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Article

Digital signal detection and recognition in the communication field combining DAEN and CNN

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Abstract: In communication, the detection and recognition of digital signals have always faced problems such as low adaptability and high misclassification rate. To address these issues, this study innovatively fused the deep auto-encoder network with convolutional neural networks to construct a novel digital signal detection and recognition model. Firstly, this study utilized the powerful feature extraction capabilities of the deep auto-encoder network to extract key feature information from massive amounts of data. Then these features were combined with convolutional neural networks to construct a detection and recognition model. These results confirmed that the constructed digital signal detection and recognition model had values of 93.75% and 94.18% in data detection recognition rate and average classification accuracy, respectively. Meanwhile, this model also performed well in terms of data processing accuracy and recall. In the comparison of data processing, the accuracy and recall rates were 93.59% and 94.67%, respectively, and the performance of data detection and recognition was better than that of the comparison methods. This indicates that the constructed digital signal detection and recognition model can significantly improve the reliability and robustness of signal detection and recognition. This paper brings new breakthroughs to the development of digital signal detection and recognition technology in communication.

Keywords: deep auto-encoder network; convolutional neural network; communication field; digital signals; detection and recognition

1. Introduction

With the rapid development of information technology, data show explosive growth. The types and complexity of digital signals are also increasing day by day. Communication is facing increasingly complex digital signal processing problems. How to accurately detect and recognize digital signals in complex and ever-changing communication environments becomes a focus of current research [1,2]. Meanwhile, the presence of various interferences and noise also poses great challenges to the detection and recognition of digital signals. Digital Signal Detection and Recognition (DSDR), as a key link in communication systems, is of great significance in ensuring the accuracy and reliability of information transmission. In communication systems, the main task of DSDR is to classify and recognize received signals to extract useful information [3,4]. The traditional DSDR methods are mainly based on mathematical analysis and statistical models. These methods often face problems such as high computational complexity and low recognition accuracy when dealing with complex signals [5]. In recent years, deep learning technology provides new ideas and methods for DSDR. Deep Auto-Encoder Network (DAEN) and Convolutional Neural Network (CNN), as two important deep learning models, show excellent performance in signal processing and pattern recognition. DAEN is a deep learning model based on unsupervised learning, which can extract high-level abstract features from signals through layer by layer learning of autoencoders. CNN is particularly suitable for processing image and signal data. It extracts local features from signals through convolution operations and reduces data dimensions through pooling operations, improving the model's generalization ability [6,7]. However, DAEN has weak generalization ability in data processing, while CNN has poor recognition ability for input data. Therefore, this study applies DAEN to extract digital signal features and fuses DAEN with CNN to construct a DSDR model. This study aims to use digital signal detection models to enhance the digital signal detection capability in communication, providing technical support for the effective transmission of digital signals.

Firstly, this study analyzes DSDR in communication and summarized the shortcomings of existing research. The second part utilizes DAEN to extract data features, and then fuses DAEN with CNN to construct a DSDR model. Next, performance analysis is conducted on the detection model using the constructed data. Finally, the experimental results are summarized and the advantages and disadvantages of the research methods are analyzed.

2. Related works

As communication technology develops, the complexity and diversity of digital signals continue to increase. Traditional signal detection and recognition methods are no longer sufficient to meet practical needs. Therefore, exploring new signal detection and recognition technologies to improve the accuracy and efficiency of signal recognition has important theoretical and practical significance. Numerous experts and scholars have conducted in-depth research and exploration on signal detection in communication. Liu et al. applied deep learning to signal conversion and classification to quickly identify the types of wireless communication signals and improve communication efficiency and quality. This study significantly improved the classification performance of signal data by leveraging the advantages of deep learning. However, this study only explored the classification performance of relevant deep learning, and there was relatively little research on different Signal-to-noise Ratio (SNR) [8]. To annotate digital signals in different working environments, Gao et al. used fused CNN to extract features from complex working environments, and then used Gaussian weighting to accurately analyze the data. This study significantly improved the practical application performance of IBD signals [9]. To improve the data misclassification in industrial big data, Gu et al. combined DAEN with automatic denoising to construct a multi-module information classification model. The combination of two methods significantly improved the denoising performance of signal data. However, this study only analyzed industrial big data, which had certain limitations [10]. Khani and other researchers proposed an adaptive neural signal detection method that combines deep learning techniques and iterative soft thresholding algorithms to achieve signal detection in large-scale multi input multi output systems. This method can utilize the temporal and spectral correlations in real channels to accelerate training. The results show that the adaptive neural signal detection method reduces the computational complexity of large-scale multi input multi output systems by 10 times [11]. Jinno and other scholars proposed the use of ultra flexible optical devices for biological signal collection in order to achieve stable and continuous biological signal detection. They designed an ultra flexible self powered organic optical system for monitoring photoplethysmography, and the results showed that the system could maintain 70% of its initial brightness after working in air for 11.3 h [12].

