Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 28 No. 1 (2025)

# Deep Learning Cooperative Spectrum Detection for Cognitive Radio

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***Article History:***

***Received:*** *14-07-2024*

***Revised:*** *30-08-2024*

***Accepted:*** *10-09-2024*

**Abstract:**

In a cognitive radio system, the idle licensed spectrum is to be accurately identified and utilized by the secondary user. The location of essential client signals is fundamental for the ideal use of a range by optional clients. Range detecting through profound learning limits the room for mistakes in the recognition of the free range. This examination gives knowledge into involving a profound neural organization for range and hence a profound learning-based model for spectrum sensing and detection. The deep learning cooperative system for detection is discussed in order to provide performance gain over the conventional methods.

**Keywords**: Deep Learning, Cognitive Radio, Spectrum sensing, Cooperative sensing system

## 1. Introduction

The IoT, cyber-physical systems, and other new uses and technologies have increased the need for wireless spectrum today [1]. This growth in spectrum demand will be difficult to achieve because the spectrum is a scarce resource. Due to technological limits, its expansion is difficult. The use of the spectrum has become a primary goal for researchers. Cognitive radio is a method that permits the Cognitive Users (CUs) to opportunistically make use of the band that is licensed for the main user, that is the Primary User when the principal user is not using it [2]. As a result, the PU's transmission is unaffected in any way. Other cognitive radio activities include investigation of the radio spectrum, management of spectrum, estimating the states of the channel, controlling the power of the transmitter, etc [3] which are the most important. The multipath fading, shadowing, hidden terminal difficulties, and other factors, cause the wireless communication system to have a number of fundamental limitations which has been recognized and recorded. Since the sensing of the spectrum depends on the above-mentioned parameters, the results of individual base station radio spectrum investigation may not be error-free. [4]. The errors found in the channel classification and identification are reduced based on Deep learning- based spectrum sensing. Deep learning techniques learn features on their own and do not depend on any signal features; rather, it learns the features on their own. As a result, deep learning will aid in improving channel classification performance measures [5,6]. Spectrum sensing techniques often require prior knowledge of the signal or noise power of the PU, but this information would not be accessible in utmost circumstances, particularly in communications based on non-cooperative techniques [22,23].

## 2. Spectrum Sensing

Spectrum sensing is a significant constituent of cognitive radio. It entails monitoring the radio environment for the occurrence of spectrum holes and PU detection. Spectrum decision: Spectrum decision determines the best spectrum hole for data transmission. Spectrum Sharing: Because many Cognitive Radio users share the same spectrum, a mechanism is required to coordinate network accessibility for all the stated Primary users [24,25]. Upon identification of a primary licensed user, the cognitive radio should effortlessly move to another available spectrum hole for continuing transmission [7,15]. Fig 1 depicts the cognitive cycle.

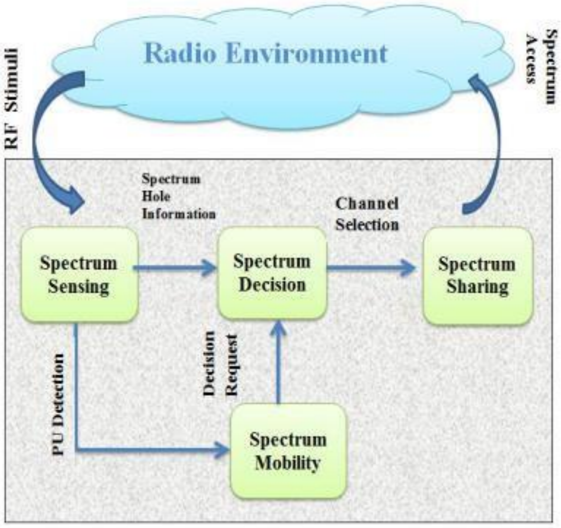


Fig1. Cycle of Cognitive Radio

Constituent of Spectrum Sensing: There are several components that make Spectrum sensing which include dimension space, hardware issues, spectrum sensing techniques, and the cooperative sensing concept which is shown in Figure 2.

