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RESEARCH ARTICLE

Cooperative Spectrum Sensing Based on LSTM-CNN Combination Network in Cognitive Radio System

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ABSTRACT Cognitive radio (CR), as an emerging technology to improve the utilization of radio spectrum, the fundamental of CR technology is spectrum sensing, due to the detection performance being affected by various factors, spectrum sensing is challenging to achieve accurately. In recent years, many spectrum sensing algorithms have been proposed, such as energy detection algorithm, matched filter detection algorithm, cyclic stationary detection algorithm, etc. However, these algorithms are model-driven and require certain prior information. If the model assumptions are inaccurate or the prior information is challenging to obtain, the algorithms' detection performance will be degraded. The development of artificial intelligence technology and deep learning provides a new way to realize spectrum sensing. In this paper, we design a cooperative spectrum sensing model based on the parallel connection of convolutional neural network (CNN) and long-short-term memory (LSTM), which makes full use of the complementary feature extraction capabilities of CNN and LSTM networks. Among them, CNN is used to extract hidden spatial features, and LSTM network is used to extract time features. Both CNN and LSTM can process the original dataset directly avoiding information feature loss when the network is connected serially. Experimental result shows that the detection performance of the proposed algorithm outperforms the conventional cooperative detection algorithm under low SNR condition. For example, when the number of cooperative users is 9 and the transmit power is 10, the detection probability of the proposed algorithm in this paper can reach more than 90%, which is much higher than the detection performance of other spectrum detection algorithms.

INDEX TERMS Cooperative spectrum sensing, cognitive radio, CNN-LSTM combination network.

I. INTRODUCTION

Due to the proliferation of wireless communication service, spectrum resources have become highly scarce [1], [2], in the fixed-allocation spectrum allocation policy, spectrum is allocated to fixed users and precludes other users from utilizing it, but in some spectrum slots, the licensed user is inactive, which leads to low efficiency of spectrum utilization [3], the overall utilization of spectrum band varies from 7% to 35% under the fixed-allocation spectrum policy [4], In order to improve the efficiency of spectrum utilization, Mitola and Maguire proposed the concept of CR in his doctoral thesis [5], the underlying principle of CR is unlicensed users reuse spectrum hole when the licensed user is absent, and none-interfering the licensed manner. Detecting the state of licensed users efficiently and accurately is the premise of CR communication [6]. By sensing these temporary spectrum holes and opportunity access to it, CR technology provides a potential solution to the trade-off between spectrum resource limitation and its demanding growth [7].

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A. CURRENT STATE OF THE ART AND MOTIVATION

Spectrum sensing algorithms can be categorized into two kinds: parametric sensing model and non-parametric sensing model [8]. The parametric sensing method needs some prior information on the primary user(PU) signal, however, prior information about PU activity is difficult to obtain in practice. Therefore, the non-parametric detection method is more suitable in the cognitive radio system.

There are many parametric sensing algorithms being proposed recently, including energy detection algorithm [9], matched filter algorithm [10], cyclostationary detection [11], periodogram-based algorithm [12], and likelihood detection algorithm [13], each of these algorithms has different advantages/disadvantages and requirements. Likelihood ratio test [14] in theory has the best detection performance, but it needs distribution information of PU signal and noise, which leads to difficulty realizing in practice. MF-based detection algorithm requires perfect knowledge of PU signal channel response and accurate synchronization [15], if the PU and secondary user(SU) do not cooperate, this algorithm may be not impossible. CSD needs the cycle period of the PU signal, which is unrealistic for many applications [16], ED algorithm does not need any prior information on the PU signal and is simple to realize, it was widely used in CR systems [17]. However, noise uncertainty has a great influence on the performance of ED detection algorithm [18]. Otherwise, spectrum sensing methods based on the received signal sampling covariance matrix has developed rapidly [19]. The covariance absolute value detection algorithm is proposed in [20], and the simulation result shows that the detection performance outperforms energy detection in the noise uncertainty condition. The literature [21] proposed the minimum eigenvalue and the maximum eigenvalue detection algorithm. Under the condition of noise uncertainty and low SNR, the detection method based on the covariance matrix has better detection performance. However, these methods need to calculate the covariance matrix, resulting in high computational complexity [22]. In addition, the threshold setting is gradual and the detection performance of the algorithm will be seriously affected if the threshold setting is imprecise.

The Non-parametric spectrum sensing method is data-driven and is not required any prior information on PU activity [23]. In recent years, the non-parametric spectrum sensing method has attracted extensive attention from academia and industry, there are many non-parametric spectrum sensing algorithms have been proposed, for instance, three spectrum sensing algorithms based on machine learning methods(KNN, logistic regression, and neural network) were proposed in the literature [24], and The experimental results show that the neural network has the best detection performance when the decision threshold is unclear, the author in literature [25] proposed a spectrum sensing methods based on support vector machine(SVM) and K-nearest Neighbor(KNN). the SVM-Radial Bisis Function(RBF) Based spectrum sensing was carried out in [26]. The authors in [27] proposed an unsupervised learning algorithm for spectrum sensing, using various statistic features of the received signal as the training dataset, spectrum sensing algorithm based on the convolutional neural network was proposed in [28], [29], and [30], the LSTM network used in spectrum sensing was proposed in [31], [32], and [33]. Although these methods have good detection performance in spectrum sensing, they are all single-node sensing and cannot overcome the influence of multipath fading and hidden terminal. In order to improve the reliability of sensing results and reduce the effect of multipath fading and hidden terminal, scholars have proposed many cooperative spectrum sensing (CSS) algorithms, for example, the author in [34] proposed an unsupervised learning CSS method based on k-means clustering, CSS based on CNN was proposed in [35], and CSS methods based on LSTM neural network were proposed in [36], the simulation results show that the detection performance of CSS outperforms conventional single-node sensing algorithm. One type of network structure can only extract one feature, and different features contain different knowledge of the PU signal [22]. Using the combination of multiple features can let SU acquires more knowledge about PU signals, and improve the detection performance. To obtain the different features of the signal, it is necessary to combine several different types of neural networks. The spectrum sensing model based on the serial connection of CNN and SVN is proposed in [1], and the serial combination of CNN and LSTM spectrum model is proposed in [37], and the result indicates that the multi-feature combination network generally outperforms conventional single-node methods at a low SNR.

