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DEEP LEARNING BASED SPECTRUM SENSING TECHNIQUE FOR SMARTER COGNITIVE RADIO NETWORKS

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ABSTRACT : *Accurate spectrum sensing is crucial for avoiding interference and maximizing spectrum band utilization or spectral efficiency in a cognitive radio network (CRN).However, conventional spectrum sensing techniques such as energy detection (ED) and cyclostationary feature detection (CFD) suffer limitations such as unreliable sensing and the problem of finding optimal detection threshold. In this paper, deep learning based detection (DLbD) technique is proposed to overcome these limitations for non-cooperative CRN under low SNR scenario .The proposed technique uses the Long Short Term Memory (LSTM) model of deep learning to learn the features of a modulated received signal in order to accurately distinguish between such signal and noise within a spectrum band. An LSTM classifier was trained using some generated signals of different modulation schemes and noise as features. The proposed DLbD technique was compared with the ED and CFD techniques using probability of detection and probability of missing as performance metrics. The simulation results reveal that the proposed DLbD technique outperforms both the ED and CFD techniques. The proposed DLbD technique is essential in fifth-generation (5G) mobile telecommunications ultra-dense networks like smart cities.*

KEYWORDS: *Spectrum sensing (SS), cognitive radio network (CRN),deep learning (DL), long short term memory (LSTM), spectral efficiency, smart network.*

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I. INTRODUCTION

Machine Learning (ML) and Artificial Intelligence (AI) applications are reshaping physical processes of modern industries. The telecommunications industry is not left behind in this trend as it acts has the enabler to the other industries through the fifth-generation (5G) mobile telecommunications technology (Holma *et al.*, 2020). The 5G mobile network provides connectivity for new use cases such as Industrial Internet of Things (IIoT) (Tiburski*et al.*, 2016;Liang*et al.*, 2018; Poirot*et al.*, 2020), and the emerging trend in telecommunications is the application of ML or AI to provide smarter device-to-device (D2D) and machine-to-machine (M2M) communications in ultra-dense networks like smart cities (Abolade*et al.*, 2018;Mardani*et al.*, 2018; Zeadally and Tsikerdekis, 2020).

Cognitive Radio (CR) technique, which was first introduced in (Mitola and Maguire, 1999), is an aspect of wireless communications that is attracting growing interest in recent times for improving spectral efficiency and the overall capacity of cellular Heterogeneous Network (HetNet) (An*et al.*, 2015;Xu*et al.*, 2017). In a Cognitive Radio Network (CRN), a CR which is also known as unlicensed or Secondary User (SU), uses an idle channel (or frequency spectrum hole) belonging to a licensed user or Primary User (PU) to communicate (Ghasemi and Sousa, 2008;Wang and Liu, 2011) as shown in Fig.1 where the SU uses the PU's idle bands B7 and B1 at separate times. This strategy helps to efficiently utilize the available but relatively scarce spectrum. However, the major challenge faced by a CRN is how to ensure that an SU's signal does not interfere with the PU's signal (Nasser*et al.*, 2021). Thus, it is highly important for the SU to accurately detect the presence of the PU so as to avoid interference or the absence of the PU so as to maximize frequency band

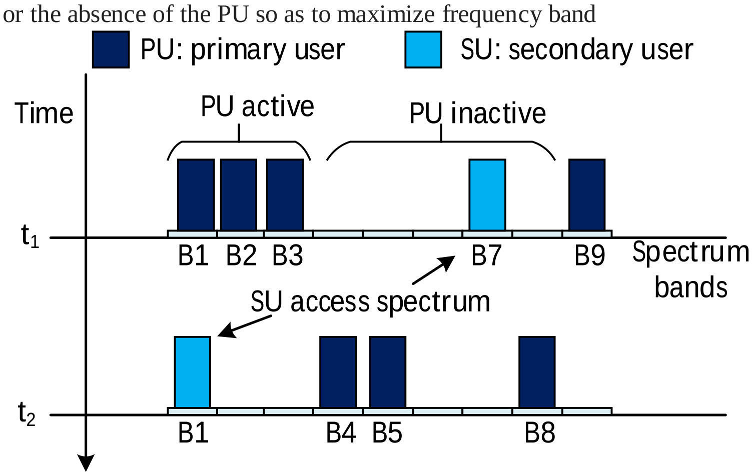

Fig.1. Dynamic spectrum access model in a CRN (Source: Song*et al*., 2012)

utilization of the network. This act of knowing the status of radio frequency bands in a CRN is referred to as Spectrum Sensing (SS) (Abdulsattar and Hussein, 2012).

The other functions of CR aside from spectrum sensing are spectrum management, spectrum mobility and spectrum sharing (Garhwal and Bhattacharya, 2011). A spectrum sensing technique can be categorized under transmitter detection (i.e. non-cooperative), cooperative detection or interference-based detection (Akyildiz*et al*., 2011).In addition, spectrum sensing could also be either narrowband or wideband; and the conventional narrowband sensing methods are Energy Detection (ED), Cyclostationary Feature Detection (CFD), Matched Filter detection (MFD) and Covariance-based Detection (CD)(Arjoune and Kaabouch, 2019).

