Intelligent Automation & Soft Computing
DOI: 10.32604/iasc.2023.023361
Article

Tech Science Press

Hybrid Deep Learning-Based Adaptive Multiple Access Schemes Underwater Wireless Networks

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Received: 05 September 2021; Accepted: 14 April 2022

Abstract: Achieving sound communication systems in Under Water Acoustic (UWA) environment remains challenging for researchers. The communication scheme is complex since these acoustic channels exhibit uneven characteristics such as long propagation delay and irregular Doppler shifts. The development of machine and deep learning algorithms has reduced the burden of achieving reliable and good communication schemes in the underwater acoustic environment. This paper proposes a novel intelligent selection method between the different modulation schemes such as Code Division Multiple Access(CDMA), Time Division Multiple Access(TDMA), and Orthogonal Frequency Division Multiplexing (OFDM) techniques using the hybrid combination of the convolutional neural networks(CNN) and ensemble single feedforward layers(SFL). The convolutional neural networks are used for channel feature extraction, and boosted ensembled feedforward layers are used for modulation selection based on the CNN outputs. The extensive experimentation is carried out and compared with other hybrid learning models and conventional methods. Simulation results demonstrate that the performance of the proposed hybrid learning model has achieved nearly 98% accuracy and a 30% increase in BER performance which outperformed the other learning models in achieving the communication schemes under dynamic underwater environments.

Keywords: Code division multiple access; time division multiple access; convolutional neural networks; feedforward layers

1 Introduction

The Underwater Sensor Network has enchanted a prominent deal of interest over the past decades on various applications in science and explorations on the diagnosis of natural disasters [1,2]. Radio Frequency (RF) in an underwater environment is enervated due to rough water conductivity. So, the audio is the only attribute to travel the long communication path [3]. Moreover, there is limitation faced by acoustic communication faces serious issues like (i) restricted bandwidth, (ii) long propagation, (iii) consumption of massive energy. These issues act as the propelling factor for acoustic communication in designing the protocols in medium access control (MAC) promotions, as shown in Fig. 1. Several MAC promotions are propounded in three various categories are (i) random access [4], (ii) reservation-based [5], (iii) schedule-based [6]. Molins et al. [7] proposed the reservation relay protocol to attain the best throughput with a massive data load. Most of the nodes participating in transmission in an underwater sensor network are not the assumption an understanding of the massive data load [8].

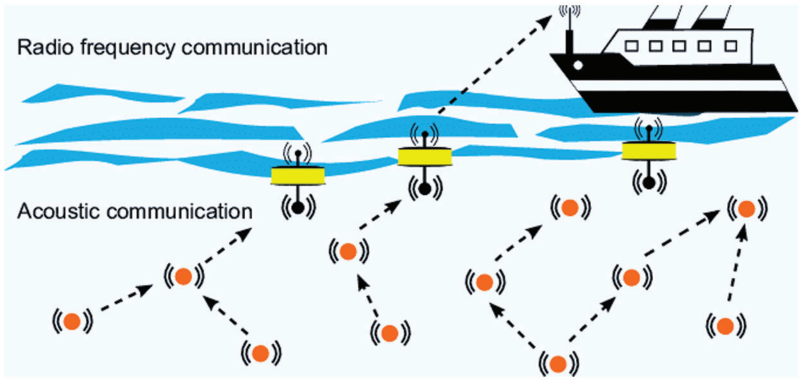


Figure 1: Radio frequency acoustic communication in underwater sensor network

The network throughput decreases, and the network is not participating in transmission data on eradicating the timeslots. To enhance the throughput, the rate of generating the data plays a significant role in underwater sensor networks. As the rate of generating the data is low, a low throughput occurs. Each time slot comprises transmission time and propagation, avoiding frame collision. The MAC protocols are further classified into three contentions they are (i) contention-based MAC without RTS/CTS, (ii) contention-based MAC with RTS/CTS, (iii) contention-free MAC to avoid frame collision.

The first contention is the modified ALOHA protocol that uses a short tone [9] to notify the neighbour nodes. In this modified ALOHA, when one participating node is aware of the notifications of transmission of packets, it reverses its transmission. Otherwise, it reschedules that transmission, leading to channel bandwidth and energy [10]. The second contention uses virtual carrier sense to extricate the energy, thereby excluding the conflicts. While during the data transmission, the node estimates the busy time and pauses the listening period. Hence sensor nodes in this contestation wait for the long round trip time to exchange the RTS/CTS [11].

Moreover, the handshake RTS, CTS protocols produce a long propagation delay, decreasing network throughput [7]. The third contention-free MAC comprises CDMA, FDMA, TDMA. Approaches of CDMA have several issues like a near-far problem, long propagation delay, and long-distance communication range, which is not adequately addressed [12]. Where else FDMA divides the frequency band into several narrow bands results in a low throughput [13].

