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RDNN for Classification and Prediction of Rock or Mine in Underwater Acoustics

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Abstract—Mines in the waters are just explosives that detonate upon contact with an object. The underwater submarine must foresee if it will encounter a mine or a rock. Lacking the development of the Ranging Sound Navigation approach, which utilizes particular variables to identify whether a surface or a barrier is made of a mine or rock, finding mines or rocks would have been extremely difficult. In our study, we demonstrate a technique for predicting underwater rocks and mines using SONAR waves. At 60 different angles, SONAR pings are employed to record the various frequencies of submerged objects. To identify whether the object in the ocean is a mine or just a rock, the submarine uses SONAR signals, which transmit sound and receive switchbacks. The mine and rock categories are predicted using the prediction models. To create these prediction models, Supervised Machine Learning Classification methods were employed.

Keywords-neural networks; SONAR; feature selection; classification; machine learning.

I. INTRODUCTION

Naval mines, often known as underwater mines, are independently triggered explosives deployed under the sea to damage an adversary’s submarines or naval ships. Since the mid-19th century, underwater mines have been in use. Mines at sea were developed in 1977, at the time of the American Civil War, by David Bushner. There are 5000 naval mines, according to estimates of Adriatic Sea debris from the two world wars.

Prior to their creation, mines could only be triggered by physical touch, but the new mines can be triggered in a variety of ways. Modern mines can be set off by changes in the water’s acoustics, pressure, or magnetic field, which causes them to detonate. We refer to these as influence mines. Underwater mines can be used in either aggressive or defensive battle. To injure military and commercial vessels, mines are deployed in hostile sea lanes.

To divert hostile submarines and ships away from key locations including areas that are better secured, defensive mines are positioned along coasts. Since mines can resemble rocks in size, state, and width, they are frequently mistaken for rocks when being identified.

To produce a more accurate result, it is preferable to employ a more precise input in order to avoid this misconception. SONAR is one technique for finding mines. The Sound Navigation and Ranging system uses sound waves to guide and locate things. As a whole, SONAR is utilized for acoustic mine detecting, which is classified as a military usage.

However, this paper focused on conducting additional research in SONAR dataset for identifying
and classifying mines or rocks materials for underwater acoustics that are based on deep learning, the use of neural networks.

Submarines equipped with mine detection systems can detect these mines before they come into contact with them, allowing them to take evasive action to avoid them or neutralize them before they explode. This can be especially important in areas where there may be a high concentration of mines, such as in or near ports, shipping lanes, or other strategic locations.

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II. EXISTING SYSTEM

In the current approach, mines are found utilizing divers who dispose of explosive ordnance, marine mammals, cameras on mine-clearing equipment, laser systems, etc., rather than a specific data set or technology that, if used incorrectly, could endanger or kill marine life. Human visual detection and identification has so far been the only effective detection technique in use. In light of this, an automated detection system would be extremely helpful in military operations, clean-up efforts, and even for a number of civilian applications like collision avoidance, salvage, and search and rescue. As technology advanced, SONAR became the main tool used to find mines.

III. PROPOSED SYSTEM

We are utilizing neural networks to locate under water mines in the proposed system. SONAR data is provided as an input to the system. CSV format is used for the input. The pre-trained model receives this input data, which is then used to process the data. The entire procedure is divided into various essential steps, from data collection to deep neural network detection, all of which have been mentioned. For this approach, the SONAR abnormal dataset was gathered from the Kaggle website. In the process of preparing data, normalization is a technique to scale numerical values in a dataset so that they are similar in value when the characteristics in the data have wide ranges. We classified the datasets for SONAR anomalies into training and testing data to train and validate the model and assess its efficacy. We are now using a neural network that is based on rock/mine detection to forecast underwater acoustic objects while also differentiating between mines and rocks.