Different spectrum sensing (SS) strategies have been proposed in literature. Rajarshi and Krusheel (2008) investigated the use of maximal ratio combining with the CFD technique and the results showed performance improvement in detection accuracy. In an attempt to improve the SS performance of the ED technique, Oh and Lee (2009) utilized the SS error function to optimize the decision threshold level. Spectrum sensing scheme that utilizes the statistical covariance of the received signal was proposed by Zeng and Liang (2009). Genetic algorithm-based SS scheme for cooperative CRN was investigated by Arshad*et al.* (2010). Bazerque and Giannakis (2010) proposed an SS technique that utilizes the basis expansion of power spectral density (PSD) in both frequency and space in a cooperative CRN. The results showed improvement over some other techniques in the detection of both idle and occupied bands. The use of frequency shift filters with the CFD technique was shown to give sensing accuracy at low SNR region(Saggar and Mehra, 2011). The use of multiple antennas with the ED technique has been shown to provide performance improvement in SS accuracy under different fading channels (Abdulsattar and Hussein, 2012). Aparna and Jayasheela (2012) investigated the fusion rule-based CFD technique in a cooperative CRN, and the results showed that the strategy gives a more accurate estimation of the received signal.

With the aim of developing a more intelligent SS, Ejaz*et al.* (2013) proposed a scheme in which an SU uses the MFD technique if the PU’s signal structure is known priori; otherwise, the SU uses the alternative detector, which is a combination of the ED and CFD techniques, where the CFD helps to cater for the region between lower bound and upper bound thresholds. A closed-form decision threshold with the ED technique was investigated by Bozovic*et al.* (2017). The authors suggested the use of PU’s signal statistics to dynamically adjust the decision threshold in varying radio channel condition. The iterative SS scheme proposed bySharma and Sharma (2018) combines fusion rule and sensing time to achieve high detection accuracy and energy efficiency of the SU. Machine Learning (ML) based SS techniques such asK-means, support vector machine, K-nearest neighbor and decision tree have been shown to outperform the conventional SS techniques (Lu *et al.*, 2016;Shah and Koo, 2018;Ahmad, 2019).Convolutional neural network model was proposed by Lee*et al.* (2019) for mitigating the problem of correlation of decisions of SUs in a cooperative CRN. Promising results have been obtained with the use of deep learning strategies for spectrum sensing (Gao*et al.*, 2019;Weng and Xia, 2020).
Most of the proposed SS techniques are based on the conventional ED, CFD, MFD, CD and their variants.

However, the application of ML or DL is currently gaining attention (Shah and Koo, 2018)due to the problems of complexity, low reliability, threshold level and need of prior knowledge associated with the conventional techniques,. Thus, this paper proposes the use of a DL-based technique using the Long Short Term Memory (LSTM) DL architecture (Shurman*et al.*, 2018) in a non-cooperative CRN. The performance of the proposed scheme is compared with both the ED and CFD techniques.

II. METHODOLOGY

A. RECEIVED SIGNAL MODEL

Assuming a non-cooperative CRN, during spectrum sensing by an SU, the signal received y(t) if no PU is present in the spectrum band is seen as Additive White Gaussian Noise (AWGN), and it is represented as (Abdulsattar and Hussein, 2012):

$$y(t) = w(t) \tag{1}$$

where$w(t)$ is the AWGN channel which is Gaussian random process with zero mean and varianceσ^2. On the other hand, the signal received by the SU if PU is present in the spectrum band is given as Abdulsattar and Hussein, 2012):

$$y(t) = h(t) \cdot x(t) + w(t) \tag{2}$$

where$x(t)$ is the signal transmitted by the PU, and $h(t)$ is the fading channel gain. Since the goal is to determine the presence or absence of a PU signal, the following hypotheses are to be tested Abdulsattar and Hussein, 2012):

$$\begin{cases} H_0: & y(t) = w(t) \\ H_1: & y(t) = h(t) \cdot x(t) + w(t) \end{cases} \tag{3}$$

whereH_0 denotes the hypothesis for "No PU signal is detected" while H_1 denotes the hypothesis for "PU signal is detected". The two hypotheses should be distinguished by a threshold value.

B. ENERGY DETECTION (ED) SPECTRUM SENSING TECHNIQUE

The ED spectrum sensing technique is less complex to implement and thus widely used. However, it is not reliable at low SNR (Saggar and Mehra, 2011). The energy detector can function in both frequency and time domain with the test statistic given as (Arjoune and Kaabouch, 2019):

$$T_{ED} = \frac{1}{N}\sum_{n=1}^{N}(y[n])^2 \tag{4}$$

where$y[n]$ is the nth received signal sample while N is the length of received signal samples. The decision can be represented as (Arjoune and Kaabouch, 2019):

$$\begin{cases} T_{ED} < \lambda_{ED}: & for\ PU\ is\ absent \\ T_{ED} > \lambda_{ED}: & for\ PU\ is\ present \end{cases} \tag{5}$$

whereλ_{ED} is the decision threshold which is based on the noise variance.

C. CYCLOSTATIONARY SPECTRUM SENSING TECHNIQUE

The cyclostationary SS is more reliable than the ED but with the tradeoff of complexity. The CFD is defined by cyclic autocorrelation function which is expressed as (Saggar and Mehra, 2011):

$$R_{xx}^{\alpha} * (k) = \sum_{n=1}^{N} R_{xx} * (n, n + k)e^{-j2\pi\alpha n f_s} \tag{6}$$

where $x(n)$, α, f_s and k are the input signal, cyclic frequency, sampling frequency and the lag value, respectively.