Yun et al. [14] proposed that the CDMA protocol for underwater sensor networks uses adaptive token polling to decrease energy consumption, excludes collision, and avoids propagation delay problems. CDMA protocols play a significant role in the underwater sensor network and are classified into two classifications. They are (i) one slot approach (ii) multi-slot approach. The one slot approach needs the transmission would be attained in one slot; therefore, one frame would be designed for the length of the timeslot added with propagation delay [15]. As the name implies, multi-slot requires more than one slot to complete the one packet transmission among the two neighbours. Compared with the other traditional time slots, CDMA approaches would enhance the network throughput and decline receiver end idle time [16].

While exploring underwater, the autonomous process is essential for declining the deadly high severe pressure in the deep-sea environment. Canny computer vision needs to be very intelligent, as the marine environment had very low illumination and low enhancements in image quality attribute to improve the autonomous process. Ferguson et al. [17] propounded the underwater image enhancement technique relayed on the deep learning method, which builds the trained data set from the category of degraded underwater images and restored underwater images [18]. The deep learning method enhances the deep-sea image quality from the training sets. CNN method in deep learning is identified as the rapid detection method [19]. Though deep learning models play a vital role in better communication, handling the more extensive datasets and achieving high performance remains the darker side of research. The paper proposes a hybrid combination of Convolutional Neural Networks (CNN) and Boosted Single Feed Forward Layers (BSFL) to select the modulation schemes under CDMA, TDMA, and OFDM underwater communication environment to overcome the above challenge. The contribution of our work is bi-folded.

1. A hybrid combination of Convolutional Neural Networks (CNN) and Boosted Single Feed Forward Layers are used for a good selection of modulation schemes under CDMA, TDMA, and OFDM.
2. Achieving better communication and high performance using the proposed model under a dynamic underwater environment.

The rest of the paper is as follows: Section-1 discusses the related works by different authors with their features and pitfalls. The System model is presented in Section-2. Additionally, channel estimated features, the working mechanism of the proposed learning model are also presented in Section-3. Section-4 demonstrates the proposed learning model's experimentation and performance evaluation with comparative analysis under the different underwater scenarios. The paper concludes with a future scope presented in Section-5.

2 Related Works

Liu et al. created a novel underwater sensor network called multimodal-network (MM-NET). The proposed multi-modal sensor architecture supports heterogeneous hardware and software. MM-NET is modelled with software-defined ratio, NDN routing, and address-based routing structure for sensors communication. The significant purpose of MM-NET is to support heterogeneous hardware structures at the front ends and provide secured communication through various MAC layers [20]. Nodes are interlinked in a distributed method called the KNN model. The limitation of the proposed model is sufficient for short-distance communication and only efficient for single-user communication.

Huang et al. studied the role of machine learning approaches on underwater acoustic communication [21]. The author focused on adaptive modulation coding (AMC) techniques that support underwater acoustic communication. The suggested aided-KNN AMC classifier differs from the typical single coding model in structure, communication, and support for uncertainty scenarios in underwater communication. In aided-KNN, a transmission mechanism called multicarrier-multiple frequency shift keying is used. The suggested adaptive modulation coding technique uses a "squared Inversion kernel function" and a clustering approach to reduce the dimensions. The limitation of the proposed supervised learning AMC model is achieved less accurate for the large-size database. Also, the features used to train the classifier are randomly selected, which affects the performance.

Park et al. adopted various supervised learning algorithms called the "Multilayer perceptron, KNN, support vector classifier, decision tree" model for forecasting the handover in underwater communication [22]. Deciding the handover buoy under uncertainty scenarios is difficult in underwater sensor networks. The proposed ML-based handover deciding technique is mainly designed to foresee the ocean current and handover buoy nodes based on the current moving directions on the network and uncertain conditions.

Decision trees achieved better performance compared to traditional algorithms. The limitation of the proposed prediction algorithm is focused on handover nodes selection, and the performance achieved is inefficient for large networks.

Rauchenstein et al. focused on minimizing the localization errors in underwater reservoirs. The author developed a regression-based learning algorithm to calibrate the localization errors of a time-difference-of-arrival (TDOA)-based acoustic sensor array [23]. Initially, locations are assumed using the approximate maximum likelihood heuristic, and a regression model is used to detect the high-error nodes removed from the network. The best data points are selected with minimum trade-offs to achieve the high-performance localization process in the underwater reservoir.

Kim et al. developed a semi-supervised learning classifier for selecting the best modulation technique among CDMA and OFDM in the underwater acoustic network [24]. The proposed ML classifier combined the convolutional neural network as feature extractor and random forest as modulation scheme selector. The significant purpose of this semi-supervised learning model is to reduce the bit-error-rate in underwater acoustic communication by extracting the dependent variables from the receiver data and selecting the modulation either as CDMA or OFDM at minimal BER. Random forest is achieved better performance in BER reduction due to the appropriate selection of modulation model than conventional CNN, DNN classifier.

