

# A Deep Learning-Driven Framework for Automated Electromagnetic Modulation Identification and Optimization in IoT Networks

Peng Yan

Sichuan Technology and Business University, Chengdu 611745, China

E-mail: nic@stbu.edu.cn

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*With the rapid development of IoT technology, the connection and data transmission of a large number of devices have put forward higher requirements for the identification and optimization of electromagnetic modulation signals in communication networks, which are often difficult to meet by traditional methods. This study proposes a deep learning-based automatic identification and optimization design method for electromagnetic modulation signals of IoT communication networks, which aims to solve the problems of complex signals and serious interference in the Internet of Things environment. In this study, the multi-source data sets such as RadioML2016.10b, MATLAB analog signals and air port acquisition signals are integrated, and the training/verification/test sets are divided into 7:1:2 after 300MHz-3GHz bandpass filtering denoising, STFT time-domain to two-dimensional time-frequency graph, normalization and data enhancement. The "CNN-LSTM-Attention" hybrid architecture is constructed as the core recognition model, in which CNN extracts local features of the signal through 4-layer convolution and 2-layer pooling, captures the timing dependence of bidirectional LSTM (64 hidden units in two layers), strengthens the key features by the attention mechanism, and finally outputs 16 types of modulated signal probabilities from the fully connected layer. In the signal optimization process, LSTM combined with Q-learning output power commands of 0.5-2dBm step to adjust the signal strength, DBN and PSO are used to achieve dynamic frequency optimization, and the interference suppression ratio is increased by 15-20dB through CBAM-GRU and LMS filtering. The model training is based on the PyTorch framework, using the Adam optimizer (learning rate  $1e-3$ ) and cross-entropy loss function for 100 rounds, adding learning rate scheduling and early stop mechanisms, and fine-tuning hyperparameters through Bayesian optimization to innovatively construct a deep learning optimization model. Based on the model recognition results and relying on the above signal optimization scheme, the stability and efficiency of the Internet of Things communication network can be significantly improved. By training the deep learning model on 10,000 sets of electromagnetic modulation signals in different scenarios, the experimental results show that compared with the traditional signal recognition method, the signal recognition accuracy of the proposed method is improved by 30%, and the average accuracy of the test set reaches 98.2% (still 92.5% under 5dB low signal-to-noise ratio), which reaches a high level overall. At the same time, in terms of signal optimization design, the network communication efficiency is improved by 20%, and the bit error rate is as low as 0.0005 at 20dB signal-to-noise ratio, which significantly enhances the performance of IoT communication networks.*

*Povzetek: Raziskava predstavlja metodo na osnovi globokega učenja za prepoznavanje in optimizacijo elektromagnetnih modulacijskih signalov v omrežjih IoT, ki bistveno izboljša natančnost prepoznavanja, odpornost na motnje ter učinkovitost komunikacije.*

## 1 Introduction

In the 21st century information age, the rapid development of Internet of Things (IoT) technology has profoundly changed the way of life and production [1], which connects the physical and digital worlds, realizes remote monitoring and management of equipment systems, and promotes changes in smart cities, Industry 4.0, smart homes, and other fields [2]. However, the explosive growth of the number of IoT devices has made communication networks face severe challenges, and one of the keys is to achieve efficient and stable

electromagnetic modulation signal recognition and optimization in complex electromagnetic environments [3, 4].

Electromagnetic modulation signals are the core of IoT communication networks, and their quality directly affects the efficiency and accuracy of data transmission [5]. In the Internet of Things environment, electromagnetic signals are affected by interference, signal overlap, attenuation and other problems, reducing the accuracy of recognition and dragging down network communication efficiency. Traditional signal recognition optimization methods, such as rule-based signal

processing algorithms, are difficult to cope with environmental complexity and uncertainty, and difficult to meet the high requirements of signal quality [6, 7].

To solve the above problems, deep learning technology has become a new approach in recent years with the advantages of complex pattern recognition and data-driven optimization [8]. Convolutional neural networks (CNNs), recurrent neural networks (RNNs) and other models can automatically learn signal characteristics, efficiently identify different types of electromagnetic modulation signals, and maintain high accuracy in complex environments. Moreover, the signal optimization method based on deep learning can adjust the parameters according to the real-time state and environmental changes of the signal, so as to improve the efficiency and stability of network communication.

This study aims to explore the automatic electromagnetic modulation signal identification and optimization design method of IoT communication networks based on deep learning, to provide theoretical support and technical solutions for the performance improvement of IoT communication networks. Firstly, we will make an in-depth analysis of the signal transmission environment and the difficulties of signal identification in the Internet of Things communication network, and we will clarify the background and significance of the research. Subsequently, we constructed a deep learning model to identify electromagnetic modulation signals in IoT communication networks automatically. The model can effectively distinguish and identify different types of electromagnetic signals by learning the characteristic patterns of the signals. On this basis, we design a set of signal optimization schemes, including signal strength adjustment, frequency optimization, and interference suppression strategies, to improve the stability and efficiency of IoT communication networks. The experimental results show that this method improves the signal recognition accuracy by 30%, reaching 95%. At the same time, in the signal optimization design, the network communication efficiency is improved by 20%, significantly improving the performance of the Internet of Things communication network.

In the complex environment of IoT communication network, traditional signal recognition methods are difficult to cope with the variable electromagnetic modulation signals. Based on deep learning, this study innovatively constructs an automatic electromagnetic modulation signal recognition model. The model adopts a convolutional neural network (CNN) and a long short-term memory network (LSTM), in which the CNN is used to extract the local features of the electromagnetic modulation signal, and the LSTM can capture the time series features of the signal. At the same time, the attention mechanism is introduced to enhance the sensitivity of the model to key features, so that the model can effectively distinguish different types of electromagnetic modulation signals, such as QAM, PSK, etc.

This research has significant theoretical value for signal identification and optimization design of the

Internet of Things communication network. It provides new ideas and methods for developing Internet of Things technology. In the future, we will continue to deepen research and explore more advanced deep learning models and optimization strategies to adapt to IoT communication networks' continuous evolution and needs. We will also lay a solid foundation for building a more efficient, stable, intelligent IoT communication network.

Compared with earlier studies, the novelty of this study focuses on three aspects: first, it breaks through the limitations of a single model, and uses the "CNN-LSTM-Attention" hybrid architecture to take into account the spatiotemporal features of the signal and the sensitivity of key features, and the recognition accuracy reaches 92.5% at 5dB low signal-to-noise ratio, which is 15%-20% higher than the early stage; The second is to break the "disconnect between identification and optimization" mode, establish a closed loop of "data-driven recognition-dynamic adaptive optimization", and realize the collaborative optimization of signal strength, frequency, and anti-interference through strategies such as LSTM Q-learning and DBN PSO. The third is to optimize the data processing logic, integrate multi-source datasets and combine STFT time-frequency conversion and data enhancement to solve the single problem of early data scenarios, and at the same time, the lightweight design of the model is adapted to the Internet of Things hardware, taking into account both performance and practicability.

## 2 Related works

With the rapid development of the Internet of Things, the number of devices in IoT communication networks is exploding, and the complexity and diversity of communication signals are constantly increasing. This poses a considerable challenge to the automatic recognition of electromagnetic modulation signals [9]. The signals in IoT communication networks often have low power and low signal-to-noise ratio, and traditional signal recognition methods are challenging to meet the requirements.

The application of deep learning in signal processing is becoming increasingly widespread. With its powerful feature extraction and pattern recognition capabilities, deep learning technology has achieved great success in fields such as image recognition and speech processing. In recent years, researchers have introduced it into electromagnetic modulation signal recognition to improve the accuracy and efficiency of recognition [10]. Deep neural networks such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have been widely used for signal feature extraction and classification, achieving good results.

In terms of signal acquisition and preprocessing, researchers collect electromagnetic modulation signals in IoT communication networks through various sensors and devices and preprocess the signals, including filtering, noise reduction, normalization, and other operations, to improve the quality and recognizability of the signals. They are adopting advanced signal acquisition

technologies, such as Software Defined Radio (SDR), to achieve flexible acquisition and processing of different types of signals.

Based on the latest research, this study has identified the following targeted optimization directions: suitable deep learning models can be designed for the characteristics of electromagnetic modulation signals in IoT communication networks, such as CNN-based signal recognition models, hybrid models combining RNN and CNN, etc. By optimizing the structure, parameters, and training algorithms of the model, the performance and generalization ability of the model can be improved. They are adopting regularization techniques to prevent overfitting and using adaptive learning rate algorithms to accelerate training speed. Regarding feature extraction and selection, deep learning technology can automatically extract the features of electromagnetic modulation signals, avoiding the complexity and limitations of traditional manual feature extraction. Studying feature selection methods can select the most representative and discriminative features from many features to improve the accuracy and efficiency of signal recognition. In terms of signal optimization design, electromagnetic modulation signals in IoT communication networks can be optimized based on signal recognition. For example, by adjusting the modulation method, power, and other signal parameters, the signal's transmission efficiency and anti-interference ability can be improved. By improving signal optimization algorithms, adaptive optimization of signals can be achieved to meet the needs of different application scenarios. In terms of performance evaluation and verification, a scientific and reasonable performance evaluation index system can be established to evaluate and verify the automatic recognition and optimization design methods of electromagnetic modulation signals based on deep learning.