D. SPECTRUM SENSING PERFORMANCE METRICS

The two commonly used metrics for evaluating the performance of any SS technique are the probability of detection and probability of missing. The probability of detectionP_d is defined as (Arjoune and Kaabouch, 2019):

$$P_d = p(H_0|H_0) \tag{7}$$

and the probability of missing$P_m$is defined as(Oh and Lee, 2009):

$$P_m = 1 - P_d \tag{8}$$

E. PROPOSED DEEP LEARNING –BASED SPECTRUM SENSING SCHEME

In the proposed DL-based Detection (DLbD) technique, an LSTM classifier was trained using some generated signals of QPSK, 4QAM, 16PSK and 16QAM modulation schemes as contained in Table 1. Some 100 different streams were generated for each of the modulated scheme and then passed through the Rayleigh fading channel to indicate the presence of PU signal. Furthermore, the AWGN signal was generated 400 times so as to have equal number of samples with the modulated signals. The signal-to-noise ratio (SNR) was fixed at -12.5 dB, which was obtained as the average of the range -25 dB to 0 dB, for all the generated samples. The generated dataset consists of 800 signal streams, and the length of each stream is 1000.

The target output of the LSTM classifier is either 1 or 0. The model classifies an input signal as “1” to indicate the detection of a PU’s signal, but outputs “0” if it does not detect a PU’s signal. Thus, the DLbD technique does not require the process of finding optimal threshold values which is necessary in the ED and CFD techniques.

The steps involved in the DLbD technique are illustrated in the flow chart of Fig.2. The DLbD technique entails creating a trained LSTM classifier to be used for detecting the presence or absence of PU in a spectrum band. The creation of the LSTM classifier starts by loading the generated dataset, which is of size 1000-by-800 samples in this work. This is followed by normalizing the data in order to remove outliers. Then the normalized data is partitioned into training set (90%) and validation set (10%). Then, the data sequence of each of the partitioned dataset and the categorical targets are converted to cell array so as to be suitable for creating the classifier.

The LSTM classifier is then created and trained using MATLAB’s *trainNetwork* function. The trained LSTM classifier is then tested with the validation dataset using MATLAB’s *classify* function to classify the input signal streamsinto1 (PU signal present) or 0 (PU signal absent).

The trained LSTM classifier is then saved for future use to detect PU signal in a spectrum band. The specifications for the LSTM model are contained in Table 2 while the graph of the training accuracy and loss is shown in Fig.3. The training process stopped at 400th iteration (or 64th epoch) with accuracy of 98.8%.

Table 1: Dataset for training the LSTM classifier

Signal	**Length of signal stream**	**Number of samples generated**
QPSK	1000	100
4QAM	1000	100
16PSK	1000	100
16QAM	1000	100
AWGN	1000	400

Table 2: Specifications of the LSTM model

Parameter	Specification
Sequence input layer	1
Sequence input length	1000 features
Number of fully connected layers	2
Activation function	Softmax
Optimizer/Solver	adaptive moment estimation (adam)
Batch size	150
Maximum epoch	100
Learning rate	0.01
PC used for simulation	64-bit OS, Core i5-5200U CPU @ 2.2GHz, 4GB RAM