Similarly, Wang et al. proposed deep learning unsupervised algorithms for modulation recognition techniques for underwater communication networks [25]. The "VGGNET" architecture is adopted as a selection classifier with an external network and random disconnection model to reduce the overfitting issues on CNN. The intense layer comprises 32, 64 neurons, and the output layer with 5 neurons corresponding to 5 possible modulations, including BPSK, QPSK, 8PSK, 16QAM, and 64QAM. The limitation of VGGNET is inefficient at the low-SNR rate in underwater communication.

3 System Model

The proposed architecture uses the system model as mentioned in [26]. The acoustic signal is attenuated concerning the distance and frequency is involved. The acoustic attenuation is expressed as to

$$A(d,f) = A_0 d^l a(f)^d \tag{1}$$

where d is the distance of transmission, f is the frequency of the acoustic signal, A_0 is the normalization factor, l be the spread function, and $a(f)$ is the absorption coefficient. In terms of dB range of frequency, the above equation can be expressed as

$$10\ log\ log\ \frac{A(d,f)}{A_0} = l.\ 10\ log\ log\ d\ + d.\ 10\ log\ log\ a(f) \tag{2}$$

The r.h.s of the above expression holds both the propagation loss of the signal and the absorption loss. The term $l.\ 10\ log\ log\ d$ corresponds to the propagation loss of signal. The term $d.\ 10\ log\ log\ a(f)$ corresponds to the loss due to absorption. The spread function ranges from 2 to 4, with $l = 2$ for the spherical spread function, *for cylindrical* spread function and $l = 1.5$ for other non-regular spread unction. Considering the acoustic signal frequency in the kHz range Eq. (2) is rewritten as

$$10\ log\ log\ a(f) = 0.11\frac{f^2}{1+f^2} + 44\frac{f^2}{4100+f^2} + 2.75\times 10^{-4} f^2 + 0.003 \tag{3}$$

For low range acoustic signals, expression (3) becomes

$$10\ log\ log\ a(f) = 0.002\ +\ 0.11\frac{f^2}{1+f^2}\ +\ 0.011f^2 \tag{4}$$

Three noise functions coexist in acoustic communication and the attenuation factor. The noise due to turbulence, wave movement and thermal noise also exists in the channel given as

$$10\ log\ log\ N(f) = N_i\ - \eta\ log\ log\ f \tag{5}$$

The loss occurs due to directional gain being ignored, and the SNR of the acoustic channel is confined as

$$SNR\ (d,f) = \frac{P/A(d,f)}{N(f)\Delta f} \tag{6}$$

where Δf corresponds to the noise the at receiver half-open transmitted signal power. The fading effect is modelled with Rayleigh fading effect, and the bit error rate (BER) is evaluated for single-bit transmission for a particular distance as

$$P_e(d) = \frac{1}{2}\left(1 - \sqrt{\frac{SNR(d,f)}{1+SNR(d,f)}}\right) \tag{7}$$

3.1 Underwater Acoustic Channel Estimation

In UWA communication, many channel parameters that affect communication performance vary with time. The BER performances of CDMA and OFDM schemes jointly depend on these parameters. Since CDMA utilizes spreading codes, the maximum data rate is less than OFDM. Thus, the design margins of the CDMA system are small to keep up with the data rate of OFDM. If the data rates of the two systems are similar and the channel variations are within the system margins, CDMA provides better BER performance than OFDM. However, when the channel variation is out of the design margins, the gain of CDMA decreases, and at a specific value, the BER performance of CDMA is lower than that of OFDM. Thus, to attain the best BER performance, the selection of two schemes needs to be developed. This section describes the parameters that affect the BER performance of CDMA and OFDM schemes. For CDMA, if the maximum excessive delay time is longer than the designed pilot length, all multipath channels cannot be estimated, causing a channel estimation error. In this case, the Rake receiver cannot fully obtain a time diversity gain. The channel estimation error occurs when the coherent time is shorter than the designed pilot interval, decreasing BER performance. When Doppler frequency (fd) shift exceeds the design margins, the BER performance of CDMA becomes low. For OFDM, when the maximum delay spread (τm) exceeds the CP, ISI is not ideally removed. A coherent bandwidth becomes narrower than the pilot spacing, which causes channel estimation errors of OFDM.

Unfortunately, several channel parameters jointly affect the BER performance. If the BER performance of all scenarios is tested and reserved for the lookup table, the selection is effortless. However, several channel parameters jointly interact, and each parameter's influence is different. In addition, the effects of the parameter variations on the modulation schemes are nonlinear, so the estimation of the effect on the BER performance is complicated. Hence we consolidate the following channel parameter which affects the modulations schemes are Doppler Frequency Shift (fd), Maximum Delay Spread (τm), Signal To Noise Ratio (SNR), Received Signal Strength (RSSI), and Delay Spread (μ).

3.2 Proposed Hybrid Learning Model

This section discusses the proposed hybrid learning models, a general overview of convolutional neural networks, and boosted single feed-forward layers.

