EXPLORING SUBMERGED HAZARDS: INNOVATIONS IN SUBMARINE ROCK AND MINE DETECTION

A MINOR PROJECT REPORT

Submitted by

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ABSTRACT

Underwater mines are common explosive bombs that are placed around a coastal region of a country, deep under the ocean to ensure safety, defence and security. This could be a threat to a submarine or any civilian boats that crosses over the mine. Though it provides enormous security, it is a threat to marines which may mistake it as a rock. Due to its similar appearance, size and placings in ocean bed, a rock can appear to be and mine and vice versa. Moreover, absence of light under ocean due to attenuation makes it impossible to capture a image to be processed. Here, SONAR technique is used to explore the ocean bed and identify rocks and mines accurately. The dataset contains 60 different angles under which rocks and mines are recorded with specific value. The main objective is to enhance the model using Ensemble learning techniques. Standalone algorithms to overcome overfitting, under fitting and feature selection. Bagging to improve stability and reduce bias value.

Along with frequency values, underwater sonar images are processed to determine the object detection to be rock or mine. This focuses on providing double standards on the object that has been encountered. When frequency waves are processed through one model, other model processes the sonar image captured. Ensemble techniques has been performed on the sonar values. It is observed that KNN fits the best before and after scaling the algorithm. RandomForest classifier has been used for bagging the model that reduces model variance and improves model stability. It combines multiple decisions made by the model and combines the previous predictions to make a robust system and to make accurate predictions. Boosting method such as AdaBoost has been employed to correct the errors made by the previous model and iteratively adjust the wights accordingly. It eliminates the weak learners and out of point learners to emphasize a good boosting in the model. Thus, to boost the overall ensemble technique, bagging and boosting method has been inculcated. As to classify the sonar images, convolutional network is used. It works the best for images classification to scan the input images using kernels to detect the image points and create a feature map. To not encounter such disaster, it is crucial to differentiate them and warn the submarines accordingly.

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ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
ML	Machine Learning
GPS	Global Positioning system
SAS	Synthetic Aperture sonar
AUV	Autonomous Underwater vehicles
ROV	Remotely Operated vehicles
GI	Geospatial Intelligence
DL	Deep Learning
KNN	K-Nearest Neighbour
SVM	Support Vector Machine
LR	Logistic Regression
FP	False Positive
FN	False Negative
TN	True Negative
TP	True Positive
MCM	Mine Counter Measure
IMO	International Maritime Organization

CHAPTER 1

INTRODUCTION

1.1 GENERAL

It is necessary to distinguish between underwater mines and rocks because accidental encounters with mine would cause the life-or-death situation. It possesses a severe threat to ships and submarines and other underwater explorers. Moreover, to human safety, it also is a threat to environment if they are misidentified as one another. Accidental encounters with rocks would harm the ships and marine lives. However, with mines, when it is encountered by accident, they explode underwater which causes physical damage to ships, submarines, and other underwater vehicles as the force of explosion can rupture the hull of a vessel, leading to flooding, structural damage, and potentially sinking which leads to fatalities. Other environmental impact it has is, generation of shockwaves which travels through water and it emits toxic substances which would be a threat to marine lives.

It also aids military as it is utmost important to distinguish these both. False alarms or misidentifications can have at most consequences. Ensuring the accurate recognition of mines is crucial for defensive and offensive military operations, as well as for protecting maritime trade routes. Lastly regulatory compliance with international maritime laws and agreements is often contingent on accurate differentiation between underwater mines and rocks. These regulations are designed to ensure the safety of navigation and to protect the marine environment. Violating these regulations can result in legal consequences and environmental liabilities. Therefore, it is important to differentiate between underwater rocks and mines to preserve environment, safety, and security.

1.2 MOTIVATION

The motivation for developing methods for submarine rock and mine detection mainly originate from the following reasons:

1. Naval Security: It is a critical aspect of maritime defence and safety. Submarine face significant threats from underwater rocks and mines along with surface vessels, which can cause disruption, damage, and loss of life. Ensuring the security of naval vessels, both military and civilian, is of outstanding importance. Here are some key points related to submarine rock and mine detection: Defence against enemy submarines, mines as naval weapons and protection of naval assets.

2. Military Operations: It’s essential to detect enemy mines and be aware of the underwater terrain for naval warfare. To avoid enemy mines and detect the presence of enemy submarines, submarine detection technology plays important role in both offensive and defensive operations. Military operations require the integration of various technologies, including sonar, magnetic anomaly detection, autonomous underwater vehicles, and specialized personnel trained in mine countermeasures in submarine rock and mine detection.
3. Environmental Protection: It can result in environmental damage through oil spills and other hazardous materials if there is an accidental contact with underwater rocks. By using Detection technology helps to protect marine ecosystems by preventing such accidents. To balance military operational needs with environmental protection is a complex task. Governments and military organizations are minimizing the ecological footprint of naval activities but still achieving their security and defence objectives.

1.3 PROBLEM STATEMENT

The maritime industry faces significant challenges in safeguarding vessels and underwater infrastructure. Current detection technologies are often limited in their accuracy, coverage, and cost-effectiveness, leading to increased risks, accidents, and operational inefficiencies. There is an urgent need to develop advanced and integrated detection solutions that can differentiate between submarine rocks and mines, providing real-time, reliable, and cost-efficient detection to enhance maritime safety, navigation, and environmental protection. To ensure the safety of underwater operations, including naval missions, underwater infrastructure maintenance, and resource exploration it is crucial to develop an effective and reliable system for submarine rock and mine detection.

It's essential to develop a system capable of real-time or near-real-time processing, as delays in mine detection could lead to catastrophic situations for practical military and civilian applications. The detection system cost-effectiveness is crucial for resource exploration and civilian sectors. By developing cost-efficient technologies and making them accessible gives significant results. Ensuring the safety of person involved in mine detection missions is important a system should be designed to reduce the risk to human operators and naval vessels.

1.4 OBJECTIVE

To develop and implement cutting-edge technologies and methods for the detection and mitigation of submerged hazards, specifically focusing on submarine rocks and mines. It also enhances the safety of naval vessels, submarines, and commercial ships by providing advanced detection capabilities for submerged hazards. Combines data from various sensors, including sonar, and imaging, to create comprehensive and reliable hazard detection systems. Achieve high accuracy in detecting and classifying underwater objects to minimize false alarms and ensure precise identification. To combine data from multiple sensor sources, create sophisticated data fusion and integration algorithms, allowing for a comprehensive understanding of the underwater environment. For sharing information related to detected mines establish secure and efficient protocols.

Develop user-friendly interfaces and training programs to effectively operate and maintain detection systems, reducing the errors and ensuring their proper utilization. Develop multispectral sensors and imaging techniques to gain more knowledge in underwater environment. This can lead in distinguishing between mines and rocks by detecting various material properties and compositions. To support humanitarian demining efforts, extend the application of mine detection technology, reducing the risk to civilian populations in mined areas. Enhance the safety and efficiency of underwater resource exploration allowing for more responsible and secure exploitation of underwater resources, such as minerals, oil, and gas.

1.5 SCOPE OF PROJECT

The scope of this project for distinguishing between underwater mines and rocks using Sonar signals is to develop a highly accurate prediction system. Due to the potential misidentification of mines as rocks, underwater mines serve as a vital component of naval defense systems, which poses a significant threat to marine life and submarine vessels. To ensure the safety and security of marine environments there is a necessary need to develop an advanced system capable of accurately classifying underwater objects.

The dataset consists of Sonar signals capturing the frequencies of underwater objects from 60 different angles to strike the metal cylinders and its bounces back to the transducer present in submarine. To get highest accuracy in prediction the study explores various classification algorithms. By harnessing the power of supervised machine learning techniques, the aim is to create robust and reliable modl capable of accurately classifying

Sonar signals and providing real-time predictions on the nature of the underwater objects encountered. By achieving a high level of accuracy in predicting underwater mines versus rocks, the proposed system aims to significantly enhance the safety and efficiency of marine operations.

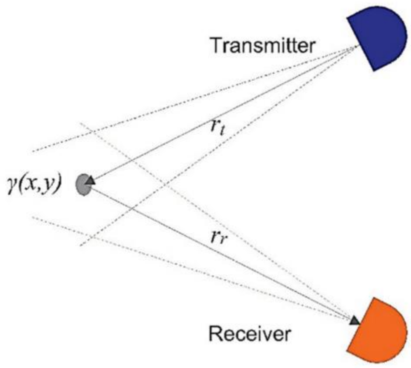


Fig 1.1 Review of Underwater Mine detection

1.6 FUNCTIONAL REQUIREMENTS

The first step of a process is software requirements which lists the requirements of a particular software system.

- Scikit learn: To reduce the dimension of the data by using scatter matrix, scale the data by using standard scalar, split the mine and rock data set into training and testing splits.
- NumPy: To process numerical data present in the dataset.
- Matplotlib: For visualizing the data in form of accuracy and losses of the trained model and to create the histogram figures of the sonar data.
- Seaborn: Is again a data visualization library for Pandas dataframes. Boxplots are used to compare algorithms and to plot box and wiskers for each of these algorithms.
- TensorFlow: To compile the model and find its losses and accuracies for each of the trained model.
- Pickle library: Is imported to serialize the trained model and create a dump of the model, which can later be loaded with rb format that can deserialize the saved model, so that predictions can be made from the web application built using streamlit.
- Streamlit library: To build a web application employing the saved machine learning model that was created using Pickle library.

1.7 NON-FUNCTIONAL REQUIREMENTS

The capacities provided by the framework are non-utilitarian requirements. It includes time constraints and requirements for the modl and progress process. The following are the examples of requirements that are not helpful:

- Speed: The system must set up the provided contribution to produce in a timely manner.
- Utilization: It is used to address the challenges associated with identifying and reducing the risks produced by submerged rocks and naval mines in fields practical applications, technologies, and methods.
- Reliability: The rate of failures in detecting rock or mine should be lower than merely the stronger structure.
- Portability: It is believed to be quite simple to implement in any framework.

1.8 HARDWARE REQUIREMENTS

It can vary depending on the specific detection methods and technologies. The following are the components used for effective identification of mine or rock:

- Processor – i3 or higher: This depends on the specific requirements and capabilities of the detection system. Such as, data processing, system complexity and compatibility.
- Hard Disk – 5 GB. It is not sufficient for the storage needs of a modern submarine rock and mine. Here are some reasons data volume, retention, redundancy, and processing & analysis.
- Memory – 1GB RAM: The memory capacity of a system can impacts its performance and ability in real-time applications. There are several considerations to remember algorithm execution and multitasking.
- Internet Connection: It faces primarily challenges due to the nature of naval operations and the underwater environment. For submarines and naval vessels may have limited connectivity. In scenarios secure and satellite communication is not used mostly for communication or data transfer.

1.9 SOFTWARE REQUIREMENTS

Programming requirements control defining the programming asset prerequisites and needs that need to be installed on a PC to provide perfect application performance. To identify potential threats in underwater environment these are vital for processing and analysing data from various sensors and systems. To enhance the safety and effectiveness of naval operations these requirements are effective. The following are some common software components required in submarine rock and mine detection:

- Windows 10 or higher: This presents several challenges and concerns such as security, closed systems, and real-time processing.
- Collab – an online python interpreter: Is an online platform that provides a cloud-based python environment for running Jupyter notebooks. Moreover, it is a convenient tool for applications like data science and machine learning tasks.
- Python 3-It plays an important role in fields like data processing, signal analysis and some onboard automation.

1.10 ENVIRONMENTAL REQUIREMENTS

Some of the important environmental requirements for running a rock and mine classification machine learning modl are:

- OS: Operating systems such as Windows, macOS, and Linux distributions GPU can be used to run the classification modl
- Support Libraries: Such as sk-learn, pandas, NumPy, mat plot lib, TensorFlow, Pickle, and seaborn and Frameworks such as Streamlit should be supported.
- Documentation: Documentation is an important aspect when building a project. It provides readability and easy understandability of the model built.
- Security: It ensures privacy and prevents unauthorized access to modl and data to maintain the integrity of the predictions and results made.
- Scalability: The project should be scalable enough to adapt to increasing users, data and complexity thus ensuring longevity and continued functionality.

CHAPTER 2
LITERATURE SURVEY

2.1 OVERVIEW

- **L. Zacchini, A. Ridolfi, and B. Allotta, "Receding-horizon sampling-based sensor-driven coverage planning strategy for AUV seabed in spections," in Proc. IEEE/OES Auton. Underwater Veh. Symp., 2020, pp. 1–6.**

Fayaz et. al [6] used a different approach on applying CNN, RCNN and YOLO based framework on pictures taken underwater. The author compares the above three algorithms to conclude RCNN has a better performance. YOLO is stated to have high speed detection that can be used for quick and real time responses. The stupor has faced a major challenge on recognizing optical content for capturing underwater images and also detection of sea grasses which would be confused with fishes and corals present underwater. To overcome these, it needs accurate and precise location to classify objects in real time. It is observed that the time cost of RCNN is fastest out of all three algorithms that are used to analyse the modl. The author has optimized GAN model that has been created to enhance the accuracy of current tracking systems when dealing with underwater data that may be distorted. The technique used on this is the AdaBoost which obtains higher frequency while compared to other boosting techniques. Thus, the model efficiently transforms the distorted underwater data into clear, non-distorted, or enhanced versions, thereby improving tracking performance.

- **M. Franchi, A. Bucci, L. Zacchini, E. Topini, A. Ridolfi, and B. Allotta,"A probabilistic 3D map representation for forward-looking SONAR reconstructions," in Proc. IEEE/OES Auton. Underwater Veh. Symp., 2020, pp. 1- 6.**

RDNN classification [3] using SVM and neural network algorithms were employed to differentiate sonar data. Principal Component Analysis and a standalone architecture were utilized to incorporate the Back Propagation NN for classifying two sets of data, within a bagging ensemble framework. Since RNNs require high-quality data for training, If the sonar data contains noise or artifacts, it can negatively impact the model's performance.

