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Improved quantum inspired evolution algorithm with ResNet50 for spectrum sensing in cognitive radio networks

Srikantha Kandhgal Mochigar[1,2], Rohitha Ujjini Matad[1]
[1]Department of Electronics and Communication Engineering, Proudhadevaraya Institute of Technology, Affiliated to Visvesvaraya Technological University, Belagavi, India
[2]Department of Electronics and Communication Engineering, Ballari Institute of Technology and Management Ballari, Affiliated to Visvesvaraya Technological University, Belagavi, India

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ABSTRACT

Spectrum is considered one of the most highly regulated and limited natural resources. Cognitive radio (CR) relies on cutting-edge technology which helps to rectify the issues related to spectrum shortage in wireless communication systems. The CR technology allows the secondary user to accomplish the process related to spectrum sensing for identifying the usage of spectrum in the cognitive radio network (CRN). Though various spectrum sensing approaches are introduced, they exhibit complexity during spectrum sensing. To overcome the issues related to spectrum sensing and utilization, this research introduces improved quantum inspired evolution (IQISE) algorithm with ResNet 50 architecture. The IQISE-ResNet 50 which helps to enhance the spectrum efficiency is used in spectrum sensing. The detection of occupied and unoccupied users in CRN is performed using ResNet 50 architecture, while the IQISE is utilized in the process of training the model and optimizing the weights to enhance spectrum sensing efficiency. The experimental results show that the results achieved by the proposed approach are more effective than S-QRNN and honey badger remora optimization-based AlexNet (HBRO-based AlexNet). For example, the probability of correct classification of the proposed approach at -10 dB for binary phase shift keying (BPSK) modulation is 0.55, whereas the S-QRNN achieves an accuracy of 0.49.

Corresponding Author:

Srikantha Kandhgal Mochigar
Department of Electronics and Communication Engineering, Proudhadevaraya Institute of Technology
Affiliated to Visvesvaraya Technological University
Belagavi-590018, Karnataka, India
Email: srikanthkm2019@gmail.com

1. INTRODUCTION

The fastest expansion of wireless applications often raises requirements for additional data rates, implementing fixed properties and to test allocation of spectrum. To successfully enhance stationary spectrum utilization regulations, the beneficial characteristics of cognitive radio (CR) using the dynamic spectrum are established [1]. CR is a kind of significant approach that is optimizable based on spectrum and addresses the problem of spectrum scarcity [2]-[4]. The CR examines the spectrum and its backdrops during the usage of radio parameters. CR intelligently maintains an active response in the radio environment around it [5]. The CR detects primary user (PU) channels and adjusts internal conditions such as carrier frequency, modulation strategy, and transferring power to ensure reliable communication in the face of random deviations in incoming radio frequency stimulation [6]. The primary network has a licensed user known as the PU using quality of service (QoS) requirement on a similar spectrum, where the PU works and secondary users (SU) are confronted with some new challenges.

A CR user (CRU) does not have licensed accessibility to a specified channel, so it must rely on a temporally free PU to communicate [7], [8]. The SU's communication is disrupted by PU. There are many challenges like the prevention of interference, QoS difficulties, and unified communication which are acute constraints in the CRN [9], [10]. The CRN is entirely responsible for spectrum sensing and spectrum management/decision. Spectrum sensing is an important function for PU that perform on the basis of sensing spectrum [11]-[13]. Spectrum sensing methods are classified based on time or frequency domain [14], [15]. Spectrum sensing techniques are classified based on whether they are wideband or narrowband. However, it is noticed that the narrowband sensing technique identifies the presence of individual channel [16]. The detection of a single channel is used to evaluate the presence and absence of radio spectrum. The existing spectrum sensing technqiues face problems due to the hidden terminals and uncertainities. In addition, the existing techniuqes provide poor accuracy due to inappropriate training and validation [17]. So, this study uses a deep learning approach to conduct an effective research and the model is trained using an optimization technique by optimizing the weights. The recent researches based on spectrum sensing in cognitive WSNs are discussed below along with their advantages and limitations.