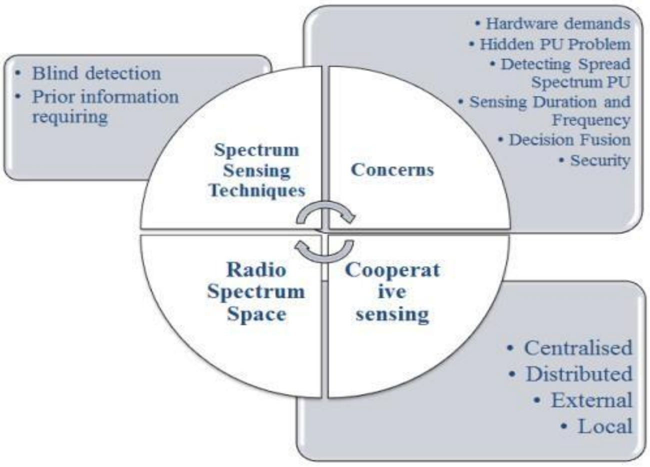


Fig. 2 Components of Spectrum Sensing

*Spectrum Space of Radio:*

Spectrum Space of Radio is an n-dimensional space that has white spaces [8], and hence the secondary user can send data via the unused spectrum. The following are some different techniques for radio spectrum space [8]:

Usage of Frequency domain: In frequency division multiple access (FDMA), signals can be broadcast concurrently and continuously while occupying their allotted frequency bands without interference.

Time-domain utilization: In cellular communication, the utilization of time division multiple access (TDMA) provides an unused spectrum for a short period of time, which can be used for cognitive users.

Usage of Spatial domain: The longitude, latitude, elevation, and distance of the PU are sensed in the spatial dimension, allowing spectrums that are not used in the area, not occupied by the spectrum [26].

*Spectrum Sensing Challenges:*

Hardware Necessities: The entire cost of the system rises as CR clients want high-resolution Analog to Digital Converters (ADCs) and high-speed signal processors [9,17].

Hidden Primary User Problem: The main issue of the concealed primary user in CR makes both cognitive radio and the primary user transmitter out of range and each is in contact with the main user. Because the CR and PU transmitters are not in range, they may transmit at the same time due to which interference occurs at the primary user. The cooperative sensing method helps in solving the hidden PU issue.

Detection of Spread Spectrum Primary User: Detection of primary user is difficult, particularly for those who employ spread spectrum techniques, because the strength of the PU is diffused over a wide range of frequencies.

Sensing Interval and Transition Time: It is necessary and important for the band to be relinquished for SU immediately after the unused spectrum is discovered [27,28]. The real-time implementation offers hurdles, necessitating a shorter sensing interval and a shorter transition phase.

a) Spectrum Sensing Techniques

Fig 3 depicts the classification of spectrum sensing methods. These approaches are divided into two categories, namely Need for the Prior Statistics and Blind Detection. Prior statistics of several critical signals, channels, and noise parameters is required for previous information needing, however, blind detection does not require such prior knowledge [10,18].

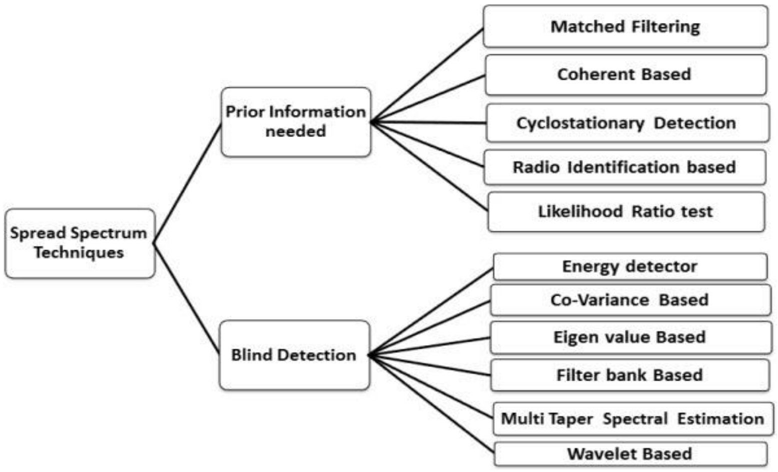


Fig 3 Classification of Spectrum Sensing Techniques

Table 1 compares the strategies outlined previously in terms of a number of key parameters. This comparison can aid in the selection of a technique for a specific application.

