# Classification of Underwater Target using Deep learning and Active Sonar Systems

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## ABSTRACT

Underwater Acoustic (UA) target identification is a challenging and crucial sonar system task in marine remote sensing operations, particularly when complicated sound wave propagation characteristics are present. Most conventional machine learning (ML) algorithms generally encounter difficulties while trying to develop the costly recognition model for huge data analysis. In this paper utilized the task is to train a network to discriminate between sonar signals bounced off a metal cylinder and those bounced off a roughly cylindrical rock. We suggest a method utilizing a dense CNN model for identifying targets underwater. All previous feature maps are intelligently reused in the network architecture. to maximize classification rates under a range of compromised circumstances while achieving little computational expense. Our classification model beats classical ML approaches, achieving an overall accuracy of 96.77% based on the experimental findings assessed on the real-world data set of active sonar. The objective is to train a network to distinguish between sonar signals that bounce off roughly cylindrical rocks and those that bounce off a metal cylinder.

KEYWORDS: Classification Mines, Dense CNN, Active Sonar Systems, Underwater Target Recognition, Acoustic Signal Processing and Mine Detection and Identification.

## الملخص:

يعد تحديد الأهداف الصوتية تحت الماء (UA) مهمة صعبة وحيوية في أنظمة السونار المستخدمة في عمليات الاستشعار عن بُعد البحرية، خاصة عند وجود خصائص معقدة لانتشار الموجات الصوتية. غالبًا ما تواجه خوارزميات التعلم الآلي التقليدية (ML) صعوبات في تطوير نموذج للتعرف يتطلب تكلفة عالية عند تحليل البيانات الكبيرة. في هذه الورقة، تم استخدام مهمة تدريب شبكة للتفريق بين الإشارات الصوتية المرتدة عن أسطوانة معدنية وتلك المرتدة عن صخرة أسطوانية الشكل تقريبًا. نقترح طريقة تستخدم نموذج شبكة عصبية تلافيفية كثيفة (Dense CNN) لتحديد الأهداف تحت الماء. يتم إعادة استخدام جميع خرائط الميزات السابقة بذكاء داخل بنية الشبكة لزيادة معدلات التصنيف في ظل ظروف متعددة مع تقليل التكلفة الحاسوبية. يتفوق نموذج التصنيف المقترح على النماذج الأخرى المتطورة للشبكات العصبية التلافيفية (CNN) والمناهج التقليدية للتعلم الآلي، حيث حقق دقة إجمالية بلغت 96.77% بناءً على النتائج التجريبية التي تم تقييمها على مجموعة بيانات حقيقية لأنظمة

السونار النشط. الهدف هو تدريب شبكة لتمييز الإشارات الصوتية المرتدة عن الصخور الأسطوانية الشكل تقريبًا وتلك المرتدة عن أسطوانة معدنية.

## 1. INTRODUCTION

Sound Navigation Ranging, the method of gathering of underwater acoustic signal and processing it to detect a target's characteristic is known as ranging, or sonar, target identification. Sonar systems have a long and rich history. Leonardo da Vinci is credited with using sonar for the first time in history in 1490 [14]. To detect oncoming ships, this technique used a pipe held to the ear and the ocean. Sonar systems have advanced significantly during World Wars 1 and 2, when scientists created methods to find enemy ships and submarines [14]. Since then, sonar equipment, signal processing, and sea floor mapping have all been the subject of ongoing study.
All nation's armed forces are making every effort to repel intruders from their homeland. With the development of marine technology, it is now essential to locate and follow the target before it gets near enough to launch an assault by taking active measures. In modern naval warfare, the detection and classification of underwater objects are crucial for the safety and success of military operations. Underwater target classification is one of the most complex challenges in the field of marine acoustic sensing, as the intricate and noisy underwater environments require precise and effective solutions. In these environments, active sonar is used to detect and analyze targets based on acoustic signals that propagate underwater. The classification of naval mines versus rocks is among the most critical applications due to its significance in military and research contexts.

