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# Semi-supervised-based automatic modulation classification with domain adaptation for wireless IoT spectrum monitoring

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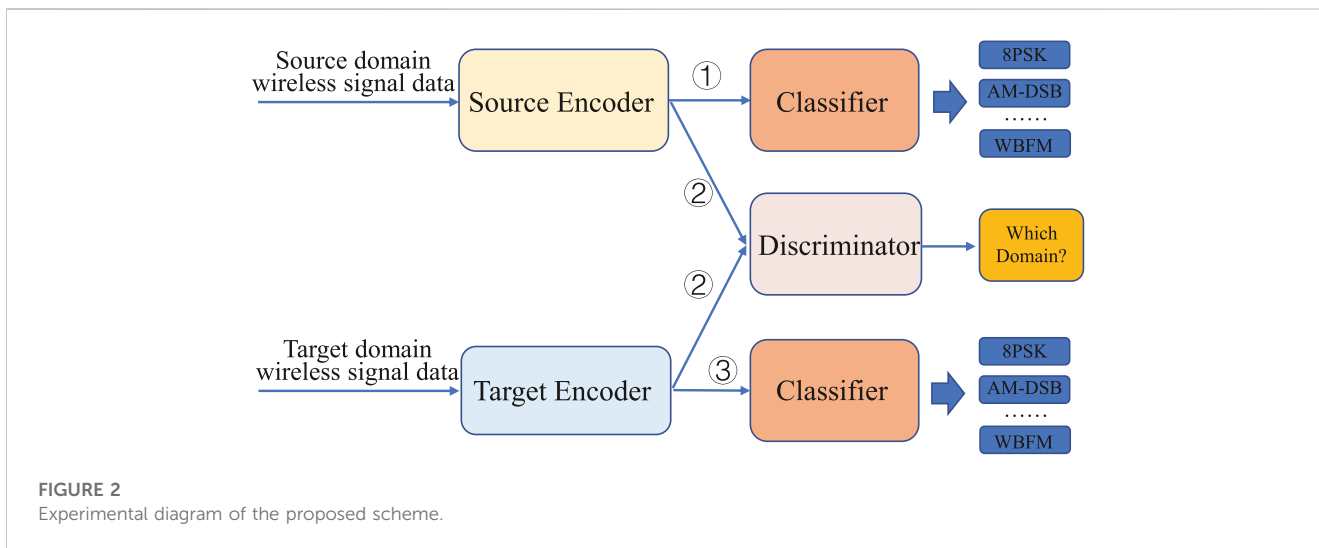
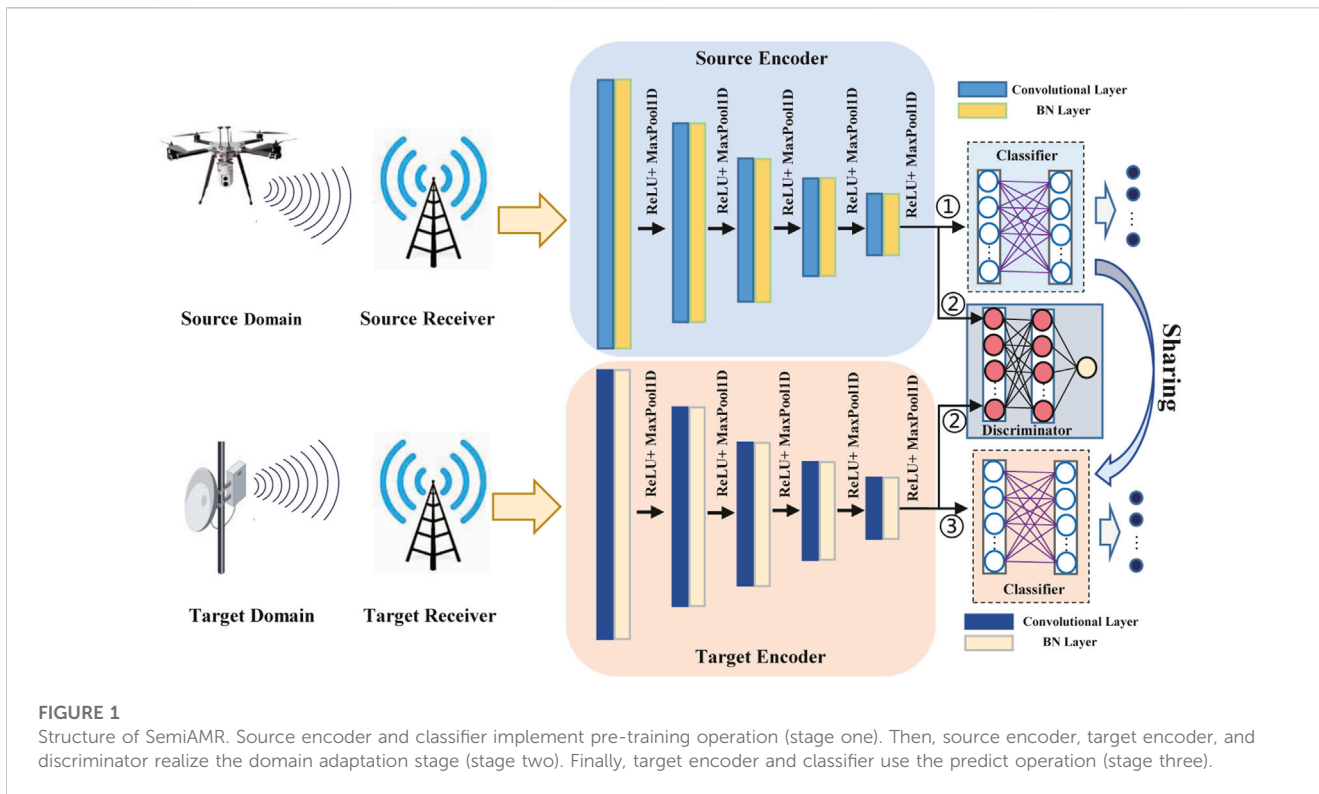
Dramatic advances in wireless networks have led to the Smart IoT, which may enable new modes of information transfer. Generally, data-driven advanced artificial intelligence (AI) techniques can be used in smart IoT networks, which prones to a lot of unexpected challenges. Enabling efficient management of spectrum resources based on cognitive radio is considered to be an effective means to address the limited spectrum resources. As a key technology in CR, automatic modulation recognition (AMR) is developing towards intelligence with deep learning as the main approach. Deep learning (DL) has been widely applied to AMR for possible improvement of recognition accuracy, while the superb performance highly depends on high-quality and well-labeled datasets. Consequently, these requirements prone to poor performance in the environments where the datasets are not well-labeled. Motivated by this, domain adaptation is considered for AMR in this paper, and a novel network architecture is proposed therein, termed semi-supervised automatic modulation recognition (SemiAMR). Specifically, source domain high SNR data are mapped by the source encoder to the classification domain and classified by the classifier, where the source data with labels enable this training process. Next, the discriminator and the target domain encoder are trained by determining whether the data is from the target or source domain. Finally, the target domain encoder and classifier are combined and are used to infer the data labels of the target domain. Experimental results state that the accuracy of proposed SemiAMR achieves 1% to 27% improvements when compared with classical schemes under the target domain condition where there is no corresponding labeled data and signal-to-noise ratios (SNRs) varies from  $-20$  dB to  $-4$  dB.