Although these spectrum sensing models based on multi-feature combination networks have achieved good detection results, most of these models are series connected with each other, and the feature information will inevitably be lost in the extraction process. To solve this problem, we proposed a muti-features combination network based on a parallel CNN-LSTM network, and simulating results have proven it was feasible, Multifeaturs Combination Network consists of a ''CNN-LSTM'' module and a combination-net'' module. The CNN-LSTM model extracts the hidden spatial and temporal features. then the Combination-net receives the features and merges the Multifeatures, finally completing the spectrum sensing.

B. CONTRIBUTIONS

The contribution of this paper can be summarized as:

- This paper proposes a new spectrum detection model based on the parallel combination of the CNN network and LSTM, which is a special network structure. Although cooperative spectrum sensing has been extensively studied, as far as the author knows, it is the first time that parallel combines CNN and LSTM for cooperative spectrum sensing.
- To make the proposed CNN-LSTM model robust and unbiased in the large SNR range. The SNR of the training dataset varies at large ranges, which ensures that the detection performance of the proposed algorithm does not degrade at the low SNR.
- This algorithm uses data-driven to overcome the difficulty of obtaining prior information in reality. It uses the SU receives signal to calculate the cycle and duty cycle

of spectrum occupancy, which solves the problem of threshold calculation difficulty in conventional detection algorithms.
- Through simulation, we confirm that the proposed method can achieve a higher detection accuracy than conventional CSS approaches, especially under hard decision conditions. Moreover, our simulation results show that the computational intensity is low enough, which facilitates the method deployment of the proposed method in practice.

C. PAPER ORGANIZATION

The rest of this paper is organized as follows, some previous related works are summary in Section II, Section III provides a definition of spectrum sensing, which include theories, and basic concepts. The system model describes in Section IV, while Section V describes the experiment's setup. Section VI discusses the simulating results and draws a conclusion of the paper in section VII.

II. RELATED WORK

Convolutional Neural Networks(CNN) have an outstanding ability to extract hidden spatial correlation features of data, conventional CNN has the structure of sparse connections, pooling, and weight sharing. A feedforward CNN consists of an input layer, some convolutional layers, a pooling layer, and a fully connected layer, the complete convolutional layer's operation is shown as follows:

$$X^L = f(W^{(L)} \otimes X^{(L-1)} + b^{(L)}) \tag{1}$$

where L represents the layers series number, $X^{(L-1)}$ is the previous layer output feature map, $X^{(L)}$ denotes the result of current layer network functional mapping; $W^{(L)}$ means layer's convolution kernel, The bias value is shown as $b^{(L)}$, $f(\cdot)$ indicates the activation function, which can improve the nonlinearity representation ability of the network. In this study, the Relu activation function is used in each hidden layer, which is shown as:

$$f(x) = relu(x) = \begin{cases} x & x \leq 0 \\ 0 & other \end{cases} \tag{2}$$

Long-term and short-term memory(LSTM) network is a kind of gated recurrent unit. It has an overall framework basically consistent with standard recurrent neural networks, but the internal calculation unit is designed more subtly and ingeniously. LSTM network can remember information for a long time, which can avoid the phenomenon of gradient vanishing and gradient explosion in RNN. Many works show that researchers have improved and extended the network based on LSTM to get a more complex and complete function, and achieved good results in respectively practical applications task.

The multi-feature combination network based on different network types can extract the data features map from multiple dimensions, obtain more information about the spectrum state from the received signal, and improve the detection accuracy. In addition, LSTM network is good at extracting temporal features from time series signals, but not good at processing correlation signals, while CNN is good at extracting features from correlation data. The feature extraction capabilities of LSTM network and CNN are complementary, and the combination of CNN and LSTM can significantly improve the ability of the algorithm to extract hidden feature maps from the received signal. At present, the common combination method is to connect LSTM network at the back of CNN, but this combination method has obvious defects. The data processed by LSTM network is previously processed by CNN, and the signal's temporal information is inevitably lost. If the LSTM network and CNN are combined in parallel, both LSTM and CNN can directly extract the hidden features from the original data, then combine the features extracted from the respective networks to avoid feature information loss during serial connection. The parallel processing method also shortens the time delay of calculation data and improves the spectrum sensing efficiency. The simulation results prove that the parallel connects LSTM and CNN method outperforms conventional methods.

The spectrum sensing problem is a classical binary hypothesis testing problem, and the design of the classifier has an indispensable effect on the sensing results. The softmax function is the most popular output function for two categories of classification tasks, which are shown as:

$$P(y|x) = \frac{\exp(W_y \cdot x)}{\sum_{c=1}^{C} \exp(W_c \cdot x)} \tag{3}$$

Cross entropy loss is the loss function corresponding to the softmax function, which can be written as:

$$L = -\sum_{k=1}^{M} x_k \log(P_k) \tag{4}$$

III. PROBLEM STATEMENT

As the key technology to improve the utilization of wireless radio spectrum, CR has acquired much attention in recent years. Moreover, spectrum sensing is fundamental to the CR, during the spectrum sensing process, SU receives the signal from receiving antenna, then detects the status of the PU, when the PU state is inactive, each SU can access the specific spectrum hole. while the PU signal is existence, the spectrum state is considered as occupied under the H_1 hypothesis, if the PU signal is absent, the spectrum state is considered idle under the H_0 hypothesis. the spectrum sensing process is to find a method to accurately detect the PU activity.