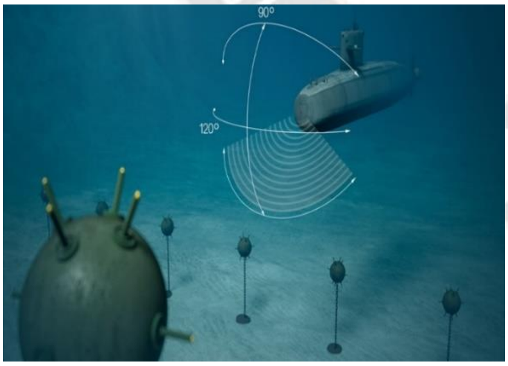

Figure 1. Detection of mines by Submarine

IV. LITERATURE REVIEW

SONAR, or Sound Navigation and Ranging, is an acronym. The fundamental idea behind SONAR is to broadcast sonic waves in order to locate objects [1]. Acoustic waves are transverse waves travelling at a certain speed across elastic medium that cause mechanical vibrations. Based on the duration between the transmission of the echo and its return, using the object's speed as a preliminary step, a target distance can be determined [2]. However, acoustic waves propagate more quickly in water than in air. When sound travels through water as opposed to air, the sound intensity related to this speed changes. Temperature, pH, salinity, and depth are the variables which contribute to this accelerated process. According to estimates, the pace of sound in water ranges between 1405 and 1550 meters per second [3].

Vibrations are produced by acoustic signals. They can be classified by their frequency, represented by their time period(T) or in Hz, which is related to frequency based on the formula T=1/frequency. In the air, the communication frequency might rise to 300 Giga Hz. Between 10 Hz and 1 MHz are the frequencies used in underwater applications. Following are the primary restrictions on the frequencies employed for a specific application.

- The extent of each particle's local motion in the transmission medium near the point of equilibrium
- The speed of fluid in relation to this motion
- The deviation from the hydrostatic pressure's mean is known as acoustic pressure

One of the key challenges in detecting rocks or mines in underwater environments is the noisy and complex nature of the acoustic signals. The use of machine learning techniques can help to address this challenge by enabling the automatic detection and classification of different types of objects based on the features of their acoustic signals. Several studies have used machine learning algorithms for this purpose, with varying degrees of success **Error! Reference source not found.**.

In one recent study, researchers used a support vector machine (SVM) algorithm to classify SONAR signals into different categories, including rocks, mines, and other objects **Error! Reference source not found.**. The SVM algorithm was trained on a large dataset of labeled SONAR signals, and achieved an overall classification accuracy of over 90% on a test set of previously unseen signals.

Another study used a deep learning approach, specifically a convolutional neural network (CNN), to classify SONAR signals into two categories: rocks and non-rocks. The CNN was trained on a dataset of simulated SONAR signals, and achieved a classification accuracy of around 85% on a test set of real-world SONAR data. In both of these studies, the researchers used SONAR data in CSV format as input to their machine learning algorithms **Error! Reference source not found.**. CSV is a commonly used

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format for storing tabular data, and is well-suited to storing the time-domain and frequency-domain features of SONAR signals. Overall, these studies demonstrate the potential of machine learning techniques for the detection of rocks or mines in underwater environments using SONAR data in CSV format **Error! Reference source not found.**. However, further research is needed to improve the accuracy and robustness of these techniques, and to address the challenges posed by real-world conditions such as varying water depths, bottom types, and environmental noise.

In addition to these studies, there have been several efforts to develop specialized hardware for underwater acoustics, such as the use of arrays of hydrophones to improve the resolution and accuracy of SONAR signals. These advances in hardware have the potential to improve the quality of SONAR data and enable more effective use of machine learning techniques for object detection in underwater environments. While machine learning approaches have shown promise for the detection of rocks or mines in underwater acoustics, there are several challenges that must be addressed. One key challenge is the limited availability of labeled data, which can make it difficult to train accurate machine learning models **Error! Reference source not found.**. Another challenge is the need to account for the complex and dynamic nature of underwater environments, which can affect the propagation of sound waves and make it difficult to distinguish between different types of objects. Despite these challenges, the use of machine learning techniques for the detection of rocks or mines in underwater environments is an active area of research, with significant potential for practical applications in areas such as underwater navigation, search and rescue, and military operations. With continued research and development, it is likely that these techniques will become increasingly effective and widely used in the years to come.

