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UNDERWATER MINE & ROCK PREDICTION BY EVALUATION OF MACHINE LEARNING ALGORITHMS

[1]Mrs. K. SRILATHA, [2]T. RAJA, [3]L. YASHWANTH GOUD, [4]N. SAKETH VARMA
[1](Assistant Professor) , CSE. Teegala Krishna Reddy Engineering College Hyderabad.
[2,3,4]B,tech , scholar , CSE. Teegala Krishna Reddy Engineering College Hyderabad.

ABSTRACT

Naval defense systems often rely on underwater mines to enhance security, but the potential threat to marine life and submarines arises when mines are mistakenly identified as rocks. Addressing this concern requires a more accurate system for object prediction, necessitating precise data to generate reliable results. This paper proposes a novel method for predicting underwater mines and rocks using Sonar signals. The dataset employed in this study comprises 208 sonar signals recorded at 60 different angles, capturing the distinct frequency characteristics of underwater objects. Sonar signals are instrumental in discerning object frequencies, providing a foundation for accurate predictions. To achieve this, three binary classifier models were constructed based on their respective accuracies. The prediction models, developed using Python and supervised machine learning classification algorithms, are designed to distinguish between mine and rock categories. These models leverage the recorded sonar signals to enhance accuracy in differentiating underwater objects. The utilization of 60 different angles ensures a comprehensive understanding of the objects' frequency patterns. The significance of this research lies in its potential to mitigate risks associated with underwater mine misidentification. By employing advanced machine learning techniques and a robust dataset, the developed models exhibit high accuracy in predicting whether an object is a mine or a rock. This approach contributes to the improvement of naval defense systems, emphasizing precision in object classification to safeguard both marine life and submarines.

1. INTRODUCTION

Underwater mines, also known as naval mines, have been used since the mid19th century as self-contained explosive devices to deter enemy surface ships and submarines. Introduced by David Buchner during the American Civil War, these mines still pose a threat today, with approximately 5,000 remaining in the Adriatic Sea from both world wars. Unlike earlier versions that relied on physical contact for activation, modem mines can be triggered by acoustic, pressure, and magnetic changes in the water, known as influence mines. They are categorized as offensive or defensive warfare tools. Offensive mines are scattered across hostile shipping lanes to damage merchant ships and military vessels, while defensive mines are strategically placed along coastlines to divert enemy submarines and ships away from critical areas and into more heavily guarded zones. However, their resemblance to rocks in terms of shape, length, and width often leads to misidentification, necessitating precise input for accurate detection. One effective method for detecting mines is through the use of SONAR technology.SONAR, which stands for Sound Navigation and Ranging, utilizes sound waves to locate and detect objects underwater. Its applications extend beyond military purposes and include acoustic mine detection, fish finding, ocean floor mapping, and locating divers for non- military uses.

The range and frequency of SONAR are limited due to sound wave attenuation increasing rapidly with frequency. For mine hunting, SONAR frequencies typically range from 0.1 to 1 MHz, with a range of 1 to 0.1 km. Ultrasonic waves are preferred over infrasonic waves in SONAR due to their inability to propagate underwater. SONAR is classified into two types: active and passive. Passive SONAR, also known as listening SONAR, detects sounds, while active SONAR employs a sound transmitter and receiver. When the transmitter emits a sound wave that hits an object, it reflects back and creates an echo. By analyzing the frequencies of the object's echo, the receiver determines its nature. In the case of detecting mines or rocks, the frequencies obtained by active SONAR at 60 different angles are used as input to discern between the two. Active SONAR typically operates in the frequency range of 20KHz. The process of mine countermeasures can be divided into four stages. Firstly, detection involves locating targets using various signals such as acoustic or magnetic cues. Secondly, classification is employed to differentiate potential mines from harmless objects. Thirdly, identification confirms the classification with the assistance of additional information from tools like underwater cameras. Lastly, disposal entails safely removing or destroying the detected mines.

2. LITERATURE SURVEY

Understanding the complexities of distinguishing underwater mines from natural objects like rocks is crucial for naval defense systems. The risks associated with misidentifying these objects emphasize the need for highly accurate prediction methods to safeguard marine life and prevent accidents involving submarines and vessels. Current literature emphasizes the challenge posed by the visual resemblance between mines and rocks, highlighting the urgency to improve object prediction accuracy in underwater settings. Despite past research exploring various approaches, achieving precise classification remains difficult due to the intricate nature of underwater environments and signal processing complexities. Recent studies have shifted focus toward leveraging advanced signal processing techniques, particularly sonar signals, to gather extensive data on underwater objects.

