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A Deep-Learning-Based Method for Spectrum Sensing with Multiple Feature Combination

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Abstract: Cognitive radio networks enable the detection and opportunistic access to an idle spectrum through spectrum-sensing technologies, thus providing services to secondary users. However, at a low signal-to-noise ratio (SNR), existing spectrum-sensing methods, such as energy statistics and cyclostationary detection, tend to fail or become overly complex, limiting their sensing accuracy in complex application scenarios. In recent years, the integration of deep learning with wireless communications has shown significant potential. Utilizing neural networks to learn the statistical characteristics of signals can effectively adapt to the changing communication environment. To enhance spectrum-sensing performance under low-SNR conditions, this paper proposes a deep-learning-based spectrum-sensing method that combines multiple signal features, including energy statistics, power spectrum, cyclostationarity, and I/Q components. The proposed method used these combined features to form a specific matrix, which was then efficiently learned and detected through the designed ‘SenseNet’ network. Experimental results showed that at an SNR of -20 dB, the SenseNet model achieved a 58.8% spectrum-sensing accuracy, which is a 3.3% improvement over the existing convolutional neural network model.

Keywords: multiple feature combination; deep learning; I/Q components; spectrum sensing; low SNR



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1. Introduction

Over the last ten years, the relentless advancement of communication services and the rapid increase in mobile user numbers have catalyzed the introduction of innovative wireless mobile applications and services. On one hand, the demand for spectrum resources is increasing due to the diverse services that require massive connectivity and high-quality communication [1]. On the other hand, communication systems are constrained by multiple practical factors, such as antenna size, electromagnetic wave properties, device performance, and transmission and reception power, making the genuinely available spectrum resources increasingly scarce and strained [2]. Therefore, enhancing spectrum utilization under the limited and scarce conditions of spectrum resources is a current research focus [3].

In order to address this issue, experts have suggested using cognitive radio and its spectrum-sensing technology [4]. With a significant focus on secondary users, this method aims to enhance spectrum usage by opportunistically utilizing unlicensed primary users’ unused spectrum by detecting their lack of communication activity. Secondary users must detect and refrain from using the same frequency bands as primary users while the latter are active, especially in regions where primary user signals are weak. Improving the system’s ability to detect signals in low-SNR conditions can enhance secondary users’ utilization of peripheral spectrum resources. This will enable them to effectively strategize and regulate spectrum usage, reducing overall system interference.

Conventional methods for spectrum sensing primarily encompass energy statistics [5], cyclostationary detection [6], and matched filter detection [7]. While these techniques are effective under specific conditions, their general applicability is constrained. For instance, cyclostationary detection is effective at lower SNR and is considered the most efficient among the traditional spectrum-sensing techniques. However, it requires prior information about the primary user's signal, resulting in longer detection times and increased complexity. Overall, traditional methods are constrained by their application scenarios and face challenges, such as noise and multipath fading, making extending them to other fields and scenarios difficult.

In recent years, applying deep learning in various fields has become a focal point and hot topic among researchers. Deep learning, with its excellent adaptive advantages and nonlinear modeling capabilities, has been effectively applied in the field of communications, offering new research ideas and approaches [8]. Deep learning can effectively address the aforementioned issues, and this paper focuses on deep-learning-based approaches.

Researchers have employed well-known network models, including convolutional neural network (CNN) [9], long short-term memory network (LSTM) [10], and artificial neural networks (ANN) [11], to extract different characteristics of signals for spectrum-sensing tasks. These models have demonstrated superior performance compared to conventional single-node spectrum-sensing methods. Many deep learning approaches lack awareness of the underlying structure of the source signal. Most deep learning methods use blind sensing to recognize the underlying structure of the primary signal. For instance, in [12], Tekbiyik K and colleagues proposed a deep learning method that calculates the cyclostationary characteristics of signals through the spectrum correlation function to perform spectrum sensing on cellular communication data, achieving better performance than the support vector machine (SVM) model [13]. In the fields of modulation recognition and Industrial Scientific Medical (ISM), researchers typically use the fast Fourier transform, I/Q features, and CNN classifiers to identify signals and interference [14].

Current research in spectrum sensing in deep learning focuses on using better networks or optimizing existing neural networks in combination with other modules to further solve problems in this field. In [15], the researchers adopted CNN as the benchmark model. On this basis, they integrated new transformer networks and bidirectional long short-term memory to form a novel network, which enhanced the detection probability under -20 dB. Moreover, the F1 score was superior to that of the original network. Scholar Salma Benazzouza [16] employed lightweight CNN as the detection network, concurrently extracted the time–frequency information of the signal, and transformed it into a spectrogram as the neural network input. Based on the original approach, this method demands fewer computing resources and enhances the detection efficiency. In [17], the researchers proposed an optimized CNN network to learn the underlying structure of modulated signals extracted by energy detectors, addressing the impact of the SNR wall on the detection process. The network is based on the convolutional long short-term memory deep neural network (CLDNN) model and includes a feature fusion layer in the neural network. Experimental results showed that the optimized model performed better than typical CNN and deep neural network (DNN) [18], showing stable performance across different modulation orders. This experiment considered only a single feature, similar to cyclostationary characteristics in deep learning applications.