V. METHODS

A neural network is a group of algorithms designed to find hidden patterns in a piece of data by employing a technique that imitates how the brain of a human behaves. In this scenario, a system of neurons called a neural network can be either organic or synthetic. Since neural networks are capable of adapting to changing input, the network can produce the best outcome without having to change the output criterion **Error! Reference source not found.**. The artificial intelligence-based idea of neural networks is quickly gaining prominence in the design of trading systems. If we incorporate neural networks into our model, we can improve its accuracy **Error! Reference source not found.**. To distinguish the items, for example rocks or mines, in order to generate high quality images, machine learning algorithms like decision trees, KNN, gradient boosters, and SVM algorithms were utilized. Using neural networks, we can accurately predict the object by adding the appropriate layers to the model that has to be trained **Error! Reference source not found.**.

The three main parts of a neural network are an input layer, a processing layer, and an output layer. Various factors may be used to weight the inputs. There are nodes and connections between these nodes in the processing layer, which is concealed from view, that are intended to be comparable to the neurons and synapses in an animal brain. A deep neural network, commonly referred to as a deep learning network, at its most basic level consists of two or more processing layers. Deep neural networks are based on machine learning networks that are continuously improved by comparing predicted results to actual outcomes and then revising future predictions **Error! Reference source not found.**.

VI. METHODOLOGY

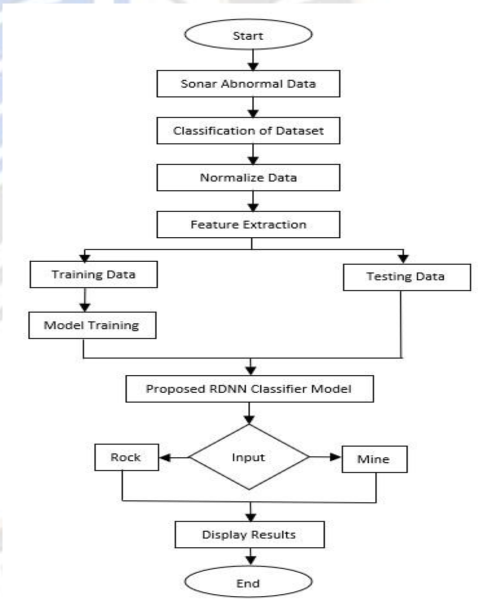

Figure 2. Flowchart

Step1: Gather the SONAR data from the designated repository.
Step2: Sort the dataset by its attributes and labels.
Step3: To convert the values of the dataset's numerical columns to a common scale, normalize the data.
Step4: Reduce the quantity of unnecessary data in the data collection by using feature extraction.
Step5: Data should be divided into training and testing.
Step6: Input the training data for model training to apply it to proposed RDNN classifier model.

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Step7: Evaluate the results in accordance with the SONAR dataset used as the trained model's input.
Step8: Demonstrate the results.

VII. Data Analysis

The dataset used in this study was obtained from the UCI machine learning repository, which is referenced in Table. On the basis of a neural network-based methodology, this high generalization was achieved. The work was carried out in Python 3.7 settings to increase accuracy and improve performance. The referenced resource for the data set is

https://www.kaggle.com/datasets/ypzhangsam/SONARalldata

This data set is used in the proposed research.

Mines	Rocks	Total
111	97	208

Figure 3. Labels in the Dataset

There are 208 different SONAR data sets available in the source. 111 of these data were designated for mines, and the Rock material is allocated the remaining 97 data. The dataset contains 60 features that can be used to train the model and produce accurate results.to determine whether the target is a rock or a mine in this illustration, we employ active SONAR frequencies that were captured at 60 various angles.

