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Blind LTE-U/WiFi Coexistence System Using Convolutional Neural Network

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ABSTRACT With the rapid development of wireless communications technology, long term evolution (LTE) technology in unlicensed bands (LTE-U) can effectively solve the lack of spectrum resources. However, the competition in LTE-U and wireless fidelity (WiFi) will seriously interfere their communication quality, which making the friendly coexistence of LTE-U and WiFi becomes a hot research area. In this paper, we propose a classification algorithm based on deep learning to realize the identification of LTE-U and WiFi signal. Experiment results use mixed data at different signal to noise ratios (SNRs) and compare the classification results within two data forms. Experimental results show that our proposed deep learning-aided method can effectively distinguish LTE-U and WiFi signals and further achieve their friendly coexistence.

INDEX TERMS Automatic LTE-U, WiFi, in-phase and quadrature, deep learning, unlicensed band.

I. INTRODUCTION

In recent years, with the development of the internet of things technology and the advent of the era of big data [1]–[4], smart wireless devices have shown an explosive growth trend. However, wireless spectrum resources are very limited, and they are gradually unable to meet people's growing traffic demands [5], [6]. Limited spectrum resources and exponentially increasing user service requirements are a common problem faced by all mobile operators at present [7]. In the current situation where the increase of licensed spectrum is limited, in order to solve this problem, researchers have set their sights on fully utilized unlicensed spectrum resources [8]–[10]. Unlicensed-band long term evolution (LTE) technology is regarded as one of the key technologies to solve the scarcity problem of spectrum in next-generation wireless communications [11].

However, wireless fidelity (WiFi) is an important wireless technique in the unlicensed frequency band and it is widely used in daily life [12]. It has a wide coverage and a large number of users. After the introduction of LTE-Unlicensed (LTE-U) in unlicensed bands, LTE-U shares channel resources with WiFi systems in Fig. 1. WiFi uses the CSMA/CA access mechanism of the collision avoidance channel access method [13]. Its back-off mechanism will cause the existing LTE-U signal to seriously deteriorate the performance of the WiFi network, resulting in a decrease in WiFi throughput [14]. At the same time, the quality of service (QoS) guarantee mechanism in the LTE-U system allows it to carry out normal business [15]. Eventually, the LTE-U system can preferentially preempt channels, which causes it to occupy WiFi channel resources in unlicensed bands [16], and brings non-negligible interference to the WiFi system.

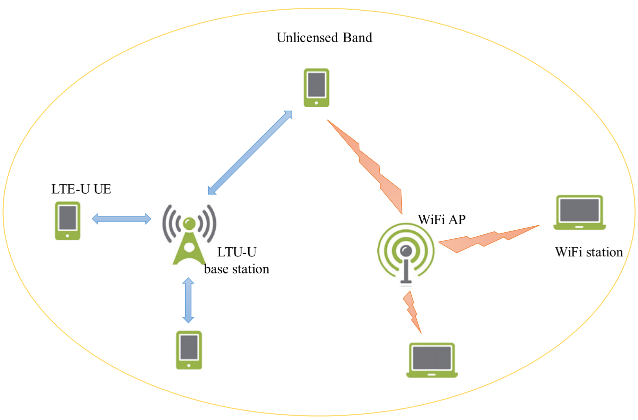

FIGURE 1. The LTE and WiFi coexistence system in unlicensed band.

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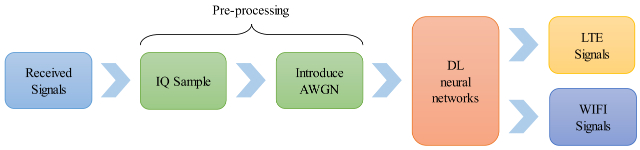

FIGURE 2. Structure of proposed LTE-U/WiFi coexistence system.

Therefore, the biggest challenge faced by LTE technology in unlicensed bands is the issue of friendly coexistence with WiFi systems [17].

