Intelligent Spectrum Sensing Using Optimized Machine Learning Algorithms for Cognitive Radio in 5G Communication

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Abstract

Spectrum Sensing plays an important role in cognitive radio which is used to resolve the co-existence issue and to optimize the available spectrum efficiency. However, the upcoming 5G communication involves the diversified scenarios with distinguished characteristics which makes spectrum sensing more difficult to serve different application in terms of high performance and flexible implementation. Also motivated by this challenge, the paper proposes the new algorithm which implemented the novel bat optimized multi-layer extreme learning machine and works on different input vectors such as received signal strength, distance, Energy and channel ID and classifies the users for the better classification and sensing. Moreover, to prove the suitability of the proposed algorithm in terms of performance under 5G scenario for health care applications, we have compared the other spectrum sensing techniques and parameters such as sensitivity, selectivity and channel detection probability. Ultimately the results demonstrate that the proposed spectrum sensing has outperformed the other algorithms and shows its capability to adopt for various 5G scenario.

Keywords: Spectrum sensing, BAT optimized extreme learning machines, Cognitive radio, Health care applications

1 Introduction

Fifth Generation communication has taken a huge wave in recent years, due to its capability of its high data rates and new applications [1] to enhance service provisioning which can meet the requirements of upcoming diversification, thereby providing users with better quality of service (QoS) and quality of experience (QoE). In order to provide high-quality services in 5G networks effectively, it is mandatory to adopt the heterogeneous networks such as multiple-output-multi-input (MIMO), cognitive Internet of things (C-IoT), software defined networking and so on [2]. However, with the integration of various technologies, 5G wireless communication has reached its new peak of complexity in implementation. This is due to the exponential growth of mobile data services and traffic which has made the impact of severe spectrum scarcity. As one of the most fascinating technology of 5G communication is Cognitive Radio (CR) which now draws the attention among the researchers [3].

Generally, CR is considered an intelligent technology that is the next wireless communication system with the capabilities of sensing, analysis, and decision making for dynamic resource allocation and spectrum management [4-6]. Even so, some problems still exist in the cognitive radio networks (CRNs) at real-time resource allocation, such as global constrained optimization [7], high computation time, and complexity. To reduce the emergence of these problems, CR users are expected to have smarter learning and decision making abilities by interacting with the environment. Fortunately, advent of artificial intelligence algorithms can be providing the solutions to above problems of cognitive radio.

Furthermore, 5G networks can take advantage of integrating the artificial intelligence algorithms over the Cognitive Radio (CR), which gives the intelligence over the decision making in terms of spectrum sensing and management. In [8], the AI and machine learning techniques are introduced, and the role of learning is emphasized in CR.

Many papers have been hustling in the usage of machine learning algorithms in cognitive radio for an effective detection of spectrum to be utilized by the primary users. Many machine learning algorithms such as Probabilistic Neural Network [9], Support Vector machines (SVM) [10], Naïve Bayes (NB), even reinforcement learning (RL) [11] were used as an effective spectrum sensing methods for Cognitive radio. But all these machine learning methods consumes the more time and has computational complexity while implementing in the 5G scenario.

Extreme learning machines (ELM) is the one of the categorization of neural networks has been finding its place in spectrum sensing application due to its less complexity and high sensing performances. These are characterized by single feed forward neural networks with the auto-tuning of hidden neurons. Moreover, these kind of auto-tuning property leads to the instability of the network which results in the inaccurate sensing problems.

Hence the paper proposes the new implementation of BAT algorithm to optimize the hidden neurons of ELM which is then leads to the optimized ELM. These optimized networks can generate more accurate predictions in terms of sensing and find its good place in 5G communication. To best of our knowledge, these kind of optimized learning algorithms are first to be utilized in 5G based cognitive radio systems for an effective spectrum sensing mechanism.

The rest of the paper is organized as follows Section-II discusses about the related works by one authors. The system model, proposed architecture, technical details about extreme

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DOI: 10.53106/160792642022072304017

learning algorithms and BAT algorithms were presented in Section-III. The experimentation mechanism with result analysis were discussed in Section-IV. Finally, the paper concludes with future scope in Section-V.

2 Related Works

M. Kalpana Devi et al. [12] presented an iPSO ("Intelligent Particle Swarm Optimization) algorithm in a CRN ("Cognitive Radio Network") to solve handoff issues among PU (Primary Users) and Secondary Users (SUs). Generally in stable channel allocation strategy, there is a lack of spectrum. Here the SUs are usually enforced to do handoff operation when there is a high priority arrival of PU. This hand off problem is finally encountered by the proposed IPSO algorithm. This framework recommends the dynamic spectrum sensing to know the free channels in the spectrum to overcome handoff problem. Also, this framework achieves high data transmission with extraordinary handoff performance. The total performance is improved in terms of throughput, SNR function, bandwidth of SU and fitness function. But this framework struggles in PU identification when it is not in the coverage range and detecting the perfect signal spectrum is sometimes difficult because of the wide range of frequency.