- **David P. Williams, “The Mondrian detection algorithm for sonar imagery,” IEEE Trans. Geosci. Remote Sens., vol. 56, no. 2, pp. 1091–1102, Feb. 2018.**

  David P. Williams et. al [1] proposed the concept of synthetic aperture sonar to detect objects using resonant zone downrange that checks the threshold of sub-patches of SAS image. It exhibits SAS data image that are accumulated from six different geographical locations and their diversified seafloor character is being observed using LF imagery. Using single band and dual band functionalities, for SAS images so that analytical detection probability can be derived. The muesli complexity calculates the spatial complexation, using the formula $S(A) = (H2 + V2)^{1/2}$. Here, H and V are the results of final image that is being filtered and A id the vertical and horizontal kernel of Sobel. Thus, the author has concluded in the formula for developing the SAS imagery accumulations.

- **Jun Liu, Yu Gou, Tong Zhang, Xinyi Jiang, XinQi Du, XuanZhang, “A-KNN: An adaptive method for constructing high-resolution ocean modl”, IEEE J. Ocean. Eng., vol. 46,no. 1, pp. 195–205, Jan. 2021, doi: 10.1109/JOE.2020.2980456**

  Jun Liu et.al [16] has proposed a model that involves KNN regression technique to enhance the initial dataset by filling in significant gaps. The objective is to create a new dataset that is evenly spaced, with data points precisely 1 meter apart. The approach detailed in this paper results in a substantial enhancement in the vertical data resolution when applied to training the k-nearest neighbor regression model. Because of the significant expenses associated with underwater nodes and their protective equipment, merely increasing the deployment of sparsity underwater nodes will not address the problem.

- **Konstantinos Pelekanakis, Luca Cazzanti, Giovanni Zappa and João Alves, “Decision Tree-Based Adaptive Modulation for Underwater Acoustic Communications”, IEEE Int. Geosci. Remote Sens. Symp., 2019, pp. 9455–9458, doi: 10.1109/IGARSS.2019.8898742**

  Konstantinos et. al [9] concluded that on using decision tree based adaptive modulation, so that the BER rate is fairly precise. Since underwater channels are highly variable, influenced by factors like water temperature, salinity, and movement. This variability can make it challenging to adapt modulation schemes effectively in real-time. Thus, reflecting the natural realm and in harmony with the nature, the decision tree does not always give away the accurate BER rate.

CHAPTER 3

SYSTEM ARCHITECTURE AND DESIGN

3.1 ARCHITECTURE DIAGRAM

Sonar datasets are firstly obtained and data cleaning is done to eliminate unwanted and corrupted images. Then CNN model is invoked for the dataset to create a model that is trained on the dataset provided. Feature Engineering is performed in form of convolutional architecture and is then split into training data and new data. As of training data, learning algorithm is passed to train a model. The results from the new data and the trained model gives score model which evaluates the F1 score, accuracy, precision and recall of the model that is trained. Finally, the model is then evaluated and is ready to predict whether the given input is either rock or a mine.

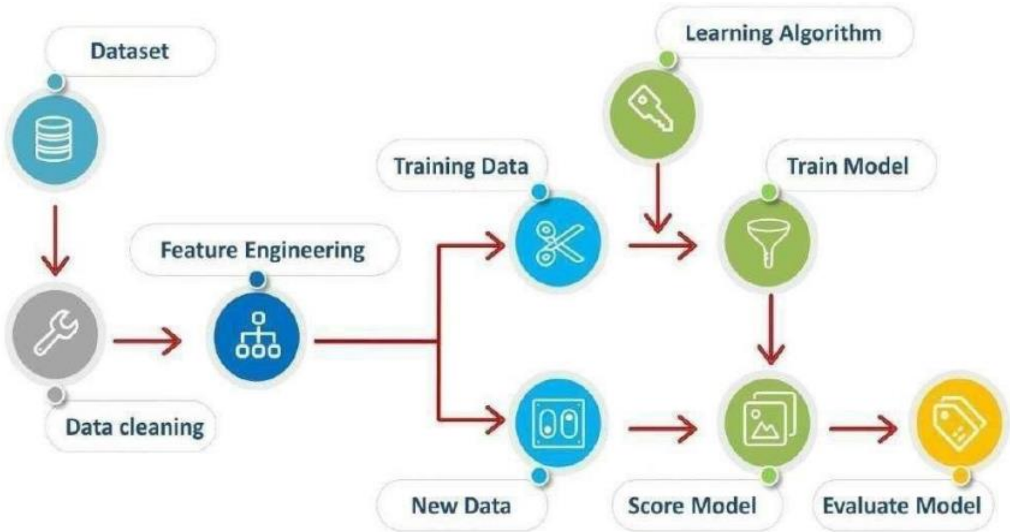


Fig 3.1 Architecture Diagram for Proposed method

3.2 USECASE DIAGRAM

Unified Modelling Language (UML) is a visual representation of interaction between actors and system. In this case the system could be a sonar. Here is a simplified diagram for submarine rock and mine detection:

1. Actors:
   - System: It checks the transmitted and received sonar signals.
   - Commander: The person operates and monitors the sonar system.

2. Relationships:
    - Associations:
        - ➢ The system is associated with training and predicting the model to differentiate between submarine rock and mine.
        - ➢ The commander with sending sonar signals in 60 different angles.

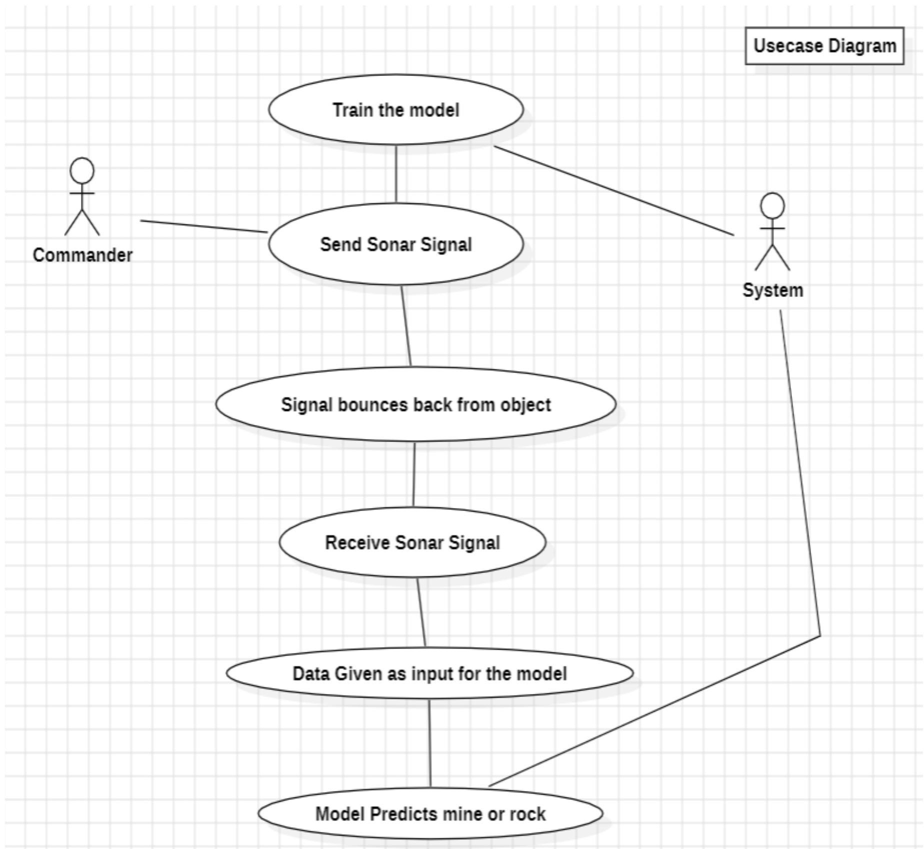


Fig 3.2 Use case diagram

3.3 CLASS DIAGRAM

This represents the various classes and their relationships. The below diagram describes attributes and objects:

- Commander: Represents the main class for submarine operations, including operating and monitoring the sonar system.
- Device: This is subclass for sonar data, including train the model, detect object, get readings and classify objects.
- Trained Model: To invoke the model and classifies rock or mine by using different algorithms.

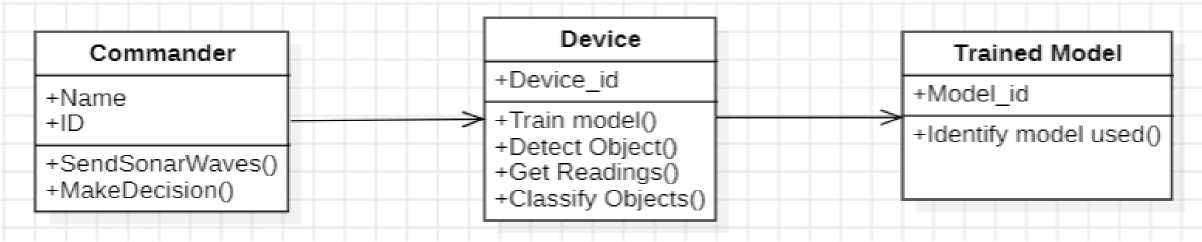


Fig 3.3 Class diagram

3.4 SEQUENCE DIAGRAM

It illustrates the order of messages and interactions between objects or components in the system over a period. The primary actors are the commander, system, and model. Here is a simplified diagram:

- First step in this take place by system trains the model.
- The commander initiates the sequence by sending sonar readings to the system.
- System invokes the model and sends information again back after detecting submarine rock or mine.
- The interaction between commander and system include detect object, classify object and acts accordingly.
- Arrows represent the flow of messages between two components.

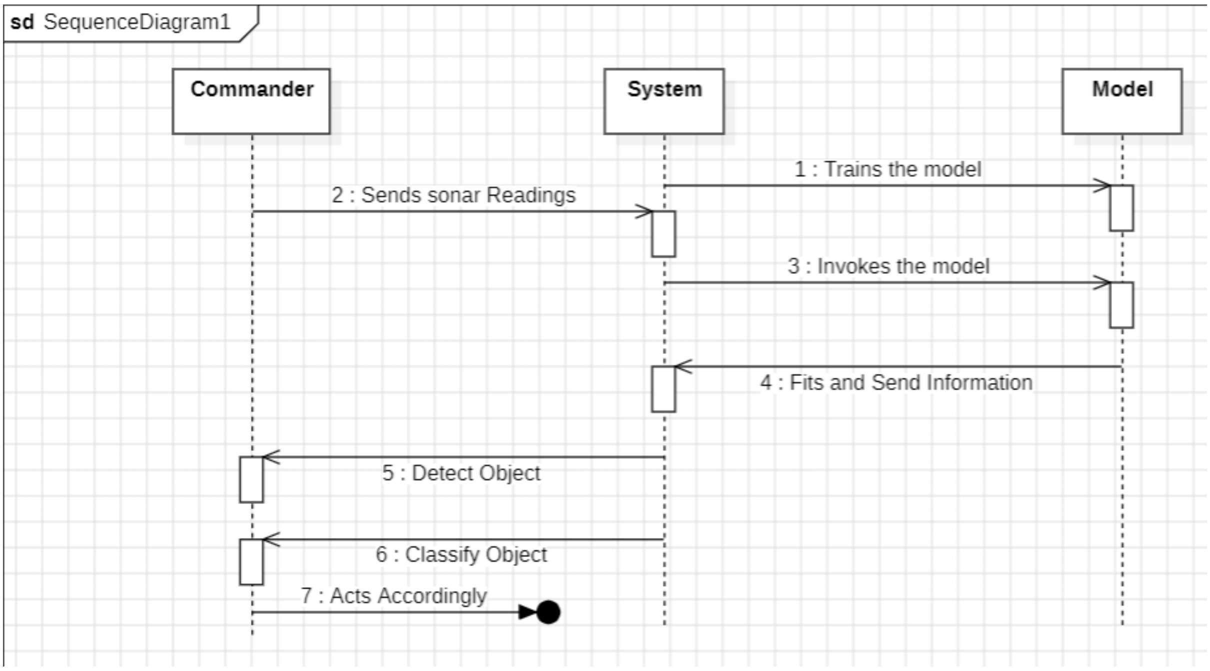


Fig 3.4 Sequence diagram

3.5 ACTIVITY DIAGRAM

This involves breaking down the process into a series of steps and activities. Here is a simplified diagram for this task:

- The process begins with initialization of system.
- Collect the data from surroundings and collected sonar data is analysed for anomalies.
- The system differentiates between submarine rock and mine.
- If it is mine then rise alarm and for rock records location.
- This is final step to identify and classify mine or rock.

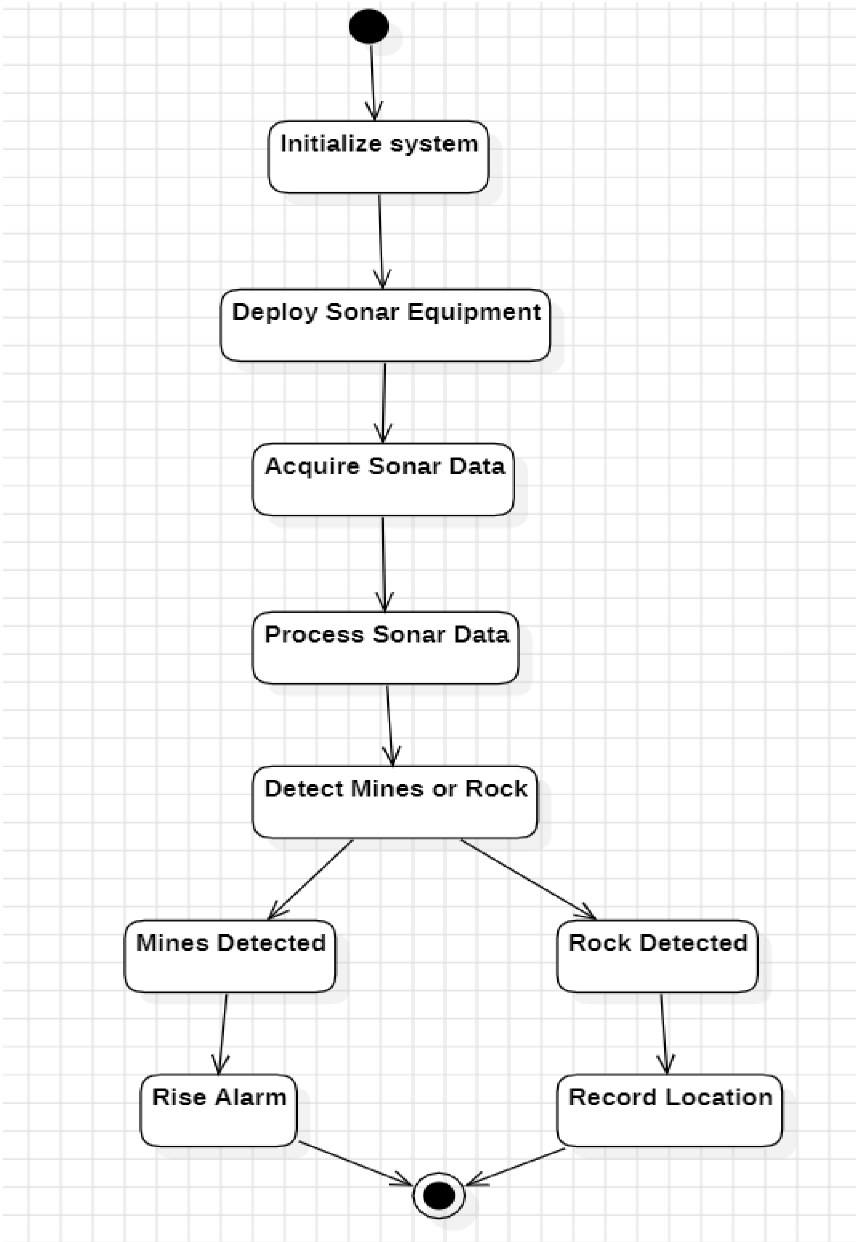


Fig 3.5 Activity diagram

3.6 COMMUNICATION DIAGRAM

This shows the interactions and message exchanges between various components and systems involved in the process. It is shown in below diagram:

- The sub system initiates the sequence by deploying sonar data, including deploy acquisition, alarm signal and recording location.
- Second step, data processing which includes detection logic and system status.