Researchers have explored various methods to solve the problem of friendly coexistence between LTE and WiFi. License assisted access (LAA) technology is an unlicensed band LTE technology with LBT function, that is, as long as the channel is free. Hence, it can access transmission [18]. Cano *et al*. proposed a novel proportional fair distribution scheme to ensure the fair coexistence of LTE and WiFi [19]. Based on the LAA technology, Naim *et al*. developed a novel analytical model that uses Markov chains to accurately model the LAA listen-before-talk solution [20]. In order to enhance the fairness of LTE-U, an adaptive scheme called mLTE-U has been proposed [21].

With the rapid development of deep learning [22], it has gradually been applied to wireless communications [23]–[31], the internet of things [2], [17], [32], [33] as well as direction of arrive estimation [34]–[39]. In order to adapt to changes in the wireless environment [40], the advantages of Q-learning have been fully reflected [41], [42]. mLTE-U is enhanced by Q-learning technology, which is used to independently select the appropriate combination of TXOP and mute periods, so that it can provide reasonable coexistence between co-located mLTE-U and WiFi networks [43].

In this paper, we propose a deep learning based method to achieve friendly coexistence of LTE and WiFi. Due to the outstanding performance of convolutional neural networks (CNNs) in feature extraction. Our proposed method can accurately classify the signals coexisting with LTE and WiFi under in-phase and quadrature (IQ) samples, thereby achieving friendly coexistence of LTE-U/WiFi signals.

The structure of this article is as follows. We introduce the system model in Section II. Section III describes the analysis of data and algorithms. The simulation results in Section IV show the outstanding performance of our proposed method. Finally, we summarize our work in Section V.

II. SYSTEM MODEL

A. THE LTE-U/WiFi COEXISTENCE SYSTEM

In this paper, we identify the LTE and WiFi signals in unlicensed band by using deep learning algorithms, in order to deal with the vicious contention among the LTE-U and WiFi system in wireless channel. Fig. 2 shows the model of the LTE-U/WiFi friendly coexistence system proposed in this article. After receiving the unknown signals by using professional spectrum device, we firstly pre-process them on demand, such as IQ sampling and introducing Gaussian white noise. Subsequently, different DL neural networks are connected to the processed signals for training. Thus, we analyze the classification performance of the coexistence scheme based on the test and verification results.

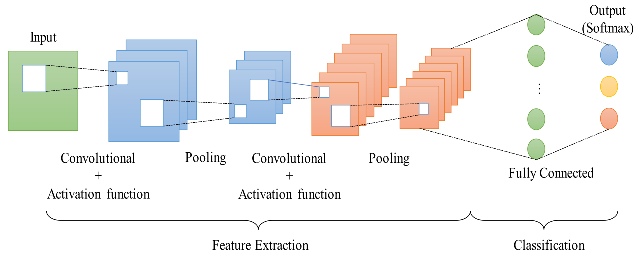

FIGURE 3. Structure of classical convolutional neural network.

B. CLASSICAL CONVOLUTIONAL NEURAL NETWORK

In the past few years, deep learning algorithms have been widely used by experts and scholars in many cutting-edge fields such as image processing and language processing. What's more, deep learning algorithms have outperformed human recognition in some areas of recognition and performed very well. Therefore, many research teams have begun to adopt deep neural networks, especially CNN, in wireless communications. CNN is famous for its powerful image recognition capabilities. The main input of CNN is the image. After training, CNN could classify these images, such as cars, houses, etc. Additionally, the image is a matrix of pixels in computer language. Each pixel matrix contains three dimensions, namely image width, image height, and RGB value.