This research aims to develop and test an advanced intelligent classification system that utilizes Dense Convolutional Neural Networks in conjunction with a active sonar system to distinguish underwater targets, particularly focusing on differentiating between naval mines and rocks. The study seeks to contribute scientifically by enhancing the accuracy and effectiveness of underwater acoustic sensing systems through the application of deep learning techniques, which have proven efficient in various fields. In this work, we consider there is a submarine. Submarine of one country is going underwater to another country and enemy country is planted some mines, it explodes when some subject comes into contact with it in the ocean. there will be also rocks in the ocean. The submarine wants to predict it. Our project is to make a system that can predict whether the object beneath the submarine is a mine or a rock. How this is done is submarine uses a sonar that sends a sound signal, the signal is then processed to detect whether the object is (mine or rock).

## 2. RESEARCH PROBLEM

It is represented in the accurate classification between sea mines and rocks using the reflected acoustic signals that contain noise and distortions in marine environments. Given the limitations of traditional machine learning methods that require large resources and lack accuracy in degraded conditions, the need for a computationally efficient system that can achieve accurate classification in complex conditions while reducing computational effort, this system lies in the use of dense convolutional neural networks (Dense CNN) to improve classification in sonar systems and obtain high classification accuracy.

## 3. RESEARCH OBJECTIVE:

The main objective of this research is to develop and test an autonomous system based on convolutional communication networks (Dense CNN) that is involved with an active sonar system, which can be accurately distinguished underwater, with a focus on differentiating between sea mines and rocks.

## 4. PREVIOUS STUDIES

Ghafoor & Noh, (2019) Their work emphasizes an integrated underwater architecture that combines various sensor technologies and advanced signal processing techniques to improve detection accuracy [1]. Yang et al, (2020) Their study highlights the potential of machine learning algorithms to enhance sonar performance by improving target classification and reducing false alarms [2]. Park et al, (2023) proposed a novel pulsed active sonar system using generalized sinusoidal frequency modulation [3]. Abu et al, (2024) introduced a track-before-detect in active sonar arrays [4]. Hwang et al, (2024) developed an attention-based complementary learning model for active target [5]. Khan et al, (2024) reviewed methodologies in underwater target detection using deep learning [6]. Liang et al, (2023) presented a method for estimating the depth of active sonar targets using echo structures in bottom bounce areas [7]. Xi & Ye, (2023) explored sonar image target detection using simulated noise and shadow enhancement techniques [8]. Olivastri et al, (2024) developed a sonar-based Autonomous Underwater Vehicle positioning system [9]. Kajiwara, (2024) examined developments in maritime security and underwater surveillance technology [10]. Li et al, (2024) reviewed recent advances in acoustic technology for aquaculture [11]. Gao et al, (2024) surveyed state-of-the-art underwater acoustic (UA) signal denoising algorithms [12]. Ard & Barbalata, (2023) focused on sonar image composition for semantic segmentation using machine learning [13]. Kubicek, (2023) Her work contributes to making AI-driven sonar systems more transparent and interpretable, which is crucial for their deployment in critical applications [14]. Kim et al, (2024) proposed a method for real data-based active sonar signal synthesis [15]. Kumar et al, (2024) explored high-frequency asymptotic scattering for submarine acoustic target strength modeling [16]. Naidu et al, (2024) discussed the selection of suitable signals for passive and active sonar detection in deep and shallow water communication system[17]. Zou & Zhao, (2023) developed a path planning algorithm for underwater vehicles based on sonar detection probability [18]. Talebpour, (2023) proposed a hydrophone underwater localization approach in shallow waters [19]. Chaphalkar, (2024) His research focuses on improving the real-time capabilities of AUVs in detecting and tracking surface targets using sonar [20]. Doan et al, (2020) presented an underwater acoustic target classification method based on a dense convolutional neural network [21].Liu & Fang, (2024) introduced an interactive transient model correction method for active sonar target tracking[22].

## 5. THE BASIC CONCEPTS

The basic concepts related to the paper that will help us to understand and comprehend the paper very well.

### 5.1. Acoustic Wave Propagation

The propagation of sound in a fluid medium like water is governed by the wave equation.

$$\nabla^2 - \frac{1}{c^2}\frac{\partial^2 P}{\partial t^2} = 0 \qquad (1)$$

Where:

$P$ is the acoustic pressure. $C$ is the speed of sound in water. $t$ is time.