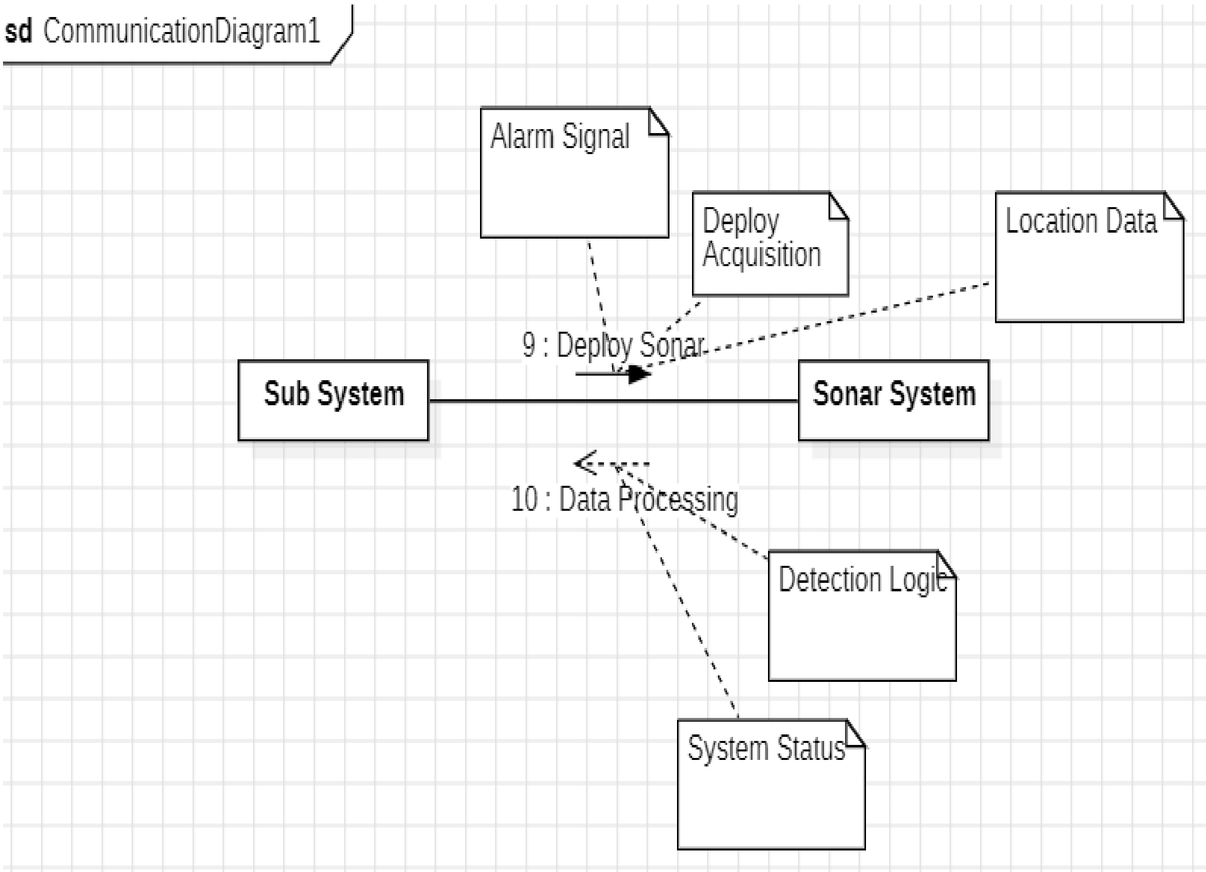


Fig 3.6 Communication diagram

The process begins with a sensor array deployed in the underwater environment. These sensors, which includes sonar devices, acoustic sensors, and underwater cameras, capture data and information from the surroundings. The sensor array continuously collects data, which includes sonar echoes, acoustic signals, and images of the underwater area. This raw data is then transmitted to the data processing unit. The sub system relates to sonar system. When the location data is obtained, it is processed with detection logic and warning alarm is sent when the system encounters any danger along with the system status.

3.7 STATE CHART DIAGRAM

This illustrates the different states and transactions that submarine's system go through the detection process. Here is a simplified diagram:

- Process takes place in several steps, the first step is to classify the dataset.
- Evaluate and choose algorithms like knn, svm and lr.
- Calculate accuracy and loss to predict the model.
- Based on particular model send input as mine or rock and display the result.

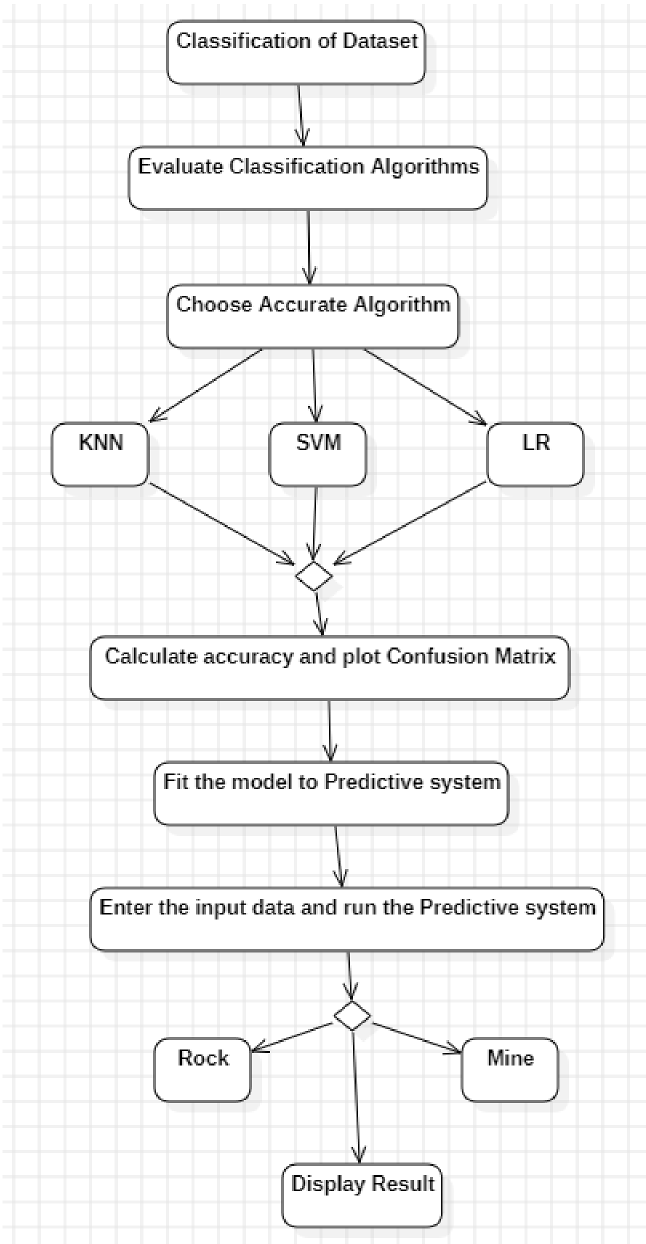


Fig 3.7 State chart diagram

3.8 ENTITY RELATIONSHIP DIAGRAM

This illustrates the relationship between different entities and makes decision based on particular entity. Explained in the following diagram:

1. Entity:
   - Transducer
   - Sonar system and images
   - Echoes
   - Underwater objects
2. Relationships:
   - Transducer depicts the sonar images and sends signals in 60 different angles.
   - Signal Bounces back and generates echo if it is not a mine or rock.
   - And underwater objects are classified based on the reflected images and records readings.

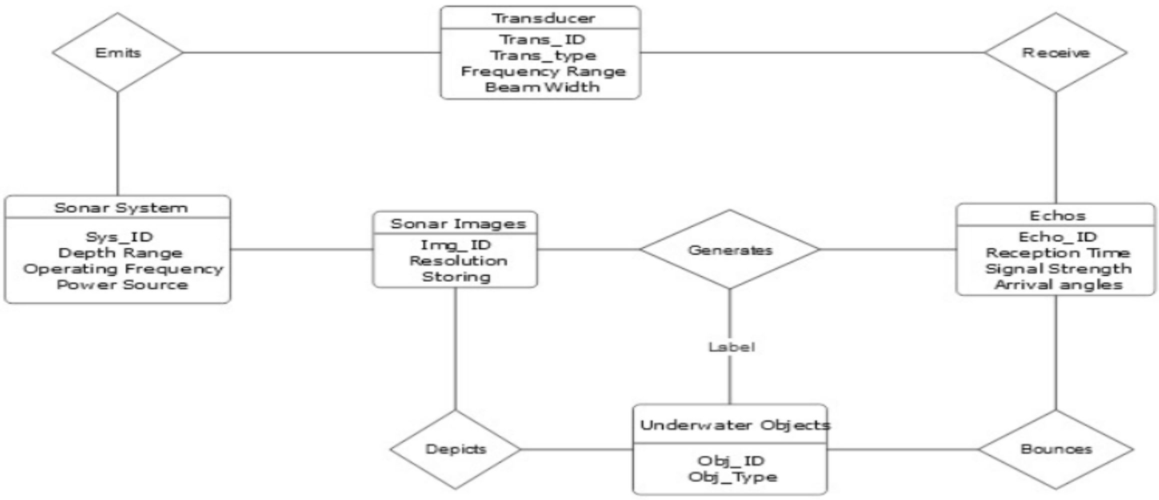


Fig 3.8 ER diagram

The sonar system emits frequency waves from the transducer and the echoes are bounced back to the transducer. Sonar system has depth range, operating frequency ad power sources as its components. Transducer has frequency range and bean width as its components. The echoes that transmit has specific IDs, reception time, signal strength and arrival angles as its entity and each of these values are recorded to generate sonar images. These objects depict the sonar images when the frequencies are bounced back to the transducer.

CHAPTER 4

METHOLODOGY

4.1 EXISTING SYSTEM

Machine learning modl can classify and identify these underwater hazards such as mine or rock by detecting the unique acoustic signatures of objects. In this process features like signal frequency, amplitude, and echo characteristics are crucial. To analyze the temporal patterns in acoustic data Recurrent Neural Networks (RNNs) are commonly employed, it is classified based on their distinct sound profiles. Specific acoustic patterns are recognized by RNNs which is associated with different objects and making it highly effective in underwater environment. Moreover, the combination of acoustic signal processing with machine learning techniques enables the development of accurate systems for the identification and classification of underwater mines and rocks. These systems are crucial for enhancing safety in maritime operations, underwater exploration, and military applications.

4.1.1 RNN LAYERS

RNN process the data sequentially. By altering their weights, the output of the hidden layer is fed as input to the same layer.

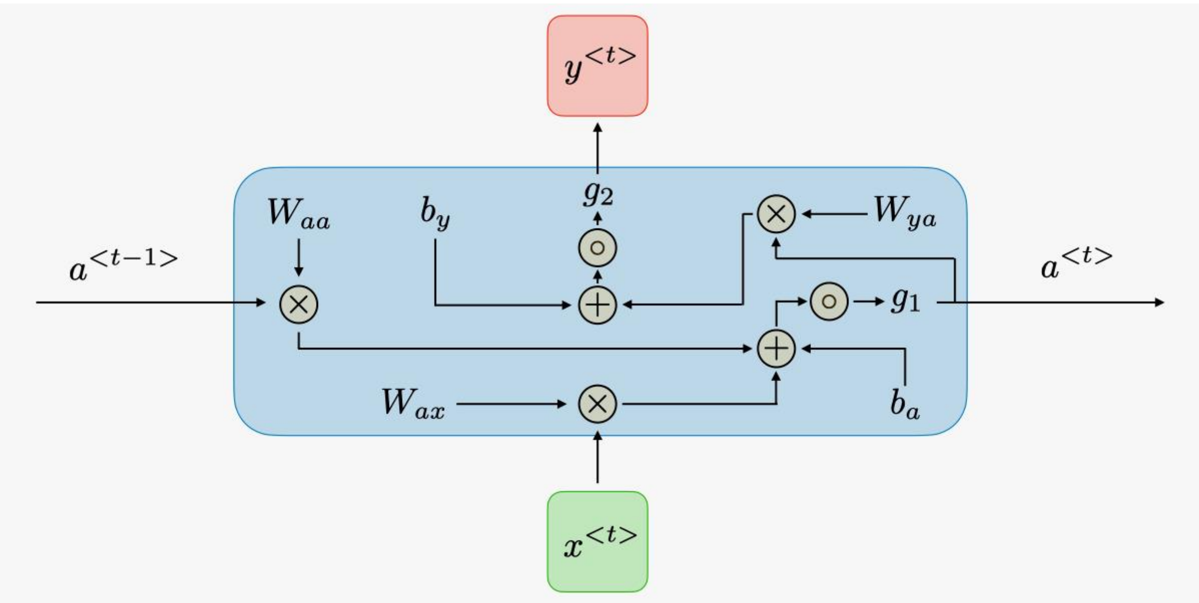


Fig 4.1 Simplified diagram of RNN

The middle layer is the hidden layer with its own activation function, wights and biases. Each of these wights gets updated to achieve the output of certain outcome. y<t> is the output neuron that is obtained after processed. Recurrent neurons have ability to memorize certain information is and use them for next layer to process. Thus, it has memory of past inputs. They also share the same set of parameters, enabling better learning algorithms and classifications.

