Journal of Electronics, Electromedical Engineering, and Medical Informatics
Multidisciplinary: Rapid Review: Open Access Journal Vol. 6, No. 4, October 2024, pp: 370-381; eISSN: 2656-8632

RESEARCH ARTICLE OPEN ACCESS

Manuscript received April 27, 2024; revised June 22, 2024; accepted July 26, 2024; date of publication October 20, 2024
Digital Object Identifier (**DOI**): https://doi.org/10.35882/jeeemi.v6i4.441

How to cite: M. Saraswathi, E. Logashanmugam, "Bi-directional Long Short-Term Memory with Bird Mating Optimizer based Spectrum Sensing Technique for Cognitive Radio Networks", Journal of Electronics, Electromedical Engineering, and Medical Informatics, vol. 6, no. 4, pp. 370-381, October 2024.

Bi-directional Long Short-Term Memory with Bird Mating Optimizer based Spectrum Sensing Technique for Cognitive Radio Networks

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ABSTRACT Cognitive radio networks (CRN) enable the wireless devices to sense the radio spectrum, determine the frequency state channels, and reconfigure the communication variables for satisfying the QoS needs by reducing the energy utilization. In cognitive radio, the detection of principal user signals is crucial for secondary users in order to create the best use of available spectrum (CR). Conventional spectrum sensing systems have a high percentage of missed detections and false alarms, making it difficult to use the spectrum effectively. For resolving the drawbacks of traditional energy detection models, this paper presents a new spectral sensing technique for cognitive radio networks (SST-CRN). Recently published research in spectrum sensing has placed a high value on deep learning that is model-agnostic as a result of this. In deep learning, long-short term memory (LSTM) networks are particularly effective at extracting temporal and regional information from input data. The suggested Bidirectional Long Short-Term Memory (Bi-LSTM) with Bird Mating Optimization (BMO) model allows for the faster and more simple creation of nonlinear threshold-based systems than was before achievable. The proposed Bi-LSTM with BMO technique involves two stages of operations namely offline and online. The offline stage creates the non-linear threshold value to detect energy. In addition, the online stage automated selects a decision function saved in offline stage for determining the existence of primary user. The experiments were carried out, and the findings were analyzed using the RadioML2016.10b data set. The proposed Bi-LSTM with BMO approach has a major impact on cognitive radio networks by increasing spectrum sensing accuracy and lowering false alarm rates. This enhancement improves spectrum use, reduces interference with licensed users, and facilitates the deployment of dependable and adaptable CRNs. The experimental results display that the proposed Bi-LSTM with BMO improves accuracy on the dataset, particularly at -20 dB, with a 44.10% reduction in miss detection probability and a 13.55% reduction in sensing error (SE) for QPSK 16. In future implementing and testing this combined approach in real-world cognitive radio networks to validate its performance under various conditions.

INDEX TERMS Bird Mating Optimization, Deep learning, Bidirectional Long Short-Term Memory, Non-linear thresholds, Spectrum sensing, Cognitive Radio Networks.

I. INTRODUCTION

The 5G paradigm and the quick development of wireless communication technologies have made spectrum restricted, which has raised the value of spectrum resources dramatically. Following the campaign's recommendations, frequency bands are used between 7 percent and 34 percent of the time, demonstrating that spectrum resources are grossly underutilized on a global scale. Cognitive as a possible solution, radio (CR) technology has been considered [1, 2]. To find a middle ground between spectrum availability and demand increase. Its goal is to repurpose the existing unused area. A certain range of frequencies within the electromagnetic spectrum is referred to as a frequency band, sometimes called a spectrum hole or white space. No intervention is made to ensure that the licensed user is protected opportunistically. In the CR network, the licensed user (PU) is the principal user, while the uninhibited operator (SU) is the secondary user. Unauthorized user as a subordinate user (SU). The basic concept behind Cognitive Radio (CR) is to provide Secondary Users (SUs) with transient data access by making use of available licensed bands in a non-interfering and opportunistic way [3, 4]. This involves the deployment of extremely dependable and effectual Spectrum detection techniques.

The need for wireless spectrum has increased as a result of the Internet of Things, Hyperphysical Systems, and other novel uses and technologies. Because spectrum is limited and there are technological barriers to its growth, meeting the rising demand for it will be difficult. The Federal Communications Commission (FCC) discovered in a 2003 research that spectrum is still underutilized despite its importance. As a result, the primary goal of researchers has switched from maximizing spectrum utilization to optimizing spectrum utilization. In this exciting new technology, secondary users (SUs) can have opportunistic access to a primary user's (PU) licensed band when the principal user is not actively using it. This results in nobody affecting the PU's transmission. The most significant cognitive radio activities are those connected to wireless scene analysis and range organization, channel state estimation, transmission power regulation, and other related tasks. In this research, the goal is to optimize primary and secondary user coexistence and spectrum consumption by range sensing grounded on radio scene examination in order to reduce radio interference [5].

Despite the fact that the main objective of spectrum sensing is to find opportunistic white spaces in real time, the decision-making technique may also be used to generate PU activity statistics and occupancy trends as a side consequence of the process. The data on PU activity offer all of the information that is required for this purpose. This includes the durations of the busy and idle times, their averages, higher-order moments, and distributions. It also includes the shortest intervals of these periods. In order to enhance spectral efficiency, optimize CR system performance, plan spectrum sensing, select the best spectrum band and operating channel, and predict future patterns of spectrum occupancy in the CR network, statistical information can be utilized. The scientific community has been concentrating more and more on statistics pertaining to primary user activity and spectrum occupancy computation in recent years.

The improvement of 6G wireless communication technologies, which are predicted to provide remarkable speeds, very low latency, and ubiquitous connectivity, will mainly rely on Spectrum Sensing (SS). Sensing errors, including missed detections and false alarms, can be brought on by SS. False alarms occur when secondary users wrongly classify the presence of principal users, causing wasteful spectrum avoidance and inefficient consumption. Missed detections occur when main users go unnoticed, causing negative interference with continuing interactions. The efficiency and durability of SS systems may be impacted by these defects [7].