The SONAR system determines the sound's distance traveled by combining the sound speed in the water with the time the reflection was detected. Distance is equal to known sound speed in water times (sound delay computed upon return / 2). This indicates that variations in sound speed may have a significant impact on the precision of a target's distance measurement. In saltwater bodies, sound travels at a typical speed of 1500 m/s. Nevertheless, this figure changed according to the salinity, temperature, and operational depth of the system.

### 5.2. Sonar System Response

In active sonar systems an acoustic projector generates a sound wave that spreads outward and is reflected back by a target object. A receiver picks up and analyzes the reflected signal and may determine the range, bearing, and relative motion of the target. In order to calculate the target's range, bearing, and relative velocity, active sonar uses a projector and a receiver as shown in figure 1 [19]. A target item reflects back the sound wave that the acoustic projector sends out into space. After then, the reflected signal is picked up and examined by the receiver.

Submarine ships are one type of active SONAR. By using the temporal interval between the capture of the echo and the transmission of acoustic energy, submarines may identify things nearby.

The development of sophisticated contemporary instruments has not only made it possible for us to identify the existence of objects but also to precisely ascertain their size, form, and orientation [22].

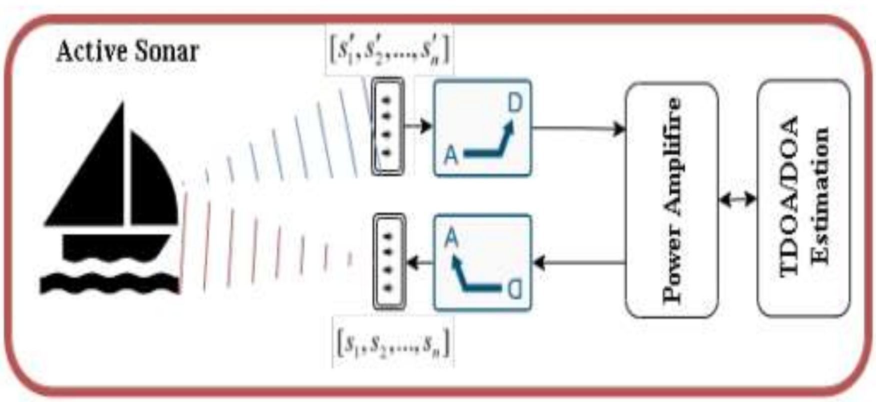



**Fig. 1. Active Sonar [19].**

### 5.3. Dense Net for Classification

A feed-forward convolutional neural network (CNN) design called Densely Connected Convolutional Networks (DenseNet) connects each layer to every other layer. By recycling features, this enables the network to learn more efficiently, lowering the number of parameters and improving the gradient flow during training. The foundation of DenseNet architecture is a simple and fundamental idea: a dense block gives each layer access to all of the characteristics of all levels that came before it by concatenating the feature maps of all of those levels. Each layer in a traditional CNN can only access the properties of the layer that came before it. Transition layers and dense blocks make up DenseNet's design. In a dense block, every convolutional layer is connected to every other layer [21].

This is achieved by creating a "shortcut" link by connecting the output of each layer to the input of the layer below it. The network can expand efficiently because the transition layers reduce the size of the feature maps between dense blocks. used in speech recognition, audio synthesis, and production applications of audio processing. Sonar underwater target classification, such as distinguishing between naval mines and rocks, DenseNet can be used to analyze sound signals accurately and reuse features learned from previous layers to enhance pattern recognition [6].

## 6. METHODOLOGY AND INTERPRETATION

This paper is based on the use of public sonar information. The utilized data sets were gathered from the Kaggle website's open-sourced inventory. Excel format is used to see the log data. which has 208 samples with 60 features each representing the energy level measurements at various frequencies. These examples were labeled either as “Mine” (M) or as “Rock” (R), depending on how the sonar signal was reflected from a metal cylinder mimicking a mine or a rock. To make data ready for model training, the binary numerical values of “Mine” and “Rock” were used. Subsequently, an 80-20 split was used to randomly assign records into train and test sets for learning patterns in training set and evaluation of unseen test data by the model respectively. The standard deviation is critical as it helps in normalizing input features such that they have mean of zero and unit variance necessary to maintain stability and convergence throughout training process.

