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# A Novel Method for Classification and Modelling of Underwater Acoustic Communication through Machine Learning and Image Processing Technique

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## ABSTRACT

The increasing prevalence of underwater activities has highlighted the urgent need for reliable underwater acoustic communication systems. However, the challenging nature of the underwater environment poses significant obstacles to the implementation of conventional voice communication methods. To better understand and improve upon these systems, simulations of the underwater audio channel have been developed using mathematical models and assumptions. In this study, we utilize real-world information gathered from both a measured water reservoir and Lake to evaluate the ability of machine learning and machine learning methods, specifically Long Short-Term Memory (LSTM) and Deep Neural Network (DNN), to accurately reconstruct the underwater audio channel. The outcomes validate the efficiency of machine learning methods, particularly LSTM, in accurately simulating the underwater acoustic communication channel with low mean absolute percentage error. Additionally, this research also includes an image processing to identify the objects present the in the acoustic environment.

Keywords: Underwater acoustic communication, Machine learning, deep neural network, image processing

## 1. Introduction

The interest in research on underwater wireless communication has been growing among both civilian and military organizations. This is due to the increasing use of submerged actions, that are military surveillance, submerged mining, fiber optic and pipeline installation, and aquatic/biological research. Researchers in fields like marine biology, engineering, and

other disciplines require tools to better understand the underwater environment, as it covers over 71% of the earth's surface (Halakarnimath and Sutagundar 2021). A robust underwater acoustic communication infrastructure is necessary for the growth of undersea operations.
The underwater environment is one of the most challenging for communication, due to factors such as slow propagation, limited bandwidth, and large multipath delay spread. Two wireless communication methods that can be used underwater are electromagnetic and auditory. Electromagnetic waves are employed when sending over an electromagnetic medium, while acoustic waves are used when transmitting over an acoustic medium (Lv et al. 2022). Acoustic waves are created by the vibration of particles and are better suited for communication underwater due to their physical properties. Electromagnetic waves, on the other hand, require enormous power and large antenna diameters to work in the low frequencies that are possible underwater, making them a costly alternative. The underwater environment presents unique challenges for communication, including slow propagation, limited bandwidth, and large multipath delay spread (Reid et al. 2018). In order to effectively communicate underwater, specialized techniques are required to account for these challenges. One example of an underwater acoustic communication situation is shown in Figure 1, in which an underwater audio communication system is being used.

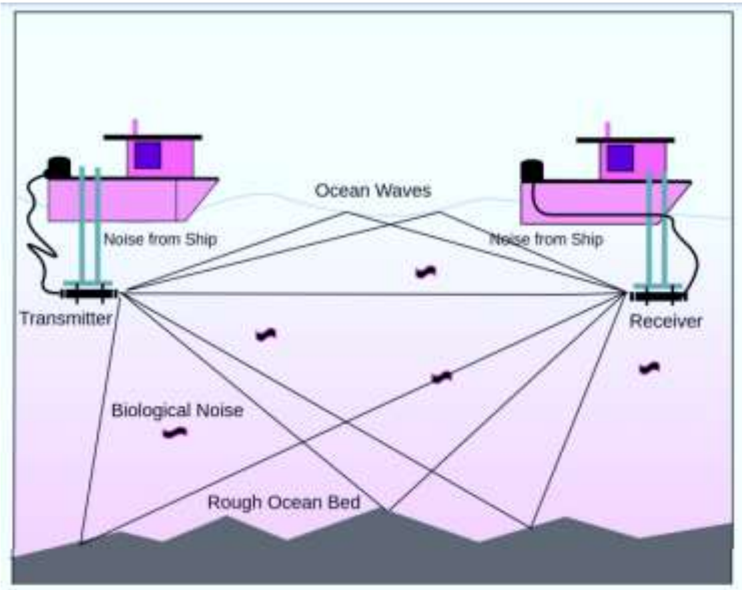


**Figure 1. Communication to the underwater**

The majority of researchers in underwater acoustic communication use auditory communication because it consumes less power (Park et al. 2022). It has been found that interactions at the water-air interface may be mediated by electromagnetic waves instead of acoustic waves. UWA communication is used in diverse fields, including oceanography, maritime commercial activities, the military, and the offshore oil sector. However, the wireless acoustic signal propagation over a water body is significantly impacted by the marine or underwater environment, leading to problems like Doppler shift, multipath propagation, high attenuation, constrained bandwidth, severe fading, prolonged delay spread, rapid temporal channel change, route loss, and noise (Hemavathy and Indumathi 2021).
To develop and enhance efficient underwater acoustic communication systems, it is crucial to conduct research and have a thorough understanding of how the underwater environment