**TABLE 1.** Spectrum Sensing Techniques comparison

| | **Prior Information Needing** | | | | **Blind Detection** | |
|---|---|---|---|---|---|---|
| | **Coherent Detection** | **Matched Filter** | **Cyclo stationary Detection** | **Radio Identification Based** | **Energy Detector** | **Covariance Based** |
| **Sensing Time** | High | High | High | Medium | Low | Medium |
| **Robustness against SNR** | High | High | High | Medium | Low | Medium |
| **Detection Performance** | Medium | High | Low | Medium | Low | Low |
| **Accuracy** | High | High | Low | Medium | Low | Medium |
| **Complexity** | Medium | High | Medium | Medium | Low | Medium |
| **Power consumption** | Medium | High | High | High | Low | Low |

## 3. Deep Learning for Spectrum Sensing

Deep learning is a machine learning method for obtaining information in the same way as people do. Data science, which concentrates on statistics and predictive modeling [11,16], contains deep learning as a major constituent. Deep learning is considered a method to automatically predict analytics at its utmost basic level. Deep learning algorithms are developed in an order of growing complication and abstraction, compared to typical machine learning algorithms, which are linear. A cognitive radio scenario with many antennas is investigated. The major user signals are transmitted by a multi-antenna system of the primary user transmitter. The model of the spectrum sensing using Deep neural network is shown in Figure 4. The sampling and network training phases of the DNN model are split into two parts. During the sampling phase, the major user information is changed. The training and testing of this information are carried out in the training stage so that when a sample that is unknown occurs, the network can make a good choice [12].

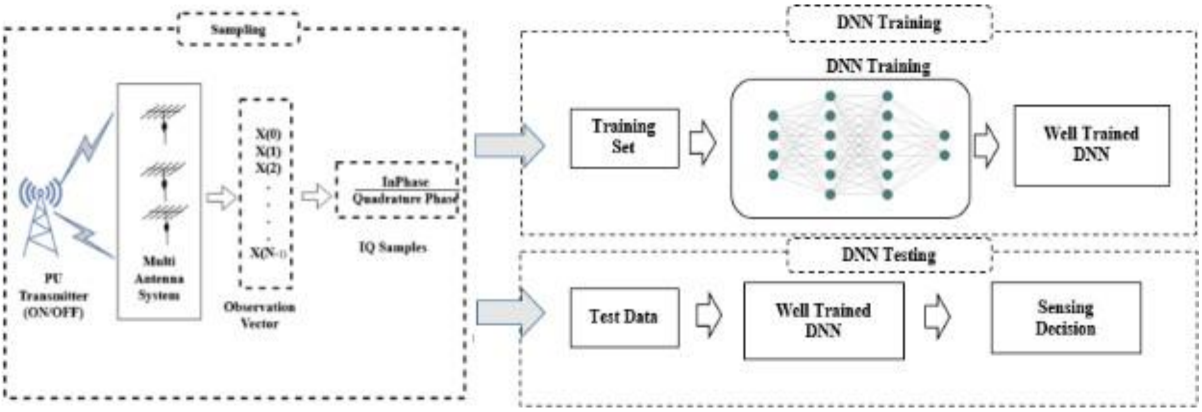


Fig. 4 A model of Deep Neural Network

Deep Neural Networks are employed in a data-driven strategy for the purpose of extracting features from the training set. The test metric is constructed on a binary sorting problem with a single-hot vector representing the label. The model is shown in Figure 4.

Consider the expression X(m) = [x1(m), x2(m),.............xN(m)]$^T$, where M is the signal sample length, M= 0, 1,..........., -1 is the m$^{th}$ received signal, and $x_i$(m) is the m$^{th}$ discrete time sample present at the CR terminal's i$^{th}$ antenna. The spectrum sensing problem is a binary hypothesis test problem [21]: **$H_1$: X(m) = R(m) + U(m),**

**$H_0$: X(m) = U(m). (1)**

R(m) signifies the signal vector that has been affected by fading of the channel and also by path loss. A noise vector with zero mean and a circularly symmetric complex Gaussian (CSCG) is represented as U(m). As a result, hypothesis $H_1$ denotes the presence of PU, while hypothesis H0 denotes its absence [20]. To generate the modified set of received signals, the in-phase constituent

(I) and quadrature (Q) constituents are eliminated from M received signals of the multi-antenna system

**$X_I$ = Imag(X(m))**

**$X_Q$ = Real(X(m)) (2)**

**$\dot{X}$ = ($X_I$, $X_Q$)**

The training and test vectors are then created by labeling the received signals. The following is a representation of the labeled set:

$$(\hat{X}, Y) = (\hat{x}^{(1)}, y^{(1)}), (\hat{x}^{(2)}, y^{(2)}), .................(\hat{x}^{(s)}, y^{(s)}) \quad \textbf{(3)}$$