S. Chilakala et al. [13] proposed a "reduced energy consumption strategy" to indicate the energy level during the spectrum sensing. Here are all the SU are involved in taking local decision about spectrum. In this framework, that is a fusion center which has the responsibility to collect all the local decisions. Diffusion center has its own threshold value. 1st counter count reach its threshold value or greater than threshold, this fusion center intimate the PU by sending stock report. Best jaundice process, the primary users dynamically occupies the spectrum. With the help of these feedback signal from the fusion centers, this framework significantly reduces the energy consumption during spectrum sensing. But this framework has less throughput and lead to computational overhead under 5G networks.

ZB Omariba et al. [14] Proposed "linear cooperative spectrum sensing" (LCSS), for the secondary users spectrum allocation. This framework allocates the spectrum to the secondary users when it is not used by the primary users. It achieves efficient performance in spectrum usage. This framework significantly achieved false alarm rate, probability of detection and probability of miss detection as low as less than 1. This indicates that this framework has high efficiency when compared with non CSS. The main drawback of this framework is, CR needs a cognitive operation to operate in licensed frequency band and mainly with the primary user. But still the framework doesn't have license and same priority with PU to function in a license band.

T. C. Thanuja et al. [15] Utilized ED (Energy Detection) method is for CSS. The main objective of this framework is optimize the sensing of spectrum. This framework detects the channel individually and transmits the entire information to the Specific Base station (BS). This BS is responsible for taking decision on the existing PU. Generally sensing time, throughput, and energy consumption are the main parameters which affects the spectrum sensing. Hence this framework focused on optimal throughput of the SU and achieves throughput of 99% which also results in good SNR. But main drawback of this framework is, sometimes it requires prior knowledge of PU signal and it adds complexity in receiving signal and increased delay.

A. S. Chavan et al [16] focused to create CSS for ad hoc networks. This framework done an analysis to produce less energy consumption and reliable sensing of spectrum. The defined trust based model will protect the CR-MAMETs from the malicious attacks like "SSDF (Spectrum Sensing Data Falsification) and ISSDF (Insistent SSDF)".

M. S. Khan et al. [17] Utilized GA ("Genetic Algorithm') for determine the optimal weighted co efficient vector against SUs sensing. In order to reach the final global decision, these weighted outcomes are utilized by SDF ("soft decision fusion"). This framework adopts the ED technique for the energy sensing in spectrum and which is compared with adaptive threshold. Generally, in spectrum sensing framework, the cooperative user are having different fading effects and these are not suitable to treat their sensing notifications which are same as global decisions at FC ("Fusion Centre"). The proposed GA based technique optimally selects the threshold and coefficient vector. The Minimum FAR ("False Alarm Rate"), low error probability and high detection is achieved by the proposed technique by analyzing individual user's reports of spectrum sensing in global decision. Hence the proposed GA based CSS outperforms the other existing schemes like MGC ("maximum gain combination"), KL ("Kullback-Leibler") divergence ad count Decision strategy. But main drawback this framework is increased delay for spectrum sensing.

K. Kirubahini et al. [18] Introduced a novel CSS technique is proposed. This framework comprises of 2 segmentation stage in time domain. In 1st segmentation stage, the spectrum samples are considered and compared with threshold value. In the next stage, various statics were taken and final segmentation signal is carried out. Then detected signal frequency is computed. The graph presented with SNR and probability of detection. Finally the results indicates that this framework outperforms the covariance based spectrum sensing method as well as energy detection method. This framework gives better results in low SNR rates also. But this framework has less throughput and not suitable for 5G frameworks.

S. Surekha et al. [19] Aim is to increase the ED accuracy under both low SNR as well as uncertainty noise environment. This framework proposed "Normalized Modified LMS technique". This technique significantly detects the PUs signal. So the accurate patient data can be collected and it can be contrasted with other general ED technique. This framework can helps in collecting exact data of patients through Wi-Fi and based on the collected information, the Physicians can make first aid by using mobile gadgets and also can suggest better treatment. This framework struggles in real time framework and implementation of this framework in 5G environment is highly complex.

3 System Model

This section deals with the system model for spectrum sensing in Cognitive radio networks and as well as the different methodology involved in the machine learning based spectrum sensing. Moreover, system model which has been implemented suits for 5G communication system with intelligence algorithm.

We propose the two tier learned distributed networking (LDN) framework, which applies machine learning technologies for sensing the spectrum of the 5G cellular networks to guarantee CR users' QoS requirements, and to maximize the utilization of spectrum resources.

The proposed distributed networking framework based on 5G consists of following tiers which is shown in Figure 1.

1. CR users (Combination of Primary User (PU) and Secondary User (SU))
2. Gateways (Normally connected with the Cloud or Base Stations)

In the first tier, 5G framework of the cognitive radio scenario is considered, which is composed of multiple cells with abundant CR users who attempt to transmit data to the base stations which are processed and stored in cloud. In general, CR users include multiple PUs and SUs, and PUs have higher priority for accessing the spectrum. In each cell, machine learning and cognitive networks are integrated for resource allocation. Each user interacts with the Cognitive radio network's environment in which they intelligently learn each other's behaviors to perform dynamic spectrum allocation which then increases the efficiency of spectrum allocation ultimately so that data can be uploaded in the cloud as quickly as possible. Both the Pus' and Sus' learns adaptively by adopting the powerful machine learning algorithms, which is discussed in detail in the preceding section.