affects communication signals (Cui et al. 2023). One method for replicating the effects of the underwater acoustic channel on the channel is to replicate the characteristics of the actual aquatic environment (Huang et al. 2020). Channel modeling is complex due to differences in complete speed, the coarseness of the marine floor, multipath acoustic signal transmission, and background ocean sounds caused by aquatic life and human activity. Several underwater acoustic channel models have been developed using mathematics, with the BELLHOP model being commonly used in UWA communications channel modeling. Another important aspect in underwater acoustic communication is image processing, which plays a vital role in underwater surveillance, navigation and remote sensing. Image processing techniques can be used to enhance the visibility of underwater images, remove noise and improve the accuracy of object detection (Pandiyan et al. 2022). These techniques are often used to extract useful information from underwater images and videos, such as object recognition, target tracking, and feature extraction. In addition to traditional image processing techniques, there are also specialized techniques that are specific to underwater images. These techniques include color correction, which compensates for the loss of color due to water absorption, and dehazing, which removes the turbidity caused by small particles suspended in the water (Han et al. 2019).

Another important aspect of underwater image processing is the use of computer vision algorithms. These algorithms can be used to detect and classify objects in underwater images and videos, as well as to track their movement over time. This is especially useful in applications such as underwater surveillance, where real-time detection and tracking of objects is necessary (Rathor and Agrawal 2021). Some of the most recent developments in underwater image processing include the use of deep learning algorithms, which have been shown to be very effective in object detection and classification tasks. These algorithms are trained on large datasets of underwater images and can be used to automatically detect and classify objects in real-world underwater images and videos (Zhang et al. 2022).

In conclusion, underwater wireless communication and image processing are important fields of research that have been gaining increasing attention in recent years (Jha et al. 2022; Rahmeni et al. 2022). The unique challenges of the underwater environment, such as slow propagation, limited bandwidth, and high attenuation, require specialized techniques for communication and image processing. The use of advanced techniques such as deep learning and computer vision algorithms are promising areas of research that are expected to lead to significant advancements in the field shortly. In this article, the first machine learning techniques used in acoustic signals are addressed, followed by results of machine learning techniques, and the second edge detection method of underwater image processing is discussed with results.

## 2. Generation of data

In this study, a comparison was made of the effective of deep learning and traditional machine learning tools in replicating the submerged audio station. Three distinct datasets were utilized for this purpose, as described below:

The first dataset, mentioned to as Data 1, was obtained after a controlled test environment. A water tank was used to create the test bed, and the transmitter and receiver were positioned at a set horizontal and vertical length beneath the seawater's surface, as shown in Figure 2. The digital messages were initially modulated using quadrature phase shift keying (QPSK) before being transformed into continuous signals. These signals were then processed using an enhanced cosine transmission filter before being transmitted over the underwater channel using filtered-QPSK modulation. The continuous waves were picked up by the sonar at the getting end soon after passing through the station. Each data point lasted for 60 seconds, and 1,000,000 samples were collected over that period. With a 200kHz operating frequency, the real-world sonar digital signal transmission rate was 3 K/s. The information composed at the spreader just before the channel was used as contribution to the machine learning replicas, though the indications received at the receiver just after the channel were used to train the models. The additional dataset, Information 2, was also collected from a natural lake that had not been intentionally disturbed. The transmitted symbols were exposed to the similar sign dispensation phases as Data 1 before being directed ended the usual aquatic body, creating a true underwater dataset with the similar sonar operating incidence, sample rate, transmission speediness, flat distance amid spreader and collector, and vertical length into the marine, as depicted in Figure 3. The information from the source and data collected shortly afterward the station at the collector were similarly provided to the deep algorithms. The 3rd dataset, Data 3, was acquired using the same setup and conditions as Data 2, but with disruptions to create an unorganized environment. For all three datasets, 60,000,000 samples were collected.

