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RESEARCH ARTICLE

Signal Automatic Modulation Classification and Recognition in View of Deep Learning

TIANPEI XU[1] AND YING MA[2]
[1]College of Education, Hulunbuir University, Hulunbuir 021008, China
[2]College of Software, Nanchang Hangkong University, Nanchang 330063, China
Corresponding author: Ying Ma (marian_edu@163.com)

ABSTRACT With the advancement of 5G technology, wireless communication resources such as channels and spectrum become scarce. This necessitates ensuring the efficiency and security of signal modulation and demodulation, which imposes higher requirements for wireless communication systems. However, signal modulation has the problems of large amount of data, low recognition accuracy and various types. In this study, a classification network of automatic modulation classification recognition algorithm for signal-to-noise ratio is proposed to solve the problem that traditional noise reduction algorithms will damage signals with high signal-to-noise ratio, consequently reducing the accuracy of signal recognition. In order to solve the problem of high complexity of network model algorithm, in particular, a signal automatic modulation classification and recognition algorithm based on neural network autoencoder is proposed. Experimental results show that the accuracy of signal automatic modulation classification recognition in the algorithm increases as the increase of modulation signals and tends to be stable. When the modulation signal is 0dB, the recognition accuracy gradually converges to the highest, and reaches 81.6% when the modulation signal is 18 dB. In contrast, the DenseNet algorithm has the lowest recognition accuracy, with only 77.5% recognition accuracy when the signal modulation classification is 18dB, a difference of 4.1%. This indicates that the algorithm performs exceptionally well in automatic signal modulation classification, and its complexity is lower than other comparative network models, providing certain advantages.

INDEX TERMS Neural network self coding, convolutional long short term memory network, automatic signal modulation, signal-to-noise ratio classful network.

I. INTRODUCTION

Modulation recognition of communication signals is a crucial aspect of information modulation processing and a helpful tool for managing radio spectrum resources [1]. In the communication system, the methods for automatic modulation classification recognition are mainly divided into model-based and deep learning-based [2]. However, model-based methods have shown to be insufficiently accurate when handling complex signal relations with varying modulation modes and bit rates [3]. The method based on deep learning can realize automatic learning of signal features through feature extraction and classification recognition by multi-layer neural network, so as to realize automatic modulation classification and recognition of signals [4]. This article focuses on the significance of intelligence realization for radar, sonar and other equipment [5]. The primary contribution is the introduction of a new recognition algorithm for Automatic Modulation Classification (AMC) based on deep learning. The aim is to address accuracy and complexity concerns in automatic modulation classification of signals. This algorithm can not only improve the accuracy and efficiency of signal modulation recognition, while reducing the complexity and further promoting the development of communication technology. In order to meet the requirements of the majority of users on the high efficiency and safety of signal modulation as the goal, we look forward to providing strong support for the future development of communication technology. The research content is mainly separated into five; The first is an introduction, describing people's demand for wireless

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communication systems in the contemporary context of communication technology development; The second is a relevant review on the application of DL as well as AMC technology in various fields, including the current research status of many scholars on these two technologies; In the third, aiming at the accuracy of signal modulation classification and the complexity of network model, the classification and recognition algorithm in view of DL and AMC technology is studied. The first section analyzes the principle of NN and signal automatic modulation, while the second section studies the signal automatic modulation classification algorithm of signal to noise ratio (SNR) classful network, The third section is the study of signal automatic modulation classification algorithms in view of NN self coding; The fourth analyzes the RA and complexity of the algorithm for automatic signal modulation through comparative experiments, as well as the degree to which it solves complexity when facing massive data; The fifth is a summary and outlook on the relevant methods and outcomes.

II. RELATED WORKS

AMC technology is a key component of intelligent wireless communication; Because of its stronger robustness and higher accuracy, it is often utilized for wireless source identification and shielding surrounding interference to improve Spectral efficiency; Many scholars have conducted considerable research on this technology. Qiph et al. proposed several AMC methods based on prototypes and variants of convolutional neural networks (CNNS). A waveform-spectrum multimode fusion (WSMF) method based on deep residual network (Resnet) is used to realize AMC. The feature fusion strategy is used to fuse the multi-mode features of the signal to obtain more discriminant features. The simulation results show that compared with the traditional CNN-based single-mode information AMC method. The proposed method has better performance, can distinguish 16 kinds of modulation signals, and can also work well in higher-order digital modulation types [6]. Wang et al. presented an AMC in view of Federated learning, and introduced balanced Cross entropy for addressing the class imbalance. The test illustrates that the difference in average accuracy between FedeAMC and CentAMC is less than 2%, the risk of Data breach is low, and it will not result in a serious performance loss [7]. Saleem and Saifullah proposed a new technique for designing a kind of special arrays utilizing strategy encoding elements on the surface of the ground, for the reduction of broadband bistatic and monostatic backscatter energy levels. The results indicate that the antenna array significantly reduces the backscattering field of both x-polarized and y-polarized incident waves, and the measurement outcomes of the prototype produced are in agreement with the experimental results [8]. Zhang et al. proposed an AMC feature fusion scheme based on convolutional neural networks (CNN). The scheme aims to extract more discriminant features by merging various images and hand-crafted signal features. Firstly, 8 manual features and different image features are extracted, and then the image features and manual features are combined to form joint features, and the multi-modal fusion model is used to fuse joint features. The research results show that the scheme has excellent performance, achieving a classification accuracy of 92.5% even when the SNR is -4 dB [9].

DL is a method of feature-learning in view of sample features. It forms complex features more suitable for classification by analyzing and restructuring simple features of data, so it is extensively utilized in many aspects, and many experts have carried in-depth study on it. Wang et al. proposed a learning based fault localization method that improves effectiveness by fusing fault diagnosis features from different dimensions. Firstly, it proposes a method of locating faults by mining software behavior graphs, and secondly, a wide depth learning fault location method in view of multiple feature groups [10]. The study utilizes the Wide&Deep model as the sorting strategy to enhance fault localization by investigating relevant correlations. Experiments have shown that this model outperforms existing learning based methods in terms of early fault detection capabilities [11]. Le et al. proposed a DL based model to detect cracks and evaluated its quality using multiple error measurement standards. The results showed that the accuracy, recall, specificity, F1 score, and accuracy of the training dataset were 99.5%, 99.8%, 99.5%, 99.5%, and 99.7%, respectively, providing evidence for the effectiveness of the DL-based approach [12]. Yan et al. proposed a new artificial intelligence tool HLDnet in view of DL. HLDnet uses the joint intersection decision algorithm for evaluating the proportion of common lesion areas detected on two types of Colposcopy images, and improving the detection accuracy of HSIL+areas. The experiment illustrates that the accuracy, sensitivity, and specificity of the test data are 0.86, 0.82, and 0.90. This improves the accuracy of automatic cervical precancerous screening and helps to increase the availability of cervical precancerous detection for people around the world [13]. Wu et al. proposed a multi-feature fusion AMC method based on convolutional neural networks (CNN). The modulated signals are converted into cyclic spectrum (CS) and constellation diagram (CD) respectively, and then a two-branch CNN model is built to fuse the features learned by CS and a CD together. Experimental results show that this method can achieve the same or better results with greatly reduced learning parameters and training time [14].

In summary, DL and AMC technology have matured in the application field. However, with the advancement of information technology, AMC technology still has shortcomings. Signal modulation is susceptible to interference from factors such as noise and frequency attenuation in complex signal environments. In some communication systems, the RA of signal automatic modulation is low, and overfitting is prone to occur when facing massive data, resulting in a decrease in the accuracy of recognition technology. Therefore, further research on the improvement of AMC technology is of great significance.

III. SIGNAL AUTOMATIC MODULATION CLASSIFICATION AND RECOGNITION ALGORITHM IN VIEW OF DL

The traditional AMC technology recognizes modulated signals by comparing a large number of features, mainly separated into two: one is in view of likelihood theory; This method requires high complexity to obtain prior conditions. Another method is in view of feature extraction; This method attributes the modulation classification process in view of feature extraction to a pattern recognition problem. This approach enhances the accuracy compared to traditional manual recognition; However, this method requires suitable classifiers for signal feature extraction and has high computational complexity. Therefore, this study focuses on the above issues and conducts research on signal automatic modulation classification and recognition algorithms in view of DL.

A. RESEARCH AND ANALYSIS OF NN AND SIGNAL MODULATION

In practical communication, modulation and demodulation are the key technologies. Modulation is to load the information signal to the specified carrier, which is then retrieved using demodulation techniques. First, the input analog signal is converted into a digital signal. Then, the relationship between the carrier frequency and the digital signal frequency is used to modulate, that is, the frequency spectrum of the signal is moved towards the low frequency region through frequency addition processing. Figure 1 [15] illustrates the specific modulation process.

