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Prediction of Underwater Sonar Targets

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Abstract: Classification of underwater SONAR returns is necessary for detecting sea mines under the oceans as they impose serious threats to ships and submarines. 'Connectionist Bench (Sonar, Mines vs. Rocks) Data Set' chosen from UCI machine learning repository is considered. The dataset is in the form of a CSV file with 60 attributes and 208 records, 111 patterns obtained by bouncing SONAR signals off a metal cylinder at various angles and under various conditions and 97 patterns obtained from rocks under similar conditions. Standardization preprocessing technique is carried out on the data. Standard-scalar utility class is used to generate scaled data. k-Nearest Neighbour and Standard Vector Classifier classification algorithms are used to train the model, evaluate these algorithms and calculate the model accuracy in each case. Principal Component Analysis is performed for feature selection and the models are tuned using optimal hyperparameters to obtain better accuracy. As a result, the Standard Vector Classifier model gives a better accuracy of approx. 93 % compared to the k-Nearest Neighbour model which gives approx. 88%.

Keywords: Machine learning, SONAR, k-Nearest Neighbour, Standard Vector Classifier

I. INTRODUCTION

Underwater mines are a strategic military tool to protect any country's naval borders. These mines consist of an explosive material, sensing device and a fuse mechanism that triggers an explosion when ships or other submarines come in contact with it. This was the scenario during previous generations, but the newly developed mines, on the contrary, are equipped with advanced technology, such that their sophisticated sensors even detect some combinations of acoustic and magnetic signals. There are some other mines that are equipped with artificial intelligence to detect any false signals that trigger the explosion. Several mines have been implanted in the oceans during World War II and even today , so that countries protect their naval borders from enemies. They pose an extreme threat to ships and submarines and thus must be detected and eliminated. SONAR technique is commonly used to detect these mines. SONAR, which stands for sound navigation and ranging, is a sound propagation technology used primarily for underwater communication, navigation, and/or object identification. The SONAR returns are then used to identify the objects the waves were reflected from. But, it is hard to correctly determine if the target identified is a mine or a rock.
The dataset used contains SONAR signals reflected off of a metal cylinder and a cylindrically shaped rock positioned on a sandy ocean floor. The impinging pulse was a wideband linear FM chirp (ka = 55.6), and both targets were around 5 ft (1.52 m) long. Returns were gathered over a distance of 10 meters from the cylinder at 90° aspect angles and from the rock at 180° aspect angles.

II. LITERATURE SURVEY

Elakkiya, Jincys, Rejinan, and Tamilmalar in Classification of SONAR targets using advanced neural networks [1], discuss classification of SONAR targets into rocks and mines using Meta-Cognitive Neural Network (MCNN) and Extreme Learning Machine (ELM) classifiers to achieve an acceptable efficiency. It further elaborates on the strategies given by MCNN like sample delete strategy, neuron growth strategy etc and advantages of ELM due to no tuning required for the hidden layer. After analyzing the performance of MCNN and ELM, the paper concludes that the training efficiency of MCNN is 81.7% and testing efficiency is 87.5% while that of ELM is 88% and 84% respectively.
Abdul-Qader in Techniques for classification: rocks vs mines [2]. It is concerned with a procedure for separating metal cylinders (mines) from objects having cylindrical shapes (rocks) utilizing SONAR signals and the three methods listed below: NN, ANFIS and kNN. Use of sequential forward selection method makes three techniques give a better accuracy. KNN gives a better accuracy of 93.27%. ANFIS gives the best accuracy of 100%. NN gives a better accuracy of 88.42%.
Simon Fong, Suash Deb and team in [3] Underwater Sonar Signals Recognition by Incremental Data Stream Mining using conflict analysis, describe a novel preprocessing strategy called iDSM-CA that stands for incremental data stream mining with conflict analysis using UCI SONAR dataset. This method has been shown to have advantages in terms of

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speed and effectiveness in delivering a noise-resistant streamlined training dataset for incremental learning, using SONAR data to distinguish between metal and rock items.

