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Software Classification and Detection of Communication Signals Using Artificial Neural Networks

Ali Arkan AL-Ezz[1], Nada Sharis[2], Firas M Al-Salb

[1,2] Iraqi Ministry of Education
[3] Al-Nahrain University

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*Correspondence: Ali Arkan AL-Ezz
Email: alialtayer313@gmail.com

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Abstract: Spectrum distribution and channel detection have long been seen as an impending addition to intelligent radios for wireless communications systems with permit-free groups. Standard approaches have been put forth to handle periodic scanning as a signal characterization technique for applications where carrier frequencies and transmission speeds are unclear, despite the fact that it is computationally complex and requires a considerable amount of realization time to implement satisfactorily. Only in situations where the baseband signal is accessible have Artificial Neural Networks (ANN) been used for signal categorization. By combining these processes, a more reliable and efficient classifier might be produced, reducing the need for web-based computation in situations when a large amount of preparation is done separately. In order to test and classify mixed signals of QPSK and MSK modulation under noise, we use a new check-out signal classification method in this study that combines FFT spectral analysis with neural networks. The ANN methodology describes how to provide this method. The results showed that the LM function provided the best outcomes such that probabilities of $\boldsymbol{P_d}$ and $\boldsymbol{P_{fa}}$ have optimal values of 0.991 and 0.005 respectively, with 10 hidden layer neurons number.

Key Words: Artificial Neural Networks (ANN), Wireless Communications, QPSK and MSK modulation, Signal Classification.

Introduction

Rapid channel testing is necessary to assess spectrum accessibility and connection quality as interest in spectrally productive communications frameworks grows. The term "cognitive radio" (CR), which was first used by Joseph Mitola in, has recently attracted a lot of attention in the field of wireless radio design (Viterbi & Omura, 2013). The FCC has expressed interest in the CR concept as a means of resolving spectrum access conflicts brought up by the virtual lack of free directs in unlicensed organizations. The CR's ability to identify, characterize, and adapt to its RF environment is perhaps its most intriguing feature. The ensuing adaptation cycle may be motivated by a few simple goals, such as "limit obstruction" or "augment throughput," or it may even be symbolized by a more complex dynamic interaction (Vapnik, 2013). With the help of these capabilities, a CR may uncover phantom assets that are momentarily underused and activity in approved groups without interfering with permitted administrations. As a result, spectrum detection by CR cannot be limited to only screening the force in certain recurrence groups of interest; instead, it must take into account discovery and distinguishable evidence for requests to avoid blockage (Singh et al., 2017). Late exploration efforts use the cyclostationary highlights of signals as a categorization technique, which has been found to be more effective than coordinated filtering and simple energy identification (Nayak et al., 2015). As a non-intelligent approach, energy recognition is easy to implement and does not need prior knowledge of sign limits, such as transporter recurrence or sign data transfer capacity. However, it is incredibly vulnerable to in-band blocking, which significantly alters commotion levels (Koo & others, 2016). More importantly, an energy finder can only determine whether a signal type is present; it cannot distinguish between different signal types. Furthermore, even though the energy finder is fundamentally prepared to recognize spread spectrum signals, it is insufficient for setting up this type of interface (Jamali & others, 2017a).

Common waveform classification techniques, such as those in, typically take advantage of signal characteristics, such as rapid recurrence, abundance, or stage data, and produce distinct components for each type of tweak by carrying out routine signal handling tasks, such as recording minutes or applying modifications again. The highlights that are generated are then categorized using either an example classification computation or a choice hypothesis-driven technique that leads to various theory testing (Mafarja, 2023). However, in every situation, either a baseband representation or crucial signal preparation steps are needed. Leading work in computerized radio sign location is presented by Spooner and Brown in their method, which considers the categorization of a vast number of balancing kinds, makes use of the second, just as large, request time variation, sporadic cumulative capabilities (Jamali & others, 2017b). In this study, we use a similar method from a phantom connection perspective to classify a recharged check-out signal. We suggest using neural networks to do the categorization after preprocessing in order to overcome classification problems where the sign's transporter and transfer speeds are unclear. Our results confirm that neural networks, which have long been regarded for design acknowledgment and adjustment categorization, are robust to a variety of situations, including commotion and interfering indications (Jamali & others, 2016).