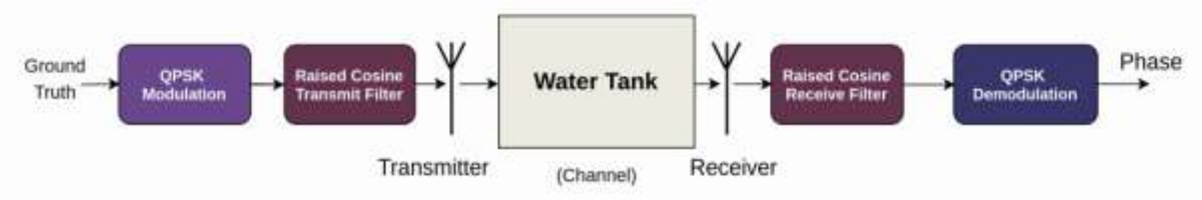


**Figure 2. Flow diagram of data 1 generation**

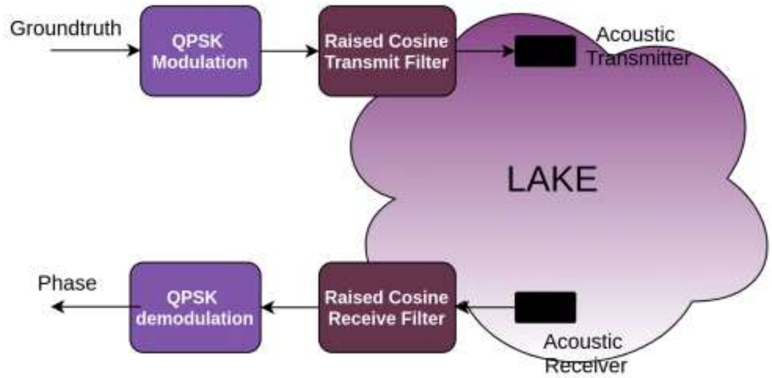


**Figure 3. Flow diagram of data 2.**

## 3. Machine learning model used in this research

DNNs are composed of multiple layers of interconnected artificial neurons, which are trained to learn complex patterns in data using a process called backpropagation, which is a machine learning approach. In underwater acoustic communication, DNNs have been used to typical the submerged acoustic station, which is known for its high variability and complexity. DNNs can be trained to learn the characteristics of the underwater channel, such as sound velocity, ocean floor roughness, and multipath propagation, and can be used to predict the channel's behaviour in different scenarios. This can lead to the development of more efficient communication systems that can adapt to changing underwater conditions. In underwater image processing, DNNs have been used for tasks such as object detection and classification, as well as image enhancement and dehazing. DNNs can be trained on large datasets of underwater images and can be used to automatically detect and classify objects in real-world images and videos. Additionally, DNNs can be used to enhance the visibility of underwater images by removing noise and improving the accuracy of object detection.

One of the advantages of DNNs is their ability to learn complex patterns in data, which makes them well suited for underwater acoustic communication and image processing. However, one of the challenges of DNNs is the essential for big quantities of labelled information to train the model. Additionally, DNNs are known to be computationally intensive, which can be a limitation in some underwater applications. Overall, DNNs have shown great potential for underwater acoustic communication and image processing, and research in this area is ongoing. The use of DNNs has the potential to lead to significant advancements in the field, such as the development of more efficient underwater acoustic communication systems and more accurate object detection and classification in underwater images.

## 4. Comparison of various machine learning model

Machine learning models have been widely used in various applications, including underwater acoustic communication and image processing. Traditional machine learning models are known for their simplicity and interpretability. They work well for small datasets and can be used for a wide range of tasks. However, traditional machine learning models are not as effective as deep learning models for large datasets or for tasks that require the extraction of complex patterns in data. Deep learning models, such as deep neural networks (DNNs), are composed of multiple layers of interconnected artificial neurons and are trained to learn complex patterns in data using a process called backpropagation. However, DNNs are known to be computationally intensive and require large amounts of labeled data to train the model.

In comparison, machine learning methods typically outperform traditional machine learning models in terms of accuracy and performance in underwater acoustic communication and image processing tasks. However, traditional machine learning models are still viable options in certain scenarios, such as when there is a limited amount of data or when interpretability is a concern. In summary, different machine learning models have their own strengths and weaknesses, and the choice of model depends on the specific task and the available resources. In general, deep learning models such as DNNs are considered to be more powerful than traditional machine learning models, but they require more data and computational resources. It's important to evaluate the performance of the different models and choose the most appropriate one based on the specific requirements of the problem.