Gomaa *et al.* [18] introduced a hybrid framework to detect the cooperative CR using additive wavelet transform (AWT) and haar discrete wavelet transform (HDWT) along with homomorphic decomposition to diminish the noise before the decision-making process. The hybrid framework was evaluated with the fusion rules based on cooperative spectrum sensing with a fixed time. Moreover, the enhancement performed using the hybrid framework helped to minimize the noise of primary signals and achieve high throughput with minimal error. However, the fusion of HDWT alone was not appropriate for spectrum sensing.

Budati and Valiveti [19] developed a matched filter detection approach along with a dynamic threshold with the help of the generalized likelihood ratio test (GLRT) and nyman pearson (NP). The suggested approach enhanced the probability detection and minimized the missed detection rate along with the false alarm rate. The sensitivity of the receiver in the suggested approach was higher, offering better efficiency. However, the false detection occured for varying threshold values in this model.

Usman *et al.* [20] developed an additive white gaussian noise (AWGN) model based on false alarm probability, detection, and miss detection probability. The simulation plots of AWGN were based on the entropy-based approach which helped to improvise the spectrum sensing at lower signal-to-noise ratios. The entropy approach utilized in this research was based on the discrete Gaussian distribution function due to its ability of energy measurement ratio. The efficiency of the suggested framework was based on the signal-to-noise ratio and the probability of a false alarm rate. Nonetheless, the randomization of threshold values tended to diminish the efficiency of detecting false alarm rates.

Bani and Kulkarni [21] developed a hybrid spectrum sensing approach using a hybrid detector (HD) based on a matched detector (MD) and energy detector (ED). The HD worked on both conditions based on the presence and absence of PU. The evaluation of the HD model took place in the environment related to the Rayleigh fading channel. The parameters such as a probability of false alarm and SNR were considered while detecting the spectrum. Nevertheless, the hybrid framework required the whole information of the PU to sense the spectrum signals.

Ahmed *et al.* [22] introduced optimal spectrum sensing in multiple input multiple output (MIMO) based cognitive radio wireless sensor networks (CR-WSN). Initially, the estimator correlator detector (ECD) and generalized likelihood detector (GLD) were utilized in identifying the uncertainities. Next to this, a composite hypothesis detector (CHD) was developed to detect the unknown and uncertain noise statistics. Nonetheless, the suggested approach faced issues related to hidden terminals and uncertainties.

Ghasemzadeh *et al.* [23] introduced a stacking quasi-recurrent neural network (S-QRNN) for high efficient automatic modulation classifier for CR internet of things (IoT). The S-QRNN layers were utilized in the stage of feature extraction which provided low latency with minimal recurrent pooling. The dense layers among two consecutive QRNN layers helped to maintain the efficiency of the classifier’s performance. The dense layers among two consecutive QRNNs were implemented to regulate the growth rate with minimal complexity. Nevertheless, the execution latency of the suggested approach was comparably higher due to inappropriate training and validation.

Dewangan *et al.* [24] introduced honey badger remora optimization-based AlexNet (HBRO-based AlexNet) for spectrum sensing. The suggested framework helped to enhance the spectrum efficiency based on licensed spectrum bands in SU while the PU were in the inactive stage. HBRO was the combination of the honey badger algorithm (HBA) and the remora optimization algorithm (ROA) which was used in the process of training the HBRO algorithm. But, the framework experienced temporal complexities while achieving higher performance.

Overall, the existing approaches based on cognitive spectrum sensing faced issues due to the presence of hidden terminals and uncertainties. Moreover, the existing approaches faced issues due to inappropriate training and validation. So, this research introduced an effective spectrum sensing approach using optimization-based ResNet 50 in CR to build a spectrum sensing mechanism, thereby overcoming the issues in existing techniques. In addition, the suggested framework overcame the issues faced by centralized or decentralized techniques such as ED, cyclostationary detectors, or MD. The major findings of this research are as follows:

– This research introduced an effective spectrum sensing approach using improved quantum inspired evolution (IQISE)-ResNet 50 in the CRN environment. The ResNet 50 is used to classify whether the user is occupied or unoccupied in CRN, whereas the IQISE algorithm is used to train the ResNet 50 and optimize the weights to enhance the spectrum sensing efficiency.
– The evaluation of proposed model is performed using DEEPSIG dataset by considering the probability of detection and probability of false alarm rate for Rayleigh and Rician channels.