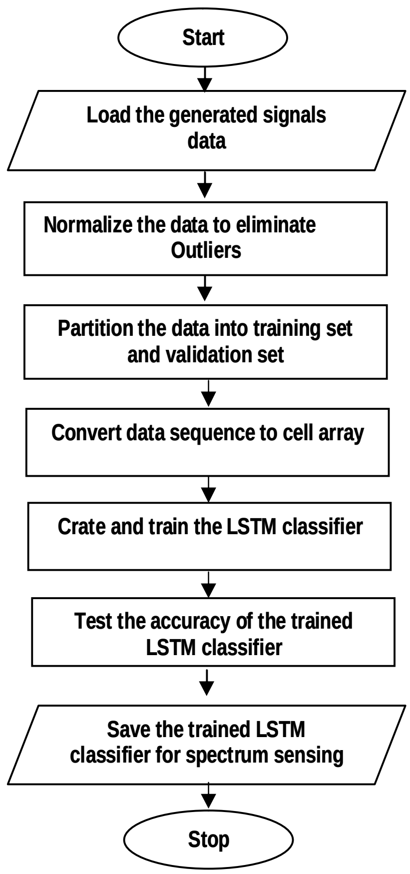

Fig. 2: Proposed DL-based Detection (DLbD) technique for spectrum sensing

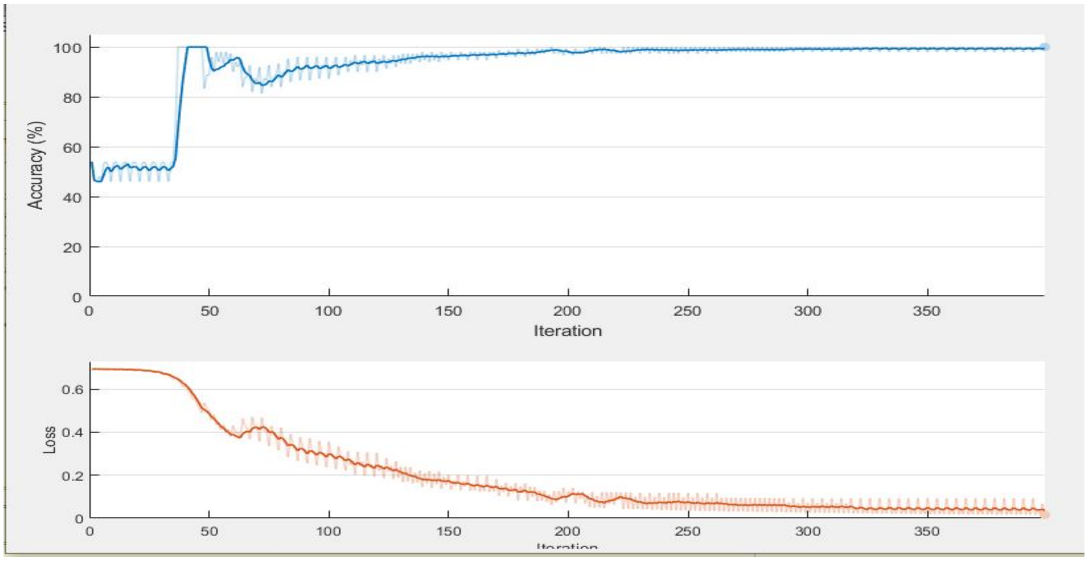

Fig. 3: Graph of the LSTM classifier's training accuracy and loss

III. RESULTS AND DISCUSSION

The proposed DL-based detection (DLbD) scheme was simulated in MATLAB and the performance compared with the ED and CFD techniques using probability of detection (P_d) and probability of missing (P_m) as performance metrics. Results are presented for QPSK, 4-QAM, 16-PSK and 16-QAM modulation schemes for values of SNR ranging from -25 dB to 0 dB. The low SNR region gives better insight into the effectiveness of an SS technique. For each value of SNR, the simulation was repeated 100 times (or channel realizations) and the results averaged .In each iteration, randomly generated information bits were modulated and transmitted over the Rayleigh fading channel plus AWGN. Then the DLbD technique was applied to the received signal to detect whether a PU is present or absent on the channel. The decision threshold for QPSK and 4-QAM signals was set to 0.35 while the threshold for 16-PSK and 16-QAM signals was set to 0.5 for both ED and CFD techniques.

The P_d results for the QPSK signal are shown in Fig.4. The three SS techniques achieve P_d of 1 at SNR value of -11 dB, which indicates that all the schemes are able to accurately detect the PU signal if the SNR is -11 dB and above. However, by averaging over all the SNR values, mean P_d of the DLbD, CFD and ED are 0.96, 0.81 and 0.67, respectively. This reveals that the proposed DLbD scheme gives about 16%improvement over the CFD scheme and about 30% improvement over the ED scheme. In addition, CFD is superior to ED which is in agreement with studies from the literature.

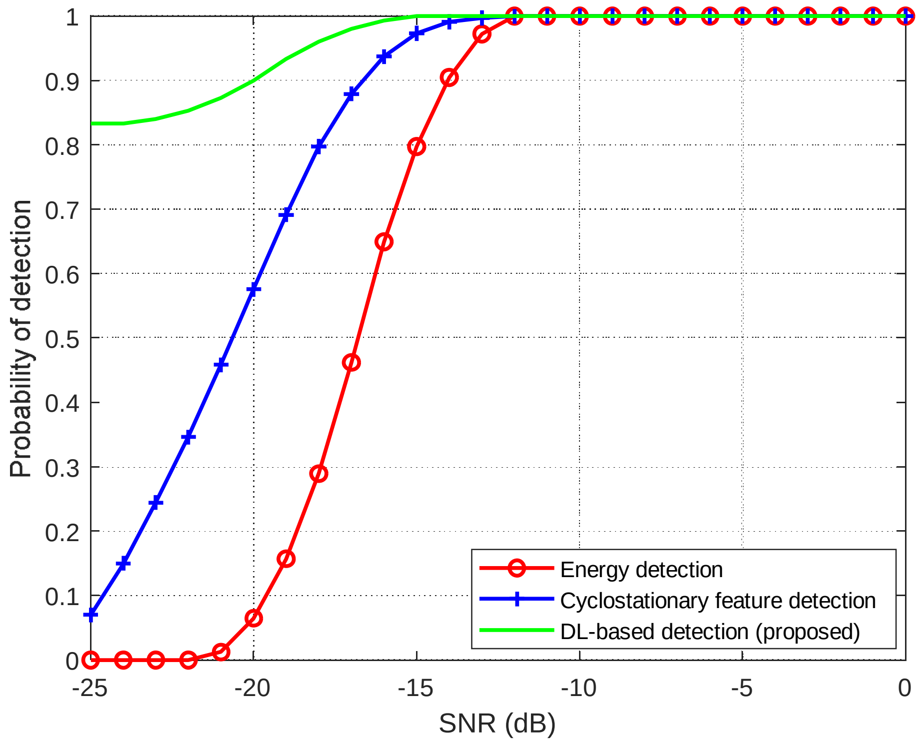

Fig.4. Probability of detection (P_d) versus SNR for QPSK signal

Fig.5 presents P_d results for the 4-QAM signal. The DLbD gives mean P_d of 0.94, CFD gives 0.71 while ED gives 0.54. This also reveals that the DLbD scheme is about 24% more accurately than the CFD and about 43% more accurately than the ED scheme in sensing PU's signal. The P_d performances of the schemes when 16-QAM signal is sensedare shown in Fig.6. The mean P_d achieved by the DLbD, CFD and ED schemes are 0.91, 0.65 and 0.25. This reveals the superiority of DLbD over CFD and ED with about 29% and 73%, respectively. The robustness of the DLbD scheme is also revealed in Fig.7 for the 16-PSK signal in which the mean P_d of DLbD is 0.94, mean P_d of CFD is 0.82 and mean P_d of ED is 0.66. This also reveals that DLbD has about 13% and 30% performance gains over the CFD and ED schemes, respectively.