3.3 System Overview

Fig. 2 shows the complete working mechanism of the proposed architecture. The proposed architecture works in two different phases. The convolutional neural network extracts the channel features based on the input data in the first phase. In the second phase, single feed-forward layers are trained with the features extracted from the CNN to predict modulation schemes' CDMA or OFDM schemes. The less computational time and high speed are two essential advantages of single feedforward layers, which trigger the research to predict the modulation schemes.

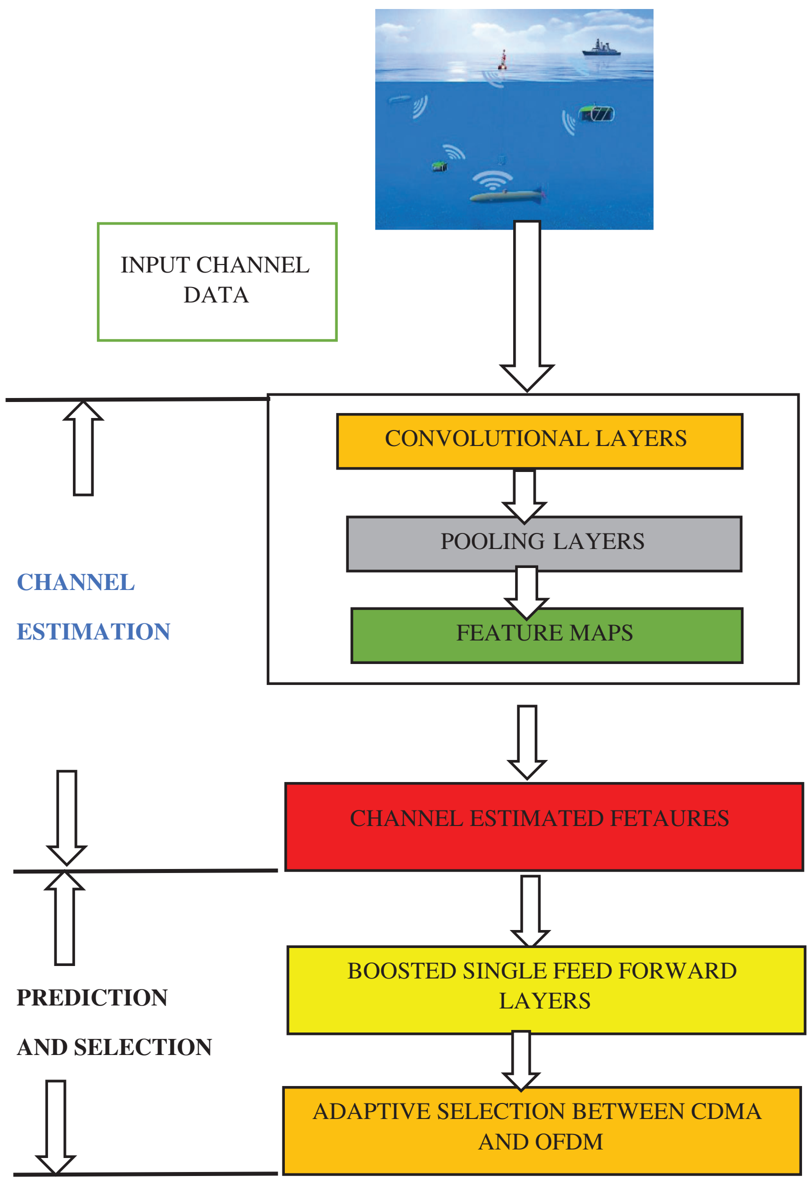


Figure 2: Overall block diagram for the proposed architecture

3.4 Convolutional Neural Networks-An Overview

A convolutional neural network (CNN) is a biologically propelled advancement of Multi-Layer Perceptron MLP. CNN is broadly utilized for picture characterization, picture bunching, and object identification in pictures. They are additionally utilized for optical character acknowledgement and regular language handling. Aside from pictures, when addressed outwardly as a spectrogram, CNNs can likewise be applied to sound. Additionally, CNN's have been applied straightforwardly to message examination, just as in chart information with convolutional diagram networks. The condition of quality craftsmanship proficiency of CNN contrasted with its gauge calculations makes it an accomplishment in numerous fields.

Fig. 3 in CNN shows that the highlights are recognized using otherwise called bits channels. A channel is only a network of qualities, considered loads prepared to distinguish explicit highlights. The reason for the channel is to do the convolution activity, which is a component insightful item and entirety between two networks. The preparation of the CNN is secured by lessening the measure of repetition present in the information. Thus, the measure of memory devoured by the organization is likewise decreased. One basic strategy to accomplish this is max pooling, in which a window disregards input information and the most extreme worth inside the window is pooled into a yield framework. The calculation is made proficient for including extraction by connecting various convolution layers and max-pooling tasks. The information is handled through these deep layers to deliver the element maps, which are at last changed over into an element vector by going through an MLP. It alludes to a fully connected layer that performs undeniable level thinking in the created model.