## KEYWORDS

automatic modulation classification, wireless IoT, semi-supervised learning, domain adaptation, convolutional neural network

## 1 Introduction

With the continuous evolution of next-generation communication technology, multi-band, ultra-broadband, high frequency, and internet of everything (IoX) seem the main direction of attention, prone to the extremely complex wireless environment and fine-grained multi-dimensional network resources [1–3]. In this context, traditional model-driven wireless communication is inapplicable due to the exponential growth of wireless terminals and increasing communication overhead. On the contrary, data-driven model,



such as artificial intelligence (AI), etc. [4, 5], brings new impetus to wireless communication, relying on its powerful capacity of feature learning. As a key technology of wireless communication, automatic modulation recognition (AMR) is facing new opportunities and potential with the assistance of AI [6].

Typically, traditional AMR schemes mainly contain likelihood-based (LB) scheme [7, 8] and feature-based (FB) scheme [9]. The modulation modes are determined by likelihood value for LB while the features of FB are pre-designed by experts and leveraged to infer the accurate label. However, both LB and FB are well-designed and low-robust, resulting in limited accuracy. Recently, deep learning (DL) is widely applied to AMR, processing the baseband signal

intelligently and extracting the valuable feature automatically [10, 11]. Z. Zhang *et al.*; [12] proposed a CNN-LSTM dual-stream structure to implement AMR, which leveraged the temporal in-phase/quadrature and amplitude/phase feature. S. Huang *et al.*; [13] proposed a novel grid constellation matrix (GCM)-based AMC method using a contrastive fully convolutional network (CFCN), which brought promising classification performance and better robustness. However, the aforementioned AMR schemes are driven by abundant training data and large-scale parameters [14, 6]. To collect a rich dataset with accurate labeling seems a difficult task in the practical scenarios, limiting the performance of DL-based AMR schemes.