VIII.Feature Selection

Feature selection is a critical aspect of machine learning, which involves selecting a subset of relevant features or variables from a dataset that are most informative for the model to learn from. The process of feature selection involves identifying and removing redundant, irrelevant, or noisy features that can adversely affect the model's accuracy or performance.

In the context of a CSV data, feature selection involves analyzing the columns (features) of the data and deciding which columns should be used as input to the machine learning algorithm. Here is a step-by-step process of feature selection on CSV data in machine learning:

- **Data Preprocessing:** Before performing feature selection, it is important to preprocess the CSV data to handle missing values, handle categorical data, and normalize the data.
- **Feature Extraction:** Feature extraction involves creating new features by combining the existing ones or transforming them into a more useful representation. This can be done using techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), or Non-Negative Matrix Factorization (NMF).
- **Correlation Analysis:** In this step, we analyze the correlation between different features in the CSV data. Highly correlated features may indicate redundancy in the data and can be removed.
- **Univariate Feature Selection:** Univariate feature selection involves analyzing each feature individually and selecting the most significant ones based on statistical tests such as chi-square, t-test, or ANOVA.
- **Model-Based Feature Selection:** Model-based feature selection involves training a machine learning model on the data and analyzing the feature importance score of each feature. The model can be a simple linear regression or a complex ensemble of models.
- **Recursive Feature Elimination:** Recursive Feature Elimination (RFE) is an iterative method of feature selection that involves training a model and eliminating the least important feature in each iteration until a predetermined number of features are selected.
- **Regularization:** Regularization involves adding a penalty term to the model to prevent overfitting and to encourage sparse solutions. L1 and L2 regularization can be used to select a subset of features.
- **Feature Importance Analysis:** This is a post-hoc analysis of the selected features, which involves analyzing the contribution of each feature to the model's accuracy or performance. This can be done using techniques such as permutation importance or Shapley values.

IX. Evaluation Of Model

The traditional approach to assessing classification models is accuracy. The percentage of correctly identified examples in a set of examples is what is referred to as accuracy.

Accuracy = (Number of correctly predicted events) / (Total number of predictions)

Because perceiving of accuracy is simple, beginners prefer it to other techniques. In reality, we only apply it when the dataset allows it. Although it is not entirely unreliable as a means of evaluation, other, and occasionally

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superior, approaches are frequently disregarded. We frequently encounter issues when evaluating a model only on accuracy. One of them is modelling evaluation on unbalanced datasets. Consider the situation when we must determine whether a person is a positive, optimistic person or a negative, pessimistic person. Accuracy will be a very inaccurate metric if 90% of the samples in our dataset belong to the positive group and only 10% to the negative group. A model that accurately predicts someone's attitude 100% of the time will have a 90% success rate. This model will be "very high" accurate while also being worthless for data that hasn't been seen before. Accuracy is frequently combined with other techniques due to its limitations. Making a confusion matrix is one technique to see if we can utilize accuracy as a metric.

Evaluation of a model is a critical aspect of machine learning that determines how well a model performs on a given task. The evaluation process involves testing the model on a dataset that was not used for training, and comparing the model's predictions to the true values or labels of the test data. The goal of evaluation is to assess the model's performance, identify its strengths and weaknesses, and make improvements as needed. There are several different evaluation metrics that can be used to measure the performance of a machine learning model, depending on the specific task and the type of data being used. Some common evaluation metrics include:

- Accuracy: This is a simple and commonly used metric that measures the percentage of correct predictions made by the model on the test data.
- Precision and Recall: These metrics are used for classification tasks, and measure the model's ability to correctly identify positive and negative examples in the test data. Precision is the percentage of true positive predictions among all positive predictions, while recall is the percentage of true positive predictions among all true positive examples in the test data.
- F1 Score: This is a composite metric that combines precision and recall into a single score, and is often used as a more balanced measure of a model's performance on classification tasks.
- Mean Squared Error (MSE) and Root Mean Squared Error (RMSE): These metrics are commonly used for regression tasks, and measure the difference between the model's predicted values and the true values of the test data.