The rest of the paper is organized as follows: section 2 presents the proposed approach. The results and analysis are presented in section 3 and the conclusion of this research is presented in section 4.

2. IQISE-BASED RESNET FOR SPECTRUM SENSING IN COGNITIVE RADIO NETWORK

This research introduces an IQISE-based ResNet in a CRN environment to sense the cognitive spectrum. The spectrum sensing technique is utilized to detect the empty spectrum which acts as a significant component of CRN. The architecture of ResNet 50 [25] is used to detect the spectrum and IQISE algorithm to train the model and optimize the weights. The schematic representation of IQISE-based ResNet is presented in Figure 1.

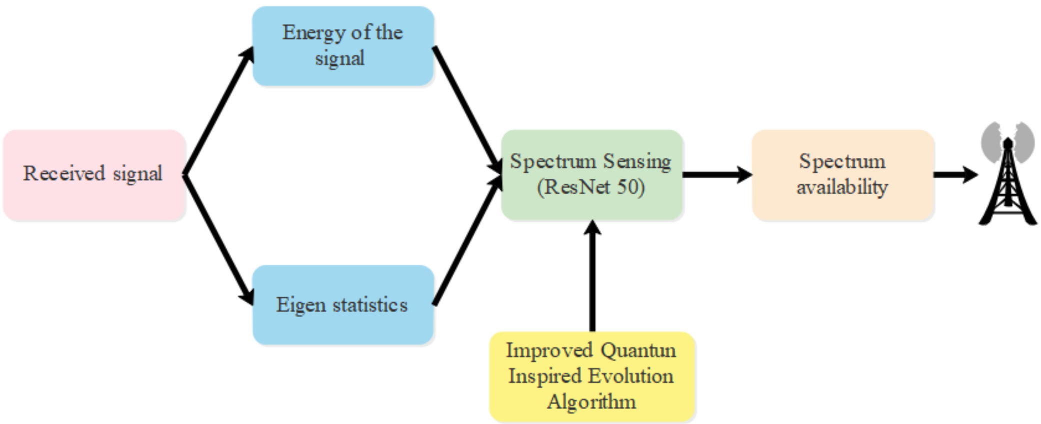

Figure 1. Schematic representation of IQISE based ResNet

2.1. System model

The CR framework considered in this research is made up of s transmitters and x receivers which are known as sensors because transmitters are involved in transmitting signals. Data communication among s transmitters and x receivers occurs in CRN environment via radio channels. To perform transmission, it is necessary to determine if any channel is available for communication in CR. As a result, CR searches for free channels, and when one is found, the connection is established in CR. This research introduces the IQISE algorithm with ResNet architecture to identify the channel availability. The suggested framework determines the channel's availability based on the energy of signal and Eigen statistics. Therefore, the matrix A is modeled by samples obtained at the receiver as presented in (1):

$$A = [A_{uv}]_{a\times b} \tag{1}$$

Where, the vth data sample received by uth sensor is represented as A_{uv}.

But, the gain acquires the channel, noises and signals broadcasted rely as a factor to determine matrix A. The signals that are transmitted are organized as a signal matrix which is represented as X, presented in (2):

$$X = [X_{cv}]_{s \times b} \quad (2)$$

Where, the total count of transmitters is denoted as s, the signal achieved using c transmitter is represented as X_{cv} and the total data sample is denoted as b. The transmission completed by radio channels is performed with the help of a band that is unoccupied.