Methodology

The research methodology connects signal processing techniques with artificial intelligence to perform Artificial Neural Network (ANN) classification of communication signals. A simulation of actual communication environments involved subjecting QPSK and MSK modulated signals to additive noise before generating the signals. Neural network input vectors originated from spectral features obtained by processing these signals with a band-pass filter followed by Fast Fourier Transform (FFT) evaluation (Gholamhosseinian, 2021). The evaluation of classification accuracy depended on adjustments in the FFT length.

Model architecture used a multi-layer perceptron (MLP) for which multiple hidden layer neuron configurations were tested to find the most suitable structure (N. Farsad & others, 2013). MATLAB's Neural Network Toolbox includes the implementation of two learning algorithms namely Levenberg-Marquardt (LM) and Scaled Conjugate Gradient (SCG) for comparison purposes. The ANN evaluation process depended on its success rate for signal categorization between H_0 and H_1 groups where detection probability (Pd) and false alarm rate (Pfa) served as the key assessment metrics. Supervised learning served the training process by monitoring mean squared error (MSE) and gradient values together with validation failures and receiver operating characteristics (ROC). The simulation kept uniform evaluation parameters for maximum epochs together with performance criteria and validation protocol verification. The network displayed its best performance through LM algorithm in combination with 10 hidden neurons resulting in Pd = 0.991 and Pfa = 0.005. This analytical system proofed that ANN technology integrated with spectral analysis enables successful signal classification under noise conditions thus providing an expandable tool for cognitive radio frameworks (Srinivas & others, 2012).

Result and Discussion

The Neural Networks Structure

The biological neuron

One remarkable biological cell that measures information is the biological neuron. According to, the human brain has an enormous number of neurons—roughly 1011—with each neuron being connected to 103–104 other neurons. A typical neuron is essentially made up of the three portions that are shown in Figure 1:

a. The dendrites, which are the contributions of the neuron, gather the electrical data from the sensory system (Goodfellow et al., 2016).
b. The component which interprets such data also returns an electronic message indicating the kind of drive.
c. The axon that transmits the active sign to nearby neurons.

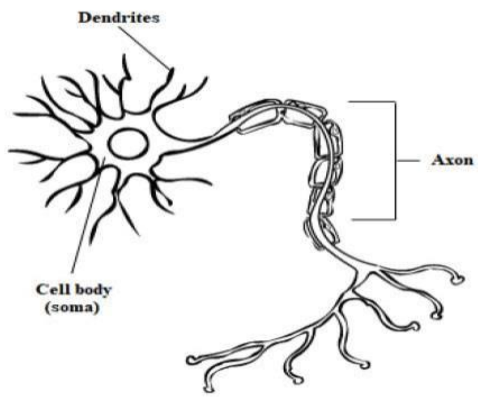

Figure 1.
The biological neuron structure

Neurons Structure

Figure 2 shows a formal neuron, which is a numerical capacity that is thought of as a biological neuron model. The basic building blocks of a fictitious neural network are called formal neurons. The total numerical model of a formal neuron is covered in the accompanying graphic (Farsad & others, 2017):

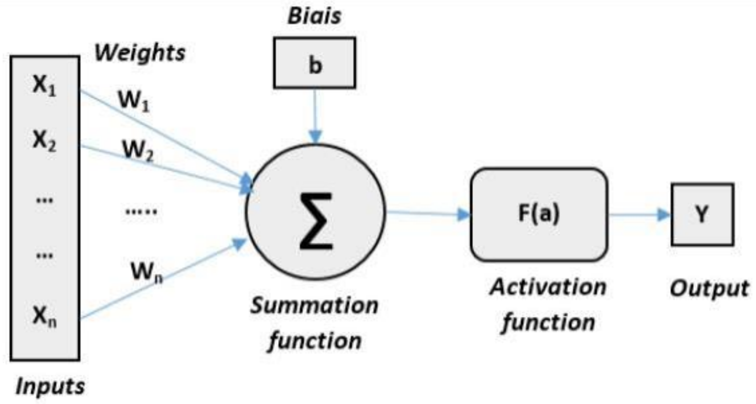

Figure 2:
Numerical model of the formal neuron.