In addition to these metrics, there are also techniques for evaluating the performance of a model over time, such as cross-validation and learning curves. Cross-validation involves dividing the dataset into multiple subsets, training the model on each subset, and testing it on the remaining data. This approach can help to improve the robustness and generalizability of the model. Learning curves, on the other hand, show how the model's performance changes as the size of the training data increases. This can help to identify whether the model is overfitting or underfitting the data, and can inform decisions about how to adjust the model architecture or hyperparameters.

It is important to note that evaluation is an ongoing process, and should be done regularly throughout the development of a machine learning model. This allows for continuous improvement and refinement of the model, and can help to avoid overfitting or other common pitfalls in machine learning. In general, a good evaluation process involves careful consideration of the specific task, the type of data being used, and the appropriate metrics and techniques for measuring the model's performance.

X. IMPLEMENTATION

1. Data preprocessing
    - Loading the data

```
submarine_data = pd.read_csv("sonar_csv.csv")
```

- Describe the class labels of the data

```
# Print the sample count of the rock and mine
submarine_data['Class'].value_counts()
```

```
Mine    111
Rock     97
Name: Class, dtype: int64
```

- Feature selection

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```
import pandas as pd
from sklearn.ensemble import GradientBoostingClassifier
import numpy as np

# Load sample dataset
df = pd.read_csv("sonar_csv.csv")
X = df.iloc[:, :-1].values  # Features
y = df.iloc[:, -1].values   # Labels

# Train a Gradient Boosting classifier
clf = GradientBoostingClassifier(n_estimators=100, random_state=1)
clf.fit(X, y)

# Get feature importances from the trained model
importances = clf.feature_importances_

# Sort the features by their importance in descending order
indices = np.argsort(importances)[::-1]

# Select the top 20 features based on their importance
X_selected = X[:, indices[:10]]

# Print the indices of the selected features
print("Selected features:", indices[:10])
```

```
Selected features: [10 44  3 26 15 35 20 46 51 14]
```

- Separating the features and labels present in the data

```
# Separate the input features and output labels
X = submarine_data.iloc[:, :-1].values
y = submarine_data.iloc[:, -1].values
```

- Performing data transformation on labels

```
# Convert the class labels from strings to numeric values
le = LabelEncoder()
y = le.fit_transform(y)
```

- Splitting the data into training and testing

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

2. Training the model
   - Adding layers to the model

```
# Create a neural network classifier
clf = MLPClassifier(hidden_layer_sizes=(100, 50), activation='relu', solver='adam', alpha=0.0001,
                    max_iter=1000, random_state=1)
```

   - Fit the model

```
# Train the classifier on the training data
clf.fit(X_train, y_train)
```

3. Predicting the output using the trained model

```
# Define a new input data point to make a prediction on
new_data_point = [[0.0076,0.074,0.1721,0.2584,0.4449,0.7552,0.5757,0.2341,0.1015,0.0091]]

# Standardize the new input data point using the same scaler used for training
new_data_point_standardized = scaler.transform(new_data_point)

# Make a prediction on the new data point using the trained classifier
predicted_class = le.inverse_transform(clf.predict(new_data_point_standardized))