Tasks needful a lot of energy are essential for signal sampling, processing, and decision-making algorithms in signal security. These processes have the potential to suggestively rise power consumption, particularly when difficult signal environments and high sample rates are complicated. Energy efficiency becomes an essential factor, especially for networks and devices that run on batteries [8]. SS may cause a delay in the process of spectrum handoff. Secondary users are moved via spectrum handoff to different frequency bands when significant user activity is detected. During this process, delays in finding, assessing, and switching to an open channel might cause delays in spectrum handoff, which can have an adverse effect on real-time applications and service quality [9].

Using the duty cycle and channel occupancy rates, for example, we did a performance analysis. With the use of a variety of beta distributions, the authors created both a deterministic and a stochastic model for range residence. Additionally, the estimation of idle/busy periods was researched using an exponential distribution, whereas realistic approximations such as the Pareto and modified Pareto distributions were investigated as realistic approximations [10-12]. The above-mentioned research looked at the optimal spectrum sensing approach, as well as an ideal set of conditions. Spectrum sensing in PU mobile environments is the subject of this paper. We devised a Bird Mating Optimization (BMO)-based approach for rapid and little-cost range detection. PUs, deprived of attempting to pinpoint their actual position. The term "power units" is an acronym for "power units." It is expected that the mobility paradigm with random waypoints would be applied. We study PU activity's effect in combination with other variables. The effect of SU flexibility on the presentation of range sensing. Instead, we experience collectively through network agents. The number of subunits (SUs) [13, 14].We also provide an optimum design that makes the most of the available resources. Every agent in the network has its own set of benefits. According to the report, the solution we propose saves over in terms of efficiency. Spectrum sensing consumes 80% of your attention and effort. There's something for everyone in our approach, whether it's on college campuses or in amusement parks.

Recurrent neural networks (RNNs) are made to recognize relationships and patterns over time in order to calculate sequential input. One feature that sets recurrent neural networks (RNNs) apart is their feedback mechanism, which permits information to endure and move through the network's hidden states. This distinguishes them from traditional feed-forward neural networks and makes them especially useful for jobs that include sequential or time-series data. Every time step of an RNN entails producing output and updating the hidden state by fusing an input vector with the hidden state from the preceding time step. RNNs can generate outputs or predictions more easily because of their recurrent nature, which allows them to capture dependencies over the whole input sequence. An RNN's hidden state can be thought of as a history of the way the network has processed the input sequence. RNNs can handle input sequences of dissimilar lengths and are skilled at modeling temporal relationships in the data. Since gradients either decrease or expand exponentially with time, RNNs may have trouble managing long-term dependencies. This issue is known as the vanishing or overflowing gradient problem. Bi-LSTM was established to deal with this problematic.

Currently spectrum sensing techniques, such as matched filtering, cyclostationary feature recognition, and energy detection, each have special benefits and drawbacks. Since of its simplicity of use and low processing overhead, energy detection is frequently designated. Its efficacy is diminished in conditions with low Signal-to-Noise Ratio (SNR) due to its incapacity to differentiate among signal and noise. When the signal is known, matched filtering provides better detection performance; but, as it depends on earlier acquired information about the signal, it is less flexible in dissimilar spectrum circumstances. Cyclostationary feature detection, while noise-resistant, is computationally demanding and problematic to implement.

Bi-LSTM networks present a workable option in this condition. Their ability to procedure data sequences both forward and backward progresses prediction capabilities and lets them to accurately model long-term dependencies. When paired with the Bird Mating Optimizer (BMO), a nature-inspired optimization method, the spectrum sensing process may be fine-tuned for highest performance while maintaining accuracy and computing economy. This introduction lays the foundation for a new and sophisticated spectrum sensing technique that creates use of both Bi-LSTM and BMO's strengths, finally advancing the improvement of more effective and sophisticated cognitive radio networks. It does this by proposing a thorough review of related work and pointing out the shortcomings of existing methods.

The use of deep learning to ranges is covered in this work. This study proposes the "DLSenseNet" (Deep learning-based range detecting network) approach. Spectrum sensing's objective is to precisely classify underutilized range and to use it to maximize spectrum utilization while minimizing meddling. The study is separated into the following sections: The second section discusses spectrum sensing research, the third section details the suggested approach, and the fourth section details the experimental setting. Section 5 discusses the findings, which are then concluded in Section 6.

II. LITERATURE SURVEY

M. R. Vyas et al [15]. Spectrum sensing's main premise is to regulate whether the PU is there or not. Research on spectrum sensing as a deep learning (DL) and machine learning (ML) classification challenge is not very extensive. An important illustration is the research being done on spectrum detection with artificial neural networks (ANNs). This study presented forth a novel ANN-based hybrid sensing technique that combined training features with statistical and energy metrics. Liu C. and colleagues in recent times, [16] suggested using a naïve Bayes classifier to detect the OFDM signal in low SNR situations. In addition, only a limited number of research have employed the DL approach for spectrum detection. For example, spectrum sensing of OFDM signals with CNNs has been proposed, as has CNN-based supportive detection and stacked auto-encoder-based spectrum sensing. The ML/DL frameworks make use of a shallow/deep multilayer perceptron network as their neural network architecture.

A CNN-LSTM detector is an LSTM detector created by Xie et al. [17] that combines CNN and LSTM algorithms. Covariance matrices derived from sensor data comprise the input. Regardless of noise uncertainty, the CNN-LSTM detector continuously outperforms other detectors in terms of performance.

Models for deep learning Gao et al. [18] presented Detect Net and Soft Combination Net for spectrum sensing and range detection and obligating range detection, respectively. They examined how well the model performed in comparison to the energy detection strategy and discovered that by taking advantage of the modulated signals' underlying structure information, they could get a sub spatial presentation gain over conservative supportive detection methods. According to the findings of each investigation, deep learning technology has superior spectrum sensing capabilities than conventional sensing techniques.

Han et al. [19] et al. proposed using a CNN-based model that incorporates cyclostationary feature recognition and incoming energy signals to train the data in order to improve result accuracy. The deep cooperative spectrum sensing (CSS) approach was first presented by Lee et al. [20]. As shown below, CNN uses a convolutional neural network to extract individual SUs from each sensing decision. A hard or soft combination can be used to improve sensing accuracy when compared to conventional approaches, depending on the application.

The SenseNet architecture, created by Chandhok et al. [21], is used for broadband range detection and involuntary inflection categorization in wireless networks. It was tested using AWGN, Rayleigh, and Rayleigh with doppler frequencies to see how well the model performed. The model was trained with in-phase data, quadrature data, and amplitude data, and its performance was evaluated with in-phase data.