Conventional spectrum sensing algorithms design test statistics based on the distribution information of noise or signal, then use the received signal to calculate the test statistics and compare it with the preset threshold λ. When the test statistic $T(y)$ is greater than the threshold value λ, it means that the spectrum is occupied, otherwise, it is an idle spectrum, which can be represented as:

$$T(y) \leq \lambda H_0$$
$$T(y) > \lambda H_1 \tag{5}$$

The realization of single node sensing method is simple, and each node can complete spectrum sensing independently, however, the practice has proved that multi-path fading and shadow fading have a great influence on single-node spectrum sensing algorithms' performance, to improve the reliability of detection results, cooperative spectrum sensing(CSS) algorithm has been proposed.

Compared with single-node spectrum sensing, CSS merges data from different sensing nodes through a fusion center which can improve reliability. The most commonly used CSS algorithm can be divided into three categories: centralized cooperative spectrum sensing, distributed cooperative spectrum sensing, and relay cooperative spectrum sensing. Centralized cooperative spectrum sensing is the most widely used algorithm because of its low computational complexity and deployment difficulty. The centralized cooperative spectrum sensing algorithm can be divided into hard fusion and soft fusion when it comes to data fusion algorithms. Hard fusion requires the local node to judge spectrum state and only transmits 1-bit information to the fusion center, which has less channel occupancy. Soft fusion does not need the local node to make a judgment of the spectrum state, so it has lower requirements on the local node. However, the whole received signal needs to be transmitted in reporting channel, which will occupy more spectrum. hence choosing a suitable date merge method is a compromise between spectrum occupied and detection accuracy, In general, the hard fusion process can be divided into And rules, k-out-N rules, and or rules.

And criterion: All local decision results are uploaded to the Fusion center by a reporting channel, if all the SUs determine that the PU signal exists, the fusion center will determine the spectrum state as occupied, otherwise it is judged that the PU is inactive The detection probability P_d and false alarm probability P_f can be respectively expressed as:

$$P_d^{CSS_{and}} = \prod_{i=1}^{N} P_{d,i} \tag{6}$$

With P_f:

$$P_f^{CSS_{and}} = \prod_{i=1}^{N} P_{f,i} \tag{7}$$

OR criterion: As long as one of the local user's spectrum sensing results is occupied, the fusion center determines the PU active, otherwise PU inactive, the P_d and P_f of the OR Criterion can be said to as:

$$P_d^{CSS_{or}} = 1 - \prod_{i=1}^{N}(1 - P_{d,i}) \tag{8}$$

With P_f:

$$P_f^{CSS_{or}} = 1 - \prod_{i=1}^{N}(1 - P_{f,i}) \tag{9}$$

K-out-of-N criterion: in the CR network with N cognitive users, if the K or more among the N SUs detection results supports the decision of the PU signal existence, the final decision of the spectrum band is occupied. The detection probability and false alarm probability of this method are respectively:

$$P_d^{CSS_k} = \sum_{i=k}^{N} \prod_{j=1}^{i} P_{d,j} \prod_{k=1}^{N-i}(1 - P_{d,k}) \tag{10}$$

With P_f:

$$P_f^{CSS_k} = \sum_{i=k}^{N} \prod_{j=1}^{i} P_{f,j} \prod_{k=1}^{N-i}(1 - P_{d,k}) \tag{11}$$

where N is the total number of SUs, j is the current number of SUs that decision spectrum occupied K represents the number of SUs decision threshold that determine the spectrum occupied which can be said as:

$$K = \lceil \frac{N+1}{2} \rceil \tag{12}$$

With the development of deep learning, many cooperative spectrum sensing algorithms based on deep learning have been proposed. Neural networks can automatically learn the hidden features of the received signals and find the difference between the SUs received signal data under the two conditions of spectrum occupied and spectrum idle, then use this difference feature to complete spectrum sensing.

IV. SYSTEM MODEL

A. SCENARIOS MODEL

In this subsection, we introduce the proposed cooperative spectrum sensing system model. The key to spectrum sensing is to obtain the frequency usage of PUs in a specific frequency band. Assuming that the SU senses the spectrum periodically, during each sensing period the channel is time-invariant. There are two types of signals received by the SU. One is the signal received when the spectrum is occupied, at this time, the signal received is the superposition of the signal transmitted by the PU and noise, The other is received when the spectrum is idle, the received signal contains only noise. The spectrum sensing problem can be modeled as the classical binary hypothesis testing problem, which corresponds to spectrum occupancy and spectrum idle respectively.

$$y_i = \begin{cases} \omega_i(n) & H_0 \\ s(n)h_i(n) + v_i(n) & H_1 \end{cases} \tag{13}$$

where h_i is the channel gain from the PU-TX to the I_{th} SU-RX, $s(n)$ is the PU signal, $\omega_i(n)$ denotes the additive Gaussian white noise with 0 means and variance δ_n^2.

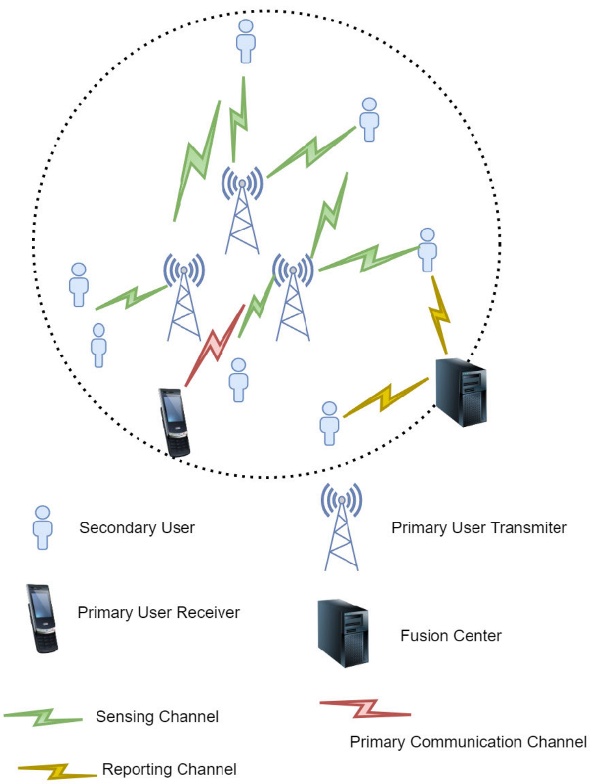

FIGURE 1. System model for cooperative spectrum sensing.