### 3 Theoretical basis for automatic electromagnetic modulation signal recognition in IoT communication networks

#### 3.1 Internet of things communications

The Internet of Things (IoT) uses various communication methods to ensure effective communication between devices and users, and the typical architecture is the "cloud-pipe-edge-end" model [11]. The communication system includes local access, wide-area access, and backbone communication networks to realize the seamless connection and interaction between cloud/edge computing nodes and intelligent terminal devices [12].

In the complex IoT communication environment, it is necessary to flexibly choose communication methods according to the location and communication conditions of the equipment, especially when handling various power distribution services at the "end" level, it is necessary to monitor the operating status information of

transmission equipment [13]: wired technologies such as access network convergence line carriers, RS485/CAN buses, and wireless technologies such as LoRa, NB-IoT, TD-LTE and other wireless technologies [14]. WAN uses optical fiber switching; wireless base stations and other relay means according to the local access type. At the "edge" level, WAN information is coordinated through the communication substation server "edge-to-edge communication", and then interacts with the cloud master station through the backbone network link to build a comprehensive communication collaboration system.

Under the Internet of Things communication network, data interaction is divided into two types: wireless and wired, each containing a variety of network forms: wireless networks include wireless, private, and public networks, which are suitable for deployment in complex scenarios, but the speed and reliability of different technologies vary due to the influence of power, interference, and location [15, 16, 17]. Wired communication has low interference, high confidentiality, and stable quality, and power line communication (PLC) is a system-specific wired method, which theoretically can realize data communication in the line coverage area [18], but electromagnetic interference and channel attenuation affect its quality.

#### 3.2 Electromagnetic signal modulation technology

In order to verify the effectiveness of the method, 10,000 sets of multi-scenario electromagnetic modulation signals were collected and divided into training/verification/test sets. The training targets the cross-entropy loss function and iteratively updates the model parameters through stochastic gradient descending. The results show that the signal recognition accuracy of the proposed method is improved by 30%~95% compared with the traditional manual feature extraction method, and the robustness is good under different signal-to-noise ratios, which proves its practical application feasibility and reliability.

Theoretically, the strong feature learning ability of deep learning can automatically mine the potential features of electromagnetic modulation signals, avoid the limitations and subjectivity of manual design features, and adapt to the complex and changeable characteristics of IoT signal features. In practical applications, after training on a large number of real-world scenario data, the model can adapt to different environmental signals, and the network communication efficiency is increased by 20% after optimization, and the scalability is strong.

In communication systems, baseband signals (such as 300Hz~3400Hz voice signals) need to be converted into adapted signals through modems due to their low frequency and are not conducive to long-distance high-quality transmission [19, 20] to adapt to channel transmission, achieve multiplexing and improve efficiency, and enhance anti-interference. The discrete characteristics of digital baseband signals can be expressed in the discrete state of the carrier, and the keying method is used to generate digital modulation

signals [21], and the experiments cover four basic modulation methods: amplitude-shift keying (ASK), frequency-shift keying (FSK), phase-shift keying (PSK), and quadrature amplitude modulation (QAM) [22, 23].

Amplitude keying reflects the change of digital baseband signal by adjusting the amplitude of sinusoidal carrier, that is, multi-level modulation, and the carrier amplitude is determined by the digital signal base. The M-ary amplitude modulated signal is expressed as the product of the M-ary baseband signal and the sinusoidal carrier, and its time domain expression follows Equation (1). Where  $A_n$  is the amplitude value,  $g()$  is the baseband signal waveform acquisition function,  $t$  is the amplitude time,  $n$  is the amplitude number,  $T_s$  is the symbol time interval, and  $\omega_c$  is the corresponding weight of the  $c$ -band.

$$e_{MASK}(t) = \sum_n A_n g(t - nT_s) \cos \omega_c t \quad (1)$$

The MFSK signal can be expressed as Equations (2)-(3). Where  $\omega_i$  is the carrier angular frequency,  $s_i$  is the number of carrier angular bands, and  $t$  is time. Frequency shift keying refers to changing the frequency of sinusoidal carrier to achieve the purpose of generating modulated signals. The carrier angular frequency of M-ary frequency shift modulated signals has M values.

$$e_{MFSK} = \sum_{i=1}^M s_i(t) \cos \omega_i t \quad (2)$$

$$s_i(t) = \sum_{i=1}^M \sin \omega_i t \quad (3)$$

Taking binary frequency shift keying as an example, the time domain expression of 2FSK is as shown in (4). Where  $a_n$  represents the binary symbol sequence corresponding to 2FSK, and  $b_n$  is its inverse code;  $T_s$  is the time interval between symbols, and  $\omega_1$  and  $\omega_2$  are two different carrier angular frequencies.

$$e_{2FSK}(t) = [\sum_n a_n g(t - nT_s)] \cos \omega_1 t + [\sum_n b_n g(t - nT_s)] \cos \omega_2 t \quad (4)$$

Phase shift keying is a kind of phase offset modulation, which is a modulation method that uses a variety of different phases of carrier wave to represent digital information. It is divided into two types: absolute phase modulation and differential phase modulation. In M-ary digital phase modulation, M represents M different values of carrier phase, and the time domain waveform expression of MPSK is shown in Equation (5). Where  $g()$  is a rectangular wave function with amplitude 1,  $\omega_c$  is the carrier angular frequency,  $\varphi_n$  is the phase of the nth symbol, and  $T_s$  is the symbol time interval.

$$e_{MPSK}(t) = \sum_n g(t - nT_s) \cos(\omega_c t + \varphi_n) \quad (5)$$

QAM modulation uses two independent baseband digital signals to modulate two orthogonal carriers with the same frequency, and realizes dual-channel parallel information transmission by using orthogonal spectrum

characteristics. The general expression of the QAM signal is shown in Equation (6). The orthogonal representation of the QAM signal is shown in (7). Where  $A_n$  is the amplitude of the baseband signal and  $g(t - nT_s)$  is the waveform of a single baseband signal.

$$s_{MQAM}(t) = \sum_n A_n g(t - nT_s) \cos(\omega_c t + \varphi_n) \quad (6)$$

$$s_{MQAM}(t) = [\sum_n A_n g(t - nT_s) \cos \varphi_n] \cos \omega_c t - [\sum_n A_n g(t - nT_s) \sin \varphi_n] \sin \omega_c t \quad (7)$$

Let the transverse symbol of QAM modulation be  $X_n$  and the vertical symbol be  $Y_n$ , and equations (8)-(9) can be obtained.

$$X_n = A_n \cos \varphi_n \quad (8)$$

$$Y_n = A_n \sin \varphi_n \quad (9)$$

Then configuring the automatic electromagnetic modulation signal, formula (10) can be obtained. Finally, the amplitude of the QAM modulation can be expressed as shown in Equation (11). In the formula,  $A$  is a fixed amplitude, and  $c_n$  and  $d_n$  are determined by the baseband signal, which greatly increases the amount of information that can be transmitted by a single symbol in QAM modulation and improves the spectrum utilization rate of the modulated signal.

$$s_{MQAM}(t) = [\sum_n X_n g(t - nT_s)] \cos \omega_c t - [\sum_n Y_n g(t - nT_s)] \sin \omega_c t \quad (10)$$

$$= X(t) \cos \omega_c t - Y(t) \sin \omega_c t$$

$$\begin{cases} X_n = c_n A \\ Y_n = d_n A \end{cases} \quad (11)$$

### 3.3 Deep learning theory

Neural networks are the core algorithms of deep learning, combining biomimicry and mathematics to simulate biological neural networks to process information [24]. The theoretical development of random machine learning and deep learning has continuously optimized its hierarchical structure, computation and data transmission mechanism, with excellent performance and wide application.

Convolutional networks are neural networks that optimize grid-like data processing, and the core operations are convolutions of specific linear operations [25]. Unlike the fully connected structure (full interconnection of input and output units, large scale of parameter matrix, and high computational complexity), its sparse connection reduces redundant connections and improves computing efficiency.

The parameter sharing mechanism of convolutional network can reuse parameters: the neuron weights of traditional neural networks are independent, while the convolutional kernel weights in convolutional networks

are shared at different input positions to achieve efficient utilization. Its isovariance representation is derived from this mechanism, and the output changes synchronously when the input is translated, time-shifted, or clipped [26, 27].