In recent years, some scholars have tried to use neural networks to learn various features of signals to further improve the detection probability under low SNR. Scholars Dong Han et al. [19] extracted and further preprocessed the energy features and cyclostationary features of the primary user signal and noise and subsequently input them into CNN. Experimental results demonstrated that the detection probability of the deep learning method based on two features at -20 dB was higher than that of the deep learning method based on cyclostationary features. However, in spectrum-sensing tasks that need to detect transient signals or signals that change with time, CNN's time correlation extraction and learning may not be effective. As a fundamental feature of signals, energy is the

primary research focus for scholars. In [20], scholars proposed a hybrid spectrum-sensing technology based on artificial neural networks. They used the likelihood ratio test statistics and the energy feature of signals as the training data for the neural networks. The optimal detection performance of this approach was improved by approximately 60% compared to traditional energy detection methods. Meanwhile, scholar Yue Geng, in [21], considered combining multiple signal features as inputs for CNN, achieving good results in the range from -10 dB to 5 dB, but the general two-dimensional CNN could not effectively extract the spatial and temporal correlation features of signals. System performance was poor when the SNR was below -14 dB, suggesting the introduction of gated recurrent units (GRU) and redesigning the model to further optimize performance. In summary, the above-related research shows the great potential of deep learning combined with multiple signal features in spectrum-sensing tasks. By exploring different combinations of signal features and designing appropriate neural networks, we can solve relevant problems in specific fields and further improve detection accuracy and robustness.

Based on the above insights and findings in the literature, we propose a deep-learning-based multi-feature spectrum-sensing method, which focuses on solving the problem of unstable detection capability of a single feature in low-SNR environments and is characterized by further extracting and learning the underlying information of the signals. Compared to existing multi-feature spectrum-sensing methods, we further combine the phase information of the signal, namely the I/Q features, so that the feature matrix can more comprehensively represent the signal's information. We then introduce the LSTM layer to enhance the processing ability of time series information, further improving the detection probability. The primary contributions of this paper are as follows.

- (1) We decompose the co-directional and orthogonal vectors of the signal, process them to obtain the I/Q features, and combine them with the existing feature matrix to express the underlying information of the received signal more completely.
- (2) We introduce the LSTM structure and optimize the design of a new neural network concerning CLDNN to improve the model's ability to extract relevant features.
- (3) By learning multiple features of the signal through the designed SenseNet, the detection ability of the model at low SNR is improved.

Therefore, this paper mainly studies the deep learning method and detection of multiple feature combinations of extracted signals through a neural network under low SNR. The structure of this paper is as follows: Section 2 introduces the general model of spectrum sensing and the model of signal and noise required for simulation. In Section 3, the method of extracting four features of the signal and the combination process is introduced in detail, and the structure of SenseNet proposed in this paper is further explained. In Section 4, the simulation results of the multi-feature combination method based on deep learning are presented and analyzed. In Section 5, we analyze and discuss the limitations of this study and possible future research efforts. Finally, the critical conclusion is reached in Section 6.

2. System Model

2.1. Sensing Model

In the realm of spectrum sensing within cognitive radio systems, the sensing approach is commonly represented as a binary classification model. This involves observing and determining whether the primary users' channels are idle or busy. Signal detection by the secondary users is thereby framed as a binary hypothesis testing problem, as illustrated in Equation (1) below:

$$\begin{aligned} H_0 : y(n) &= w(n) \\ H_1 : y(n) &= h \cdot s(n) + w(n) \end{aligned} \quad (1)$$

Within a defined frequency spectrum, H_0 and H_1 correspond to the hypotheses that the primary cognitive signal is, respectively, absent and present. The equation explicates the variables as follows: $y(n)$ symbolizes the n th received sample, $w(n)$ symbolizes the additive

noise, which is characterized by a circularly symmetric complex Gaussian distribution with a zero mean, $s(n)$ symbolizes the signal originating from the primary user, and h symbolizes the constant channel gain throughout the sensing period.

The evaluation of a spectrum-sensing algorithm is principally gauged by several performance indicators: detection probability, false-alarm probability, and missed detection probability, among others. Detection probability is defined as the probability that the secondary user accurately identifies the presence of the primary user, denoted by $P_d = P_r\{H_1|H_1\}$, when the primary user is indeed present.

The false-alarm probability is defined as the likelihood, denoted by $P_f = P_r\{H_1|H_0\}$, that a secondary user erroneously perceives the presence of the primary user when the primary user is actually absent.

The effectiveness of an improved model is measured by its ability to maintain a consistent false-alarm probability while demonstrating an enhanced detection probability, particularly in environments characterized by low SNR.

2.2. Signal and Noise Model

This work examines the placement of sensing nodes for secondary users and the transmitters of primary users' signals linked to these nodes within a specific frequency range. The proposed approach involves performing M sensing and sampling. The experiment uses two modulation signals, namely QPSK and 8PSK, to serve as the fundamental signals for the primary user signals. In order to replicate a reasonably accurate situation, the carrier frequencies of these two modulation signals are set to be 10 kHz, and they traverse a multipath Rayleigh fading channel. To assess the effectiveness of this model in situations with weak signals and high noise, the tests are predominantly carried out within an SNR range of -20 dB to 5 dB.

The noise signal consistently adheres to a generalized Gaussian distribution to more accurately match the data and facilitate later enhancements to the model. The probability density distribution provides a more precise understanding of the observable condition:

$$f_X(x) = \frac{1}{2\alpha\Gamma(\frac{1}{\beta})} \exp(-\frac{|x|^\beta}{\alpha}), x \in \Re \quad (2)$$

The scale parameter, α , and the shape parameter, β , govern the probability density function of the noise signal. By setting the shape parameter β to 2, we obtain the additive white Gaussian noise (AWGN).

3. Using the SenseNet Network to Learn the Combined Features of the Signal

Figure 1 illustrates the flowchart of the deep learning spectrum-sensing algorithm proposed in this paper. Initially, we extracted energy, power spectrum, and cyclostationary features from the obtained observational data. Then, we extracted the in-phase and quadrature components of the signal and performed energy calculations and normalization. The four retrieved features were organized in sequence. Subsequently, the four retrieved features were organized in the respective sequence to construct the feature matrix, and the dimensions of the matrix were adjusted to match the neural network it will traverse. Next, we input the feature matrix into the specialized neural network, called SenseNet. In SenseNet, we trained this feature matrix to perform binary classification tasks and achieve the corresponding detection performance. Ultimately, it determines whether the primary user's status is occupied.