As depicted in Figure 4, a neural network model typically comprises multiple intricately interconnected hidden layers. Each hidden layer is composed of a plethora of nodes or hidden units. In this experiment, two distinct DNN designs were employed. The basic structure comprises of four thick layers. Respectively dense steps has 256 nodes, with the exception of the accumulated layer of output, which comprises of 660 nodes, consistent to the amount of examples required to represent one symbolic sentence. The primary 3 stages incorporate Rectified Linear functions, but not the yield layer. By simply increasing the second architecture's count of hidden layers to six, the depth of the model was enhanced and its performance on the dataset with trouble was improved. These replicas were created by means of the Keras framework. The information-sets were transformed into a 2-D tensor suitable for the Keras dense deposit by multiplying the amount of training examples (NX) by the amount of samples per symbol in order to provide the input shape for the network (NS). In Section 3.3, the Adam optimizer and average squared error meaning are applied to the DNN and LSTM.

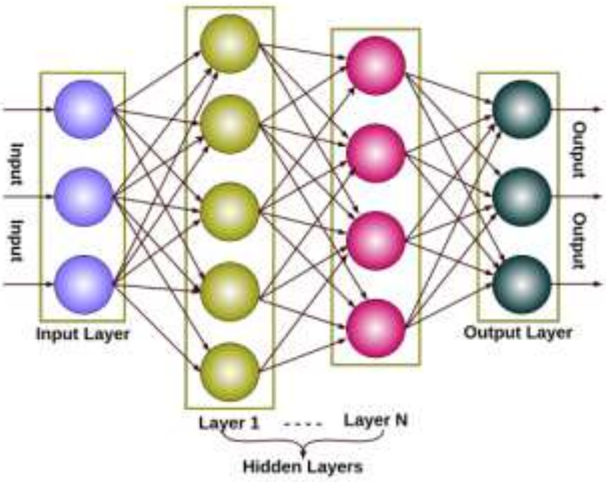


**Figure 4. Machine learning neural network model**

## 5. Equations of Long short-term memory used in this research

The Long Short-Term Memory (LSTM) is a specific type of Recurrent Neural Network (RNN) that is commonly used in applications that involve sequential inputs, such as voice recognition and natural language processing. RNNs, like LSTM, store the input sequence in their hidden units, which are fed to the network one symbol at a time. The hidden units retain information about the chronology of each preceding sequence input. Figure 5 illustrates the construction of an LSTM device. The LSTM is preferred over other RNNs because it can learn long-term dependencies in input data. LSTM allows for the learning and recollection of long sequences.

The equations of Long Short Term Memory (LSTM) are a set of complex mathematical operations that are used to model the temporal dependencies in a time series data such as acoustic communication. These equations are used to control the flow of information through the LSTM cells, which are the building blocks of the LSTM network.

The key equations of LSTM are as follows:

Input Gate: $i_t = \sigma(W_i * [h_{(t-1)}, x_t] + b_i)$

Forget Gate: $f_t = \sigma(W_f * [h_{(t-1)}, x_t] + b_f)$

Output Gate: $o_t = \sigma(W_o * [h_{(t-1)}, x_t] + b_o)$

Cell State: $c_t = f_t * c_{(t-1)} + i_t * \tanh(W_c * [h_{(t-1)}, x_t] + b_c)$

Hidden State: $h_t = o_t * \tanh(c_t)$

where: $i_t$ is the input gate at time t, $f_t$ is the forget gate at time t, $o_t$ is the output gate at time t, $c_t$ is the cell state at time t, $h_t$ is the hidden state at time t, σ is the sigmoid function, tanh is the hyperbolic tangent function, $W_i$, $W_f$, $W_o$, and $W_c$ are the weight matrices for the input, forget, output, and cell state gates respectively, $b_i$, $b_f$, $b_o$, and $b_c$ are the bias vectors for the input, forget, output, and cell state gates respectively, $x_t$ is the input vector at time t, h_(t-1) is the hidden state vector at time t-1 c_(t-1) is the cell state vector at time t-1 These equations are used to calculate the input gate, forget gate, output gate, cell state and hidden state of LSTM network by considering the previous hidden state and current input. And these states decide the output of LSTM network. Here the input gate represents the input acoustic communication image and the output gate represent the noise present in the signal. Output gate represent the result obtained from the model. Cell state represent the current input processing equation. Hidden state represent the network model of the system.