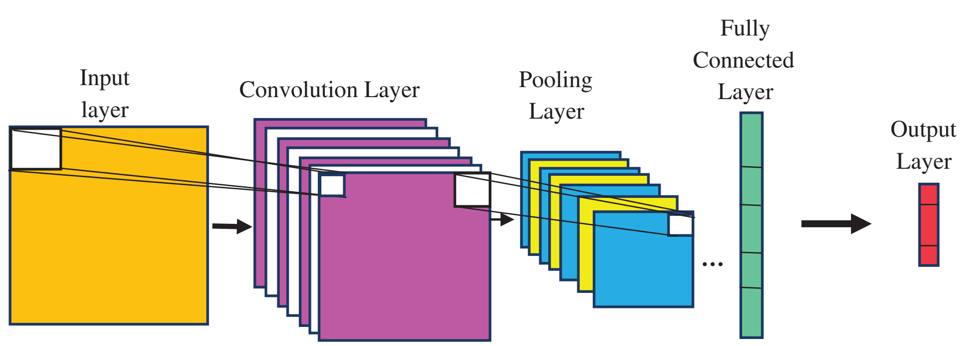


Figure 3: Schematic representation of convolution neural networks

3.5 Ada-Boost Algorithm

In this approach, hybrid ensemble learning algorithms are formed by integrating the LSTM [27] networks with Ada-Boost Learning algorithms. Freund et al. [26] was the first to propose the Ada-Boost algorithm, which strengthens the weak classifiers. Usually, the Ada-boost algorithm strengthens the week classifiers by updating their weights until classification/prediction accuracy is obtained as maximum. The final model is robust when every weak classifier satisfies its performance rather than guessing. The pseudo-code for the ADA-boost, used in a proposed network, is explained next.

Algorithm 1: Pseudo Code for Ada-Boost Algorithm

1 Inputs Samples Training Sets $\{x_i, y_i\}$ where $x = \{x_1, x_2, x_3, x_5 \ldots\ldots x_n\}$ where n = no of input samples and $y_i \in (1, -1)$ where y_i is the label associated with x

2 Initialize D(k) = n

3 For k = 1, 2, 3, …………….K

4 Train the weak classifier using the distribution D_k

5 Calculate the error function, e_k, concerning the function D(k)

6 $e_k = P_r(h_k(x_k$ is not equal to $y_k))$ where h_k is the hypothesis function

7 Choose $\alpha_k = 0.5\ \{\ln(1 - e_k)/e_k\}$ where α_k is the weight of the h_k,

8 Reinitialize the weight with D_{k+1}

9 Calculate the error function and repeat step 5

10 If an error is less than e_k

11 Then the output is calculated by $H(x) = \text{sign}(\sum \alpha_k h_k)$

12 End

13 End

3.6 Proposed Boosted CNN Models

In the proposed, estimated features are trained by the proposed boosted feed-forward layers that replace the traditional backpropagation layers in traditional CNN. The mechanism of feedforward layers is based on the principle of long short-term memory. Fig. 4 shows the architectural diagram for the proposed learning model.

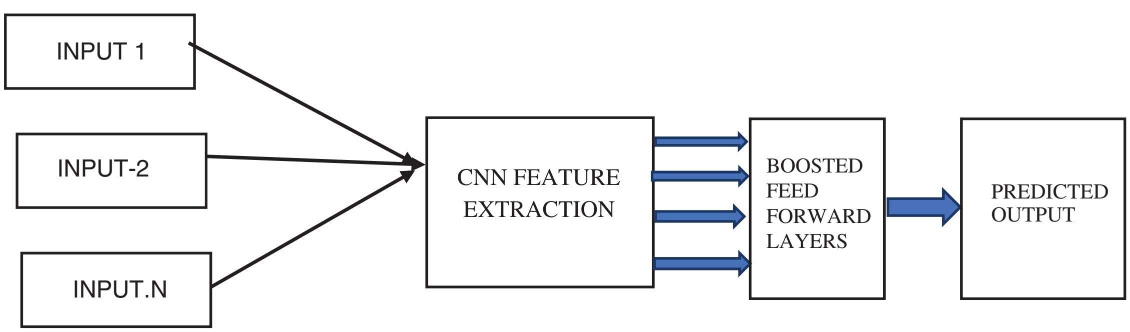


Figure 4: Block diagram for the proposed architecture

The convolutional layer uses six layers, followed by the RELU activation and batch normalization. A selection method between the CDMA, TDMA, and OFDM is developed based on the estimated features. Since this model is used for larger datasets, it maintains less misclassification and high performance. Hence the proposed algorithm uses the boosted feedforward layers to select the different techniques. Since the ADA-boost algorithm is used in the proposed algorithm, accuracy is boosted even after adding larger data samples. The boosted training networks are trained on estimated channel factors with the modulation techniques associated with the CDMA, TDMA, and OFDM mechanisms. The pseudo-code for the proposed algorithm is depicted in Algorithm-2