## 7. THEORETICAL BACKGROUND

For ages, sonar technology has played a significant role in exploring the underwater, navigating and detecting things. By emitting sound waves and analyzing the echo that comes back when they hit an object; sonar systems have been applied to this end. Such environments include underwater conditions characterized by low visibility where optical systems are usually ineffective. Active acoustic sensors are extensively employed for several purposes including locating and classifying submerged objects such as mines and rocks [11].

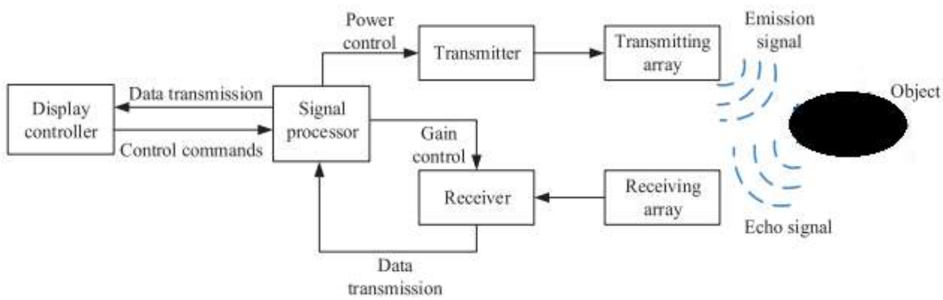



**Fig. 2. Diagram of the working principle of acoustic system. Active acoustic systems [11].**

Sonar technology involves signal processing as shown in figure 2 of sound waves at its core. The reflected signal has information about the size, shape, material, or how far the object is when sonar waves contact it. However, these signals are difficult to interpret due to various reasons such as noise, multipath propagation and complex features of underwater environment. Conventional methods of sonar signal processing encompass matched filtering, beamforming and time-frequency analysis among others. These techniques have proven useful in many applications but may not be able to cope with the wide variability and complexity of real-world underwater scenarios.

Deep learning, particularly machine learning, has brought a revolution to many fields as it enables systems learn intricate patterns from data directly. In the sonar domain, machine learning models can be trained to identify objects depending on the properties of the reflected signals. Convolutional Neural Networks (CNNs) are one of types of deep learning models that are especially good at this task because they can learn spatial hierarchies of features automatically given data. CNNs have displayed substantial potential in a range of applications such as image and signal processing, including classification of sonar data [6].

## 8. MATHEMATICAL MODELLING

Calculate the underwater acoustic parameters Using the underwater acoustic empirical formula, the acoustic velocity of each mesh grid point is calculated based on the temperature, salinity and depth [18]. The acoustic velocity formula uses:

$$c = 1449.2 + \Delta c_T + \Delta c_{TS} + \Delta c_Z \qquad (2)$$
$$\Delta c_T = 4.6T - 0.55T^2 + 0.00029T^3 \qquad (3)$$
$$\Delta c_{TS} = (.34 - 0.01T)(S - 35) \qquad (4)$$
$$\Delta c_Z = 0.016Z \qquad (5)$$

$T$ is the temperature value in degrees Celsius, $S$ is the salinity value in thousandths, and $Z$ is the depth value in meters. In addition, according to the sea depth and the type of seabed sediment, the average value of the acoustic parameters of the seabed sedimentary layer is calculated [18].

Passive sonar performance prediction. Use the equation:

$$SE = SL - TL - NL + DI - DT \qquad (6)$$

Where:

$SE$ is the signal margin, $SL$ is the target sound source level, $TL$ is the propagation loss, $NL$ is the marine environmental noise level, $DI$ is the receiving directivity index, and $DT$ is the detection threshold [18].