In order to tackle the problems caused by noisy power uncertainty, Zhang and colleagues [22] responded to the sensing task by framing it as an organizational challenge and concentrating on the power prototype of the received signal. They presented the concept of transfer learning and proved that it is more efficient than techniques like the maximal minimal eigenvalue ratio and frequency domain entropy.

D. Lopez et al. [23]. A drawback of the shallow/deep multilayer perceptron network is that it lacks memory elements, which makes it incapable of storing data. As a result, as seen in the following example, multilayer perceptron networks are inappropriate for modelling temporal data or time series. This improved Recurrent Neural Network (RNN) architecture, which makes use of LSTM technology, is especially appropriate for time series issues because of its substantial short-term memory capacity. This helps to better synchronize historical (past timestamps) and current information (present timestamps) in a time series, which is why LSTMs—which are often used with temporal data—can be used with. LSTMs do this by using several gates within a single neuron.

Yu et al., [24]. There are only a few research that have employed LST networks on radio range information in the literature. Authors [25] suggested using LSTM networks in a spectrum prediction method. LSTM networks were employed

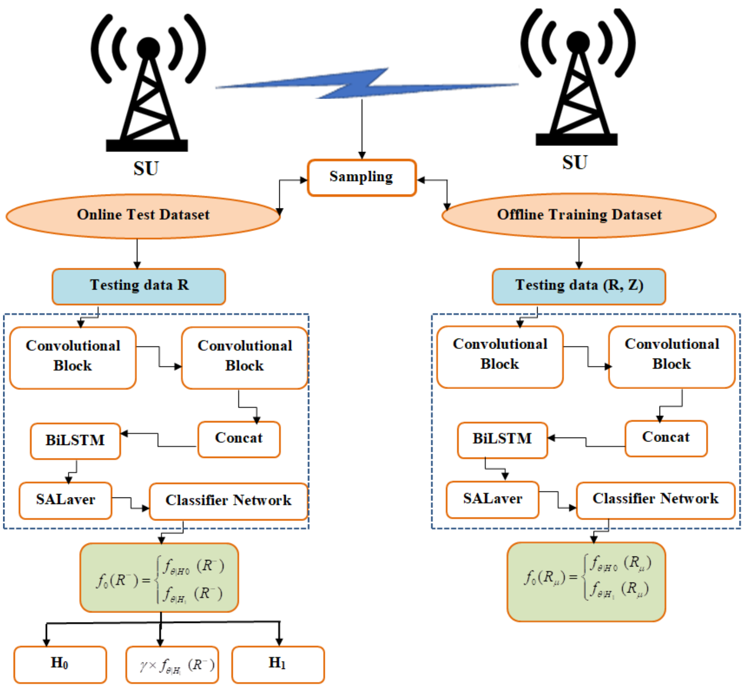

FIGURE 1. The proposed model for Bidirectional Long Short-Term Memory (Bi-LSTM) with Bird Mating Optimization (BMO).

in a different investigation to address the modulation classification issue. Additionally, the authors used the Taguchi technique to tune the LSTM network's hyperparameters for range predictions. In addition, the authors [26] used the LSTM network to estimate mobile traffic. But the research mentioned above especially addressed the issue of spectrum prediction and in the process proved the accuracy of numerous machine learning methods.

Previous research has indicated an extensive discrepancy in the literature regarding the properties of spectrum sensing in cognitive radio settings. Furthermore, there has been insufficient emphasis on optimizing the essential problems for efficient application in real-life situations. Many academics have investigated different approaches and methods, taking into account variables like hardware constraints, cohabitation with older systems, dynamically changing channels, and complexity. The optimization of deep learning models with respect to computational complexity, energy efficiency, and detection accuracy has not, however, received enough attention. Cognitive radio systems could benefit greatly from bridging this gap.

A. FORMULATION OF THE PROBLEM

Spectral sensing is a classification issue (sometimes known as a binary hypothesis challenge problematic) with two possible outcomes. The received signal examples during the first discovery interval are specified in equation (1) and the conventional signal examples throughout the second detection interval are specified in equation (2) [27].

$$z_u = \begin{cases} H_0 : \{w_u(n)\}^N{}_{n=1} \\ H_1 : \{he^{(2\pi n f_c + \varphi_u(n))j} S_u(n) + w_u(n)\}^N{}_{n=1} \end{cases} \quad (1)$$

The term r(n) signifies the nth established signal example during the u-th discovery retro, where N denotes the example distance, i.e., each detection period receives N signal samples; $s_u(n)$ signifies the PU signal at the n-th sample during the u-th detection interval; h denotes the channel gain during the detection time, which is assumed to be constant; f_e denotes the normalized center incidence balance; $p_u(n)$ denotes phase noise at the nth sample; and w(n) denotes addictive noise. The absence of PU and the presence of PU are represented by the symbols Ho and H1, respectively.

Due to the many signal occurrences during the discovery period, the formula can be reduced to (1) because the recommended technique does not require prior knowledge of the noise level or PU signal.

$$R_u = [r_u(1), r_u(2).......r_u(N)] \quad (2)$$

We integrate R and tagzu in order to generate an exercise instance with the conditions of Ho and H1 (Ru. Zu). The following equation (3) can be used to quantify the likelihood of missing a detection as well as the likelihood of receiving a false alarm.

$$\begin{aligned} P_{md} &= \Pr ob\{H_0 \mid H_1\} \\ P_{fa} &= \Pr ob\{H_1 \mid H_0\} \end{aligned} \quad (3)$$

The probability distribution function is represented by Prob (). For spectrum sensing, Pmd and Pfa are both essential performance markers. The article presents a resilient detection model that performs well in difficult low signal-to-noise ratio (SNR) settings. It is characterized by low probabilities of false alarms (Pfa) and missed detections (Pmd). When sensing error is assessed as a performance indicator, Pmd and Pfa consistently have an average value of 30%.

III. THE PROPOSED METHOD

An DL-based range detection technique for s users in cognitive radio schemes is planned in this object, which is available online. Our method only uses raw data; it does not need previous data of the PU's signal strength or noise level. The suggested spectrum sensing approach, depicted in FIGURE 1, includes both offline exercise and online detection phases, and it is described in detail below [28]. To begin, the DNN used in this article is skilled utilizing exercise data gathered during the primary and secondary user sensing phases described earlier in this article. The newly obtained signal data is then sent into a well-trained DNN for online discovery, resulting in the likelihood that Ho and H1 are two words that begin with the letter H being strongminded. It is determined whether or not the PU is present based on this probability. It is detailed in detail here how the offline exercise module, the online discovery unit, and the creation of the suggested deep neuronal network are all accomplished.