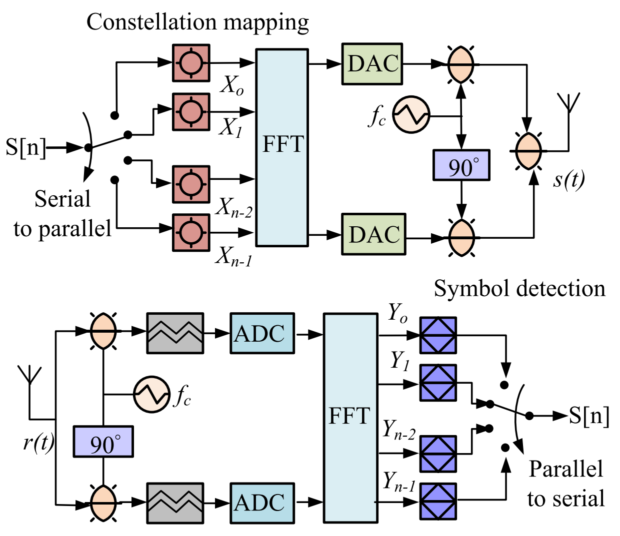


FIGURE 1. Principles of signal modulation and decoupling.

The process of transforming the original signal that needs to be transmitted into a suitable high-frequency signal by adding a carrier signal is called signal modulation. The expression for transmitting and receiving signals in a general environment is shown in equation (1).

$$x(t) = \mathrm{Re}\left\{\alpha e^{j2\pi\varphi} e^{j2\pi\Delta ft} C(t) e^{j2\pi f_c(t-t_o)}\right\} + n(t) \quad (1)$$

In equation (1), $C(t)$ serves as the complex envelope of a complex signal; $n(t)$ represents the additive noise used; φ is the phase shift; f_c is the carrier frequency; Δf serves as the carrier frequency offset; α serves as the channel amplitude; $\mathrm{Re}\{\bullet\}$ represents the real part of the signal. In practical applications, three common types of adjustment signals are mainly modulated. Firstly, the expression of the orthogonal amplitude modulation signal transmitted through the channel is shown in equation (2).

$$x(t) = \mathrm{Re}\left\{\sum_{m=1}^{N} R_m e^{j\theta_n} p(t-(m-1)T_s) e^{j(2\pi f_c+\theta_c)} + n(t)\right\}, \quad 0 < t < T = NT_s \quad (2)$$

In equation (2), N is the number of IS sequences; R_m is the amplitude of the IS; a_m and b_m are the in-phase and orthogonal components of the signal, respectively; f_c is the carrier signal; T_s is the periodic interval of the signal; $p_{(t)}$ serves as the transmitted baseband signal; θ_c serves as the tracking error of the carrier signal; $n(t)$ represents the white Gaussian noise used. The second is the broadband frequency modulation signal transmitted through the channel, whose expression is shown in equation (3).

$$x(t) = A\sum_{k=1}^{K} s_k^{(i)} e^{j(2\pi f_c t+\phi_k)} g(t-(k-1)T) \quad (3)$$

In equation (3), T represents the cycle time of the signal; $s_k^{(i)}$ is the k-th signal sequence in the i -th type modulation signal; $g(t)$ serves as the unit impulse response of the shaping filter. Furthermore, there are phase shift keying modulation signals and frequency shift keying modulation signals transmitted through the channel, which are expressed in equation (4).

$$\begin{cases} x_{PSK}(t) = \sqrt{S}\sum_{i=1}^{N} e^{j\varphi_i} u_T(t-iT), \\ \varphi_i \in \left\{\frac{2\pi}{M}(m-1), m = 1, 2, \ldots, M\right\} \\ x_{FSK}(t) = \sqrt{S}\sum_{i=1}^{N} e^{j(\omega_i t+\theta_i)} u_T(t-iT), \\ \omega_i \in \{\omega_1, \omega_{20}, \ldots, \omega_M\}\, \theta_i \in (0, 2\pi) \end{cases} \quad (4)$$

In equation (4), S serves as the power of the signal; T represents the cycle time of the signal; u_T is the standard unit pulse of duration T. In the study of automatic modulation recognition technology, the integration of neural networks has significantly advanced the field. In particular, Convolutional Neural Networks (CNNS) have attracted attention due to their excellent ability to extract spatial features. Combined with pooled layer sampling and other technologies, CNN effectively reduces the required parameters, thus preventing the network structure from being too complex, while ensuring the efficiency and accuracy of the model. The output expression of the convolutional layer (CLA) is shown in equation (5).

$$y_{i,j} = g(\sum_{i,j}^{n} \theta_{(n-i)(n-j)} x_{ij} + b) \tag{5}$$

In equation (5), x_{ij} represents the feature mapping of the input data; θ_{ij} represents the parameters of the convolutional kernel; $g(\bullet)$ is the Activation function; b serves as the bias of the NN. Recurrent neural network (RNN) is utilized to various signals with time characteristics to make the results more accurate. The hidden state (HS) S_t updates the information of the newly input x_t after each time step, and the expression of the update function is shown in equation (6).

$$S_t = f(Ux_t + WS_{t-1}) \tag{6}$$

In equation (6), W serves as the weight of the HS; U serves as the weight of the new input; S_t represents the HS at time step t, containing information extracted from all time steps up to t. There are three commonly used network models, specifically the Inception network, ResNet network, and DenseNet network structure, which are applied in comparative experiments of NN. Among them, the Inception network adopts a parallel approach to collect more scale features. The network structure is shown in Figure 2.

During image recognition, the depth of the network and training parameters tend to increase over time, leading to overfitting of the network. The Inception network can increase the sparsity of the deep network structure and save computing resources. Secondly, the ResNet network applies a fusion technique that combines the original input signal and the extracted features from the convolutional unit. This approach allows the network to maintain its performance despite increased depth and effectively addresses the issues of gradient explosion and disappearance [16]. Finally, the DenseNet network adopts convolutional layer connection to solve the problem of feature loss of input information at the end of a deep network. Then discard factor is introduced to prevent overfitting phenomenon.

B. SIGNAL AUTOMATIC MODULATION CLASSIFICATION AND RECOGNITION ALGORITHM IN VIEW OF SNR CLASSFUL NETWORK

In order to solve the problem that the denoising algorithm may reduce the recognition accuracy of high SNR signals, the researchers use SNR classification network to automatically classify and recognize signal modulation. As a part of the signal pre-processing, the SNR classification network is introduced, and the features are extracted by convolutional neural network and classified by unsupervised clustering method [17]. This helps to determine the high-SNR and low-SNR classification boundaries of the signal. The SNR classification network is a network model that uses deep learning techniques to distinguish signal from noise. By learning the characteristic difference between signal and noise, the effective classification of input data is realized. Figure 3 depicts the structure of the network.

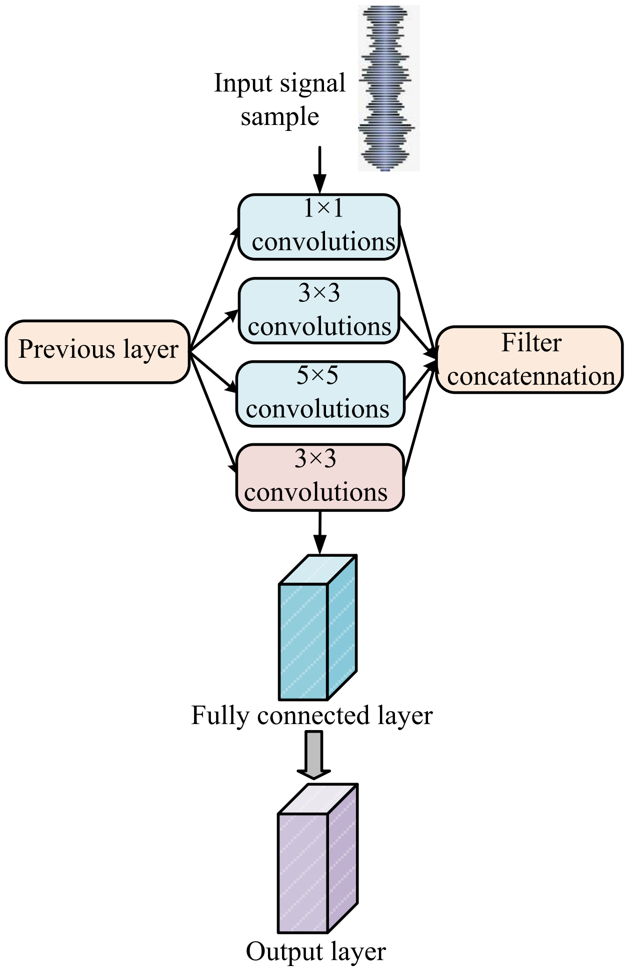


FIGURE 2. Inception network architecture.