SL.NO Algorithm-2 // Pseudocode for the Proposed learning model

```
Inputs: Doppler Frequency Shift (fd), Maximum Delay Spread (τm), Signal To Noise Ratio (SNR),
Received Signal Strength (RSSI) and Delay Spread (μ)
Output: Selection of CDMA, OFDM, TDMA
For n = 0 to N − 1 where N is iteration = 1000
    T = Convolutional Layer(τm, SNR, RSSI, fd, μ)
        F = Concatenate (T) where T is Channel Estimated Features
            X = Boosted_FeedForward (F)
  If X == x1       // where x1 = predicted threshold for CDMA at SNR
              //CDMA is predicted, and Selected
 Else if X == x2    // where x2 = predicted threshold for OFDM at SNR
                //OFDM is predicted and selected
  Else
                 // TDMA and Other Technique is selected
End
End
End
```

4 Results and Discussion

Metrics such as accuracy, sensitivity, specificity, recall, and f1-score are calculated to evaluate the performance of the proposed architecture. Tab. 1 shows the mathematical expressions for calculating the metrics used for evaluating the proposed architecture.

Table 1: Mathematical expressions for the performance metrics' calculation

SL.NO	Performance metrics	Mathematical expression
01	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Sensitivity or recall	$\frac{TP}{TP+FN}\times 100$
03	Specificity	$\frac{TN}{TN+FP}$
04	Precision	$\frac{TN}{TP+FP}$
05	F1-Score	$2.\frac{Precison * Recall}{Precision+Recall}$

Note: TP is True Positive Values, TN is True Negative Values, FP is False Positive and FN is False-negative values.

4.1 Parameter Estimation

Tab. 2 presents the underwater acoustic parameters used for the simulations. The datasets were used for the generation of UWA datasets. Nearly 60000 data were used which 70% were used for training and 30% for testing.

Table 2: Underwater channel parameters used for simulations (CDMA)

Sl.NO	UWA specifications	Parameters
01	Number of datasets	60000
02	Maximum delay	0–30 ms
03	Doppler frequency	0–10 Hz
04	SNR	2–12 db
05	RSSI	−40 to −87 dBm
06	Modulations	16-QAM
07	Multiple access technique	CDMA
08	Spreading factors	12
09	Date rate	200 kbps
10	CP length	30 ms
11	Pilot spacing	20
12	Frequency reptation	3 m

The 6000 input samples at the first layer were filtered by 128 convolutional filters with a length of six, followed by ReLu. Zero padding is used for them. After Batch normalization, the same convolution was executed. The optimizer function utilized Adam. L2 kernel regularization with $\beta = 0.001$ was set to prevent over-fitting. The batch size and epoch were 34 and 120, respectively.

Figs. 5 & 6 show the validation curve of the proposed architecture in detecting the modulation techniques. From Fig. 5, it is found that the proposed architecture reaches its maximum accuracy after 200 iterations and remains constant till 1000 iterations. A similar fashion of performance is found in Fig. 6 also. The ROC curves in Fig. 7 of the proposed framework detect the category different multiple access classification effectiveness.

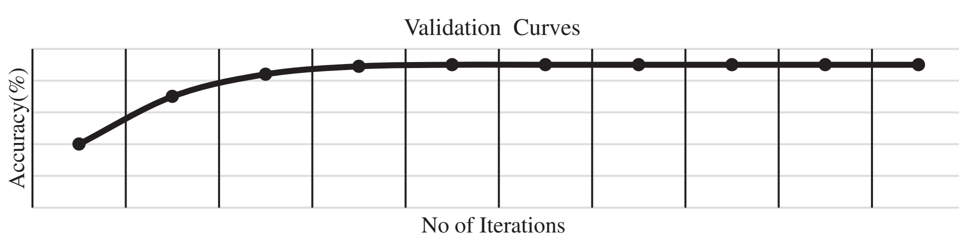


Figure 5: Validation curve for the proposed architecture in detecting the CDMA based modulations

Tabs. 3 and 4 presents the comparative analysis between the performances proposed for 9000 and 12000 samples. From Tab. 5, it is found that the proposed algorithm has shown the accuracy of 98.6%, 100% precision, 99.23% recall, and a high f1score of 98.89% in detecting the CDMA type signals. Also, the proposed algorithm has exhibited similar performance in detecting the OFDM. From the above tables, it is clear that the proposed boosted ensemble algorithm has exhibited consistent performance though the data samples are increased.