A. Offline Training

We marker the conventional rare signal information in order to generate the training data set for the proposed DNN based on the states of Ho and H1, which we then use to train the DNN. The notation can be interpreted as equation (4) as follows [29].

$$(R,Z)=\{(R_1,z_1),(R_2,z_2)......(R_U,z_U)\} \tag{4}$$

When Ru is used to represent the label for Zu in € (0, 1), it particularly refers to the occurrence u-th from the labeled exercise dataset (R, Z), where u is any integer between 1 and U. In this case, each instance of Ru is converted into a N x 2 vector of real values, where R stands for the input data. The quadrature components are positioned in the first column and the in-phase components in the second column of this vector representation. The fact that Zu = 0 and Zu = 1 indicate the Ho and H1 conditions, respectively, is what is most notable. The labelled working out data set includes a total of U observations. In this paper, the terms (R, Z) refer to exercise exam ples that were conducted in a variety of SNR scenarios. In other arguments, after exercise, the planned DNN is capable of dealing with instances with dissimilar SNRs [30].

Given that range detection can be regarded of as a tough double hypothesis problem, here equation (5) considers the intended deep learning model's offline exercise to be a two-classification task.

$$z_u=\begin{cases}[1,0],H_0\\ [0,1],H_1\end{cases} \tag{5}$$

As illustrated in equation (6) and (7), the proposed DNN generates a two-by-one period groove course normalized by the SoftMax function31, which is then divided by two.

$$f_0(R_u)=\begin{cases}f_{0|H0\ (R_u)}\\ f_{0|H_1\ (R_u)}\end{cases} \tag{6}$$

$$f_0\,|\,H_0(R_u)+f_{0||}H_1(R_u)=1 \tag{7}$$

Where foH, (R1) denotes the consistent appearance of Hi (ie, the class score of H1), and fo(-) denotes the model's limits and look, correspondingly; foH, (R1) denotes the consistent appearance of Hi; foH, (R1) denotes the consistent appearance of Hi; foH, (R1) denotes the consistent expression of Hi; foH, (R1) denotes the consistent appearance of Hi; (ie, the session groove of H1). The likelihood of the hypotheses is expressed using a probability distribution function, which is represented by equation (8):

$$\begin{aligned}H_0:\Pr ob(z_u=0\,|\,R_u;\theta)&=f_{0|}H_0(R_u),\\ H_1:\Pr ob(z_u=1\,|\,R_u;\theta)&=f_{0|}H_1(R_u),\end{aligned} \tag{8}$$

In this case, Prob (zu = i|Ru; 0) = foH, (Ru) with I = 1 or 0 is equivalent to foH, (Ru). Equation (9) is subsumed by the following:

$$\Pr ob(Z\,|\,R;\theta)=(f_\theta H_0(R))^{1-Z}\,(f_\theta H_1(R))^Z \tag{9}$$

A neural network's exercise objective is to increase the likelihood of a specific result. Equation (1) specifies the objective of the proposed DNN as "maximizing probability," which is the target function as follows in equation (10).

$$L(\theta)=\Pr ob(Z\,|\,R;\theta)=\prod_{u=1}^{U}(f_\theta H_0(R_u))^{1-Z}\,(f_\theta H_1(R_u))^Z \tag{10}$$

And equation (11) defines the log likelihood.

$$l(\theta)=\log L(\theta)=\sum_{u=1}^{U}(1-z_u)\log(f_{\theta|}H_0(R_u))+z_u\log(f_{\theta|}H_1(R_u)) \tag{11}$$

The optimum situation limit can be found by minimizing the irritated-entropy function32, represented by F, which is equal to negative (0) between the model distribution and the training data. The following equation (12) is used to define it.

$$F(\theta)=-l(\theta)=\sum_{u=1}^{U}z_u\log(f_{\theta|}H_0(R_u))+(1-z_u)\log(1-f_{\theta|}(R_u)) \tag{12}$$

The optimal parameter, 0*, for the intended DNN is obtained through offline training, as indicated by Equation, and may be used to maximize probability L (0) and minimize negative log likelihood I (0) in equation (13).

$$\theta^*=\arg\max L(\theta)=\arg\min(-l(\theta)) \tag{13}$$

During the offline exercise phase, the parameter 0 is continually updated through back spread pending the best limit θ^* is reached.

B. Online Recognition

This study acquires a healthy-qualified DNN specified by equation (14) when the offline training phase is completed:

$$f_0(R_u) = \begin{cases} f_{0|H0\ (R_u)} \\ f_{0|H_1\ (R_u)} \end{cases} \tag{14}$$

in which fo- (-) and fo-H, (R) denote, respectively, the well-qualified DNN and the session groove of H1, and where R is an unlabeled distance of a programme that conducts online detection, and it is used in this section. If a new unlabeled example is input into the well-qualified DNN, the efficiency of the PU is measured by associating the production session score fo-H, (R) to a preset threshold y (0x1), as indicated in equation (15):

$$f_{\theta*}(R) = \begin{cases} f_{\theta|H_0\ (R)} \\ f_{\theta*|H_1\ (R)} \end{cases} \tag{15}$$

We can determine the signal status of the PU (whether it is present or absent) by calculating whether fo-H, (R) is greater than y. Or, to put it another way, the ultimate classification outcome is determined by the category that receives the highest-class score. We set the value of y to be 0.5 in this example.

C. Bird Mating Optimization (BMO)

1) Principles of Bird Mating Optimization (BMO)

If there are subdivisions in interplanetary with only two attributes, "position" and "velocity," the probable solution to the optimization issue replaces each particle here. "Velocity" describes the speed of the gesture, whereas "position" describes the direction of motion. To provide each resident with the greatest possible experience, the subdivisions constantly adjust their location based on their own unique experiences. The BMO is first set up to generate data. We are iteratively selecting the "optimal particle" from among a random selection of possible solutions. To work within the constraints of the existing environment and to adhere to those constraints in order to arrive at the best explanation to the problematic [31-33].