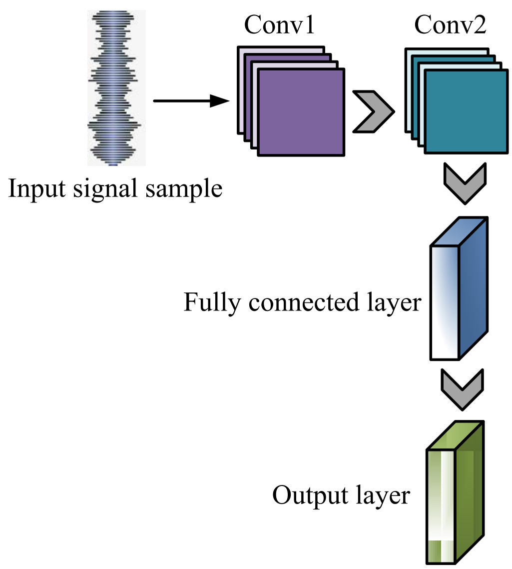


FIGURE 3. Signal-to-noise ratio classful network architecture.

The network consists of CNN layer, full connection layer (CLA), input layer (ILA) and output layer (OLA). The expression of Loss function of CNN is demonstrated

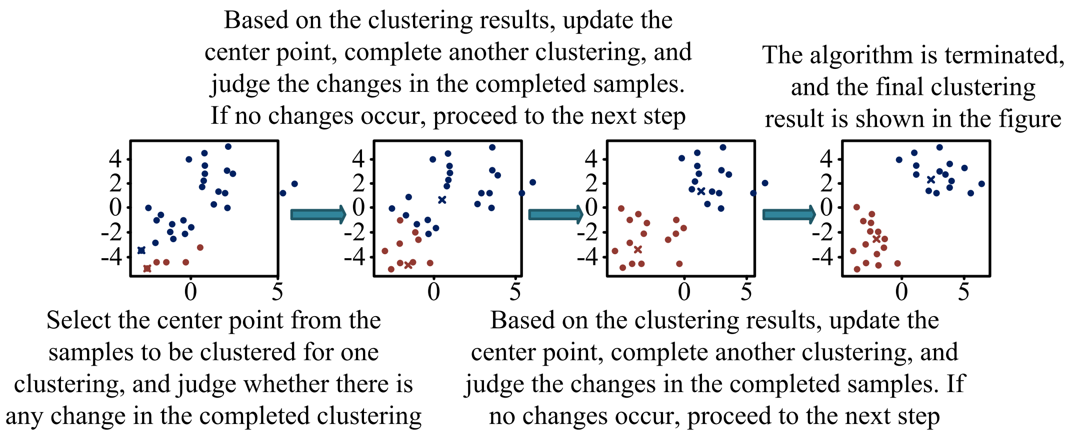


FIGURE 4. Specific process of KA.

in equation (7).

$$L_{snr} = \sum_{i=1}^{N} \hat{y}_{snr}^{(i)} \log y_{snr}^{(i)} + (1 - \hat{y}_{snr}^{(i)}) \log(1 - \log \hat{y}_{snr}^{(i)}) \quad (7)$$

In formula (7), L_{snr} is the Loss function of SNR; $y_{snr}^{(i)}$ represents the signal-to-noise ratio (STNR) label value of the IS; $\hat{y}_{snr}^{(i)}$ represents the predicted STNR of the IS; N is the quantity of IS samples. The K-means algorithm is widely used in signal processing. This clustering algorithm realizes effective clustering by optimizing the function to determine the distance between each element and the selected center point [18]. The traditional K-means algorithm first randomly selects K initial clustering centers in the sample data set. The algorithm then calculates the distance from each sample to these centers. The sample is then assigned to the nearest cluster, and the cluster center for that cluster is recalculated. The process is shown in Figure 4.

The completely random selection of cluster center points in the KA can significantly impede convergence and the initial positioning of these center points strongly impacts performance and training time. Consequently, the KA is optimized and mathematical methods are used to select the cluster center points. The optimization function expression of this algorithm is demonstrated in equation (8).

$$J = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2} \quad (8)$$

In equation (8), x_i is the coordinate of each signal sample; μ represents the cluster center point; N serves as the quantity of samples of the signal. An LSTM network is a specific type of recurrent neural network that interacts through a chain of repeating units. The network is composed of multiple cells, each with two outputs, cell state and data output. This structure enables the LSTM network more efficient in processing time series data [19]. The P-CL network, on the other hand, is a deep network structure connecting convolutional neural networks and short and long time memory networks (LSTM) in parallel. This structure can simultaneously perform two-layer feature extraction, thus saving time and cost. The structure of the network is shown in Figure 5.

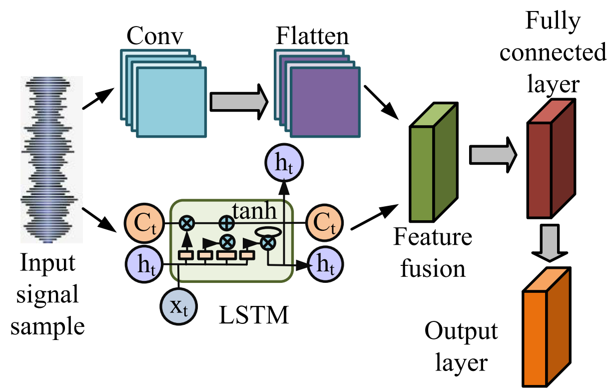


FIGURE 5. P-CL network structure.

The CL network is composed of three layers of CNN, two layers of short-term memory network and one layer of full CLA in parallel. It includes the upper CLA and lower LSTM parts, and the extracted features from both layers are fused through the fusion layer, ensuring sufficient signal feature extraction [20]. When the two layers of LSTM layers contain multiple unit structures, the complexity and accuracy of the network are optimal. The expression for the output x_{L2} of the IS x after passing through the two layers of LSTM layers is shown in equation (9).

$$\begin{cases} x_{L1} = LSTM(x, h_t) \\ x_{L2} = LSTM(x_{L1}, h_t) \end{cases} \quad (9)$$

In equation (9), $LSTM(\bullet)$ represents the computational function in the LSTM layer. Finally, feature processing is performed by the fully connected layer (COLA), and the OLA is classified using the *Soft* max function. Equation (10) shows the formula for calculating the classification.

$$\begin{cases} O_{dense} = f(W_d o_{C+L} + b_d) \\ O_{output} = \sigma(W_o o_{dense} + b_o) \end{cases} \tag{10}$$

In equation (10), o_{dense} is the output of the fully COLA; o_{C+L} is the output after feature fusion; o_{output} is the output of the OLA; b_d is the offset of the fully COLA; b_o is the bias of the OLA; $\sigma(\bullet)$ is the *Soft* max function; W_d is the weight of the fully COLA; W_o is the weight of the OLA. The whole architecture of SNR classification network algorithm includes preprocessing module, SNR classification module and modulation type recognition module [21]. First, the input signal is processed by the preprocessing module. The SNR classification module is then responsible for classifying these signals as either high or low. Signals with a high noise ratio are retained, while signals with a low noise ratio are denoised. Finally, the classified signal is fed into the PC-L network for further training, testing, and classification [22].

C. AUTOMATIC MODULATION CLASSIFICATION AND RECOGNITION ALGORITHM IN VIEW OF NN AUTOENCODER

In order to meet the requirements of research and discussion on the characteristics of network signal extraction under other conditions, the automatic modulation classification recognition algorithm is further discussed in this study. In order to reduce the complexity of this algorithm and save calculation cost, LSTM self-coding method is adopted. Firstly, the input information is normalized. Secondly, the time feature of the signal is extracted deeply through the long and short time memory network. Norm is defined as the real number $p \geq 1$, and its definition formula is shown in Formula (11).

$$\|x\|_p := \left(\sum_{i=1}^{n} |x_i|^p\right)^{\frac{1}{p}} \tag{11}$$

When $p = 2$ is the L_2 norm, it represents the open root of the sum of squares of all elements in a vector. When $p = 1$ is the L_1 norm, it represents the sum of the absolute values of all elements in a vector. The regularized objective function is demonstrated in equation (12).

$$J(\vec{\theta}) = \frac{1}{2}\sum_{I=1}^{m}(h_{\vec{\theta}}(x^{(i)}) - y^{(i)})^2 + \lambda \sum_{j=1}^{n}\theta_j^2 \tag{12}$$

In formula (12), λ denotes the regularization parameter, θ denotes the convolution kernel parameter, which is expressed in the mathematical sense as the square root of the sum of squares of the elements of the vector [23]. In addition, the frequencies of L_1-norm and L_2-norm are shown in Figure 6.