The system model studied in this paper is shown in Figure 1. It is composed of K PUs, M SUs, and a fusion center. In this paper, we assumed that the probability of each of the PUs occupying the spectrum is 50%, signal power decreases with the square of the distance between transmitter and receiver, and the fusion center selects a specific frequency band and controls the SUs to sensing this spectrum band. secondary, the CR users upload the received data through the reporting channel, Finally, the fusion center randomly selected several SUs to cooperate to complete the spectrum sensing. The power of the received signal can be expressed as follows:

$$P_{Rcv\_signal} = \frac{P\_Tx}{d^2} \tag{14}$$

The matrix of the received signal is:

$$Y = \begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(N) \end{bmatrix}^T = \begin{bmatrix} y_1(1) & y_1(2) & \dots & y_1(N) \\ y_2(1) & y_2(2) & \dots & y_2(N) \\ \vdots & \vdots & \vdots & \vdots \\ y_M(1) & y_M(2) & \dots & y_M(N) \end{bmatrix} \tag{15}$$

where N is the size of the sample, M denotes the number of the SU, and the signal received by the single antenna SU can be expressed as:

$$\begin{aligned} y(n) &= HX(n) + W(n) \\ &= \begin{bmatrix} h_{11} & H_{12} & \dots & h_{1N} \\ h_{21} & H_{22} & \dots & h_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ h_{M1} & h_{M2} & \dots & h_{MN} \end{bmatrix} \begin{bmatrix} x_1(n) \\ x_2(n) \\ \vdots \\ x_N(n) \end{bmatrix} + \begin{bmatrix} w_1(n) \\ w_2(n) \\ \vdots \\ w_N(n) \end{bmatrix} \\ &= \begin{bmatrix} S_1(n) \\ S_2(n) \\ \vdots \\ S_M(n) \end{bmatrix} + \begin{bmatrix} w_1(n) \\ w_2(n) \\ \vdots \\ w_N(n) \end{bmatrix} \end{aligned} \tag{16}$$

where $y(n)$ is the SU received signal, Each column represents sample signals received simultaneously by different SU, and each row represents the SU received signal series.

B. PROPOSED SPECTRUM SENSING MODEL

In order to overcome the loss of information feature when different types of network serial connections, we connected LSTM network and CNN network in parallel, After multiple simulations, the model with optimal spectrum sensing results is shown in Figure 2. The details of the model hyperparameters are shown in Table 1.

TABLE 1. Hyperparameter of proposed LSTM-CNN.

Serial number	Network layer type	Output feature dimension	kernel size	stride
1	InputLayers	$256 \times 2 \times N$	-	-
2	Convolution1d_1 layer	248×128	9	1
3	Convolution1d_2 layer	244×128	5	1
4	MaxPooling1d layer	122×128	2	2
5	Flatten layer	15616	-	-
6	LSTM_1	256×128	-	-
7	LSTM_2	128	-	-
8	Concatenate	15744	-	-
9	Fully connected layer 1	256	-	-
10	Fully connected layer 2	128	-	-
11	Fully connected layer 3	64	-	-
12	Softmax layer 2	2	-	-

V. EXPERIENTIAL SETUP

We build a small-scale CRN to generate a dataset. In this paper, we assumed that the PU randomly occupies the spectrum band, and each SU can receive signals from PU. noise power and channel conditions are time-invariant during a sensing period. the signal sent by each PU transmitter modulated with BPSK. The power of the PU signal decays inversely with the square of the distance, and the position of PU and SU remains constant during sensing.

During the simulation time, the PU-TX randomly transmits 256 byte-length frame to the SU-RX, SU observes and extracts features from these received signals for spectrum state decision-making. In our simulation, we assume that the probability of PU-TX occupies is 0.5.

We aim at studying the performance of the proposed LSTM-CNN-based algorithm and several other CSS algorithms in a conventional CRN scheme. In spectrum

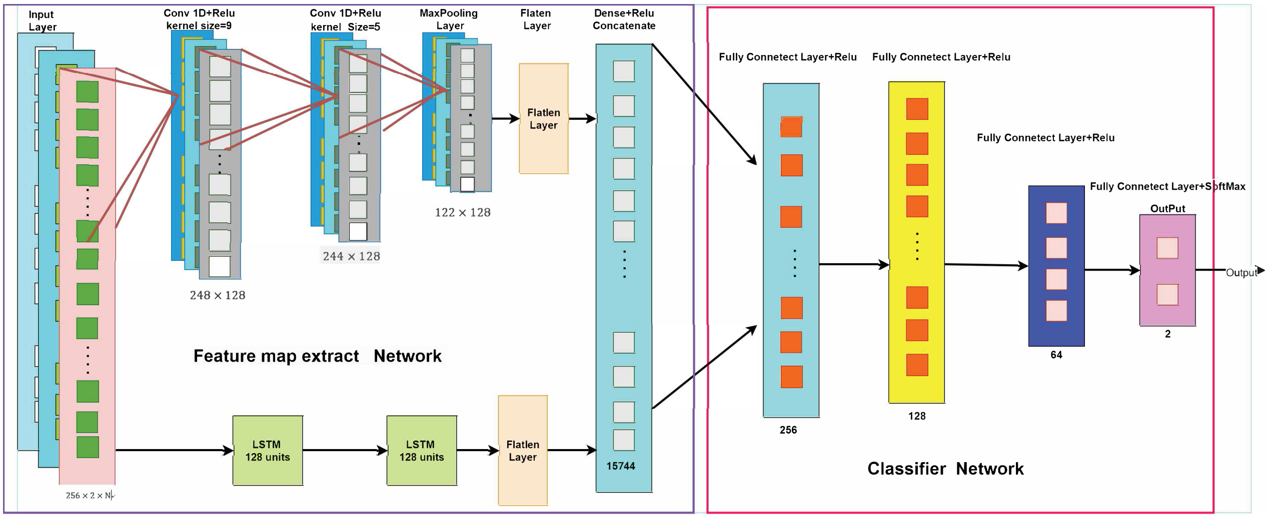

FIGURE 2. Architecture of the proposed model.