The n inputs of the formal neuron shown in the above picture are denoted by the symbols $\{X_1, X_2, \ldots, Xn\}$. A weight denoted by $\{W_1, W_2, \ldots, Wn\}$ is assigned to each line that interfaces these contributions to the summation intersection. The following is how to find the net info yin (Fouladi, 2021).:

$$y_{in} = x_1.w_1 + x_2.w_2 + \cdots + x_n w_n + b \quad (1)$$

The work of enactment (a) is an essential component of a neuron. Limit work, direct capacity, sigmoid capacity, and so on are examples of initiation capacities. Because of its nonlinearity, which allows for the inexact calculation of any capacity, we have chosen to use a sigmoid capacity in our study (figure 3). Finally, the following recipe provides the neuron's yield $\boldsymbol{y}$ (Cao & others, 2014):

$$\mathrm{y} = F(y_{in}) \sum w_i * x_i + b \quad (2)$$

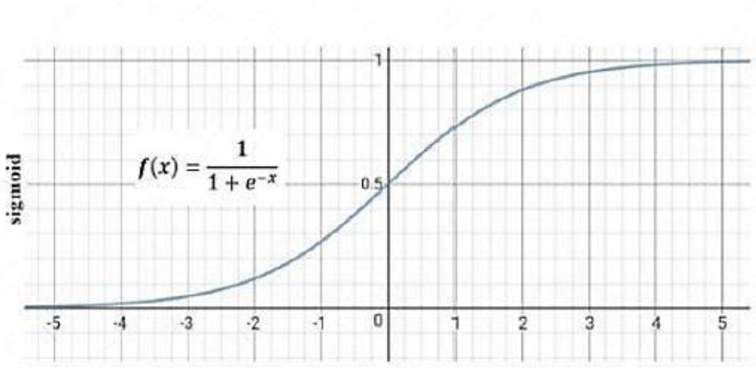

Figure 3:
Demonstration of the sigmoid function.

Multi-Layer Perceptron

One type of feed-forward synthetic neural network with about three hub layers is the multi-facet perceptron (MLP) (figure 4). From a variety of data sources $\{X1,2,\ldots,X\text{n}\}$, it generates a number of yields $\{y_1, y_2, \ldots, y_m\}$. Every hub, save for the information hubs, is a neuron that makes use of a nonlinear initiation work (N. Farsad & others, 2013)

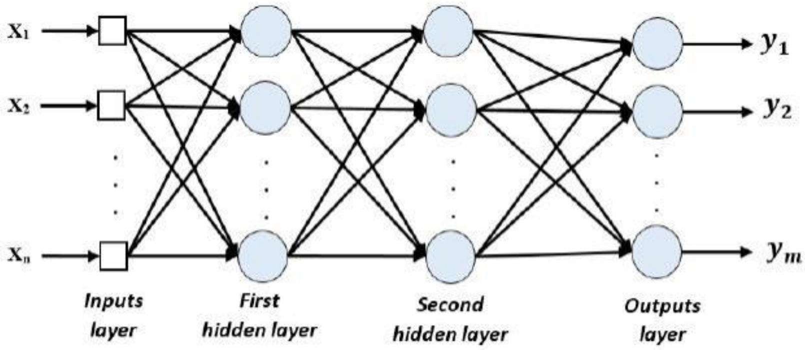

Figure 4:
Block diagram of MLP model.

A neural network with learning capabilities is set up with information and target pair designs. Information that isn't immediately identifiable might be separated out using MLP. The propagation (BP) method, is a supervised learning approach, which is specifically used to prepare it. Its goal is to restrict the global error calculated at the yield layer by the connection problems (D. P. N. Farsad & Goldsmith, 2017) :

$$(t)= y_d\,(t) - y_m\,(t) \qquad (3)$$

Such that, $y(t)$ denotes the ideal outcome, and $y_m\,(t)$ indicates the calculated neuron result. The MLP is created using a number of predetermined sources of information and yields in the BP algorithm's iterative supervised learning method. The global error Equation (4) determines $E\text{g}\,(t)$; the gradient descent approach can reduce this error (Zainudin, 2023).

$$(t)=\frac{1}{2}\sum_{i=1}^{n}\left(y_{d,i}(t) - y_{m,i}(t)\right)^2 \qquad (4)$$

In this paper, we will present a subjective comparison between two preparing algorithms, semi newton and form slope, where the pre-owned preparing capacities are separately train-lm (Levenberg Marquardt (LM)) and train-scg (Scaled Conjugate Gradient (SCG)). A few preparing algorithms might be utilized for the MLP network training (Elrharras et al., 2016).