Yan innovatively integrated backpropagation networks with CNN to construct an improved CNN to enhance signal transmission and anti-interference performance in wireless communication. Through continuous training and recognition optimization, this model significantly improved its convergence speed. This meant that the model provided accurate results more quickly when processing large amounts of data. The accuracy of signal recognition was significantly improved [13]. Chen et al. conducted in-depth research on the detection and analysis performance of linear frequency modulation signals. This study utilized fractional Fourier transform to aggregate and classify signals, effectively solving complex problems in signal recognition. Through simulation experiments, using CNN to classify signals significantly improved the detection and processing capabilities of linear frequency modulation signals. This brought new breakthroughs to signal processing technology [14]. In addition, Latha et al. used CNN to construct a recognition specific network architecture, which improved recognition efficiency by simplifying digital signals in two-dimensional images. This study not only improved the accuracy of digital signal recognition, but also showed significant improvements in noise cancellation and data recognition performance. This injected new vitality into the digital signal recognition for two-dimensional images, promoting rapid development in this field [15]. Wang’s research team proposed a method of using convolutional neural networks combined with wavelet transform for radar system design in order to improve signal recognition accuracy in complex electromagnetic environments. This method utilizes wavelet transform and deep learning techniques for signal preprocessing analysis, and designs an optimized convolutional neural network for feature fusion processing at the decision layer. The results show that the radar system designed by this method effectively improves recognition performance in complex electromagnetic environments [16]. Researchers such as Yıldırım et al. proposed a new deep one-dimensional convolutional neural network model to improve the detection accuracy of abnormal EEG signals. The model utilizes a complete end-to-end structure to classify EEG signals without any feature extraction. The results show that the model effectively reduces the classification error rate of abnormal EEG signals [17].

In summary, digital signal detection in communication plays an important role in communication. Numerous scholars have achieved significant results in digital signal detection and classification in this field. However, further research is needed on the adaptability of different SNRs, working environments, or signal types. Therefore, this study innovatively integrates DAEN and CNN to construct a digital signal data detection and classification model. This model can fully utilize the advantages of both networks to enhance the data monitoring ability in digital signal detection and classification. This can provide strong guarantees for the stable operation of the communication system.

3. Construction of a digital signal detection and recognition model combining DAEN and CNN

Firstly, this study utilizes DAEN to extract data features to improve DSDR. Then, based on feature extraction, DAEN and CNN were fused to construct a DSDR model to improve the digital signal detection and classification in communication.

3.1. Signal data feature extraction based on DAEN

In digital signal detection in communication, digital signals contain rich information, which is often hidden within complex signal structures. Therefore, effective extraction of these hidden information is necessary to obtain sufficient data features for data detection and classification. DAEN can extract the inherent patterns and features of digital signals layer by layer. In communication, DAEN can deeply explore the features in these signals and transform them into more easily processed and classified forms [18,19]. Before conducting digital signal feature extraction, this study first requires pre-training, optimization, and other processing of the digital signal to improve the accuracy of digital signal feature extraction. The main purpose of digital signal pre-training is to adjust and optimize the parameters and characteristics of the signal to better adapt to subsequent feature extraction. **Figure 1** shows the DAEN feature extraction model.

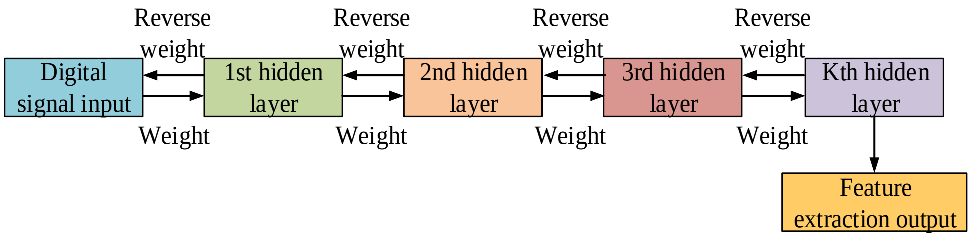


Figure 1. DAEN feature extraction model.

As shown in **Figure 1**, in the DAEN network feature extraction model, the digital signal is first input, and then processed through weight processing in the first hidden layer, second hidden layer, and third hidden layer, finally reaching the *K*-th hidden layer. Then reverse the weights from the *K*-th hidden layer and perform a reverse operation, and finally output the feature extraction. In DAEN, research is conducted on encoding and decoding digital signals. Encoding is the mapping of the encoder from the input vector to the hidden layer of the activation function, which can be defined by Equation (1).

$$h = S_f(Wx + p) \tag{1}$$

In Equation (1), h represents encoding mapping. The process of encoding mapping is the process of converting information from one form to a digital or binary form. S_f represents an activation function. Wx represents a matrix weight between the input and hidden layers of an input vector x. p represents a bias vector on a hidden layer. Decoding is the mapping of data from the hidden layer to the output layer, which can be defined by Equation (2).