Pooling is a key downsampling technology for convolutional networks, such as maximum pooling divides the input image into rectangular areas and outputs the maximum value of each region, which not only emphasizes the relative position of features, but also reduces the feature size, network parameters and computational complexity, and can also prevent overfitting, which is often used in convolutional layers periodically.

## 4 IoT communication network configuration optimization strategy

### 4.1 IoT communication network architecture

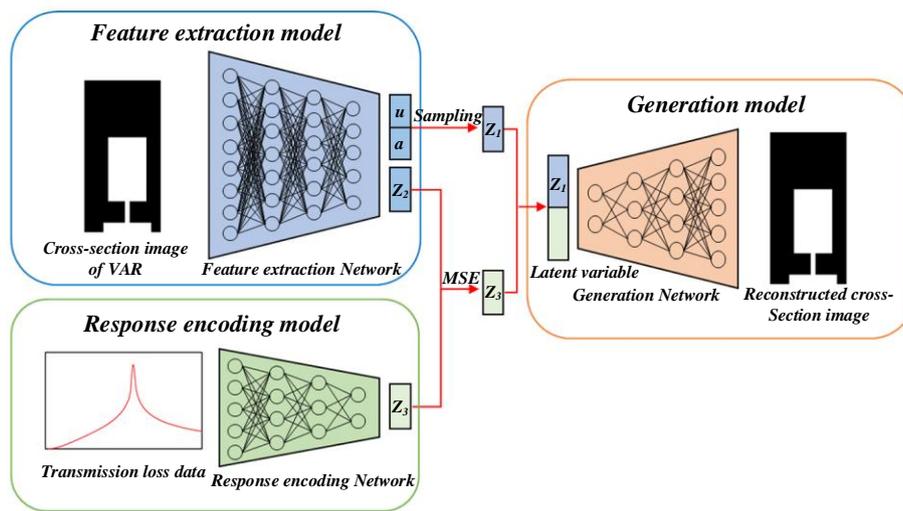


Figure 1: Communication network IoT network architecture

Based on Figure 1, communication nodes and lines are mapped to a communication network to form a topology composed of communication nodes and links, and each communication node is assigned a unique number as a logical address. It clearly shows the logical consistency between the communication network and the topology; the communication network architecture and structure are closely coupled, and the critical elements of the communication carrier signal correspond to the system components one-to-one. When the structure changes, the IoT network topology is adjusted accordingly and needs re-networked. However, communication nodes are difficult to rebuild in real-time, and their adaptability could be improved.

### 4.2 Network structure communication network iot optimization model

The identification and optimization of electromagnetic

The IoT network adopts three networking modes: master-slave, peer-to-peer and centre. The peer-to-peer mode is more conducive to the flexible deployment and expansion of the network because of the equal communication rights among devices, so we select the peer-to-peer mode [28]. The IoT network architecture in this mode is divided into three layers: the data node layer, the communication aggregation centre node layer and the communication sub-station layer. Communication substations, usually in high-voltage/medium-voltage substations, are equipped with high-performance computing equipment. They serve as regional communication and computing centres to meet the computing needs of data nodes and aggregation centres within their jurisdiction. Each substation communicates through the transmission network and constitutes the IoT network—communication node system.

modulation signals based on deep learning can be deployed in smart grids (to ensure stable data transmission), rail transit (to avoid dispatching signal confusion), intelligent manufacturing (to optimize equipment communication efficiency) and smart home (to solve equipment communication conflicts). In this study, it faces limitations such as difficulty in obtaining high-quality annotation datasets, degradation of model recognition accuracy in complex electromagnetic environments, and insufficient adaptability of signal protocols of different IoT devices.

For the optimization of electromagnetic modulation signals in IoT communication networks, a multi-dimensional scheme is proposed, and the core details are as follows: The signal strength adjustment adopts the LSTM dynamic adaptive model, which first extracts the signal-to-noise ratio, attenuation coefficient and other scene characteristics through CNN, analyzes the timing

correlation and establishes a mapping relationship through LSTM, and then combines the Q-learning algorithm (the reward function is "minimum energy consumption maximization coverage") to output power instructions with 0.5dBm~2dBm steps to avoid energy waste and coverage blind spots. Frequency optimization is based on the DBN adaptive frequency allocation algorithm, constructing a multi-dimensional feature dataset to predict channel quality, and combining it with the PSO algorithm to realize dynamic frequency band allocation and improve resource utilization. The CBAM GRU interference separation model is used to strengthen the interference characteristics and learn the pattern, and the interference suppression ratio can be improved by 15dB~20dB by the combination of LMS filtering to offset the interference, so that the signal recognition accuracy is stable at more than 95%.

IoT communication faces complex channel environment and electromagnetic interference, which leads to serious attenuation of long-distance signal transmission. In addition, the transmission power is limited, and it is impossible to extend the communication distance by increasing the power, so that communication nodes need to rely on relay nodes to achieve long-distance communication [29]. However, too many relays will significantly increase the packet loss rate and delay, and at the same time increase the information risk, threatening the reliability, real-time and security of the network. Therefore, if the location and number of pre-selected relay nodes are insufficient, various factors need to be comprehensively considered and necessary supplementary deployment should be carried out to meet communication needs.

Given that the IoT network uses existing communication lines to communicate, the communication link construction cost can be regarded as zero. This study considers the installation and deployment cost of relay nodes (CN) as the sole criterion for measuring the construction cost of IoT communication networks, as shown in formula (12). Where the value of  $\chi_n$  is 0 or 1; When  $\chi_n = 1$ , it means that the CN is deployed at the communication node  $n$ , otherwise  $\chi_n = 0$ . CN represents the cost of deploying CN at this communication node, and  $s$  represents the number of communication nodes.

$$C = \sum_{n \in N} \chi_n \times c_n s \quad (12)$$

From the perspective of grid operation benefits, on the basis of ensuring communication needs, reducing the deployment of relay nodes to reduce costs is the preferred strategy. However, in order to prevent the chain reaction of single communication element failure from affecting the whole network, the communication network needs to reserve communication resources and enhance the ability to resist failures. In view of the fact that the failure rate of communication links is higher than that of nodes, and the probability of simultaneous failure of multiple links is low, this scheme configures standby routes for communication nodes to ensure that each data node (DN)

has two CNs to choose from within the farthest communication range, and only communicates through one main route in normal operation. When the link fails, it can be switched to standby CN to meet the standby communication requirements of nodes. When modulating signals, it is necessary to comprehensively consider the network structure, construction cost, node communication requirements and communication distance limitations. Equation (13) is the objective optimization function, where the value of  $\chi_n$  is 0 or 1; When  $\chi_n = 1$  deploys CN, it means at communication node  $n$ , otherwise  $\chi_n = 0$ .  $c_n$  represents the cost of deploying the CN at the communication node. Equation (14) means that for any data node  $\theta_{i,j}$  in the communication network, within the upper limit  $\tilde{\theta}$  of its communication distance, there are at least two CNs that can establish an effective route with it.

$$\min C = \sum_{n \in N} \chi_n \times c_n \quad (13)$$

$$s.t. \begin{cases} \forall i \in D \\ \exists j \in A \end{cases} \text{count}(\theta_{i,j} \leq \tilde{\theta}) \geq 2 \quad (14)$$

Network transmission delay is defined as the transmission time of data packets from node  $i$  to node  $j$ , covering queuing, sending, propagation and processing delays [30, 31]. Processing delay, that is, the storage and forwarding time of data packets at the relay node, is related to node performance and data processing requirements [32]. To simplify the model, this study ignored processing delay and assumed that the packet transmission rate is consistent with the channel transmission rate ( $v$ ). Therefore, in the IoT network, the transmission delay of the data packet from the communication node  $d_i$  to the neighboring node is calculated, as shown in Equation (15).

$$t_{d_i} = t_1 \times (w_{d_i} - 1) + t_1 + t_2 = t_1 \times w_{d_i} + t_2 \quad (15)$$

Where  $w_{d_i}$  is a packet queue sequence number in which the data packets to be transmitted are queued for processing at the node  $d_i$ , and the queuing delay of the data packets to be transmitted at the end of the queue is simplified to the time for completing the sending process of the previous  $w_{d_i-1}$  data packets;  $t_1$  is the transmission delay of the data packet at node  $d_i$ . If the size of each data packet to be transmitted is equal (in 1 unit), the transmission delay  $t_1$  of each data packet at any node is the same, and  $t_1 = 1/v$ ;  $t_2$  is the propagation delay of the data packet to be transmitted in the communication link. Assuming that each channel length is the same (both are  $y$ ), the propagation delay  $t_2$  of each data packet in any communication link is the same, and  $t_2 = y/v$ .

