[1*]**Sonali Mondal**

[2]**Manash Pratim Dutta**

[3]**Swarnendu Kumar Chakraborty**

A Hybrid Deep Learning Model for Efficient Spectrum Sensing in Cognitive Radio

Journal of Electrical Systems

Abstract: - The massive developments of gaming devices as well as mobile apps have increased the demand of bandwidth. In wireless communication, cognitive radio (CR) technique has shown a significant amount of improvement in optimal utilization of spectrum band. Spectrum sensing is a very important strategy through which new scope for spectrum sharing can be detected. In CR, spectrum sensing is crucial. To estimate spectrum sensing performance, two metrics are mostly considered, i.e., probability of detection (PD) and probability of false alarm (PFA). Traditional sensing approaches often face problems due to PD and PFA. These two constraints can affect spectrum utilization. Spectrum sensing is a type of binary classification problem and researches have shown that neural network has achieved high accuracy in this aspect. This research work focuses on the utilization of deep neural network (DNN) for accurately sensing unoccupied spectrum band. The benefits of convolutional neural networks (CNN) and recurrent neural networks (RNN) are combined in our proposed hybrid model i.e. ResNet-LSTM. In our study, RadioML2016.10b dataset is used for the experiments. The results showed that proposed model found to be efficient when compared to the existing techniques such as CNN, ResNet, LeNet, LSTM, CLDNN. Further, while compared with earlier models like CNN-LSTM, DetectNet and DLSenseNet, the proposed hybrid model "ResNet-LSTM" has shown better spectrum sensing performance. Proposed ResNet-LSTM framework achieved 96.97% prediction accuracy with 96.52% precision and 96.83% recall. The prediction time reduced by 0.14 msec than CNN-LSTM model.

Keywords: Cognitive radio, deep learning, deep neural networks, long short-term memory, spectrum sensing.

I. INTRODUCTION

The amalgamation of wireless communications, Internet of Things (IoT) and Artificial Intelligence (AI) result exponential growth of wireless devices. This caused the scarcity of spectrum resources [1–3]. Nowadays CR technique has come up as a remarkable approach to develop spectrum utilization. Basically spectrum access strategies are of two types, i.e., Concurrent spectrum access (CSA) and Opportunistic spectrum access (OSA). The prime idea of CR is OSA. The transmission of PU is unpredictable. This is why it is found that during some time slots, geographic directions or frequency bands PUs remain idle or inactive. Such type of spectrum band where the PU is inactive is called "spectrum hole". If any PU or legacy user is not using a channel at certain time slot, then it can be termed as spectrum opportunity [4]. In OSA model, if any spectrum opportunity or spectrum hole is discovered, SU utilizes the carrier frequency, bandwidth as well as modulation scheme and makes a configuration so that these unutilized spectrum bands which are known as spectrum holes can be utilized for transmission. Temporarily, SU is allowed to use PU's spectrum band, such that no interference is created. When the PU becomes active or it opts to transmit then the SU instantaneously stops its transmission and the spectrum band is released to the PU immediately. In this way, in OSA technique, without having any dedicated spectrum band SU can utilize PU's spectrum for transmission and also, PU's integrity as well as transmission is safeguarded. For smooth implementation of OSA technique, SU should be aware of spectrum holes' information. This is done to ensure PU's quality of service (QoS) [5]. Consequently, to keep an eye on the condition of the distinguished spectrum band is very important. This periodic observation of the spectrum band is called spectrum sensing (SS) [6]. For detecting the spectrum holes and monitoring primary spectrum periodically, this spectrum sensing is performed by SUs. It is a signal detection method; existence of noise may affect its accuracy. Large-scale shadowing and small-scale fading are very popular examples of channel impairments that cause inaccuracy in sensing the spectrum [5].

[1*]Corresponding author: Author 1 Affiliation: Department of Computer Science & Engineering, National Institute of Technology Arunachal Pradesh, 791113, India . Email : sonali.mondal94@gmail.com

[2]Author 2 Affiliation: Department of Computer Science & Information Technology, Cotton University, Assam, 781001, India. Email: manashpdutta@gmail.com

[3]Author 3 Affiliation: Department of Computer Science & Engineering, National Institute of Technology Arunachal Pradesh, 791113, India. Email: swarnendu@nitap.ac.in

CR technique has done massive improvement in utilization of spectrum band. Spectrum sensing is very important in cognitive radio. Spectrum sensing which is co-operative in nature can be used when numerous SUs prevail for improving the sensing accuracy [7-12]. Due to the insufficient spectrum resources in the 3G and 4G network, advancement of wireless applications has been affected. Spectrum scarcity is a major short coming of 3G and 4G network [13]. To achieve good wireless communication system proper utilization of spectrum band is very essential. Mitola et al. studied cognitive radio technique to improve spectrum utilization [14]. In this technique when PU is idle, SU can access the unused band opportunistically. In this way, without having any dedicated spectrum band, SU can transmit keeping PU's transmission unhampered. Haykin et al. identified some of the major roles of cognitive radio like, transmitted power control, channel-state estimation, radio scene analysis & spectrum management etc. [15]. At present researchers should focus to increase the utilization of spectrum band. There are some traditional spectrum hole detection techniques such as, cyclostationary feature detection, energy detection, match filter etc. [16, 17]. Here, statistical information of noise as well as signal is required to perform sensing. Hidden terminal problems, multipath fading, shadowing, etc. are some major drawbacks of wireless communication system. Due to these drawbacks, the result of radio scene analysis for individual base stations might be erroneous. This is why spectrum sensing is not flawless [18]. As the noise and signal are very complex in nature, AI based deep learning approach is highly appreciated.

Deep learning is used for big data analysis that helps in pattern recognition, natural language processing application, bioinformatics, computer vision etc. [19]. In wireless communication systems like, spectrum sensing, resource allocation schemes, signal modulation recognition, deep learning based algorithms are greatly implemented for better outcome [20]. Deep learning base approaches efficiently reduce the classification error also it can enhance channel identification. Such techniques are independent of signal features; it can automatically learn those features. This automatic feature learning capacity of deep learning approaches facilitate to improve classification metrics [21, 22].

In this study, a deep learning based spectrum sensing approach is implemented. The main motive of our study is to improve spectrum utilization by correctly identifying the unutilized spectrum band. The residual part of the manuscript has been arranged as follows. Existing deep learning based spectrum sensing approaches are described in section 2. The system model is elaborated in section 3. Our proposed framework is presented in section 4. Experimental setup is presented in section 5. Experimental outcomes along with discussions are elaborately represented in section 6, while conclusion of the study is presented in section 7.

II. EXISTING DEEP LEARNING BASED APPROACHES FOR SPECTRUM SENSING

Application of deep learning based approaches has shown significant improvement in various fields. In this study, we only focused on spectrum sensing with the help of deep learning. Some of those remarkable approaches are discussed in this section.

An artificial neural network (ANN) model was designed by Vyas et al. [23] for sensing. Here the signal's energy and the likelihood ratio test factor are utilized as training feature. Han et al. [24] designed a CNN model which trains data depending on cyclostationary feature detection and received energy signals. To achieve distinct SU, Lee et al. [25] designed a novel CNN model that operates on any kind of sensing decision. In this study, a deep learning based cooperative sensing technique called deep cooperative spectrum sensing is proposed, that might be hard or soft combined achieving more accurate sensing than other traditional approaches. Chandhok et al. [26] designed a model "SenseNet" for wideband sensing. They have utilized this model for automatic modulation classification. To train the model quadrature-phase, amplitude-phase and in-phase were utilized. Here performance is evaluated over Rayleigh, AWGN and Rayleigh having doppler channels. Spectrum sensing is a type of classification problem, Zheng et. al. [27] designed a transfer learning based technique where training is done based on the power of the received signal to overcome noise power ambiguity issue. It showed better result than maximum minimum eigen value ratio as well as frequency domain entropy base technique. Peng et al. [28] also incorporated a transfer learning based sensing framework. The deep spectrum sensing model's outcome is validated.