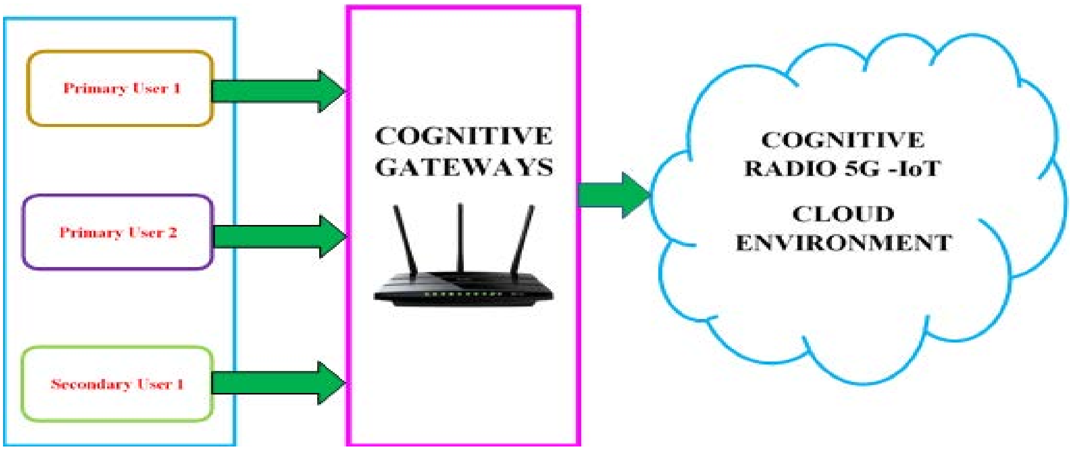

Figure 1. System model used in the proposed architecture

In the tier-II architecture, collection stations consist of cloud processing which has many advantages, such as reducing compute costs, integrating resources, and flexibility. A cloud processing center is a place for centralized data processing, which involves cloud computing and various artificial intelligence (AI) algorithms. The gateways are used to transmit various data to the cloud processing center, in which servers centrally store and process data for further application and decision.

3.1 Proposed LDN Framework

In the section, intelligent spectrum sensing using the proposed learning algorithms were discussed.

We have considered the scenario with multiple PUs and SUs. Each PU and SU are considered as cognitive user, while the other users and the 5G networks are regarded as the environment. Each users learns and makes decisions by extracting the features by interacting with the environment, and dynamically allocates spectrum resources to maximize the benefit of each users. In this scenario, PU and SU are equipped with integrated SOC in which the bio-signal data such as temperature (T), blood pressure (B.P), heart rates (H) are measured and send to cloud for the processing. Figure 2 shows the proposed framework which implements the learning models for an effective spectrum sensing.

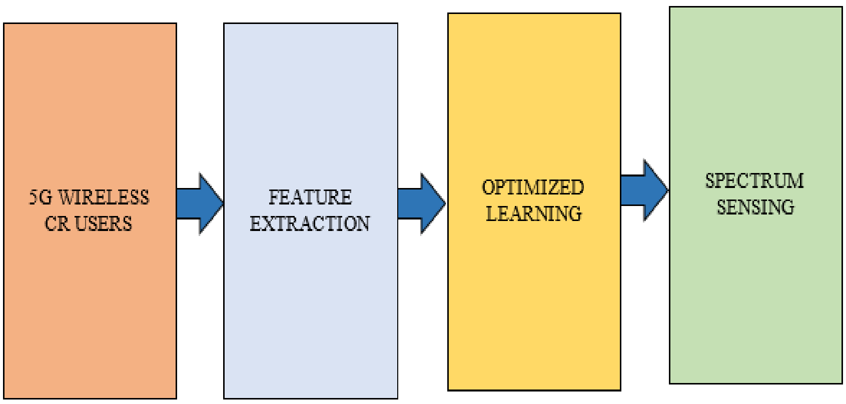

Figure 2. Proposed learning framework for an effective spectrum sensing

3.1.1 Feature Extraction

For better spectrum sensing, features such as energy vectors and data vectors are collected and used for training the proposed machine learning model. For calculating the energy vectors, the proposed system employs the adaptive energy - distance models which are expressed as follows as

$$E(Total) = 1/N\left[Nn = 1\left[E(PU)\right] \times d \times n\right. \quad \textbf{(1)}$$

$$E(Total) = 1/N\left[Nn = 1\left[E(SU)\right] \times d \times n\right. \quad \textbf{(2)}$$

Where E is the total energy vectors, N is the total number of received samples, E (PU) and E (SU) are the primary and secondary energy vectors, and d is the distance of users from the gateways deployed and n is the no of data bytes.

This energy consumption from the primary and secondary users is stored as the X and Y vectors in the center of the Cognitive gateway, which are used as the training the classifiers.