In which Ẋ depicts the input of a deep neural network, in this example with I-Q components. Y is part of the set, which includes the labels [1, 0] and [0, 1], which represent the H1 and H0 hypotheses, respectively. The number of samples also known as observations is given by s, the s$^{th}$ sample is x(s), and the s$^{th}$ observation is labeled as unoccupied or busy by y(s). DNN helps in extracting data-driven features available in the training set. [21]. With the following single label vector the test metric is dependent on a binary sorting problem:

$$Y = \begin{cases} [1,0]^T, & H_1 \\ [0,1]^T, & H_0 \end{cases} \quad \textbf{(4)}$$

## 4. Detector Based on Neural Network

A single node is used for simulation in a DLSenseNet model which depends on a neural network. The same is shown in Fig 5. The radio scene will be received by this single node, which will examine it locally. Spectrum sensing is a binary sorting problem of incoming inputs and a traditional neural network outperforms conventional machine learning models in this regard. The inception module is modified to create the new model [13]. The convolution layer in the inception module now has long short-term memory with completely coupled layers.

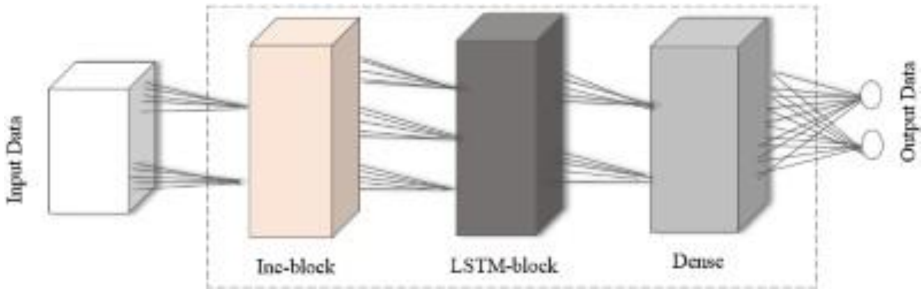


Fig. 5 Model-based on neural network

The signals that are received from the multi-antenna system are fed into the system, which in turn is subsequently branded for the availability or unavailability of PU. Based on previously unseen observations, the expected output is appropriately identified. It's because it's in-phase and quadrature. The initial structure, which balances generality and difficulty, encouraged the inclusion of extra layers. In a traditional deep neural network, signals of the individual layer can only be relayed to the higher layer, and samples are processed at different intervals of time. Modeling of changes in time sequences is impossible, although encoding with simply fixed- dimensional vectors is doable. As a result, the LSTM layer is included in the network that is suggested, in order to determine deep-rooted dependency, as IQ data are time domain. Additionally, different modulation methods modify signals in different ways, and LSTM is capable of effectively learning these temporal connections [14,15]. The dimensions are modified after concatenation so that they may be supplied to the LSTM layer.

The suggested network has five convolution layers, namely, the max-pooling layer, LSTM layer, and finally one fully linked layer. A varied number of neurons along with the hidden layers are used to train the proposed deep neural network. The size of the layer and the number of cells is determined after thorough training. The activation functions ReLU and softmax are utilized to introduce non-linearity to the network. Dropout is employed for the aim of regularisation. This is done to avoid overfitting. The network parameters are optimized using the ADAM optimizer. The categorical cross-entropy was employed as the loss function. Both the learning rate as well as batch size was set. The spectrum sensing system is efficient and reliable.

**Parameter for data**

Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol X No. Y (20--)

| | |
|---|---|
| Modulation scheme | :BPSK, QPSK, 8PSK, QAM16 |
| Sample length | :8 |
| SNR Range | :-20dB or -18dB |
| Training samples | :5000 |
| Testing samples | :2000 |
| Validation sample | :2000 |

## 5. Results and Discussion

The evaluation metrics considered here are the probability of detection ($P_d$) and the probability of false alarm ($P_f$). The chance of announcing the presence of the primary user when the spectrum is actually occupied is $P_d$, while the likelihood of declaring the existence of PU when the spectrum is truly vacant is Pf. Figures 6, 7, and 8 illustrate the detection performance along with their respective false alarms, with 64-bit sample length, 128, and 256 on signals that perform 16- QAM modulation.