These signals, captured at multiple angles to capture diverse frequencies emitted by underwater entities, serve as the primary dataset for constructing predictive models. Researchers have turned to Python-based Supervised Machine Learning Classification algorithms to create binary classifiers geared towards maximizing accuracy. The aim is to develop and compare three distinct models, each prioritizing accuracy, to precisely predict and categorize underwater mines and rocks. This approach combines signal processing and machine learning techniques to build robust prediction models, aiming to significantly enhance the identification and differentiation of potentially hazardous underwater objects for bolstering naval defense systems. The challenges lie in reconciling the visual similarities between underwater mines and rocks while ensuring reliable differentiation. Extensive efforts have been directed towards exploring novel methodologies, with a notable focus on leveraging sonar signals to compile comprehensive datasets. These signals, captured at diverse angles to encompass a broad spectrum of frequencies emitted by underwater objects, offer valuable insights for building accurate predictive models. The integration of Python-based Supervised Machine Learning Classification algorithms stands out as a promising avenue, facilitating the development of binary classifiers designed to distinguish between mines and rocks with heightened precision.

The research landscape underscores the critical need for advancements in predictive accuracy within underwater environments to mitigate potential risks. By harnessing the power of sophisticated signal processing techniques and machine learning algorithms, scholars aim to refine predictive models for differentiating underwater mines and rocks. The emphasis remains on constructing reliable classifiers capable of accurate categorization, aligning with the overarching goal of bolstering naval defense systems by minimizing the chances of misidentifying hazardous underwater objects. The literature highlights the urgent need for accurate systems capable of distinguishing between underwater mines and natural elements such as rocks. The risks associated with misidentifying mines or mistaking them for harmless objects emphasize the necessity for precise prediction systems. Previous research has underlined the challenges in differentiating mines from rocks due to their visual resemblance, necessitating more accurate prediction systems in underwater environments. Achieving high precision in object classification remains a complex task due to the complexities of underwater environments, signal processing intricacies, and the need for reliable predictive models. In summary, the literature reflects a concerted effort to address the challenges posed by the visual resemblance between underwater mines and rocks. Leveraging sonar signals and machine learning techniques, researchers endeavor to create robust predictive models that accurately distinguish between these objects. The ultimate aim is to enhance the efficacy of naval defense systems by significantly improving object identification and reducing the potential risks associated with misclassification in underwater environments.

3. SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE

System architecture shows that a dataset is collected from the Kaggle website. This is the raw training data, which is likely a dataset of sonar readings from different types of objects, such as mines and rocks. The next step is Data Preprocessing which prepares the training data for the model by performing tasks such as cleaning the data, handling missing values, and converting the data to the appropriate format. Once the data is preprocessed, it is split into Training Data and Testing Data. The training data is used to train the classification model, while the

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testing data is used to evaluate the performance of the model on unseen data. The next step is to Train the Model. In this case, a Logistic Regression Model is used. Logistic regression is a simple but effective classification algorithm that is well-suited for this task. Once the model is trained, it can be used to classify new sonar data. For each new sonar signal, the model will predict whether the object is a mine or a rock.

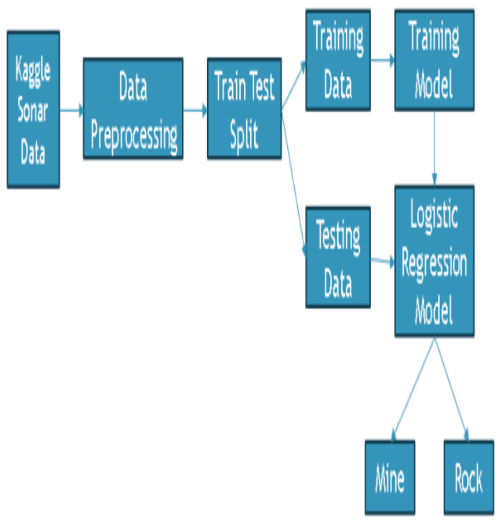

Fig 1 System Architecture

ACTIVITY DIAGRAM

Activity Diagrams in UML serve to visually represent dynamic workflows, showcasing the sequence and conditions of activities within a system or business process. The key components include nodes, representing actions or decisions, and transitions, illustrating the flow between these nodes. Initial and final nodes mark the activity's start and end. Control flows connect actions, specifying the order of execution, while decision nodes enable branching based on conditions. Forks and joins manage parallel flows, and swim lanes partition activities among different entities for clarity.

- Nodes: Represent actions or decisions.
- Transitions: Illustrate flow between nodes.
- Initial and Final Nodes: Indicate activity start and end.
- Control Flows: Connect actions, defining execution order.
- Decision Nodes: Facilitate branching based on conditions.