These results have shown that the overall probability of detection performance of the proposed DLbD technique for all the modulation schemes investigated is 0.94 (or 94%). The DLbD scheme is able to detect the presence of a PU signal more accurately than the ED and CFD schemes because the network layers of the LSTM classifier learns the inherent features of the modulated signal thereby making the model to be capable of distinguishing between modulated signals and noise.

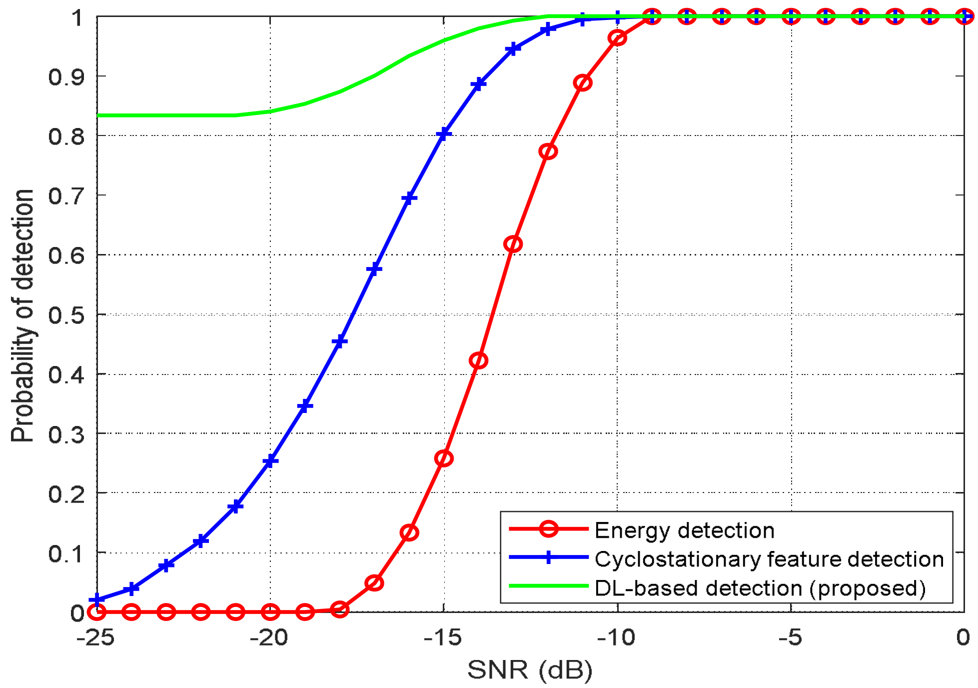

Fig.5. Probability of detection (P_d) versus SNR for 4-QAM signal

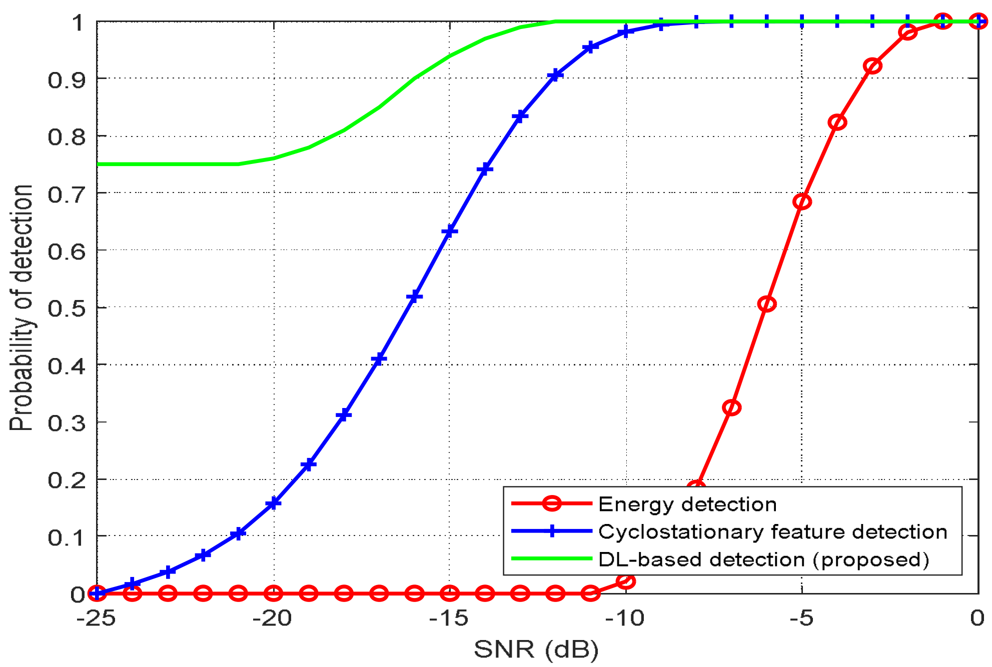

Fig.6. Probability of detection (P_d) versus SNR for 16-QAM signal

The results in Fig.8 shows the P_m performance of the SS schemes for QPSK signal evaluated for SNR values from-25 dB to 0 dB. The DLbD incurs the lowest meanP_m value of 0.096 while CFD and ED incur 0.19 and 0.33, respectively. This reveals that DLbD gives the lowest P_m; thereby having performance gain of about 33% over CFD and 65% over ED. It is observed in Fig.9 for 4-QAM signal that the mean P_m values of 0.14, 0.29 and 0.46are obtained by DLbD, CFD and ED, respectively. This also reveals that DLbD outperforms CFD and ED by about 52% and 70%, respectively. Similar trend is observed for 16-QAM signal in Fig.10and 16-PSK signals in Fig.11. The DLbD, CFD and ED fail to detect the 16-QAM signal with mean P_m values of 0.17, 0.35 and 0.75, respectively; however, the performances of CFD and ED are inferior to DLbD by about 51% and 77%, respectively. In Fig.11, the 16-PSK signal's detection is missed by DLbD, CFD and ED with mean P_m values of 0.12, 0.18 and 0.34, respectively. This implies that DLbD gives the lowest P_m on the 16-PSK signal, and is about 33% and 65% lower than CFD and ED, respectively.