We implement a single projector that produces a series of chirp signals with a broad bandwidth duration product for high pulse compression in order to perform active acoustic detection. A full array of $N$ hydrophones is positioned around the platform to collect the reflections. The data obtained from the $N$ sensors is then beamformed and matched filtered to move it to the angle distance domain. The end product is a 2D matrix where each sample has an angle of arrival and a time-of-arrival that, if the sound speed is known, may be translated to a distance. The m$-t$™ hydrophone with $N$ sources is represented as having the following time domain input [4].

$$S_m(t) = \sum_{n=1}^{N} d\left(t - \tau_m(\theta_n)\right) + \eta_m(t), \qquad (7)$$

Where d(t), $\tau_m(\theta_n)$, and $\eta_m(t)$ stand for the signal waveform, the time delay of the n-*th* source with azimuth denoted by $\theta_n$, and the clutter noise [4].

The time delay is given by

$$\tau_m(\theta_n) = \frac{1}{c} P_m \cdot \varpi(\theta_n), \qquad (8)$$

Where $c$ is sound velocity at water, $P_m$ is the cartesian location of the m-*th* hydrophone, and $\varpi(\theta_n)$ is the spatial direction of the n-*th* source given by

$$\omega(\theta_n) = \begin{bmatrix} \cos(\theta_n) \\ \sin(\theta_n) \end{bmatrix}, \qquad (9)$$

The finite-element method is commonly used for calculations involving a wide range of physics fields. The acoustic target strength (TS) represents the strength of the scattered signal in a particular direction [16].

$$TS(\theta, \phi) = 20\ log_{10}\left(\frac{R}{P_S(r, \theta, \phi)}\right) \qquad (10)$$

$$P_S(r, \theta, \phi) = \frac{k^2}{4\pi} e^{ikR} \frac{1}{R} e^{i\phi(\theta,\varphi)} \qquad (11)$$

Where:

K= wave number equal to $\frac{\omega}{c}$ where $\omega$ angular frequency. R = distance from the source to the observation point.

$\phi(\theta, \varphi)$= represents the scattering phase function.

## 9. METRICS FOR MODEL EVALUATION

To evaluate the performance of the conventional neural network model, several classification metrics are used, including accuracy, precision, recall, and F1-score as utilizing in equations 12,13,14,15.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \qquad (12)$$

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

$$Recall = \frac{TP}{TP + FN} \quad (14)$$

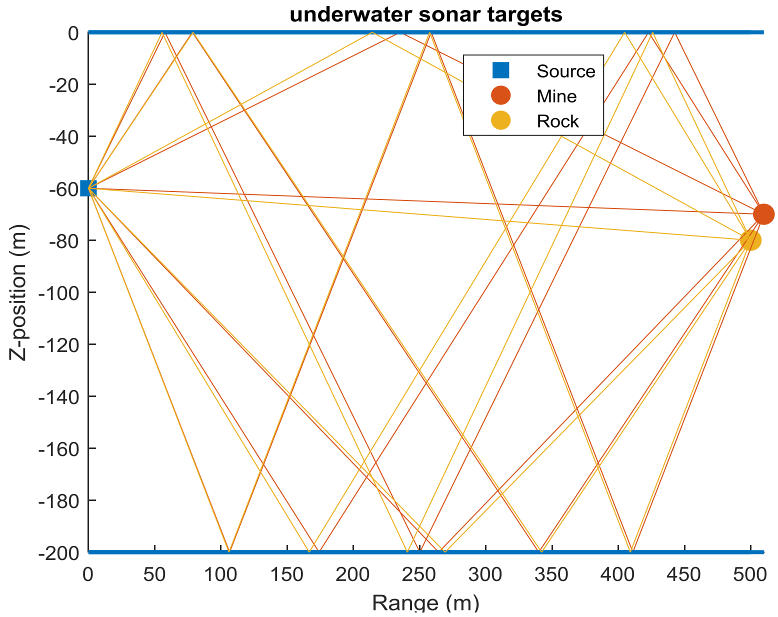
$$F1 - Score = \frac{2\, x(Precision\ x\ Recall)}{Precision + Recall} \quad (15)$$

True Positives (TP): Correctly predicted mines.
True Negatives (TN): Correctly predicted rocks.
False Positives (FP): Incorrectly predicted rocks as mines.
False Negatives (FN): Incorrectly predicted mines as rocks.