The distance between the users and cognitive gateways are calculated based on the RSSI (Received Signal Strength Indicator) which is then given by the expression as shown in eq. (3).

$$RSSI = 10\left[\frac{\left(P_o - F_m - P_r - 10n\ \log(f) + 30n - 32.44\right)}{10n}\right] \quad \textbf{(3)}$$

Where P_o is the power of the signal (dBm) in the zero distance, P_r is the Signal power (dBm) in the distance, f is the signal frequency in MHz, F_m is the Fade margin and n is the path-loss exponent.

These features are stored on the cognitive gateways for primary users and secondary users separately and employed for training the machine learning models.

3.2 Proposed Optimized Machine Learning Models

This section discusses about the principle of extreme learning machines optimized by the BAT algorithms.

3.2.1 Extreme Learning Machines-An Overview

After extracting the features, Extreme learning machines proposed by G.B. Huang [20] was used, in which the network utilizes the single hidden layer, high speed and accuracy and preparing velocity, great speculation/exactness, and universal function approximation capabilities [21].

In this sort of system, the 'L' neurons in the hidden layer are required to work with an activation function that is vastly differentiable (for instance, the sigmoid function), though that 2of the output layer is straight. In ELM, hidden layers does not need to be tunes màndotrily. In ELM, the hidden layer compulsorily need not be tuned.

The loads of the hidden layer are arbitrarily appointed (counting the biàs loads). It isn't the situation that hidden nodes are irrelevant, however they need not be tuned and the hidden neurons parameters can be haphazardly produced even in advance.

That is, before taking care of the training set data. For a single-hidden layer ELM, the system yield is given by eq. (4)

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta \quad \textbf{(4)}$$

Where x → input

β → Output weight vector and it is given as follows as

$$\beta = \left[\beta_1, \beta_2, \dots\dots\dots\dots .\beta_L\right]^T \quad \textbf{(5)}$$

H(x)→ output hidden layer which is given by the following eqn

$$h(x) = \left[h_1(x), h_2(x), \dots\dots\dots\dots\dots h_L(x)\right. \quad \textbf{(6)}$$

To determine Output vector O which is called as the target vector, the hidden layers are represented by eqn (4).

$$H = \begin{bmatrix} h(x_1) \\ h(x_2) \\ \vdots \\ h(x_N) \end{bmatrix} \quad \textbf{(7)}$$

The basic implementation of the ELM uses the minimal non-linear least square methods which are represented in Eq. (5).

$$\beta' = H * O = H^T\left(HH^T\right)^{-1} O \quad \textbf{(8)}$$

Where H∗ → inverse of H known as Moore−Penrose generalized inverse.

Above eqn can also be given as follow

$$\beta' = H^T\left(\frac{1}{c}HH^T\right)^{-1} O \quad \textbf{(9)}$$

Hence the output function can be find by using the above eqn

$$f_L(x) = h(x)\beta = h(x)H^T\left(\frac{1}{c}HH^T\right)^{-1} O \quad \textbf{(10)}$$

ELM uses the kernel function to yield good accuracy for the better peformance. The major advantages of the ELM are minimal training error and better approximation. Since ELM uses the auto-tuning of the weight biases and non-zero activation functions, ELM finds its applications in classification and prediction values. The detailed description of ELM's equations can be found in [22-23]. The pseudo code for the ELM is shown in Algorithm 1.

Step 1: Training Sets of 'N' data with an Activation Function and n Hidden neurons.

Step 2: Input weights are assigned and biases are assigned.

Step 3: Calculate the hidden matrix H

Step 4: Calculate the Output weight Matrix β

Step 5: Classify /predict the values

3.2.2 Drawbacks of ELM

Even though the Extreme learning machines proves to be efficient in both training and testing, the major disadvantage is the non-optimal tuning of input weights and biases. Also to adjust the optimal weights, ELM uses multiple hidden layers when compared with the other conventional learning algorithms which may affect the accuracy of detection.

In overcome the above drawback, a new bio-inspired BAT algorithm is used to optimize the input weights and bias factors to produce the high accuracy of classification. The major advantages of BAT algorithms are as follows as

1. High Efficiency than PSO, GA and other heuristic algorithms [24]
2. Faster and versatile search space.

The working mechanism of BAT algorithm is explained in the preceding section.

3.2.3 Bat Algorithms

The standard bat calculation depended on the echolocation or bio-sonar attributes of microbats. In light of the echo cancelation calculations, X. S. Yang [25] (2010) built up the bat calculation with the accompanying three glorified guidelines:

1. All bats use echolocation to detect separation, and they likewise ‘know’ the distinction between sustenance/prey and foundation obstructions in some mystical manner
2. Bats fly arbitrarily with speed vi at position xi with a recurrence fmin, fluctuating wavelength _ and loudness A0 to look for prey. They can consequently modify the wavelength (or recurrence) of their transmitted pulse and alter the rate of pulse emission r 2 [0, 1], based on the nearness of their objective;

In spite of the fact that the loudness can fluctuate from numerous points of view, we expect that the loudness shifts from an extensive (positive) A0 to a minimum constant value Amin.