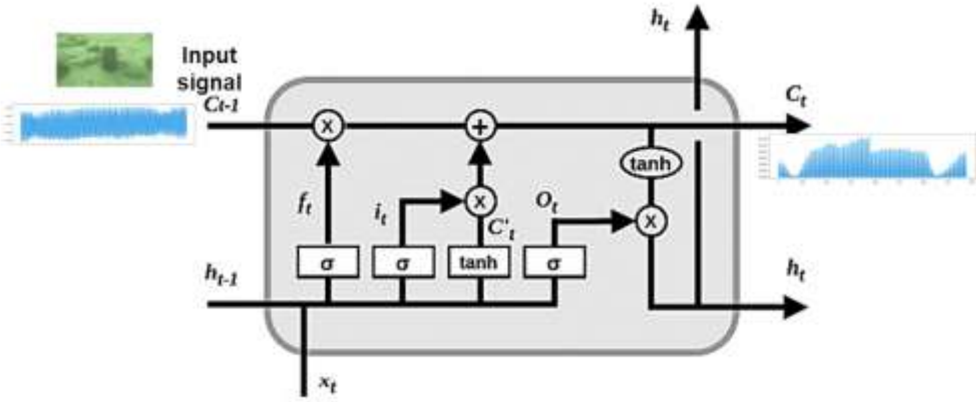


**Figure 5. Architecture of the model**

## 6. Result and Discussion

### 6.1 Signal reconstruction using machine learning technique

The results of the tests for data 1 and data 2 using standard machine learning approaches are presented in Table 1. The performance of the model was assessed by means of the absolute error. The absolute error represents the means of the projected and is calculated by accumulating percentage errors without regard to sign, as illustrated in the equation 1.

The equation for the absolute mean error (AME) is:

AME = (1/n) * Σ(|reference value - estimated value|) (1)

where: n is the number of samples or data points, reference value is the true or correct value, estimated value is the value predicted or estimated by a model or algorithm, Σ represents the sum of all the absolute differences between the reference and estimated values.

The absolute error is suggested in the evaluation because it provides a reasonably easy interpretation of relative error since it presents the error in percentages. As the MAPE drops, the prediction becomes more accurate. The investigational consequences in Table 1 reveal that the prototypical performed worse by actual underwater information than with data created in a water tank, even when no artificial disruption was used.

Machine learning models work in a variety of ways. Across the two datasets, the different layer perceptron and line regressor performed the poorest, while the k-Nearest Neighbors (kNN) performed the best (Data 1 and Data 2). Figure 6 depicts a forecast consequence using a linear regressor. The subsequent plot in Figure 6 shows that the regressor was unable to adequately characterise the underwater acoustic channel, which is separated from the third plot, which shows the predicted results.