Fig. 3 shows the structure of a typical CNN. It is obvious that CNN also composed of one input layer, one hidden layer and one output layer, just like a general deep neural network. It can be seen from the figure that after taking the image as an input, convolutional layer, pooling layer and fully connected layer in the hidden layer can extract abstract features from multiple aspects in order to achieve accurate recognition. For instance, the convolutional layer is the first to extract the input image's features, which is convolved with the pixel matrix by using a plurality of pre-set two-dimensional convolution kernels. After each convolutional layer, a pooling layer needs to be connected to compress parameters and simplify network complexity. In general, the convolutional layer and the pooling layer appear in pairs. The more they appear, the more features are extracted by CNN, and the higher the recognition accuracy. After a series of convolutions and pooling, there is a fully connected (FC) layer which is included in all traditional neural network architecture. Each layer of the FC layer is one-dimensional, and each layer of neurons is associated with all activations of the previous layer. Finally, our output layer contains a Softmax classifier which could calculate the probability of an image belonging to each category in order to ultimately implement image recognition. Inspired by this, we can replace the image with the data of LTE-U/WiFi signals in the form of a three-dimensional matrix as the input of the CNN, which may accurately identify the signal.

III. DATA AND ALGORITHM ANALYSIS

A. RECEIVED DATA PRE-PROCESSING

In this section, we pre-process the received LTE-U and WiFi signal data. The software used for pre-processing is MATLAB R2018a, which is an efficient data processing software and is always used in signal simulation for wireless communication experiments. Meanwhile, our signal data is collected by an organization called EWINE PROJECT in TCD who collects a variety of signal data from laboratory environments. For the accuracy of the experiment, we used 80,000 signal samples which LTE and WIFI each accounted for a half. These signal data are subject to IQ sampling, labeled with its corresponding wireless communication technology. Importantly, this system is trained on a mixed dataset, consisting of nine datasets with SNRs $= \{-20, -15, \cdots, 15, 20\}$ dB. Finally, 75% of the signal samples are used for training, and the remaining 25% are selected for model verification.

1) RANDOM PHASE OFFSET

In fact, the data collected by the laboratory is too ideal and not similar with the actual wireless signals cause the training models are not extensive. Therefore, we introduce a random phase offset to the signal data in order to simulate the phase offset and energy loss produced in the actual signal during the wireless channel. To explain how to achieve random phase offset, we define x(n) as the received LTE-U or WiFi signal, and it obeys

$$\sum_{n=0}^{N-1} |x(n)|^2 = 1 \tag{1}$$

Please note that y(n) as the processed signal that is the received discrete-time complex sampled by Nyquist criterion, and it is defined as

$$y(n) = Ae^{j\Delta\theta}x(n) + w(n), \quad n = 0, 1, \ldots, N-1 \tag{2}$$

where A represents the scale factor, $\Delta\theta$ represents phase offset which obeys a random distribution of $(0, \pi)$. Hence, w(n) is the additive noise and N means the number of sampling points. After adding the random phase offset, we can verify whether the deep learning model which performs well under idealized conditions can also continue to be great in real situations.

2) IN-PHASE & QUADRATURE OR AMPLITUDE & PHASE

After adding the random phase offset to the received signal, we sample the signal at the rate of 15 Mbps, and the IQ sampling data of the signal is more favorable for the neural networks to extract different features. Since the real and imaginary parts of the signal represent the in-phase and quadrature values of the signal, we combine the real and imaginary parts into a $2 \times N$ matrix R_{IQ}, denoted as:

$$R_{IQ} = \begin{bmatrix} real(y(0)) & real(y(1)) & \cdots & real(y(N-1)) \\ imag(y(0)) & imag(y(1)) & \cdots & imag(y(N-1)) \end{bmatrix} \tag{3}$$

which is a real matrix with dimensionality $2 \times N$ and it is the input of neural network. In other words, if the neural networks can extract features from IQ data, they can also extract features of Amplitude & phase (AP) data. According to the mathematical derivation, we define the amplitude formula of the signal $m_{amp}(y(n))$ as

$$m_{amp}(y(n)) = \sqrt{real^2(y(n)) + imag^2(y(n))} \tag{4}$$

we also define the phase formula of the signal $m_{pha}(y(n))$ as

$$m_{\mathrm{pha}}(y(n)) = \arctan(\frac{imag(y(n))}{real(y(n))}) \tag{5}$$

where N represents the number of sampling points. Thus, we combine the real and imaginary parts into a $2 \times N$ matrix M_{AP}, which denotes as:

$$M_{AP} = \begin{bmatrix} m_{\mathrm{amp}}(y(0)) & m_{\mathrm{amp}}(y(1)) & \cdots & m_{\mathrm{amp}}(y(N-1)) \\ m_{pha}(y(0)) & m_{pha}(y(1)) & \cdots & m_{pha}(y(N-1)) \end{bmatrix} \tag{6}$$

which is a real matrix with dimensionality $2 \times N$ and it is also the input of neural network. Furthermore, with the IQ and amplitude/phase (AP) matrices of the received signals, we can use them as the input to several deep learning models so that we can compare the ability of extracting abstract features and recognition accuracy of them.

B. PROPOSED CNN MODEL PARAMETER

In this section, a CNN model proposed in our LTE-U/WiFi coexistence system will be explained in detail. The training, verification and testing of CNN models in this experiment were carried out on Keras 2.2.2, who is based on Python3.7.1 with tensorflow 1.1.0 software library. In addition, Keras is an advanced object-oriented software library that allows the Central Processing Unit (CPU) and Graphics Processing Unit (GPU) to fully collaborate with each other. In our setup, all model training is done on the computer with two NVIDIA GTX 2080Ti GPUs and 8 Intel Xeon E3 CPUs.

The detailed structure and specific parameters of the CNN model used in this paper are shown in the Fig. 1. The input to the neural network is the LTE-U and WiFi signal data through pre-processing, whose size is 2×1024 IQ or AP data. The number of sample size is 40,000. It can be clearly seen from the figure that the subject of CNN consists of two parts: feature extraction part and classification part. Details are as follows:

Obviously, the convolutional layer can extract the abstract features of the data from multiple aspects, so that the feature extraction part consists of two convolutional layers with different parameters. The first convolutional layer consists of 128 convolution kernels, each of which has a dimension

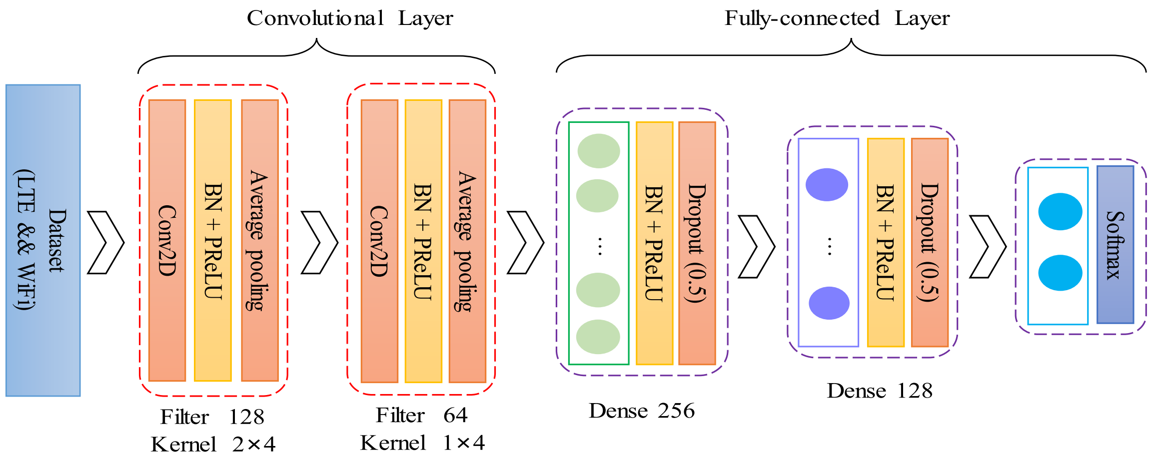

FIGURE 4. **Structure of CNN model proposed in this paper.**

of 2×4. Those kernels are convolved with the wireless channel data of the input layer, respectively. Further, the second convolutional layer is composed of 64 convolution kernels with dimension 1×4, who are convolved with the output of the first convolutional layer, aiming to find the abstract features that the first convolutional layer has not extracted. After each convolutional layer, we add the BN layer and the activation function layer. The BN layer normalizes the data in order to prevent the data extraction from the previous layer changing the laws of the original data. Now the activation function generally is expressed as PReLU, the upgrade version of ReLU, who can effectively accelerate convergence, reduce over-fitting and improve the efficiency of model training. Importantly, one pooling layer often appear with one convolution layer, performing average pooling and reducing parameters.