Implementation of Neural Networks

The artificial neural networks (ANNs) have been suggested as finders for range detecting (Figure 5), the ANN detection section engineering is comparative to the ED indicator in which the power estimation block is supplanted by an ANN model as presented in (Figure 6) (Sangodoyin, 2021).

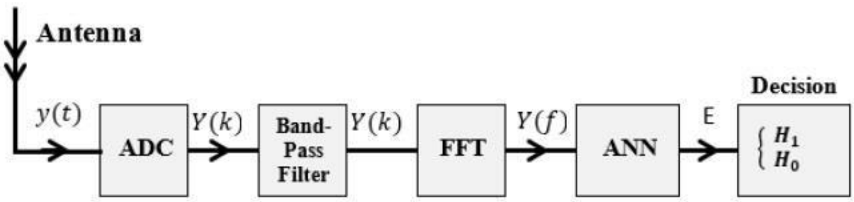

Figure 5:
Block diagram of ANN location outline.

The data layer neurons sum, n, is fixed by the value of foci (highlights) in the FFT vector collected waveform, and it may be 1024. Additionally, one might employ single neuron in the yield layer (either $H0$ or $H1$) (Elrharras et al., 2014):

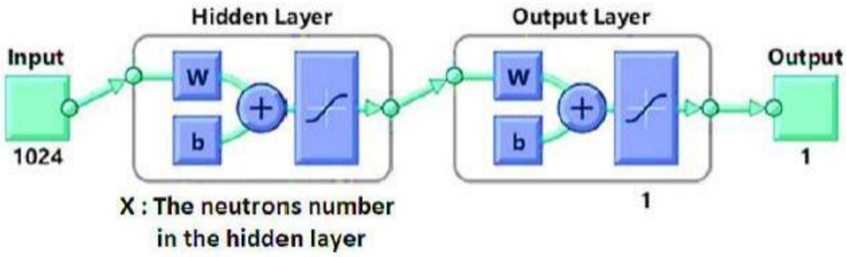

Figure 6.
Structure of the ANN architecture.

The exhibition of an energy finder can be described utilizing two probabilities: Pd the likelihood of recognition and P_{fa} the bogus caution likelihood. The likelihood of identifying a sign in the interest frequency, whenever such signal is really introduced (H_1). Bombed location produces impedance against the PU. The value ofP_d might be determined using the following formula (Dahlman & others, 2013):

$$p_d = p\,(\,Decition\ \frac{H_1}{H_1}) = \frac{N_c}{N} \times 100\% \tag{5}$$

Where, P_{fa} is the likelihood since the examination dishonestly concludes that the interest frequency is involved, whereas it is free (H_0). The range productivity might be minimized through employing the false alarm. We used the equation to calculate P_{fa} (Cao & others, 2014):

$$p_{fa} = p\,(\,Decition\ \frac{H_1}{H0}) = \frac{N_e}{N} \times 100\% \tag{6}$$

Where:

N_c is the occasions in which the waveforms is distinguished, while H_1;
N_e is the occasions in which the waveforms is distinguished, while H_0;
N is the quantity of the caught waveforms.

Simulation Results

Typically, supervised learning strategies consist of two basic phases: order and preparation/learning. We have cautiously tested a few structures along various secret layer sizes for every preparatory job in order to find the utmost useful number of neurons in the secret layer(Benmammar et al., 2017). The mean squared error (MSE) will be employed to quantify preparation errors. Our network has been assembled and prepared using MATLAB Neural Network Toolbox. Every preparation task has the following fixed parameters: execution goal=0, time=Inf, min_grad=1e^{-010}, max_fail=10, 1000 greatest preparing ages, and six approval checks. The results obtained for different preparation capabilities with different architectures are summarized in Table 1 (Bonin, 2023).