Assume that a space has m subdivisions in its population, that the ith particle's current position is Xi,t, and that its current velocity parameter is Vi,t. Individual extremes in terms of values pbesti and global ideal solutions are two terms that come to mind. The two parameter values on which each particle "concentrates" its attention is denoted by the letters gbesti. Both of these systems are currently the best options for the swarm, with the former being the best solution and the latter being the finest alternative. Each particle's V and X are continually changing as a result of the "supervision" of these dual limits. During the quest for the pbesti and gbest limits, the subdivision acquires its efficient V and X limits by solving the following equations (16) and (17) for the particle.

$$V_{i,t+1} = w.V_{i,t} + c_1.Rand.(phest_i - X_{i,t}) + c_2.Rand.(gbest_i - X_{i,t}) \tag{16}$$

$$X_{i,t+1} = X_{i,t} + V_{i,t+1} \tag{17}$$

2) BMO optimized Bi-LSTM algorithm flow

Step 1: Define the population size, velocity, iteration count, learning rate, and spatial position requirements to set the learning process's parameters. It is created a particle Xi,0(h1, h2, lr,n) that is a member of the population and has random properties, which belongs to the population. A hidden layer neuron is represented by the initial 'h', whereas neurons in the first hidden layer are represented by the letters 'h1', 'h2', and so on. Furthermore, in the LSTM, the letters lr and n stand for the learning rate parameter (lr) and the number of algorithm iterations (n), respectively.

Step2: Connecting the generated particles Xi,0 to the LSTM parameters is essential for assessing the population's performance. Three distinct types of data sets have been used in this process: training, validation, and prediction. Once the requirements are satisfied, obtain the parameters ytrain and ytest using the training set as the method's input. These two parameters, and, respectively, represent the output values of the training and validation sets as follows in equation (18) [34, 35]. In addition, use the following formula to get the individual fitness score by using the variables ytrain and ytest to represent the expected output values for the training and validation sets, the below equation (19) and (20) as follows correspondingly:

$$fit_i = \frac{1}{2}(MSE_{train} + MSE_{test}) \tag{18}$$

$$MSE_{train} = \frac{1}{n}(y_{train} - y^{-}{}_{train})^2 \tag{19}$$

$$MSE_{test} = \frac{1}{n}(y_{test} - y^{-}{}_{train}) \tag{20}$$

In the present article, the training and validation sets' weights for Mean Square Error (MSE) are equalized. The model's fitness function is equal to 0.5, which is the outcome of multiplying each weight separately and then adding them collectively. This article suggests a novel training set fitness function that considers both training set fitness mistakes and validation set validation errors [36]. This is done since most previous studies relied on fitness in error of training sets and because overfitting causes unsatisfactory prediction outcomes.

Step 3: Calculate the suitability worth fiti and the dual strictures pbest and gbest by starting with the suitability value

of the first subdivision and recording each particle's historical ideal position.
Step 4: The subdivision's speed and location are efficient for each repetition of the calculation using Equations (16), (17) and (18). The fitness value of the recently found particle in the population is used to update the values of the global best (gbest) and the individual best (pbest).
Step 5: After BMO training, the LSTM model analyzes the load data and, after the algorithm has run as many times as permitted by the technique, produces prediction values for power load.

IV. EXPERIMENTAL SETUP

The design technique is discussed in detail in this section. To improve our classification model's accuracy and robustness, we performed a variety of categorization methods and compared them with ours that exist.

A. Dataset Generation and Pre-processing

The baseline dataset RadioML2016.10b by O'Shea and Corgan is freely available on the internet. Ten different forms of modulated signals are included in the collection: two analogue and eight digitals. The SNR values and the modulation type are included. In between -20 dB and +18 dB, SNR values are spread in increments of two decibels. We looked at eight different forms of digitally modulated transmissions with variable signal-to-noise ratios to see how they performed. Positive samples are those that include these signals in their composition. The undesirable occurrences consist of preservative noise produced with the same magnitude as the input sign by the use of a zero-mean, circularly symmetric complex gaussian (CSCG) distribution. A two-dimensional vector of n dimensions, comprising an infinite number of samples for the in-phase and quadrature apparatuses, was supplied to the deep neural network for every training sample. There are several parameters to the dataset, which are listed in the Table. Exercise, authentication, and challenging sets of data were created for each of the three stages. Table I represent the dataset parameters. The dataset was partitioned into train, validation, and test sets.

TABLE 1
Dataset Parameters

Parameters	Value
The range of SNR	−20 dB~18 dB in 2 dB increment
Modulation scheme	QPSK, QAM16
The sample length	64,128,256,512
A training example	153,000
Validation examples	51,000
Example of Testing	51,000

B. Performance Evaluation Metrics

$$P_d = \frac{a}{a+b} \tag{21}$$

$$P_m = 1 - P_d \tag{22}$$

$$P_f = \frac{c}{c+d} \tag{23}$$

$$SE = Average(P_f, P_m) \tag{24}$$

The model was skilled and authenticated before it was put to the test to see how well it performed. The evaluation metrics used in this section are the chance of detection (Pd) as follows equation (21), probability of miss detection (Pm) as follows equation (22), false alarm rate as follows equation (23) and the detection error (SE) as follows equation (24). There is a chance Pd of identifying the existence of the primary user when the spectrum is in use, and a probability Pf of indicating the presence of a main user when the spectrum is essentially empty. Both probabilities were assessed with signals that varied in SNR. The likelihood of a false alert and the likelihood of a missed detection were averaged, and the result was divided by two (Pm) to get the SE. There is a danger of misdetection equal to the probability of reporting a spectrum empty while the PU is present.

V. RESULTS

In this section we display the imitation outcomes to prove that the proposed method performs. Numerous characteristics, including as inflection methods, example duration, and organization replicas, are studied to see how they affect the results. On several deep neural network designs, including CNN, ResNet, Bi-LSTM, Convolutional Long Short-Term Deep Neural Networks (CLDNN), and others, we assess the efficacy of our model. Furthermore, we contrast our model against established range detecting models as CNN-Bi-LSTM and DetectNet. As a minimum requirement for a suitable model, we require a little likelihood of untrue alarm, which according to the IEEE 802.22 standard should be between zero and one-tenth of one percent, a little detection mistake, and a high chance of discovery (TABLE 2).