sensing problems, detection probability P_d and false alarm probability P_f are usually used to evaluate the detection performance. In this study, we also use these two metrics to evaluate the proposed model. Detection probability refers to the probability that the detection result is occupied when the spectrum is occupied, and false alarm probability refers to the probability that the detection result is occupied when the spectrum is idle. The higher the detection probability is, the stronger protection for PU will be, but it will also increase the false alarm probability and reduce the spectrum utilization rate. Spectrum sensing is a trade-off between P_d and P_f to meet the different system requirements. The knowledge about false alarm probability and detection probability is discussed in [38].

VI. SIMULATION RESULT AND DISCUSS

As shown in Figure 6, the whole process of spectrum sensing using deep learning technology can be divided into three parts: data generation, offline network training, and online spectrum sensing.

A. DATESET GENERATION

In this paper, the dataset for training and testing are generated under different SNR levels, the SNR range is $[-20dB, 10dB]$, step is 2, Monte Carlo simulation is carried out 5000 times under each SNR. and the parameters of the dataset are shown in Table 2, The location Settings for PU and SU are shown in Table 3. we assumed that during the spectrum sensing period, the power of noise and the distance between the SU and the PU is remaining unchanged. Different SNR can be obtained by changing the transmitting power of PU, in this paper, the signal power range is $[0, 100]W$, and the noise is the additive white Gaussian noise with a mean value of 0 and a noise power of $-143dbm/Hz$. The SU receives different signal power due to the distance from the PU, the SNR on each sensing node is different.

The mathematical expression of the PSK signal can be described as:

$$x(t) = A\sum_{n} \alpha_n g(t - nT_s)\cos(2\pi f_c t + \Phi_n + \theta) \tag{17}$$

where ϕ_n is the modulation phase, $\phi_n \in \{\frac{2\pi m}{M}, m = 0, 1, \ldots, M-1\}$, M is the modulation order of signal.

The noise received by each SU is additive white Gaussian noise with the same power. It is assumed that the noise power does not change during the whole spectrum sensing period. When the number of SU is 3, the pure noise signal received by each node is shown in Figure 3.

When the number of PU is 1 and the transmitting signal power is 100w, the PU pure signal received by each sensing node is shown in Figure 4. As can be seen from the figure, when the distance between the sensing user and the PU-TX is further away, the received signal attenuation is more serious and the power is smaller. At this time, at the same noise power lever the node farther away from the PU user is more likely to be submerged in the noise.

When the number of PU users is 1 and the PU transmitting power is 100W, the signals received by three different PU are shown in Figure 5. From the Figure, we can see that when added noise, the amplitude of the SU received signal will fluctuate. The farther SU is from the transmitting antenna, the smaller the power of the received PU signal, the smaller difference between the PU signal and noise signal, and the more difficult it is for the algorithm to identify the two signals. After the distance is large enough, the algorithm will be completely unable to complete the classification of the two signals.

Accurately labeling the received signal data set is the basis of applying deep learning model to spectrum sensing. There

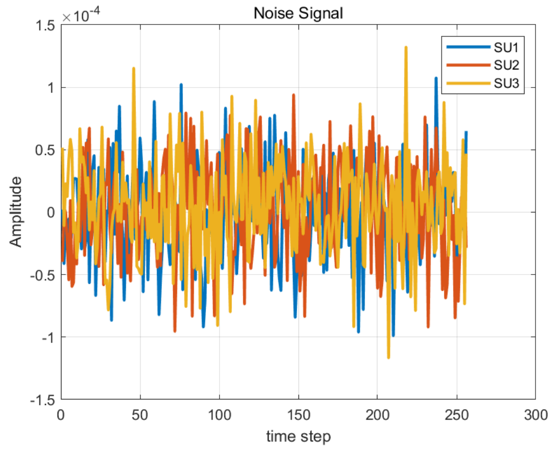

FIGURE 3. SU received noise signal.

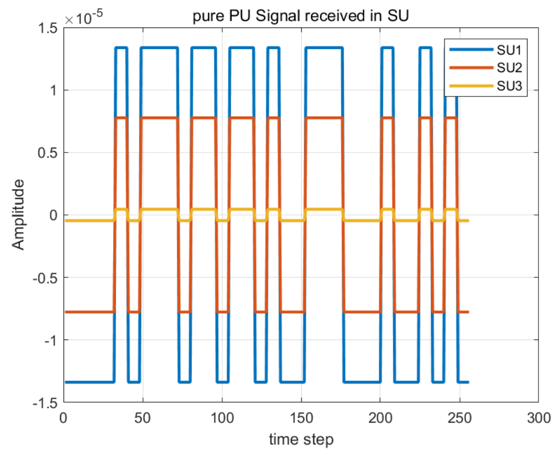

FIGURE 4. Pure PU signal at transimit Power = $100W$.