Table 2:
Detection with false alarm Probabilities when examining of ANN trainer

Hidden Layer Neurons Number	**Employed Training Function**	P_d	P_{fa}
3	LM	0.974	0.018
	SCG	0.992	0.012
10	**LM**	**0.991**	**0.005**
	SCG	0.975	0.0210

According to the results, the preparatory job 'train_lm' with eight secret neurons yields the best presentation. The accompanying table introduces the probabilities P_d and P_{fa}.

Table 3:
The ANN learning false alarm probabilities detection

P_d	P_{fa}
0.991	0.005

In this research, tow modulated signals have been examined, the QPSK as well the MSK. The modulated signals have been simulated using MatLab2020 m. files. Also, the detection and processing system illustrated in Figure 5 has been simulated with ANN technique (Sumbul, 2021). The received modulated signals have been mixed and filtered using band pass filter (BPF), then processed by FFT function using different FFT lengths. The job of the FFT function is to show the spectral components of the entered signals. Finally, the ANN algorithm will be learned using scaled conjugate gradient SCG and least mean LM as an activation function to search for the optimal energy values in order to find the final decision of the type of the entered signal. The results of the simulation are shown in the following figures (Srinivas & others, 2012).

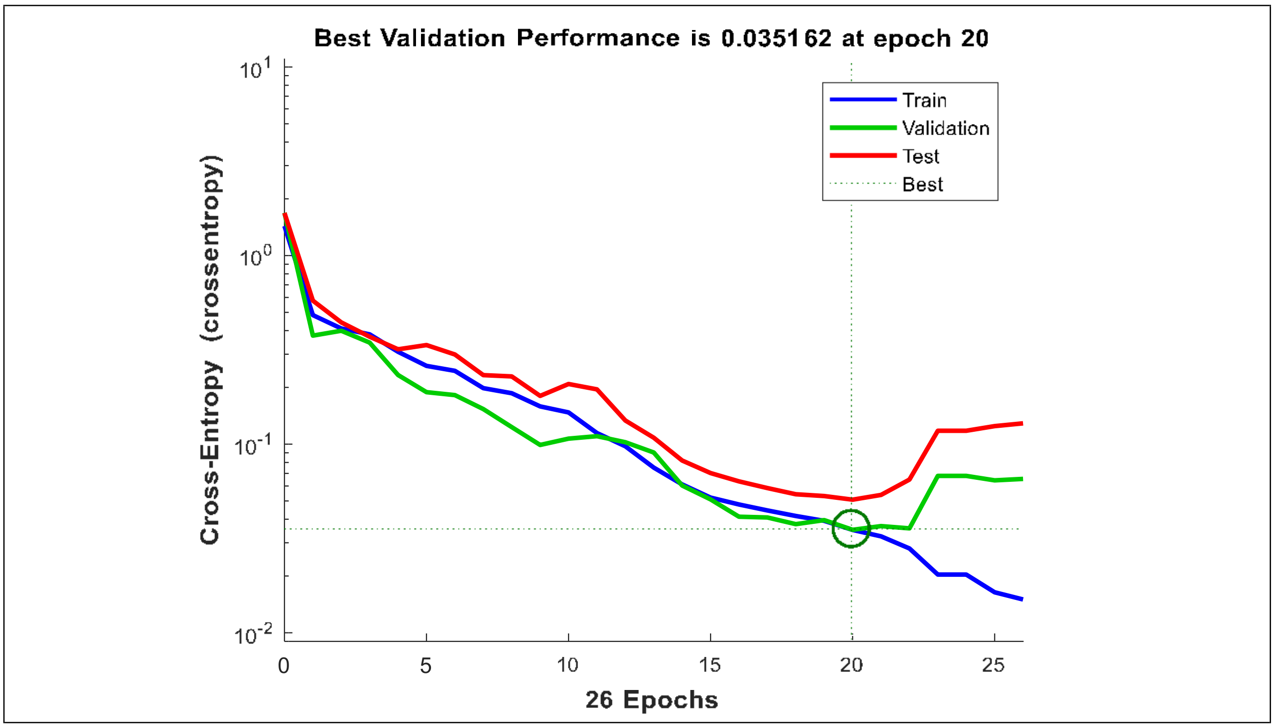

Figure 7.
Results of the ANN test signals Cross-Entropy performance.