The findings show that the proposed Bi-LSTM with BMO strategy not only improves detection accuracy and reduces false alarm rates, but it also has computational efficiency equivalent to other machine learning algorithms. Conventional approaches, while less computationally complex, do not provide appropriate detection accuracy and reliability, especially under low SNR situations. The usage of Bi-LSTM improves the management of temporal dependencies in spectrum data, and the BMO guarantees that the model parameters are tuned for peak performance. This combination overcomes the limits of both classic spectrum sensing methods and machine learning-based approaches, resulting in a more robust and accurate solution for cognitive radio networks. Furthermore, the technique's ability to support upcoming technologies such as IoT and 5G networks by providing dependable and adaptable spectrum management solutions emphasizes its practical importance. Highlighting these applications underscores the research's larger relevance and contribution to the advancement of cognitive radio networks (FIGURE 2 FIGURE 3, and FIGURE 4).

The QAM16 and QPSK modulated signals' performance characteristics are shown in the tables for sample lengths of 64, 128, 256, and 512, respectively. The diverse sample lengths are intended to demonstrate the models' efficacy across extensive variety of example sizes, according to the researchers. Applications for spectrum sensing are shown using CNN and Bi-LSTM BMO architectures in deep neural network models. Pd values are displayed with a 20 dB signal-to-noise ratio (SNR). One benefit of our DLSenseNet model is that Pf is minimized. Despite having a low Pf, the ResNet model is unable to reach high Pd.LeNet has a low Pf, yet it is unable to reach a high Pd, resulting in a substantial sensing error. Pd is also good in the inception model, although Pf is substantially greater than in previous models. Out of all the networks that were tested, this one has the lowest sensing error and the best ratio of detection probability to false alarm rate. Because of this, the DLSenseNet model reduces the number of false alarms it generates while also improving detection accuracy. Because of this, the DLSenseNet model is capable of detecting spectrum occupancy with an extremely high level of accuracy (TABLE 2, TABLE 3, and TABLE 4)).

TABLE 2
Performance measurements for QAM16 signals with 64 and 128 sample lengths are compared to each other

	64 Sample Length			128 Sample Length		
models	Pf (%)	SE(%)	Pd(-20 dB)(%)	Pf (%)	SE (%)	Pd(-20 dB)(%)
CNN	1.70	15.25	24.25	2.70	17.25	26.25
LeNet	0.10	15.50	24.50	1.10	16.50	25.50
ResNet	0.00	14.88	26.75	0.00	17.88	26.85
LSTM	0.64	17.22	26.72	0.44	18.22	24.72
CLDNN	0.46	15.75	32.22	0.34	15.95	29.22
DLSenseNet	1.20	14.75	35.76	2.20	15.75	33.76
Bi-LSTM BMO	0.00	11.75	49.10	0.00	12.75	47.10

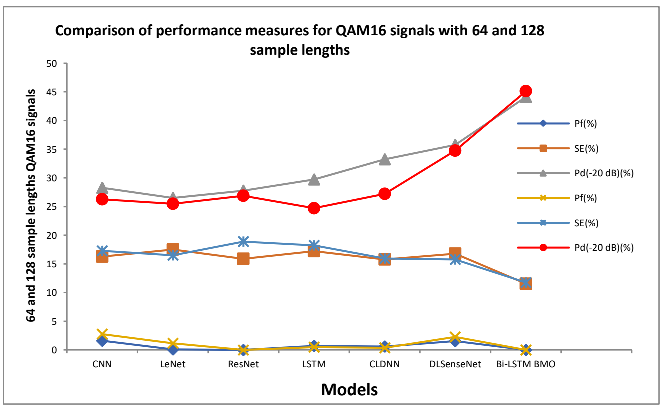

FIGURE 2. **A comparison of performance measures for QAM16 signals with 64 and 128 sample lengths.**

TABLE 3
A comparison of performance metrics for QPSK signals with example lengths of 64 and 128

	64 ExampleDistance			128 ExampleDistance		
models	Pf(%)	SE(%)	Pd(-20 dB)(%)	Pf(%)	SE(%)	Pd(-20 dB)(%)
CNN	1.60	16.25	28.25	2.75	17.25	26.25
LeNet	0.11	17.50	26.50	1.15	16.50	25.50
ResNet	0.00	15.88	27.75	0.00	18.88	26.85
LSTM	0.69	17.22	29.72	0.46	18.22	24.72
CLDNN	0.57	15.75	33.22	0.34	15.95	27.22
DLSenseNet	1.54	16.75	35.76	2.27	15.75	34.76
Bi-LSTM BMO	0.00	11.55	44.10	0.00	11.75	45.10

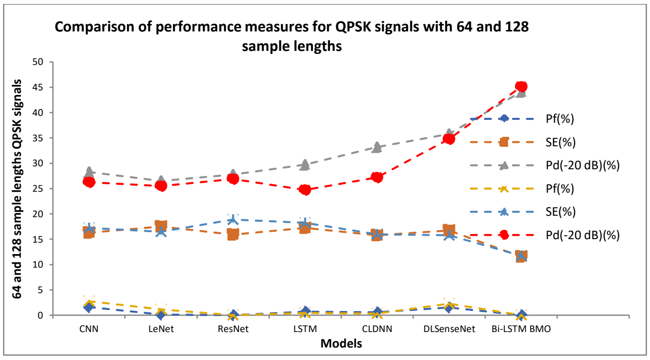

FIGURE 3. **Performance metrics for QPSK signals with 64 and 128 samples are compared.**

TABLE 4
A comparison of performance measurements has been carried out for QAM16 signals with 256 and 512 sample lengths.