Represents a simple activity diagram depicting the workflow of a sonar-based prediction system. It starts with the user collecting sonar data, providing it to the admin. The admin then preprocesses the data, trains a machine learning model, predicts the object type (mine or rock), and finally returns the result. The diagram illustrates the sequential flow of actions from data collection by the user to the prediction result provided by the admin.

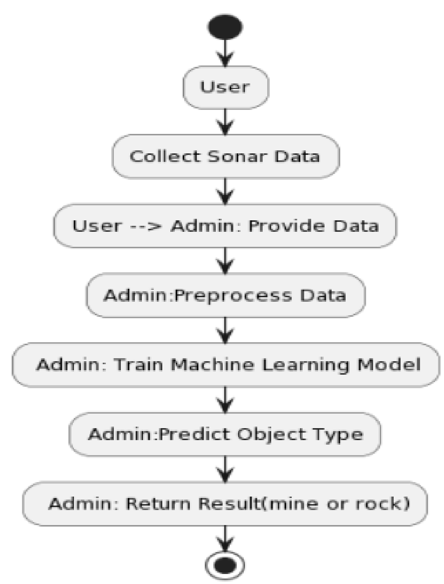

Fig 2 Represents Activity Diagram

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4. OUTPUT SCREENS

	0	1	2	3	4	5	6	7	8	9	...	51	52	53	54	55	56	57	58	59	60
0	0.0200	0.0371	0.0428	0.0207	0.0954	0.0986	0.1539	0.1601	0.3109	0.2111	...	0.0027	0.0065	0.0159	0.0072	0.0167	0.0180	0.0084	0.0090	0.0032	R
1	0.0453	0.0523	0.0843	0.0689	0.1183	0.2583	0.2156	0.3481	0.3337	0.2872	...	0.0084	0.0089	0.0048	0.0094	0.0191	0.0140	0.0049	0.0052	0.0044	R
2	0.0262	0.0582	0.1099	0.1083	0.0974	0.2280	0.2431	0.3771	0.5598	0.6194	...	0.0232	0.0166	0.0095	0.0180	0.0244	0.0316	0.0164	0.0095	0.0078	R
3	0.0100	0.0171	0.0623	0.0205	0.0205	0.0368	0.1098	0.1276	0.0598	0.1264	...	0.0121	0.0036	0.0150	0.0085	0.0073	0.0050	0.0044	0.0040	0.0117	R
4	0.0762	0.0666	0.0481	0.0394	0.0590	0.0649	0.1209	0.2467	0.3564	0.4459	...	0.0031	0.0054	0.0105	0.0110	0.0015	0.0072	0.0048	0.0107	0.0094	R

5 rows × 61 columns

Fig 3 Represents Sonar Dataset

The output shows 4 rows and 60 columns. The rows and colums represent different sonar readings of rock and mine.

	0	1	2	3	4	5	6	7	8	9	...	50	51	52	53	54	55
count	208.000000	208.000000	208.000000	208.000000	208.000000	208.000000	208.000000	208.000000	208.000000	208.000000	...	208.000000	208.000000	208.000000	208.000000	208.000000	208.000000
mean	0.029164	0.038437	0.043832	0.053892	0.075202	0.104570	0.121747	0.134799	0.178003	0.208259	...	0.016069	0.013420	0.010709	0.010941	0.009290	0.008222
std	0.022991	0.032960	0.038428	0.046528	0.055552	0.059105	0.061788	0.085152	0.118387	0.134416	...	0.012008	0.009634	0.007060	0.007301	0.007088	0.005736
min	0.001500	0.000600	0.001500	0.005800	0.006700	0.010200	0.003300	0.005500	0.007500	0.011300	...	0.000000	0.000800	0.000500	0.001000	0.000600	0.000400
25%	0.013350	0.016450	0.018950	0.024375	0.038050	0.067025	0.080900	0.080425	0.097025	0.111275	...	0.008425	0.007275	0.005075	0.005375	0.004150	0.004400
50%	0.022800	0.030800	0.034300	0.044050	0.062500	0.092150	0.106950	0.112100	0.152250	0.182400	...	0.013900	0.011400	0.009550	0.009300	0.007500	0.006850
75%	0.035550	0.047950	0.057950	0.064500	0.100275	0.134125	0.154000	0.169600	0.233425	0.268700	...	0.020825	0.016725	0.014900	0.014500	0.012100	0.010575
max	0.137100	0.233900	0.305900	0.426400	0.401000	0.382300	0.372900	0.459000	0.682800	0.710600	...	0.100400	0.070900	0.039000	0.035200	0.044700	0.039400

8 rows × 60 columns

Fig 4 Represents statistical measures of the data

The output represents the statistical measures of the sonar data, including the count, mean, standard deviation (std), minimum (min), 25th percentile, 50th percentile (median), 75th percentile, and maximum (max) values for each column of the data.