A highly accurate model will do well in terms of identifying the right class for most samples. Fanatical is the word that best describes precision and it is expressed as true positives out of all positive predictions. A high precision means a low false positive rate, which means that when it predicts mines, it is correct. Conversely, recall measures the number of true positives predicted out of all the actual positive examples, indicating how much of the mine’s dataset was labelled by this model. High recall indicates that the model can detect mines [2].
The F1-score provides a balanced measure for assessing how well a classifier performs because it is the harmonic mean between its precision and recall values. This is very important if there are imbalances in class representation as both precision and recall will be accounted for under these circumstances.
When a model has high levels of precision, recall and f1 score, then that suggests that neural network has effectively learnt to tell apart rock reflections from sonar from those resulting from underwater mines hence; making such models useful tools in subaqueous target classification problems.

## 10. RESULTS AND DISCUSSION

Detecting Underwater Targets using an Active Sonar System fort this case study demonstrates how to model a two-target, active monostatic sonar scenario (Mine and Rock) utilized in figure (3).
An isotropic projector array and a single hydrophone unit make up the sonar system. The form of the projector array is spherical. The hydrophone receives the backscattered signals. Both direct and multipath contributions are present in the received signals.
Environment Underwater in a shallow water setting, there are several pathways via which sound can propagate from the source to the target. In this case, a channel with a depth of 200 meters and a constant sound speed of 1520 m/s is supposed to have seven pathways. Employ a 0.5 dB bottom loss to emphasize the effects of the various pathways, and Operating frequency (Hz), fc = $20\ X10^3$.




**3 .Fig.The (Mine and Rock)underwater sonar target .**

Extracting training and test curves from training to drawing training and testing curves for accuracy the training and validation accuracy and loss curves are plotted to visualize the model's performance over the training epochs.

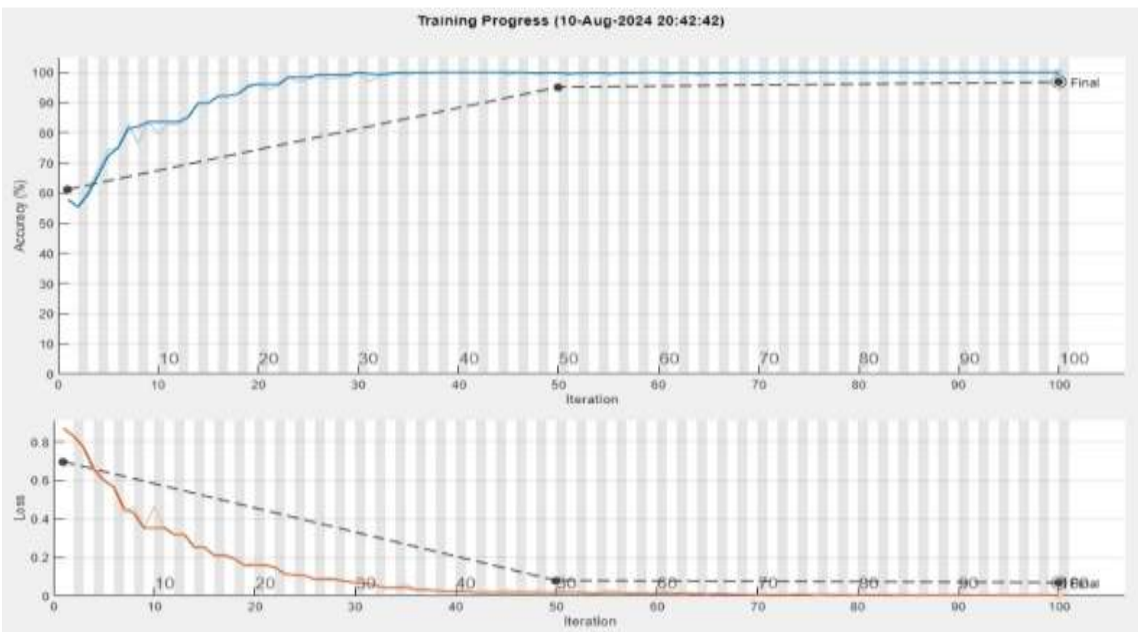



**Fig4** the model's performance over the training epochs for t**raning progress for Dense CNN**.

As shown in figure bellow (4) utilizing the number of true positives, true negatives, false positives, and false negatives, which provides insight into the classification performance for each class (mines and rocks). The figure (4) shows a training progress graph for a classification model, the graph contains two plots Accuracy vs. Iterations (top plot) and Loss vs. Iterations (bottom plot). The top plot represents the model's accuracy during training over iterations, where accuracy starts at around 60%, increases and plateaus near 96.77% showing that the model has achieved high performance. The bottom plot shows the training loss (error) over iterations, initially, the loss is high, around 0.8, but it rapidly decreases as the model learns, to decrease and stabilizes near zero, indicating that the model has minimized its error.