The classification part is also attractive, consisting of three FC neural networks. The neurons of each layer of the FC layers are closely connected to the neurons of previous layer. The first FC layer contains 128 neurons and the second FC layer contains 64 neurons. Similarly, we also added the batch normalization (BN) layer and the PReLU activation function layer after this two FC neural networks. However, it is essential for a FC layer to contain the dropout layer who can reduce the network complexity and has a value of 0.5. The third fully connected layer, also as the output layer of the CNN structure, uses the Softmax function, who outputs the predicted probability of the input signal category.

C. ACCURACY EVALUATION

In order to evaluate the LTE-U/WiFi coexistence system more objectively, we will not only analyze the classification accuracy of various algorithms, but also use some additive performance evaluation as indicators of various algorithms. The concerned indicators consist of precision and recall, whose detailed definition will be explained below, respectively.

To understand the concept of precision and recall, we must understand the meaning of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) firstly. In general, both TP and TN are predictive pairs, TP is a positive class, and TN is a negative class. Hence, we consider LTE-U as the positive class and WiFi as the negative class and the detailed description of these indicators is defined as:

- TP indicates that a LTE-U signal sample is predicted as an LTE-U signal sample by the classification algorithm, it is verified and predicted correctly.
- TN indicates that a WiFi signal sample is predicted as a WiFi signal sample by the classification algorithm, it is verified and predicted correctly.
- FP indicates that a WiFi signal sample is predicted as an LTE-U signal sample by the classification algorithm, and the prediction result is incorrect.
- FN indicates that a LTE-U signal sample is predicted as a WiFi signal sample by the classification algorithm, and the prediction result is incorrect.

Furthermore, precision, the number of samples that are correctly predicted to be positive class divided by all the samples that are predicted to be positive class, is expressed as:

$$P_{precison} = \frac{TP}{TP + FP} \tag{7}$$

and recall, the number of samples that are correctly predicted to be positive class divided by the number of samples that are positive class, is expressed as:

$$P_{recall} = \frac{TP}{TP + FN} \tag{8}$$

Since the number of samples for each signal in this paper is the same, the recall is equal to the prediction accuracy who is expressed as:

$$P_{accurary} = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

IV. SIMULATION RESULTS

A. COEXISTENCE PERFORMANCE ANALYSIS FOR LTE-U/WiFi SYSTEM

In this section, we send two kinds of LTE-U/WiFi signal data to different deep neural network algorithms for training.

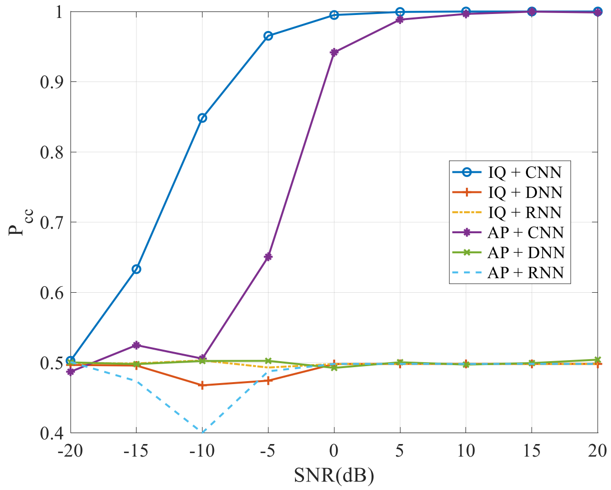

FIGURE 5. Correct classification probability for IQ & AP data with different DL algorithm.