RNN's use non-linear activation functions to overcome uneven mappings. This also improves their learnability. It is directly proportional to accuracy of the model, thus there would be increased accuracy for the model. Major drawback of the model is its vanishing gradient and explosive gradient. It also has difficulties in memorizing previous layers outputs. To overcome this, LSTM is introduced which consists of input gate, forget gate and output gate. Hyperbolic tangent function is common activation function employed in RNN. It is represented as

$$\tanh(x) = (e^{x} - e^{-x}) / (e^{x} + e^{-x})$$

It takes the range between (-1,1) which helps in non-linear classification tasks.

Other activation functions such as sigmoid is used for binary classifications.

$$\sigma(x) = 1 / (1 + e^{-x})$$

It takes the range between 0 and 1.

SoftMax in multi classification tasks. It works on probabilistic distribution over the outputs using the following representation.

$$\text{SoftMax}(x) = ex / \sum(ex)$$

Therefore, SoftMax converts the final output of the network into a probability distribution over different classes, enabling classification or prediction.

4.2 PROPOSED SYSTEM

A Predictive system for underwater submarine rock and mine detection is developed using machine learning on a dataset obtained by sending sonar signals in 60 different angles to strike the metal cylinders and it bounces back to the transducer present in submarine. And for images side scan sonar is used. Based on their unique frequency characteristics our modl precisely differentiate between rock and mine. We implemented new algorithms to improve the safety and effectiveness of Mine Countermeasure (MCM) in classifying mines and protecting naval vessels. Sonar images are given as the input and these algorithms examine texture based, geometrical and spectral features. Moreover, machine learning has limitations, deep learning overcomes them with its ability to work with huge amount of data and it makes easier to classify rock or mine.

Deep learning algorithms face provocations in mine detection due to limited high quality data availability. Sonar simulation and augmentation label this issue. Transfer learning and algorithm fusion improve reliability. By combining classical image processing with deep learning inflate performance and reduces unbalanced data effects. Sonar, utilizing acoustic waves and measures the time taken to bounce back the object allows to calculate the distance. For transmission and reflection, we will use properties like water properties, frequency effect performance and hydrophones.

4.2.1 CONVOLUTIONAL NEURAL NETWORK:

Convolutional neural networks (CNNs) are used for the classification of sonar pictures because to its particular architecture and exceptional ability to recognize patterns in images. They are good at identifying little details or patterns in pictures, like corners, edges, and textures. Additionally, it have translation invariance, which means they can identify patterns in images regardless of where they are located, and its hierarchical structure makes it possible to learn complicated features by combining simpler ones, which enhances their comprehension of picture content. This decrease the amount of parameters, improving efficiency and lowering the danger of overfitting, by implementing parameter sharing in convolutional layers.

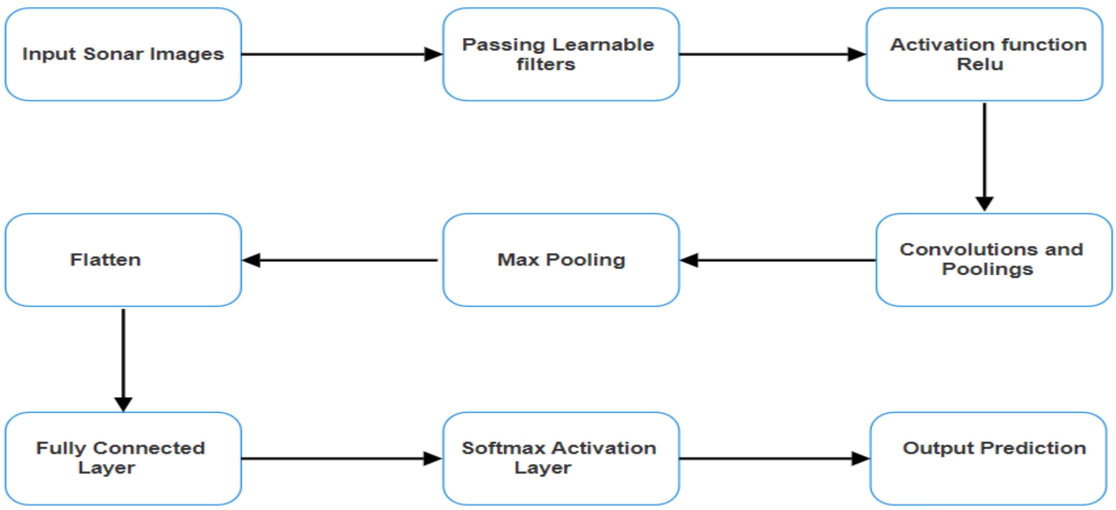


Fig 4.2 Block diagram for proposed method

First, the sonar images are sent to learnable filters, which then pass over the input sonar images and pick out specific characteristics. In this instance, max pooling is utilized to examine data that is sporadically spaced between convolutional layers, reducing spatial dimensions while maintaining crucial information and boosting the computational efficiency and stability of the network. The completely connected layers come next, where high-level reasoning using the flattened feature maps is done. An output layer, which generates class probabilities in classification tasks, is the result of these layers. By minimizing a loss function and using gradient descent and backpropagation to optimize filter weights and biases, CNNs learn from labelled data during training. Until the model performs to a sufficient level, this iterative procedure is continued.

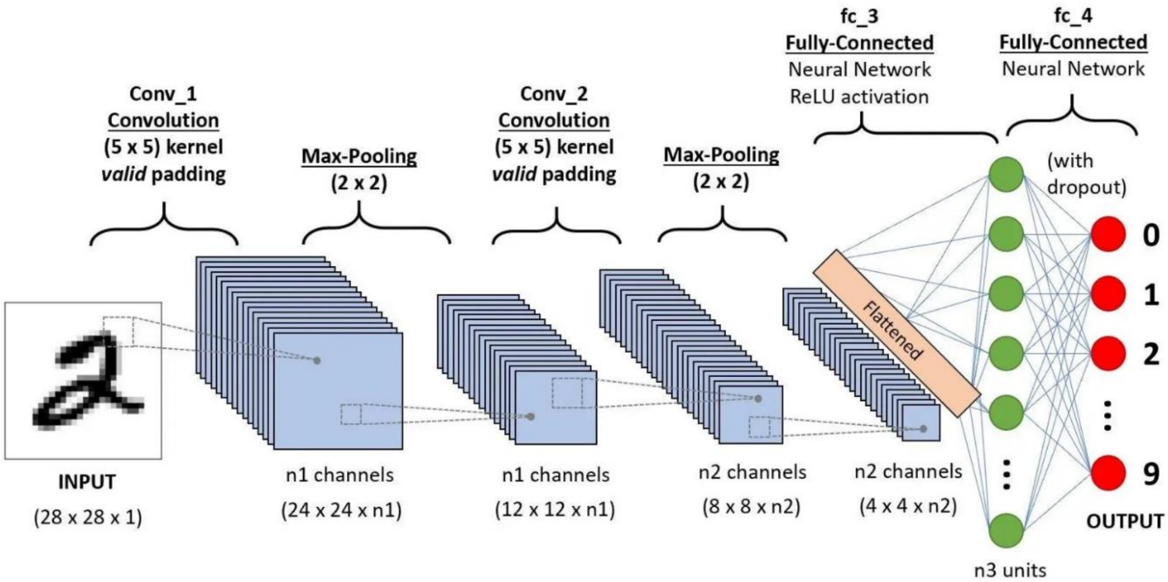


Fig 4.3 CNN Network

ReLu Activation function-The feed forward neural network analyses the data and classify the objects. CNN has multiple layers to divide and analyse the images including convolutional layer, activation layer, pooling layer, dense layer, and an output layer. The images are firstly divided into pixels of 256 x 256 x 3. These 3-dimensional images are then converted to 2 dimensions. The sequential model has n channels. Firstly, conv2D is applied for the value 16 with the kernel size of 3x3 with stride value 1.

Pooling-Max pooling is performed onto the resulting layer. Max pooling obtains the maximum value in the reduced spatial dimension. It performs down sampling technique and only stores the maximum value in the pixels and discards rest of the values. By this method, it retains the important features of the images to help classifying the given input image. It also reduces over fitting and provides effective image analysis.

After max pooling in the first recursion, the convolution is performed again on the set of neurons until the features are extracted. The appropriate activation function is chosen for each of these resulting conv layers. In the proposed methodology, ReLu activation is employed for all the layers.

Fully connected layer-When the final max pooling is done, fully connected neural network is obtained by connecting every neuron of one layer to the next layer. It allows complex relations and loanabilities to be learnt and provides flexibility to the system. Dense layer is obtained by flattening the feature map by converting 2-dimensional to 1-dimentional vector. The first level of flattening consists of 256 neurons and uses ReLu activation function. In the second level of flattening, all 256 neurons would be mapped to a single output neuron using sigmoid activation function. Sigmoid activation is used here because, the final prediction is if the object encountered is rock or a mine which has only two possible predictions.

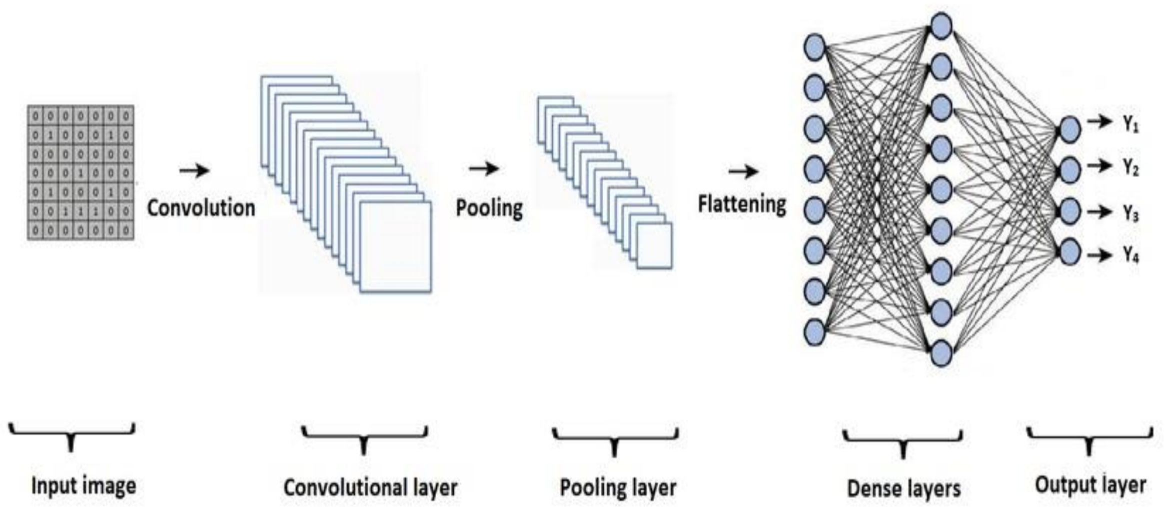


Fig 4.4 Representation of Dense and output layer

Therefore, the pixel images of underwater sonar images are fed to input layer, resulting in convoluted map of the input image. ReLu activation function and max pooling is repeatedly performed until the features are extracted to identify the class division the image falls into. The pooled feature map is then flattened using dense layer and fed to the fully connected layer to obtain the accurate prediction.

4.2.2 ENSEMBLE LEARNING:

To enhance predictive accuracy and improve model robustness ensemble methods support the collective capabilities of multiple machine learning algorithms. To get accurate results algorithms like Logistic Regression, K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Naive Bayes, Decision Tree, Random Forest, and AdaBoost can be ensembled. Each and every algorithm of these gives distinct strengths to the ensemble's overall predictive power. To illustrate, K-Nearest Neighbours gives valuable probabilistic outputs, KNN excels at instance-based predictions, SVMs refine decision boundaries, and Naive Bayes accurately handles probabilistic classification, Decision Trees capture complex relationships, Random Forests offer effective bagging techniques, and AdaBoost stands out in boosting performance. Esm often achieve superior performance in machine learning across many applications, including classification and regression tasks by combining these diverse perspectives and strategies.

Ensemble learning is effective in learning strategies and sources of error. This makes more robust predictions. However, it's important to maintain a balance between model diversity and computational resources, as esm with too many base modl can become computationally expensive. It is used in competitions and real-world applications where achieving high predictive accuracy is crucial. And compared to other modl it gives accurate results.

4.3 SENSOR SYSTEM

A sonar system typically starts with a transducer, which is a device that emits sound waves into the water. These sound waves are often in the form of high-frequency acoustic pulses. Underwater sonar systems use acoustic waves to capture images of underwater environments by emitting sound pulses, receiving echoes, and processing the data to create images. When the sound waves encounter an object, they bounce back as echoes. These echoes are received by the same transducer or another receiving transducer. For images side scan sonar is used to capture underwater objects. Additionally, they collect numerical data on mines and rocks based on the acoustic back-scatter of sound waves. This involves analysing the strength or intensity of the echoes received from underwater objects.