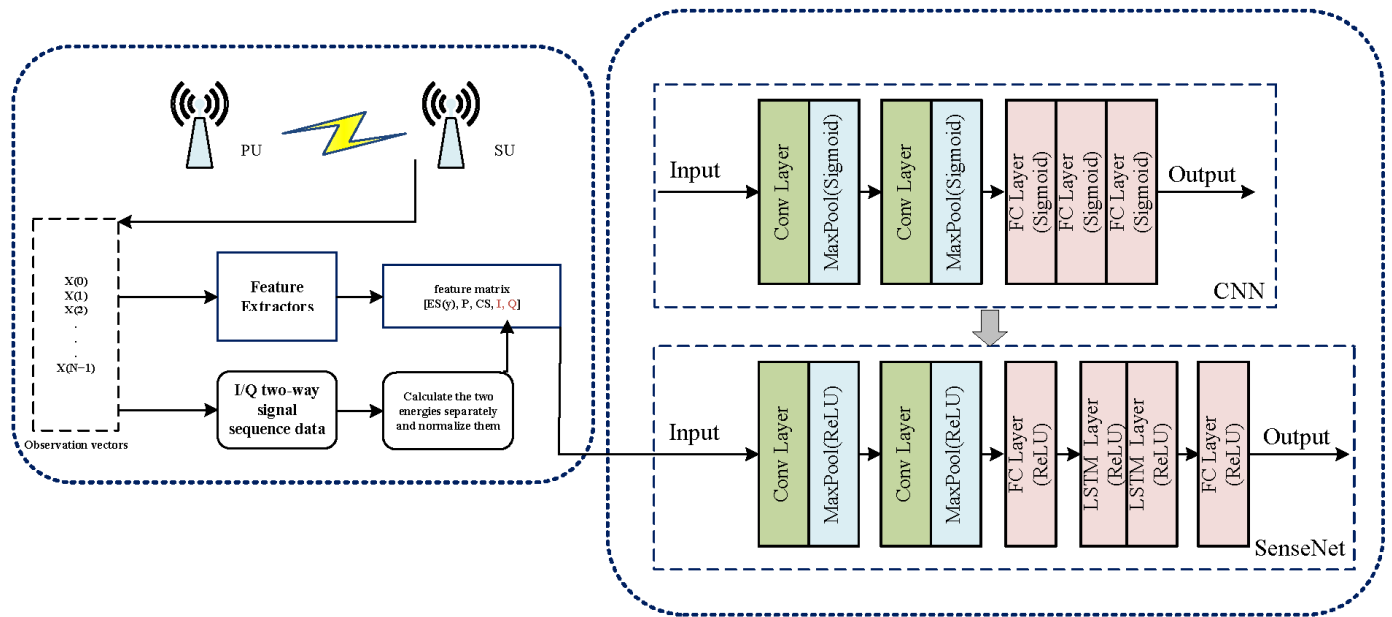


Figure 1. Flowchart of the deep learning spectrum-sensing algorithm proposed in this paper.

3.1. Multiple Feature Combination

3.1.1. Energy Statistics

Energy statistics are a prevalent approach in traditional spectrum sensing due to their straightforward detection mechanism and ease of implementation. This method fundamentally operates by calculating the energy of the received signal, either in the time or frequency domain, and then comparing it to a predetermined threshold to ascertain the presence of the primary user. The calculation is executed as follows:

$$ES(y) = \frac{1}{X} \sum_{n=0}^{X-1} |y(n)|^2, n = 1, 2, \dots, N-1 \quad (3)$$

The formula processes the sampled received signal, $y(n)$, over X samples and computes the average energy statistics for each segment of the received signal sequence. The derived energy statistical feature is subsequently denoted by $E = [E\hat{S}_1, E\hat{S}_2, \dots, E\hat{S}_M]^T$.

3.1.2. Power Spectrum

The signal power is a crucial characteristic of a signal, and the power spectral density (PSD) provides insights into the distribution of this power. Let us consider a finite-length received signal sequence, denoted as $y(k)$. The estimation of the power spectral density can be expressed as follows:

$$S_y(k) = \frac{1}{N} |y(k)|^2 = \frac{1}{N} |FFT[y(k)]|^2, k = 0, 1, \dots, N-1 \quad (4)$$

Let $FFT(y(k))$ represent the Fourier transform of the received signal sequence, $y(k)$, with the period N of the Fourier transform chosen as the period for calculating the power spectrum. The computed power spectrum features of the received signal sequence are stored in the feature vector $P = [P_1, P_2, \dots, P_M]^T$.

3.1.3. Cyclostationary Features

Different modulation and noise signals have distinct statistical characteristics, such as means, variances, and covariances. Observing a signal's cyclostationary features (including mean, variance, and autocovariance) can help distinguish signals from different sources. The procedure for calculating cyclostationary features is outlined below.

The periodic autocorrelation function of a signal is usually used to measure the autocorrelation of a signal at different time lags and takes into account the periodicity that may be present in the signal, which is calculated as follows:

$$R_x^\alpha(\tau) = \lim_{T \rightarrow \infty} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t + \frac{\tau}{2}) x(t - \frac{\tau}{2}) e^{-j2\pi\alpha t} dt \quad (5)$$

Afterward, the acquired autocorrelation function is subjected to a discrete Fourier transform to obtain the spectrum autocorrelation function:

$$S_x^\alpha(f) = \int_{-\infty}^{+\infty} R_x^\alpha(\tau) e^{-j2\pi f\tau} d\tau \quad (6)$$

$$S_x^\alpha(f) = \lim_{T \rightarrow \infty} \lim_{Z \rightarrow \infty} \frac{1}{TZ} \int_{-\frac{Z}{2}}^{\frac{Z}{2}} X_T(t, f + \frac{\alpha\tau}{2}) X_T^*(t, f - \frac{\alpha\tau}{2}) d\tau \quad (7)$$

Finally, the obtained computational results are saved in the feature vector: $CS = [CS_1, CS_2, \dots, CS_M]^T$.