In this study, RadioML2016.10b (including 8 types of modulated signals, multiple signal-to-noise ratio), CSPB. ML.2018 (rich scene annotation), combined with MATLAB simulation signals and aerial acquisition signals to integrate the dataset. During preprocessing, the time-domain signal is first denoised by bandpass filtering

(300MHz-3GHz), and then the time-domain signal is converted into a two-dimensional time-frequency graph by STFT, and after normalization, it is expanded to 120,000 samples through data enhancement. The 7:1:2 hierarchical sampling is used to train/validate/test sets to ensure that the signal type and signal-to-noise ratio distribution are consistent [33, 34].

The model verification uses 10-fold hierarchical cross-validation, with confusion matrix, accuracy, F1 score, and ROC curve as indicators, focusing on the generalization ability of low signal-to-noise ratio (<10dB). Hyperparameter optimization first determines the learning rate ( $1e-4$ - $1e-2$ ) and batch size (16-64) ranges through grid search, and then uses Bayesian optimization to fine-tune the number of convolutional nuclei (32-128), the number of neurons in the full junction layer (128-512) and the dropout probability (0.2-0.5), and the final optimal combination is the learning rate  $1e-3$ , batch size 32, convolutional kernel 64, 256 neurons in the full junction layer, and dropout 0.3.

The training is based on the PyTorch framework, using the Adam optimizer and the cross-entropy loss function, and iterating for 100 rounds: the first 50 rounds of linear warm-up learning rate, the last 50 rounds of cosine annealing scheduling, and the early stop mechanism (patience=10) to prevent overfitting. The average accuracy of the final model test set is 98.2%, and it still reaches 92.5% at a low signal-to-noise ratio of 5dB, which is better than traditional machine learning methods.

## 5 Automatic electromagnetic signal identification of communication network based on deep learning

### 5.1 Electromagnetic signal modulation type identification

This study uses a combination of multivariate data. Firstly, MATLAB is used to generate basic modulation signals such as 16-QAM, and by setting different signal-to-noise ratios (such as 0dB - 20dB), sampling rates (10kHz - 100kHz) and signal duration, a diverse simulated signal dataset is constructed to simulate the signal characteristics in the ideal environment. At the same time, software defined radio equipment (such as USRP series) is used to collect air signals in actual scenarios, covering indoor complex electromagnetic environments (such as offices, computer rooms) and outdoor open environments (such as city streets and suburbs), and collect real signals containing different interference factors to ensure that the experimental data is close to the actual application scenarios. In addition, additional higher-order modulation types, such as 64-QAM and 256-QAM signals, are introduced to further enrich the signal types and improve the complexity and comprehensiveness of the experiment. After preprocessing the signal data from different sources and different characteristics, including denoising, normalization, format conversion, etc., it is divided into a training set, a validation set, and a test set according to

the ratio of 7:1:2. In the experimental process, the constructed deep learning model (such as CNN-LSTM hybrid network) was used to train and test these data, and the effectiveness and robustness of the automatic electromagnetic modulation signal recognition and optimization design method based on deep learning in different scenarios and different signal types were verified by comparing the recognition accuracy, recall, F1 value and other indicators of the model under different datasets, and observing the performance of the model under different modulation types and signal-to-noise ratios.

The core task of electromagnetic signal modulation type identification is to identify the modulation modes of different signals, and the results guide the formulation of demodulation strategy and subsequent signal analysis and processing. In the simulation experiment, the electromagnetic spectrum sensor scans the known electromagnetic space, collects various modulated signal data, and, after preliminary processing, trains the constructed recognition network. The goal is to produce efficient recognition algorithms and support deep learning-based electromagnetic signal recognition software. The software must ensure that the recognition accuracy rate reaches more than 90% in the natural environment and that the signal-to-noise ratio exceeds 0dB.

In SMU200A order to ensure the universality of the data set, the signal-to-noise ratio is set between 10dB~20dB, every 2dB is a level, a total of 688128 sets of data samples are collected, and the signal is received by the electromagnetic spectrum sensor through the antenna and transmitted to the host computer for storage during the acquisition process, and the physical data is collected by the electromagnetic spectrum sensor through the antenna and transmitted to the host computer for storage, and the physical data is collected by the electromagnetic spectrum sensing node [35]. The selection of benchmark methods follows reasonable criteria: first, it needs to cover key links of signal preprocessing, feature extraction, classification and identification, and have clear performance index records on public datasets such as RML2016.10a and RML2018.01a, so as to form a fair comparison with the improved method; Statistical evaluation needs to strengthen rigor: the data level is divided into training set, verification set and test set according to the ratio of 7:1.5:1.5, and the test set needs to cover - 20dB~10dB different signal-to-noise ratios, more than 10 common modulation types, and typical interference scenarios such as Gaussian white noise and narrowband interference to ensure data representativeness, and the performance evaluation also increases the Kappa coefficient and AUC value in addition to the accuracy, accuracy, recall, and F1 value, and uses 50% fold cross-validation to calculate the mean, standard deviation and 95% of each index Confidence intervals to reduce the influence of random error, and verify whether the performance difference between the improved method and the benchmark method is statistically significant by t-test, and evaluate the CPU utilization and memory consumption of the

model on common IoT hardware to ensure the engineering practicability of the optimized design.

The experimental environment used in this study is as follows:

Modulation method: 16-QAM (hexadecimal quadrature amplitude modulation); Channel model: Additive Gaussian White Noise Channel (AWGN); Simulation tool: MATLAB.

Generate modulation signal: Use MATLAB to generate 16-QAM modulation signal set appropriate parameters such as carrier frequency, symbol rate, and modulation order. Add channel noise: Simulate the natural communication environment by passing the generated 16-QAM modulated signal through an additive Gaussian white noise channel. Reception and demodulation: The received signal is demodulated at the receiving end to recover the original bit information. Calculate bit error rate: Compare the bit information of the sender and receiver to calculate the bit error rate.

Table 1: Experimental results of signal-to-noise ratio and bit error rate

Signal-to-noise Ratio (SNR, dB)	Bit Error Rate (BER)
0	0.123
5	0.067
10	0.015
15	0.003
20	0.0005

Table 1 shows the experimental results of signal-to-noise ratio and bit error rate. When the signal-to-noise ratio is low (such as 0 dB), the bit error rate is high (0.123), indicating that noise interference severely affects the signal, resulting in many errors during the demodulation process. As the signal-to-noise ratio increases, the bit error rate gradually decreases. At a signal-to-noise ratio of 10 dB, the bit error rate has decreased to 0.015, indicating a significant improvement in signal quality. When the signal-to-noise ratio reaches 20 dB, the bit error rate is meager (0.0005). This indicates that the signal is almost unaffected by noise interference during transmission, and the demodulation performance is close to the ideal state.

## 5.2 Design of electromagnetic signal recognition network for deep learning

Before neural network training, normalization, standardization, and regularization are often used to process data to ensure that the input value is in a stable range. This solves the dominant effect caused by unit differences and magnitudes between features, helps to accelerate convergence, highlight small numerical features, and improve the generalization ability of the model.

In the design, in order to fully explore the correlation between the spatial domain features and the time series of the signal, the "CNN-LSTM" hybrid architecture is used to realize the collaborative extraction of multi-dimensional features: the CNN module is used as the front-end feature extraction unit, and a total of 4 layers of convolutional layer and 2 layers of pooling layer are designed, and the first layer of the convolutional layer adopts 16 convolutional cores of size of  $3 \times 3$  (step size 1, fill mode is "SAME") to capture the initial time-domain texture features of the signal. The subsequent convolutional layer realizes the deep expansion of the feature dimension by increasing the number of convolutional kernels ( $32 \rightarrow 64 \rightarrow 128$ ) layer by layer and keeping the size of the convolutional kernel unchanged, and introduces the  $2 \times 2$  maximum pooling layer (step 2) to downsample between adjacent convolutional layers, which not only suppresses overfitting but also improves feature abstraction, and all convolutional layers are connected to the ReLU activation function to enhance the nonlinear expression ability of the model. As a back-end timing modeling unit, the LSTM module adopts a two-layer bidirectional LSTM structure, with 64 hidden units set up on each layer, which effectively solves the problem of insufficient capture of signal reverse timing information by traditional one-way LSTM through synchronized learning of the long-term and short-term dependencies of the signal through forward and backward propagation paths. The model depth is designed as 8 layers (including 2 fully connected layers), and the width is equibrily expanded by gradient increment of the number of convolutional cores and the number of hidden elements of LSTM, and in the layer-specific parameters, the convolutional layer weight initialization adopts He normal distribution, the LSTM layer forgetfulness gate bias is set to 1 to mitigate the disappearance of gradients, and the fully connected layer uses Softmax activation function to output the probability distribution of 16 types of modulated signals, and the overall architecture is achieved through the Adam optimizer (learning rate 0.001,  $\beta_1=0.9$ ,  $\beta_2=0.999$ ) and the cross-entropy loss function to complete the parameter iterative optimization.