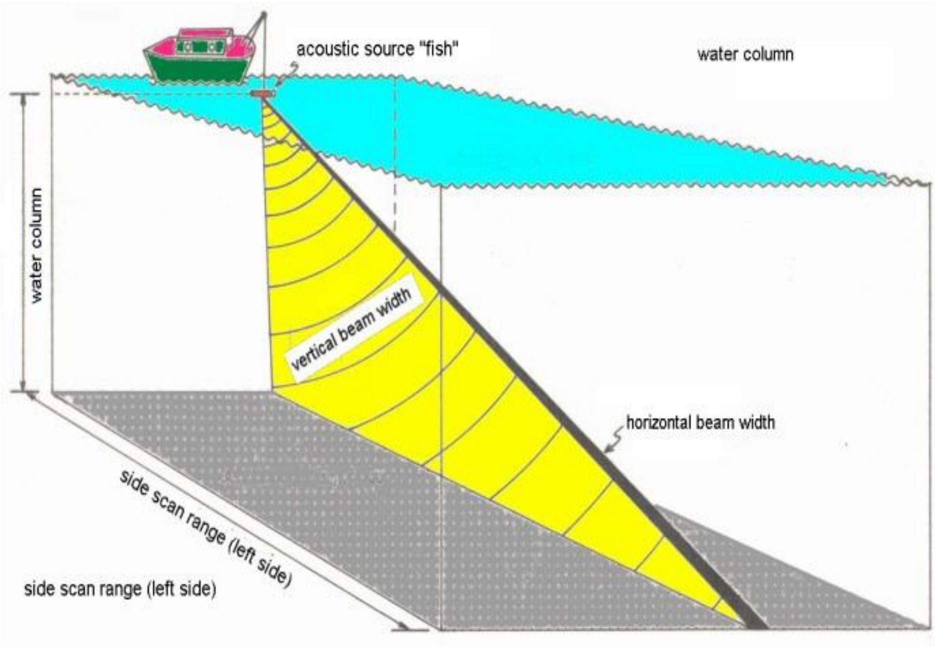


Fig 4.5 Image of side scan sonar

4.4 DATA COLLECTON

For the collection of numerical data, sonar systems emit acoustic signals into the water and measure the time it takes for these signals to travel to objects and return as echoes. This time-based data, along with the intensity or amplitude of the echoes, is a fundamental component of the data collection process. This echoed data provides crucial information about distances to underwater objects and their acoustic characteristics. These data values are recorded at 60 different angles for 104 rocks and 104 mines.

Simultaneously, sonar systems can collect images of the underwater environment. These data-driven images are formed by processing the echoes received from objects and underwater features. We use side-scan sonar to create detailed two-dimensional images of the seafloor and any objects or structures on it. The intensity of echoes is used to create grayscale images, where brighter regions correspond to stronger echoes.

4.5 PREPROCESSING

The sonar image data are divided into training, testing and validation batches. We have a total of 7 batches with 4 batches in training, 2 batches in validation and 1 batch for testing. As of sonar dataset, 80% of sonar data is allocated training and remaining for testing the prediction model.

4.6 FEATURE EXTRACTION AND CLASSIFICATION ALGORITHMS

Now implementing Conv2D deep model, firstly we create an empty sequential model. Giving 256x256x3 image as input, we add 2D convolutional layer to the model with 16 filters and each of these having a 3x3 kernel with stride value 1. ReLu activation function is used in this case to tackle vanishing gradient problem. Then we add a 2D max-pooling layer to the sequential model. We repeat the steps again with lower number of filters for 3 iterations to capture high level feature and manage computational complexity. Then flattering out the model, we use dense function to reduce to 256 layers using ReLu activation function. Doing the same for the next dense layer, we use sigmoid for binary classification of whether the image belongs to mine or rock classification.

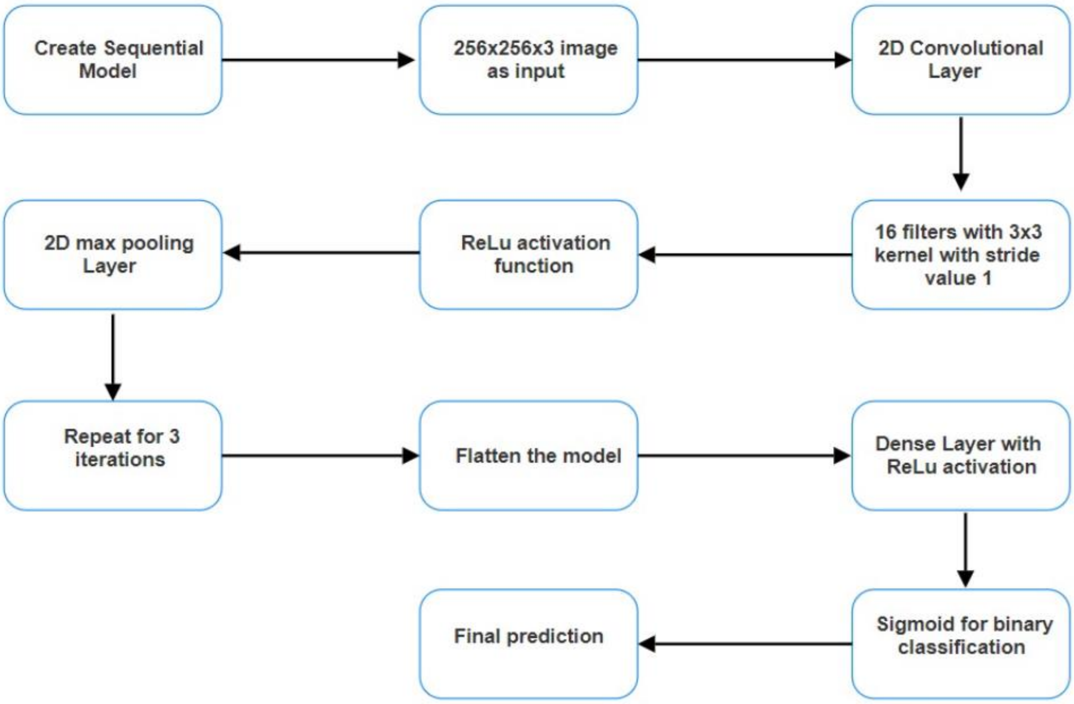


Fig 4.6 Diagram for how CNN works

As for sonar data, we use ensemble techniques to observe the best performing algorithms out of all the algorithms. It is observed that K-Nearest Neighbours performs better than any other algorithm. Even after scaling, scaled K-Nearest Neighbours has the better performance. Thus, opting for KNN model, by applying threshold which is also enhanced with regularization techniques to prevent overfitting. Once the training is done, now the model is ready to predict the new data by estimate probabilities and classify examples into one of the two possible outcomes i.e., the object is rock or mine.

CHAPTER 5
CODING AND TESTING

5.1 IMPLEMENTATION

The following system requirements were used in this project:

- **Language:** Python
- **Packages and libraries used:**

➢ **Scikit learn:** Used for classification, regression, clustering and featuring easy-to-use tools and a wide range of algorithms.

➢ **NumPy:** Used for numerical operations, providing support for arrays, matrices, and mathematical functions, making data manipulation and computation efficient.

➢ **Matplotlib:** To create static and interactive visualizations, including charts, plots, and graphs for data analysis.

➢ **Seaborn:** It provides data visualization library, offering an easy and attractive way to create informative statistical graphics.

➢ **TensorFlow:** To compiles and simplifies the model and find its losses and accuracies for each of the trained model.

➢ **Pickle library:** It allows serializing (converting to a byte stream) and deserializing (converting back) objects, enabling data storage and retrieval.

➢ **Streamlit library:** It simplifies web app development, employing the saved machine learning model that was created using Pickle library by enabling easy creation of interactive data-driven applications with minimal code.

5.1.1 Train.py

Training for submarine rock and mine detection involves several steps to improve the effectiveness and reliability of the detection system. In training it go through steps like data collection gather a diverse and representative dataset of underwater environments where submarine rocks and mines are expected to be encountered, data preprocessing clean and preprocess the collected data to handle noise, sensor signals and missing values, feature extraction may include features object size, shape, acoustic characteristics, and motion patterns, splitting the dataset divide the dataset into three parts which is named as training, testing and validation, selecting modl consider ensemble methods like Random Forests or AdaBoosting for improved accuracy, train the selected modl on the training data using the ground truth labels, model evaluation assess the modl performance in stints of fp and fn, which are critical in mine classification applications, fine-tuning refines the modl based on the expected results.

```
In [8]: import tensorflow as tf
        import os

In [9]: gpus = tf.config.experimental.list_physical_devices('GPU')
        for gpu in gpus:
            tf.config.experimental.set_memory_growth(gpu, True)

In [10]: len(gpus)

Out[10]: 0

In [11]: os.listdir('Data')

Out[11]: ['mines', 'rocks']

In [12]: import cv2

In [14]: pip install micropython-imghdr
```

Fig 5.1 Importing the libraries

```
In [46]: #Plotting accuracy and Loss
         fig = plt.figure()
         plt.plot(hist.history['loss'], color='teal', label='loss')
         plt.plot(hist.history['val_loss'], color='orange', label='val_loss')
         fig.suptitle('Loss', fontsize=20)
         plt.legend(loc="upper left")
         plt.show()
```

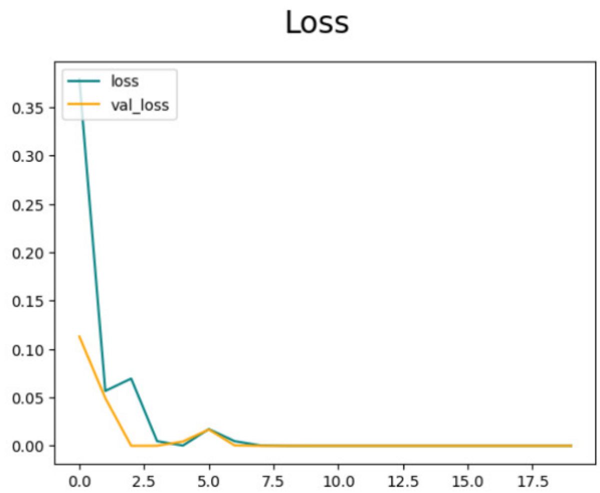


Fig 5.2 Loss Graph

```
In [47]: fig = plt.figure()
         plt.plot(hist.history['accuracy'], color='teal', label='accuracy')
         plt.plot(hist.history['val_accuracy'], color='orange', label='val_accuracy')
         fig.suptitle('Accuracy', fontsize=20)
         plt.legend(loc="upper left")
         plt.show()
```

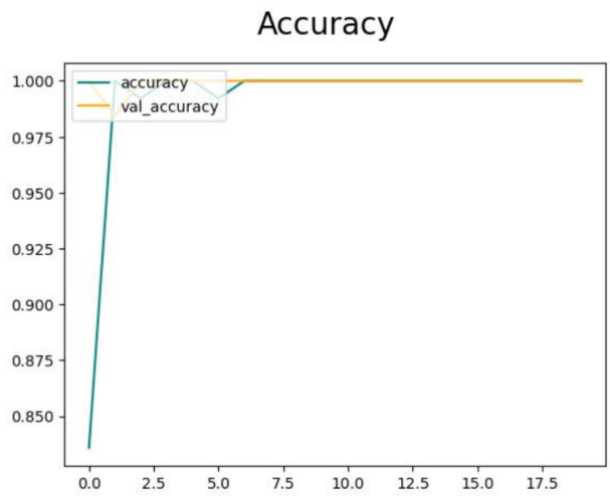
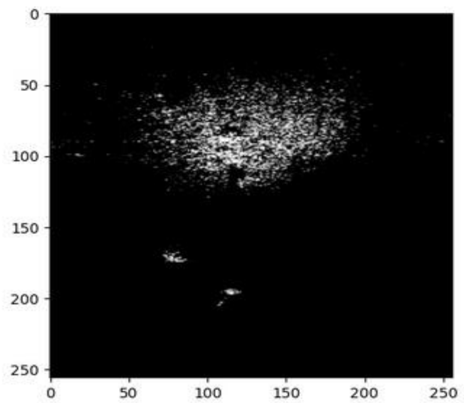


Fig 5.3 Accuracy Graph

```
In [53]: resize = tf.image.resize(img, (256,256))
         plt.imshow(resize.numpy().astype(int))
         plt.show()
```




```
In [54]: resize.shape

Out[54]: TensorShape([256, 256, 3])

In [55]: np.expand_dims(resize, 0).shape

Out[55]: (1, 256, 256, 3)

In [56]: yhat = model.predict(np.expand_dims(resize/255, 0))

         1/1 [==============================] - 0s 79ms/step

In [57]: yhat

Out[57]: array([[0.]], dtype=float32)

In [58]: if yhat > 0.5:
             print('Rock')
         else:
             print('Mine')

         Mine
```

Fig 5.4 Final Prediction

5.1.2 Csv.py

This file contains sonar values of submarine rock and mine detection. In this side scan sonar is sent to the underwater objects like rock or mine and reflects with different sonar frequencies then it is stored in sonar transducer. Sonar signals are sent in 60 different angles it records the different value for each signal.