Each bat Motion is associated with the velocity vit and initial distance xit with the ‘n’ number of iterations in a dimensional space or search space. Among all the bats, the best bat has to be chosen depends on the three rules which are stated above. The updated velocity vit and initial distance xit using the three rules are given below.

$$fi = f\min + \left(f\max - f\min\right)\beta \quad \textbf{(11)}$$

$$xit = xit - 1 + vit \quad \textbf{(12)}$$

Where β € (0, 1) fmin is the minimum frequency =0 and fmax is the maximum frequency which initially depends on the problem statement. Each bat is initially allocated for the frequency between the fmin and fmax. Consequently, bat calculation can be considered as a frequency tuning calculation to give a reasonable blend of investigation and exploitation. The emission rates and loudness basically give a mechanism to programmed control and auto-zooming into the district with promising solutions.

The BAT algorithm is used to tune hyperparameters of ELM for achieving the better performance. The input bias weights, hidden layers, epochs are considered to be hyperparameters of learning models. In this case, BAT’s characteristics of r searching the prey are used as the main term to optimize the hyperparameters of ELM networks. Initially, random number of weights and biases are passed to the ELM. The accuracy of the proposed model is coined as the fitness function which is given in equation (13). For each iteration, input bias and weights are calculated by using the mathematical equations (11) and (12) effectively. These weights are then feed to the ELM network in which fitness function are calculated. If the fitness function is equal to the threshold, then the iteration stops or will be iterated continuously.

$$Fitness\ unction = ax\ (Accuarcy) \quad \textbf{(13)}$$

Table 1 depicts the parameters of BAT algorithm used for the hyper parameter optimization. In the spectrum sensing, we have used the bat optimized extreme learning machines for classification of users in order to make an effective spectrum sensing in which the energy vectors, data vectors and distance are taken as the input features, precalculated spectrum slots act as the output layer. Table 2 presents the optimized parameters used for spectrum sensing.

Table 1. BAT parameters used for hyper parameter Optimization

Sl.no	Bat parameters used	Description
01	No of BATS	15 (Initial)
02	Initial Velocity	20%
03	No of Iterations	250
04	Initial Loudness	0.9
05	Initial Pulse rate	0.9
06	Minimum Frequency	0 KHZ
07	Active threshold	99% Accuracy in Prediction/Classification

Table 2. Optimized parameters for spectrum sensing

Sl.no	Hyper parameters	Values
1	Learning rate	0.001
2	Batch size	40
3	Number of epochs	200
4	Hidden layers	10
5	Optimizer	BAT
6	Activation function Used	Sigmoidal
7	Loss function	MSE

The proposed learning model classifies the available spectrum slots effectively with the help of above mentioned parameters and features.

4 Performance Evaluation

4.1 Dataset Description

The experimentation is carried out using the hardware setup as mentioned in Table 3. The hardware consist of different sensors connected with the NODEMCU and WIFI transceivers. The software includes GNURADIO and Python 3.8. GNU radio captures the signals and python based analyzer is used to capture the signals which are then used to detect the PU signals.

Table 3. Simulation parameters used for the experimentation

Sl.no	Specification Parameters	Description
01	Number of Primary users	25
02	Number of Secondary Users	15
03	Gateways used	10
04	Noise Background	AWGN/Gaussian Noise
05	Signal to Noise ratio (SNR)	-20 to +20 dbm

To evaluate the performance of the proposed learning algorithms, parameters such as probability of false alarm, probability of miss detection and accuracy of detection were evaluated under SNR ratio which is depicted in Table 4.

Nearly 5000 data samples were collected at different environmental conditions in which SNR variations with adaptive distance are taken as the important criteria for evaluation. Nearly 70% data were taken as training and remaining 30% has been considered for testing. Meanwhile, the performance of the proposed model has been calculated at the different SNR at different distances using the metrics mentioned in preceding tables.

Table 4. Mathematical expression for calculating the different performance metrics

Sl. No	Performance Metrics	Mathematical Expression
01	Prediction accuracy (P_a),	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Recall	$\frac{TP}{TP+FN}$
03	Precision	$\frac{TN}{TP+FP}$
04	Probability of detection (P_d)	Total Number of Primary User (PU)/Total Number of Users (PU+Noise Signals)
05	Probability of Missing Ratio (Pm)	1-(P_d)
06	Probability of False Alarm (P_f)	Number of Noise Signals Diagnosed /Total Number of Users (PU+Noise Signals)

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Table 5. Performance metrics of the proposed algorithm at distance D=12 m (from nodes to gateways)

SNR (db)	Performance Metrics				
	Accuracy	Precision	P_d	Recall	P_f
-20	0.992	0.990	0.1020	0.994	0.100
-15	0.991	0.99	0.0992	0.993	0.099
-10	0.990	0.989	0.0945	0.993	0.099
0	0.990	0.988	0.0923	0.993	0.092
5	0.989	0.987	0.0901	0.992	0.092
10	0.988	0.982	0.0892	0.992	0.090
15	0.988	0.982	0.0890	0.992	0.0890
20	0.988	0.982	0.08890	0.991	0.0824