# Print the predicted class label
print("Predicted class label:", predicted_class)
```

```
Predicted class label: ['Rock']
```

XI. Conclusion

In the proposed study, deep learning-based neural networks with statistical analysis have been used to apply the RDNN classifier model for metal classification; specifically rock or mine in underwater acoustics signals in underwater communication can be eliminated using SONAR technology. However, our rock or mine detecting neural network approach yields improved results. Hyper parameters must be used to the dataset for an improved underwater acoustic categorization of items like rocks and mines in order to increase prediction accuracy. The use of naval mines to obstruct ships and limit naval activities has substantial detrimental effects on the economy and the environment. There are now two methods for finding mines: one uses SONAR waves, while the other use human labour. As the risk for the latter is greater, using SONAR signals has shown to be a preferable choice. By using neural networks, we can watch and understand how the prediction system operates. In order to create a prediction model that performs better, we can compare and assess the accuracy by evaluating the model. Python is an open-source programming language, and because its calculation is quicker than many others, its price may fall with time. With the help of this initiative, we hope to make the procedure straightforward and simple to complete.

References

[1] Analysis of Hidden Units in a Layered Network Trained to Classify SONAR Targets" in Neural Networks, Vol. 1, pp. 75–89(1988).

[2] Z. Yang, B. Luo, D. Liu, and Y. Li, "Adaptive synchronization of delayed memristive neural networks with unknown parameters," IEEE Trans. Syst., Man, Cybern. Syst., vol. 50, no. 2, pp. 539–549, Feb. 2020.

[3] L. Fei-Fei, R. Fergus, and P. Perona, "One-shot learning of object categories," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 4, pp. 594–611, Apr.

[4] Baburao Markapudi, Kavitha Chaduvula, D.N.V.S.L.S. Indira &Meduri V. N. S. S. R. K. Sai Somayajulu, "Content-based video recommendation system (CBVRS): a novel approach to predict videos using multilayer feed forward neural network and Monte Carlo sampling method", published in the journal of

Multimedia Tools and Applications (Springer Nature), published on 11th August 2022. PP:1-27, https://doi.org/10.1007/s11042-022-13583-8 Impact factor: 2.577 (2021), Five year impact factor: 2.396 (2021) (SCIE)

[5] J. Kim, V. D. Calhoun, E. Shim, and J.-H. Lee, "Deep neural network with weight sparsity control and pre-training extracts hierarchical features and enhances classification performance: Evidence from whole-brain resting-state functional connectivity patterns of schizophrenia," Neuroimage, vol. 124, pp. 127–146, 2016.

[6] D. Deng, Y. Zhou, J. Pi, and B. E. Shi, "Multimodal utterance-level affect analysis using visual, audio and text features," 2018, arXiv: 1805.00625.

[7] X. Zhong and Y. Gao, "Synchronization of inertial neural networks with time-varying delays via quantized sampled-data control," IEEE Trans. Neural Netw. Learn. Syst., vol. 32, no. 11, pp. 4916–4930, Nov. 2021.

[8] L. Wang, Y. Shen, Q. Yin, and G. Zhang, "Adaptive synchronization of memristor-based neural networks with time-varying delays," IEEE Trans. Neural Netw. Learn. Syst., vol. 26, no. 9, pp. 2033–2042, Sep. 2015.

[9] Dr GVSNRV Prasad, "Adaptive Optimization-enabled Neural Networks to handle the imbalance churn data in churn prediction", International Journal of Computational Intelligence and Applications, Dec-2011.

[10] Shaik Salma Begum & Dr D. Rajya Lakshmi, "Combining optimal wavelet statistical texture and Recurrent Neural Network for Tumor detection and Classification over MRI", Multimedia Tools and Applications, ISSN 1380-7501, January 2020, Springer.

[11] Shaik Salma Begum & Dr D. Rajya Lakshmi, " An Efficient Spatial Fuzzy C-Means Algorithm with Optimized Recurrent Neural Network for MRI Brain Tissue Classification", TEST Engineering and Management, ISSN:0193-4120 Page No: 13254-13266, March- April 2020.

[12] Shaik Salma Begum & Dr D. Rajya Lakshmi, "GLCM of Fuzzy Clustering Means for Textural Future Extraction of Brain Tumor in Probabilistic Neural Networks", International Journal of Innovative Technology and Exploring Engineering, ISSN: 2278-3075, Volume-9, Issue-1, November 2019.