	0	1	2	3	...	56	57	58	59
0	0.0200	0.0371	0.0428	0.0207	...	0.0180	0.0084	0.0090	0.0032
1	0.0453	0.0523	0.0843	0.0689	...	0.0140	0.0049	0.0052	0.0044
2	0.0262	0.0582	0.1099	0.1083	...	0.0316	0.0164	0.0095	0.0078
3	0.0100	0.0171	0.0623	0.0205	...	0.0050	0.0044	0.0040	0.0117
4	0.0762	0.0666	0.0481	0.0394	...	0.0072	0.0048	0.0107	0.0094
..	...	...	...	...	...	...	...	...	...
203	0.0187	0.0346	0.0168	0.0177	...	0.0065	0.0115	0.0193	0.0157
204	0.0323	0.0101	0.0298	0.0564	...	0.0034	0.0032	0.0062	0.0067
205	0.0522	0.0437	0.0180	0.0292	...	0.0140	0.0138	0.0077	0.0031
206	0.0303	0.0353	0.0490	0.0608	...	0.0034	0.0079	0.0036	0.0048
207	0.0260	0.0363	0.0136	0.0272	...	0.0040	0.0036	0.0061	0.0115

```
[208 rows x 60 columns]
0      R
1      R
2      R
3      R
4      R
      ..
203    M
204    M
205    M
206    M
207    M
Name: 60, Length: 208, dtype: object
```

Fig 5 Represents separating data and labels

The fig shows that the mines and rocks data & labels are separated.

Making a Predictive System

```
[19] input_data = (0.0307,0.0523,0.0653,0.0521,0.0611,0.0577,0.0665,0.0664,0.1460,0.2792,0.3877,0.4992,0.4981,0.4972,0.5607,0.7339,0.8230,
                  0.9173,0.9975,0.9911,0.8240,0.6498,0.5980,0.4862,0.3150,0.1543,0.0989,0.0284,0.1008,0.2636,0.2694,0.2930,0.2925,0.3998,
                  0.3660,0.3172,0.4609,0.4374,0.1820,0.3376,0.6202,0.4448,0.1863,0.1420,0.0589,0.0576,0.0672,0.0269,0.0245,0.0190,0.0063,
                  0.0321,0.0189,0.0137,0.0277,0.0152,0.0052,0.0121,0.0124,0.0055)

     # 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')

['M']
The object is a mine
```

Fig 6 Represents object is mine

The input data is predicted to be a mine because the prediction model has learned that the given input data are more likely to be associated with mines.

Making a Predictive System

```
[21] input_data = (0.0260,0.0192,0.0254,0.0061,0.0352,0.0701,0.1263,0.1080,0.1523,0.1630,0.1030,0.2187,0.1542,0.2630,0.2940,0.2978,0.0699,
                   0.1401,0.2990,0.3915,0.3598,0.2403,0.4208,0.5675,0.6094,0.6323,0.6549,0.7673,1.0000,0.8463,0.5509,0.4444,0.5169,0.4268,
                   0.1802,0.0791,0.0535,0.1906,0.2561,0.2153,0.2769,0.2841,0.1733,0.0815,0.0335,0.0933,0.1018,0.0309,0.0208,0.0318,0.0132,
                   0.0118,0.0120,0.0051,0.0070,0.0015,0.0035,0.0008,0.0044,0.0077
     )

     # 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
```

Fig 7 Represents object is rock

The input data is predicted to be a rock because the prediction model has learned that the given input data are more likely to be associated with rock.

5. CONCLUSION

Our project "Underwater mine and rock prediction by evaluation of machine learning algorithms" are used to detect rocks and mines in the ocean bed. Naval mines are an effective method for blocking ships and restricting naval operations which result the significant negative economic and environment impacts. There are two existing ways to detect a mine, one by using sonar signals and the other by using manpower. Using Sonar signals has been better option as the risk for the letter is more. The data is collected stored in a CSV file. By using different machine learning techniques we can observe and understand the nature of the predictive system. By the evaluation of algorithms, we get to check and compare the accuracies to build a better performing prediction model. A python in open-source software and the machine computation is also faster many others and the cost might decrease dependently .Through this project, we want to make the process a bit easy and simple to achieve and use.

6. FUTURE ENHANCEMENTS

For future enhancements, could involve advanced deep learning models like CNNs or RNNs to boost accuracy in classifying underwater mines and rocks using sonar signals. Real-time data augmentation and adaptive learning methods could optimize performance across diverse underwater conditions. Utilizing ensemble learning for more precise predictions and integrating anomaly detection algorithms could differentiate between standard objects and potential threats. Developing a userfriendly interface for naval personnel to interpret and validate model predictions would facilitate practical deployment and decision-making in defense systems.

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