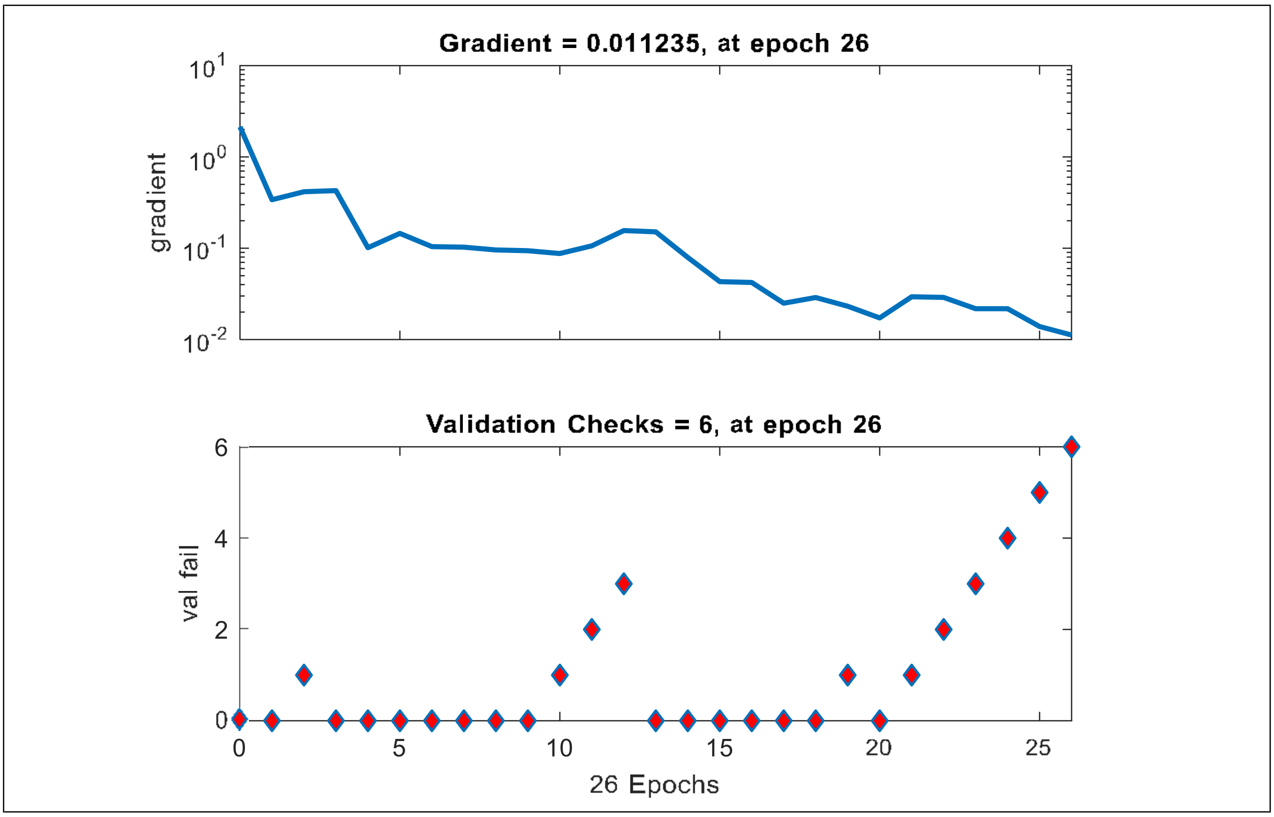

Figure 8.
Results of the ANN gradient and val-fail training state.