Along with the covariance matrix, the energy of the signal along with Eigen statistics are evaluated from the signal, provided as input to the ResNet architecture to validate the availability of input and the energy statistics. The Eigenvalue of the covariance matrix is represented in (3):

$$\{K_1 \geq K_2 \geq \cdots K_a\} \quad (3)$$

The energy statistics are represented in (4):

$$K = \frac{K_1}{\frac{1}{a}\sum_{u=1}^{a} K_u} \quad (4)$$

Where, the Eigenvalue of uth sensor is represented as K_u and the Eigen statistics are represented in (5):

$$L = \frac{1}{s \times v^2} \sum_{u=1}^{a} K_u \quad (5)$$

Where, the noise factor is represented as v.

2.2. Spectrum sensing using ResNet-50

During the phase of spectrum sensing [26], the SU identifies the availability of resources to minimize interference and enhance the usage of spectrum resources in CR. This study utilizes ResNet 50 architecture to distinguish the availability of spectrum in the network. The architecture of ResNet is presented in Figure 2.

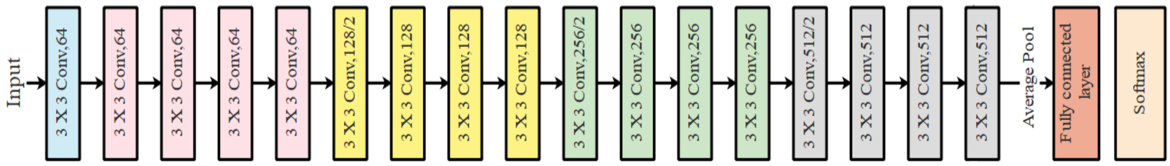

Figure 2. Architecture of ResNet 50

ResNet-50 design has 50 layers in five blocks. The residual function, F, for each of these blocks has three convolution layers with the dimensions (1 × 1), (3 × 3), and (1 × 1), respectively. This block's output Z is derived by averaging its input x and residual function F as shown in (6). The weight matrix W_i of three successive convolution layers is updated by F on x. The input image I which has the shape (84 × 84 × 3) is used to extract features provided to ResNet-50, while the output of $conv5\_block3\_out\_layer$, $ResNet_{conv5\_block3\_out\_layer}$ is employed for the final classification. $ResNet_{feature\_texture}$ is formerly converted using a flattened layer to produce 1D vector output of Y_{ResNet} that is demarcated in (7) and (8), correspondingly.

$$Z = F(x, W_i) + x \quad (6)$$

$$ResNet_{feature\_texture} = ResNet_{conv5\_block3\_out\_layer(I)} \quad (7)$$

$$Y_{ResNet} = flatten\,(ResNet_{feature\_texture}) \quad (8)$$

The deep neural network classifier's functional design uses the extracted feature to predict a class. The concatenation of the two features is done after taking the features from separate models. As a result, the concatenation layer creates a single one-dimensional hybrid feature vector called Y_{Hybrid} which is given in (9):

$$Y_{Hybrid} = concatenate\ (Y_{Inception}, Y_{ResNet},) \tag{9}$$

The energy of signal K and Eigen statistics L are provided as input for ResNet for spectrum sensing in CR. The output achieved through ResNet-50 is represented as R.

2.2.1. Training ResNet-50 using IQISE

In this article, the multi methods of standard normal distribution, Mexh wavelet function, and adaptive quantum state update are utilized to enhance the low search ability and difficulty in determining QDE. The IQISE utilizes the Mesh wavelet function to prevent mutation coefficient fall into the local optima and ensure diversity. The quantum Non-gate mutation is utilized to mutate quantum chromosomes to retain memory in its optimal position.