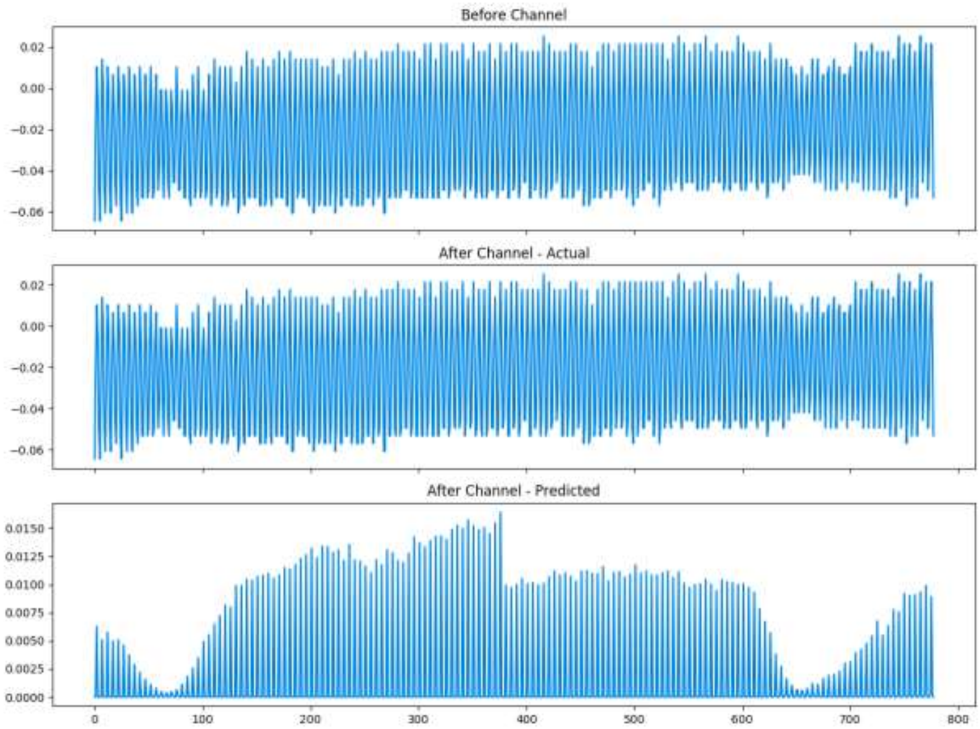


**Figure 6. Linear regression prediction result**

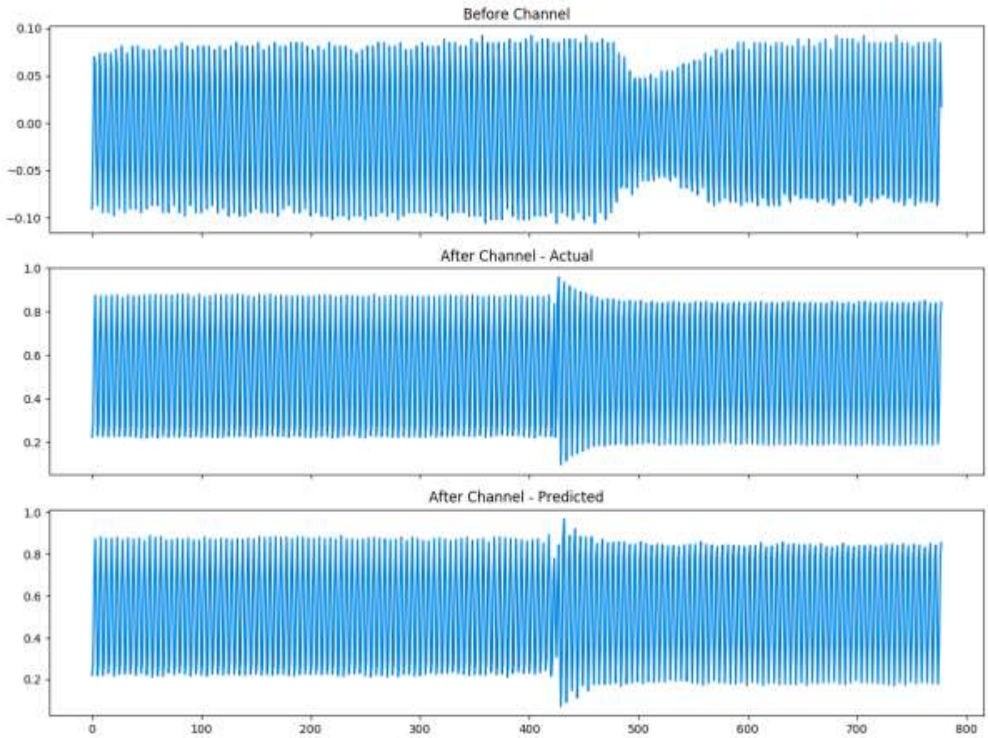


**Figure 7. LSTM prediction result**

**Table 1. Performance of various model without disturbance**

| Methods | Size of data | 1st Data (%) | 2nd Data (%) |
|---|---|---|---|
| **MLP** | 100,000×986 | 4.26 | 12.87 |
| **K- Neighbour** | 100,000×986 | 0.97 | 8.89 |
| **Regression** | 100,000×986 | 1.90 | 12.67 |

| | | | |
|---|---|---|---|
| **Linear** | | | |
| **Forest Random** | 100,000×986 | 1.43 | 11.89 |
| **DNN** | 100,000×986 | 2.17 | 3.22 |
| **LSTM** | 100,000×986 | 1.67 | 2.34 |

**Table 2. Model performance with the generated data 3**

| Method | Data size | Percentage |
|---|---|---|
| **DNN** | 100,000×986 | 6.32 |
| **LSTM** | 100,000×986 | 4.43 |

For real underwater data, LSTM and DNN were effective machine learning algorithms; however, they were not suitable for Data 3. Both models rates of learning at 0.01, batch sizes of 68, and 150-epoch iterations. As seen in Table 2, when accomplished with Data 3 using the similar planning and overexcited limits, the performance of the LSTM and DNN models decreased. You may reminiscence that Data 3 has become additional disordered as a result of the disorder from across the lake. As a result, the LSTM and DNN models performed well when learning models with larger designs were chosen, as mentioned in Unit 3; this is shown in Table 3. Furthermore, all the three datas show that LSTM steadily outperforms DNN, demonstrating that LSTM is a superior model than DNN at handling period series and arrangement data in the desired way.