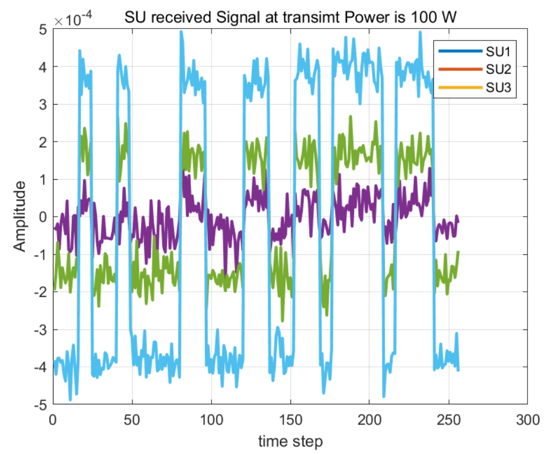

FIGURE 5. Different SUs received Signal at transmit power $100W$.

are two types of signals received by the SU, one is that the received signal contains only noise, and the other is composed of PU signal and noise. In the received signals with PU signals, the SNR range is $[-20dB, 10dB]$, and the required SNR of the SU terminal can be achieved by changing the transmitting power. When labeling the SU signal, the signal

TABLE 2. Dataset parameters.

modulation type	BPSK
size of samples	256
number of SU	1,3,5,7, 10, 15
Samples per SNR	50000
Train dataset ratio	0.7
Validate dataset ratio	0.2
Test dataset ratio	0.1
PU signal power range	[0,100] step 5
SNR range	$-20dB \sim 0dB$ in $2dB$ increments

TABLE 3. Position of PU and SU.

PU	Position	SU	Position
1	[0,0]	1	[0,0.5]
2	[0,0.5]	2	[0,0.75]
3	[0,0.75]	3	[0,1]
-	-	4	[0,1.25]
-	-	5	[0,0.5]
-	-	6	[0,0.75]
-	-	7	[0,1]
-	-	8	[0,1.25]
-	-	9	[0,1.5]
-	-	10	[0,1]
PU Transmit power range	$0W \sim 100W$ in $5W$ increments		

containing PU signals is labeled as 1, and other noise signals are labeled as 0. 70% of the labeled data is randomly selected as the training dataset and 20% as the validation dataset. 10% as the test dataset, the process of producing dataset for LSTM-CNN is described in Algorithm 1.

B. TRAIN THE LSTM-CNN MODEL

The training process of the algorithm is shown in algorithm 2. The 70% labeled data set is randomly selected as the training data set of the model. At each epoch, a Batch_size of data is randomly selected from the training data set to train the model, calculate the error between the model output and the labeled data, and backpropagate the error, separately calculating the gradient of the error at each layer to update the model parameters. After the model is trained, the validation data set is used to verify the model to check whether the model is overfitting. If the model performs well in the validation data set, the model is saved and used for spectrum sensing in online detection.

C. MODEL EVALUATION

Once the model is well-trained, we use the test dataset to evaluate the detection performance of the model. The evaluation process is shown in algorithm 3. The dataset under different SNR conditions is input into the algorithm one by one. After