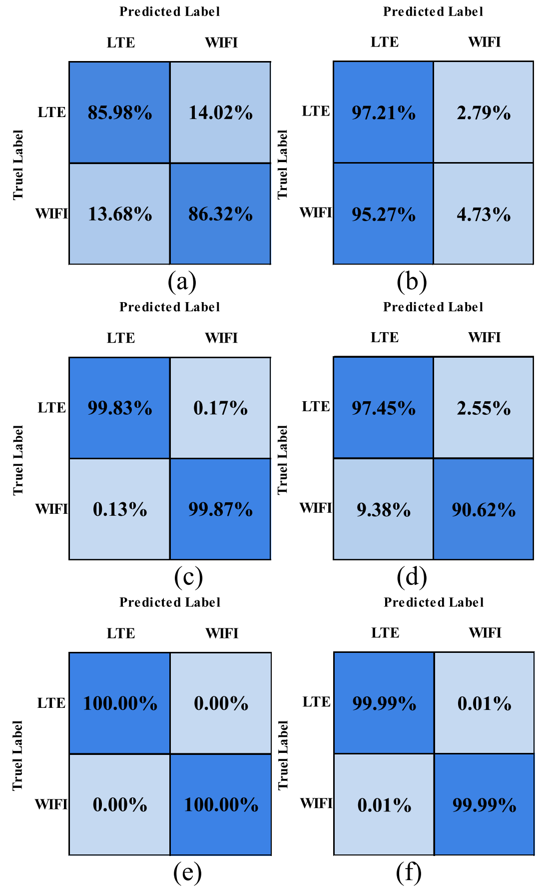

FIGURE 6. Confusion matrices for both IQ & AP data in CNN model for different SNRs: (a) IQ SNR= −10dB; (b) AP SNR= −10dB; (c) IQ SNR=0dB; (d) AP SNR=0dB; (e) IQ SNR=10dB; (f) AP SNR=10dB.

The first data form is In-phase & quadrature, and the other is Amplitude & phase. What's more, those three DL training models which we have choose are: CNN, fully connected deep neural network (DNN) and recurrent neural network (RNN). The detailed algorithm analysis and evaluation are shown below.

1) CORRECT CLASSIFICATION PROBABILITY

Firstly, we analyze the classification accuracy of the LTE-U/WiFi system proposed in this article. The signal-to-noise ratio (SNR) range of the received signal is from −20dB to 20dB, as shown in Fig. 5. This figure illustrates the classification performance of two different data presentation forms (IQ and AP) training under three deep learning algorithms. We can clearly observe that the correct classification probability of CNN model is excellent, which is higher than 90% when SNR is better than 0dB. Additionally, the identification probability can reach almost 99% at high SNRs. In contrast, the other two deep learning algorithms' classification accuracy is always around 50% no matter what SNR is, which means that the signals cannot be distinguished. Furthermore, we can find that the identification accuracy of the IQ data is 96%, while the AP data classification accuracy of 67% in CNN training model for −5dB of SNR. More precisely, when the SNR is higher than 5dB, the classification performance of the two input data forms is the same. This indicates that the input data in the form of IQ with CNN training model can effectively distinguish the LTE-U and WiFi signal.

2) CONFUSION MATRIX FOR IQ DATA AND AP DATA

Next, in order to compare the impact of different input data forms on the CNN training model, Fig. 7 shows the confusion matrix of CNN models with two input data forms at different SNRs. More specifically, Fig. 6a and Fig. 6b represent the confusion matrix of IQ data and AP data when SNR is −10dB. We can observe that taking the AP data form as the input the system makes the entire system recognize the WiFi signal as the LTE-U signal, which is not ideal. Moreover, Figs. 6(c-f) represent the confusion matrix of IQ and AP data when SNR is 0dB and 10db, respectively. Obviously, with