For better outcome, Xie et al. [29] designed a novel framework named CNN-LSTM detector. To design this model they used convolutional neural network (CNN) and long short term memory (LSTM). Here, initially the covariance matrices derived from sensing data, are considered as input which is fed to CNN. Then LSTM is utilized for final outcome. The proposed detector shows superiority in such a scenario where presence of noise is uncertain. Cheng et al. [30] designed a novel deep learning based model for OFDM system. For feature extraction, here a stacked auto-encoder is used. The result of this study helped Gao et al. [31] to design another deep learning based novel framework. Here, authors designed two models named 'DetectNet' and 'SoftCombinationNet' respectively, for spectrum sensing as well as cooperative spectrum sensing (CSS). Information regarding the basic structure of the modulated signal is used here. The proposed framework is compared with the energy detection technique. A significant gain in performance is also observed than any other existing CSS techniques. Solanki et al. [13] suggested a deep learning based approach and designed a model named DLSenseNet for sensing. Here, the received signal's structural information is considered.

Geng et al. [32] proposed a novel deep learning based feature extractor that extracts features under varying SNR condition. The feature matrix is used for training the CNN model. When various features were combined, the accuracy was significantly improved. Authors claimed that, performance of their model was better than traditional approaches. To regulate the energy consumption for transmission, Sivaranjani et al. [33] used Improved LSTM (ILSTM) and Improved Extreme Learning Models (IELM) to design a hybrid model named HILSTM-IELM. Conventional approaches used to suffer from various drawbacks like, due to the change of SNR value the energy detector's performance usually degrades, for match filter detector PU signal's knowledge is very essential. Cyclo-stationary detectors are sophisticated. This framework achieved superior performance in terms of accuracy and sensitivity. Kumar et al. [34] studied the CNN and RNN based spectrum sensing approaches and analyzed their performance in CR systems. According to their study, RNN can capture the temporal dependencies from the sequential data that is vital for sensing task while the signals evolve over the time. Deep learning based approaches have good adaptation as well as generalization capacity to various signals and in different conditions. This flexibility helps to improve accuracy even in the challenging scenario while spectrum condition is also diverse. As per their study, it is evident that CNN and RNN are two deep learning techniques which are gaining popularity for their efficient performance than traditional methods. Zhang et al. [8] studied that, deep learning based approaches could automatically extract as well as learn the features of the signals and the correlation information between those signals. Usually, any prior knowledge regarding the detected signal is not required here. This quality of deep learning techniques offers great opportunity for applications. To enhance sensing accuracy, Sumithra et al. [35] combined the advantages of Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP) to design a hybrid framework called LSTM-MLP. Here, signal noise is considered as the primary feature for observation as well as prediction of channel. It reduces the sensing delay also improves the prediction time for unoccupied channel detection.

Deep learning based techniques achieve significantly high accuracy in sensing task than the conventional approaches. The research work of Xie et al. [29] and Solanki et al. [13] and the outcome of their study is the motivation of our implementation which is presented in this paper.

III. System model

In this study, we considered multiple antenna base CR system. To transmit PU signals, there is a PU transmitter which consists of multiple antennas. A hybrid DNN framework is designed for spectrum sensing. Proposed approach has two phases ie. sampling phase and network training phase. Fig. 1 represents the proposed DNN model. Initially, during sampling phase the PU signal is modified. In training phase the proposed model is trained so that, at the arrival of any unknown samples it can take robust decision.

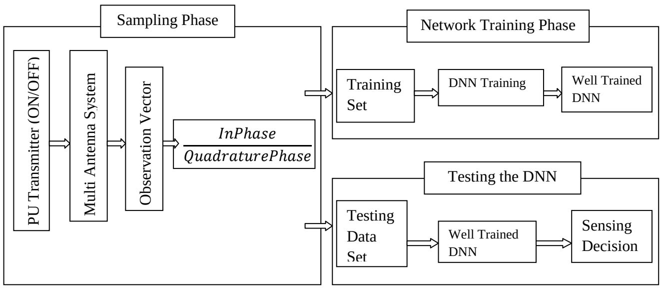

Figure. 1. DNN Architecture

Let us assume that, $S(k)=[s_1(k),s_2(k),.....,s_x(k)]^T$

Here, x denotes sample length of the signal, $k = 0, 1, \dots, K-1$ indicates the k^{th} received signal and $s_i(k)$ represents the k^{th} distinct time sample present at i^{th} antenna of cognitive radio terminal. Spectrum sensing at a cognitive radio terminal that consists of multi-antenna system, is represented as binary hypothesis testing problem [20, 36]:

$$H_0: S(k)=N(k)$$
$$H_1: S(k)=X(k)+N(k) \quad (1)$$

Here, H_0 denote that, received signal contains only noise and H_1 signifies that both signal and noise are present in the received signal. $S(k)$ denotes signal vector suffering from path loss and channel fading. The circularly symmetric complex Gaussian (CSCG) noise vector having zero mean is denoted by $N(k)$. Hypothesis H_0 denotes the absence of PU, whereas H_1 implies PU's presence. Here, to get customized set of received signal $\hat{S}$ the in-phase (I) and quadrature (Q) components are obtained from K signals received from multi-antenna system.

$$S_I = Imag\, S(k)$$
$$S_Q = Real\, S(k) \quad (2)$$
$$\hat{S} = (S_I\ , S_Q)$$

To obtain training and testing vectors, the received signals are labeled as follows:

$$(\hat{S}, R) = (\hat{s}^{(1)}, r^{(1)}), (\hat{s}^{(2)}, r^{(2)}), \ldots\ldots, (\hat{s}^{(j)}, r^{(j)}) \quad (3)$$

The input to the proposed model with the I-Q element is denoted by $\hat{S}$. R belongs to the set {1,0} having labels [0,1] and [1,0] representing the hypothes is H_0 and H_1, respectively. j denotes number of observations or samples. $s^{(j)}$ denotes the j^{th} sample and $r^{(j)}$ is the level of the j^{th} observation that indicates the status either vacant or busy. DNN efficiently extracts the features. Feature extraction is done from training set furnished in a data driven mode. Now the test statistic is designed depending on binary classification problem. In this classification problem the label is determined as a one-hot vector:

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

IV. Proposed Framework

PU transmission is very random. Due to this sporadic transmission, PU becomes inactive in some time slots, geographic directions or frequency bands. Spectrum sensing is performed by SU to find unoccupied or vacant spectrum band. These unutilized spectrum bands are termed as spectrum hole. For maximum spectrum utilization, accurate detection of spectrum hole is very important and for this, periodic monitoring of PU is very essential. In our approach we have designed a hybrid model that consists of Residual Network (ResNet) and LSTM. Deep learning is a special type of machine learning technique having a number of intermediary layers of interconnected nodes for non-linear processing for the complex representation of data. The technique is very useful for big data analysis which is very helpful for bioinformatics, computer vision, natural language processing application, pattern recognition etc. [19]. Deep learning based algorithms are implanted to a great extent in various aspects of wireless communication systems like, signal modulation recognition, resource allocation schemes, spectrum sensing etc. [20].