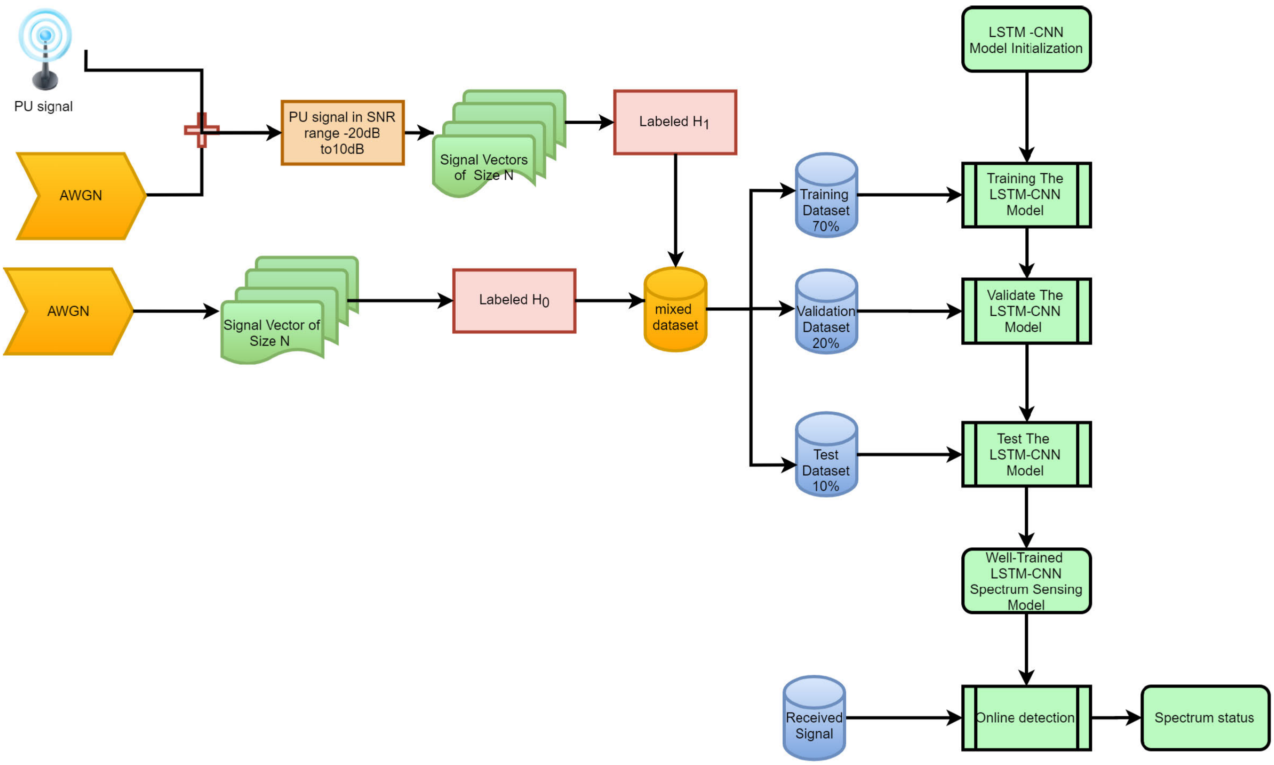

FIGURE 6. **Process of the proposed LSTM-CNN methods.**

Algorithm 1 Dataset Generated for Proposed LSTM-CNN CSS Algorithm

Require: Rcv_signal y
Ensure: Dataset $Y \leftarrow [y, label]$
Procedure of Create Dataset(rcv_signal, N, Label)
frame_len$\leftarrow \frac{length(Rcv_signal)}{N}$
noise_signal$\leftarrow$ AWGN with the power of $-143dbm$
PU_signal$\leftarrow$ BPSK signal with dimensions $1 \times N$ and the power is 1
for SNR in $-20dB \sim 10dB$ **do**
  for i $\in MC\_num$ **do**
    if randn>0.5 **then**
      snr_in_decimal$\leftarrow 10^{\frac{SNR}{10}}$
      PU_TX_Power $\leftarrow snr\_in\_decimal \times d^2$
      PU_TX_signal$\leftarrow PU_signal * \sqrt{PU_TX_Power}$
      Rcv_signal $\leftarrow PU\_TX\_signal + noise\_signal$
      label $\leftarrow 1$
    else if randn<0.5 **then**
      Rcv_signal$\leftarrow noise_signal$
      label $\leftarrow 0$
    end if
    return {Rcv_signal,label}
  end for
end for

forwardpropagation, the model will output a decision result, then the result is compared with the input dataset's label.

Algorithm 2 Training of Proposed LSTM-CNN CSS Algorithm

Procedure Train(X, y, α, Batch_size,Epochs)
for i in Epochs **do**
  Train_data, label$\leftarrow$ extract(Dataset, Batch_size)
  output $\leftarrow$ forward(LSTM-CNN,Train_data)
  error $\leftarrow \|label - output\|^2$
  Eorror$\leftarrow$ backwardpropagate(LSTM-CNN,error)
  hyperparameter$\leftarrow$ Updata(LSTM-CNN,Eorrors, α)
end for

If the output result is the same as the data label, it means that the decision is correct; if the output result is different from the data label, it means that the spectrum sensing result is wrong. Detection probability and false alarm probability are two commonly used evaluation indicators in cognitive radio. Detection probability represents the probability that the output result of the model is 1 when the input dataset is labeled as 1, and false alarm probability represents the probability that the output result of the model is 1 when the input dataset label is 0. During model evaluation, if the label of the input data set is 0 and the output result of the model is 1, the number of false alarms is increased by 1. If the input dataset is labeled 1 and the output result is 1, the number of correct detections increases by 1. Then the false alarm probability of the model is obtained by calculating the ratio of the number of false alarms to the total number marked 0,

Algorithm 3 Training of Proposed LSTM-CNN CSS Algorithm

Procedure test(LSTM-CNN_model,Dataset)
for i $\leftarrow$ test_num **do**
  test_data, label $\leftarrow$ extract(Dataset, 1)
  $H_0\_num \leftarrow 0$
  $H_1\_num \leftarrow 0$
  $H_0\_error\_num \leftarrow 0$
  $H_1\_correct\_num \leftarrow 0$
  result $\leftarrow$ predict(LSTM-CNN,Dataset)
  if label is 0 **then**
    $H_0\_num \leftarrow H_0\_num + 1$
    if result is 1 **then**
      $H_0\_error\_num \leftarrow H_0\_error\_num + 1$
    end if
  end if
  if label is 1 **then**
    $H_1\_num \leftarrow H_1\_num + 1$
    if result is 1 **then**
      $H_1\_correct\_num \leftarrow H_1\_correct\_num + 1$
    end if
  end if
  $P_d = \frac{H_1\_correct\_num}{H_1\_num}$
  $P_f = \frac{H_0\_error\_num}{H_0\_num}$
end for

and the detection probability is obtained by calculating the ratio of the total number correctly detected to the total number labeled 1. The P_f and P_d of the spectrum sensing model proposed in this paper are denoted in equations 18 and 19, respectively:

$$P_f = \frac{H_0\_error\_num}{H_0\_num} \tag{18}$$

$$P_d = \frac{H_1\_correct\_num}{H_1\_num} \tag{19}$$

The detection probability and false alarm probability of different spectrum sensing algorithms under the same SNR are calculated to evaluate the detection performance of different algorithms. Under the same SNR, the algorithm with a higher detection probability and lower false alarm probability has better detection performance.

D. EXPERIMENT RESULTS AND DISCUSS

In this part, some simulation experiments are carried out to analyze the performance of the proposed algorithm. The specific parameters are set as follows. Unless otherwise stated, the number of PU is P = 3, and the number of SU users participating in cooperative spectrum sensing is [1, 3, 5, 7, 9, 11]. it is assumed that the noise is additive white Gaussian noise and the transmitted signal is a BPSK signal. During the experiment, each SNR was simulated 5000 times. The Adam optimization algorithm is used to enhance the robustness and convergence of the proposed CNN-LSTM model, which reduces the model's training time and the classification error

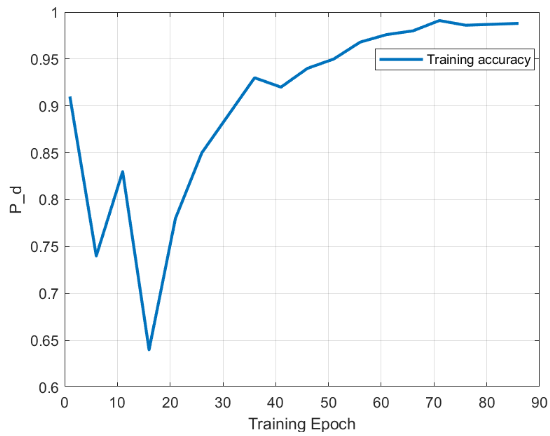

FIGURE 7. Relationship between training cycle and P_d.