a. Mexh wavelet based on mutation co-efficient

The mutation coefficient F_0 acts as the significant factor where the Mexh wavelet function helps to maintain population diversity and speed up convergence. The Gauss function's second derivative is Mexican Hat. Mexh wavelet improves the localization properties that minimize the CR, the localized search is performed around the parent population which is useful to enhance the convergence speed and accuracy. The mutation coefficient based on Mexh wavelet is represented in (10):

$$F_0 = \frac{2}{\sqrt{3}}\pi^{-\frac{1}{4}}.(1 - x^2).e^{-\frac{x^2}{2}} \tag{10}$$

b. Standard normal distribution for crossover co-efficient

The CR crossover coefficient value in quantum operation denotes the crossover probability based on transmitting data obtained from the parent solution. The higher CR value, the more the new population relies on the mutation procedures and inherits fewer details through parent population, resulting in a wider range of global searches and less chance of getting to the local optima. The smaller CR, on other hand, promotes local search within parent population and improvises the convergence and accuracy of sensing. The mathematical expression of standard normal distribution is represented in (11):

$$CR = N(0,1) \tag{11}$$

c. Update based on adaptive quantum state technique

It is utilized in regulating the rotation angle and chromosome’s position at the individual iteration. The quantum rotation angle adaptive state update strategy is described in (12) and (13):

$$\Delta\theta_i^t = \theta_{min} + fit\ \times (\theta_{max} - \theta_{min}) \times rand \times \exp(G/G_m) \tag{12}$$

$$fit = (fit_{best} - fit_i)/fit_{best} \tag{13}$$

Where, the lower angle limit is denoted as θ_{min}, the optimal fitness value is denoted as fit_{best}, the optimal fitness value is denoted as fit_i and random value is represented as $[0,1]$. The current and the maximal iteration are respectively represented as G and G_m. The feasibility is evaluated based on the above fitness function used in the process of spectrum sensing with higher fitness functions. Finally, the process of the algorithmic approach is terminated until the optimal outcome is achieved.

3. RESULTS AND ANALYSIS

This section presents the experimental analysis while evaluating the proposed approach based on various scenarios. The suggested approach is implemented in MATLAB software with the system configuration of Intel i7 processor, windows 11 OS and 8 GB RAM. The proposed spectrum sensing model is evaluated using the data obtained from the DEEPSIG dataset [27]. The dataset is comprised of 24 varying analog and digital modulation classes which are comprised of air recordings and 2 million samples. The data present in DEEPSIG is in hdg5 format like floating points.

3.1. Performance analysis

The performance of the proposed framework is evaluated based on the probability of detection, probability of false alarm rate and sensing time. The performance of the proposed approach is evaluated with Rayleigh, Rician channel, and state-of-the-art techniques such as convolutional neural network (CNN), logistic regression (LR), and LeNet. The CNN, LR, and LeNet are the deep learning architectures that are utilized in spectrum sensing. CNN is well-suited for analyzing and processing spectrograms or other representations of frequency spectra. The LR is known for its effectiveness in binary prediction tasks, so it is taken for evaluating the proposed approach. The feature extraction capability of LeNet is useful for capturing patterns in the frequency domain. So, these three states of approaches are considered for evaluating the performance of the suggested approach. Table 1 presents the results obtained while evaluating the proposed approach based on probability of detection for 50 epochs.

Table 1. Evaluation for the probability of detection

Methods	Type of channel	SNR					
		-20	-15	-10	-5	0	5
CNN	Rayleigh	0.09	0.32	0.74	0.92	0.94	0.94
	Rician	0.07	0.38	0.92	0.94	0.96	0.96
LR	Rayleigh	0.11	0.36	0.75	0.94	0.95	0.95
	Rician	0.08	0.35	0.90	0.97	0.97	0.98
LeNet	Rayleigh	0.14	0.38	0.77	0.93	0.93	0.93
	Rician	0.07	0.34	0.91	0.93	0.95	0.96
IQISE-ResNet 50	Rayleigh	0.20	0.40	0.80	0.98	0.99	0.99
	Rician	0.12	0.37	0.95	0.98	0.98	0.99

The results from Table 1 show that the proposed IQISE-ResNet 50 achieves a better probability of detection when compared with the state-of-the-art deep learning architectures. The results are evaluated for different SNR values. For instance, the probability of detection when SNR is -20 is 0.12 for the Rician channel which is comparably better than the existing methods. Figure 3 represents graphical validation for the evaluation of the probability of detection.