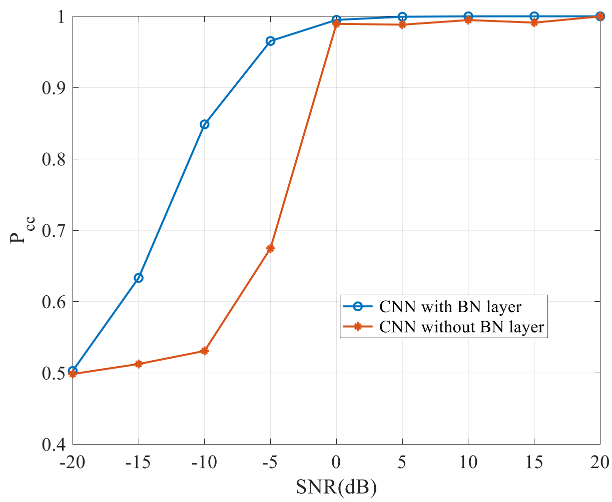

FIGURE 7. Correct classification probability of the CNN model with or without the BN layer.

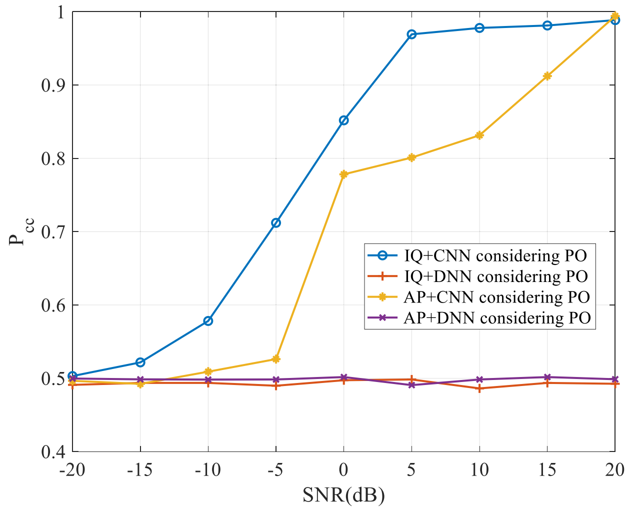

FIGURE 8. Correct classification probability for IQ & AP data considering random phase offset.

SNR increasing, the label prediction results become good and close to 100%. Overall, the label prediction results in the form of IQ data are significantly better than in the form of AP data, and the use of the IQ data form as the coexistence system input makes the entire model converge faster.

3) BN LAYER'S PERFECT PERFORMANCE

Based on the above results, we found that using IQ data as the input to the coexistence system and using CNN as the training model to the system can achieve better discrimination of LTE-U and WiFi signals. Then, we need to adjust the model of CNN to achieve the best classification results. Fig. 7 shows the classification accuracy of the CNN model with or without the BN layer. When SNR is greater than 0dB, the BN layer has little effect on the classification result. However, the classification accuracy is significantly reduced and the convergence becomes slower, without feature standardization of BN layer, when SNR is less than 0dB. Therefore, the BN layer are added to the CNN models of the entire systems proposed in this paper.

B. EXPERIMENT RESULTS FOR LTE-U/WiFi SIGNAL WITH RANDOM PHASE OFFSET

In this part, the random phase offset is added to the received LTE-U and WiFi signal data, which aims to simulate a more realistic wireless channel environment. As shown in Fig. 8, the input signal data form is still IQ and AP and two deep learning algorithms, CNN and DNN, are used. Fig. 8 shows that even if there is an unknown phase offset in the signal data, CNN can still accurately distinguish the LTE signal under the condition of high SNRs. Not surprisingly, DNN still performs bad. Further, using IQ data as the system input is significantly better than using AP data.

Similarly, Fig. 9 demonstrates the confusion matrix of CNN model who introduces phase offset. When the SNR is -10dB, it is noticed that taking the AP data form as an input make the overall system recognize the WiFi signal as an LTE signal. What's worse, when the SNR is 10dB, the performance of CNN who uses AP data as input to recognize LTE signals is very poor. Therefore, even if the random phase offset is assigned, the classification effect of CNN who uses IQ data form as input is still very good and has good robustness.