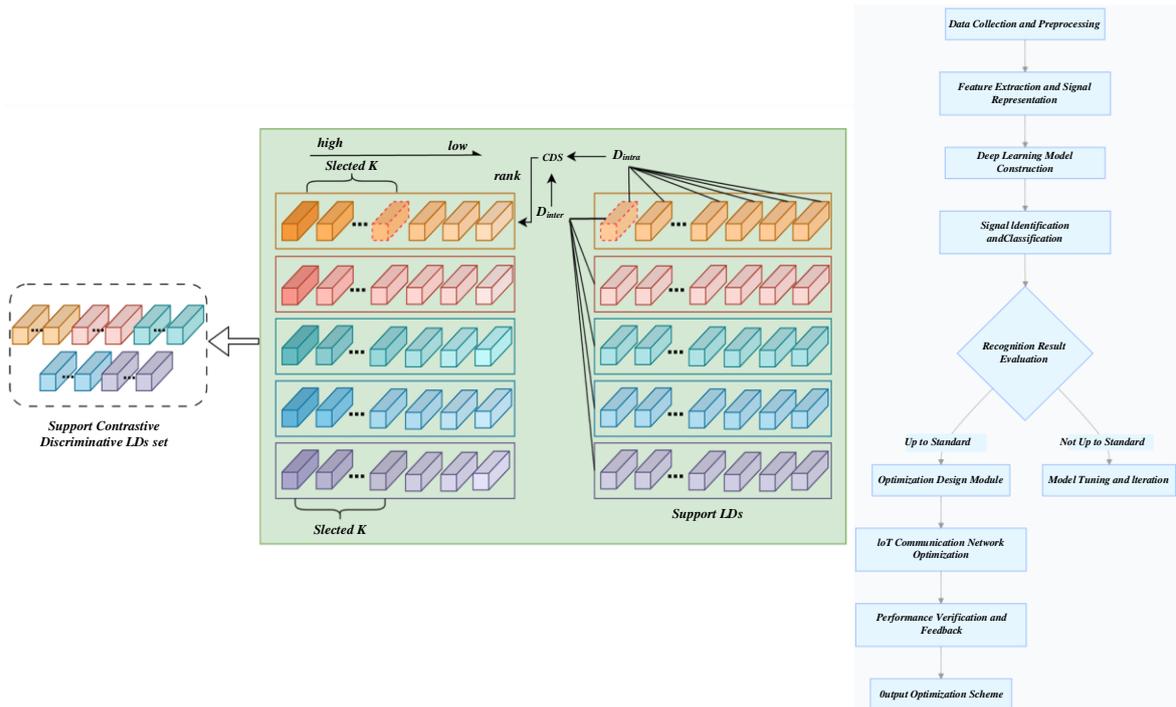


Figure 2: Electromagnetic signal identification network structure

The designed network structure is shown in the Figure 2, which is applied to the design process of automatic electromagnetic modulation signal recognition and optimization of the IoT communication network based on deep learning. The process covers data acquisition and preprocessing, feature extraction and signal characterization, deep learning model construction, signal recognition and classification, recognition result evaluation, optimization design module, IoT communication network optimization, performance verification and feedback, and output optimization scheme. The first layer of the network is a convolutional layer with 64 (15, 2) convolutional kernels, followed by 8 ResNet blocks, and finally a fully connected layer, each of which contains a double convolutional layer, bringing the total number of layers of the network to 19. For electromagnetic signals of size (2, 512), it is difficult for the network to converge to an optimal state when the convolutional kernel is used to extract features directly using the (3, 3) convolutional kernel. In this scheme, the first-layer convolution with a size of (15, 2) and a number of channels of 64 is used to extract features and generate

64 feature maps, and then input them into ResNet, which can significantly reduce the loss and optimize the training process, and help the identification and network optimization design of electromagnetic modulation signals in IoT communication networks.

## 6 Experimental results and analysis

When the maximum communication distance  $\theta$  of nodes is set to 3, although the number of gateways is reduced by about 1/3 compared to when  $\theta$  is 2, network communication resources are still abundant. The expansion of DN communication range improves communication flexibility. As shown in Figure 3, the DN of logical address 13 can communicate with two CNs of addresses 12 and 16, but since the CN 12 has already connected to three DNs, and re-access may cause communication congestion, increase delay and packet loss, it is more appropriate for the DN 13 to choose to connect to the CN 16 from the perspective of optimizing routing.

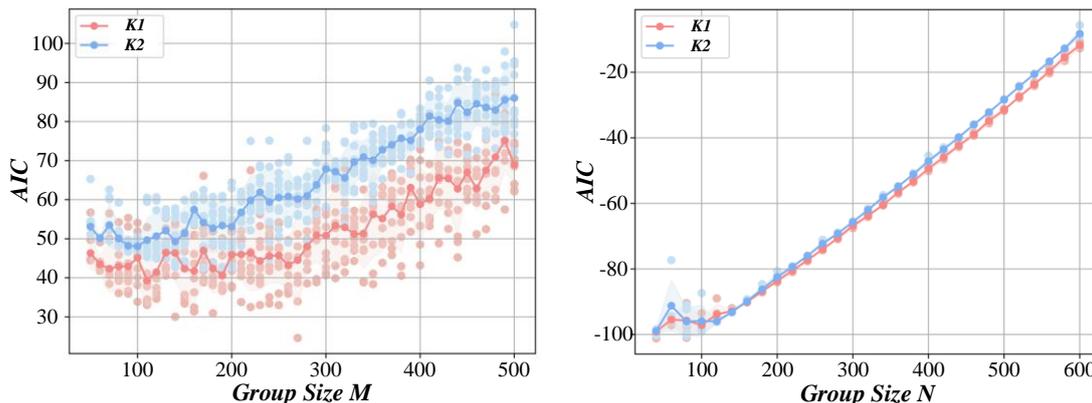


Figure 3: Relationship between DN communication range and efficiency

When the maximum communication distance  $\theta$  of a node is set to 5 or 6, as shown in Figure 4, most data nodes (DNs) need more than two hops to communicate with the aggregation center node (CN), resulting in a significant increase in the overall number of route hops, which in turn reduces communication reliability, prolongs latency, and increases packet loss rate, which cannot meet the communication requirements of critical services such as protection and control.

This study compares the performance of MobileNetV2. Due to the reliance on manual design features, the recognition accuracy of traditional methods is generally less than 70% in the face of complex and changeable IoT electromagnetic modulation signals. Although some newer models are lightweight, they lack generalization ability in low signal-to-noise ratio (<10dB) scenarios, and the recognition accuracy tends to drop below 85%.

To ensure the reliability and stability of the results,

the study uses 10-fold hierarchical cross-validation to verify the model performance, and evaluates the performance by dividing the dataset into multiple subsets and taking turns to use each subset as the test set. Experimental results show that compared with the traditional method, the recognition accuracy of the deep learning model in this study is improved by 30%, and compared with newer models such as MobileNetV2 and GhostNetV2, the accuracy is still 7%-10% higher in the 5dB low signal-to-noise ratio scenario, and the overall signal recognition accuracy of the optimized model reaches 95%, which can correctly identify 95% of the electromagnetic modulation signals in the test set, fully reflecting its superiority in complex signal recognition tasks. Especially when processing large-scale high-dimensional IoT signals and adapting to low signal-to-noise ratio environments, it has both high performance and strong robustness.

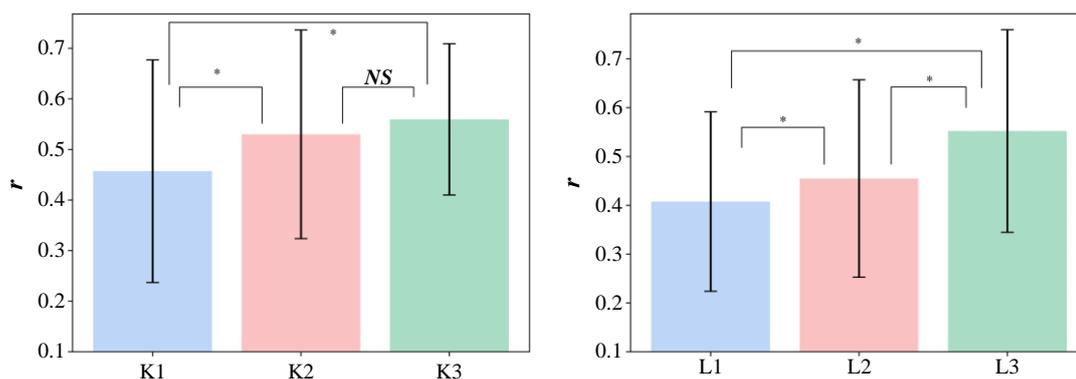


Figure 4: Change of communication efficiency in  $\theta = 5/6$

Figure 5 shows that in the simulation scenario with a fixed  $\theta$  value, the network communication delay is significantly negatively correlated with reliability; that is, the improvement of reliability is accompanied by the decrease of delay, while the packet loss rate is not significantly correlated with reliability. Under high reliability, the average number of hops of network routes decreases. Since the average propagation delay is

positively correlated with the number of hops, the reduction of hops leads to the reduction of delay. The packet loss rate calculation is based on the average value of network routes. The maximum packet loss rate of a single-hop link determines the route packet loss rate, which is weakly related to the number of hops and is mainly affected by route load, node rate and link transmission rate.