3.1.4. I/Q Component

In communication systems, two carriers can represent a modulated signal: one is the in-phase vector, and the other is the quadrature vector. Decomposing the composite signal into these two independent components allows for better identification of the actual part of the signal, resistance to interference, and improved analysis of the signal's amplitude and phase information. The formulas for the two independent vectors are as follows:

$$\begin{aligned} I &= \text{Image}(y(n)) \\ Q &= \text{Real}(y(n)) \end{aligned} \quad (8)$$

MATLAB R2022a obtained the I/Q characteristics by segregating the real and imaginary components of the signal, computing the mean energy of each component, and subsequently standardizing the highest value. The extracted I/Q component features were saved in the feature vectors, $I = [I_1, I_2, \dots, I_M]^T$ and $Q = [Q_1, Q_2, \dots, Q_M]^T$, respectively.

Finally, the feature matrices of the four types of signals were combined. First, for the energy statistics features, the average energy of M segments was calculated and then transposed to adjust the size of the matrix. Next, the power spectrum features were obtained by magnifying the results calculated using the Fourier transform and the pwelch method by a factor of 100 and were stored in an $M \times 1$ vector. Finally, the four types of features were arranged in order to form a matrix. Its size matched the input layer of the designed SenseNet, and the final feature matrix was represented as: $[ES(y), P, CS, I, Q]$, with a matrix size of $M \times 6$. The process of feature extraction of the signal is shown in Figure 2 below.

3.2. SenseNet Network Infrastructure

Two-dimensional convolutional neural networks are the most commonly used foundational networks in the fields of image classification and image data processing. They possess two spatial dimensions, height and width, which make them suitable for processing image data. Regarding spectrum sensing, local features of the spatial correlation characteristics of received signals can be extracted. However, for dealing with time series data that have significant spatiotemporal correlations, recurrent neural networks (RNN), such as LSTM and GRU, may be a more suitable and efficient choice.

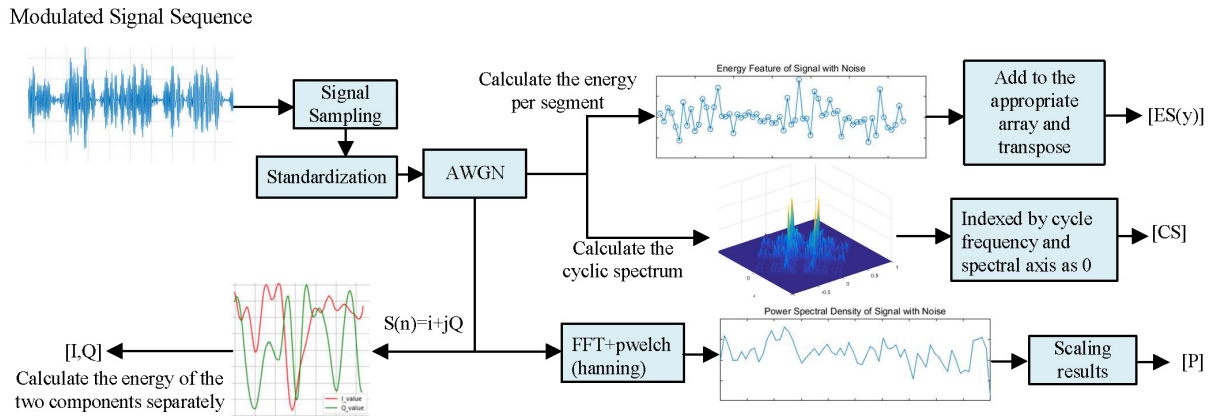


Figure 2. Schematic diagram of the extraction process of each feature of the signal sequence.

Figure 3 illustrates the SenseNet network structure we proposed for spectrum sensing, which is primarily composed of convolutional and LSTM layers. The signals received by secondary users were processed through a feature extractor to obtain a multi-feature combination matrix. We treated the signal's feature matrix as a $1 \times 64 \times 6$ image, which was then input into the SenseNet network. This network first used two 2D convolutional layers to process the input data to obtain sufficiently accurate local features, thereby extracting features from multiple time points to reduce irrelevant data. The data entered convolutional layer 1 from a single channel, generating four feature maps, and convolutional layer 2 further extracted features from the four feature maps of the previous layer, outputting eight feature maps. The functions performed by the two convolutional layers can be expressed as:

$$X(t) = f(W(t) \otimes X(t-1) + b(t)) \quad (9)$$

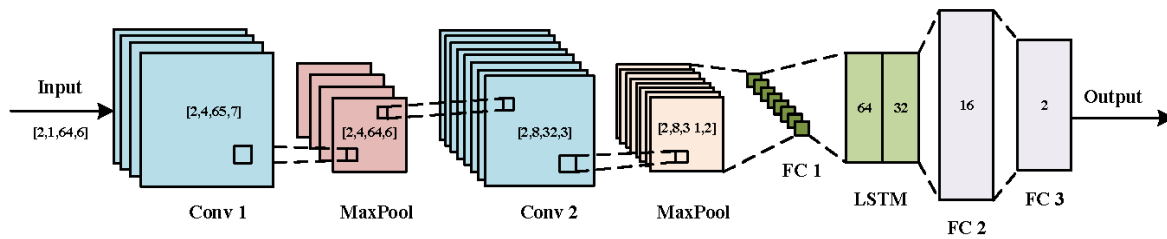


Figure 3. Proposed SenseNet network architecture.