Jetty Bangaru Siddhartha, T. Jaya and V. Rajendran, in [4] RDNN for classification and prediction of Rock/Mine in underwater acoustics, investigate the use of deep learning-based neural networks to identify and discriminate pebbles or materials resembling mines in the SONAR dataset for underwater acoustics. In addition, we compare the network differentiating performance of our proposed neural network-based layers with those of existing deep learning models by analysing accuracy and loss metrics as metrics evaluation.

M. Khishe and M.R. Mosavi in [5] Improved whale trainer for SONAR datasets classification using neural network. Classifying various SONAR dataset using Whale Optimization Algorithm (WOA) algorithm for training Multi-Layer Perceptrons Neural Network. The results demonstrate that new classifiers perform better than the others in terms of avoiding becoming stuck at local minima, classification accuracy, and convergence speed. The results are compared to well-known meta-heuristics trainers.

E. Coiras, J. Groen, and team in [6] Automatic Target Recognition in Synthetic Aperture Sonar Images Based on Geometrical Feature Extraction. Sonar target recognition in SAS images using a supervised classification approach. Geometrical extraction method. — this method employs geometrical features and seeks to use the enhanced image fidelity available in both target highlight and shadow response. Data is generated from (SIGMAS) Synthetic Image Generator for Modeling Active Sonar. Cylindrical targets showed the best classification results, but oil drums were the most challenging to recognise from different grazing angles and features.

Jongwon Seok in [7] Active Sonar Target Classification Using Multi-Aspect Sensing and Deep Belief Networks. For active SONAR target classification to enhance classification performance, a multi-aspect-based sensing system is provided. In order to create 3-dimensional highlight models, the active SONAR returns from targets are synthesized using the ray tracing algorithm. To extract the features, FrFT (Fractional Fourier transform) is applied to SONAR returns. With the FrFT-based features, four different targets are classified using deep belief networks. The proposed feature extraction method showed better performance than the conventional neural network classifier.

Shaik Firasat Ali and Abdul Rasool MD in [8] Sonar data classification using multilayer perceptron), brief about classification of SONAR data with the help of Deep learning using a multilayer perceptron (and the perceptron is being used as a linear classifier). The model generated here runs for 1000 epochs, where in each epoch the whole input data is used to train the model. Each epoch's cost, mean square error, and training accuracy are calculated and shown. With an epoch count of 999, the model can accurately predict whether the object might be a rock or a mine with an accuracy of roughly 85%.

III. HYPOTHESIS

Underwater Mines can be easily mistaken for rocks, hence they possess a large threat to the marine life and the military vessels. There are no existing systems that differentiate accurately between mines and rocks using the frequency data received by the SONAR. With this project, using the SONAR technique to get the reflected wave frequency values, they can be effectively classified into Rocks and Mines with an acceptable accuracy rate. Thus, increasing the chances of discovering mines safely.

The SONAR data is fed to the model, which is trained using Machine Learning Algorithms to classify the objects identified into mines and rocks, based on the data received. The model then classifies the target object into mine or rock and notifies if a mine is found. This way, the ship/submarine will be alerted and can safely detour around the mine.

IV. METHODOLOGY

The Sonar data is acquired from UCI machine learning repository and pre-processed. Since the data is generated under laboratory conditions, where the SONAR signals are reflected off a metal cylinder and rocks, not many errors or noises are present. The dataset is checked for any null values and removed. Standardization technique is further used to preprocess the data. Standard-scalar utility class is used to perform standardization. The scaled data generated has zero mean and unit variance. This diminishes many off-diagonal terms of the covariance matrix, so it makes the data more easily interpretable, and the coefficients more directly meaningful, since each coefficient is applying more primarily to that factor, and acting less through correlation with other factors.