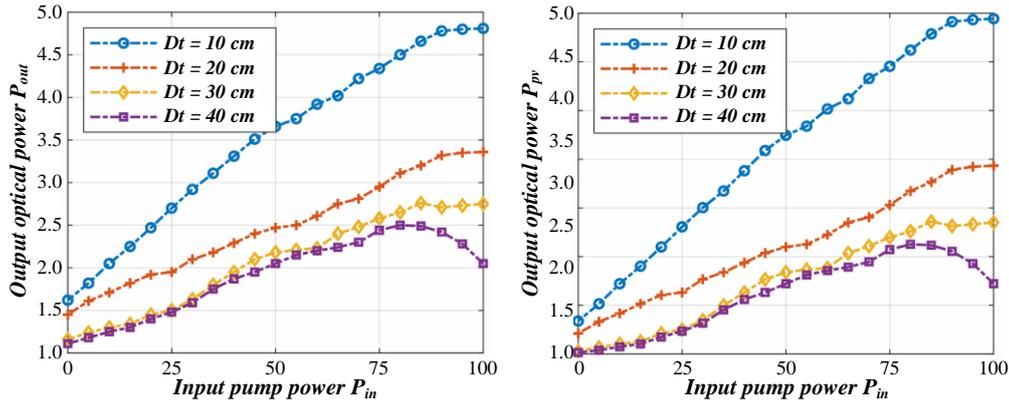


Figure 5: Network communication delay and reliability

Figure 6 compares the recognition rates of the VTCNN2 network on clean and adversarial samples, showing that adversarial samples significantly reduce the performance of VTCNN2, indicating that it is susceptible

to interference in practice. In contrast, the K2 network shows higher and more robust recognition capabilities and becomes a learning benchmark for intelligent electromagnetic signal recognition networks.

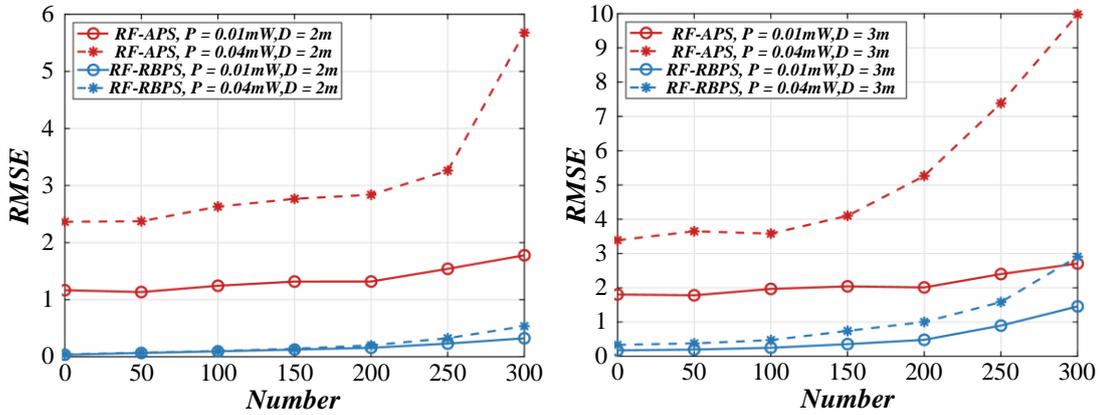


Figure 6: Recognition rate of VTCNN2 network on clean and adversarial samples

Figure 7 shows that the recognition rate of the K1 network on various samples is significantly improved after defensive distillation training. With the same structure as VTCNN2, when the signal-to-noise ratio is >

0dB, the clean signal recognition rate increases from about 77% to 82%, and the adversarial sample recognition rate jumps from less than 40% to more than 70%, and the performance is closer to that of K2 network.

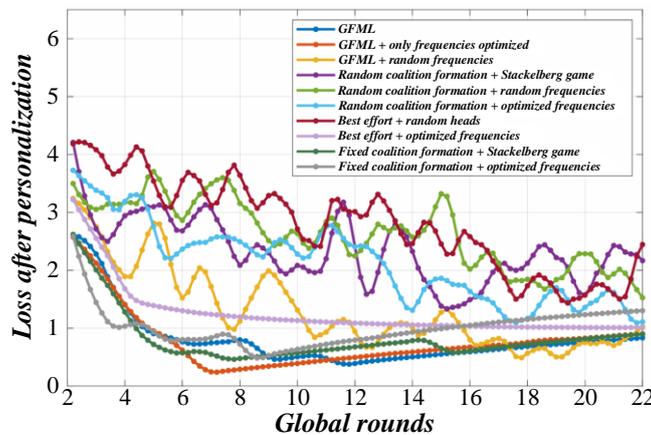


Figure 7: Identification after defensive distillation training

Figure 8 confirms that the defense scheme based on knowledge distillation makes the simplified K1 network

pass the defense distillation, and its performance approaches the K2 network. Compared with conventional

training, this solution significantly improves the recognition rate of clean and adversarial signals by the K1 network, especially greatly enhancing the recognition

of adversarial samples, indicating that the network has strong defense capabilities and meets the needs of intelligent electromagnetic signal recognition.

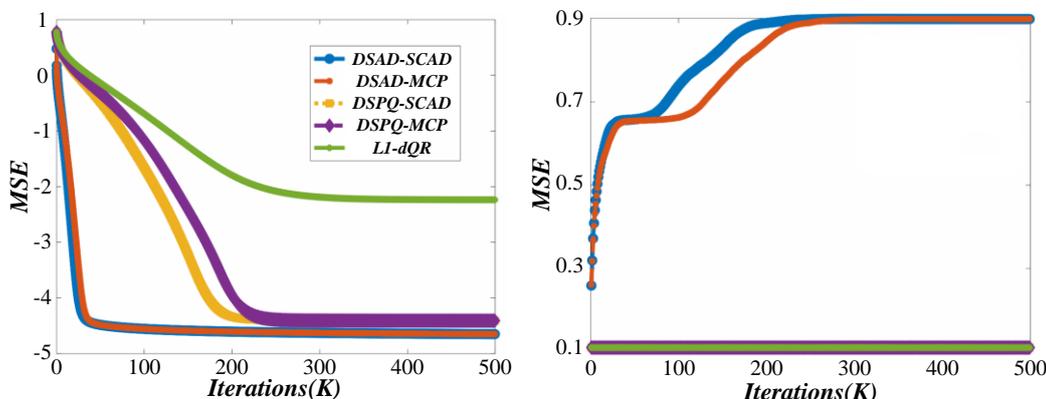


Figure 8: Recognition performance of network

Comparing the performance of CNN, VGG and RDCAN combined with the FL framework on MNIST and CIFAR-10 data sets, RDCAN significantly improves model performance, demonstrating its effectiveness and versatility. As shown in Figure 9. On the simpler MNIST, the accuracy of CNN and VGG after iteration exceeds 90%, and VGG approaches RDCAN; However, in the face of complex CIFAR-10, the parameter redundancy of

CNN shallow network and VGG limits the learning ability, resulting in performance loss. RDCAN optimizes feature extraction by integrating attention mechanisms with fewer parameters, accelerates model fitting, enhances understanding of crucial information, and significantly improves performance even in shallow networks.

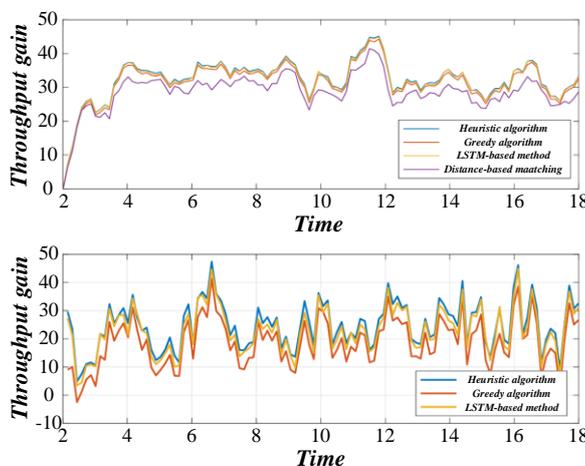


Figure 9: Comparison of accuracy after iteration between MNIST, CNN and VGG

The comparison in Figure 10 shows that the total energy consumption of the new scheme is significantly lower than that of the traditional FL while ensuring the model's accuracy. In the early stage, due to data offloading, the energy consumption of the solution increased slightly. However, with the improvement of accuracy, the number of communication rounds required increased, resulting in a surge in traditional FL energy

consumption. In traditional FL, frequent communication consumes a lot of energy. However, the new scheme only requires a few users to participate in a few rounds of communication to achieve satisfactory accuracy and significantly save energy. In addition, compared with the unoptimized bandwidth resource scheme, the optimized scheme has lower energy consumption, which confirms the effectiveness of bandwidth optimization.