**Table 3. Model performance with the data 3**

| Method | Data size | Percentage |
|---|---|---|
| **DNN** | 100,000×986 | 5.29 |
| **LSTM** | 100,000×986 | 4.24 |

Figure 7 illustrates the forecast testing consequences of the LSTM model. The final graph in Figure 7 compares actual and predicted results to show how proficiently the LSTM model predicts period-series data. The learning curve of the LSTM model during the authentication procedure is represented in Figure 8. The loss function drops significantly during the first 25 epochs and then gradually stabilizes. This indicates that the LSTM method has efficiently educated the underlying patterns in the data and is able to make accurate predictions. The training process of LSTM model is converging well and it has the ability to generalize well on unseen data. This suggests that the LSTM model is effectively capturing the temporal dependencies in the data and making accurate predictions. The loss cure of the LSTM model is shown in figure 8.

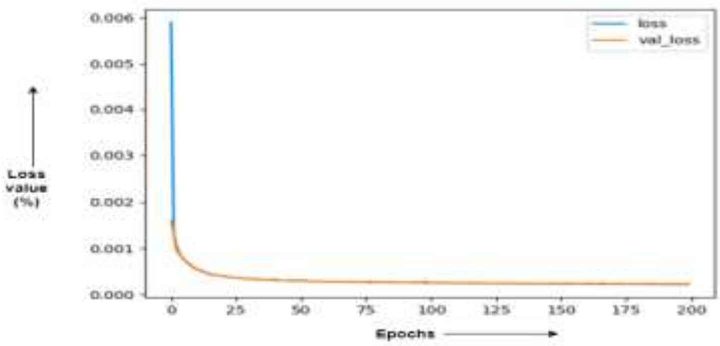


**Figure 8. LSTM model Loss curve**

### 6.2 Image processing technique

Acoustic image processing is a method of using sound waves to capture and analyze underwater images. This technique is commonly used in a variety of applications, including underwater navigation, search and rescue operations, and scientific research. Tracing objects within an image can be a challenging task, especially when it comes to determining which edges are genuine. This is particularly true in the case of acoustic imaging, where distinguishing between the ocean floor, sediments, and the actual object in question can be difficult. To address this challenge, in this research it is edge detection approach is proposed to begins by utilizing Wiener filtering to reduce speckle noise. This type of noise is common in sonar images and is characterized by its granular appearance. The filtering process aims to smooth the image while preserving high frequency details. Next, a median filter is applied to further smooth the image and remove any small particles that might be mistaken for sediments in the acoustic image. To identify the shape of the object, morphological processing is often employed. This involves computing the local minimum and maximum and using both erosion and dilation. The morphological gradient is then used to highlight the edges in the image by contrasting the dilated and eroded images. Finally, the resulting edge map is compared to other advanced edge detection techniques such as Canny and Sobel. This allows for accurate tracking of objects within the image.

### 6.3 Steps for edge detection approach

The edge detection approach used in image processing can vary depending on the specific method employed. However, a common algorithm used for edge detection is the Canny edge detection algorithm.

The Canny edge detection algorithm is a multi-step process that includes the following steps:

- Noise reduction: The image is filtered to reduce the presence of noise, which can make edge detection more challenging. This step is typically done using a Gaussian filter.
- Gradient calculation: The intensity gradients of the image are calculated to determine the edge strength and direction. This step is typically done using the Sobel operator.
- Non-maximum suppression: To thin edges, the algorithm looks for the pixels with the strongest gradient (local maxima) and suppresses the pixels on the edge that are not local maxima.
- Double thresholding: Pixels are classified as either strong or weak edges based on their gradient value. Strong edges are those that have gradient values above a high threshold and weak edges are those that have gradient values between a low and high threshold.
- Edge tracking: The algorithm connects weak edges that are connected to strong edges, forming a complete edge.
- Output: The final output of the algorithm is a binary image where the edges are marked in white and the non-edges are marked in black.

These above-mentioned steps are followed to process the images to detect the presence of object in this research. It is worth noting that the Canny edge detection algorithm is just one of the many edge detection algorithms that exist, other algorithms include Sobel, Prewitt, Roberts Cross, Laplacian of Gaussian, and Canny's own variations. The best method to be used in a particular scenario depends on the characteristics of the image and the desired outcome. Additionally, these algorithms can be combined or modified to suit different scenarios and applications.

