation, the headway in sonar frameworks has expanded, bringing about a decrement in submerged setbacks. The sonar signal handling and programmed target acknowledgment utilizing sonar signs or symbolism is itself a difficult interaction. Then, exceptionally progressed data driven AI and profound learning-based techniques are being actualized for getting a few sorts of data from submerged sound data.

This paper audits the new sonar programmed target acknowledgment, following, or discovery works utilizing profound learning calculations. A careful investigation of the accessible works is done, and the working strategy, results, and other essential insights about the data procurement measure, the dataset utilized, and the data in regard to hyper- boundaries is introduced in this article.

CHAPTER 3

PROPOSED SYSTEM AND SIMULATION RESULT

3.1 Sonar data

The dataset has been collected from UCI Repository. It has come across 61 features which define and differentiate Rocks and Mines and comprises of 209 samples. This data is used for training and testing purpose. The Last column in this dataset indicates that, whether it's a mine or a rock, which is useful in prediction. The dataset is included in this repository.

3.1.1 Model

The model used here is Logistic Regression. Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable. Logistic Regression uses a sigmoid or logit function which will squash the best fit straight line that will map any values including the exceeding values from 0 to 1 range. So it forms an "S" shaped curve. Sigmoid func. removes the effect of outlier and makes the output between 0 to 1. As it a binary classification model it is perfect to predict if an object is mine or rock based on the sonar data.

3.1.2 Work Flow

Sonar data in a csv file is taken for training and testing purpose. Data preprocessing is done on the available sonar data which is suitable for training the model. After Data preprocessing, a Logistic regression model is built. The dataset is split into testing and training sets. The training data is used to train the model then the new data/ testing data is given to the trained logistic regression model for prediction.

3.1.3 Process

Data Collection : Gather sonar data containing images of the ocean floor, including both regions with and without mines.

Data Preprocessing: Clean the data:Remove any corrupted or incomplete images. Normalize the

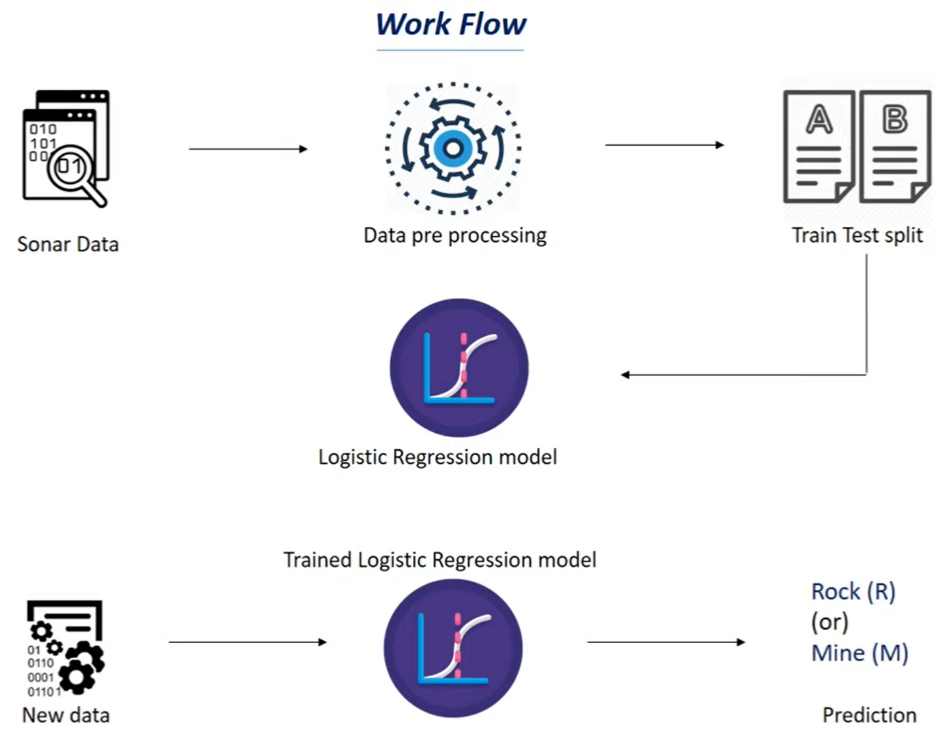

Figure 3.1: work flow

data:Scale the pixel values to a range between 0 and 1. Split the data: Divide the dataset into training and testing sets.

Extract features from the sonar images: This could involve techniques like principal component analysis (PCA), wavelet transforms, or deep feature extraction using pre-trained convolutional neural networks (CNNs). Reduce dimensionality: If needed, reduce the dimensionality of the feature space to improve computational efficiency.