	64 ExampleDistance			128 ExampleDistance		
models	Pf(%)	SE(%)	Pd(-20 dB)(%)	Pf(%)	SE(%)	Pd(-20 dB)(%)
CNN	1.55	16.25	28.25	2.75	19.25	26.25
LeNet	0.23	17.50	28.50	1.15	16.50	25.50
ResNet	0.00	15.88	27.75	0.00	18.88	28.85
LSTM	0.69	17.22	27.72	0.46	18.22	24.72
CLDNN	0.57	15.75	33.22	0.34	15.95	27.22
DLSenseNe t	1.60	16.75	35.76	2.27	15.75	34.76
Bi-LSTM BMO	0.00	11.55	42.10	0.00	11.75	46.10

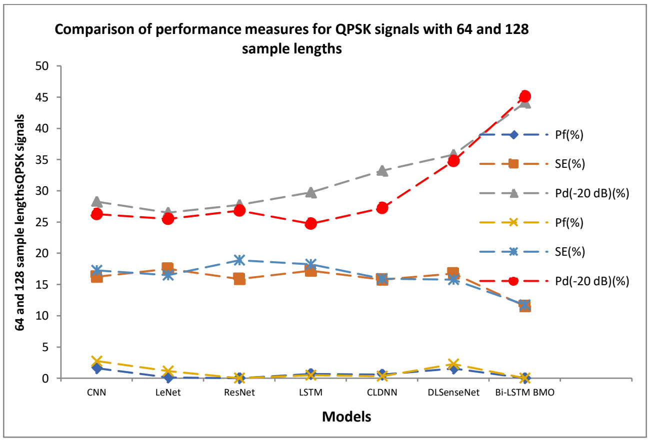

FIGURE 4. **Performance metrics for QPSK signals with 64 and 128 samples are compared.**

TABLE 5
Contrast of concert measures for QPSK16 signals with 256 and 512 sample lengths

	64 ExampleDistance			128 ExampleDistance		
models	Pf(%)	SE(%)	Pd(-20 dB)(%)	Pf(%)	SE(%)	Pd(-20 dB)(%)
CNN	4.60	18.25	28.25	2.75	19.25	26.25
LeNet	0.11	19.50	26.50	1.15	18.50	25.50
ResNet	0.00	20.88	27.75	0.00	18.88	26.85
LSTM	2.69	17.22	29.72	0.56	18.22	24.72
CLDNN	0.57	15.75	33.22	0.34	15.95	37.22
DLSenseNet	2.54	16.75	35.76	2.27	15.75	44.76
Bi-LSTM BMO	0.00	13.55	44.10	0.00	11.75	48.10

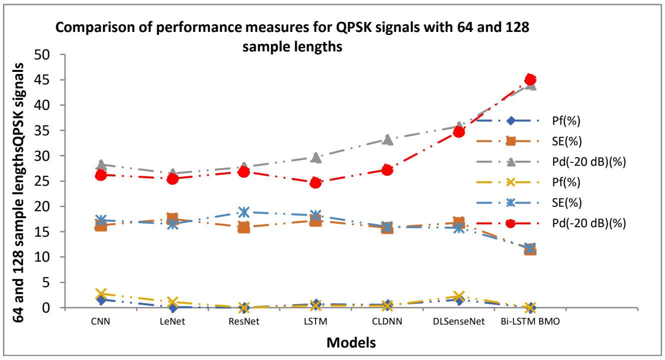

FIGURE 5. **Comparison of performance metrics for 64 and 128 sample length QPSK signal.**

The above Tables compare the planned DL Sense Net model to the before described Detect Net and Bi-LSTM-BMO models in terms of sensing performance. According to tables, the DL Sense Net outperforms previous research in terms of the proportion of false alarms and the chance of detection. The suggested model increases the likelihood of detection while reducing false alarms. Overall, the proposed approach looks to be a promising spectrum sensing option. Cognitive radio is a branch of radio that focuses on the brain (TABLE 5, FIGURE 5).

The DL Sense Net spectrum sensing technology is introduced in the proposed study. The models decide whether the range is engaged or empty based on the evaluation of the circumstance. When it comes to classification difficulty The improved performance indicates that the primary source has been accurately identified and is being used. Transmission of data by users throughout the radio frequency spectrum.

Bit Error Rate (BER):

The ratio of mistake bits to total bits sent is the official definition of bit error rate, or BER. A transmission system's performance quality can be assessed by looking at its BER value. A transmission system may achieve reduced BER by taking into account the greater SNR and improved transmission channel. A percentage is commonly used to compute BER. Using equation (25) BER is computed [37].

$$BER = \frac{Number\ \ of\ \ Error\ \ Bits}{Total\ \ Number\ of\ \ Bits\ Sent} \tag{25}$$

As an illustration, if there are two mistake bits out of ten in a transmission system, then the above equation derived from above equation (26) BER is computed.

$$BER = \frac{2}{10} \times 100\% = 20\% \tag{26}$$

TABLE 6
Bit error rate (ber) analysis for Bi-LSTM BMO model

SNR (dB)	CNN	LeNet	ResNet	LSTM	CLDNN	DLSenseNet	Bi-LSTM BMO
0	0.1	0.096	0.093	0.09	0.085	0.08	0.07
5	0.098	0.091	0.090	0.087	0.079	0.076	0.066
10	0.093	0.089	0.087	0.081	0.075	0.070	0.060
15	0.087	0.080	0.067	0.078	0.068	0.057	0.048
20	0.080	0.078	0.060	0.070	0.061	0.050	0.042
25	0.078	0.068	0.057	0.066	0.048	0.047	0.036
30	0.070	0.058	0.053	0.060	0.024	0.023	0.010

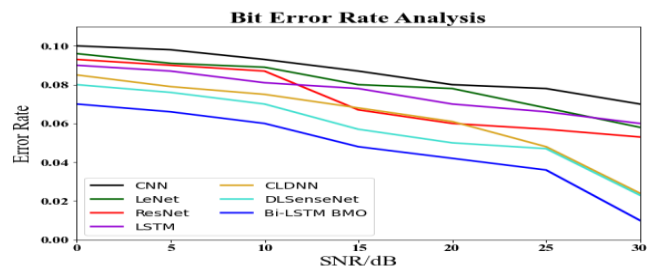

FIGURE 6. Bit error rate analysis for bi-LSTM BMO model.

FIGURE 6 and TABLE 6 display an BER comparison of the Bi-LSTM-BMO strategy with other well-known methods. The DL technique has an enhanced performance while reducing BER, as shown in the graph. For example, the Bi-LSTM-BMO model's BER value for 5dB is 0.066, while the BER values for the CNN, LeNet, ResNet, LSTM, CLDNN and DLSenseNet models are 0.098, 0.091, 0.090, 0.087, 0.079 and 0.076, respectively. The Bi-LSTM-BMO model, however, has demonstrated its best performance for various data sizes with low BER values. In a similar vein, for 30 dB, the BER value for the Bi-LSTM-BMO is 0.010, whereas, for the CNN, LeNet, ResNet, LSTM, CLDNN and DLSenseNet models, it is 0.070, 0.058, 0.053, 0.060, 0.024 and 0.023, respectively.