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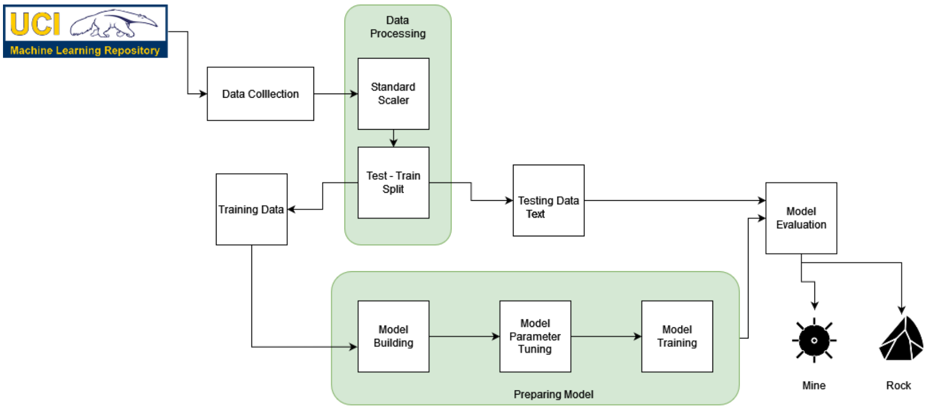

Fig 1. Architecture diagram of the proposed system

The Data is then split into Train-Test to train and test the model, respectively. The split ratio is 70% training data and 30% testing data. The Training Data trains the ML model (using different algorithms – LDA : Linear Discriminant analysis, SVM : Support Vector Machine, KNN : k-nearest neighbours, CART : Classification and Regression Trees, NB : Naive Bayes classifiers) and the Testing Data is used to evaluate the accuracy of the model. Due to the small size dataset, KFold cross-validation technique is used to evaluate the model.

Due to the dataset having too many features, Principal Component Analysis is used to offset the curse of dimensionality. A few features are selected from the 60 original and are used to train the classifiers. Most promising ones are selected after spot testing the scaled data on the principal components.

Accuracy of the classifiers are further enhanced by choosing optimal hyperparameters based on the algorithm selected, (number of neighbours, k for KNN; kernel and C value for SVM). The final models are fitted, and testing results are generated. Metrics like accuracy, f1-score, roc-auc value are used to evaluate them. Confusion matrices and roc-auc curves are used for better understanding and visualization of results.

Algorithm	Unscaled data	Scaled Data	PCA + Scaled
NB	0.682721	0.682721	0.790809
CART	0.728309	0.734191	0.752574
KNN	0.758824	0.808456	0.867647
SVM	0.765074	0.826103	0.831985
LR	0.777574	0.754412	0.743015

Fig 2. Result table of Algorithm Spot Testing

KNN and SVM show promising results after using processed data along with PCA.
Therefore, models for KNN and SVM were trained with parameter tuning to increase the accuracy.

Parameter tuning for KNN:

- The parameter for KNN is the "number of neighbours", i.e., k. A range of odd numbered k values are taken from 1 to 21 and the mean training and testing scores are calculated, tabulated and plotted.
- k = 3 gave the best testing results.

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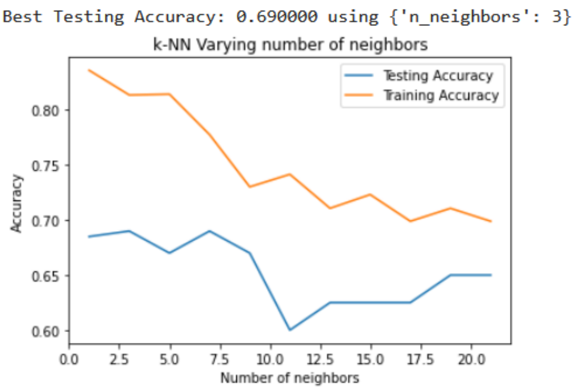

Fig 3. Testing and Training Accuracy for a range of neighbors

Parameter tuning for SVM:

- The parameters for SVM are kernel function and C, where C is a regularization parameter which controls the degree of misclassification allowed.
- The kernel functions used here are : rbf, linear, sigmoid and polynomial. C values range from 0.1 to 2.0. Mean testing scores are calculated using these values.
- C = 1.7 and Kernel = rbf gives the best mean testing scores.