After training the model, we calculated the performance metrics of the model by applying Equations (12 ,13,14, and 15.) the results as shown in table **1.**

**Tabel 1: The performance of classification metrics for training model**

| Accuracy | 96.77% |
|---|---|
| R-call | 1.00 |
| F1-score | 0.97 |
| Precision | 0.94 |

In figure (5) shows the confusion matrix used to evaluate the performance of a classification model, the horizontal axis (Predicted Class) represents the classes that the model classified (predicted class) while the vertical axis (True Class) represents the true classes (actual class).

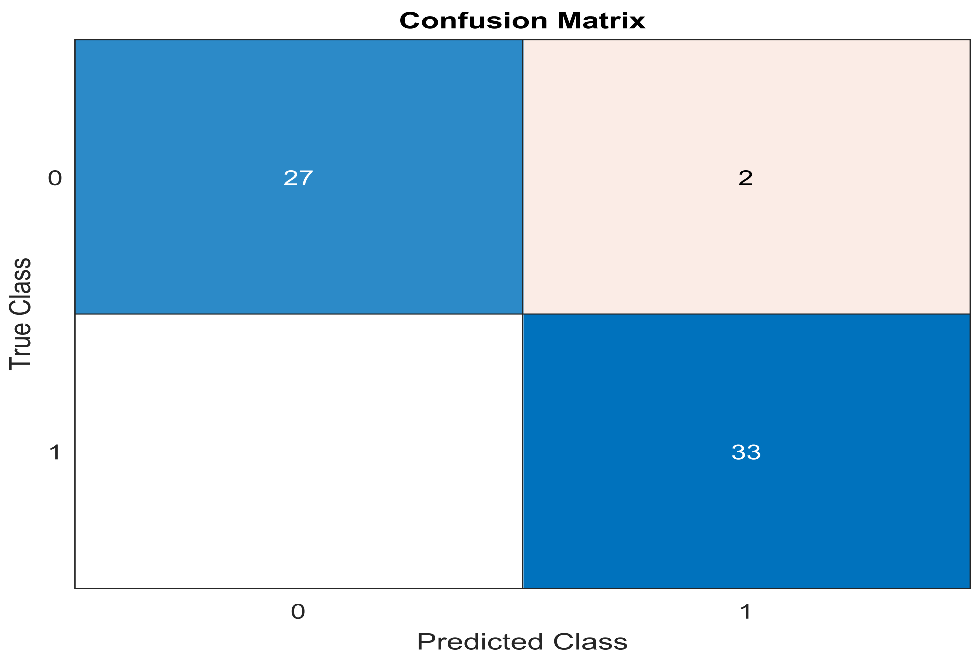



**Fig 5.** Confusion matrix

From figure (5) the results of Confusion Matrix:

True Positive (TP) = 33 represents the number of samples that were in class "1" and were correctly classified as "1."

True Negative (TN) = 27 the number of samples that were in class "0" and were correctly classified as "0."
False Positive (FP) = 2 the number of samples that were in class "0" but were incorrectly classified as "1" (false alarms).
False Negative (FN) = 0 the number of samples that were in class "1" but were incorrectly classified as "0" (missed cases).
We can calculate False Alarm Rate that equal