Spectrum sensing is a binary classification problem and researches have shown that deep learning based approaches have achieved high accuracy in this aspect. We have utilized this technique and designed a hybrid model that has combined the advantages of ResNet and LSTM to achieve a significant accuracy. Fig. 2 presents the diagram of our proposed hybrid model. Performance of CNN is better and the outcome is more accurate than any other conventional machine learning model.

The benefits of CNN and RNN are combined in our proposed hybrid model names ResNet-LSTM. It consists of two major components. The first part consists of convolutional layer and pooling layer. The primary task of this part is feature extraction. The second part contains LSTM and dense layer. This part utilizes the features for classification. LSTM layer is added to identify the chronological dependency in data. LSTM is very efficient for classification. ResNet is a CNN model which is trained for extracting the features from input. CNN layers are present for investigating the spatial relations also, it can learn complex features that leads to more accuracy in classification task. The detection performance is improved predominantly after utilizing this proposed ResNet-LSTM model. It contains several layers like convolutional layer, max pooling layer and fully connected layers. The fully connected layer is the final layer which generates the feature vector as output. LSTM is type of RNN which is trained to predict a sequence of labels based on inputs. ResNet-LSTM model contains five convolutional layers having 64, 128, 256, 512, 1024, and 2048 filters of size (3,3), followed by max pooling layer, an LSTM layer of 2048 units, a fully connected layer having 512 neurons and an output layer having one neuron. Fig. 3 represents the detailed architecture of ResNet-LSTM model which is proposed in our study.

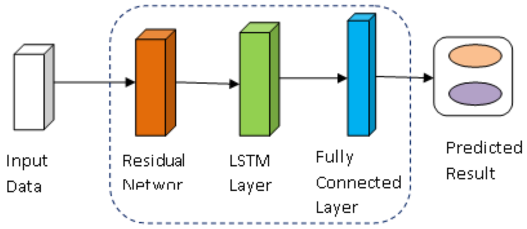

Figure 2 : Proposed hybrid model

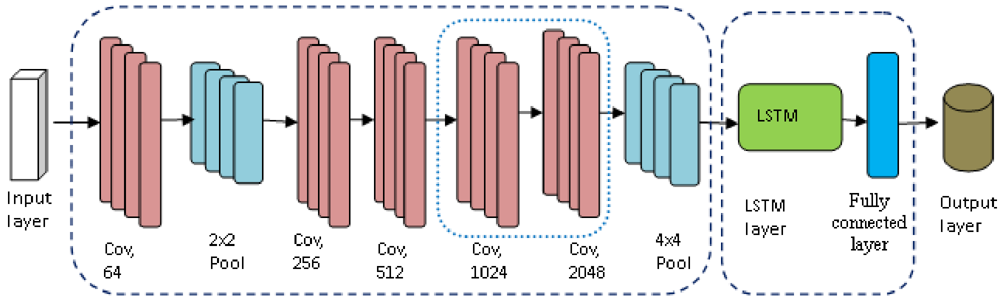

Figure 3: Proposed ResNet-LSTM architecture

Here, input denotes in-phase as well as quadrature component of received signal. The proposed model comprises of a ResNet and the LSTM block along with a fully connected layer that generates predicted result as output. The optimized hyper-parameters for ResNet-LSTM model is presented in table 1.

Table 1 : Optimized hyper-parameter

Hyper-parameters	**Proposed ResNet-LSTM model**
Neurons in the dense layer	512
Batch size	64
Initial learning rate	0.001
Dropout ratio	0.2
Optimizer	Adam

Here, received signal from the system having multiple antenna, is considered as the input to the system. Depending on PU's existence it is labeled. The predicted output is accurately labeled based on previous unnoticed observation. As we are working on the in-phase as well as quadrature components, these two time domain details constitute the input vector. Equation (5) shows the input as $\hat{S}$. From equation (2) we can write:

$$\hat{S}=(S_I\ , S_Q)$$

Hence,

$$S_I \leftarrow Imag\ (S)$$
$$S_Q \leftarrow Real\ (S) \tag{5}$$

Proposed model is independent of energy, even in varying background noise its generalization capacity is very good. This is why normalization is performed. Also, the signal's structure could be well utilized, even in the absence of interference. The received signal is complex in nature. Hence, before the received signal is separated into training and testing sets, energy normalization is performed on this signal [37]. This is represented in equation (6):

$$Energy = \sum_{i=1}^{x} \left(|\hat{S}_i|\right)^2 \tag{6}$$
$$\hat{S}_{norm} = \hat{S}/Energy$$

Here, $\hat{S}_{norm}$ is the input and designed model performs sensing operation for CR node. Equation (7) represents the convolution operation. Here, C_i is the output of the i^{th} convolution layer. In the following expression σ represents activation function, β denotes the bias and weight is denoted by ω_{conv} .

$$C_i = \sigma\left(\beta + \sum \omega_{conv}\ \hat{S}_{norm}\right) \tag{7}$$

Equation (8) denotes max-pooling operation where X is the pooling size.

$$\rho = max_{x\in X}(\hat{S}_{norm}) \tag{8}$$

In any typical deep neural network, signals from each layer are passed only to the higher layer for sample processing. At different time intervals, these sample are independent of each other. Here, encoding can be done only with the vectors of fixed dimensionality. But modeling of variations in time sequence is not possible. IQ data pertains to the time domain data character. Hence, LSTM layer is connected with the network to decide long term dependency. Moreover, signals modulated by various modulation techniques shows the sign of different characteristics features. LSTM can learn these temporal dependencies very efficiently [38].

Output of the ResNet model is sent to the LSTM layer to learn temporal features. Equation (10) represents the detailed calculation of the outputs of LSTM layer. LSTM learns long term dependency by determining information to be remembered and forgotten.

$$\begin{gathered}
\alpha_t = tanh\ (\omega_c C_i + x_c h_{t-1}) \\
i_t = \sigma(\omega_i C_i + x_i h_{t-1} \\
f_t = \sigma(\omega_f C_i + x_f h_{t-1} \\
O_t = \sigma(\omega_O C_i + x_O h_{t-1} \\
C_t = i_t \odot \alpha_t + f_t \odot C_{t-1} \\
h_t = O_t \odot tanh\ (C_t)
\end{gathered} \tag{10}$$

Here, i_t , O_t, f_t, h_t and C_t denote the input gate, output gate, forget gate, short term state, long term state, respectively. Also, sigmoid function, hyperbolic tangent activation function and component-wise multiplication are denoted by σ, tanh, and ⊙ respectively. ω_* and x_* represents weight matrices for different gates, where * represents C, i, f, O. Now, α_t analyzes the previous state and the current input. After analysis is done by α_t, particularly which section of α_t is necessary to add with long term state is decided by input gate. Forget gate used to decide unnecessary parts, also erases those redundant parts. It is decided by the output gate which part of long term state should be chosen as output. The memories are dropped where long term as well as short term state exists. It is added by the gates. The hidden state h_t and memory state C_t are considered as input and transmitted to the next LSTM layer. The inputs are processed by LSTM layer and output from this LSTM layer is represented as l_t which is sent to the fully connected layer. Now, fully connected layer works on the output of the preceding layer. The mechanism is shown in equation (11). Hence, we can get the concluding output related to the spectrum occupancy. The plots are elaborately presented in the result section.

$$prob = \sigma(\omega_{dense}^{T}\ l_t + \beta) \tag{11}$$

In this study categorical cross entropy loss function is applied to reduce the error. This loss function is represented in equation (12).

$$\mathcal{L}_{\mathrm{cce}}(r^{ss}, r) = -\sum_i (r[\mathrm{i}] \log r^{ss}\,[\mathrm{i}] + (1 - r[\mathrm{i}]) \log(r^{ss}[\mathrm{i}])) \tag{12}$$

Here, r^{ss} represents the predicted value. The actual value is denoted by r. Hence, depending on the amount of loss, we can calculate the gradient. It can be utilized to update the weight, represented in equation (13).

$$\omega^{ss} = \omega^{ss} - \eta(t)\omega^{ss}\mathcal{L}_{cce} \tag{13}$$

V. Experimental Setup

In this section design methodology is discussed. To establish our proposed model’s accuracy and robustness, it is compared with some latest models.