$$y = S_g(\tilde{W}x + q) \tag{2}$$

In Equation (2), y represents decoding mapping. The process of decoding mapping is the process of converting digital or binary information back to its original form. S_g represents the mapping function. $\tilde{W}x$ represents the matrix weight value between the hidden and input layers of x. q represents the bias vector on the output layer. After completing the encoding and decoding operations, the digital signal parameters are labeled. By training the signal parameters during training, corresponding optimization results can be obtained. The optimal training parameters are used as the optimal solution for signal parameters, and decoding operations are used to decode the signal parameters. The decoding results are compared with the optimal parameters in terms of proximity, which can be expressed using Equation (3).

$$J(\theta) = \frac{1}{N}\sum_{x \in S} L(x(S_f(Wx + p)) \tag{3}$$

In Equation (3), $J(\theta)$ represents proximity. θ represents signal parameters. N represents the number of decoded information. L represents the decoding length. After completing the comparison of decoding proximity, this study used gradient descent method to further optimize and adjust the input and output layers to ensure the minimization of proximity values. By continuously iterating and updating parameters, the gradient descent method can gradually optimize the input and output layers of DAEN, achieving the minimum decoding proximity. **Figure 2** shows the flowchart of feature extraction and classification for DAEN data.

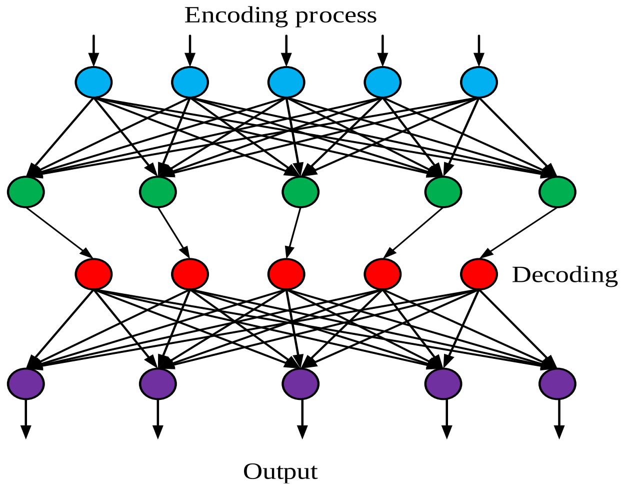


Figure 2. DAEN data feature extraction and classification flowchart.

As shown in **Figure 2**, in the data feature extraction and classification process of DAEN network, the autoencoder performs mapping encoding from the hidden layer to the output layer. After the autoencoder is trained, its output is used as the input of the next autoencoder for decoding operation. The next autoencoder is trained sequentially until the decoding proximity reaches the minimum value, and then its output is outputted. After obtaining the minimum value, wavelet transform can be used for feature extraction. When extracting features from digital signals, Fourier transform cannot analyze the frequency characteristics of local time-domain signals. This will affect the performance of digital signal analysis and cannot provide effective support for subsequent interference suppression or signal processing. Therefore, this study utilizes wavelet transform for feature extraction. Wavelet transform can change the shape of the window without changing its size, thus providing a time-frequency window that follows frequency changes. The wavelet transform is represented by Equation (4).

$$X(a,b) = \frac{1}{\sqrt{a}} \sum_{-\infty}^{+\infty} x(b-na)\psi(\frac{n}{a}) \tag{4}$$

In Equation (4), $X(a,b)$ represents the coefficient after wavelet transform. a represents the signal scale parameter. b represents the signal translation parameter. n represents the sample parameter value of signal data. ψ represents the frequency of wavelet transform. Wavelet transform can be used for multi-resolution analysis of signal data, and local features of the signal can be obtained during signal processing. When analyzing large-scale signal data, the overall characteristics of these signal data can also be obtained [20]. After obtaining signal data features through wavelet transform, the computational complexity of wavelet transform is relatively high, especially when dealing with large-scale signal data. This may require longer computation time and higher computing resources. Therefore, this study utilizes sparse theory to improve DAEN and reduce computational complexity. **Figure 3** shows the data feature extraction based on wavelet transform combined with sparse theory.

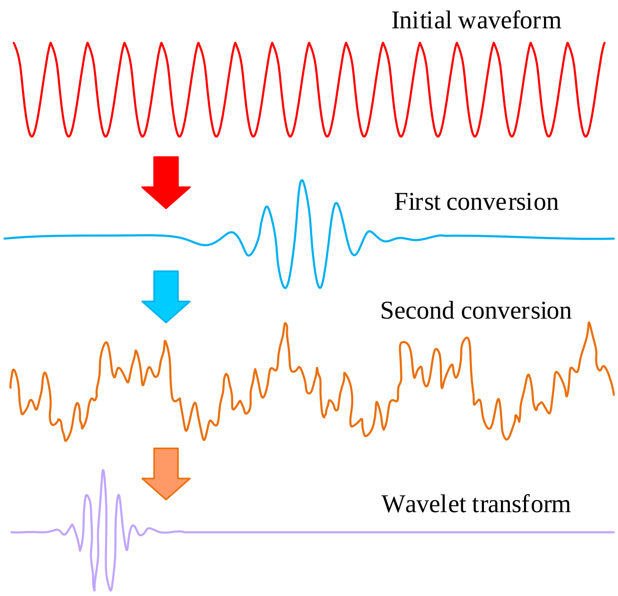


Figure 3. Flowchart of data feature extraction based on wavelet transform combined with sparse theory.