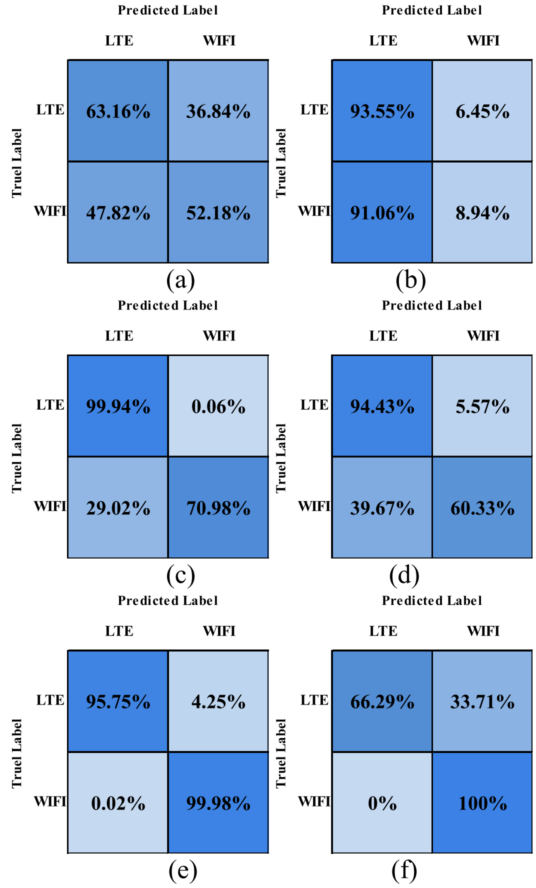

FIGURE 9. Confusion matrices for both IQ & AP data considering phase offset in CNN model for different SNRs: (a) IQ SNR= -10dB; (b) AP SNR= -10dB; (c) IQ SNR= 0dB; (d) AP SNR=0dB; (e) IQ SNR= 10dB; (f) AP SNR= 10dB.

C. ADDITIVE PERFORMANCE EVALUATION: PRECISION AND RECALL

Last but not least, we evaluate other indicators: accuracy and recall, which can be seen in Table 1 and Table 2, respectively. According to the definition, it can be considered that the recall and accuracy are numerically the same since the number of training samples is consistent. Focusing on the precision, the effect of phase offset on the CNN model is reduced by 20% on average when SNR $= 0$ dB. Another point is that when the AP data is used as input and the phase offset is taken into account, the precision reaches 1, but the recall is only 66%. The phenomenon shows that the recognition on WiFi signal is very good, but it can hardly identify LTE signal. In general,

TABLE 1. Precison of CNN model.

Precision	-10dB	0dB	10dB
IQ + CNN	0.8627	0.9987	1
AP + CNN	0.5050	0.9122	0.9999
IQ + CNN Considering PO	0.5691	0.7750	0.9998
AP + CNN Considering PO	0.5067	0.7042	1

TABLE 2. Recall of CNN model.

Recall	-10dB	0dB	10dB
IQ + CNN	0.8598	0.9983	1
AP + CNN	0.9721	0.9745	0.9999
IQ + CNN Considering PO	0.6316	0.9994	0.9575
AP + CNN Considering PO	0.9355	0.9443	0.6629

the impact of the input data form on our classification system is less than that of the random phase shift.

V. CONCLUSION

In this paper, we have proposed a classification algorithm based on CNN model in order to realize the identification of LTE-U and WiFi signal. In the data preprocessing period, we added random phase offset and used different data forms as the input of the model to compared their difference. In addition, the CNN training model has trained on the mixed data, consisting of nine datasets with SNRs $= \{-20, -15, \ldots, 15, 20\}$ dB. This signal identification algorithm can effectively distinguish LTE-U and WiFi signals and make them coexistent friendly. Finally, the experimental comparison results show that using IQ data as the input of the CNN classification model can converge faster and have better robustness. In future work, we will collect more complex actual signals and adjust the model parameters to make system more universal.

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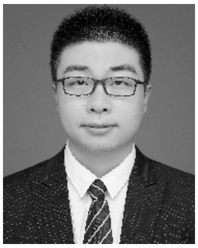

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