$$FAR = \frac{FP}{FP + TN}$$

$$= \frac{2}{27+2} = \frac{2}{29} \approx 0.069 \ (6.9\%)$$

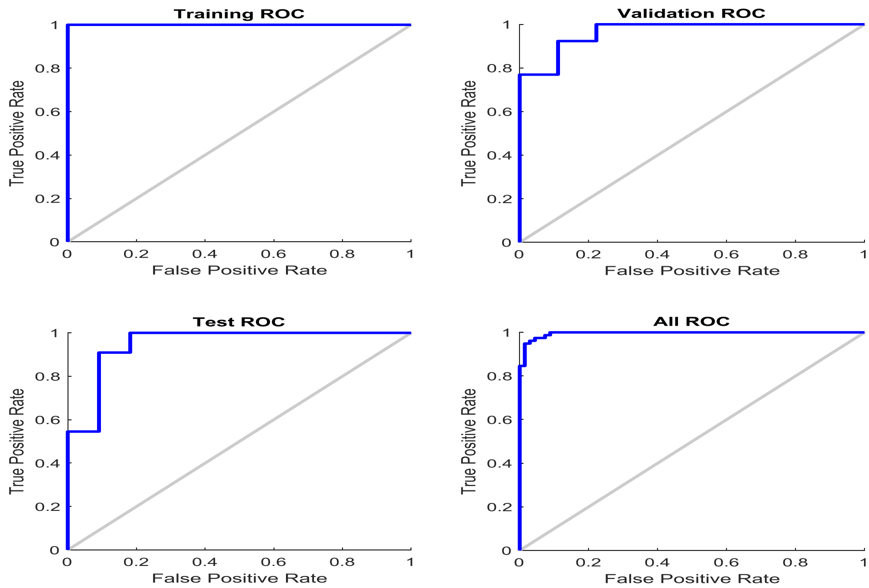



**Fig 6.** Receiver operating characteristic.

It used to compare classes and trained models to see if they perform differently in the Receiver Operating Characteristic (ROC) curve as shown in figure 6 where The AUC values are in the range from 0 to 1, and larger AUC values indicate better classifier performance. The Area Under Curve (AUC) value under a ROC curve, corresponds to the integral of a ROC curve true positive rate (TPR values) with respect to false positive rate (FPR) from FPR = 0 to FPR = 1.

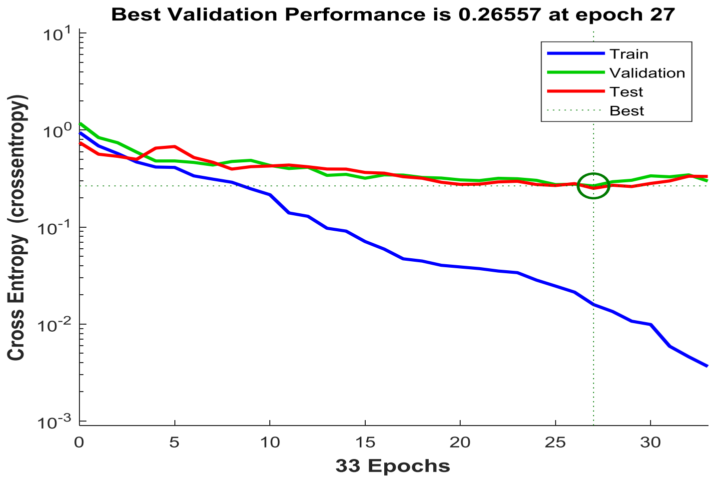



**Fig 7.** Best validation performance.

Figure (7) shows that the model performs well as it learns gradually without showing signs of overfitting. The results indicate that the model achieves a good balance between training and validation, which means that the model is able to generalize to new data effectively.

## 11. CONCLUSION AND RECOMMENDATIONS

Because sonar operates in complex environments that may include rocks, mines, and other marine life, and is susceptible to acoustic interference and signal attenuation, the model was able to distinguish between targets. This model can be used in real applications where we need to distinguish underwater objects using sonar signals, detection of sea mines, identifying sunken objects and exploring the marine environment, by analyzing the accuracy of CNN equal to 96.77%, R-call = 1.00, F1-score = 0.97 and Precision= 0.94. A highly accurate model will do well in terms of identifying the right class for most samples.

This model can be selected as the best virtual neural network model to perform a specific task based on its accuracy in correctly classifying signals, and this model is suitable for applications that require accuracy and fast response, such as marine detection or military applications.

Recommendations: The model performs very well, making it useful in applications that require high-precision identification of important targets such as sonar target tracking.

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