A. Generation of Dataset and Preprossing

For dataset we have used RadioML2016.10b [40] which is extensively used baseline dataset for modulation recognition [31]. O’Shea and Corgan [41] generated this baseline dataset which is publically accessible. It contains ten different types of signals among them eight are digitally modulated and remaining two are analog modulation. SNR value ranges from -20 dB to +18 dB maintaining 2 dB intervals. In this proposed approach, for simulation purpose, we have used 8 types of signals that are modulated digitally at varying SNR values. These are the positive samples and the circularly symmetric complex gaussian (CSCG) noises are the negative samples. We have applied a frequently used split ratio of 3:1:1 to partition the whole dataset into three sets for the purpose of training, validation and testing. Each of the training sample consists of $'k'$ samples. These samples were fed to proposed model in $2 * k$ vectors with the in-phase and quadrature components that is parted into complex time samples. The dataset parameters are presented in table 2.

Table 2: dataset parameters

Parameter	**Value**
Modulation scheme	PAM4, QAM16, QAM64, 8PSK, QPSK, BPSK, GFSK and CPFSK
Length of Sample	64, 128, 256, 512
SNR range	-20db ~18db maintaining 2 db intervals
Training sample	153,000
Validation sample	51,000
Testing sample	51,000

B. Metrics for performance evaluation

To estimate the efficiency of the ResNet-LSTM model, before testing, firstly it is trained and validated. Here probability of false alarm (P_f) and probability of detection (P_d) are considered as the metrics for evaluation [25]. For measuring the performance, these two main metrics are also applied. The former one is the probability of finding PUs' existence while they are inactive. On the other hand, the latter one is the probability of PUs' existence while they are really active. This is why, it illustrates the amount of safety to the PUs. High probability of detection indicates improved PUs' safety. Low P_f implies that there is more transmission opportunity which the SUs can utilize, and in this way, efficiency of the SUs is improved and this is how higher throughput is achieved. From this perspective, a successful spectrum sensing design must consist of increased PD and reduced PFA. These metrics are mostly contradictory. Higher PFA reduces SUs' scope for accessing the spectrum. Both, P_d and P_f are calculated for varying SNR values of the received signal. P_m denotes probability of misdetection. It is the possibility of declaration of spectrum's vacant state while PU actually exists. The formulas to calculate the performance evaluation metrics are presented in table 3. To evaluate these values, we used the values of confusion matrix which is constructed after executing the sensing operation on test set. There are four predictive labels that usually analyze the detection performance of ResNet-LSTM model: True positive (TP), True negative (TN), False positive (FP) and False negative (FN). TP and TN are the correctly predicted labels. Here, TP represent the instances when ResNet-LSTM accurately classified the sensed input as H_1 hypothesis i.e. PU is present. Similarly, TN represents the instances when the trained ResNet-LSTM model correctly identified H_0 hypothesis i.e. PU is absent. FP and FN are the incorrect predictions. Here, FP denotes the case where, the proposed model incorrectly labels H_0 hypothesis as H_1. FN refers to the vice-versa cases, where the actual input H_1 is wrongly classified by ResNet-LSTM model as H_0.

Accuracy (P_a): The ration of correctly predicted labels (TP and TN) with respect to total instances.

Precision ($\mathcal{P}$): The purity of TP labels i.e. the ration of correctly predicted TP labels out of all the positive (TP and FP) predicted labels.

Recall ($\mathcal{R}$): It is also known as true positive rate or the sensitivity. It denotes the completeness of TP labels i.e. the ratio of correctly predicted TP to the actual number of TP labels as per the ground truth data.

Table 3: Formula to calculate performance evaluation metrics

Metrics	**Formulae**
Accuracy (P_a)	$\frac{TP+TN}{TP+TN+FP+FN}$
Recall ($\mathcal{R}$)	$\frac{TP}{TP+FN} \times 100$
Precision ($\mathcal{P}$)	$\frac{TN}{TP+FP}$
Probability of detection (P_d)	$\frac{Total\ no.of\ PU}{Total\ no.of\ users(PU+Noise\ signals)}$
Probability of false alarm (P_f)	$\frac{Total\ no.of\ Noise\ signal\ diagnosed}{Total\ no.of\ users(PU+Noise\ signals)}$
Probability of missing ratio (P_m)	$1-P_d$

VI. Result and Discussion

To show the performance of ResNet-LSTM model the simulation result is presented and analyzed here. The outcome of several parameters such as sample length, modulation scheme, and classification model is also considered in our study. Outcome of our designed model is compared with some existing DNN models like, CNN, convolutional long short-term deep neural network (CLDNN), inception model, LSTM, LeNet, residual network (ResNet). Also, we compared the ResNet-LSTM model with previously reported approaches such as CNN-LSTM [29], DetectNet [31] and DLSenseNet [13]. According to IEEE 802.22 standard, the P_f value of any desirable sensing model should be between 0 and 0.1, while the value of P_d is high [39].

The performance metrics of QAM16, QPSK signals for sample length 64, 128, 256, 512 are compared with proposed model and existing models as well as early reported models and presented in table 4 & 5. In this study, for comparison purpose the value of P_d is considered at -20 dB signal-to-noise ratio (SNR). Proposed ResNet-LSTM model has achieved the lowest P_f than any other existing as well as early reported models. Besides having the lowest P_f it achieved the highest P_d which proved its superiority. From the results it is very clear that, P_f of ResNet is very low but it is incapable of achieving high P_d. Though P_d of inception model is good but its high P_f value is not desirable according to IEEE 802.22 standard. After studying the outcome, desirability of proposed approach is obvious as it achieved the highest P_d while keeping the P_f very low. Good balance between P_d and P_f is maintained. Hence, it is assured that proposed ResNet-LSTM model have high detection accuracy and very low probability of false alarm. Among the existing approaches ResNet-LSTM can detect spectrum occupancy more accurately.

According to the simulation outcome presented in table 4 & 5, it is obvious that our proposed model "ResNet-LSTM" is superior than the previously reported models [29], [31], [13]. The proposed model shows better performance as it has achieved high P_d and and reduced P_f. Outcome of the proposed model whether the spectrum is vacant or occupied, is considered as a classification problem.

From the data represented in table 4 & 5, it is clear that our proposed model has proven its superiority over previous works. The overall result clearly indicates that in cognitive radio, proposed "ResNet-LSTM" model is an excellent option for spectrum sensing. The better performance accurately identifies the PU's transmission over the spectrum.