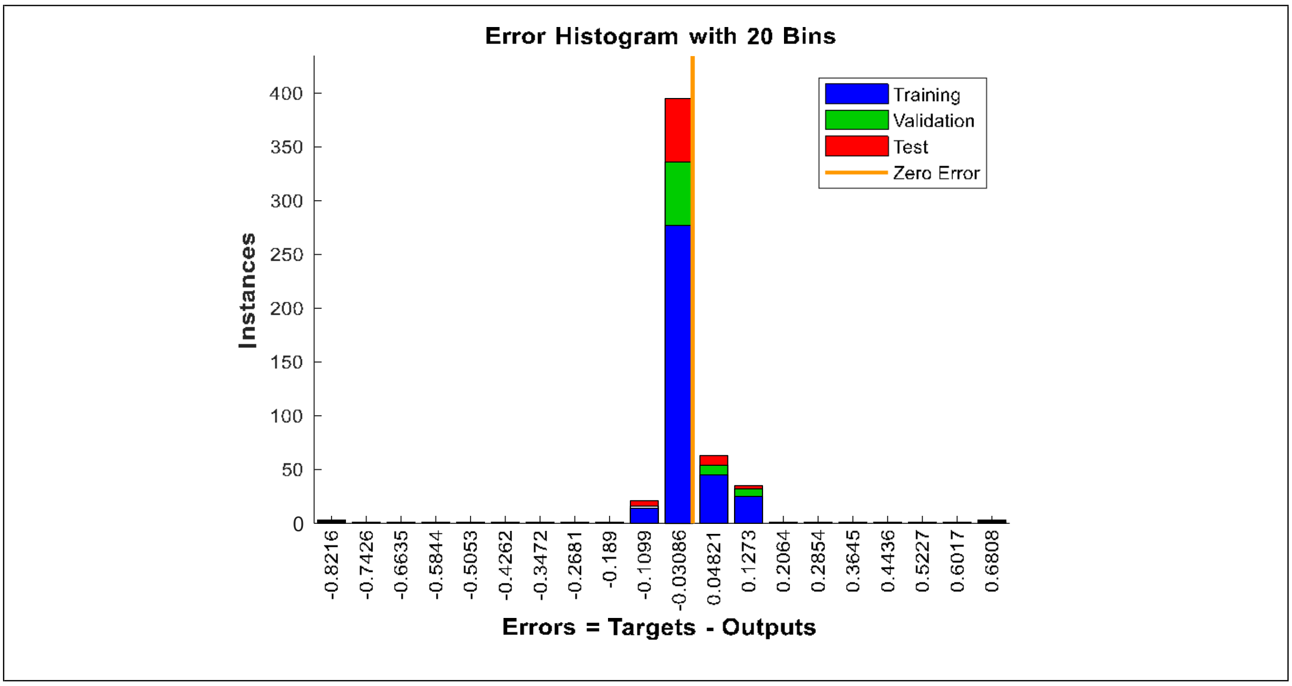

Figure 9.
Results of the ANN error histogram.