The probability of missing results of the DLbD, CFD and ED techniques are in conformity with the probability of detection results. Consequently, the overall probability of missing performance of the proposed DLbD technique for all the modulation schemes investigated is 0.90 (or 90%). In Fig.12, the average detection time, in millisecond, of the DLbD, CFD and ED techniques are investigated using 16-PSK signal. The results show that the DLbD, CFD and ED give average detection time of 5.40ms, 1.25ms and 0.11ms, respectively, which reveals that ED is the fastest followed CFD whereas DLbD is the slowest.

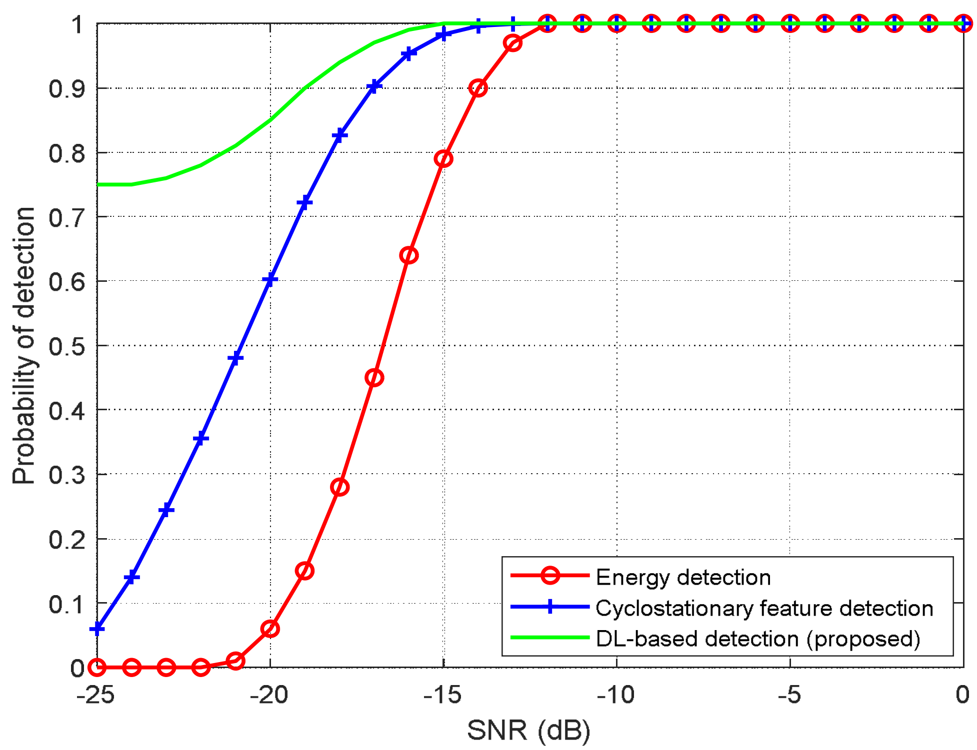

Fig.7. Probability of detection (P_d) versus SNR for 16-PSK signal

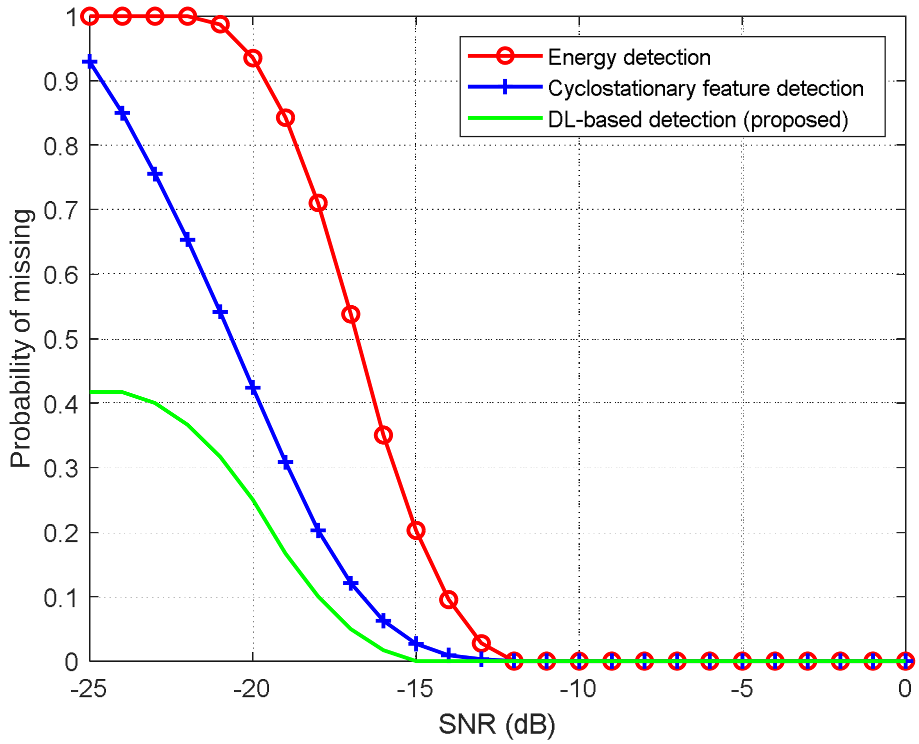

Fig.8. Probability of missing (P_m) versus SNR for QPSK signal

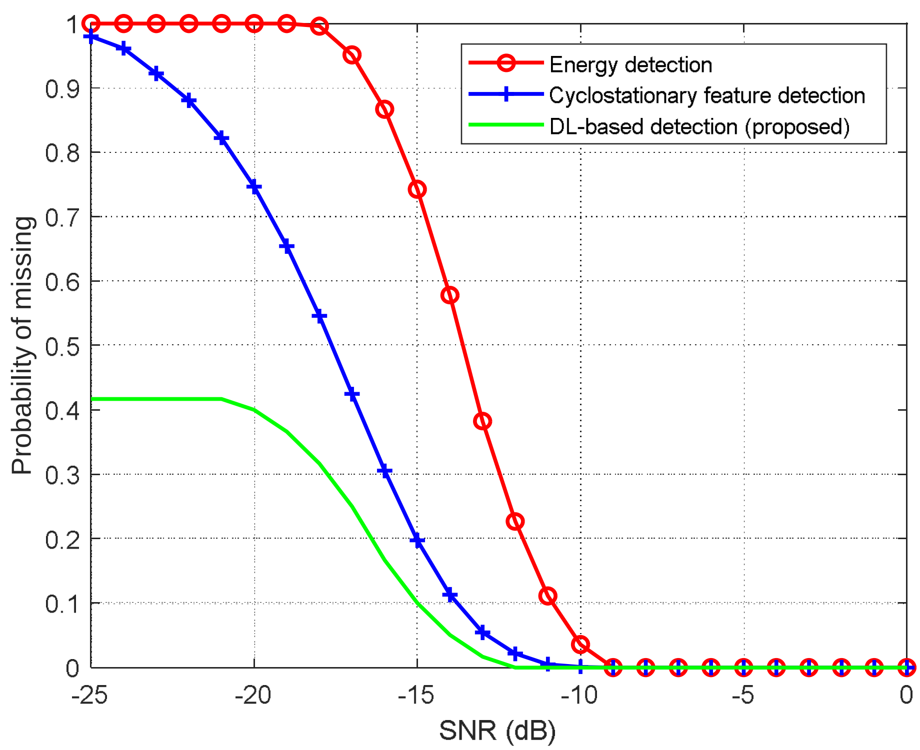

Fig.9. Probability of missing (P_m) versus SNR for 4-QAM signal