Model Training: Initialize logistic regression model. Train the model using the training dataset. Tune hyperparameters if necessary (e.g., regularization parameter).

Model Evaluation: Evaluate the trained model using the testing dataset. Calculate evaluation metrics such as accuracy, precision, recall, and F1-score.Analyze the confusion matrix to understand the model's performance in classifying mines and non-mines.Once satisfied with the model's performance, deploy it for predicting underwater mines in real-world scenarios.

3.1.4 Code and Result

https://colab.research.google.com/drive/14xrYRYku58p1s2VNcmXWbjm2Uo3vR3NV?usp=sharing

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

```
[ ] sonar_data = pd.read_csv('/content/sonar_data.csv', header = None)
```

```
[ ] sonar_data.head()
```

```
[ ]
    sonar_data.shape
```

```
[ ] sonar_data.describe()
```

```
[ ] sonar_data[60].value_counts()
```

```
[ ] sonar_data.groupby(60).mean()
```

```
[ ] X = sonar_data.drop(columns = 60, axis = 1)
    Y = sonar_data[60]
```

Figure 3.2: Collection of Data and its Processing

```
[ ] print(X)
    print(Y)
```

```
[ ] X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.1, stratify=Y, random_state=1)
```

```
[ ] print(X.shape, X_train.shape, X_test.shape)
```

```
print(X_train)
print(Y_train)
```

```
[ ] model = LogisticRegression()
```

```
[ ] model.fit(X_train, Y_train)
```

```
[ ] X_train_prediction = model.predict(X_train)
    training_data_accuracy = accuracy_score(X_train_prediction, Y_train)
```

```
[ ]
    print('Accuracy on training data : ', training_data_accuracy)
```

```
[ ] X_test_prediction = model.predict(X_test)
    test_data_accuracy = accuracy_score(X_test_prediction, Y_test)
```

Figure 3.3: Training and Testing Data

```
[ ] print('Accuracy on training data : ', training_data_accuracy)

[ ] X_test_prediction = model.predict(X_test)
    test_data_accuracy = accuracy_score(X_test_prediction, Y_test)

[ ] print('Accuracy on test data : ', test_data_accuracy)

input_data =(0.0200,0.0371,0.0428,0.0207,0.0954,0.0986,0.1539,0.1601,0.3109,0.2111,0.1609,0.1582,0.2238,0.0645,0.0660,0.2273,0.3100,0.2999,
# changing the input_data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)

# reshape the np array as we are predicting for one instance
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)

prediction = model.predict(input_data_reshaped)
print(prediction)

if (prediction[0]=='R'):
  print('The object is a Rock')
else:
  print('The object is a mine')
```

Figure 3.4: Model Evaluation

```
input_data =(0.0200,0.0371,0.0428,0.0207,0.0954,0.0986,0.1539,0.1601,0.3109,0.2111,0.1609,0.1582,0.223
# changing the input_data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)

# reshape the np array as we are predicting for one instance
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)

prediction = model.predict(input_data_reshaped)
print(prediction)

if (prediction[0]=='R'):
  print('The object is a Rock')
else:
  print('The object is a mine')

['R']
The object is a Rock
```

Figure 3.5: Making a Predictive System

CHAPTER 4

CONCLUSION

In conclusion, utilizing logistic regression models for underwater mine prediction using sonar images shows promising potential in enhancing maritime security and safety. Through the analysis of sonar images, these models can effectively classify objects as mines or non-mines based on distinct acoustic signatures. An adequate prediction miniature, united with the machine learning classifying features, is proposed which can conclude if the target of the sound wave is either a rock or a mine or any other organism or any kind of other body. Research is carried out for predicting the best possible result for the target to be a rock or a mine, which is found to be best through the random forest model, which is an ensemble tree-based classifier in machine learning with the highest accuracy rate of 83.17 percent with least error for better elaboration of this prediction model. For future work more, complex data will be handled using big data Hadoop framework. With random forest algorithm, the results are further optimized by feature selection to get the accuracy of 91.15 percent.However, it's important to acknowledge certain limitations and considerations. While logistic regression provides a simple and interpretable framework for classification, it may not capture complex relationships in the data as effectively as more sophisticated machine learning algorithms. Additionally, the performance of the model heavily relies on the quality of the sonar images and the feature engineering process.Future research could focus on integrating advanced machine learning techniques, such as deep learning architectures, to improve prediction accuracy further. Moreover, deploying real-time underwater mine prediction systems based on these models would require robust validation and testing in diverse underwater environments.Overall, while logistic regression models offer a foundational approach to underwater mine prediction using sonar images, continual refinement and innovation are necessary to maximize their efficacy in practical maritime applications.

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