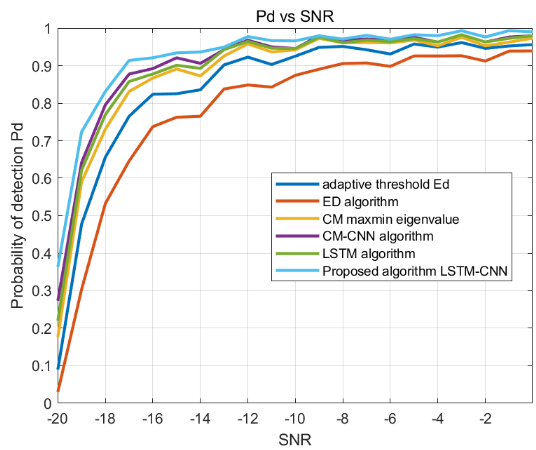

FIGURE 8. Detection probability of each algorithm under different SNRs.

of the proposed model. Finally, good detection performance is obtained.

1) RELATIONSHIP BETWEEN TRAINING CYCLES AND P_d

As shown in Figure 7, the detection performance P_d of the spectrum sensing algorithm which based on the combination of parallel LSTM and CNN proposed in this paper is fluctuates at the beginning of the training process, with the increase of the training epoch, the detection probability of the algorithm gradually stabilizes at about 98.64%, This detection probability basically meets the detection standard of cognitive communication.

2) COMPARISON OF ALGORITHM PERFORMANCE

Different spectrum sensing algorithms have different detection performances at the same SNR level. The P_d the Receiver Operations Characteristics(ROC) of the single-node energy detection, adaptive threshold energy detection, CM maximum eigenvalue, CM-CNN, SVM, LSTM, LSTM-CNN are shown in Figure 8. As can be seen from Figure 8, the detection performance of the LSTM-CNN algorithm significantly outperforms other spectrum sensing algorithms at lower SRN

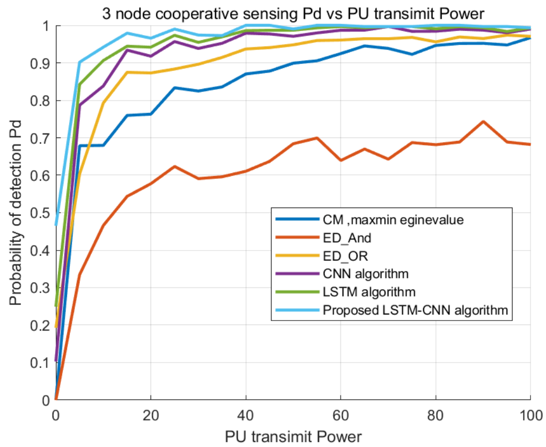

FIGURE 9. ROC Curve of each Algorithm at 3 users cooperative sensing.

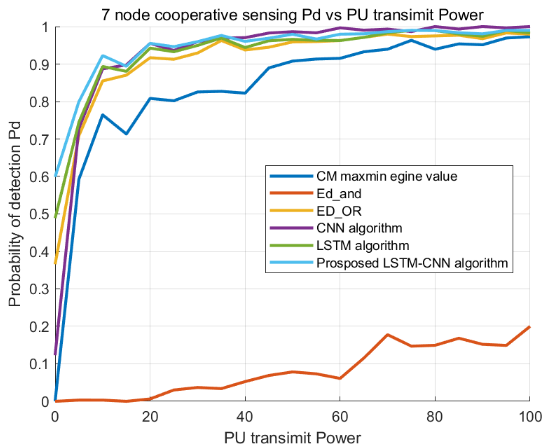

FIGURE 10. ROC Curve of each Algorithm at 7 users cooperative sensing.

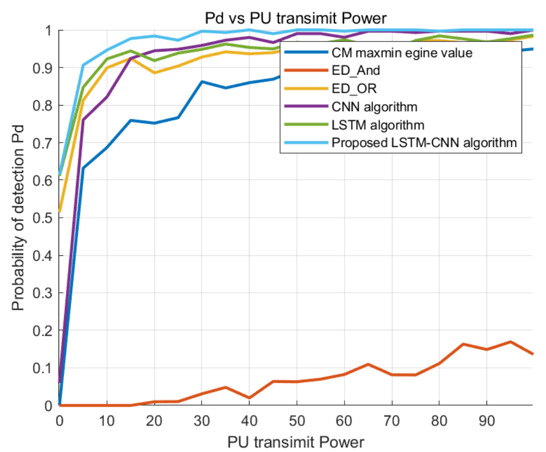

FIGURE 11. ROC Curve of each Algorithm at 9 users cooperative sensing.

lever, such as when SNR is -16dB, the detection probability of the proposed algorithm can reach more than 90%, which is much higher than other detection algorithms.

Then the 3 SUs cooperative sensing detection ROC is expressed in Figure 9, the 7 SUs cooperative sensing detection ROC is expressed in Figure 10, and the 9 SUs cooperative sensing detection ROC is expressed in Figure 11. As shown in this figure, under the and criterion, the more users participate in cooperative spectrum sensing, the lower the probability of spectrum occupation as a result of detection; under the or criterion, the more users participate, the higher the probability of spectrum occupation as a result of the detection. However, the proposed parallel spectrum sensing method, no matter whether at low SNR, or high SNR, the detection accuracy is higher and the detection performance is better than other detection methods. For example, when the cooperative user is 7 and the transmitting power is $20W$, the accuracy of the proposed LSTM-CNN method can reach 94.6%, which is significantly higher than other detection algorithms.

VII. CONCLUSION

This paper presents a spectrum sensing model of CNN-LSTM, detecting the state of PU activity through the received signal, using parallel CNN network and LSTM network to extract different features of the received signal, make full use of the advantages of CNN network and LSTM network, and solving the problem of feature information loss in serial connection by using a parallel connection. This algorithm realizes spectrum perception by learning the labeled historical data without computing the decision threshold. The simulation results have proven that the spectrum sensing methods based on the CNN-LSTM network investigated in this paper has a higher detection probability than CNN and LSTM algorithms at the low SNR, and the detection performance of the algorithm increases with the number of cooperate SU.

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