The convolutional layer's output was transformed into a feature vector with 64 dimensions by replicating the output of the fully connected layer. This layer is designed to combine and re-map the learned local features for higher-level abstract representations. Next, the data passed through two LSTM layers, whose excellent learning ability for temporal correlation makes them particularly effective for processing sequential data. The operation of the LSTM layers can be represented as:

$$\begin{aligned} h_t^{(1)}, C_t^{(1)} &= LSTM1(x_t, h_{t-1}^{(1)}, C_{t-1}^{(1)}) \\ h_t^{(2)}, C_t^{(2)} &= LSTM2(x_t, h_{t-1}^{(2)}, C_{t-1}^{(2)}) \end{aligned} \quad (10)$$

Here, x_t represents the input to the first-layer LSTM at time step t , while $h_{t-1}^{(1)}$ and $C_{t-1}^{(1)}$ represent the hidden state and cell state of the first-layer LSTM from the previous time step, respectively. Similarly, $h_{t-1}^{(2)}$ and $C_{t-1}^{(2)}$ represent the hidden state and cell state of the second-layer LSTM from the previous time step. The ultimate result was categorized by the successive fully connected layers.

Following the convolutional layers, the technique of maximum pooling (MaxPool) was employed without padding to decrease the spatial dimensions of the features and improve their resilience. The second pooling layer further decreased the spatial dimensions. The Rectified Linear Unit (ReLU) was the activation function used after each layer. Table 1 provides a comprehensive overview of the hyperparameters calculated using a rigorous cross-validation process.

Table 1. Hyperparameters of the proposed SenseNet network.

Hyperparameters	Value
Number of convolution kernels per convolutional layer	4, 8
Convolution kernel size	2×2 , 2×2
Cell unit for each LSTM layer	32, 16
Output dimensions for each fully connected layer	64, 32, 2
Optimizer	Stochastic Gradient Descent
Learning rate	0.01
Batch size	32

Compared to CNN, the CLDNN model offers better flexibility and scalability. It combines the advantages of CNN and LSTM to capture signals' spatial and temporal characteristics more effectively, demonstrating excellent potential in processing complex signal tasks [22]. By adjusting the number of LSTM and DNN layers and the activation functions following each layer's structure, the model can often be further adapted to the type of data input into the network, achieving better performance. We used a dataset comprising four feature combination matrices of QPSK signals and conducted model-tuning experiments and extensive cross-validation by altering the positioning of the LSTM and DNN layers and varying the activation functions, thus obtaining the optimal parameters and model. Figure 4 displays the parts of the models with a relatively high average detection accuracy (i.e., the average of the best performance of the models at each SNR during the training process) during the experiments. By changing some of the network's structure and activation functions, the neural network showed different performance trends for signal feature data under low-SNR conditions.

The model with two convolutional layers, one fully connected layer, two long short-term memory layers, and two final completely connected layers had the greatest performance, according to the data in Table 2. The model attained a mean accuracy of 91.03% within the -20 dB to 5 dB range, establishing it as the most optimal model among those examined. Therefore, we defined model 4 as SenseNet, a deep learning model suitable for learning a combination of four features.

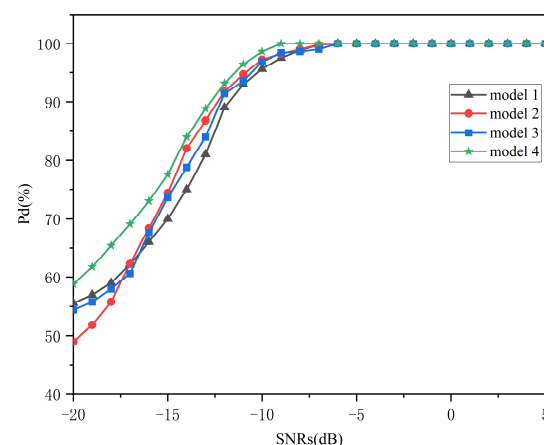


Figure 4. Detection performance of some neural network models with different internal structures.

Table 2. Average performance of selected neural network models.

Model	Architecture	Average Detection Accuracy
Model 1	2COV + Sigmoid + 3FC + Sigmoid	88.49%
Model 2	2 COV + ReLU + 2FC + ReLU 2LSTM + 1FC + ReLU	88.89%
Model 3	2 COV + ReLU + 1FC + ReLU + 2LSTM + 2FC + SoftMax	88.87%
Model 4	2 COV + ReLU + 1FC + ReLU + 2LSTM + 1FC + ReLU	91.03%

4. Experimental Analysis and Result Discussion

4.1. Experimental Environment

The software required for the experiment was the R2022a version of MATLAB, Python 3.7, Pytorch 2.0.1 deep learning framework. The hardware platform for the experimental environment was the Windows 11 64-bit operating system. The processor was AMD Ryzen 7 5800H (3.20 GHz) and the graphics card was NVIDIA GeForce RTX 3050 Ti Laptop GPU.

4.2. Data Generation and Model Training

The experimental datasets utilized in this study were generated by MATLAB. These datasets principally consisted of noisy modulated signal samples of QPSK and 8PSK, as well as signal samples containing only noise. The SNR ranged from -20 dB to 5 dB. The sampling rate of each signal sample was 2000 Hz, and it underwent transmission across a multipath Rayleigh fading channel, with a path delay vector of $[0 \text{ s}, 0.001 \text{ s}]$. The negative samples were comprised of the previously specified additive white Gaussian noise. This study partitioned the dataset into training, validation, and testing sets using the conventional split ratio of 6:2:2. The parameters of the dataset are shown in Table 3 below.