The colored ellipse serves as the true value of the input data, and the radius of the circle represents the error between the predicted data of the L_2-norm and the true data; Therefore, by changing the radius of the circle, it can be tangent to any point of the colored ellipse. Autoencoder ϕ is the neuron

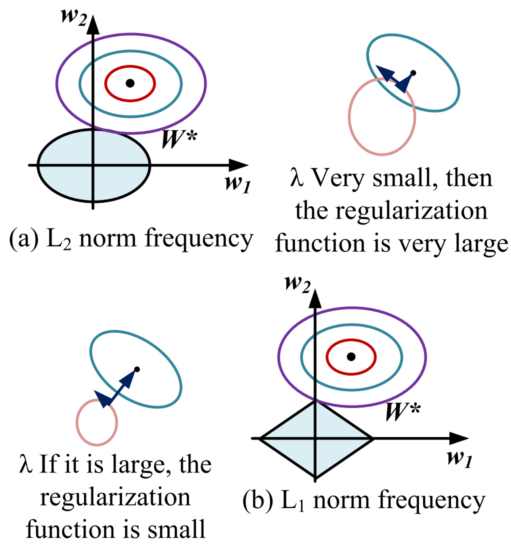


FIGURE 6. **L1 and L2 norm frequencies.**

matrix connecting ILA and OLA, and decoder φ is the neuron matrix connecting hidden layer and OLA. The expression of encoder ϕ is shown in equation (13).

$$\phi, \varphi = \underset{\phi,\varphi}{\arg\min} \|x - y\|^2 \tag{13}$$

In equation (13), $\|\bullet\|$ is the norm, and the expression in the feature space of the data from the ILA of the encoder to the hidden layer is shown in equation (14).

$$h = \sigma_1(W_1 x + b_1) \tag{14}$$

In equation (14), W_1 serves as the weight coefficient of the encoder; $\sigma_1(\bullet)$ serves as the Activation function of the encoder; b_1 represents the bias vector of the encoder. The information is reconstructed by the decoder from the data processed by the hidden layer, and the expression for the mapping process is shown in equation (15).

$$y = \sigma_2(W_2 x + b_2) \tag{15}$$

In equation (15), W_2 represents the weight coefficient of the encoder; $\sigma_2(\bullet)$ serves as the Activation function of the encoder; b_2 represents the bias vector of the encoder. The fitting process of Autoencoder is to find the minimum error of reconstruction amount y, and its expression is shown in Formula (16).

$$L(x, y) = \frac{1}{m}\|x - \sigma_2(W_2(W_1 x + b)) + b_2\|^2 \tag{16}$$

In equation (16), m serves as the quantity of input SA. The Autoencoder corrects and improves the Error function by back propagation, separating noise from the data to get the real data. On this basis, the hidden layer in the Autoencoder is changed to LSTM network, and the LSTM denoising Autoencoder structure that can extract time series is obtained, as shown in Figure 7 [24].

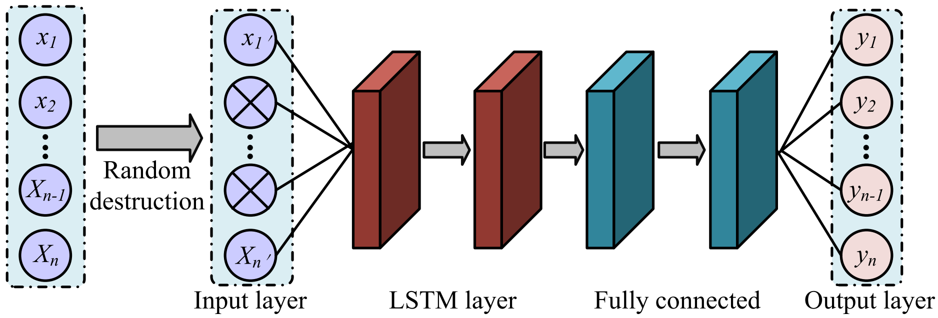


FIGURE 7. LSTM denoising Autoencoder structure.

The architecture of LSTM based denoising Autoencoder consists of ILA, LSTM network layer, full CLA and OLA. The expression of OLA is shown in Formula (17).

$$\hat{p_k} = \frac{e^{o_{2k}}}{\sum_{k=1}^{K} e^{o_2}} \tag{17}$$

In equation (17), o represents the output of the fully COLA; $\hat{p_k}$ is the likelihood of predicting input data. Using a two-layer LSTM network as the encoder and a two-layer fully COLA as the decoder, the relevant formula is demonstrated in equation (18).

$$\hat{x}_j = W_{dec}h_j + b_{dec} \tag{18}$$

In equation (18), $\hat{x}_j$ represents the jth recovered SA; W_{dec} represents the weight coefficient of the decoder; b_{dec} represents the offset vector of the fully COLA. The signal automatic modulation classification recognition algorithm model based on SNR classification network can recognize and classify different modulated signals effectively. Firstly, the signal is classified by the SNR classification network to ensure the integrity of the signal with high SNR, and the signal with low SNR is denoised. Secondly, the auto-encoder mechanism is applied to further strengthen the ability of neural network to capture and recognize signal patterns. The network model integrates advanced neural network technology and deep signal processing methods to ensure the accuracy and integrity of data transmission.

IV. EXPERIMENTAL ANALYSIS OF SIGNAL AUTOMATIC MODULATION CLASSIFICATION AND RECOGNITION ALGORITHM IN VIEW OF DL

To verify the accuracy of the signal automatic modulation classification and recognition algorithm learned in depth, the SNR Classful network and P-CL network are tested. The running environment of the learning model is 3.70 GHz Intel i7-8700K processor, GeForee GTX 1080 Ti Computer graphics card and 32GB memory computer, Raspberry PI 3 and Raspberry PI 4 processors, and the learning framework is TensorFlow 1.14.0. The SNR Classful network is composed of two layers of convolution layer, one layer of full CLA and one layer of OLA; The convolution layer contains 130 convolution nuclei with the size of 1 * 3 and 2 * 3, the full junction layer contains 260 neurons, and the OLA has 25 neurons. The Activation function is ReLU function. The P-CL network consists of three CLA, two LSTM layers, one fully COLA, and one OLA. The IS are classified using the Softmax function; The training set and test set respectively use sample signals from RMI to evaluate the algorithm performance of the STNR network and P-CL network. The Python software was used for network construction for testing and training [25]. The dataset is demonstrated in Table 1.

TABLE 1. Relevant parameters of the RadioML2022.11a dataset.

Signal parameters	Specific values
Sampling points	130
Sample Rate	210
Maximum sampling rate offset	60
Number of signals	225000
Number of symbols per signal	10
SNR (dB)	-20:2:18

Table 1 shows that for the performance test of the STNR Classful network, the simulation experiment is carried out using the open source radio dataset RadioML. This dataset is generated by GNU Radio during complex channel defects, therefore it is very suitable for wireless communication environments in practical applications. To test the impact of DA on the accuracy of signal automatic MR in practical applications, the algorithm was combined with traditional CNN, DenseNet, Inception, and ResNet networks to compare the RA of classical network denoising and non denoising. The specific RA comparison chart is shown in Figure 8.

Figure 8 shows that the ResNet network has the most significant improvement in RA after using the denoising algorithm, which is 5.1% higher than when not denoised. The other three networks have also correspondingly improved some RA. Among them, DenseNet network increased by 2.4%, Inception network increased by 1.9%, and CNN network increased by 2.6%. In Figure 8 (a), at the beginning of the experiment, the CNN network's classification accuracy was comparable to that of the CNN network with the denoising algorithm. As the modulation signal increased, the network with the denoising algorithm showed an increasing trend when the modulation signal was −18, and then