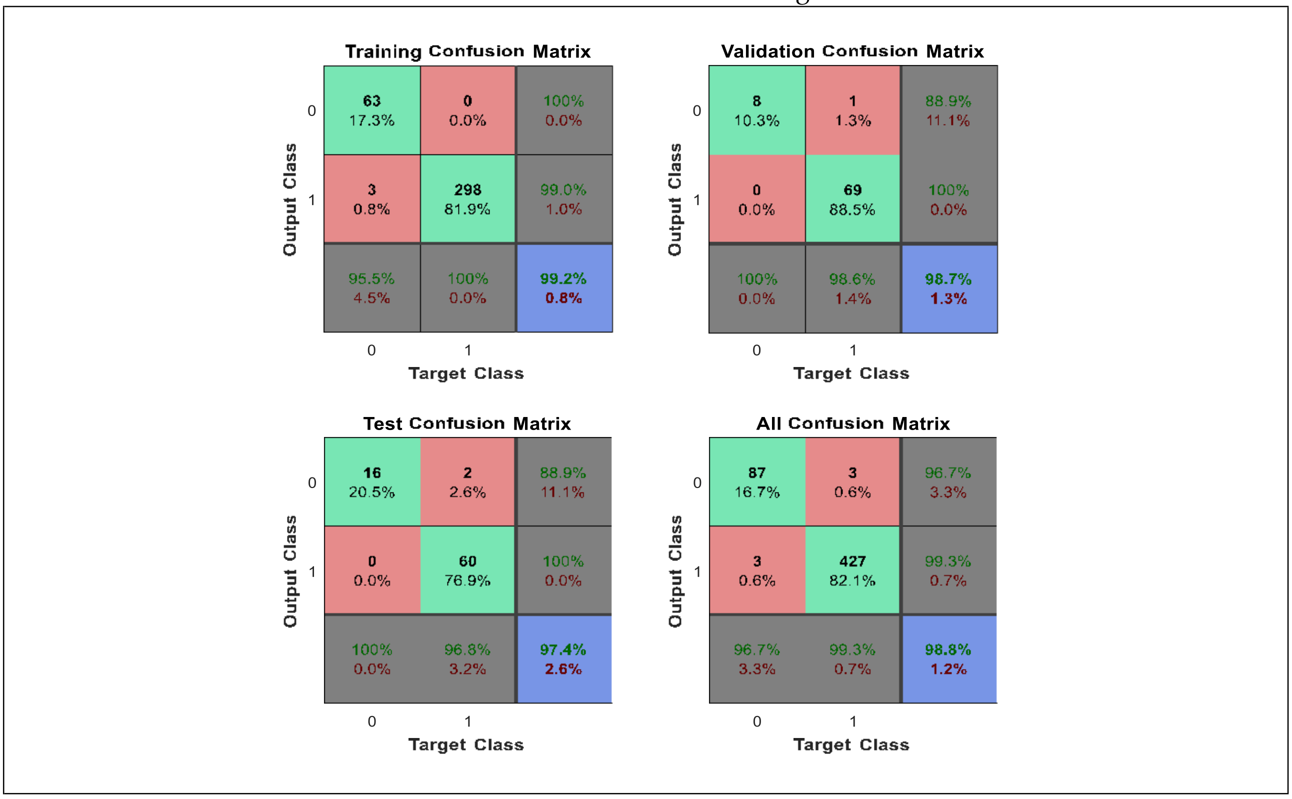

Figure 10.
Confusion matrices of the training, validation, and test training.

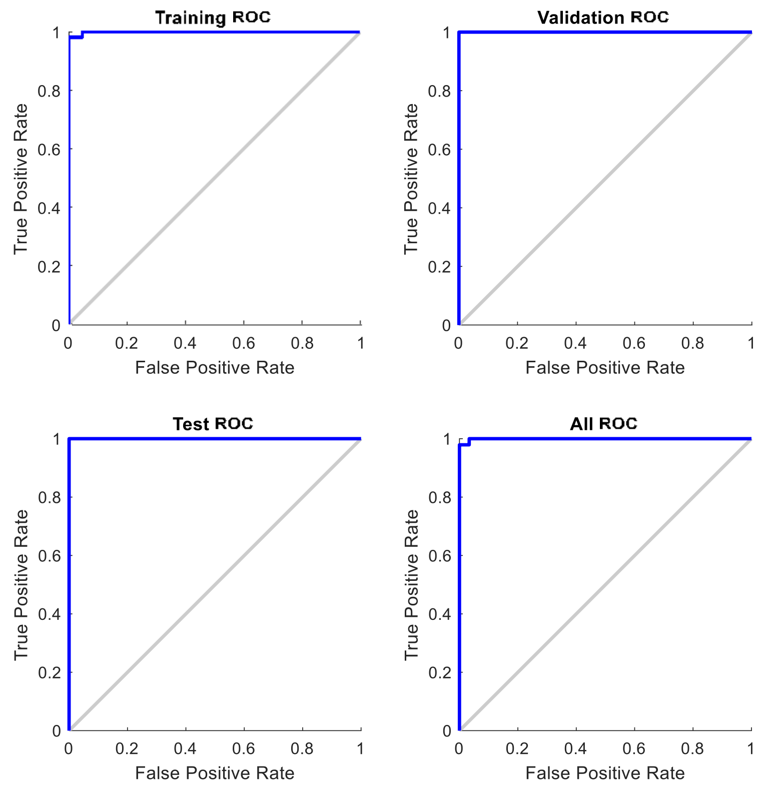

Figure 11:
Results of the ANN receiver operating characteristics

Conclusion

The present study employs Artificial Neural Networks (ANN) for signal classification. To examine and classify composed waveforms of QPSK and MSK modulation with the effect of noise, we employ a reestablished check out signal classification with the aid of FFT spectral investigations and neural networks. ANN algorithm is employed to perform complex calculations in this study. By utilizing two different activation functions the scaled conjugate gradient SCG and least mean LM functions, the training of the mixed signals have been simulated and the results showed that the LM function provided the best outcomes such that probabilities of $\boldsymbol{P_d}$ and $\boldsymbol{P_{fa}}$ have optimal values of 0.991 and 0.005 respectively, with 10 hidden layer neurons number. Actually, several classifications techniques, such as SVM, KNN, and spectral energy detection algorithms might be used to perform the same task.

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