Packet Error Rate (BER):

The Packet Error Rate (PER) is a metric used in networking and communication systems to quantify the likelihood of packet loss or errors during transmission. It signifies the ratio of incorrectly received packets to the entire number of transmitted packets, expressed as a percentage or a fraction. Mathematically, PER is defined following equation (27) [38].

$$PER = \frac{N}{B} \tag{27}$$

where, N represents Number of incorrectly received packet, B represents total number of transmitted packets. It provides a measure of the reliability of packet delivery in digital communication systems, crucial for assessing the quality and performance of data transmission.

TABLE 7
Packet error rate (per) analysis for Bi-LSTM BMO model

SNR (dB)	CNN	Le Net	ResNet	LSTM	CLDNN	DLSenseNet	Bi-LSTM BMO
0	0.1	0.01	0.099	0.098	0.095	0.092	0.09
5	0.099	0.099	0.097	0.096	0.093	0.089	0.089
10	0.095	0.095	0.090	0.090	0.088	0.081	0.082
15	0.090	0.089	0.088	0.088	0.079	0.078	0.079
20	0.087	0.082	0.082	0.080	0.071	0.071	0.071
25	0.079	0.078	0.078	0.076	0.076	0.068	0.068
30	0.070	0.071	0.070	0.070	0.069	0.065	0.062

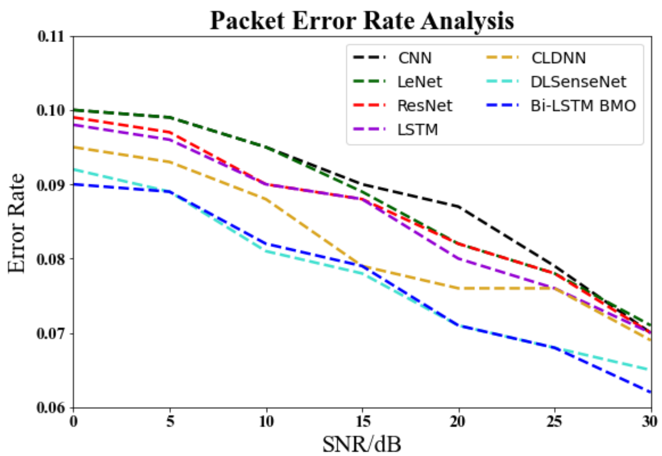

FIGURE 7. Packet error rate analysis for bi-LSTM BMO model.

FIGURE 7 and TABLE 7 display a PER comparison of the Bi-LSTM-BMO strategy with other well-known methods. The DL technique has an enhanced performance while reducing PER, as shown in the graph. For example, the Bi-LSTM-BMO model's PER value for 5dB is 0.09, while the PER values for the CNN, LeNet, ResNet, LSTM, CLDNN and DLSenseNet models are 0.099, 0.099, 0.097, 0.096, 0.093 and 0.089, respectively. The Bi-LSTM-BMO model, however, has demonstrated its best performance for various data sizes with low PER values. In a similar vein, for 30 dB, the PER value for the Bi-LSTM-BMO is 0.062, whereas, for the CNN, LeNet, ResNet, LSTM, CLDNN and DLSenseNet models, it is 0.070, 0.071, 0.070, 0.070, 0.069 and 0.065, respectively.

VI. DISCUSSION

The proposed method Bi-LSTM-BMO integration enables effective learning and prediction of spectrum availability by capturing temporal dependencies in signal data from both previous and future states. The BMO improves performance by refining sensing parameters, resulting in more precise detection of available channels. These findings show that this approach has the potential to outperform traditional spectrum sensing techniques, especially in complex and dynamic radio settings where precise and fast detection of spectrum opportunities is crucial.

This research improves CRNs' capacity to reliably and effectively detect available spectrum, which is critical for maximizing network performance and decreasing interference. This technique, which captures temporal dependencies in both directions and optimizes sensing settings, can greatly increase spectrum sensing reliability in dynamic contexts, allowing for more effective radio spectrum usage. This could result in higher total network throughput, lower latency, and more efficient use of limited spectral resources, ultimately improving CRNs' capabilities in managing the increasingly congested radio spectrum.

The proposed method Bi-LSTM-BMO has key limitation is the computational complexity, which makes them more demanding in terms of memory and processing power because of their bidirectional design. Low-latency responses are critical in real-time spectrum sensing applications, where this can be especially difficult. Furthermore, while though the BMO aids in refining the sensor settings, it may add more computing cost, decreasing the system's efficiency in dynamic environments where quick adaptation is required. The quantity and quality of training data have a significant impact on this approach's success as well. The Bi-LSTM model might have trouble generalizing in settings with little data or where the spectrum characteristics very quickly, which could result in less-than-ideal sensing outcomes.

VII. CONCLUSION

A ground-breaking Wireless Regional Area Network technology, cognitive radio makes use of available spectrum in an opportunistic manner, allowing for the creation of new Wireless Regional Area Networks. Detection of the radio spectrum is an essential difficulty in cognitive radio technology. Traditional spectrum sensing systems have a variety of disadvantages that are inherent in their design. This article provides the "DL Sense Net," a deep neural network-based perfect for range detection that was developed in conjunction with other researchers. In comparison to other sensing models, such as the Deep learning, Bi-LSTM-BMO, residual network, inception, Le Net, and Detect Net, it exhibits an improvement. The methods' performance was evaluated using typical spectrum sensing metrics. According to the experimental results, the suggested Bi-LSTM with BMO improved dataset accuracy, particularly at -20 dB, decreased the likelihood of miss detection by 44.10%, and decreased the sensing error (SE) for QPSK 16 by 13.55%. The findings highlight the significance of advanced machine learning techniques, such as Bi-LSTM, in understanding temporal relationships and estimating spectrum availability with high precision. Furthermore, the use of BMO for parameter optimization improves the adaptability and efficiency of the spectrum sensing process. Reliable spectrum sensing is crucial for enabling Internet of Things (IoT) devices and future 6G networks to operate effectively in spectrum-constrained environments. Investigate methods to enhance the security and privacy of spectrum sensing operations to mitigate potential threats and vulnerabilities.

DECLARATIONS

Data Availability: Data will be made available on request.

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

Conflicts of Interest: The authors declare that there are no conflicts of interest to report about the current study.

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