Table 4. Performance metrics comparison between proposed model and existing models as well as early reported models for QAM16 signals with different sample length

Models	**Proposed by**	**Sample Length 64**		**Sample Length 128**		**Sample Length 256**		**Sample Length 512**	
		P_d(-20dB) (%)	P_f(%)	P_d(-20dB) (%)	P_f(%)	P_d(-20dB) (%)	P_f(%)	P_d(-20dB) (%)	P_f(%)
CNN	Existing DNN model	25.78	01.95	27.42	03.84	31.28	08.23	36.21	11.24
Inception		35.17	15.82	39.89	20.75	37.41	20.14	39.71	17.93
ResNet		26.12	00.00	25.80	00.00	24.39	00.00	26.21	00.17
LeNet		25.75	00.05	28.15	0.57	26.43	00.96	28.07	01.85
LSTM		25.36	00.28	29.98	03.02	28.90	03.81	27.48	01.04
CLDNN		26.07	01.05	31.79	05.63	35.70	07.54	43.86	05.03
CNN-LSTM [29]	Xie et al.	24.10	00.45	25.28	01.57	27.10	03.02	26.41	04.03
DetectNet [31]	Gao et al.	26.37	01.44	27.72	03.41	35.01	09.87	42.07	13.90
DLSenseNet [13]	Solanki et al.	39.60	00.00	40.97	0.00	42.07	00.00	46.98	00.04
ResNet-LSTM	Present study	**40.05**	00.00	**41.25**	0.00	**43.72**	00.00	**47.31**	00.03

Table 5. Performance metrics comparison between proposed model and existing models as well as early reported models for QPSK signals with different sample length.

Models	Proposed by	Sample Length 64		Sample Length 128		Sample Length 256		Sample Length 512	
		P_d(-20dB) (%)	P_f(%)	P_d(-20dB) (%)	P_f(%)	P_d(-20dB) (%)	P_f(%)	P_d(-20dB) (%)	P_f(%)
CNN	Existing DNN model	28.54	01.08	28.79	03.26	33.64	09.83	35.62	13.63
Inception		36.23	15.98	39.27	20.03	39.98	21.93	43.05	16.27
ResNet		24.17	00.00	27.19	00.00	26.51	00.00	25.33	00.06
LeNet		24.53	00.08	27.05	00.00	27.08	00.72	27.93	01.96
LSTM		25.16	01.38	28.96	03.06	30.74	03.84	29.14	01.85
CLDNN		27.35	01.25	30.18	06.81	36.70	08.79	44.89	07.51
CNN-LSTM [29]	Xie et al.	26.80	00.97	24.81	01.09	25.23	01.38	28.01	04.10
DetectNet [31]	Gao et al.	26.38	01.73	26.32	02.87	32.68	08.99	45.90	16.42
DLSenseNet [13]	Solanki et al.	40.79	00.00	39.77	00.00	43.32	00.00	47.70	00.08
ResNet-LSTM	Present study	**41.06**	00.00	**40.15**	00.00	**44.81**	00.00	**48.73**	00.06

The performance comparison of different existing DNN models for varying sample length, on the signal modulated by QAM16 modulation technique is presented through figures 4 to 7. Performance of these models for SNR -20dB to 18 dB is presented in figures 4 and 5. For QAM16 signal for sample length 64 and 128, Inception model has shown good detection performance but its high P_f value affects its efficiency. Though P_f of ResNet is low but its P_d value is also very low which degrades the performance. In this aspect, detection performance of ResNet-LSTM is better than existing approaches.

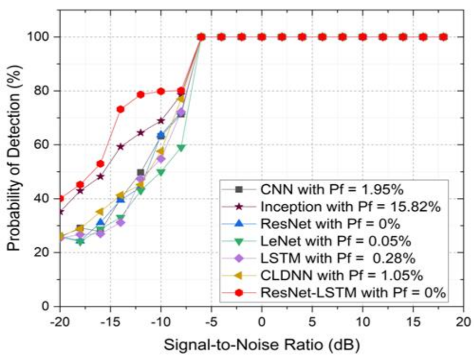

Figure. 4. Performance comparison between ResNet-LSTM and other existing models for sample length 64 for QAM16 modulation for SNR -20 dB to 18 dB

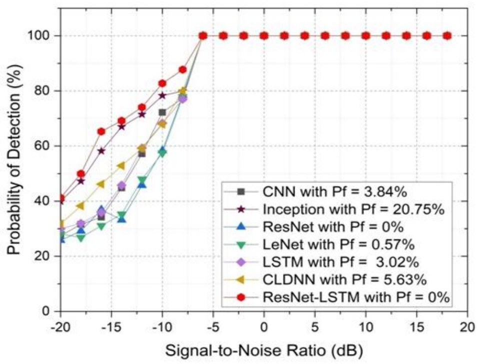

Figure: 5 Performance comparison between ResNet-LSTM and other existing models for sample length 128 for QAM16 modulation for SNR -20 dB to 18 dB

Because of distortion, signals at low SNR i.e. -20 dB to 0 dB, contain very less amount of information than high SNR i.e 0 dB to 18 dB. The models that have good detection capability at low SNR, can perform significantly better in high SNR. For better understanding of the simulation result, figures 6, 7, 10 and 11 represent the detection performance of different models at low SNR range from -20 dB to 0 dB, for QAM16 and QPSK signals for sample length 256 and 512. Though both ResNet and proposed model achieved the lowest P_f but low P_d value of ResNet has proved its inferiority. Here, proposed ResNet-LSTM model has shown outstanding detection performance.

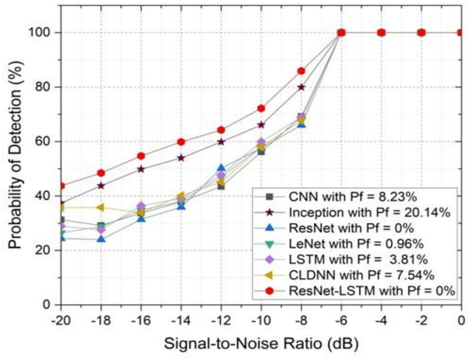

Figure: 6 Performance comparison between ResNet-LSTM and other existing models for sample length 256 for QAM16 modulation for SNR -20 dB to 0 dB

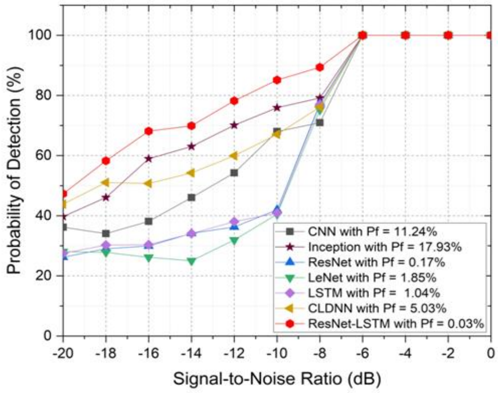

Figure: 7 Performance comparison between ResNet-LSTM and other existing models for sample length 512 for QAM16 modulation for SNR -20 dB to 0 dB

Efficiency of different existing DNN models for varying sample length, of QPSK signal is compared and graphically presented in figures 8 to 11. Figures 8 and 9 represent QPSK signal's detection performance for sample length 64 and 128 at SNR -20 dB to 18 dB. ResNet, LeNet and proposed ResNet-LSTM model all the three models achieved the lowest P_f value but the significantly high P_d of our proposed approach proved its superiority than existing approaches.