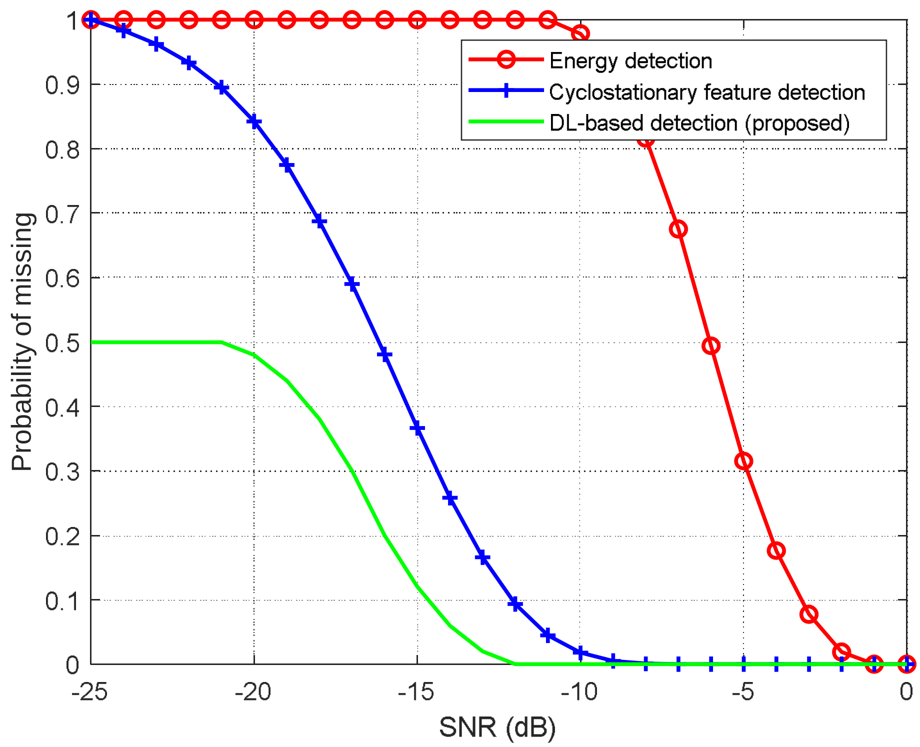

Fig.10. Probability of missing (P_m) versus SNR for 16-QAM signal

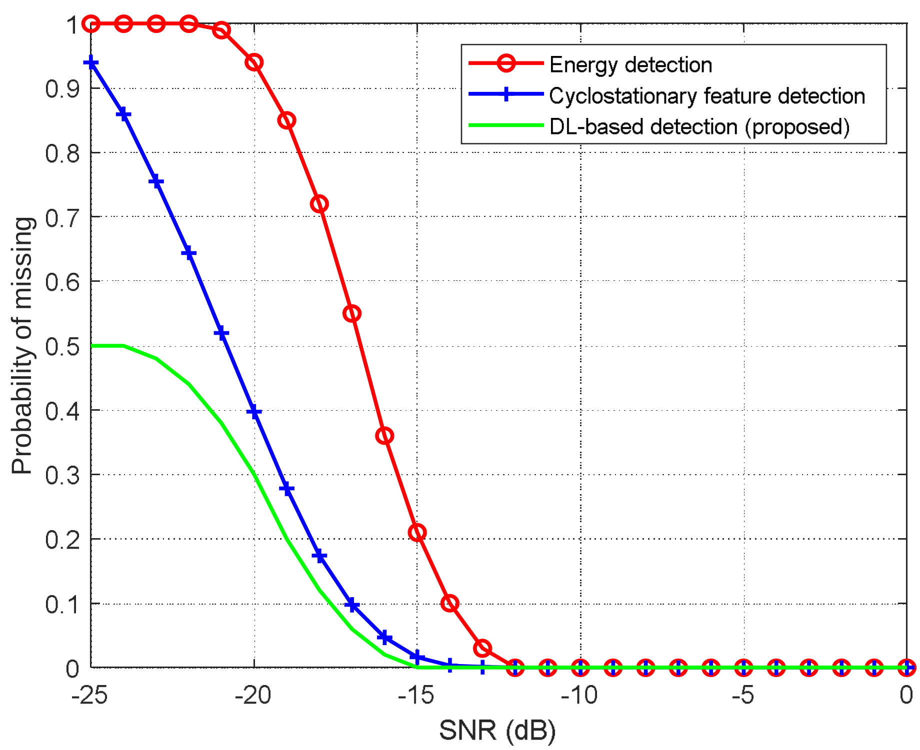

Fig.11. Probability of missing (P_m) versus SNR for 16-PSK signal

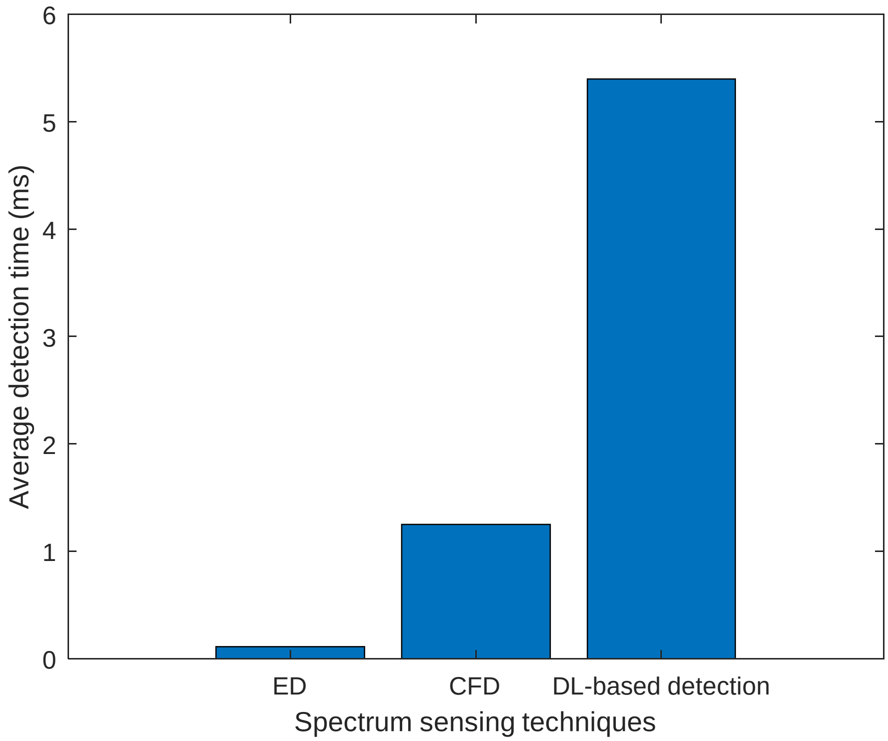

Fig.12. Average detection time comparison of spectrum sensing techniques

IV. CONCLUSION

In this paper, a deep learning (DL) based spectrum sensing technique named DL-based Detection (DLbD) is proposed for the detection of PU signal within a spectrum band so as to improve the spectral efficiency in a non-cooperative CRN. The proposed technique uses the LSTM model of DL to learn the features of a modulated signal in order to accurately distinguish between such signal and noise within a spectrum band.

The proposed DLbD technique is compared with two conventional transmitter detection techniques namely; energy detection (ED) and cyclostationary feature detection (CFD) and the performances investigated using probability of detection (P_d) and probability of missing (P_m). The results reveal that DLbD outperforms ED and CFD in both P_d and P_m. Thus, the proposed DLbD provides higher detection accuracy and invariably better reliablity in spectrum sensing under low SNR scenarios compared to the conventional techniques. Another advantage of the proposed DLbD technique is that it does not require the use threshold values.

The major limitations of the DLbD technique are the relatively high detection time and the need for large training samples for the deep learning. Therefore, future work can investigate how to address these limitations. In addition, the performance of the proposed DLbD technique in cooperative CRN can be investigated. The proposed DLbD technique is essential in fifth-generation (5G) mobile telecommunications ultra-dense networks like smart cities.

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