As shown in **Figure 3**, in the data feature extraction process based on wavelet transform combined with sparse theory, the signal data features are first subjected to initial deformation through wavelet transform, and then the signal sub bands of the first transformation decomposition are obtained. The second transformation uses sparse theory to achieve sparse representation of the signal, and finally useful feature information is extracted through wavelet transform. In the DAEN autoencoder, when the output value of the activation function approaches 1, it can be determined whether the network is in an active state. If the network is not active, it will affect the stability of feature extraction. Therefore, this study introduces sparse theory and defines the error function of DAEN, which can be represented by Equation (5).

$$J_{sparse}(\theta) = J_{ae}(\theta) + \beta \sum_{j=1}^{k} K(\rho|\hat{\rho}) \tag{5}$$

In Equation (5), $J_{sparse}(\theta)$ represents the error function. $J_{ae}(\theta)$ represents sparse penalty term. β represents the sparsity coefficient. K represents sparse dispersion value. ρ represents sparse parameters. $\hat{\rho}$ represents the probability of variable activation in the j-th hidden layer. The sparse processing of DAEN can obtain a sparse representation of the hidden layer, thereby reducing the computational complexity in the feature extraction and improving the efficiency.

3.2. Design of detection and recognition model combining data features and CNN

After using DAEN to extract digital signal data features in communication, it is difficult for DAEN to quickly classify digital signal data in systems with high real-time requirements. Therefore, this study combines CNN with DAEN to construct a signal inspection and recognition model in communication. This is because CNN has strong local perception ability and parameter sharing characteristics, which can effectively extract local features of signals and reduce computational complexity. Through convolution operations, CNN can focus on local regions of the signal and learn key features within these regions. This enables CNN to more accurately capture the detailed information of signals when processing complex signals [21,22]. The digital signal features extracted by DAEN are converted into two-dimensional images through frequency conversion to obtain the types of digital signals. Then, CNN is used to classify and recognize the two-dimensional patterns of digital signals, thereby completing the classification and detection of digital signals in communication. The frequency obtained through DAEN is defined as the receiving signal, which can be defined using Equation (6).

$$r(t) = s(t) + n(t) \tag{6}$$

In Equation (6), $r(t)$ represents the receiving signal. $s(t)$ represents the modulated signal processed by DAEN. $n(t)$ represents the type of channel. t represents the time-frequency variable. After completing the definition of the receiving signal, it is necessary to perform time-frequency processing on the generated two-dimensional graphics. The purpose of time-frequency processing is to combine the time-domain and frequency-domain of two-dimensional images to quickly find the changing patterns of the signals that need to be classified. When converting digital signals into two-dimensional images, research is conducted on two time-frequency distributions: the smooth pseudo Wigner Willie distribution and the Born Jordan distribution. That is, digital signals are effectively converted into two-dimensional images through these two time-frequency distributions. The smoothed pseudo Wigner-Ville distribution belongs to the Cohen distribution and the time-frequency distribution of cross suppression, which can be expressed by Equation (7).

$$x(t) = r(t) + \xi H[r(t)] \tag{7}$$

In Equation (7), $x(t)$ represents the analytical definition of the receiving frequency domain. ξ represents the windowing coefficient. $H[\cdot]$ represents Hilbert transform. The Hilbert transform can be represented by Equation (8).

$$H[r(t)] = \frac{1}{\pi t} \otimes r(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{8}$$

In Equation (8), $\otimes$ represents network convolution operation. ι represents a variable. d represents the Hilbert conversion coefficient. The time-frequency conversion of the Born Jordan distribution can be represented by Equation (9).

$$BJD(t,f) = \int \left[\int_{v} \phi(t-v,\tau) x(v+\tau/2) \right] ed\tau \tag{9}$$

In Equation (9), $BJD(t,f)$ represents the time-frequency conversion of the Born Jordan distribution. f represents the time-frequency coefficient. v represents the time-frequency width. e represents the time-frequency conversion coefficient. **Figure 4** shows the time-frequency signal conversion of the smoothed pseudo Wigner-Ville distribution and Born Jordan distribution.