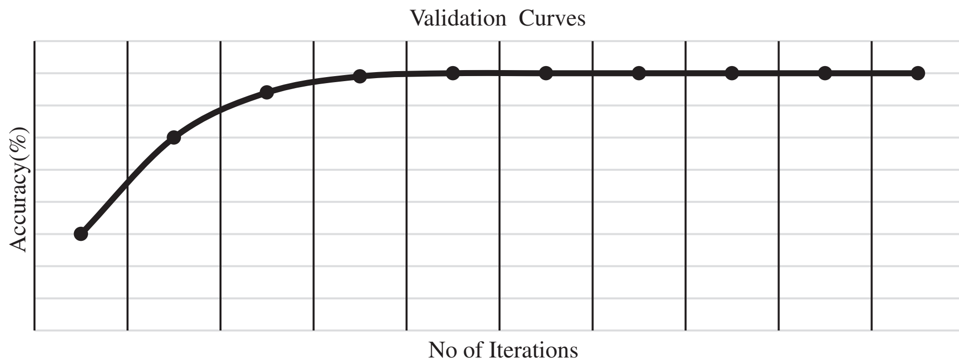
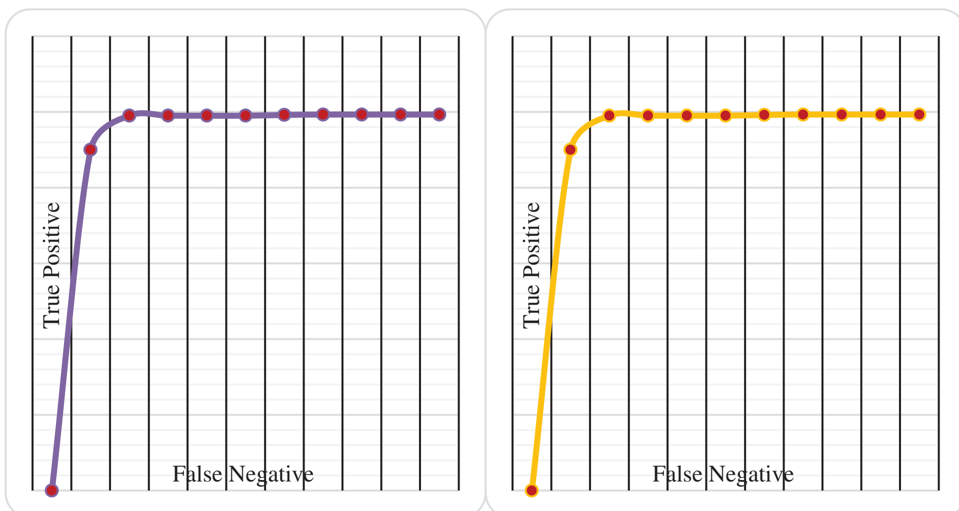


Figure 6: Validation curve for the proposed architecture detecting the OFDM modulation type



(a) (b)

Figure 7: ROC curves for the proposed algorithm (a) CDMA (b) OFDM

Table 3: Performance metrics for the proposed algorithm for the prediction of signals using 9000 samples

Sl.NO	Type of cancer	Performance metrics (%)				
		Accuracy	Precision	Recall	Specificity	F1-score
01	CDMA	98.6%	100	99.2%	97.5%	98.89%
02	OFDM	98.56%	99.4%	99.23%	99.67%	98.90%

Table 4: Performance metrics for the proposed algorithm for the prediction of signals using 12000 samples

Sl.NO	Type of cancer	Performance metrics (%)				
		Accuracy	Precision	Recall	Specificity	F1-score
01	CDMA	98.6%	99.5%	99.2%	97.5%	98.89%
02	OFDM	98.56%	99.4%	99.23%	99.67%	98.90%

Table 5: Performance analysis of different algorithms for detection of modulation under CDMA using 9000 samples

Sl.NO	Algorithm	Performance metrics (%)				
		Accuracy	Precision	Recall	Specificity	F1-score
01	CNN+RF	90%	89.5%	88.5%	88.45%	89.7%1
02	DCNN	84.5%	83.5%	84.5%	82.5%	80.4%
03	Conventional methods	85%	84.3%	83.5%	84%	83.2%
04	Proposed architecture	98.6%	100	99.2%	97.5%	98.89%

4.2 Comparative Analysis

To establish the superiority of the proposed algorithm, we have compared the other existing models, such as CNN+RF [25], traditional deep learning methods, and conventional methods.

In Tab. 6, the proposed method demonstrates 98.6% accuracy, while hybrid CNN+RF shows 90% and conventional methods show 89.5% accuracy. Also, the proposed algorithm's precision and recall shows nearly 100%, and CNN+RF shows 82%, DCNN SHOWS 84.5%, respectively. In Tab. 4, the proposed model shows 98.6% accuracy, 99.5% precision, 99.2% recall, 97.5% specificity, 98.89% F1-score for an increased sample, whereas the other algorithms have shown decreased performance. It is clear from the tables that the proposed hybrid model has shown consistent performances even though the samples are increased and a better selection method.