V. RESULT AND ANALYSIS

With the parameters for both KNN and SVM decided. Both models are trained separately using the scaled data and the identified the best parameters. The results are shown as using the accuracy, precision, recall and f1 - scores. Also, visualized using a confusion matrix.

- KNN - 88.09% accuracy

	precision	recall	f1-score	support
M	0.96	0.85	0.90	27
R	0.78	0.93	0.85	15
accuracy			0.88	42

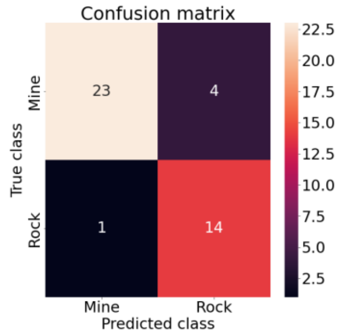

Fig 4. Classification Report and Confusion Matrix for KNN

- SVM – 92.85% accuracy

	precision	recall	f1-score	support
M	0.96	0.93	0.94	27
R	0.88	0.93	0.90	15
accuracy			0.93	42

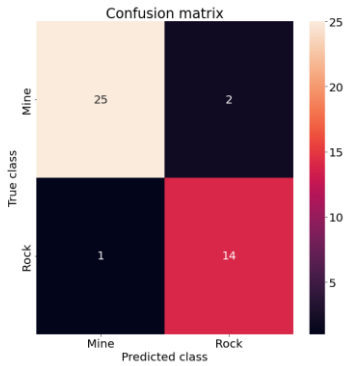

Fig 5. Classification Report and Confusion Matrix for SVM

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- ROC AUC score (KNN v/s SVM)

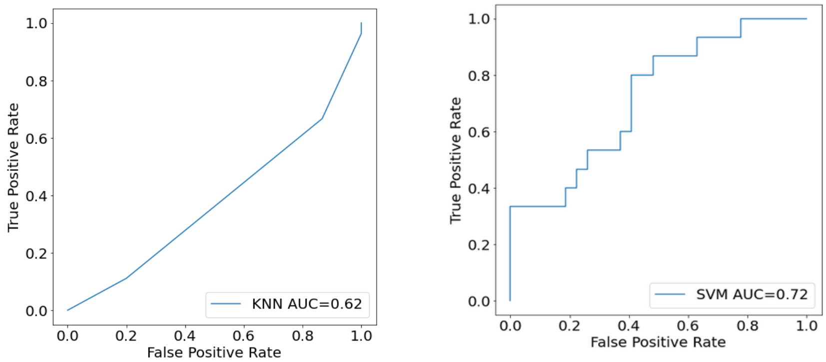

Fig 6. ROC AUC curves for KNN and SVM

kNN has an AUC score of 0.62 whereas SVM has an AUC value of 0.72. Considering the above shown metrics used to evaluate the model used, it can be concluded that SVM is best for classifying the dataset. SVM has a better accuracy rate and ROC AUC value over kNN.

VI. CONCLUSION AND FUTURE WORK

A suitable prediction miniature is proposed that, when combined with machine learning classification features, can determine whether the target of the sound wave is a rock or a mine. SVM model gives a better accuracy of approx. 93 % compared to the KNN model which gives approx. 88%. The model could effectively predict the SONAR reflected values into mines and rocks with the above-mentioned accuracies. But, the ROC AUC score for SVM is better than that of KNN; Therefore, SVM is a better choice for the following problem. The only dataset available for carrying out this project is not real world SONAR-data, but rather generated in laboratory under specific conditions with few or absolutely no errors. Future scope into collecting real sea trial data under the supervision of related experts. Also, research can be carried out into estimating distance and direction of mines using SONAR, making it easier to plot mines. Recent technologies allow one to get SONAR imagery of the surrounding, these can be used as they are far more accurate and easy to grasp.

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