Table 3. Dataset parameters.

Type of modulation	QPSK, 8PSK
Signal sampling frequency	2000 Hz
Length of generated random-bit sequence	400
SNR range	-20 dB~ 5 dB in 1 dB increments
Number of training samples	$15,600$

4.3. Performance with QPSK and 8PSK Signals

In this experiment, two signal sequences, QPSK and 8PSK, were generated by MATLAB as a dataset for the model SenseNet, which was tested by completing the training and saving the parameters, thus evaluating SenseNet and comparing the performance of the two modulated signals, QPSK and 8PSK, on this model.

The performance of the two signals under this model is shown in Figure 5 below. Figure 5a demonstrates that when the SNR was higher than -14 dB, the detection probability of QPSK under this model was higher than 80% . When the SNR reached -9 dB, the detection probability could reach 100% , which fulfilled the spectrum-sensing task well. Due to the small phase interval of the 8PSK signal, the characteristics were not as apparent as QPSK. Its detection performance was lower than that of QPSK under low-SNR conditions, and it could only achieve a better detection effect when the SNR was -11 dB. On the other hand, in the range of -20 dB to -15 dB, the declining trend of detection performance for the QPSK signal was relatively stable with the decrease in SNR, while the detection performance for the 8PSK signal was further decreased.

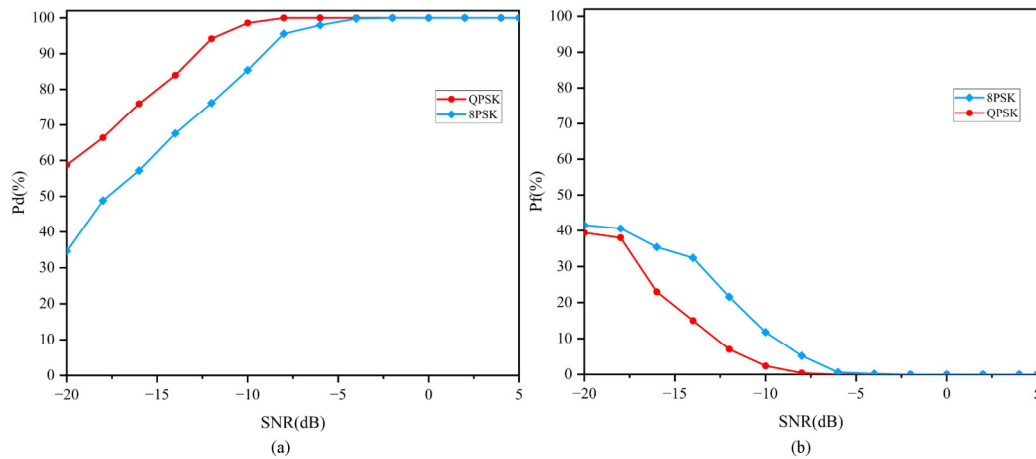


Figure 5. (a) Detection performance of SenseNet with QPSK and 8PSK signals. (b) False-alarm probability of SenseNet with QPSK and 8PSK signals.

From the false-alarm probabilities of the two signals demonstrated in Figure 5b, the false-alarm probability decreased with the increase in SNR, and the false-alarm probability of both was less than 10% when the SNR was greater than -10 dB. When the SNR was greater than -6 dB, the false-alarm probability of both was almost 0%. In addition, since 8PSK signals are susceptible to noise, their features were not as distinct and stable as QPSK, which resulted in an overall higher false-alarm probability than QPSK signals under low-SNR conditions.

In summary, the multi-feature combination method based on deep learning demonstrated better detection performance for primary user signals dominated by QPSK signals compared to the 8PSK signal under low-SNR conditions, and it also achieved a lower overall false-alarm probability.

4.4. Comparison of Feature Types

In order to evaluate the effectiveness of deep learning techniques utilizing multiple feature combinations, we compared their performance with methods based on a single cyclostationarity feature and methods based on combining energy and power spectra. In addition, experiments were conducted by adding only I/Q features without changing the CNN model to validate the performance of the added features. Figure 6 displays the results.

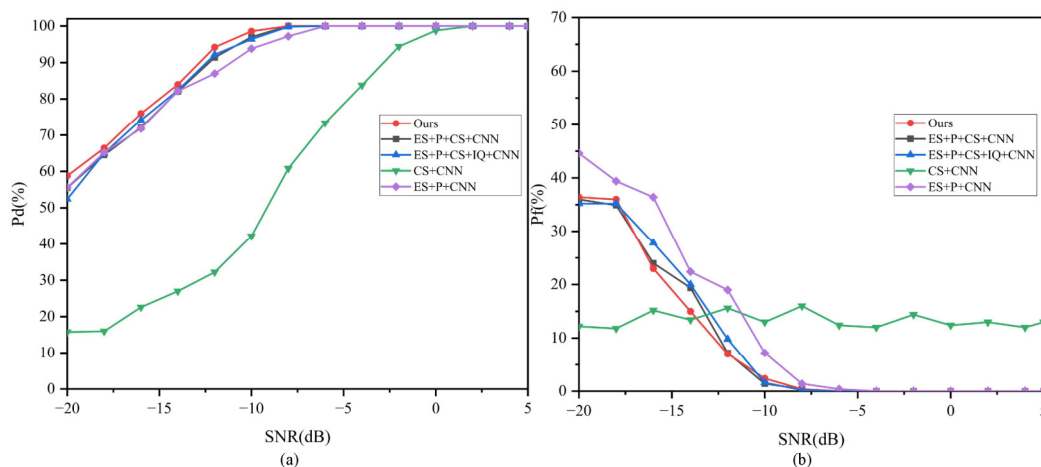


Figure 6. (a) Detection performance of deep learning models with different feature types under QPSK signals. (b) False-alarm probability of deep learning models with different feature types under QPSK signals.