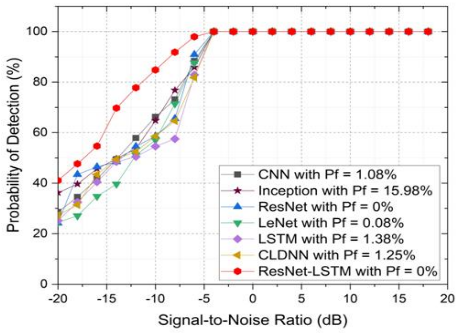

Figure: 8 Performance analysis of ResNet-LSTM with other existing models for sample length 64 for QPSK modulation for SNR -20 dB to 18 dB

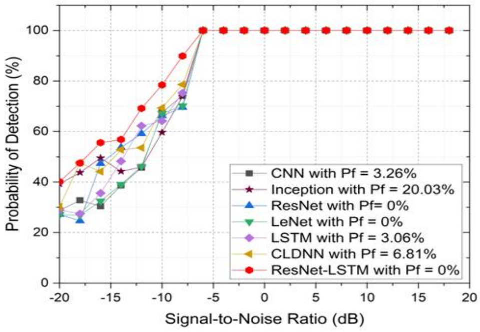

Figure: 9 Performance comparison between ResNet-LSTM and other existing models for sample length 128 for QPSK modulation for SNR -20 dB to 18 dB

Proposed ResNet-LSTM performs great because of good understanding capability for considering the modulated signals' structure. Benefits of two DNN architectures are combined in our proposed approach. ResNet performs the feature extraction. The CNN layer is there to study the spatial relation then it extracts that necessary information and learns the internal representation of the input data. The purpose to include LSTM layer is to recognize the temporal dependency for identifying long term as well as short-term dependency.

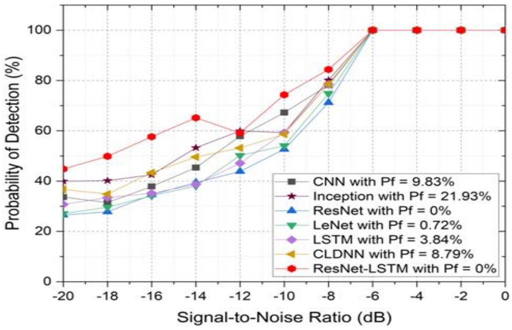

Figure: 10 Performance comparison between ResNet-LSTM and other existing models for sample length 256 for QPSK modulation for SNR -20 dB to 0 dB

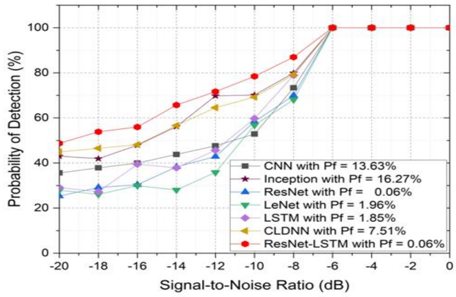

Figure: 11 Performance comparison between ResNet-LSTM and other existing models for sample length 512 for QPSK modulation for SNR -20 dB to 0 dB

When the characteristic features of the PU signal are changing, the efficiency of ResNet-LSTM is established. Fig. 12 compares and analyzes the performance of ResNet-LSTM over eight different modulation techniques at SNR -20 dB to 0 dB with 64 sample length. The performance variation is very insignificant for different modulated signals. It is implied that its performance is not very sensitive to the modulation error.

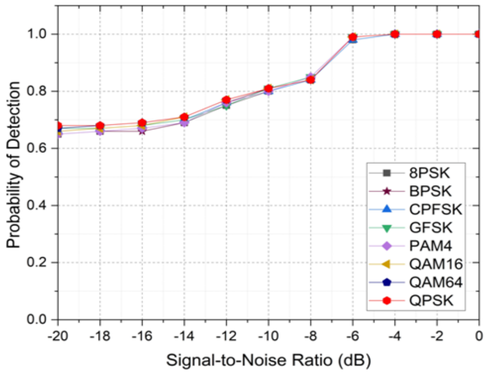

Figure: 12 Impact of different modulation schemes

Figures 13 and 14 represent the comparison between “ResNet-LSTM” and the three previously reported models. These figures demonstrate that ResNet-LSTM has achieved highest detection accuracy and lowest probability of false alarm which is most desirable for any sensing technique.

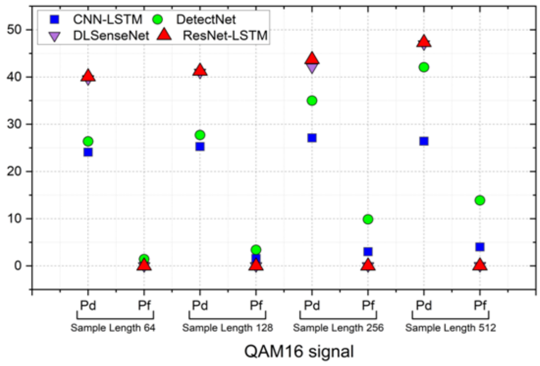

Figure: 13 Performance comparison between early reported models and ResNet-LSTM for QAM16 signal with varying sample length

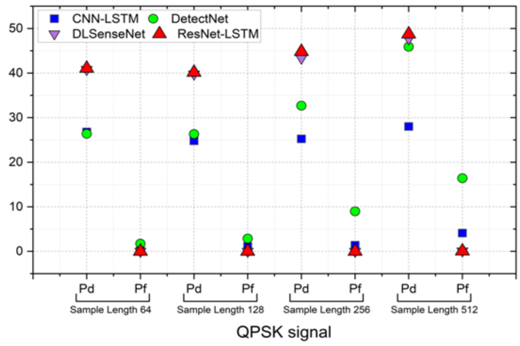

Figure: 14 Performance comparison between early reported models and ResNet-LSTM for QPSK signal with varying sample length

Fig. 15 represents the comparative performance analysis metrics. The comparative analysis of some performance metrics like, accuracy, recall, precision showed that ResNet-LSTM found to be superior when compared to other models. These metrics are computed for low SNR range (-20dB to 0dB) and presented in table 6. It was found that ResNet-LSTM model is desirable for its sensing accuracy. As per the simulation results presented in table 7, it is clear that both the training and validation accuracy increased significantly as the number of epochs increases. It achieved 97.86% training accuracy and 97.35% validation accuracy. The maximum training and validation accuracy reached at 100^{th} epochs. Comparison of training and prediction time between ResNet-LSTM and other models are presented in table 6. It was observed that, CNN-LSTM [29] takes 1180 seconds for training and required time for prediction is 1.96 msec. Proposed ResNet-LSTM model takes 1496 seconds for training which is higher than the previous model. Proposed approach takes very less prediction time i.e. 1.82 msec. The prediction time is reduced by 0.14msec than CNN-LSTM [29] model. Though ResNet-LSTM takes more time for training but its minimum prediction time proves its superiority. Fig. 16 represents accuracy comparison for varying SNR. It is observed that the proposed model demonstrated its consistent superior performance. At low SNR (-20dB to 0dB) ResNet-LSTM exceeds the second highest approach [13]. ResNet-LSTM framework achieved 96.97% prediction accuracy with 96.52% precision and 96.83% recall. In terms of accuracy, the proposed ResNet-LSTM model exceeds the second highest method.