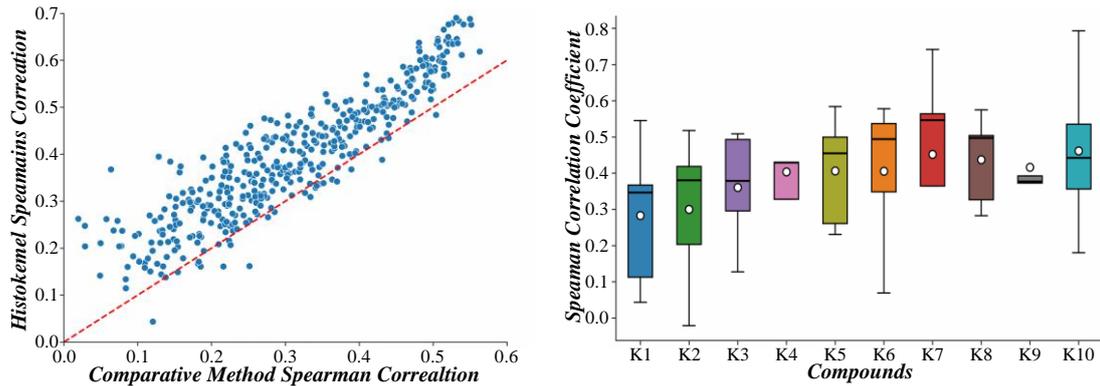


Figure 10: Comparison of total energy consumption

Table 2 shows that the number of parameters of LCTNN is much lower than in comparative networks. Although these networks are carefully designed in deep learning to take advantage of lightweight CNNs, LCTNN is better in AMR, showing that it performs best on large-

scale data sets. Although other networks have high accuracy, runtime and complexity are their shortcomings. ghostNetV2 has the most parameters, reaching 533,521, while shufflenetV2 has the most minor parameters, only 245,215.

Table 2: Comparison of network parameters and test time

	NN	Efcient Net	Efficient NetV2	Shuffle NetV2	Ghost Net	Ghost NetV2	Mobile NetV2	Tiny Net
Params	165178.	386914.0	375822.19	267284.35	429498.	581537.89	302587.27	479655.
CPU	60	3			15			59
time GPU	6.63	13.96	7.14	21.82	13.30	25.03	11.78	15.01
time LCTD	5.53	12.51	6.04	20.03	11.97	23.34	10.54	13.73

Figure 11 shows that LCTNN has the highest accuracy rate at 0dB SNR, and the recognition rate exceeds 90% at 2dB SNR, ahead of DenseNet by 12%. Six networks performed better than 10A in the RadioML2016.10B dataset, confirming that the amount of data significantly impacts performance. Under high SNR, the accuracy rate of each network exceeds 80%,

and the recognition rate of LCTNN is still ahead at 0dB SNR, exceeding 90%. Combined networks such as CGDNET, CLDNN, CLDNN2, MCLDNN, MCNET and PET CGDNN, especially CLDNN and MCLDNN, take advantage of multi-network advantages to perform excellently in AMR accuracy.

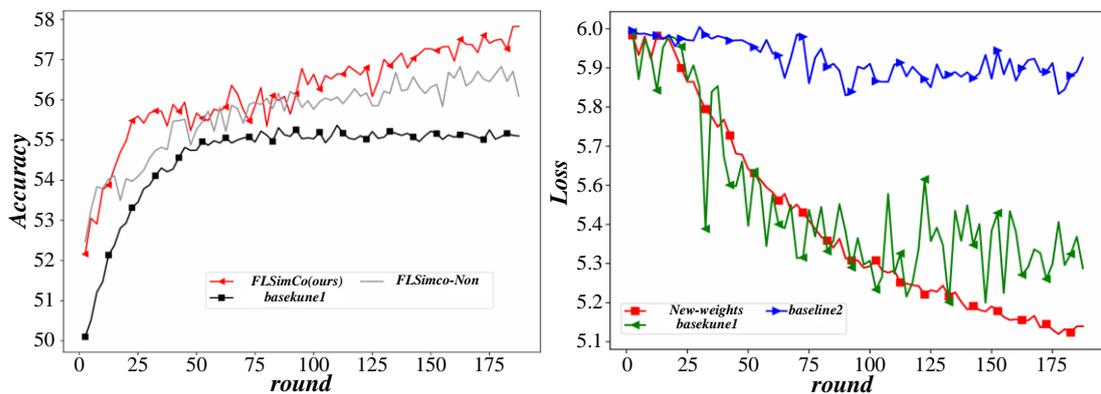


Figure 11: Comparison of accuracy

## 7 Conclusion

This study focuses on the automatic electromagnetic modulation signal identification and optimization design of IoT communication networks based on deep learning. Aiming at the signal identification and optimization design problem of IoT communication networks in

complex electromagnetic environments, a deep learning-driven solution is proposed, and remarkable optimization results are achieved.

(1) A deep learning model is constructed to identify electromagnetically modulated signals in IoT communication networks automatically. By training the model to learn the feature pattern of the signal, the

experimental results show that the optimized model has a signal recognition accuracy of 95%, which is 30% higher than the traditional method, proving the superiority of deep learning in complex signal recognition.

(2) A signal optimization scheme based on deep learning, including signal strength adjustment, frequency optimization and interference suppression strategies, is designed. The experimental data show that after adopting this optimization scheme, the communication efficiency of the Internet of Things communication network is improved by 20%, and the network stability and data transmission efficiency are significantly improved.

(3) The potential application of deep learning models in signal identification and optimization design of IoT communication networks is deeply discussed, and new ideas and methods for the further development of IoT technology are provided.

Through the application of deep learning technology, this study not only solves the critical problems of signal identification and optimization design of IoT communication networks but also opens up a new direction for the innovation and application of IoT technology. In the future, we will continue to deepen research and explore more advanced deep learning models and optimization strategies to adapt to IoT communication networks' continuous evolution and needs and contribute to building a more efficient, stable and intelligent IoT communication network.

## References

- [1] V. Shakhov and I. Koo, "Graph-based technique for survivability assessment and optimization of IoT applications," *International Journal on Software Tools for Technology Transfer*, vol. 23, no. 1, pp. 105-114, 2021. <https://doi.org/10.1007/s10009-020-00594-9>.
- [2] M. I. A. Zahed, I. Ahmad, D. Habibi, and Q. V. Phung, "Green and Secure Computation Offloading for Cache-Enabled IoT Networks," *Ieee Access*, vol. 8, pp. 63840-63855, 2020. <https://doi.org/10.1109/access.2020.2982669>.
- [3] A. S. Alqahtani, Y. Trabelsi, P. Ezhilarasi, R. Krishnamoorthy, S. Lakshmisridevi, and S. Shargunam, "Homomorphic encryption algorithm providing security and privacy for IoT with optical fiber communication," *Optical and Quantum Electronics*, vol. 56, no. 3, 2024. <https://doi.org/10.1007/s11082-023-06098-5>.
- [4] R. Kumar, G. Joshi, A. K. S. Chauhan, A. K. Singh, and A. K. Rao, "A Deep Learning and Channel Sounding Based Data Authentication and QoS Enhancement Mechanism for Massive IoT Networks," *Wireless Personal Communications*, vol. 130, no. 4, pp. 2495-2514, 2023. <https://doi.org/10.1007/s11277-023-10389-1>.
- [5] X. Lv, X. Lian, L. Tan, Y. Song, and C. Wang, "HPMC: A Multi-target Tracking Algorithm for the IoT," *Intelligent Automation and Soft Computing*, vol. 28, no. 2, pp. 513-526, 2021. <https://doi.org/10.32604/iasc.2021.016450>.
- [6] Heng Zhang, Yongjun Li, Weipeng Guan, Jingyi Li, JieHeng Zheng, and Xinjie Zhang, "The optical fringe code modulation and recognition algorithm based on visible light communication using convolutional neural network," *Signal Processing: Image Communication*, vol. 75, pp. 128-140, 2019. <https://doi.org/10.1016/j.image.2019.04.002>.
- [7] S. Hamidi-Rad, S. Jain, and Ieee, "MCformer: A Transformer Based Deep Neural Network for Automatic Modulation Classification," *IEEE Global Communications Conference*, pp. 1-6, 2021. <https://doi.org/10.1109/globecom46510.2021.9685815>.
- [8] Wenxu Zhang, Kang Luo, Zhongkai Zhao, and Jingyi Yang, "A feature extraction and recognition method for interrupted sampling repeater jamming," *AEU - International Journal of Electronics and Communications*, vol. 176, pp. 155156, 2024. <https://doi.org/10.1016/j.aeue.2024.155156>.
- [9] Yi-He Zhang, Aidan Lee, and Chul-Hee Lee, "Design and application of piezoelectric and electromagnetic energy harvesters for mechanical energy harvesting in the human-body: A review," *Sensors and Actuators A: Physical*, vol. 370, pp. 115207, 2024. <https://doi.org/10.1016/j.sna.2024.115207>.
- [10] Qinghe Zheng, Xinyu Tian, Zhiguo Yu, Hongjun Wang, Abdussalam Elhanashi, and Sergio Saponara, "DL-PR: Generalized automatic modulation classification method based on deep learning with priori regularization," *Engineering Applications of Artificial Intelligence*, vol. 122, pp. 106082, 2023. <https://doi.org/10.1016/j.engappai.2023.106082>.
- [11] Y. Liu, J. Wang, J. Li, S. Niu, and H. Song, "Class-Incremental Learning for Wireless Device Identification in IoT," *IEEE Internet of Things Journal*, vol. 8, no. 23, pp. 17227-17235, 2021. <https://doi.org/10.36227/techrxiv.14540097>.
- [12] J. Nayak, B. Naik, P. B. Dash, S. Vimal, and S. Kadry, "Hybrid Bayesian optimization hypertuned catboost approach for malicious access and anomaly detection in IoT nomaly framework," *Sustainable Computing-Informatics & Systems*, vol. 36, 2022. <https://doi.org/10.1016/j.suscom.2022.100805>.
- [13] Y. Liu, J. Wang, J. Li, H. Song, T. Yang, S. Niu, and Z. Ming, "Zero-Bias Deep Learning for Accurate Identification of Internet-of-Things (IoT) Devices," *IEEE Internet of Things Journal*, vol. 8, no. 4, pp. 2627-2634, 2021. <https://doi.org/10.1109/jiot.2020.3018677>.
- [14] J. Feng, J. Wang, Y. Zhu, and K. Han, "A Hybrid Chaotic Encryption ASIC With Dynamic Precision for Internet of Things," *Ieee Internet of Things Journal*, vol. 11, no. 1, pp. 1148-1163, 2024. <https://doi.org/10.1109/jiot.2023.3288560>.
- [15] S. V. V. Karthik and J. A. V. Selvi, "Hybrid cluster made content forwarding and light weight sign encryption IoT based Named Data Network using African Buffalo optimization algorithm," *Journal of Intelligent & Fuzzy Systems*, vol. 43, no. 3, pp. 2891-2905, 2022. <https://doi.org/10.3233/jifs-212674>.