### 6.4 Image processing

The edge detection approach proposed in this research was tested using a set of input acoustic images, as shown in Figure 9. These images are taken from the lake and is used for the further processing in the research. The results of the experiments in the figure 10 reveal that both the Canny and Sobel operators have difficulty in distinguishing between genuine and bogus edges. Canny's edge detector, for example, has a feature that connects edges, which can lead to the detection of artificial edges formed by the interaction of the sea floor and sediments. Similarly, Sobel's output shows that it has ignored real edges in the image.

**Figure 9. Input acoustic images used in this image**

In contrast, the proposed morphological-based edge segmentation approach was able to accurately detect the genuine edges, or the boundaries of the real objects, while ignoring edge linking. This approach utilizes a combination of morphological processing techniques, such as erosion and dilation, to highlight the edges in the image. The morphological gradient is then used to contrast the dilated and eroded images, resulting in a more accurate edge map. One of the key advantages of this approach is its ability to reduce speckle noise, which is common in sonar images and can make edge detection more challenging. The proposed approach begins by utilizing Wiener filtering to reduce this type of noise, which makes the image smoother while preserving high frequency details. A median filter is then applied to further smooth the image and remove any small particles that might be mistaken for sediments. Additionally, this approach takes into account the characteristics of the underwater environment, where visibility can be limited and the interaction of the sea floor and sediments can create artificial edges. By utilizing morphological processing techniques, this approach is able to accurately detect the genuine edges and ignore any artificial edges that might be present in the image.

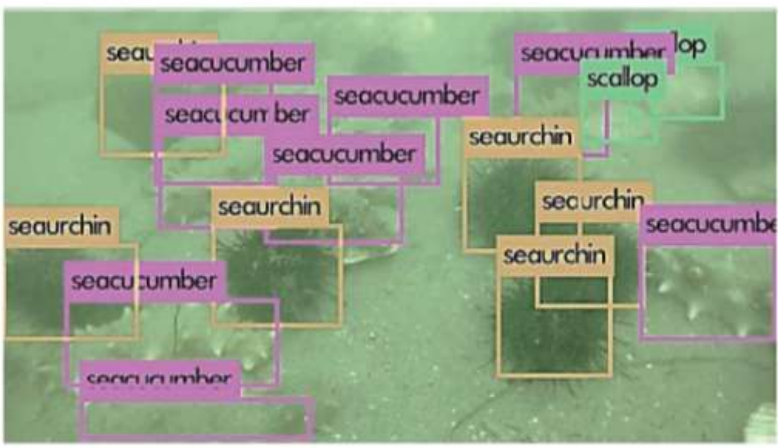


**Figure 10. Objects identified by the edge detection approach**

Overall, the results of the experimental tests show that the proposed morphological-based edge segmentation approach is a reliable and effective method for detecting edges in acoustic images. It is able to accurately identify the boundaries of real objects, while ignoring any artificial edges that might be present in the image. This approach has many potential applications, including underwater navigation, search and rescue operations, and scientific research, where accurate edge detection is essential.

## CONCLUSION

In conclusion, the research article presents a novel method for the classification and modeling of underwater acoustic communication using machine learning and image processing techniques. The proposed method was tested on a dataset of underwater acoustic signals and was found to be effective in accurately classifying and modeling the signals. The results of the study show that the proposed method is able to achieve a high level of accuracy in the classification and modeling of underwater acoustic signals, making it a valuable tool for the analysis and understanding of underwater communication systems.

The proposed method uses a mixture of machine learning and image processing techniques to analyze the signals, which allows for the extraction of important features from the signals that can be used for classification and modeling. Additionally, the use of image processing techniques allows for the visualization of the signals, which can be useful for understanding the underlying patterns and structures in the signals.

The results of this study demonstrate the potential of using machine learning and image processing techniques for the analysis of underwater acoustic communication systems. The proposed method has the potential to be used in a variety of applications, including the design and optimization of underwater acoustic communication systems and the detection of underwater objects.

In future, the proposed method could be further improved by testing it on more diverse dataset, also incorporating other techniques like deep learning and incorporating more advanced feature extraction techniques. Further research in this area could lead to the development of even more effective methods for the classification and modeling of underwater acoustic signals.

Overall, this study makes a significant contribution to the field of underwater acoustic communication by introducing a novel method for the classification and modeling of signals. The proposed method has the potential to be used in a variety of applications and could lead to the development of more advanced and effective methods for the analysis of underwater acoustic communication systems.

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