Table 6. Performance metrics of the proposed algorithm at distance D= 15m (from nodes to gateways)

SNR (db)	Performance Metrics				
	Accuracy	Precision	P_d	Recall	P_f
-20	0.992	0.990	0.1020	0.994	0.100
-15	0.991	0.99	0.0992	0.993	0.099
-10	0.990	0.989	0.0945	0.993	0.099
0	0.990	0.988	0.0923	0.993	0.092
5	0.989	0.987	0.0901	0.992	0.092
10	0.988	0.982	0.0892	0.992	0.090
15	0.988	0.982	0.0890	0.992	0.0890
20	0.988	0.982	0.08890	0.991	0.0824

Table 7. Performance metrics of the proposed algorithm at distance D=18m (from nodes to gateways)

SNR (db)	Performance Metrics				
	Accuracy	Precision	P_d	Recall	P_f
-20	0.990	0.990	0.0932	0.994	0.099
-15	0.988	0.989	0.0920	0.993	0.099
-10	0.987	0.982	0.08934	0.993	0.089
0	0.985	0.982	0.08876	0.993	0.089
5	0.985	0.981	0.08789	0.992	0.088
10	0.984	0.980	0.08657	0.992	0.088
15	0.984	0.980	0.08532	0.992	0.0873
20	0.984	0.979	0.08436	0.991	0.0867

Table 8. Performance metrics of the proposed algorithm at distance D=20m (from nodes to gateways)

SNR (db)	Performance Metrics				
	Accuracy	Precision	Accuracy	Recall	P_f
-20	0.990	-20	0.990	-20	0.99
-15	0.988	-15	0.988	-15	0.98
-10	0.987	-10	0.987	-10	0.98
0	0.985	0	0.985	0	0.98
5	0.985	5	0.985	5	0.98
10	0.984	10	0.984	10	0.98
15	0.984	15	0.984	15	0.98
20	0.984	20	0.984	20	0.98

Table 5 to Table 8 shows the performance of the proposed spectrum sensing at different distances. The performance of the proposed algorithm remains to be constant at the distance 12meters and 15meters respectively. As the distance increases, proposed algorithm has shown the minimum dip in the performance which is shown in Table 7 and Table 8. To prove the superiority of the algorithm , performance of the proposed algorithm has been compared with the other learning based spectrum sensing technique such as PALM-SS[], SVM-SS[], KNN-SS[] and Normal Energy based Spectrum Sensing under 5G-health care environment.

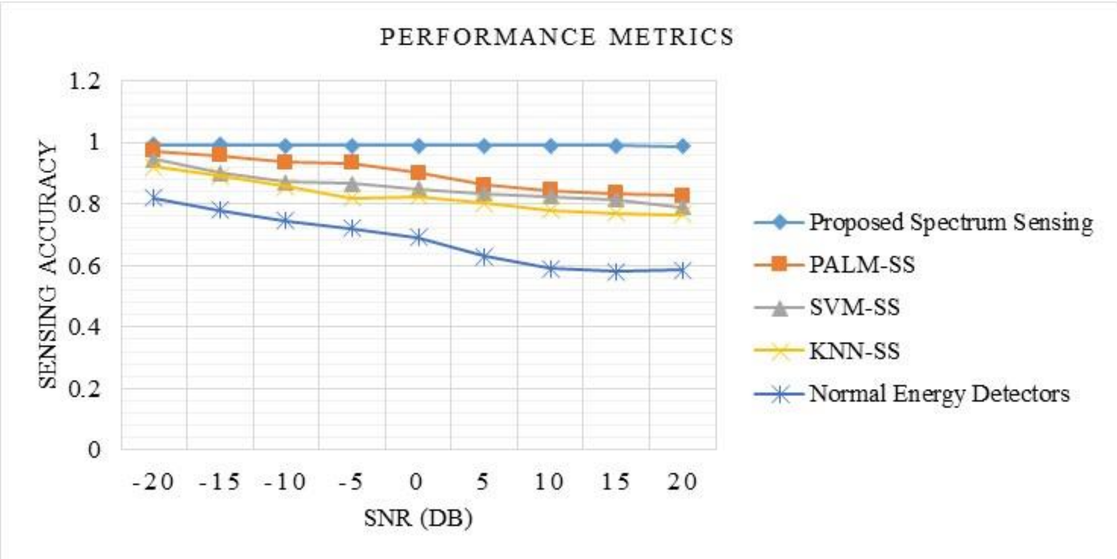

Figure 3. Sensing accuracy of the different spectrum sensing technique at distance D=12 meters

Figure 4. Sensing accuracy of the different spectrum sensing technique at distance D=15 meters