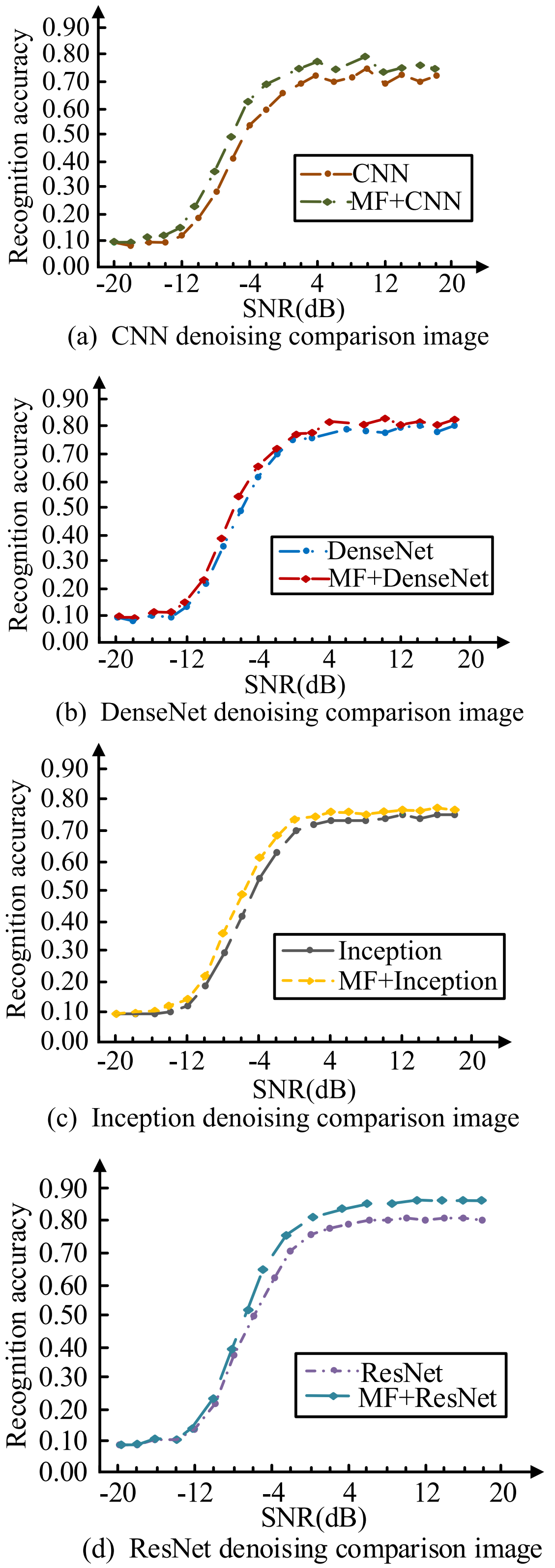


FIGURE 8. Comparison of accuracy of classical network before and after denoising.

the overall classification recognition rate was higher than that of the CNN network. In Figure 8 (b), the DenseNet network exhibits higher RA than the denoising algorithm at a modulation signal of −16 and then consistently lower classification accuracy than the denoising algorithm. In Figure 8 (c), in the range of modulation signals −20 to −18, the classification and RA of the Inception network exceeds adding DA; As the modulation signal increases, the overall classification RA in subsequent tests is lower than that of adding DA. In Figure 8 (b), the ResNet network has almost the same classification accuracy as adding DA within the range of −20 to −14 modulation signals. As the modulation signals increase in sequence, the classification accuracy of adding DA gradually increases compared to the ResNet network, and there is no downward trend. To clarify the denoising algorithm's classification impact on different modulated signals, It selects all de-noised improved Median Filtering (MF), that is (MF+P-CL) signals and undenoised (P-CL) signals, and the classification accuracy when SNR = −6dB and SNR = 10dB. In order to better understand and evaluate network performance, a detailed evaluation of the loss functions associated with the training and test datasets was performed. The result is shown in Figure 9.

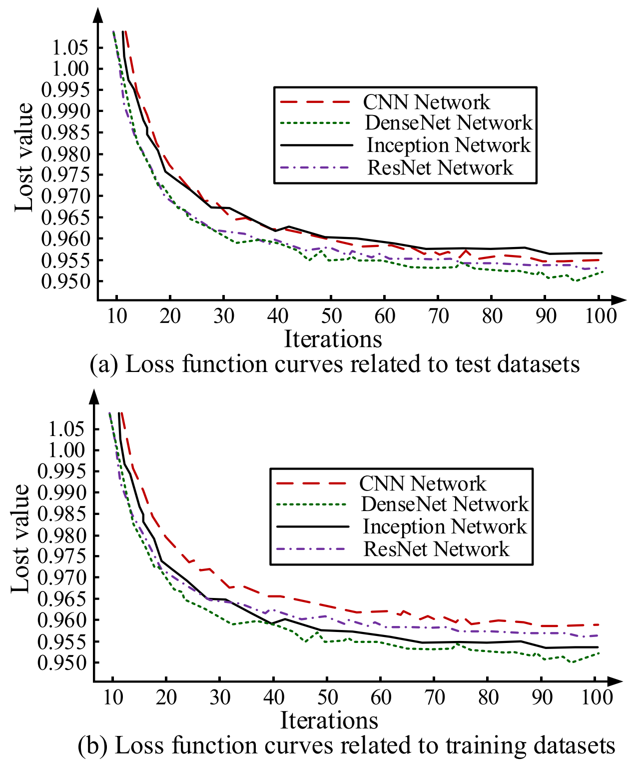
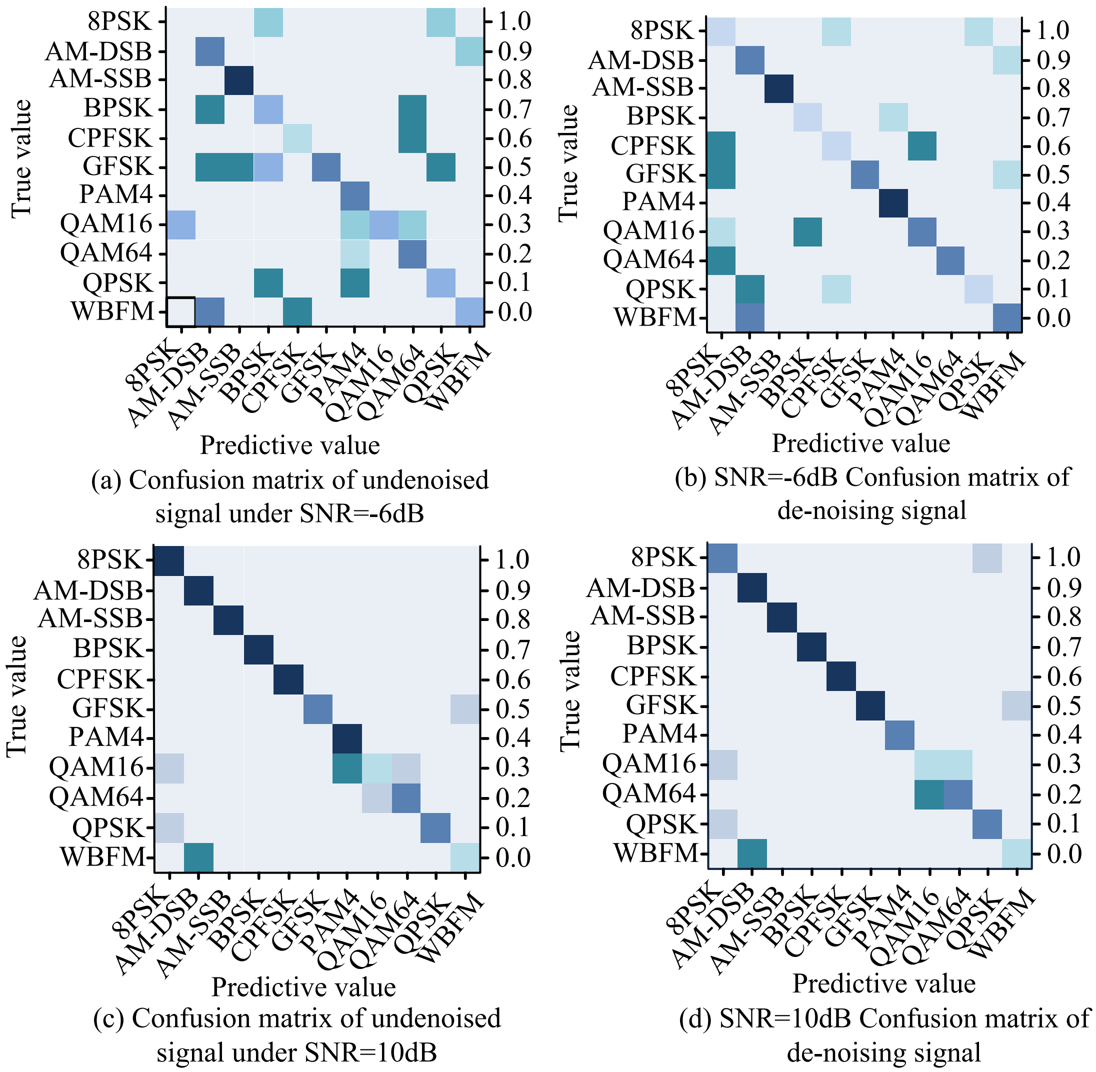


FIGURE 9. Loss function curves related to test and training datasets.

As can be seen from Figure 9, the loss function gradually stabilizes in both the test and training data sets with an increase in the number of iterations. The network gradually finds the best combination of parameters, making the gap between the predicted results and the real results smaller and smaller. It is evident from Figure 9(a) that the DenseNet network has the lowest loss function value, indicating that it performs the best and has the smallest difference between



(a) Confusion matrix of undenoised signal under SNR=-6dB

(b) SNR=-6dB Confusion matrix of de-noising signal

(c) Confusion matrix of undenoised signal under SNR=10dB

(d) SNR=10dB Confusion matrix of de-noising signal

FIGURE 10. Comparison of CM between all denoised signals and non denoised signals.