In [73]:
```
import pandas as pd
```

In [74]:
```
sonar_data = pd.read_csv("C:/Users/Sindhu/OneDrive/Desktop/Jupyter/sonar_dataset.csv")
```

In [75]:
```
sonar_data.head()
```

Out[75]:

	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
0	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
1	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
2	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
3	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
4	0.0286	0.0453	0.0277	0.0174	0.0384	0.0990	0.1201	0.1833	0.2105	0.3039	...	0.0045	0.0014	0.0038	0.0013	0.0089	0.0057	0.0027	0.0051	0.0062

5 rows × 61 columns

In [76]:
```
sonar_data.shape
```

Out[76]: (207, 61)

In [77]:
```
sonar_data.describe()
```

Out[77]:

	0.0200	0.0371	0.0428	0.0207	0.0954	0.0986	0.1539	0.1601	0.3109	0.2111	...	0.0232	0.0027
count	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	...	207.000000	207.000000
mean	0.029208	0.038443	0.043837	0.054053	0.075105	0.104599	0.121591	0.134677	0.177361	0.208245	...	0.016034	0.013472
std	0.023038	0.033040	0.038521	0.046583	0.055669	0.059247	0.061897	0.085340	0.118311	0.134741	...	0.012027	0.009628
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
25%	0.013300	0.016400	0.018900	0.024450	0.037700	0.066950	0.080600	0.080350	0.096750	0.111150	...	0.008350	0.007350
50%	0.022800	0.030800	0.034200	0.044100	0.062000	0.092100	0.105600	0.111900	0.152200	0.181000	...	0.013800	0.011500
75%	0.035800	0.048100	0.058200	0.065700	0.101050	0.134150	0.153050	0.169800	0.231500	0.269000	...	0.020700	0.016750
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

8 rows × 60 columns

Fig 5.5 Importing Sonar File

In [94]:
```
# Compare Algorithms
fig = plt.figure(figsize = (20,7), facecolor = '#3f8088')
fig.suptitle
ax = fig.add_subplot(111)
sns.boxplot(data = results)
ax.set_xticklabels(names, size=20, color='#b9f6f6', y=-0.03 )
sns.set_palette('mako')
plt.title('Ensrmble Algorithm Comparison', fontsize=25, color = '#b9f6f6', y=1.05)
plt.show()
```

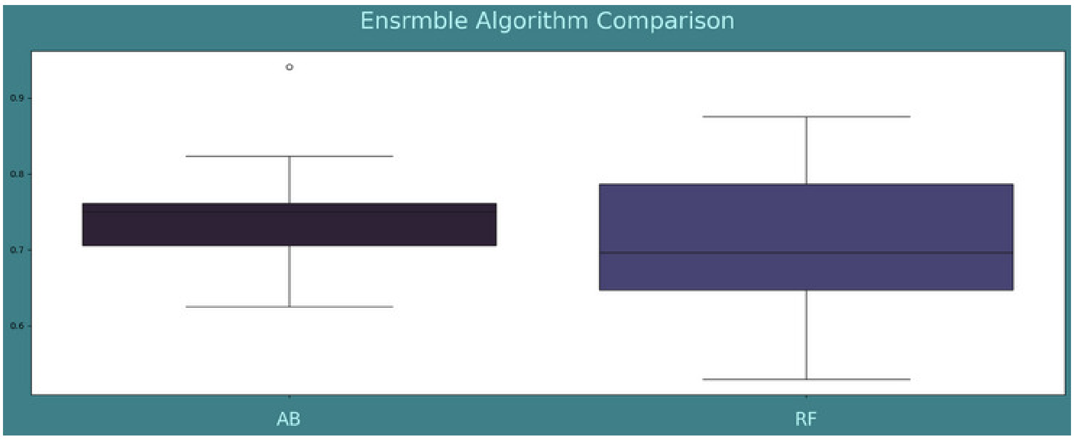


Fig 5.6 Ensemble algorithm comparison

5.2 TESTING

In testing it has several steps like test data preparation it uses a separate, previously unseen test dataset that was not used during training or validation, model testing records the model predictions and compare them to the ground truth labels for evaluation, performance evaluation analyze the confusion matrix in labels of tp, tn, fp, and fn, generalization testing test the modl on new data collected in different locations or at different times to validate their robustness, threshold tuning Adjust decision thresholds if necessary to achieve a balance between false positives and false negatives, based on the specific operational requirements, documentation and reporting provides clear and concise reports to stakeholders summarizing the performance of the detection system, continuous improvement periodically re-evaluate the detection system with new data and make necessary updates to the modl to adapt to changing underwater conditions and threats.

5.2.1 TYPES OF TESTING

- User interface: This UI ser ves as an intuitive platform for interacting with a machine learning model designed to distinguish between rocks and mines in underwater sonar data. Users can upload sonar images or data samples, and the model will provide real-time predictions. This user interface, built on Streamlit, enhances the accessibility and usability of the rock and mine detection system, making it a valuable tool for various underwater applications. As of underwater image, the input is read in the image format and the model evaluates the image based on pre-trained data. As of echoed values, the data of all 60 degrees are read as input and the pre trained model evaluates the input data as rock or mine.
- Validation: Validation typically involves assessing the system's performance under various conditions, including different underwater environments and potential challenges. It involves several steps diverse dataset use a diverse and representative dataset for validation that covers a wide range of underwater conditions, including different water depths, seabed types, and environmental factors, ground truth data can be obtained through manual surveys, underwater robots, or historical records, Employ cross-validation techniques, such as k-fold to improve the system's performance more rigorously, performance metrics consider using domain-specific metrics that account for the operational context and constraints.

```
In [95]: # Prepare SVC model
scaler = StandardScaler().fit(X_train)
rescaledX = scaler.transform(X_train)
model = SVC(gamma ='auto', C = 2.0)
model.fit(rescaledX, y_train)

# Estimate accuracy on validation dataset
rescaledValidationX = scaler.transform(X_val)
predictions = model.predict(rescaledValidationX)
print('Accuracy: ', accuracy_score(y_val, predictions))
print('\n')
print('Confusion matrix: \n', confusion_matrix(y_val, predictions))
print('\n')
print('Classification report: \n', classification_report(y_val, predictions))
```

```
Accuracy:  0.9047619047619048


Confusion matrix:
 [[18  2]
 [ 2 20]]


Classification report:
              precision    recall  f1-score   support

           M       0.90      0.90      0.90        20
           R       0.91      0.91      0.91        22

    accuracy                           0.90        42
   macro avg       0.90      0.90      0.90        42
weighted avg       0.90      0.90      0.90        42
```

Fig 5.7 Confusion matrix

5.4 USER INTERFACE

For ensuring the effective operation of these critical defense and naval technologies user interfaces for submarine rock and mine detection systems are vital. To make informed decisions and take appropriate actions these interfaces need to provide clear and real-time information to the operators.

5.4.1 Web app

C:\Users\Sindhu\Rock_Mine_MultiPageApp\HomePage.py

predictive_system.py | mine_rock_prediction_webapp.py | csv_predictive_system.py | mine_rock_prediction_csv.py* | HomePage.py

```
import streamlit as st

st.set_page_config(
    page_title = "Rock_Mine_Prediction"
)


page_bg_img = f'''
<style>
background: url("https://images.unsplash.com/photo-1542281286-9e0a16bb7366");
background-size: cover;
</style>
'''

st.markdown(page_bg_img, unsafe_allow_html=True)

st.title("*Rock!* :mountain: vs *Mine!* :bomb: Detection")
st.write('Hello,')
st.write(f'''This project focuses on detecting and distinguishing between rocks
         and mines underwater. Accurate detection ensures the safety of ships,
         submarines, and their crews by preventing collisions with underwater
         obstacles and mines, which can cause catastrophic damage. It is also
         crucial for military operations, as mines pose a significant threat to
         naval forces. Effective underwater detection systems aid in maintaining
         navigational safety, protecting maritime infrastructure, and safeguarding
         national security by enabling timely identification and neutralization
         of potentially lethal underwater threats.
         ''')
st.sidebar.success("Select a page above")
```

Fig 5.8 Home page

CHAPTER 6

RESULTS AND DISCUSSIONS

Experimental outcomes are described below, by using each possible combination of features.

6.1 K-NEAREST NEIGHBOUR

KNN is applied to differentiate rock and mine detection, specifically in the context of classification tasks. This technique is a simple yet effective algorithm that can be used for object classification when you have a labelled dataset of sensor data and corresponding labels. The accuracy for normal and scaled is shown (see table 6.1).And the output values are given below.

```
Best: 0.842647 using {'n_neighbors': 1}
0.842647 (0.093643) with: {'n_neighbors': 1}
0.836029 (0.106911) with: {'n_neighbors': 3}
0.775735 (0.121602) with: {'n_neighbors': 5}
0.799265 (0.092749) with: {'n_neighbors': 7}
0.751103 (0.058687) with: {'n_neighbors': 9}
0.707721 (0.076912) with: {'n_neighbors': 11}
0.696324 (0.084881) with: {'n_neighbors': 13}
0.696324 (0.088864) with: {'n_neighbors': 15}
0.714706 (0.083759) with: {'n_neighbors': 17}
0.690441 (0.094690) with: {'n_neighbors': 19}
0.727574 (0.095877) with: {'n_neighbors': 21}
```

Fig 6.1 Output values for KNN

Table 6.1 Classification rate for KNN

Model	Mean	Std
KNN	0.758456	0.105791
Scaled KNN	0.837500	0.102055

6.2 SUPPORT VECTOR MACHINE

In the second set of observations, it is noticed that SVM works efficiently with polynomial Kernal for both submarine rock and mine(see table 6.2)

Table 6.2 Classification rate for SVM

Model	Mean	Std
SVM	0.601471	0.160777
Scaled SVM	0.855147	0.091620

```
Best: 0.866912 using {'C': 1.7, 'kernel': 'rbf'}
0.764706 (0.093948) with: {'C': 0.1, 'kernel': 'linear'}
0.545588 (0.140576) with: {'C': 0.1, 'kernel': 'poly'}
0.546691 (0.140093) with: {'C': 0.1, 'kernel': 'rbf'}
0.710294 (0.093092) with: {'C': 0.1, 'kernel': 'sigmoid'}
0.794853 (0.075108) with: {'C': 0.3, 'kernel': 'linear'}
0.666176 (0.148757) with: {'C': 0.3, 'kernel': 'poly'}
0.790074 (0.107884) with: {'C': 0.3, 'kernel': 'rbf'}
0.759559 (0.129412) with: {'C': 0.3, 'kernel': 'sigmoid'}
0.782353 (0.085951) with: {'C': 0.5, 'kernel': 'linear'}
0.751838 (0.113164) with: {'C': 0.5, 'kernel': 'poly'}
0.789706 (0.111353) with: {'C': 0.5, 'kernel': 'rbf'}
0.759559 (0.110627) with: {'C': 0.5, 'kernel': 'sigmoid'}
0.764338 (0.077580) with: {'C': 0.7, 'kernel': 'linear'}
0.788603 (0.089093) with: {'C': 0.7, 'kernel': 'poly'}
0.813235 (0.116304) with: {'C': 0.7, 'kernel': 'rbf'}
0.771324 (0.097226) with: {'C': 0.7, 'kernel': 'sigmoid'}
0.758824 (0.101263) with: {'C': 0.9, 'kernel': 'linear'}
0.813603 (0.092235) with: {'C': 0.9, 'kernel': 'poly'}
0.837132 (0.121402) with: {'C': 0.9, 'kernel': 'rbf'}
0.765809 (0.121346) with: {'C': 0.9, 'kernel': 'sigmoid'}
```

Fig 6.2 Output values for SVM

6.3 DECISION TREE

As of the third batch decision tree performs accurately for the classification of submarine rock and mine (see table 6.3)

Table 6.3 Classification for decision tree

Model	Mean	Std
CART	0.718382	0.092559
Scaled CART	0.681250	0.103413

6.4 LOGISTIC REGRESSION

For fourth set of findings, it executes deliberately Lwith good accuracy (see table 6.4)

Table 6.4 Classification rate for Logistic regression

Model	Mean	Std
LR	0.770956	0.058802
Scaled LR	0.818750	0.066706

6.5 CONFUSION MATRIX

It displays the counts of true positives, true negatives, false positives, and false negatives which is shown below (see table 6.5)

Table 6.5 Values for confusion matrix

18	5
3	16

6.6 CLASSIFICATION REPORT

Confusion matrix helps to evaluate the model's accuracy, precision, recall, and other classification metrics shown below (see table 6.6)

Table 6.6 Values for classification report

	Precision	Recall	F1-Score	Support
Mine	0.86	0.78	0.82	23
Rock	0.76	0.84	0.80	19
Accuracy	-	-	0.81	42
Macro avg	0.81	0.81	0.81	42
Weighted avg	0.81	0.81	0.81	42

6.7 IMAGE DATASET

In image dataset it contains images for both submarine rock and mine. Based on the image model will predict whether it is rock or mine (see table 6.7). The output results for submarine rock and mine detection is shown. It gives result with accuracy 100%.