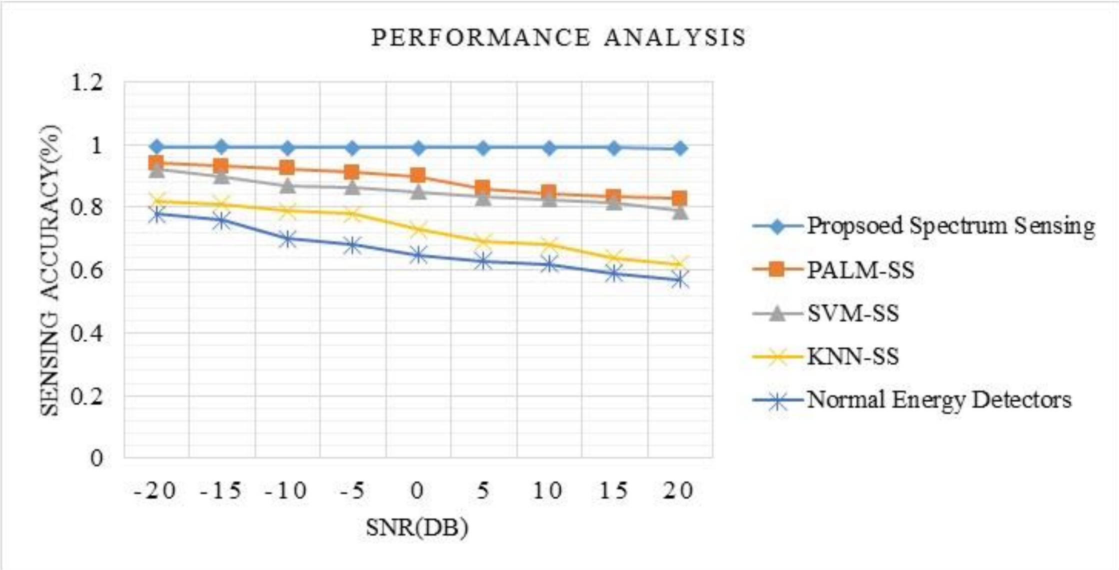

Figure 5. Sensing accuracy of the different spectrum sensing technique at distance D=18 meters

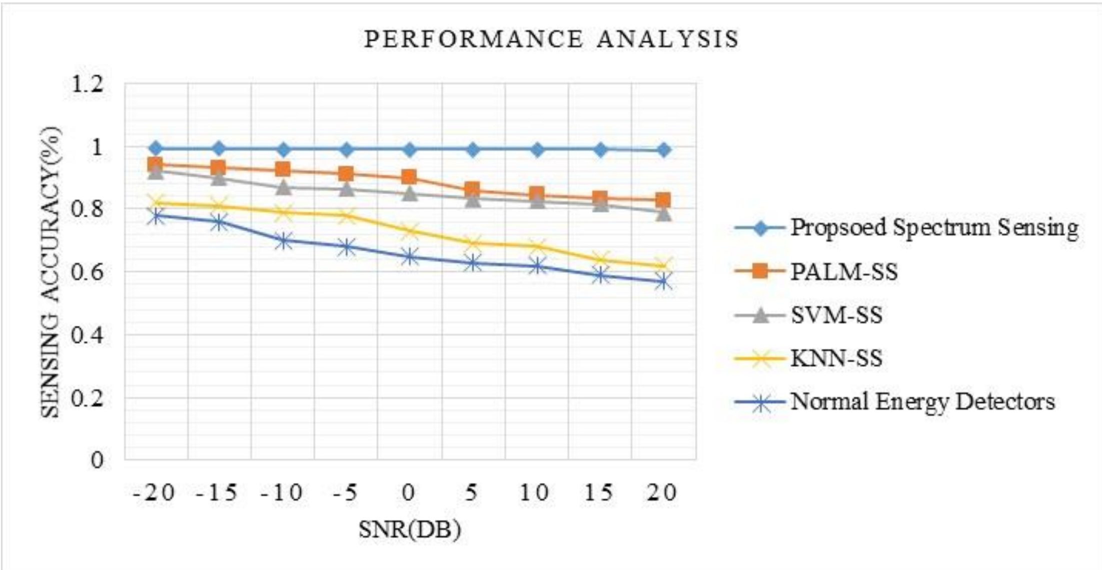

Figure 6. Sensing accuracy of the different spectrum sensing technique at distance D=20 meters