Using QPSK as the received signal and under the same experimental setup, Figure 6a demonstrates that the model based on a single cyclostationarity feature (“CS+CNN” in Figure 6) usually performed poorly at low SNR and generally required an SNR greater than 0 dB to complete the detection. In contrast, the deep learning method that combines energy and power spectra (“ES+P+CNN” in Figure 6) performed relatively well and could achieve a detection probability of about 70% at −16 dB. However, the overall performance was lower than the spectrum-aware method based on three features (“ES+P+CS+CNN” in Figure 6). Regarding the false-alarm probability, Figure 6b demonstrates that the false-alarm rate of the model using the cyclostationarity feature approach was not ideal, as it did not decrease with the increase in SNR, and the value always remained around 10% to 15%. In this paper, we proposed signal I/Q feature components for existing deep learning methods that combine energy, power spectrum, and cyclostationarity features and designed a SenseNet model suitable for learning the feature types.

The results demonstrated that the multi-feature method based on deep learning proposed in this study (“Ours” in Figure 6) enhanced the detection performance by an average of 2.3% compared to the existing method based on three features within the range of −20 dB to −7 dB, with a notable improvement of 3.3% at −20 dB. With only the introduction of I/Q features, while retaining the CNN model (“ES+P+CS+IQ+CNN” in Figure 6), the average detection probability of the model increased by about 0.33%. In addition, analyzing the relationship between the number of features in the feature combination and the detection performance, it was observed that with an increase in the number of features, the deep learning model exhibited a stronger ability to extract and learn signal features, resulting in a generally improved detection performance. Compared with the single cyclostationary feature method, the performance of the two feature combination methods based on energy features and power features was significantly enhanced, and the reduction in false-alarm probability remained relatively stable. When the cyclostationary feature was combined with the other two features, the improvement in detection probability began to decrease, while the false-alarm probability further decreased. On this basis, the multi-feature method proposed in this study further improved the detection probability of primary user signals under low-SNR conditions while keeping the false-alarm probability relatively stable.

On the other hand, Figure 6b illustrates that with changes to the feature matrix and the model’s redesign, the false-alarm rate of the method presented in this paper was almost identical to that of existing methods, consistent with the model’s performance evaluation standards under practical conditions, as previously mentioned.

In addition, we further calculated the complexity of the original CNN model and the SenseNet model in this paper, and compared the results, as shown in Table 4. It can be seen from Table 4 that in the training process of the two models, for the feature matrix dataset composed of four features, the optimal detection accuracy of SenseNet was about 1% higher than that of the CNN model. In terms of model complexity, the SenseNet proposed in this paper had slightly lower complexity compared to the original CNN model, whether measured by the number of parameters or Floating-Point Operations Per Second (FLOPs). This is because the CNN model contains multiple consecutive fully connected layers, which are the main source of the total number of parameters in the model. For SenseNet, the total number of parameters was reduced by decreasing the number of fully connected layers. Additionally, the computational complexity of the LSTM layer was lower than that of multiple fully connected layers, resulting in the total FLOPs and complexity of SenseNet being slightly lower than those of the CNN model.

Table 4. Model complexity calculation.

Model	Best Accuracy	Parameter Count	FLOPs
CNN	89.69%	80,834	287,408
SenseNet	90.65%	65,726	256,720

5. Limitations and Future Work

Compared with the existing three-feature combination methods, the multi-feature combination method proposed in this paper improved the detection performance in the low-SNR range and slightly reduced the model complexity. However, the experimental results showed that as the number of features in the feature combination increased, the growth rate of the spectrum-sensing and detection performance of the model gradually decreased. This is because the feature matrix research can more completely express the underlying information of the signal, and the impact of increasing the feature types of the signal on system detection performance was gradually reduced.

In the future, it can be considered that the feature extraction process and combination of the signal could also be completed by the neural network, with the neural network directly learning the signal and fusing different features through the concatenate layer to further improve the model's expression ability and performance. Additionally, our deep learning approach is supervised and requires a large number of labeled datasets to improve model performance. In a real-world communication environment, obtaining and labeling large amounts of communication data is relatively difficult and costly. Therefore, unsupervised learning can be considered for spectrum sensing in the future to further reduce costs. Unsupervised learning mainly analyzes and models unlabeled data, summarizing the structure and rules in the data to enable prediction and classification.

6. Conclusions

This study proposed a spectrum-sensing method based on the SenseNet neural network, which primarily learns and analyzes by examining the internal information of modulated signals. By decomposing the signal into its co-phase and quadrature components, we extracted the features of the I/Q vectors and combined them with existing feature matrices in a specific manner to form a feature matrix suitable for deep learning. First, the noise interference suffered by the signals received by secondary users conformed to a generalized Gaussian distribution and underwent multipath Rayleigh fading during transmission. Subsequently, through extensive cross-validation and model tuning, we determined a deep learning model that fit the multi-feature matrix of the signal. We then discussed the performance of the spectrum-sensing methods using a combination of different signal features under the same parameter conditions and the deep learning model. Simulation results showed that at a low SNR, the proposed spectrum-sensing method substantially improved the detection probability compared to the single-feature deep learning method based on cyclostationarity features and had a lower false-alarm probability than the combination of the power spectrum and energy statistics. Furthermore, compared to existing CNN-based multi-feature spectrum-sensing schemes, this model also improved the detection probability while maintaining a stable false-alarm rate, and it advanced the SNR point at which a 100% detection probability was first achieved to -9 dB.