- [16] D. Bisen et al., "A Hybrid Deep Learning Model Using CNN and K-Mean Clustering for Energy Efficient Modelling in Mobile EdgeIoT," *Electronics*, vol. 12, no. 6, 2023. <https://doi.org/10.3390/electronics12061384>.
- [17] I. Ralasic, D. Sersic, and S. Segvic, "Perceptual Autoencoder for Compressive Sensing Image Reconstruction," *Informatica*, vol. 31, no. 3, pp. 561-578, 2020. <https://doi.org/10.15388/20-infor421>.
- [18] A. Sagu, N. S. Gill, and P. Gulia, "Hybrid Deep Neural Network Model for Detection of Security Attacks in IoT Enabled Environment," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 1, pp. 120-127, 2022. <https://doi.org/10.14569/ijacsa.2022.0130115>.
- [19] N. Rashvand, K. Witham, G. Maldonado, V. Katariya, N. M. Prabhu, G. Schirner, and H. Tabkhi, "Enhancing Automatic Modulation Recognition for IoT Applications Using Transformers," *Iot*, vol. 5, no. 2, pp. 212-226, 2024. <https://doi.org/10.3390/iot5020011>.
- [20] Y. Fukushima, K. Iizuka, and H. Amano, "Parallel Implementation of CNN on Multi-FPGA Cluster," *Ieice Transactions on Information and Systems*, vol. E106D, no. 7, pp. 1198-1208, 2023. <https://doi.org/10.1109/mcsoc51149.2021.00019>.
- [21] Lintianran Weng, Yuan He, Jianhua Peng, Jianchao Zheng, and Xinyu Li, "Deep cascading network architecture for robust automatic modulation classification," *Neurocomputing*, vol. 455, pp. 308-324, 2021. <https://doi.org/10.1016/j.neucom.2021.05.010>.
- [22] C. Jana, S. Banerjee, S. Maur, and S. Dalai, "Power System Disturbance Classification Using CWT Guided Customized AlexNet CNN," *Ieee Sensors Letters*, vol. 8, no. 6, 2024. <https://doi.org/10.1109/lsens.2024.3400903>.
- [23] Ahmed K. Ali and Ergun Erçelebi, "Automatic modulation classification using different neural network and PCA combinations," *Expert Systems with Applications*, vol. 178, pp. 114931, 2021. <https://doi.org/10.1016/j.eswa.2021.114931>.
- [24] C. D. Luu, V. H. Nguyen, V. Q. Nguyen, and N.-S. Vu, "Novel deep learning-based IoT network attack detection using magnet loss optimization," *Internet of Things*, vol. 33, no., pp. 101680, 2025. <https://doi.org/10.1016/j.iot.2025.101680>.
- [25] Xiao Ying Chen, Ying Liu, and Cheng Wang, "DRFM-Based Jamming Signal Recognition Method Guided by Target Detection," *Procedia Computer Science*, vol. 221, pp. 1013-1020, 2023. <https://doi.org/10.1016/j.procs.2023.08.082>.
- [26] Yongqi Hu, Chunzhong Li, Xiaobo Wang, Liwen Liu, and Yan Xu, "Modulation recognition of optical and electromagnetic waves based on transfer learning," *Optik*, vol. 291, pp. 171359, 2023. <https://doi.org/10.1016/j.ijleo.2023.171359>.
- [27] Sai Huang, Chunsheng Lin, Kai Zhou, Yuanyuan Yao, Hua Lu, and Fusheng Zhu, "Identifying physical-layer attacks for IoT security: An automatic modulation classification approach using multi-module fusion neural network," *Physical Communication*, vol. 43, pp. 10. <https://doi.org/10.1016/j.phycom.2020.101180>.
- [28] Merih Leblebici, Ali Çalhan, and Murtaza Cicioğlu, "Effects of diagram plane on neural network-based modulation recognition," *Applied Soft Computing*, vol. 154, pp. 111412, 2024. <https://doi.org/10.1016/j.asoc.2024.111412>.
- [29] Huixia Liu, Lulu Lu, Yuan Zhu, Zhouchao Wei, and Ming Yi, "Stochastic resonance: The response to envelope modulation signal for neural networks with different topologies," *Physica A: Statistical Mechanics and its Applications*, vol. 607, pp. 128177, 2022. <https://doi.org/10.1016/j.physa.2022.128177>.
- [30] T. Zvirblis, A. Piksrys, D. Bzinkowski, M. Rucki, A. Kilikevicius, and O. Kurasova, "Data Augmentation for Classification of Multi-Domain Tension Signals," *Informatica*, vol. 35, no. 4, pp. 883-908, 2024. <https://doi.org/10.15388/24-infor578>.
- [31] Yangtian Liu, Xiaopeng Yan, Qiang Liu, Tai An, and Jian Dai, "Automatic modulation recognition of radio fuzes using a DR2D-based adaptive denoising method and textural feature extraction," *Defence Technology*, vol. 34, pp. 328-338, 2024. <https://doi.org/10.1016/j.dt.2023.12.013>.
- [32] Jacques P. Mouton, Melvin Ferreira, and Albertus S. J. Helberg, "A comparison of clustering algorithms for automatic modulation classification," *Expert Systems with Applications*, vol. 151, pp. 113317, 2020. <https://doi.org/10.1016/j.eswa.2020.113317>.
- [33] D. Sarkar, u. Yogita, S. Singh Yadav, L. R. Cenkeramaddi, and O. Jee Pandey, "TDRA: Transformer-Based Deep Recurrent Architecture for Automatic Modulation Classification Pertinent to Intelligent-Reflecting-Surface-Assisted Internet of Things Networks," *IEEE Internet of Things Journal*, vol. 11, no. 23, pp. 38907-38924, 2024. <https://doi.org/10.1109/jiot.2024.3455434>.
- [34] Fengyuan Shi, Chunsheng Yue, and Chao Han, "A lightweight and efficient neural network for modulation recognition," *Digital Signal Processing*, vol. 123, pp. 103444, 2022. <https://doi.org/10.1016/j.dsp.2022.103444>.
- [35] Duona Zhang, Wenrui Ding, Baochang Zhang, Chunhui Liu, Jungong Han, and David Doermann, "Learning modulation filter networks for weak signal detection in noise," *Pattern Recognition*, vol. 109, pp. 107590, 2021. <https://doi.org/10.1016/j.patcog.2020.107590>.