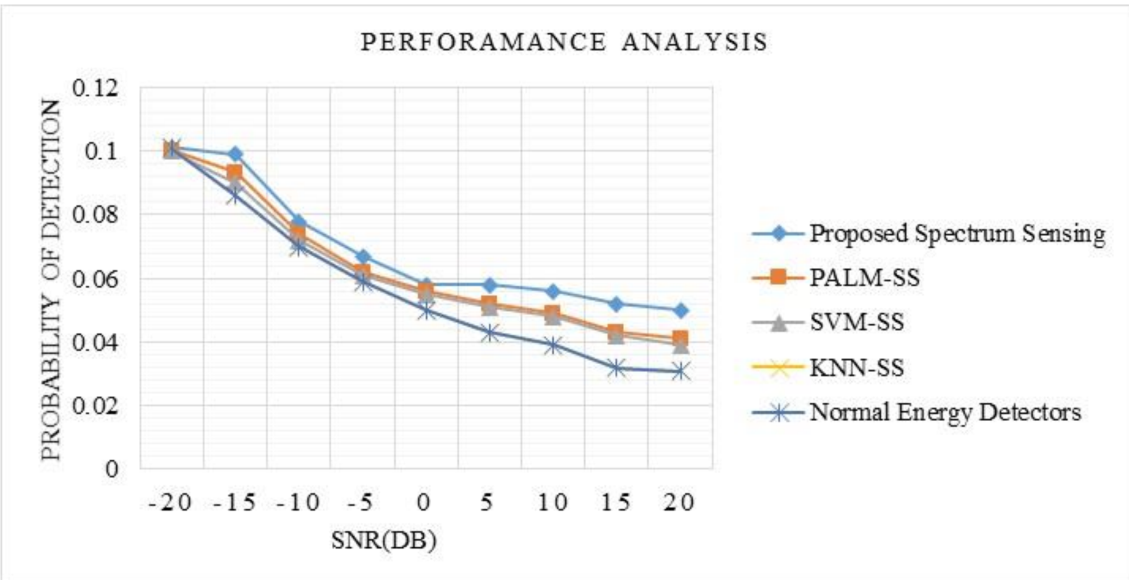

Figure 7. Probability of detection performances of the different spectrum sensing technique at distance D=12 & 15 meters

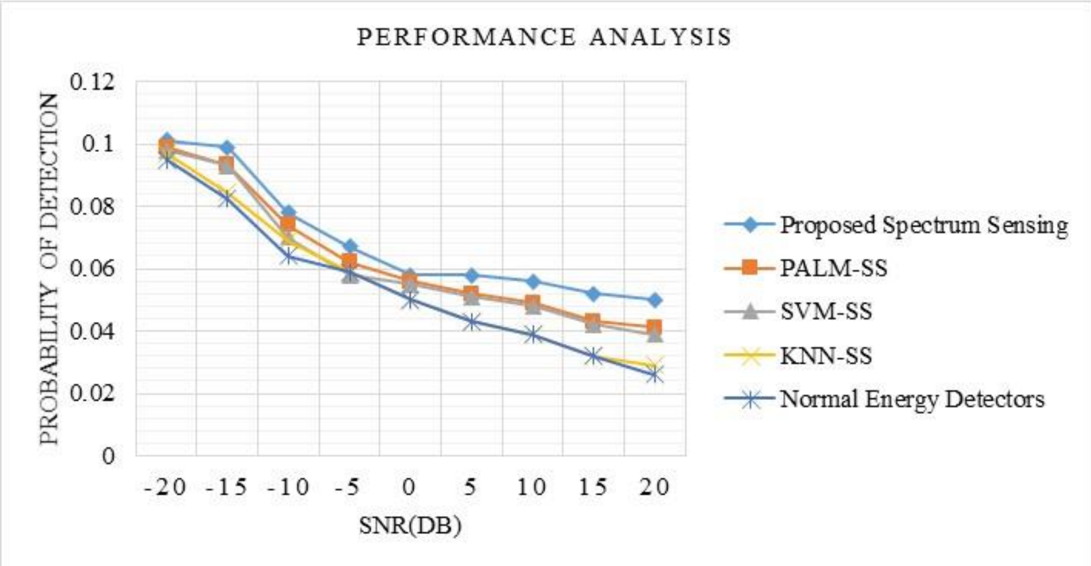

Figure 8. Probability of detection performances of the different spectrum sensing technique at distance D=18 & 20 meters

Figure 3 to Figure 6 represents the sensing accuracies of the different spectrum sensing techniques from the distances ranges from 12m to 20meters.Tthe proposed algorithm and PALM-SS has shown the better performance at the distance 12meters and 15 meters respectively. At the same scenario, other sensing algorithms has lower performances than the proposed and PALM-SS. But the proposed algorithm has outperformed PALM-SS and other algorithms as the distance increases which is evident from Figure 5 and 6. Since the proposed algorithm has in corporated the optimized hyperparameters based training network, it has edged the other algorithms in terms of sensing accuracy. Figure 7 and Figure 8 shows the probability of detection for different algorithms at different SNR and distances respectively. It is evident from the Figure and Figure 8, the proposed sensing technique has outperformed the other algorithms and makes its suitable for an efficient usage of spectrum in health care networks.

5 Conclusion

The article has introduced and implemented the novel optimized extreme learning machines (ELM) for an effective spectrum sensing in 5G Wireless Cognitive networks. We have implemented the two phases in the proposed framework, such as feature extractor and optimized extreme learning machines In the feature extractor phase, distinguished feature vectors such as Energy, RSSI and distance were collected under different SNR scenarios. Nearly 5000 samples were collected and used for evaluation. Furthermore the optimized extreme learning machines has shown accuracy with high false alarm detection. Also the proposed learning algorithms has outperformed the other machine learning algorithms and opens a new way of using the optimized extreme learning for an effective spectrum sensing in an Health care scenario. Future research will be dedicated to the study of more complex and complicated data sets with heterogeneous 5G networks and implementation of deep learning algorithms for an effective spectrum management using cognitive users.

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