Table 6: Performance analysis of different algorithms for detection of modulation under CDMA using 12000 samples

Sl.NO	Algorithm	Performance metrics (%)				
		Accuracy	Precision	Recall	Specificity	F1-score
01	CNN+RF	82%	79.5%	78%	75.45%	76%
02	DCNN	75.5%	71%	72%	70%	72%
03	Conventional methods	64%	60%	62.4%	62%	63%
04	Proposed architecture	98.6%	99.5%	99.2%	97.5%	98.89%

Figs.8–10 shows the BER analysis for the different algorithms implemented for the underwater acoustic environment. Fig. 9 shows the BER performances of the different algorithms in handling the 3000 samples and found to have stable BER performance. From Figs. 8 to 10, the proposed algorithm has shown good BER performance even though the samples increase. The enhanced ensembled model's integration into the proposed architecture has reduced the misclassification rate. Implementing the proposed hybrid model has maintained a better BER performance than other algorithms.

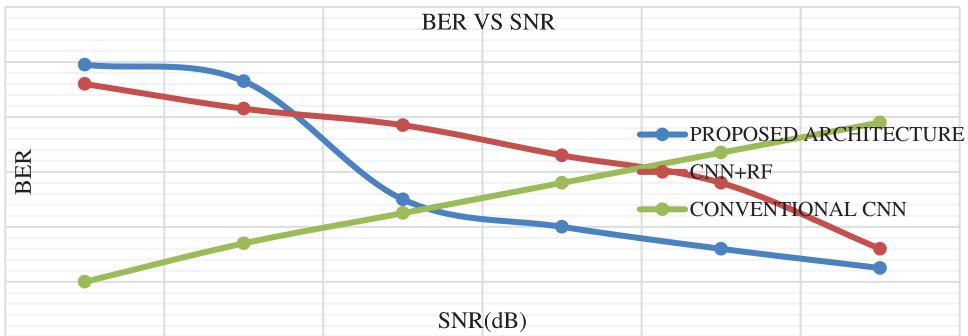


Figure 8: BER and SNR analysis for different algorithms implemented in an underwater receiver environment for 3000 samples

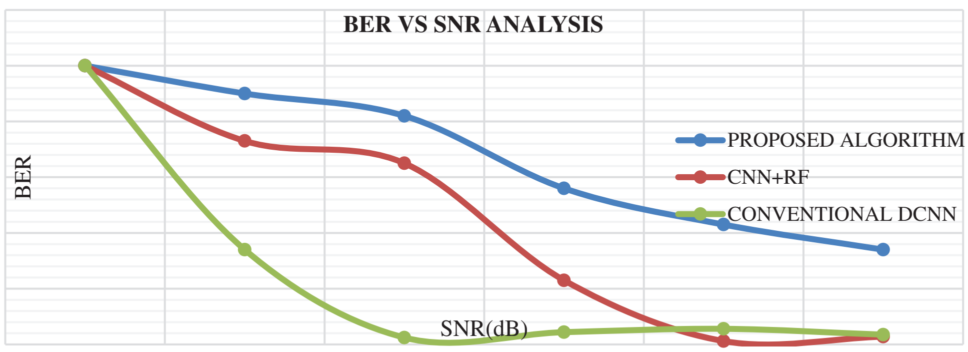


Figure 9: BER and SNR analysis for different algorithms implemented in an underwater receiver environment for 9000 samples

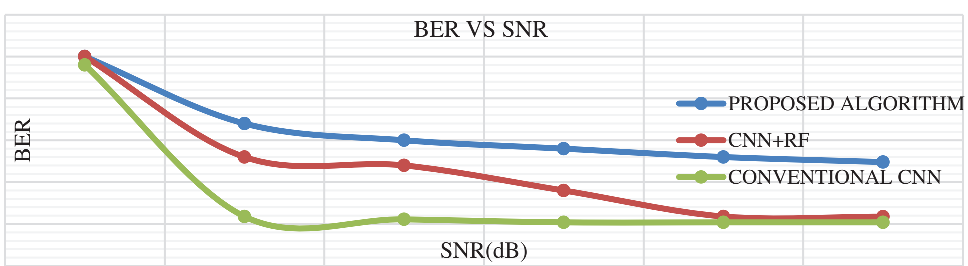


Figure 10: BER and SNR analysis for different algorithms implemented in an underwater receiver environment for 12000 samples

5 Conclusion

This research proposes the hybrid deep learning models to effectively select the CDMA and OFDM modulations to attain the BER performance for dynamic UWA parameters. CNN was utilized to extract the channel features, and boosted ensembled training network was used to predict the modulation schemes to maintain better BER performance. Extensive experimentation is carried out using many samples and compared with other algorithms such as CNN+RF and conventional CNN. The study shows that the proposed algorithm has outperformed the other learning models with less miscalculation rate and better BER performances. Further, the computational complexity of the proposed algorithm needs improvisation for better real-time implementation.

Funding Statement: The authors received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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