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References

- Chen, W.; Demirkol, I.; Mostafa, M.; Perotti, A. Mobile Communications And Networks. *IEEE Commun. Mag.* **2021**, *59*, 52–53. [\[CrossRef\]](#)
- Liu, B.; Bai, X.; Zhang, G.; Shen, J.; Xie, J.; Zhao, L.; Hong, T. A Review of Research on Deep Learning for Cognitive Radio Applications. *J. East China Norm. Univ. (Nat. Sci. Ed.)* **2021**, *1*, 36–52.
- Ali, M.; Yasir, M.N.; Bhatti, D.M.S.; Nam, H. Optimization of Spectrum Utilization Efficiency in Cognitive Radio Networks. *IEEE Wirel. Commun. Lett.* **2022**, *12*, 426–430. [\[CrossRef\]](#)
- Mitola, J. Cognitive Radio. An Integrated Agent Architecture for Software Defined Radio. Ph.D. Thesis, KTH Royal Institute of Technology, Stockholm, Sweden, 2002.
- Luo, J.; Zhang, G.; Yan, C. An Energy Detection-Based Spectrum-Sensing Method for Cognitive Radio. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 3933336. [\[CrossRef\]](#)
- Yang, M.; Li, Y.; Liu, X.; Tang, W. Cyclostationary Feature Detection Based Spectrum Sensing Algorithm under Complicated Electromagnetic Environment in Cognitive Radio Networks. *China Commun.* **2015**, *12*, 35–44. [\[CrossRef\]](#)
- Brito, A.; Sebastião, P.; Velez, F.J. Hybrid Matched Filter Detection Spectrum Sensing. *IEEE Access* **2021**, *9*, 165504–165516. [\[CrossRef\]](#)
- Dai, L.; Jiao, R.; Adachi, F.; Poor, H.V.; Hanzo, L. Deep Learning for Wireless Communications: An Emerging Interdisciplinary Paradigm. *IEEE Wirel. Commun.* **2020**, *27*, 133–139. [\[CrossRef\]](#)
- Seo, D.; Nam, H. Deep Rp-Cnn for Burst Signal Detection in Cognitive Radios. *IEEE Access* **2020**, *8*, 167164–167171. [\[CrossRef\]](#)
- Alkhouri, I.; Joneidi, M.; Hejazi, F.; Rahnavard, N. *Large-Scale Spectrum Occupancy Learning via Tensor Decomposition and LSTM Networks*; IEEE: Washington, DC, USA, 2020; pp. 677–682.
- Nasser, A.; Chaitou, M.; Mansour, A.; Yao, K.C.; Charara, H. A deep neural network model for hybrid spectrum sensing in cognitive radio. *Wirel. Pers. Commun.* **2021**, *118*, 281–299. [\[CrossRef\]](#)
- Tekbiyik, K.; Akbunar, Ö.; Ekti, A.R.; Görçin, A.; Kurt, G.K.; Qaraqe, K.A. Spectrum Sensing and Signal Identification with Deep Learning Based on Spectral Correlation Function. *IEEE Trans. Veh. Technol.* **2021**, *70*, 10514–10527. [\[CrossRef\]](#)
- Tekbiyik, K.; Akbunar, Ö.; Ekti, A.R.; Görçin, A.; Kurt, G.K. Multi-Dimensional Wireless Signal Identification Based on Support Vector Machines. *IEEE Access* **2019**, *7*, 138890–138903. [\[CrossRef\]](#)
- Kulin, M.; Kazaz, T.; Moerman, I.; De Poorter, E. End-to-End Learning from Spectrum Data: A Deep Learning Approach for Wireless Signal Identification in Spectrum Monitoring Applications. *IEEE Access* **2018**, *6*, 18484–18501. [\[CrossRef\]](#)
- Vijay, E.V.; Aparna, K. Spectrum Sensing Using Deep Learning for Proficient Data Transmission in Wireless Sensor Networks for Wireless Communication. *Ain Shams Eng. J.* **2024**, *15*, 102784. [\[CrossRef\]](#)
- Benazzouza, S.; Ridouani, M.; Salahdine, F.; Hayar, A. A Novel Spectrogram Based Lightweight Deep Learning for IoT Spectrum Monitoring. *Phys. Commun.* **2024**, *64*, 102364. [\[CrossRef\]](#)
- Gao, J.; Yi, X.; Zhong, C.; Chen, X.; Zhang, Z. Deep Learning for Spectrum Sensing. *IEEE Wirel. Commun. Lett.* **2019**, *8*, 1727–1730. [\[CrossRef\]](#)
- Zhang, X.; Ma, Y.; Liu, Y.; Wu, S.; Jiao, J.; Gao, Y.; Zhang, Q. Robust DNN-Based Recovery of Wideband Spectrum Signals. *IEEE Wirel. Commun. Lett.* **2023**, *12*, 1712–1715. [\[CrossRef\]](#)
- Han, D.; Sobabe, G.C.; Zhang, C.; Bai, X.; Wang, Z.; Liu, S.; Guo, B. 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, 14–16 October 2017; pp. 1–6.
- Patel, D.K.; López-Benítez, M.; Soni, B.; García-Fernández, Á.F. Artificial Neural Network Design for Improved Spectrum Sensing in Cognitive Radio. *Wirel. Netw.* **2020**, *26*, 6155–6174. [\[CrossRef\]](#)
- Geng, Y.; Huang, J.; Yang, J.; Zhang, S. *Spectrum Sensing for Cognitive Radio Based on Feature Extraction and Deep Learning*; IOP Publishing: Bristol, UK, 2022; Volume 2261, p. 012016.
- Salahdine, F.; Han, T.; Zhang, N. 5G, 6G, and Beyond: Recent Advances and Future Challenges. *Ann. Telecommun.* **2023**, *78*, 525–549. [\[CrossRef\]](#)

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