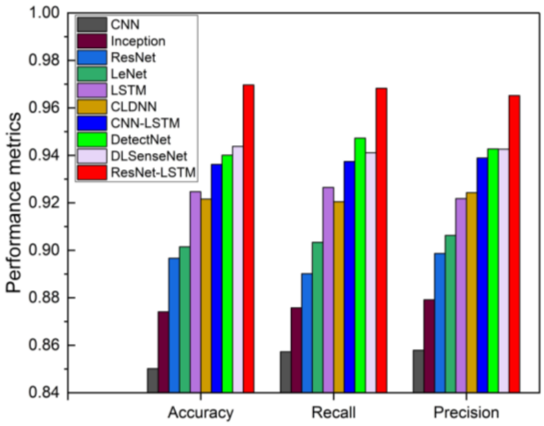

Figure: 15 Performance evaluation of ResNet-LSTM

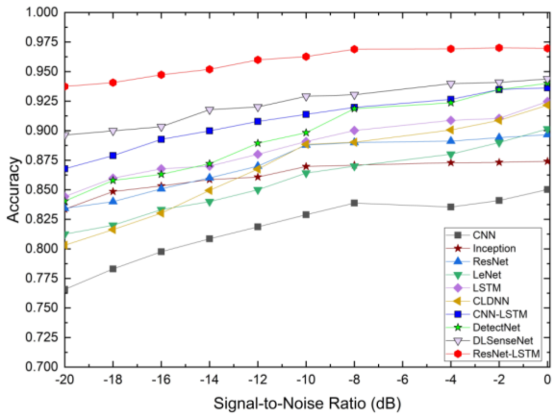

Figure: 16 Accuracy comparison ResNet-LSTM framework

Table 6. Comparison of performance metrics for different models at low SNR range (-20 dB to 0 dB):

Model details		Performance metrics			Required Time	
		Accuracy (P_a)	Recall ($\mathcal{R}$)	Precision ($\mathcal{P}$)	Training time (sec)	Prediction time (msec)
CNN	Existing DNN models	0.8502	0.8573	0.8579	1045	2.67
Inception		0.8741	0.8758	0.8792	1458	2.83
ResNet		0.8967	0.8902	0.8987	1294	2.99
LeNet		0.9015	0.9034	0.9063	1278	2.95
LSTM		0.9247	0.9265	0.9218	1264	2.49
CLDNN		0.9216	0.9205	0.9243	1862	2.34
CNN-LSTM [29]	Early reported models	0.9362	0.9374	0.9389	1180	1.96
DetectNet [31]		0.9401	0.9473	0.9427	1698	2.31
DLSenseNet [13]		0.9438	0.9411	0.9426	1792	2.19
ResNet-LSTM	Present study	**0.9697**	**0.9683**	**0.9652**	1496	**1.82**

Table 7. Training and validation accuracy for ResNet-LSTM framework:

No. of epochs	**Training accuracy (%)**	**Validation accuracy (%)**
20	95.73%	94.98%
40	95.88%	95.06%
60	96.49%	96.04%
80	97.85%	97.14%
100	97.86%	97.35%

VII. Conclusion

In cognitive radio network opportunistic utilization of spectrum resource is highly encouraged. It is very challenging to find out vacant spectrum band. Traditional sensing approaches have fundamental drawbacks. The two constraints, PD and PFA can affect spectrum utilization. Researchers have shown that, neural network achieved high accuracy in spectrum detection. We utilized this technique and designed a hybrid model that combined the advantages of ResNet and LSTM to achieve a significant accuracy. In our study, a DNN based spectrum sensing model called "ResNet-LSTM" is designed. The proposed approach has shown significant improvement compared to the existing techniques like, CNN, ResNet, LeNet, LSTM, CLDNN. While compared with some early reported models like, CNN-LSTM, DetectNet and DLSenseNet, our proposed "ResNet-LSTM" model demonstrated a better sensing result. It achieved maximum probability of detection while maintaining lowest false alarm rate. The performance was examined with standard sensing metrics. ResNet-LSTM framework achieved 96.97% prediction accuracy with 96.52% precision and 96.83% recall. The prediction time is reduced by 0.14 msec than CNN-LSTM model. The designed model has shown significant improvement in efficiency in the same service grade of the PD and PFA. In terms of accuracy, the proposed ResNet-LSTM model exceeds the second highest method. Proposed ResNet-LSTM framework is a desirable spectrum sensing approach.

References

[1] J. Mu, D. Xie, H. Huang and X. Jing, “Computation-constrained spectrum sensing in IoT-based scenarios,” IET Communications, vol. 14, pp. 3631–3638, December 2020. https://doi.org/10.1049/iet-com.2019.1367

[2] Y. Cui, F. Liu, X. Jing and J. Mu, “Integrating sensing and communications for ubiquitous IoT: Applications, trends, and challenges,” IEEE Network, vol. 35, pp. 158-167, November 2021. https://doi.org/10.1109/MNET.010.2100152

[3] Y. Zhang, J. Mu and J. Xiaojun, “Performance of multi-cell mmWave NOMA networks with base station cooperation,” IEEE Communications Letters, vol. 25, pp. 442-445, October 2020. https://doi.org/10.1109/LCOMM.2020.3029572

[4] Q. Zhao and B.M. Sadler, “A survey of dynamic spectrum access,” IEEE signal processing magazine, vol. 24, pp. 79-89, May 2007. https://doi.org/10.1109/MSP.2007.361604

[5] Y.C. Liang, “Dynamic spectrum management: From cognitive radio to blockchain and artificial intelligence,” Springer Nature, 2020. https://doi.org/10.1007/978-981-15-0776-2

[6] J.Miao, Y.Li, X.Jing, F.Zhang and J.Mu, “Spectrum sensing based on adversarial transfer learning,” IET Communications, vol.16, pp. 2059-2069, October 2022. https://doi.org/10.1049/cmu2.12459

[7] R. Ahmed, Y. Chen and B. Hassan, “Deep learning-driven opportunistic spectrum access (OSA) framework for cognitive 5G and beyond 5G (B5G) networks,” Ad Hoc Networks, vol. 123, pp. 102632, December 2021. https://doi.org/10.1016/j.adhoc.2021.102632

[8] Y. Zhang, Z. Luo, “A Review of Research on Spectrum Sensing Based on Deep Learning,” Electronics, vol. 12, pp. 4514, November 2023. https://doi.org/10.3390/electronics12214514

[9] V. Mohanakurup, V.S. Baghela, S. Kumar, P. K. Srivastava, N.V. Doohan, M. Soni and H. Awal, “5G Cognitive radio networks using reliable hybrid deep learning based on spectrum sensing,” Wireless Communications and Mobile Computing, vol. 2022, pp. 1830497, 2022. https://doi.org/10.1155/2022/1830497

[10] M. Xu, Z. Yin, Y. Zhao and Z. Wu, “Cooperative spectrum sensing based on multi-features combination network in cognitive radio network,” Entropy, vol. 24, pp. 129, January 2022. https://doi.org/10.3390/e24010129

[11] R.S. Koteeshwari and B. Malarkodi, “Compressive spectrum sensing for 5G cognitive radio networks–LASSO approach,” Heliyon, vol. 8, June 2022. https://doi.org/10.1016/j.heliyon.2022.e09621

[12] A. A. Radhi, H.A.R Akkar and H.N. Abdullah, “SDR-based intelligent cooperative spectrum sensing for cognitive radio systems”, Engineering and Technology Journal, vol. 41, pp. 435-445, February 2023. https://doi.org/10.30684/etj.2023.136258.1306

[13] S. Solanki, V. Dehalwar and J. Choudhary, “Deep learning for spectrum sensing in cognitive radio,” Symmetry, vol. 13, pp. 147, January 2021. https://doi.org/10.3390/sym13010147

[14] J. Mitola and G.Q. Maguire, “Cognitive radio: Making software radios more personal,” IEEE Personal Communications, vol. 6, pp. 13-18, August 1999. https://doi.org/10.1109/98.788210

[15] S. Haykin, “Cognitive radio: Brain-empowered wireless communications,” IEEE Journal on Selected Areas in Communications, vol. 23, pp. 201-220, February 2005. https://doi.org/10.1109/JSAC.2004.839380

[16] T. Yucek and H. Arslan, “A survey of spectrum sensing algorithms for cognitive radio applications,” IEEE Communications Surveys & Tutorials, vol. 11, pp. 116-130, March 2009. https://doi.org/10.1109/SURV.2009.090109