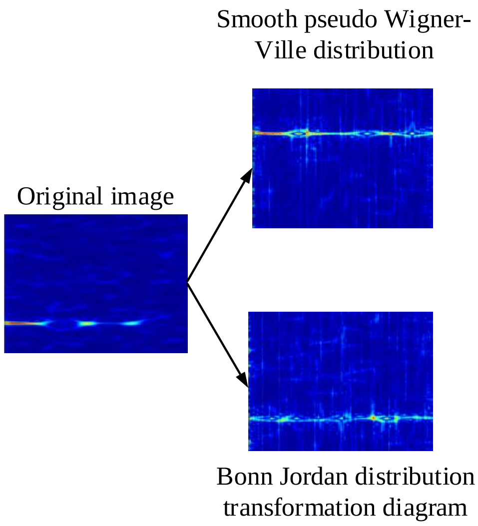


Figure 4. Signal spectra after converting two types of time-frequency signals.

In **Figure 4**, two time-frequency signal conversion methods, the smoothed pseudo Wigner Willie distribution and the Born Jordan distribution, convert the original image into two different two-dimensional images using signal modulation. After completing the conversion of two-dimensional images using two types of time-frequency, feature extraction of two-dimensional images can be carried out. The characteristics of two-dimensional images are the main basis for the accuracy of data signal recognition. This study analyzed relevant feature extraction techniques and selected zero center normalized instantaneous features as the feature extraction method. To calculate instantaneous characteristics, it is necessary to calculate the normalized instantaneous amplitude of the zero center, which can be represented by

Equation (10).

$$a_{cn}(i) = \frac{a_n(i)}{m_a} - 1 \tag{10}$$

In Equation (10), $a_{cn}(i)$ represents the normalized instantaneous amplitude at the zero center. m_a represents the average instantaneous amplitude. $a_n(i)$ represents instantaneous amplitude. After calculating the instantaneous amplitude, one month's instantaneous characteristics can be calculated using Equation (11).

$$\gamma \frac{max|[a_{cn}(i)]|^2}{N_s}_{max} \tag{11}$$

In Equation (11), γ_{max} represents the maximum value of the normalized instantaneous feature at the zero center. N_s represents the quantity of sampling points during feature extraction. After completing feature extraction, it is necessary to perform feature fusion on the data, which can concatenate the 2D image features under different modes. By concatenating feature images from different modes for feature fusion, the overall detection and classification performance can be improved [23,24]. When performing feature fusion, there are certain differences in feature labels under different modes. To ensure the consistency of feature fusion, the study uses relative entropy divergence to measure the difference in probability distribution between adjacent features, represented by Equation (12).

$$KL(u \mid w) = -\sum_{k=1}^{K} u_k \ln w_k \tag{12}$$

In Equation (12), $KL(u \mid w)$ represents the measure of relative entropy divergence. u and w represent the discrete probability distribution values of two feature images with the same length, respectively. After completing signal feature fusion, digital signal data detection and recognition operations can be carried out. When detecting and recognizing signals, this study optimizes the calculation of digital signal data detection and recognition using the Lagrange multiplier method. The detection function is minimized using this method, and the minimum value is used as the result of detection and recognition. This process can be represented by Equation (13).

$$p(k) = \frac{\sqrt{\prod mp_{\theta^m}(k)}}{\sum_j^k \sqrt{\prod mp_{\theta^m}(j)}} \tag{13}$$

Based on the analysis of the above content, a digital signal data detection and classification model is constructed by combining CNN and DAEN in **Figure 5**.

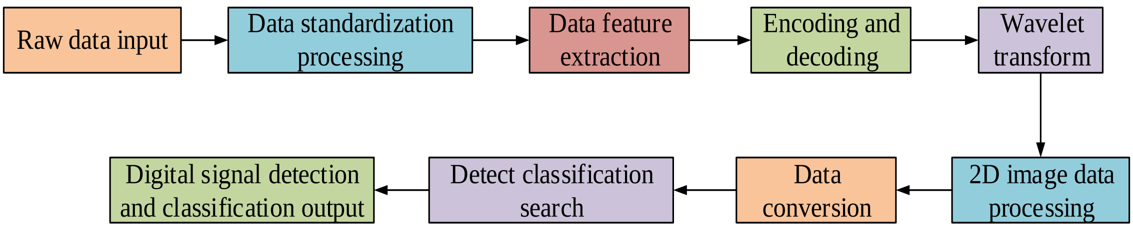


Figure 5. Construction flowchart of signal data detection and classification model combining CNN and DAEN.

As shown in **Figure 5**, in the construction process of the signal data detection and classification model combining CNN network and DAEN network, after inputting the raw data, the data is standardized, then the data features are extracted, followed by encoding and decoding, and then wavelet transform operation is performed. After obtaining the two-dimensional image data, data conversion is carried out, followed by detection and classification search, and finally the digital signal detection and classification output are detected and classified. Based on **Figure 5**, in digital signal detection, DAEN and CNN are used for data feature extraction and detection classification. Through layer by layer learning, DAEN mines and extracts the inherent rules and features in digital signals, transforming them into a more easily processed and classified form. CNN can further extract and compress key features in signals through convolution and pooling operations, thereby completing data detection and classification.