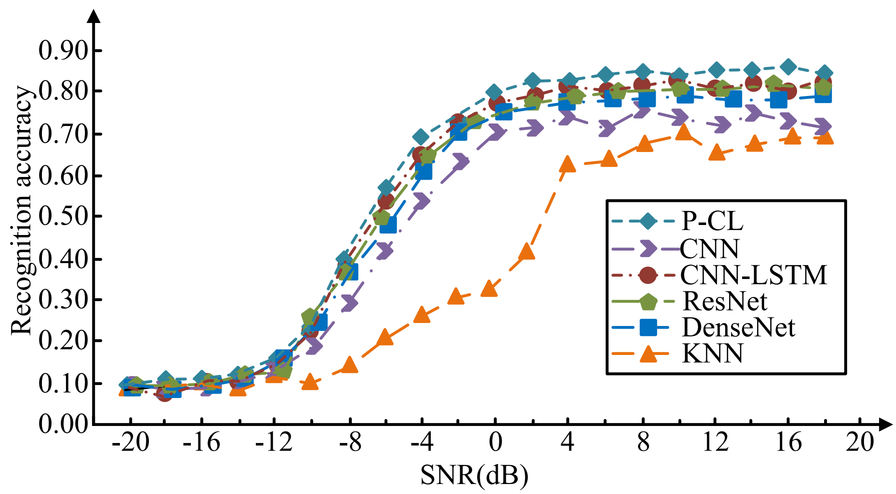


FIGURE 11. Comparison of CM between all denoised signals and non denoised signals.

the predicted and actual results. In contrast, the Inception network had a loss value of 0.963, the highest of the four networks, proving its relatively poor performance. The CNN and ResNet networks had loss values of 0.957 and 0.952, respectively. Their performance is between DenseNet and Inception. As can be seen from Figure 9 (b), it is found that

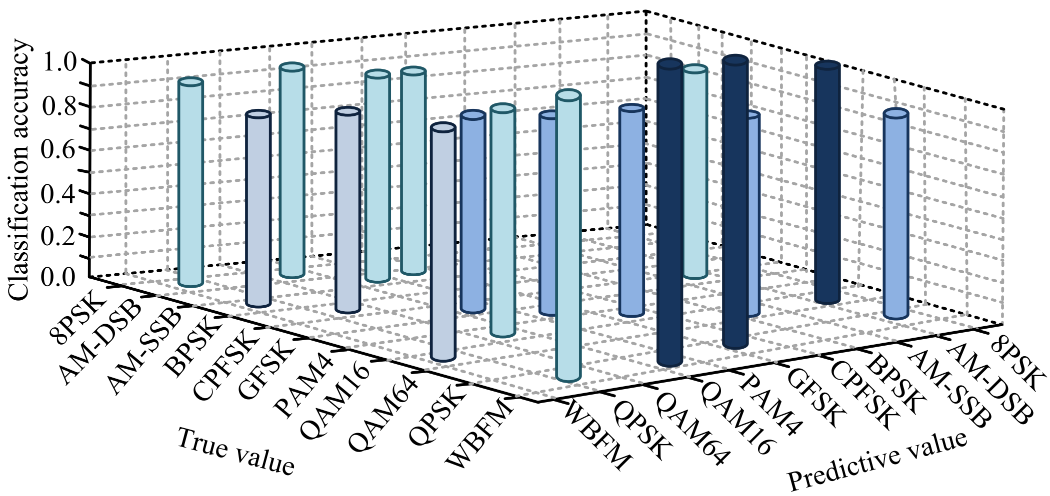


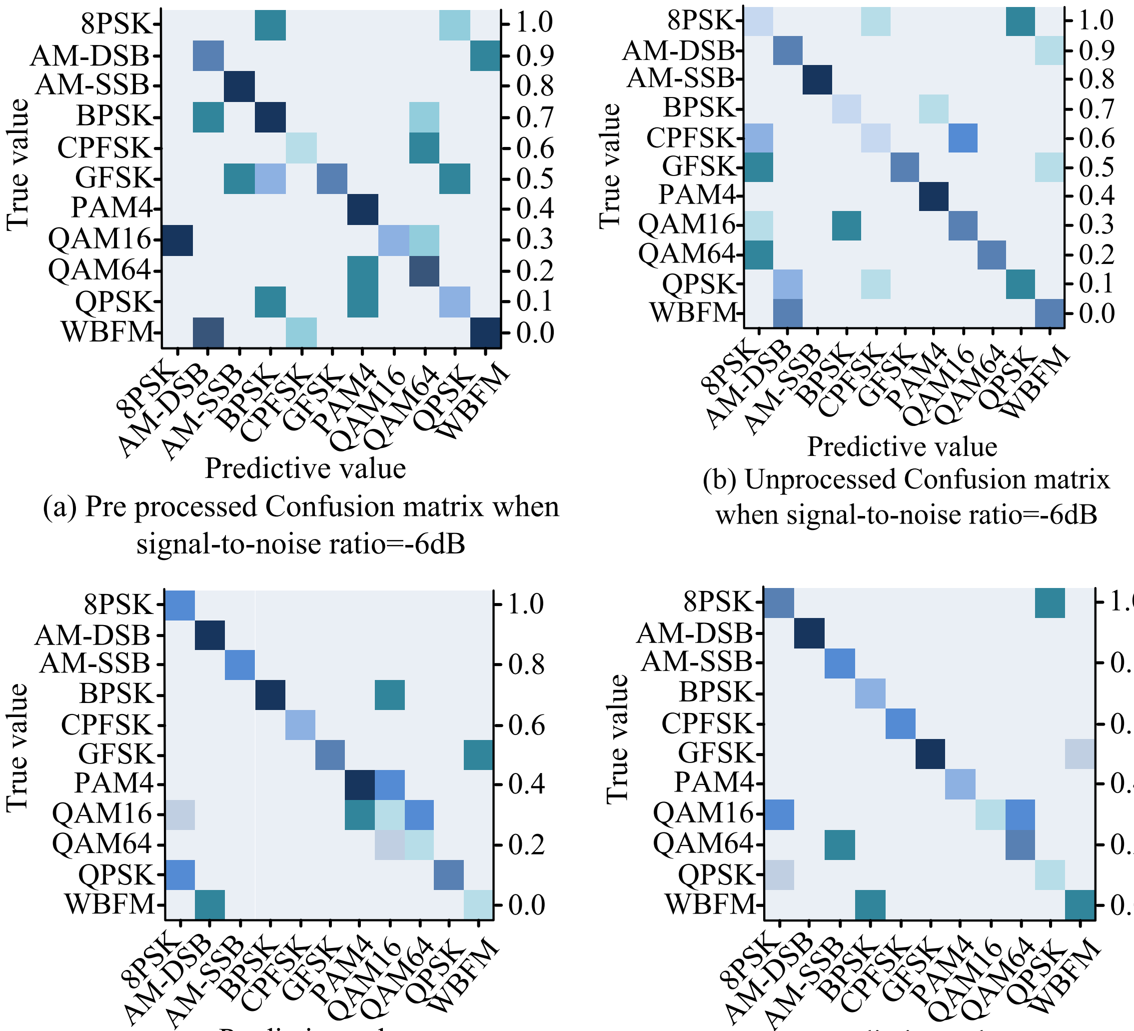
FIGURE 12. **Modulation signal classification model results at SNR=18dB.**

the loss function value of DenseNet network on the test data set is still the lowest, reaching 0.951, which proves its stable and good performance. The Inception network and ResNet network had slightly higher loss values of 0.957 and 0.959, respectively, while the CNN network had the highest loss value of 0.964. It can be seen that the DenseNet network has the best performance on both test and training data sets. This network has the lowest loss function value, indicating that the gap between the predicted results and the actual results is the smallest, and the performance is the most powerful and stable. In order to objectively assess effect of the denoising algorithm on various modulated signals, the improved Median Filtering (MF) of all denoised signals is selected, that is, the confusion matrix of (MF+P-CL) signals and undenoised (P-CL) signals, and the classification accuracy when SNR $= -6$dB and SNR=10dB. The result is shown in Figure 10.

Figure 10 shows that in the same modulated signal, the CM of the undenoised signal is clearer than that of the de noised CM, and there are more algorithms for matching the real value with the predicted value. Figure10 (a) and (b) show that 6 of the CM of the undenoised signal have a classification accuracy of more than 0.6; Among the CM of denoised signals, 8 have a classification accuracy of more than 0.6. Therefore, the improved median filtering algorithm has a significant denoising effect on the IS. The relative RA of the denoised signal is significantly higher than that of the non-denoised signal. Figure 10 (c) and (d) show that 10 of the CM of undenoised signals have a classification accuracy of more than 0.6; Among the CM of denoised signals, there are 9 ones whose classification and RA is more than 0.6. This indicates that under high STNR conditions, denoising the IS can actually affect the RA of some types of modulated signals, resulting in a decrease in the RA of both 8PSK and PAM4 signals. It indicates that the classification denoising method has certain effectiveness in modulating signals. To test the RA of the P-CL network, the performance of the P-CL network was evaluated under different STNR conditions, as illustrated in Figure 11.