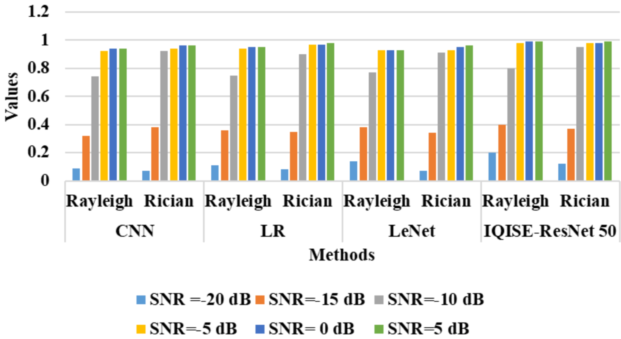

Figure 3. Evaluation for the probability of detection

The experimental outcome through Figure 3 shows that IQISE-ResNet 50 attains superior results for varying values of SNR. Comparing to the existing models like CNN, LR and LeNet, the proposed model achieves superior outcome interms of detection probability. Secondly, the performance of the proposed approach is evaluated based on the probability of a false alarm rate. The performance of the proposed approach is evaluated with Rayleigh, Rician channel, and state of art method like CNN, LR, and LeNet. Table 2 presents the results obtained while evaluating the proposed approach based on the probability of a false alarm rate for 50 epochs.

Table 2. Evaluation of the probability of false alarm rate

Methods	Type of channel	SNR					
		-20	-15	-10	-5	0	5
CNN	Rayleigh	0.09	0.30	0.47	0.73	0.88	0.94
	Rician	0.08	0.33	0.48	0.67	0.91	0.92
LR	Rayleigh	0.07	0.32	0.38	0.78	0.92	0.93
	Rician	0.09	0.33	0.36	0.39	0.88	0.89
LeNet	Rayleigh	0.10	0.35	0.68	0.79	0.92	0.95
	Rician	0.09	0.20	0.79	0.88	0.94	0.97
IQISE-ResNet 50	Rayleigh	0.07	0.28	0.32	0.46	0.59	0.82
	Rician	0.05	0.17	0.34	0.35	0.68	0.86

The results from Table 2 show that the proposed approach achieves preferable results in terms of the probability of a false alarm rate. The performance of the proposed approach is evaluated with Rayleigh, Rician channel and the state of art techniques such as CNN, LR, and LeNet. The results are evaluated for different SNR values. For instance, the probability of a false alarm rate when SNR is -20 is 0.05 for the Rician channel which is comparably higher than the existing techniques. Figure 4 demonstrates the graphical validation for evaluation of the probability of false alarm rate.

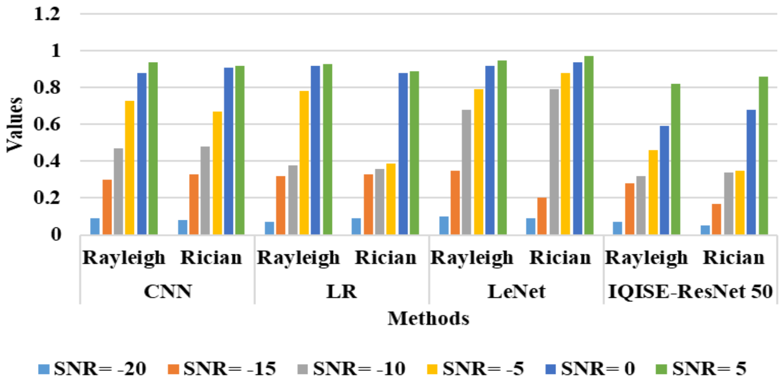

Figure 4. Evaluation of the probability of false alarm rate

Figure 4 depicts the experimental outcomes achieved by the proposed IQISE ResNet 50 interms of probability of false alarm rate. When compared to the existing models such as CNN, LR, and LeNet, the proposed model achieves minimal probability of false alarm rate. The minimal false alarm rate proves that the IQISE-ResNet 50 model attains commendable outcomes and hence tends to result in minimal false alarm rate during the spectrum sensing. Thirdly, the performance is evaluated based on the time taken during the process of spectrum sensing. The results achieves while evaluating the proposed approach based on sensing time are presented in Table 3.