4. Performance analysis of a digital signal data detection model combining DAEN and CNN

This experiment validated the digital signal data detection and classification model constructed by combining DAEN and CNN in communication. This study used the model loss value, misclassification rate, recognition results, average classification accuracy, data processing accuracy, recall rate, etc. under the same gradient as validation indicators. Simultaneously, Artificial Neural Network (ANN) and Bidirectional Encoder Representation from Transformers (BERT), one of the most advanced self supervised learning models, will be used as comparative models for performance analysis and validation.

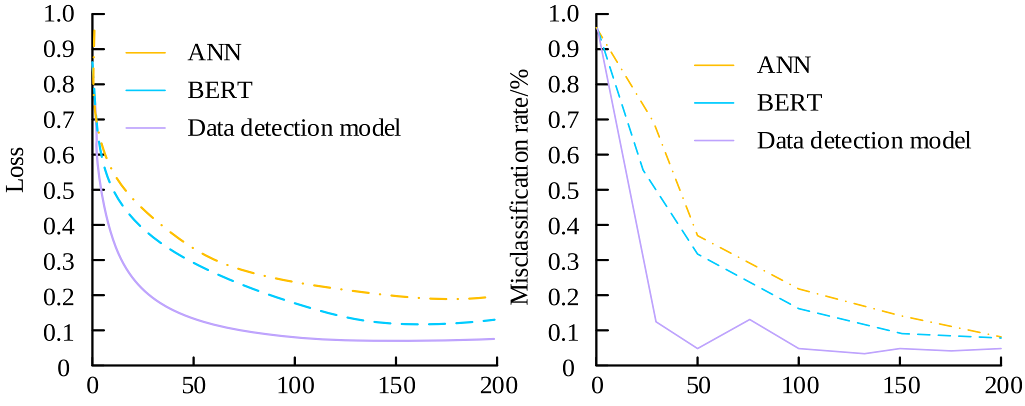
4.1. Data processing performance analysis of digital signal detection and classification models

This study set the SNR of the data signal used for detecting classification to −5~5 dB to verify the digital signal detection classification model. A total of 1269 two-dimensional images of digital signal detection in communication were collected, which were used as a dataset for performance testing. **Table 1** shows the other supporting facilities for the experiment.

Table 1. Experimental parameters.

Parameter items	Parameters
CPU	Intel Core i5-10700K, 3.8 GHz
RAM	16 GB
Operating system	Win7
Graphics card	NVIDIA GeForce RTX 3080, 10 GB GDDR6X
Memory	1TB
Source	750 W 80 + Gold
Cooling system	NZXT Kraken X63 Water-cooled radiator
Visual chunking area size	256*256*224
Resolving power	300*500

This study compared the performance of three models in the same iterative experiment to verify the data processing performance of the digital signal detection classification model. This study used iterative loss value and misclassification rate as comparison indicators. **Figure 6** shows the comparison results.

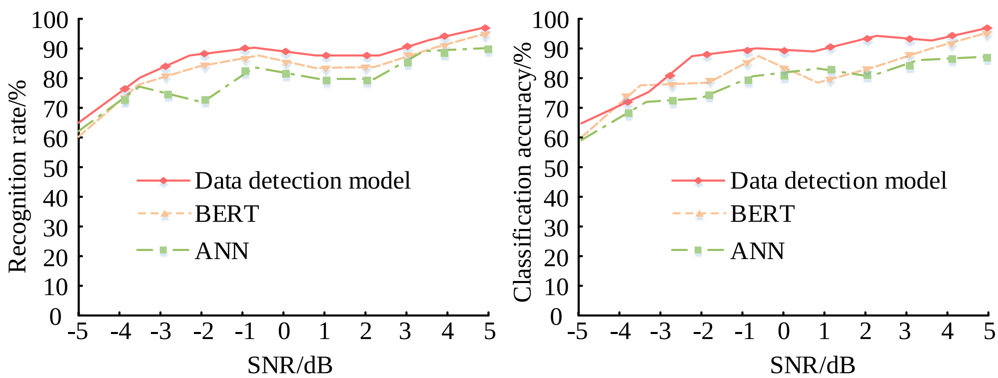


(a) Comparison results of training loss values for three models

(b) Comparison results of misclassification among three models

Figure 6. Comparison results of loss values and misclassification rates of three models.

In **Figure 6a**, the loss value of the signal data detection classification model first tended to stabilize, which tended to stabilize after 95 iterations. The loss values of ANN and BERT tended to stabilize when iterating 139 and 157 times, respectively, in data training. In **Figure 6b**, the error of the signal data detection classification model significantly decreased when iterated to 8 times, and tended to 0 when iterated to 15 times. The misclassification rates of ANN and BERT in data training tended to stabilize after 26 and 39 iterations, respectively, but did not approach 0. This indicated that the signal data detection and classification model constructed had higher robustness during the data training process. Meanwhile, the misclassification rate was significantly reduced, which greatly improved the recognition ability of digital signals.