Table 6.7 Output results

Precision	1.0
Result	1.0
Accuracy	1.0

6.8 GRAPHICAL USER INTERFACE(GUI)

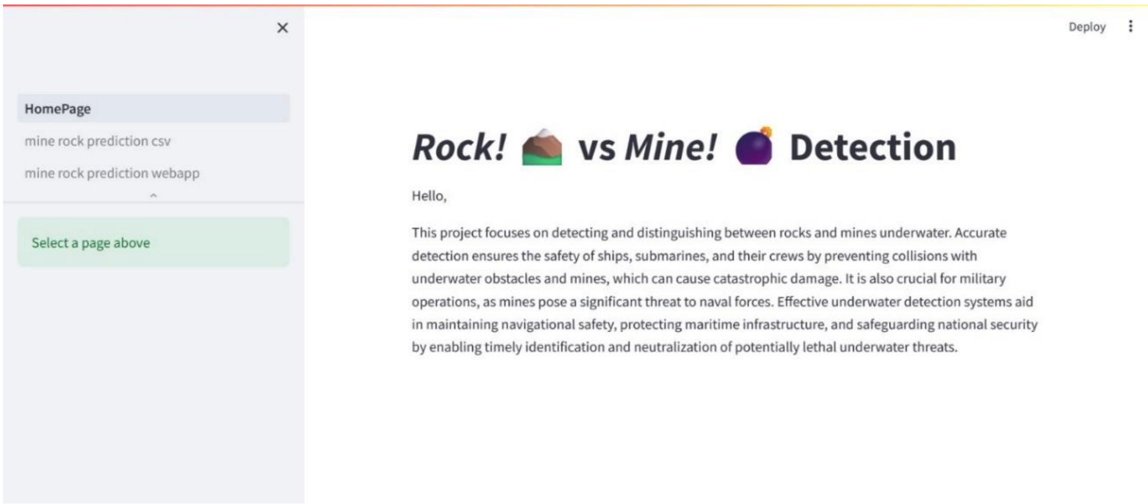


Fig 6.3 Home page for Rock and Mine Classification

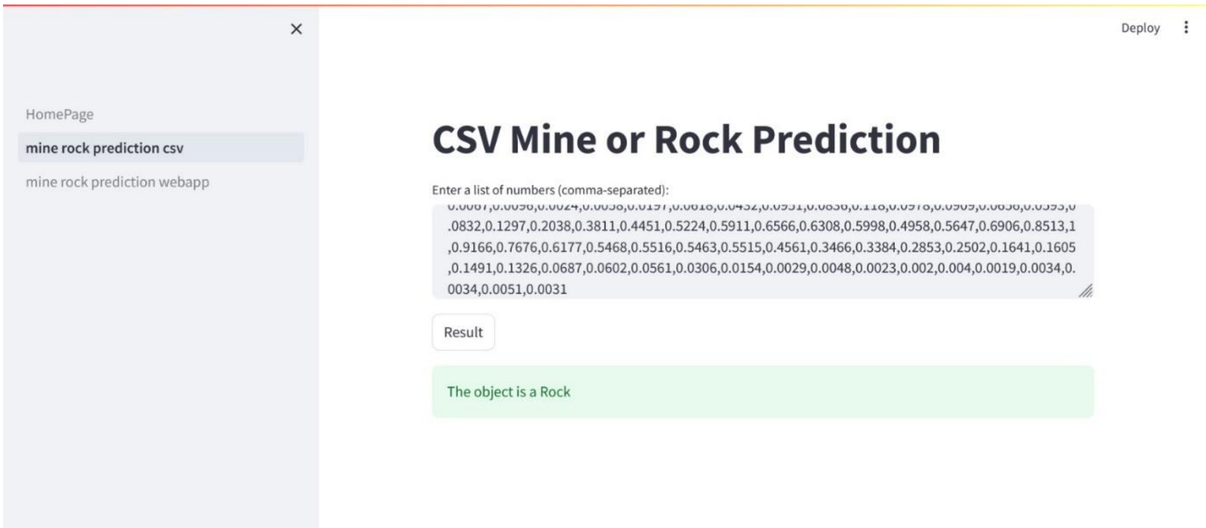


Fig 6.4 UI for sonar values

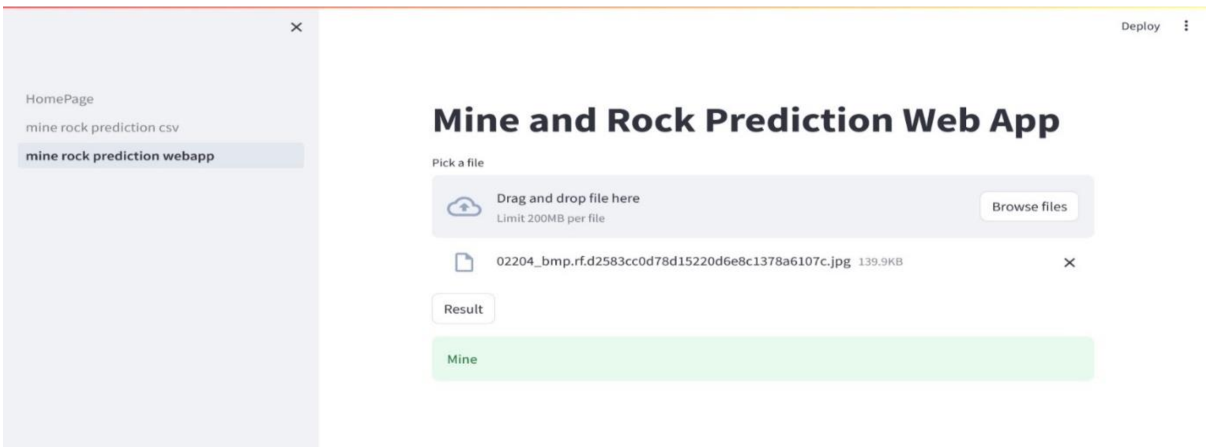


Fig 6.5 UI for Images

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

In conclusion, our study on underwater mine vs. rock detection utilizing both sonar transducer data values and sonar images has yielded valuable insights and outcomes. Through the application of Convolutional Neural Networks for sonar image classification, we have demonstrated the efficiency of deep learning in accurately discerning between submerged objects. Meanwhile, for sonar data values, our exploration of ensemble learning techniques has revealed that logistic regression emerges as the optimal choice, showcasing its proficiency in handling this specific type of data.

In future, some hybrid approaches can be used to get more efficient solutions. The field of submarine rock and mine detection is continually evolving, driven by advancements in technology and the need for improved safety and security in underwater environments. Here are some potential future enhancements like advanced sensor technologies it involve Integration of multi-modal sensors to capture a broader range of information about underwater objects, enhanced real-time data fusion techniques that combine data from multiple sensors. Technologies like sonar images from sonar transducer could be implemented for better enhancement of our model. This provides double standard verification for our model.

To further enhance the model to detect rock and mine classification underwater involves deploying a combination of techniques to improve the accuracy and efficiency of classification systems. Firstly, collect high-resolution underwater sonar or imagery data to serve as the input. It is crucial to input such images as the clarity of image determines the accuracy of the prediction. Preprocess this data by removing noise and artifacts, followed by feature extraction to identify relevant characteristics such as shape, texture, and size of objects.

Next, select an appropriate machine learning algorithm, such as convolutional neural networks for image classification that had been incorporated in this model and for sonar radical values, K-nearest neighbour performs better for this model, but it can be competed with other algorithms to obtain a better precision for the model and train the model using labelled data. Also ensure a robust labelling process, ideally with expert input, to establish better truth classifications. This provides both images as one input and sonar values as the other. Thus, the object can be processed for two times by two different modl. This ensures better accuracy and provides reliable classification in underwater environments.

REFERENCES

[1] D. P. Williams, “The Mondrian detection algorithm for sonar imagery,” IEEE Trans. Geosci. Remote Sens., vol. 56, no. 2, pp. 1091–1102,Feb. 2018.

[2] Shantanu, Aman Saraf, Atharv Tiwari, Mukesh Kumar and S Manonmani, "Underwater Mines Detection using Neural Network", INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT), vol. 09, no. 04, April 2020 A

[3] M. Franchi, A. Bucci, L. Zacchini, E. Topini, A. Ridolfi, and B. Allotta, “A probabilistic 3D map representation for forward-looking SONAR reconstructions,” inProc. IEEE/OES Auton. Underwater Veh. Symp., 2020, pp. 1–6.

[4] S. Khaledi, H. Mann, J. Perkovich and S. Zayed, "Design of an underwater mine detection system", 2014 Systems and Information Engineering Design Symposium (SIEDS), pp. 78-83, 2014.

[5] Guy Gubnitsky , Asaf Giladi, and Roee Diamant, “Validation of Targets in Sonar Imagery Using Multispectral Analysis”, IEEE JOURNAL OF OCEANIC ENGINEERING, VOL. 47, NO. 4, OCTOBER 2022.

[6] Sheezan Fayaz, Shabir A. Parah, G. J. Qureshi,2021, "Underwater object detection: architectures and algorithms – a comprehensive review",DOI:10.1007/s11042-022-12502-1.

[7] J. Folkesson, H. Chang, and N. Bore, “Lambert’s cosine law and side scan sonar modeling,” in Proc. IEEE/OES Auton. Underwater Veh. Symp., 2020, pp. 1–6.

[8] Yue Sun, Peng Yuan and Guijuan L, “Research on Classification and Recognition of Underwater Targets Based on Spark’s Decision Tree Technolog”, 2020 IEEE J. Ocean. Eng., vol. 46, no. 1, pp. 195–205, Jan. 2021, doi: 10.1109/JOE.2020.2980456.

[9] Konstantinos Pelekanakis, Luca Cazzanti, Giovanni Zappa and João Alves, “Decision Tree-Based Adaptive Modulation for Underwater Acoustic Communications”, in Proc. IEEE Int. Geosci. RemoteSens. Symp., 2019, pp. 9455–9458, doi: 10.1109/IGARSS.2019.8898742.

[10] Leonardo Zacchini, Alberto Topini, Matteo Franchi , Nicola Secciani , Vincenzo Manzari, Lorenzo Bazzarello, Mirko Stifani and Alessandro Ridolfi , “Autonomous Underwater Environment Perceiving and Modeling: An Experimental Campaign With FeelHippo AUV for Forward Looking Sonar-Based Automatic Target Recognition and Data Association”, IEEE JOURNAL OF OCEANIC ENGINEERING, VOL. 48, NO. 2, APRIL 2023.

[11] Stanisław Ho˙zy ´n, “A Review of Underwater Mine Detection and Classification in Sonar Imagery”, Electronics 2021, 10, 2943. https://doi.org/10.3390/electronics10232943.

[12] Guy Gubnitsky , Asaf Giladi, and Roee Diamant, “Validation of Targets in Sonar Imagery Using Multispectral Analysis”, IEEE JOURNAL OF OCEANIC ENGINEERING, VOL. 47, NO. 4, OCTOBER 2022.

[13] Monika S, Shakthi Sagar M, Merin Meleet, “Prediction of Underwater Sonar Targets”, IJARCCE, DOI: 10.17148/IJARCCE.2022.11793.

[14] Yiping Xie , Nils Bore , and John Folkesson, “Bathymetric Reconstruction From Sidescan Sonar With Deep Neural Networks”, IEEE JOURNAL OF OCEANIC ENGINEERING, VOL. 48, NO. 2, APRIL 2023.

[15] Elakkiya S, Jincy Francis, Rejina Parvin J, Tamilmalar S.N, “Classification of SONAR Targets Using Advanced Neural Classifiers”, IJPAM, Volume 114 No. 12 2017, 627-637.

[16] Jun Liu, Yu Gou, Tong Zhang, Xinyi Jiang, XinQi Du, XuanZhang, “A-KNN: An adaptive method for constructing high-resolution ocean modl”, IEEE

[17] S. C. James, Y. Zhang, and F. O’Donncha, “A machine learning framework to forecast wave conditions,” Coastal Engineering, vol. 137, pp. 1–10, 2018.

[18] Padmaja, V., Rajendran, V. Vijayalakshmi, P, “Study on metal mine detection from underwater sonar images using data mining and machine learning techniques”, Springer, J Ambient Intell Human Comput12,5083–5092(2021).https://doi.org/10.1007/s12652-020-01958-4.

[19] Danesh, S.A.; “Real Time Active Sonar Simulation in a Deep Ocean Environment”, Massachusetts Institute of Technology: Cambridge, MA, USA, 2013.

[20] GUANGYAO HAN; JUNFEI CUI; YISHAN SU; XIAOMEI FU “HUMAN VISION SYSTEM BASED SPARSE WAVELET TRANSFORM FOR UNDERWATER ACOUSTIC SONAR IMAGE TRANSMISSION”, IEEE

[21] Sri Ramya Yaramasu , Uppada Sai Gayatri , Vadlamani Manjusha , Vaishna C Bhanu , Koda Indu, “UNDERWATER MINE & ROCK PREDICTION BY EVALUATION OF MACHINE LEARNING ALGORITHMS”, IRJETS

[22] Bhagya Rekha, Chetla Anuhya, Srija Tuniki, Pendyala Swathi, N.Lakshmi Kalyani , Ayyadevara Sri Sai Lalitha Syamala, “Analysis of Various Underwater Rock and Mine Detection Techniques- A Typical Review”, International Journal of Research in Engineering and Science.

[23] F. Langner , C. Knauer; W. Jans; A. Ebert, “Side scan sonar image resolution and automatic object detection, classification and identification”, IEEE conference, Ocean 2009-Europe

[24] M. Neumann, C. Knauer, B. Nolte, W. Jans and A. Ebert, “Target Detection of Man Made Objects in Side scan Sonar Images – Segmentation based False Alarm Reduction” -, Acoustics’08, Paris, 2008.

[25] G. Ferri, F. Ferreira, and V. Djapic, “Multi-domain robotics competitions: The CMRE experience from SAUC-E to the European robotics league emergency robots,” in Proc. IEEE OCEANS Conf., Aberdeen, U.K., 2017, pp. 1–7.

[26] D. Reid, “An algorithm for tracking multiple targets,” IEEE Trans. Autom. Control, vol. 24, no. 6, pp. 843–854, Dec. 1979.

[27] Chih-Wei Hsu and Chih-Jen Lin, “A comparison of Methods for Multiclass Support Vector Machines”, IEEE Transactions on Neural Networks, vol.13, no.2, March 2002, pp.415-425.

APPENDIX I

This section provides information about the programming language, software, and libraries employed to implement the model using machine learning.

Python is used as the programming language due to its extensive libraries and frameworks. This project has been implemented using various packages and libraries offered by python. These pre-written libraries simplify the tasks to develop the model, thus resulting in interactive model development. The libraries used in this project are:

Scikit- It provides tools for choosing features, preparing data, and evaluating modl. Cross-validation is supported by Scikit-Learn for hyperparameter adjustment and robust model assessment. Because of its well-known straightforward and reliable API, Scikit-Learn is widely used by both novices and seasoned developers.

NumPy-It facilitates effective array operations, and its broad mathematical capabilities, which include random number generation, Fourier analysis, and linear algebra, are among its salient characteristics. NumPy is a vital tool for handling and processing numerical data because of its arrays, which are memory-efficient and provide quick, element-wise operations.

Matplot-It offers an extensive toolkit for making different kinds of plots, graphs, and charts. The customization capabilities of Matplotlib enable for exact control over all aspects of a visualization, including labels, axes, and line styles and colors. A variety of output types are supported, such as file exports and screen displays.

Pandas-Are divided into Series and DataFrame. A DataFrame is a two-dimensional tabular data structure, whereas a Series is an entity that resembles a one-dimensional array.

Computer Vision-A wide range of tools for different image and video analysis tasks are available with OpenCV.

TensorFlow-It makes neural networks, in particular, deep learning model, able to be created and trained for a variety of machine learning applications. Fundamentally, TensorFlow uses a computational graph to design and perform operations on multidimensional arrays, or tensors, which are used to represent data.

Pickle-Python has a module called `pickle` library that offers a method for serializing and deserializing Python objects. With its strong data serialization and deserialization capabilities, it saves intricate data structures in binary format on disk, such as dictionaries and lists.