Table 3. Evaluation based on sensing time (seconds)

Methods	Type of channel	SNR					
		-20	-15	-10	-5	0	5
CNN	Rayleigh	675	671	667	658	652	647
	Rician	266	258	252	248	243	238
LR	Rayleigh	678	670	668	656	640	638
	Rician	262	263	257	250	248	240
LeNet	Rayleigh	672	670	666	659	648	630
	Rician	255	250	248	240	238	220
IQISE-ResNet 50	Rayleigh	620	615	612	610	608	606
	Rician	235	225	218	210	204	198

The results from the table show the evaluation of sensing time taken by the proposed approach for different SNR values. The IQISE-ResNet 50 achieves better results when evaluated with the state of art techniques. The time taken by the proposed approach for sensing the spectrum at -20 dB for the Rician channel is 235 seconds, which is lesser than the remaining ones.

The overall results from Tables 1-3 show that the proposed framework is highly capable of detecting the probability of false alarm rate with minimal sensing time. The better result of the proposed approach is due to the usage of IQISE which helps to optimize the weight of ResNet architecture. The ResNet architecture is used in spectrum sensing and to enhance the spectrum efficiency. IQISE is used in the process of training ResNet. This helps in the precise optimization of weights and aids in better convergence while spectrum sensing.

3.2. Comparative analysis

Here, the efficiency of the proposed approach is evaluated with S-QRNN [23] and HBRO-based AlexNet [24]. The efficiency of the proposed framework is assessed with HBRO-based AlexNet in terms of probability of detection, probability of false alarm rate and sensing time. The performance of IQISE-ResNet

50 is evaluated with S-QRNN based on the probability of correct classification. The probability of correct classification is performed based on two scenarios such as; i) binary phase shift keying (BPSK) modulation and ii) 256QAM modulation. The evaluation is performed for different SNR rates from -10 dB to 30 dB and is presented in Table 4.

Table 4. Evaluation of IQISE-ResNet 50 vs S-QRNN for different modulation schemes for the probability of correct classification

Modulation scheme	Methods	SNR							
		-10	-5	0	10	15	20	25	30
BPSK modulation	S-QRNN [23]	0.49	0.51	0.62	0.98	1	1	1	1
	IQISE-ResNet 50	0.55	0.63	0.78	0.99	1	1	1	1
256QAM modulation	S-QRNN [23]	0.09	0.1	0.21	0.28	0.8	0.93	0.99	1
	IQISE-ResNet 50	0.12	0.18	0.36	0.47	0.98	0.99	1	1

The experimental results from Table 4 exhibit the experimental outcomes of the proposed approach for two modulation schemes in the dataset. For instance, the probability of correct classification of the proposed approach for -10 dB for BPSK modulation is 0.55, whereas the S-QRNN achieves an accuracy of 0.49. The combination of IQISE with ResNet 50 architecture helps to attain commendable results than the existing ones. Secondly, Table 5 shows the results achieved while evaluating the proposed approach with HBRO based AlexNet for 50 epochs.

Table 5. Evaluation of IQISE-ResNet 50 vs HBRO based AlexNet

Performance metrics	Methods	Type of channel	SNR					
			-20	-15	-10	-5	0	5
Probability of detection	HBRO based AlexNet [24]	Rayleigh	0.18	0.34	0.76	0.93	0.98	0.98
		Rician	0.08	0.31	0.93	0.97	0.97	0.98
	IQISE-ResNet 50	Rayleigh	0.20	0.40	0.80	0.98	0.99	0.99
		Rician	0.12	0.37	0.95	0.98	0.98	0.99
Probability of false alarm rate	HBRO based AlexNet [24]	Rayleigh	0.11	0.37	0.78	0.97	0.98	0.98
		Rician	0.09	0.25	0.98	0.98	0.98	0.98
	IQISE-ResNet 50	Rayleigh	0.07	0.28	0.32	0.46	0.59	0.82
		Rician	0.05	0.17	0.34	0.35	0.68	0.86
Sensing time (sec)	HBRO based AlexNet [24]	Rayleigh	630	625	620	610	610	608
		Rician	245	232	228	225	210	205
	IQISE-ResNet 50	Rayleigh	620	615	612	610	608	606
		Rician	235	225	218	210	204	198