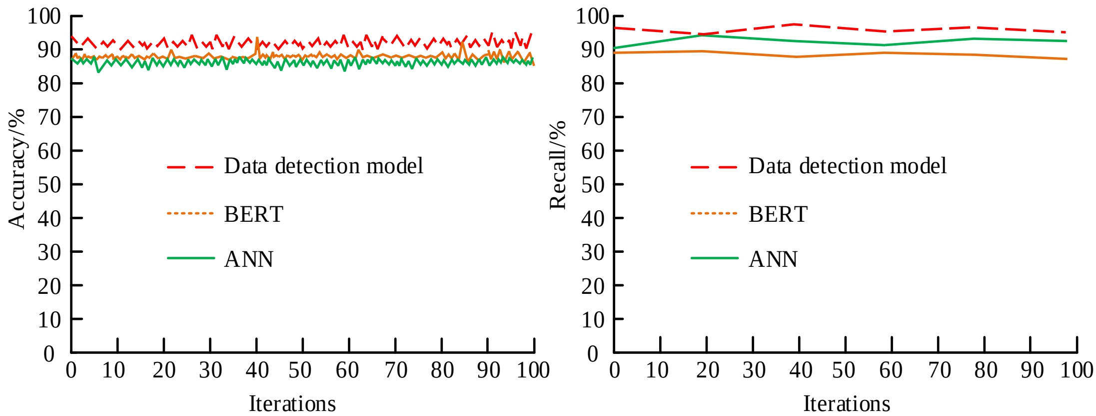


(a) The recognition rates of three models under different SNRs

(b) Classification accuracy of three models at different SNRs

Figure 7. Comparison of classification accuracy of three models under different gradients and signal-to-noise ratios.

Figure 7 shows the comparison results of classification accuracy of three models under different gradients and SNRs. In **Figure 7a**, the average recognition rate of the signal data detection classification model was 93.75%, while the average recognition rates of ANN and BERT were 85.13% and 89.81%, respectively. In **Figure 7b**, the average classification accuracy values of the signal data detection and recognition model, BERT and ANN were 94.18%, 90.05%, and 87.92%, respectively. These indicated that the signal data detection and recognition model constructed had more accurate classification ability in different gradients and SNRs, which improved the reliability of signal data classification.



(a) Comparison results of signal data processing accuracy among three models

(b) Comparison of recall rates for signal data processing of three models

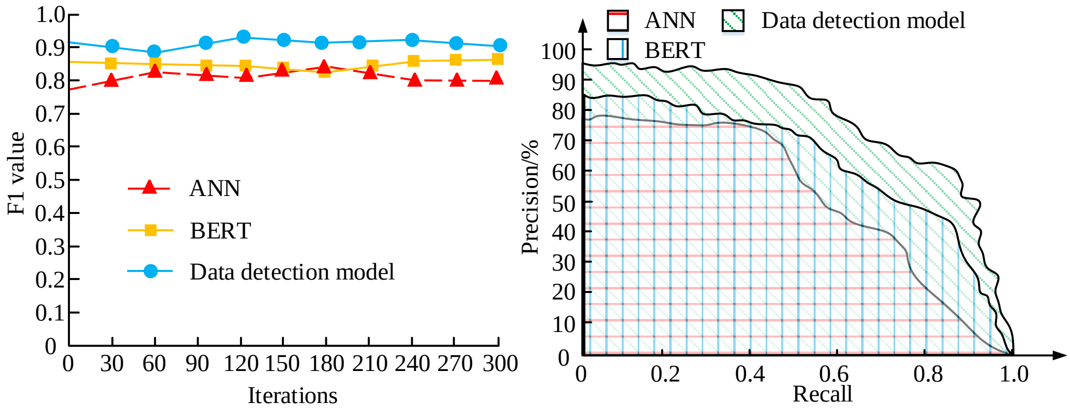
Figure 8. Comparison results of accuracy and recall of three models in signal data processing.

Figure 8 shows the comparison results of accuracy and recall of three models in digital signal data processing in communication. In **Figure 8a**, the average data processing accuracy of the signal data detection classification model was 93.59%, and the average data processing accuracy of ANN and BERT was 87.03% and 89.66%, respectively. In **Figure 8b**, the average data processing recall of the signal data detection classification model was 94.67%, and the average data processing recall of ANN and BERT was 86.53% and 88.16%, respectively. This indicated that in signal data processing, this constructed model provided better processing capabilities.

4.2. Application performance analysis of detection classification model

This study used F1 and AUC values in signal detection classification as validation indicators for validating the application performance of digital signal detection classification models.