Figure 11 shows a comparative experiment between the P-CL network and CNN, CNN-LSTM, ResNet, DenseNet, and K-Nearest Neighbor (KNN) classification algorithms. KNN is unsuitable for large-scale data, exhibiting the worst signal RA of only 62%. CNN networks have poor RA in processing time signal data, with a RA of only 76%, which is lower than all network models except KNN networks. ResNet and DenseNet networks have classification RA of 82% and 86%, respectively, which are lower than P-CL network models; This network model has certain advantages in dealing with gradient vanishing problems and can repeatedly use effective features. The CNN-LSTM network model shares a similar architecture to the P-CL network model and unsurprisingly outperforms the other models, achieving the highest RA score of 87%. However, the P-CL network model has a RA of 90%, both of which outperform the comparative experimental model. The results of the obtained STNR classification modulation signal classification algorithm at SNR=18dB are shown in Figure 12.

Figure 12 shows that there are 15 modulation signal RA rates above 95%, and some modulation signal RA rates even reach 100%. The WBFM signal and Amplitude Modulation Double Side Band (AM-DSB) signal are easily affected by the silence period during the original analog signal acquisition process. The presence of carrier signals can lead to significant errors in identifying WBFM signals and AM-DSB signals; Both QAM16 and QAM14 are susceptible to noise, making it difficult for the feature extraction of NN to accurately classify the signals. To compare the classification effects of normalized amplitude and normalized phase of L1 and L2 norms on denoising self coding, the classification accuracy of their IS and ordinary IS was compared. Figure 13 depicts the changes in RA of different signal types before and after processing.



(a) Pre processed Confusion matrix when signal-to-noise ratio=-6dB

(b) Unprocessed Confusion matrix when signal-to-noise ratio=-6dB

(c) Pre processed Confusion matrix when signal-to-noise ratio=10dB

(d) Unprocessed Confusion matrix when signal-to-noise ratio=10dB

FIGURE 13. Modulation signal classification CM under SNR=-6dB and SNR=10dB.

Figure 13 shows that the classification accuracy of LSTM denoising Autoencoder is higher than other comparison network models; Even with the lowest algorithm complexity, its RA reaches 91%. Figure 13 (a) and (b) show that in the CM with SNR $= -6$dB, most of the data have a signal recognition effect higher than 0.6 after preprocessing, while the signal recognition effect higher than 0.6 without preprocessing is less. Figure 13 (c) and (d) demonstrate that in the CM with SNR=10dB, 14 algorithms exhibit superior signal recognition performance than 0.6 post-preprocessing. Nonetheless, only 10 signals have recognition rates exceeding 0.6 pre-preprocessing. This demonstrates that the sample information after L2 norm normalization phase processing possesses higher RA for each signal than the unprocessed signal under -6dB and 10dB conditions; Even for WBFM and QAM signals with poor recognition performance, their recognition performance has been greatly improved. Compared with the difference between the classification accuracy of LSTM de-noising Autoencoder and other network models, LSTM based de-noising self encoding (ADE) model, P-CL network model, DenseNet network model, ResNet network model and LSTM network model are set. Figure 14 displays the RA results for each network model.

Figure 14 shows that the automatic signal modulation classification recognition accuracy for P-CL, DAE, LSTM, ResNet and DenseNet algorithms is evaluated, among which P-CL algorithm has the highest recognition accuracy. The recognition accuracy of 81.6% was achieved when SNR was 18 dB. Conversely, the DenseNet algorithm has the lowest recognition accuracy, achieving only 77.5% accuracy at

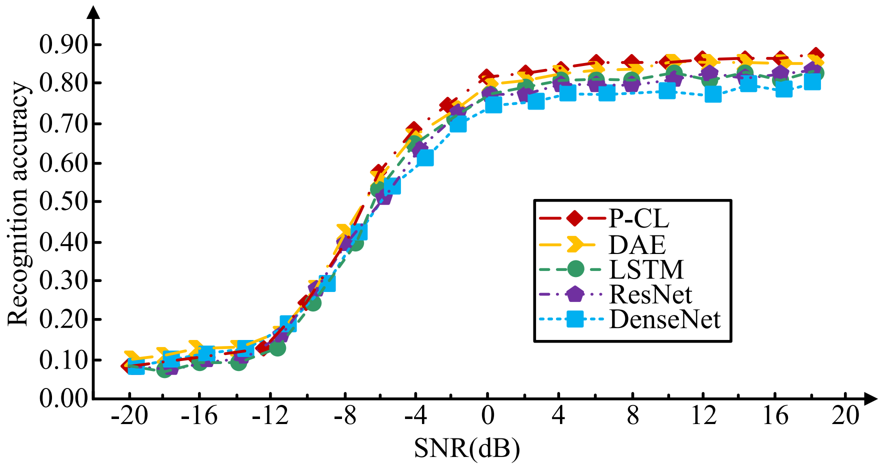


FIGURE 14. Comparison of RA of various models.

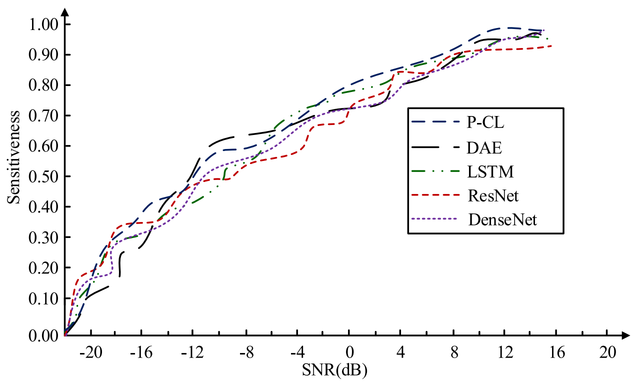


FIGURE 15. Sensitivity curve for signal automatic modulation classification and recognition based on five algorithms.

SNR 18dB, which is 4.1% lower than that of the Densenet algorithm. In terms of robustness, although the signal to noise ratio (SNR) of the signal changes, the recognition accuracy of all algorithms can improve with the increase of the modulated signal and tend to be stable. Among them, the P-CL algorithm can gradually converge even when SNR is 0dB. As can be observed, network algorithms exhibit good robustness and can maintain stable recognition performance even as signal conditions deteriorate. In terms of scalability, the recognition accuracy of all algorithms improves as data scale increases, implying their effectiveness in handling large-scale data. Even if DenseNet algorithm has the lowest recognition accuracy when SNR is 18dB, its scalability is still strong, and it has advantages that other algorithms do not have. It can be seen that all neural network algorithms show good robustness and expansibility. In addition, the signal automatic modulation classification recognition sensitivity of the P-CL, DAE, LSTM, ResNet and DenseNet algorithms was evaluated, and the results are shown in Figure 15.

As can be seen from FIG. 15, the sensitivity of five algorithms, P-CL, DAE, LSTM, ResNet and DenseNet, is improved when the signal-to-noise ratio keeps increasing.

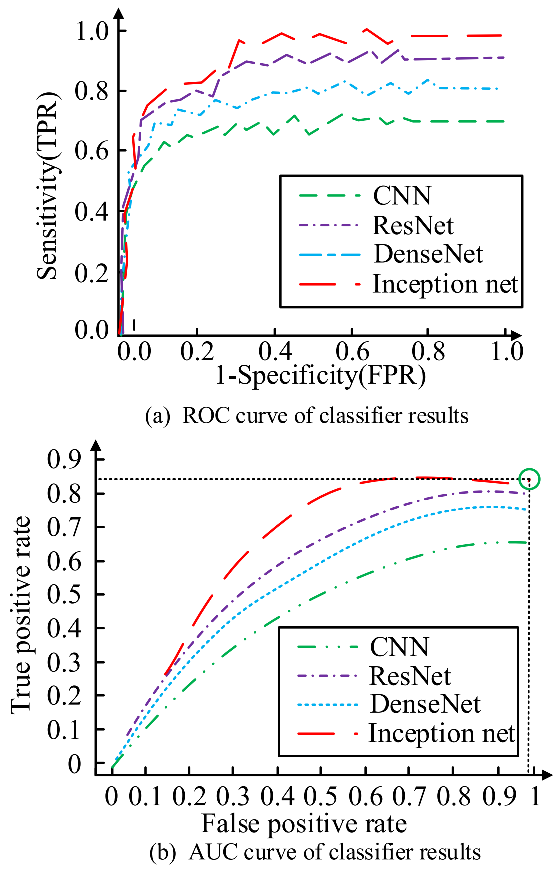


FIGURE 16. ROC result curve and AUC result curve under automatic signal modulation classification.