[17] S. Solanki, V. Dehalwar and J. Choudhary, “Cooperative spectrum sensing for PU detection in cognitive radio using SVM,” in Data Engineering and Communication Technology, Proceedings of ICDECT 2020, pp. 61-69, Springer Singapore, 2021. https://doi.org/10.1007/978-981-16-0081-4_7

[18] W. Lee and D. Cho, “Enhanced spectrum sensing scheme in cognitive radio systems with MIMO antennae,” IEEE Transactions on Vehicular Technology, vol. 60, pp. 1072 – 1085, February 2011. https://doi.org/10.1109/TVT.2011.2112676

[19] S. Peng, H. Jiang, H. Wang, H. Alwageed, Y. Zhou, MM. Sebdani and YD Yao, “Modulation classification based on signal constellation diagrams and deep learning,” IEEE transactions on neural networks and learning systems, vol. 30, pp. 718-727, July 2018. https://doi.org/10.1109/TNNLS.2018.2850703

[20] C. Lin, Q. Chang and X. Li, “A deep learning approach for MIMO-NOMA downlink signal detection,” Sensors, vol. 19, pp. 2526, June 2019. https://doi.org/10.3390/s19112526

[21] I. F. Akyildiz, B. F. Lo and R. Balakrishnan, “Cooperative spectrum sensing in cognitive radio networks: A survey,” Physical Communication, vol. 4, pp. 40–62, March 2011. https://doi.org/10.1016/j.phycom.2010.12.003

[22] S. M. Mishra, A. Sahai and R. W. Brodersen, “Cooperative sensing among cognitive radios,” in Proceedings of the IEEE International Conference on Communications, Istanbul, Turkey, vol. 4, pp. 1658–1663, June 2006. https://doi.org/10.1109/ICC.2006.254957

[23] M. R. Vyas, D. K. Patel and M. Lopez-Benitez, “Artificial neural network based hybrid spectrum sensing scheme for cognitive radio,” in IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio

Communications (PIMRC), Montreal, QC, Canada, pp. 1-7,October 2017. https://doi.org/10.1109/PIMRC.2017.8292449

[24] D. Han, G. C. Sobabe, C. Zhang, X. Bai, Z. Wang, S. Liu and B. Guo, "Spectrum sensing for cognitive radio based on convolution neural network," in Proceedings of the 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Shanghai, China, 2017, pp. 1-6, October 2017. https://doi.org/10.1109/CISP-BMEI.2017.8302117

[25] W. Lee, M. Kim and D.H. Cho, "Deep Cooperative Sensing: Cooperative Spectrum Sensing Based on Convolutional Neural Networks," IEEE Transactions on Vehicular Technology, vol. 68, pp. 3005 – 3009, January 2019. https://doi.org/10.1109/TVT.2019.2891291

[26] S. Chandhok, H. Joshi, A.V. Subramanyam and S.J. Darak, "Novel Deep Learning Framework for Wideband Spectrum Characterization at Sub-Nyquist Rate," Wireless Networks, vol. 27, pp. 4727–4746, October 2021. https://doi.org/10.1007/s11276-021-02765-1

[27] S. Zheng, S. Chen, P. Qi, H. Zhou and X. Yang, "Spectrum sensing based on deep learning classification for cognitive radios," China Communications, vol. 17, pp. 138 – 148, February 2020. https://doi.org/10.23919/JCC.2020.02.012

[28] Q. Peng, A. Gilman, N. Vasconcelos, P. C. Cosman and L.B. Milstein, "Robust Deep Sensing through Transfer Learning in Cognitive Radio," IEEE Wireless Communications Letters, vol. 9, pp. 38 – 41, September 2020. https://doi.org/10.1109/LWC.2019.2940579

[29] J. Xie, J. Fang, C. Liu and X. Li, "Deep Learning-Based Spectrum Sensing in Cognitive Radio: A CNN-LSTM Approach," IEEE Communications Letters, vol. 24, pp. 2196 – 2200, June 2020. https://doi.org/10.1109/LCOMM.2020.3002073

[30] Q. Cheng, Z. Shi, D. N. Nguyen and E. Dutkiewicz, "Sensing OFDM Signal: A Deep Learning Approach," IEEE Transactions on Communications, vol. 67, pp. 7785 – 7798, September 2019. https://doi.org/10.1109/TCOMM.2019.2940013

[31] J. Gao, X. Yi, C. Zhong, X. Chen and Z. Zhang, "Deep Learning for Spectrum Sensing," IEEE Wireless Communications Letters, vol. 8, pp. 1727 – 1730, September 2019. https://doi.org/10.1109/LWC.2019.2939314

[32] Y. Geng, J. Huang, J. Yang, S. Zhang, "Spectrum sensing for cognitive radio based on feature extraction and deep learning", In Journal of Physics: Conference Series , vol. 2261, no. 1, pp. 012016, 2022. https://doi.org/10.1088/1742-6596/2261/1/012016

[33] Sivaranjani, S., Vivek, C., "Reliable hybrid deep learning technique for an effective spectrum sensing in cognitive radio", Journal of Intelligent & Fuzzy Systems, vol. 44, no. 6, pp. 10765-10779, 2023. https://doi.org/10.3233/JIFS-224376

[34] A. Kumar, N. Gaur, S. Chakravarty, M. H. Uthansakul, M. Uthansakul, "Analysis of spectrum sensing using deep learning algorithms: CNNs and RNNs", Ain Shams Engineering Journal, vol. 15, no. 3, pp. 102505; 2024. https://doi.org/10.1016/j.asej.2023.102505.

[35] Sumithra M.G., Suriya M., "Improved Spectrum Prediction Model for Cognitive Radio Networks Using Hybrid Deep Learning Technique", International Journal of Intelligent Networks, 2024. https://doi.org/10.1016/j.ijin.2024.05.003.

[36] C. Liu, J. Wang, X. Liu and Y. C. Liang, "Deep CM-CNN for Spectrum Sensing in Cognitive Radio," IEEE Journal on Selected Areas in Communications, vol. 37, pp. 2306 – 2321, August 2019. https://doi.org/10.1109/JSAC.2019.2933892

[37] T. J. O'Shea, "Radio Machine Learning Dataset Generation with GNU Radio," in Proceedings of the 6th GNU Radio Conference, Boulder, CO, USA, vol. 1, September 2016.

[38] S. Rajendran, W. Meert, D. Giustiniano, V. Lenders and S. Pollin, "Deep Learning Models for Wireless Signal Classification With Distributed Low-Cost Spectrum Sensors," IEEE Transactions on Cognitive Communications and Networking, vol. 4, pp. 433 – 445, July 2017. https://doi.org/10.1109/TCCN.2018.2835460

[39] V. Dehalwar, A. Kalam, M. L. Kolhe and A. Zayegh, "Compliance of IEEE 802.22 WRAN for field area network in smart grid," in 2016 IEEE International Conference on Power System Technology (POWERCON), Wollongong, NSW, Australia, pp. 1-6, September 2016. https://doi.org/10.1109/POWERCON.2016.7754046

[40] X. Liu, D. Yang and A. E. Gamal, "Deep neural network architectures for modulation classification," in 2017 51st Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, USA, pp. 915-919, October 2017. https://doi.org/10.1109/ACSSC.2017.8335483

[41] T. J. O'Shea, J. Corgan and T. C. Clancy, "Convolutional Radio Modulation Recognition Networks," in 17th International Conference on Engineering Applications of Neural Networks (EANN), Aberdeen, UK, pp. 213-226, September 2016. https://doi.org/10.1007/978-3-319-44188-7_16

Conflicts of Interest:

The authors declare that they have no conflicts of interest.