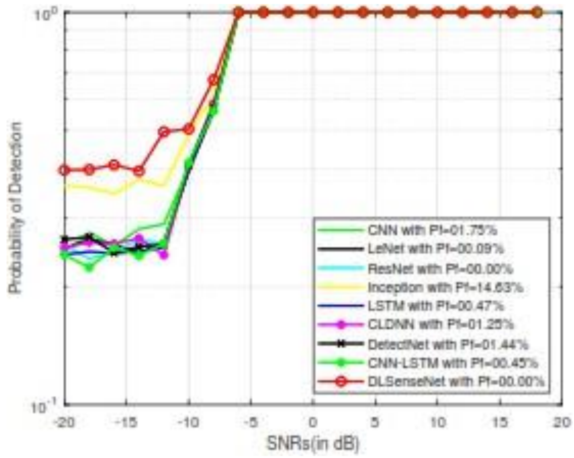


Fig. 6 Detection performance (DNN models) - 64 samples

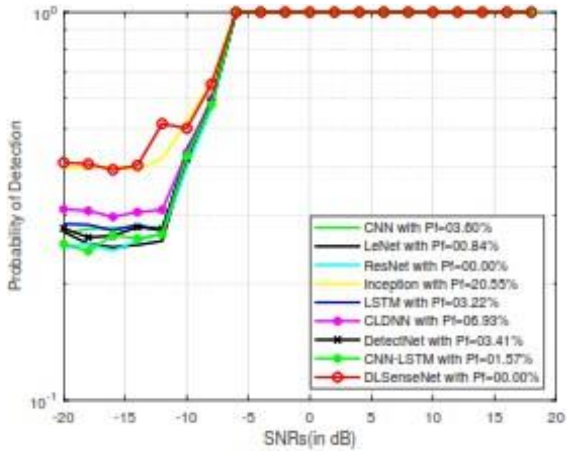


Fig.7 Detection performance (DNN models) - 128 samples

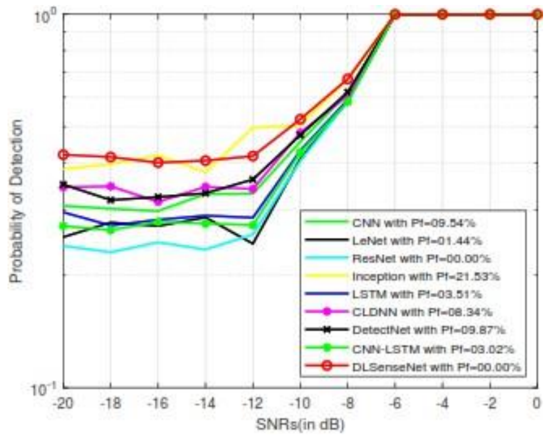


Fig. 8 Detection performance (DNN models) - 256 samples

TABLE 2 compares performance characteristics for QAM16 signals with 64, 128, and 256 sample lengths.

**TABLE 2** Performance metrics of 64, 128 and 256 sample length using QAM16 signals

| Model | 64 Samples | | | 128 Samples | | | 256 Samples | | |
|---|---|---|---|---|---|---|---|---|---|
| | $P_f$ (%) | SE (%) | $P_d$ (%) | $P_f$ (%) | SE (%) | $P_d$ (%) | $P_f$ (%) | SE (%) | $P_d$ (%) |
| CNN | 01.7 | 14.8 | 24.5 | 03.6 | 15.7 | 26.9 | 10.4 | 18.4 | 32.5 |
| LeNet | 14.8 | 24.5 | 24.9 | 15.7 | 26.9 | 27.2 | 00.9 | 14.7 | 26.2 |
| ResNet | 24.5 | 14.5 | 25.6 | 26.9 | 14.6 | 24.8 | 00.0 | 14.4 | 25.6 |
| Inception | 00.1 | 24.9 | 36.2 | 00.8 | 27.2 | 39.9 | 22.9 | 22.5 | 39.7 |
| LSTM | 14.5 | 14.4 | 24.1 | 14.6 | 14.4 | 28.5 | 04.5 | 15.8 | 29.2 |
| CLDNN | 24.9 | 25.6 | 25.1 | 27.2 | 24.8 | 31.1 | 09.7 | 17.4 | 35.5 |
| DLSenseNet | 00.0 | 19.6 | 39.6 | 00.0 | 21.7 | 40.9 | 00.0 | 13.1 | 43.3 |

## 6. Conclusion

Cognitive radio is a novel wireless network methodology that opportunistically utilizes the radio spectrum. The major problem of cognitive radio is considered to be spectrum detection. Traditional sensing of spectrum systems has inherent disadvantages for a variety of reasons. Any spectrum sensing model that relies on DNN outperforms existing sensing models such as convolutional neural networks, CLDNN, LSTM, residual networks, inception, etc. Standard spectrum sensing criteria were used to evaluate the models' performance.

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