APPENDIX II

Rock_mine_csv_prediction.py

```
import pandas as pd

sonar_data = pd.read_csv("C:/Users/Sindhu/OneDrive/Desktop/Jupyter/sonar_dataset.csv")

sonar_data.head()

sonar_data.shape

sonar_data.describe()

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt

from pandas.plotting import scatter_matrix

from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import train_test_split as split

from sklearn.model_selection import Kf, cvs, GridSearchCV

from sklearn import classification_report, confusion_matrix, accuracy_score, Pipeline,
LogisticRegression, DecisionTreeClassifier, KNeighborsClassifier,SVC

from sklearn.ensemble import AdaBoostClassifier, RandomForestClassifier

%matplotlib inline

import warnings

warnings.filterwarnings("ignore")

sonar_data.dtypes

# Histogram

sonar_data.hist(figsize=(20,10), xls = 1, yls = 1);

sonar_data.plot(kind = 'density', figsize=(20, 10), layout = (8,8) , fontsize = 1);

a = sonar_data.values
```

```
X = a[:, 0:60].astype(float) # values of all rows and all coulms from 0-60.

y = a[:, 60] # values of all rows and  columns number 60. This only has final predicted result i.e, R or M.

Xt, Xv, yt, yv = split(X, y, ts = 0.2)

#metrics

nf = 10

scr = 'accuracy'

modl = []

modl.append(('LR', LogisticRegression(solver='liblinear')))

modl.append(('KNN', KNeighborsClassifier()))

modl.append(('CART', DecisionTreeClassifier()))

modl.append(('SVM', SVC(gamma='auto')))

fin_res = []

nms = []

for name, model in modl:

    kf = Kf(n_splits=nf, random_state = 1235, shuffle = True)

    cv_fin_res = cvs(model, Xt, yt, cv = kf, scr = scr)

    fin_res.append(cv_fin_res)

    nms.append(name)

    notify = 'Model %s:   mean: %f     std: %f' %(name, cv_fin_res.mean(), cv_fin_res.std())

    print(notify)

# Box and wisker plots

fig = plt.figure(figsize = (20,7), facecolor = '#3f8088')

fig.suptitle

ax = fig.add_subplot(111)
```

```
sns.boxplot(data = fin_res)
ax.set_xticklabels(nms, size=20, color = '#b9f6f6', y=-0.03)
sns.set_palette("mako")
plt.title('Algorithm Comparison', fontsize=25, color = '#b9f6f6', y=1.05)
plt.show()
#box inside line is central tendency
# Standardization
ppl= []
ppl.append(('ScaledSVM', Pipeline([('Scaler', StandardScaler()), ('SVM',
SVC(gamma='auto'))])))
# Evaluation of algorithms
fin_res = []
nms = []
for nms, mdl in ppl:
    kf = Kf(n_splits = nf, random_state = 1235, shuffle = True)
    cv_fin_res = cvs(model, Xt, yt, cv = kf, scr = scr)
    fin_res.append(cv_fin_res)
    nms.append(name)
    notify = 'Model %s:   mean: %f     std: %f' %(name, cv_fin_res.mean(), cv_fin_res.std())
    print(notify)
fig = plt.figure(figsize = (20,7), facecolor = '#3f8088')
sns.boxplot(data = fin_res)
ax.set_xticklabels(nms, size=20, color = '#b9f6f6', y=-0.03)
sns.set_palette("mako")
plt.title('Scaled Algorithm Comparison', fontsize=25, color = '#b9f6f6', y=1.05)
```

```
plt.show()
# Esm
esm = []
esm.append(('AB', AdaBoostClassifier()))
esm.append(('RF', RandomForestClassifier(n_estimators=10)))
fin_res = []
nms = []
for names, model in esm:
    kf = Kf(n_splits = nf, random_state = 1235, shuffle = True)
    cv_fin_res = cvs(model, Xt, yt, cv = kf, scr = scr)
    fin_res.append(cv_fin_res)
    nms.append(name)
    notify = "Model %s:   mean: %f   std: %f" % (name, cv_fin_res.mean(), cv_fin_res.std())
    print(notify)
fig = plt.figure(figsize = (20,7), facecolor = '#3f8088')
sns.boxplot(data = fin_res)
ax.set_xticklabels(nms, size=20, color='#b9f6f6', y=-0.03 )
sns.set_palette('mako')
plt.title('Ensrmble Algorithm Comparison', fontsize=25, color = '#b9f6f6', y=1.05)
plt.show()
scaler = StandardScaler().fit(Xt)
rescaledX = scaler.transform(Xt)
model = SVC(gamma ='auto', C = 2.0)
model.fit(rescaledX, yt)
```

```
rescaledValidationX = scaler.transform(Xv)

predictions = model.predict(rescaledValidationX)

print('Accuracy: ', accuracy_score(yv, predictions))

print('\n')

print('Confusion matrix: \n', confusion_matrix(yv, predictions))

print('\n')

print('Classification report: \n', classification_report(yv, predictions))

input_data =(0.0336,0.0294,0.0476,0.0539,0.0794,0.0804,0.1136,0.1228,0.1235,0.0842,0.0357,0.0689,0.1705,0.3257,0.4602,0.6225,0.7327,0.7843,0.7988,0.8261,1,0.9814,0.962,0.9601,0.9118,0.9086,0.7931,0.5877,0.3474,0.4235,0.4633,0.341,0.2849,0.2847,0.1742,0.0549,0.1192,0.1154,0.0855,0.1811,0.1264,0.0799,0.0378,0.1268,0.1125,0.0505,0.0949,0.0677,0.0259,0.017,0.0033,0.015,0.0111,0.0032,0.0035,0.0169,0.0137,0.0015,0.0069,0.0051)

prediction = model.predict(inp_res)

print(prediction)

if (prediction[0]=='R'):

  print('The object is a Rock')

else:

  print('The object is a mine')

from sklearn.neighbors import KNeighborsClassifier

knn =  KNeighborsClassifier(n_neighbors = 5 , metric = 'minkowski',p =2)

knn.fit(Xt,yt)

Xt_prediction = knn.predict(Xt)

tda = accuracy_score(Xt_prediction, yt)

print('Accuracy: ', tda)

#saving the model
```

```
import pickle
fn = 'ctm.sav'
pickle.dump(knn , open(fn , 'wb'))
loadmod = pickle.load(open('ctm.sav', 'rb'))
ip_data = np.asarray(input_data)
inp_res = ip_data.reshape(1,-1)
prd = loadmod.predict(inp_res)
print(prd)
if (prd[0]=='R'):
  print('The object is a Rock')
else:
  print('The object is a mine')
```

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4	Date of Birth	27/10/2002 14/11/2002
5	Department	Dept.of Computer Science & Engineering with Specalization in Artificial intelligence and Machine Learning.
6	Faculty	Dr.M.Vimala Devi,Dr.R.A.Karthika
7	Title of the Synopsis/ Thesis/ Dissertation/Project	Exploring Submerged Hazards:Innovations in Submarine Rock and Mine detection.
8	Name and address of the Supervisor / Guide	Dr.T.R.Saravanan **Mail ID :** saravant1@srmist.edu.in **Mobile Number :** 9841644189
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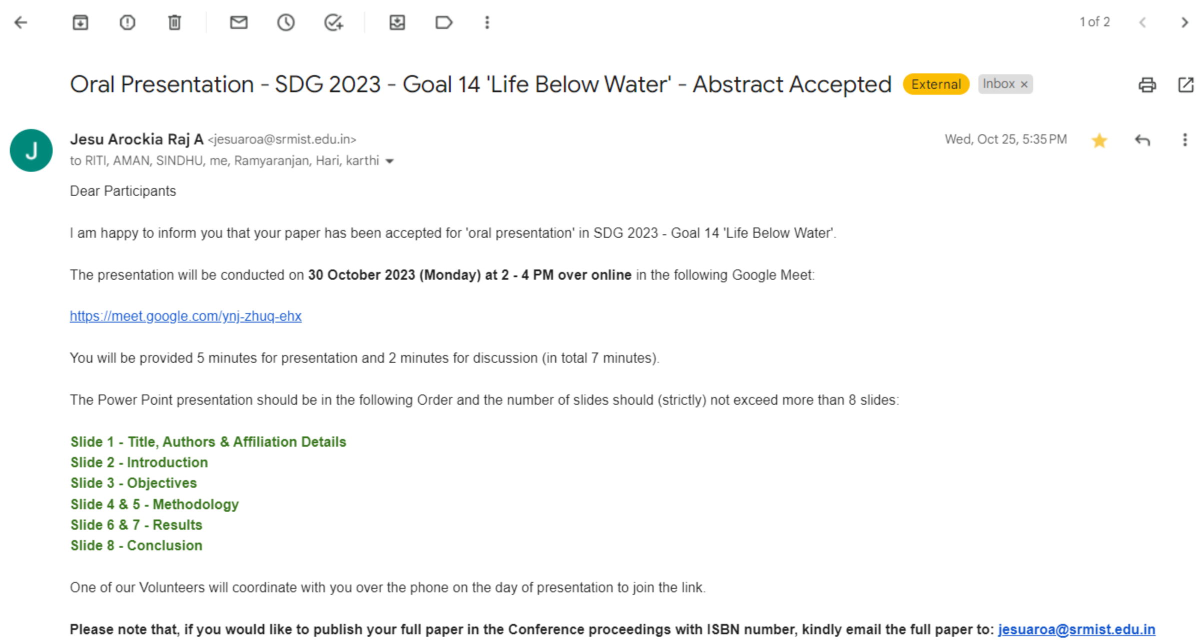

1 of 2

Oral Presentation - SDG 2023 - Goal 14 'Life Below Water' - Abstract Accepted External Inbox ×

Jesu Arockia Raj A <jesuaroa@srmist.edu.in> Wed, Oct 25, 5:35 PM

to RITI, AMAN, SINDHU, me, Ramyaranjan, Hari, karthi

Dear Participants

I am happy to inform you that your paper has been accepted for 'oral presentation' in SDG 2023 - Goal 14 'Life Below Water'.

The presentation will be conducted on **30 October 2023 (Monday) at 2 - 4 PM over online** in the following Google Meet:

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Slide 1 - Title, Authors & Affiliation Details
Slide 2 - Introduction
Slide 3 - Objectives
Slide 4 & 5 - Methodology
Slide 6 & 7 - Results
Slide 8 - Conclusion

One of our Volunteers will coordinate with you over the phone on the day of presentation to join the link.

Please note that, if you would like to publish your full paper in the Conference proceedings with ISBN number, kindly email the full paper to: jesuaroa@srmist.edu.in

Fig A.1:ICSDG 2023

ICSDG 2023 - 2nd International Conference on Higher Education Institutes' Challenges & Solutions -
organized by
Centre for Research in Environment, Sustainability Advocacy and Climate CHange (REACH),
Directorate of Research, SRM Institute of Science & Technology, Kattankulathur

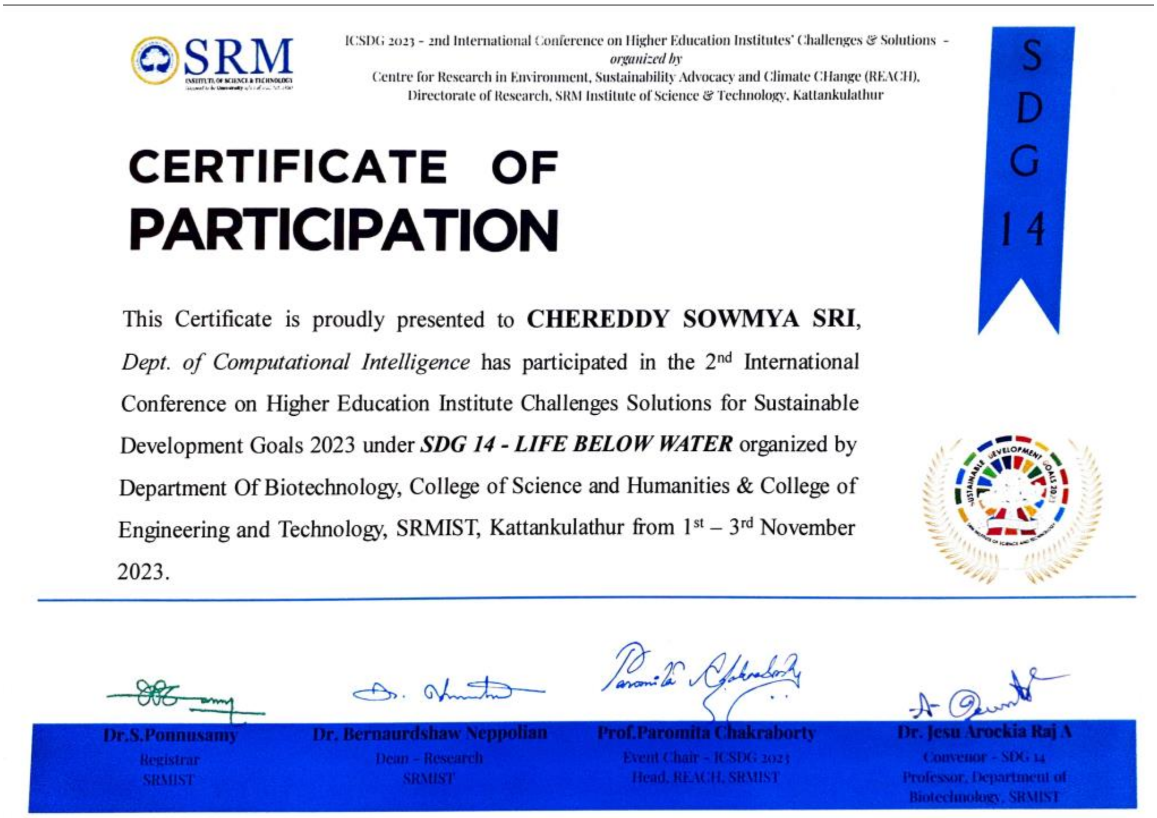
SDG 14

CERTIFICATE OF PARTICIPATION

This Certificate is proudly presented to **SINDHU KALEESWARAN**, *Dept. of Computational Intelligence* has participated in the 2nd International Conference on Higher Education Institute Challenges Solutions for Sustainable Development Goals 2023 under ***SDG 14 - LIFE BELOW WATER*** organized by Department Of Biotechnology, College of Science and Humanities & College of Engineering and Technology, SRMIST, Kattankulathur from 1st – 3rd November 2023.

Dr.S.Ponnusamy, Registrar, SRMIST
Dr. Bernaurdshaw Neppolian, Dean - Research, SRMIST
Prof.Paromita Chakraborty, Event Chair - ICSDG 2023, Head, REACH, SRMIST
Dr. Jesu Arockia Raj A, Convenor - SDG 14, Professor, Department of Biotechnology, SRMIST

Fig A.2:Conference Certificate



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Dr.S.Ponnusamy, Registrar, SRMIST
Dr. Bernaurdshaw Neppolian, Dean - Research, SRMIST
Prof.Paromita Chakraborty, Event Chair - ICSDG 2023, Head, REACH, SRMIST
Dr. Jesu Arockia Raj A, Convenor - SDG 14, Professor, Department of Biotechnology, SRMIST

Fig A.3:Conference Certificate