The experimental outcomes displayed in Table 5 shows the results achieved by the proposed approach in terms of probability of detection, probability of false alarm rate and sensing time. The IQISE-ResNet achieves preferable performance in overall metrics when compared with the existing ones. The utilization of ResNet helps to perform better during the process of spectrum sensing and IQISE is used in the process of training ResNet. This facilitates precise optimization of weights and aids in better convergence during spectrum sensing.

3.3. Discussion

This section presents the experimental outcomes achieved by the proposed research along with its advnatages in achieving better results. The evaluation of IQISE-ResNet 50 is evaluated with S-QRNN and HBRO based AlexNet. The probability of detection, false alarm rate and sensing time are considered while evaluating the proposed framework with HBRO based AlexNet. Moreover, based on BPSK modulation and 256QAM modulation, the efficiency of suggested method is evaluated. For example, the probability of correct classification of the proposed approach for -10 dB for BPSK modulation is 0.55, whereas the S-QRNN achieves an accuracy of 0.49. Moreover, the detection probability of the proposed method based on Rayeligh channel when SNR=5 is 0.99; whereas the existing HBRO based AlexNet achieves a detection probability of 0.98. Thus, the efficiency of suggested method is finer with all over metrics considered for evaluation. The combination of IQISE with ResNet 50 architecture helps to achieve superior outcomes than the existing ones. The spectrum sensing is performed using the ResNet and training the model is performed using IQISE, which helps in weight optimization and facilitates to achieve better convergence during the stage of spectrum sensing. However, ResNet-50 architecture requires a large amount of labelled data and the acquisition of labeled datasets for spectrum sensing, which is an expensive task.

4. CONCLUSION

CR is an effective approach that is used to enhance the spectrum efficiency. The design of CR technology should be used to manage the hardship based on the availability of spectrum. This study presents an efficient spectrum sensing approach in CRN to enhance the efficiency of the spectrum. The IQISE-ResNet 50 is utilized in the process of spectrum sensing in CRN which helps to enhance the spectrum efficiency. The ResNet50 is used to classify whether the user is occupied or unoccupied in CRN, whereas the IQISE algorithm is used to train the ResNet 50 and optimize the weights to enhance the spectrum sensing efficiency. The efficiency of IQISE-ResNet 50 is based on the probability of detection, probability of false alarm rate and sensing time. The experimental results prove the efficiency of the proposed framework when evaluated with the existing ones. For instance, the probability of correct classification of the proposed approach for -10 dB for BPSK modulation is 0.55, whereas the S-QRNN achieves an accuracy of 0.49. Similarly, the sensing time of HBRO-based AlexNet for the Rician channel is 245 seconds, while on the other hand, the proposed approach takes a minimal time of 235 seconds. Thus, the suggested approach attains better performance in overall metrics when evaluated with the existing techniques. In the future, the complexity of IQISE-ResNet is minimized by efficient training using hybrid optimization techniques.

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BIOGRAPHIES OF AUTHORS

Srikantha Kandhgal Mochigar is currently working as Assistant Professor in the Department of Electronics and Communication Engineering, BITM-Ballari Institute of Technology and Management Ballari, Karnataka, India. He has teaching experience of 12 years. He has published 1 journal and 2 conference papers. His area of research is spectrum sensing in CR networks. He can be contacted at email: srikanthkm2019@gmail.com.

Rohitha Ujjini Matad is currently working as Professor and Principal in PDIT-Proudhadevaraya Institute of Technology, Hosapete Karnataka, India. He has published 21 papers in referred international journals, 12 papers in national and international conferences. His area of research was spectrum sensing in CR networks. He can be contacted at email: rohithaujjini2010@gmail.com.