This shows that these five algorithms can improve the sensitivity of automatic modulation classification recognition with the increase of SNR, thus improving the accuracy of recognition. P-CL algorithm exhibits the highest sensitivity performance with a sensitivity value of 0.97. This indicates that the recognition accuracy of P-CL algorithm is also

TABLE 2. Comparison of the number of classified sample signals per second for network models in different environments.

Platform	/	De noising Autoencoder	CNN Network	LSTM network	CLDNN network
Intel i7-8700K	Average value	1263	1580	858	881
	Standard deviation	7.68	14.37	21.61	12.56
Raspberry Pi 3	Average value	120	50	21	26
	Standard deviation	1.62	2.89	2.03	0.31
Raspberry Pi 4	Average value	249	130	49	53
	Standard deviation	14.62	1.61	0.59	137
GTX1080Ti	Average value	8463	19128	7360	10261
	Standard deviation	152.54	345.24	138.26	102.47

improved when the signal-to-noise ratio is increased, and it can carry out automatic modulation classification and recognition of signals more effectively. The second-best algorithm is DAE with a sensitivity value of 0.96, also displaying excellent performance. The sensitivity value of DenseNet network and LSTM algorithm is the same, both being 0.93, which is slightly lower than that of the P-CL algorithm and DAE algorithm. However, they also show high sensitivity, indicating that these two algorithms also have better automatic modulation classification and recognition ability when the signal-to-noise ratio is increased. To enhance the visualization of the classification results, the ROC curve and AUC value curve related to the classifier results were obtained, as shown in Figure 16.

As can be seen from Figure 16, the ROC curves of CNN, DenseNet, Inception and ResNet all show an upward trend, indicating that these four networks possess the ability to enhance their classification performance. However, there are significant differences in the AUC values of the four networks, indicating that there is a gap in their overall performance. As can be seen from Figure 16 (a), the Inception network achieves the highest ROC value of 0.97, indicating excellent performance across all possible classification thresholds. The ResNet network has a ROC value of 0.91, ranking second, and also performs well. The ROC values of DenseNet network and CNN network were 0.86 and 0.74 respectively, which were lower than Inception and ResNet network, but still remained at a high level. It can be seen from Figure 16 (b) that the Inception network has the highest AUC value, which is closest to 1. This suggests that the Inception network has the best overall performance and can achieve high accuracy regardless of the classification threshold. The ResNet network ranks second with an AUC of 0.79, and its overall performance is also quite good. The AUC values of DenseNet network and CNN network are 0.74 and 0.63 respectively, which are slightly lower than the previous two. Inception networks show the best performance in both ROC values and AUC values, and their performance is quite stable and excellent at various thresholds, which can be said to be the most advantageous of the four networks. The ResNet network is not far behind, and overall performance is also very good. Although the DenseNet network and CNN network have slightly lower ROC value and AUC value, their performance is still within the acceptable range. In particular, the DenseNet network has higher ROC value and AUC value than the CNN network, and the performance is more stable. Furthermore, the algorithmic superiority of various networks across distinct platform environments was compared, with results presented in Table 2.

It is evident from Table 2 that the average number of sampled signals processed per second by LSTM-based denoising autoencoders, CNN networks, LSTM networks, and CLDNN networks varies according to the operating environment, as indicated by the mean and standard deviation of multiple experiments on each network model. Among them, whether in Raspberry Pi 4 environment or Raspberry Pi 3 environment, LSTM-based denoising autoencoder has shown significant advantages. In Raspberry Pi 4 environments, LSTM-based denoising autoencoders are 6 times, 6 times and 3 times faster than CNN networks, LSTM networks and CLDNN networks, respectively. Similarly, in the Raspberry Pi 3 environment, the LSTM-based autoencoder is 7 times faster than the CNN network, 7 times faster than the LSTM network, and 4 times faster than the CLDNN network. Compared with the other three network models, the LSTM-based autoencoder has lower algorithm complexity and higher processing speed, indicating clear advantages.

V. DISCUSS

Nowadays, with the development of communication technology and the surge of communication services, users increasingly demand efficient and secure signal modulation and reconciliation systems. However, there are many problems in signal modulation, such as various types, huge amount of data, and accurate identification of green space, which lead to a large shortage of wireless communication resources. The deep learning-based algorithm for automatic signal modulation classification and recognition is an innovative solution to existing problems. The algorithm aims to solve the issue of accuracy reduction caused by conventional noise reduction algorithms when processing signals with high SNR. The traditional noise reduction algorithm may also damage the original effective signal in the process of removing noise, thus reducing the accuracy of signal recognition. By utilizing deep learning methods, the algorithm can more accurately distinguish between signal and noise, thereby preserving high-quality signals while effectively reducing noise. However, in traditional signal processing methods, complex algorithms and highly customized solutions often require a lot of computing resources and time. However, deep learning-based algorithms avoid the complexity of requiring extensive manual feature engineering and parameter tuning by automatically learning the key features of the signal. This approach streamlines the model's complexity and enhances both scalability and the algorithm's generalization ability. Performance tests on this algorithm can verify whether the algorithm performs as expected in practical applications and provide necessary tuning information. Automatic signal modulation classification recognition algorithm based on deep learning provides a comprehensive and efficient solution designed to solve the accuracy and complexity problems in traditional algorithms. By integrating best practices in deep learning and signal processing, this algorithm has the potential to significantly improve communication technology, ensuring more accurate and efficient data transmission.

VI. CONCLUSION

Aiming at the problem that the traditional noise reduction algorithm damages signals with high SNR, and the problem that the network model algorithm is too complicated, a signal automatic modulation classification recognition algorithm based on deep learning is proposed, and the performance of the algorithm is tested. The test results demonstrate that the ResNet network's recognition accuracy improves significantly after employing the denoising algorithm, resulting in a 5.1% increase from its performance without denoising. The remaining three networks also enhance the accuracy of recognition. Among them, the DenseNet network increased by 2.4%, the Inception network increased by 1.9%, and the CNN network increased by 2.6%. In the confusion matrix of undenoised signals, there are 10 with classification accuracy above 0.6, while in the confusion matrix of de-denoised signals, there are 9 with classification accuracy above 0.6. This study indicates that when the signal-to-noise ratio is high, denoising the input signal can negatively impact the recognition accuracy of certain types of modulated signals, specifically the 8PSK and PAM4 signals. KNN is not suitable for large-scale data, and the signal recognition accuracy is the worst, only 62%; The recognition accuracy of CNN network is only 76%, which is lower than all network models except KNN network. The classification recognition accuracy of ResNet and DenseNet network is 82% and 86% respectively, both lower than that of P-CL network model. This model has certain advantages in addressing the issue of disappearing gradient and can utilize effective features repeatedly. However, the algorithm for classifying and recognizing modulation signals based on the feature network module used in this study has not achieved a high degree of accuracy, thus requiring the exploration of more suitable expert features. In addition, it is necessary to study the spatial characteristics of the signal extracted by the network under the condition of low complexity. Therefore, the algorithm proposed in this study needs further research and discussion on the characteristics of network signal extraction under other conditions.

VII. ACRONYM

The abbreviations used in this study are shown in Table 3.

TABLE 3. Abbreviation naming table.

Full name	Abbreviation
Automatic Modulation Classification	AMC
Convolutional Neural Networks	CNN
Recurrent Neural Network	RNN
k-means clustering algorithm	K-means
Dense Convolutional Network	DenseNet
ResidualNetwork	ResNet
Median Filtering	MF
K-Nearest Neighbor	KNN
Amplitude Modulation-Double Side Band	AM-DSB
Denoising autoencoder	DAE
Signal-to-noise ratio	SNR
Long Short Term Memory	LSTM
Deep Learning - CLDNN (multi-model neural network	CLDNN

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TIANPEI XU was born in Inner Mongolia, China, in 1994. He received the B.S. degree in computer application software from Jilin University, in 2016, and the Ph.D. degree in computer engineering from Chonnam National University, South Korea, in 2022.

He has been a Lecturer at Hulunbuir University, since 2022. He has authored a book and more than three articles, since 2020. His research interests include machine learning, deep learning, data analysis, and feature engineering.

YING MA was born in Beijing, China, in 1993. she received the Ph.D. degree in computer engineering from Chonnam National University, South Korea, in 2023.

Since 2023, she has been working as a Lecturer at Nanchang Hongkong University. She has published many peer-reviewed journals and international conference papers. Her research interests include machine vision, machine learning, deep learning, data analysis, and artificial intelligence.