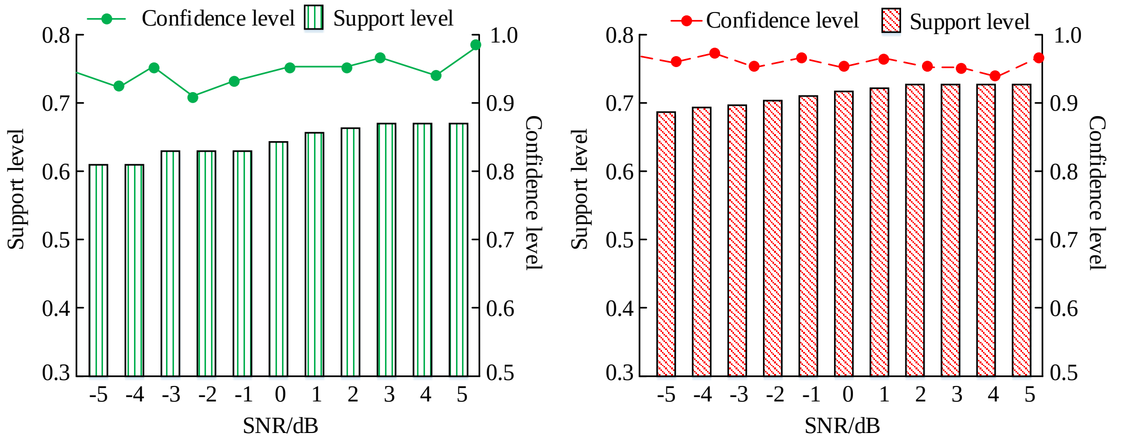
Figure 9 shows the comparison results of AUC and F1 values for three models in digital signal data classification in communication. In **Figure 9a**, there was a certain difference in F1 values among these three models. The F1 value of the data detection model was 0.92, while the F1 values of BERT and ANN were 0.87 and 0.83, respectively. In **Figure 9b**, the AUC value of the data detection model was 0.93, while the F1 values of BERT and ANN were 0.89 and 0.85, respectively. This indicated that this data detection model had higher classification accuracy and performance in digital signal data classification in communication.



(a) Comparison results of F1 values in signal classification of three models

(b) Comparison results of AUC values in signal classification of three models

Figure 9. Comparison results of AUC and F1 values of three models in signal data classification process.



(a) Data detection classification model detection support and confidence

(b) Data support and confidence true values

Figure 10. Comparison results of confidence and support between predicted and true values of data detection classification models..

Figure 10 shows the comparison of confidence and support between the predicted and true values of the data detection classification model. In **Figure 10a**, the average confidence was 0.68. The average support for monitoring classification of predictive model data was 0.94. In **Figure 10b**, the average values of confidence and support were 0.72 and 0.97, respectively, with a difference of 0.04 and 0.03 between the predicted model and the true values. This indicated that the constructed detection model had high feasibility in data detection and classification. To further verify the classification detection model, accuracy and true detection classification comparisons were conducted in the training and testing sets in **Table 2**.

In **Table 2**, when the sample size was 100 in the training set, the detection classification accuracy was 89.81%. When the sample size increased to 250, the accuracy improved to 92.84%. This indicated that the model gradually learned more effective features during training, improving classification performance. In the test set, when the sample size was 100, the detection classification accuracy was 87.69%. When the sample size increased to 250, the accuracy improved to 90.33%. This indicated that this model also had a certain generalization ability on the test set, but its performance slightly decreased compared to the training set. Although there was a certain gap between the accuracy of the predicted values and the true values, its overall detection and classification performance still had high applicability.

Table 2. Comparison results of classification detection accuracy between predicted values and true values in the training and testing sets.

Method	Training set	Detection classification accuracy/%	Test set	Detection classification accuracy/%
Data detection classification model prediction value	100	89.81	100	87.69
	150	90.08	150	88.63
	200	91.26	200	89.04
	250	92.84	250	90.33
True value	100	91.66	100	89.31
	150	92.18	150	89.95
	200	93.57	200	90.76
	250	94.05	250	91.37

5. Conclusion

In response to the low adaptability and high misclassification rate of DSDR in communication, a DSDR model was constructed by combining DAEN and CNN. Through simulation experiments, the F1 and AUC values of the data detection model were 0.92 and 0.93, respectively. The average confidence and support values of the DSDR model were 0.68 and 0.94, respectively. When the sample size increased to 250, the accuracy improved to 92.84%. This indicated that the DSDR model reduced computational complexity, shortened processing time, and achieved accurate classification and recognition of digital signals while ensuring performance. This greatly improved the accuracy and efficiency of detection and recognition, meeting the requirements of real-time and efficiency. In summary, significant research results are achieved in the study of DSDR in the communication between DAEN and CNN. This model not only improves the accuracy and efficiency of DSDR, but also brings new ideas and directions for the development of communication. This study achieves significant detection and classification results to a certain extent, but there are still some shortcomings. There have not been many experiments conducted in the presence of interference in digital signals. This will to some extent constrain the applicability of the detection classification model. The next step is to introduce interference recognition algorithms to enhance the anti-interference ability of the DSDR model.

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