TABLE 1 The details of proposed SemiAMR.

Module	Layer	Output
Source/Target Encoder	Conv1D (filters 64, size $1 \times 5$ , padding same) + BN + ReLU + Maxpool1D (size 2, stride 2)	$64 \times 64$
	Conv1D (filters 64, size $1 \times 5$ , padding same) + BN + ReLU + Maxpool1D (size 2, stride 2)	$64 \times 32$
	Conv1D (filters 64, size $1 \times 5$ , padding same) + BN + ReLU + Maxpool1D (size 2, stride 2)	$64 \times 16$
	Conv1D (filters 64, size $1 \times 5$ , padding same) + BN + ReLU + Maxpool1D (size 2, stride 2)	$64 \times 8$
	Conv1D (filters 64, size $1 \times 5$ , padding same) + BN + ReLU + Maxpool1D (size 2, stride 2)	$64 \times 4$
Classifier	FC	$256 \times 128$
	Relu + Dropout + FC	$128 \times 11$
Discriminator	FC + ReLU	$256 \times 128$
	FC	128
	LogSoftmax	2

TABLE 2 The details of the experimental dataset and implementation settings.

Parameter	Assignment
Modulation modes	8PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, 4PAM, 16QAM, 64QAM, QPSK, WBFM
SNR (Source Domain)	2 dB, 4 dB, 6 dB, 8 dB, 10 dB, 12 dB, 14 dB, 16 dB, 18 dB
SNR (Target Domain)	-20 dB, -18 dB, -16 dB, -14 dB, -12 dB, -10 dB, -8 dB, -6 dB, -4 dB
Total number of data	220,000
Learning rate	0.001

To solve the issue of insufficient samples, K. Bu *et al.* [15] proposed an adversarial transfer learning-based AMC, named ATLA, with half of the training data reduced, and the target model achieved competitive recognition accuracy by supervised learning. Besides, L. Li *et al.* [16] proposed a capsule network-based AMC architecture (CapsNet), which leveraged 3% of the dataset for training and obtained 80% classification accuracy. However, both ATLA and CapsNet do not work under the target domain without corresponding labeled training data. Recognizing modulation modes at low SNRs poses a challenge because the reduced SNR degrades the quality of the transmitted signal, making recognition more difficult. Methods to cope with this problem include enhancing the SNR, optimizing receiver parameters, adopting a multi-mode approach, and using advanced recognition algorithms [17]. In fact, modulation mode recognition under low SNR conditions is a complex task that requires consideration of multiple factors.

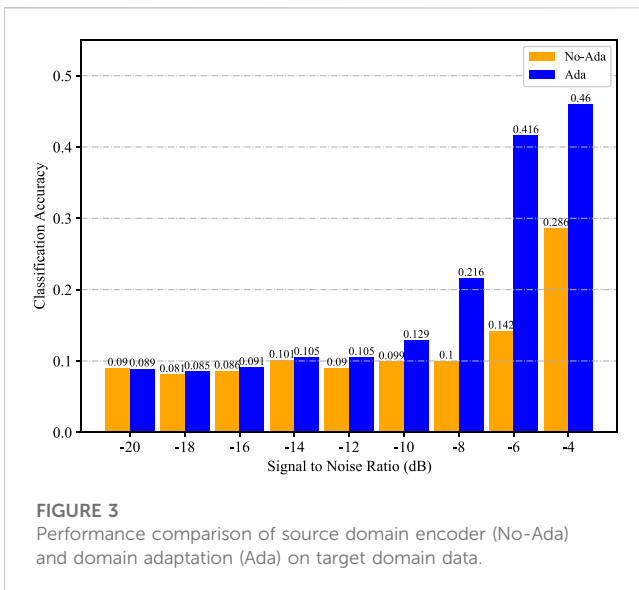
In this paper, inspired by adversarial learning, we design a semi-supervised automatic modulation recognition network (SemiAMR) to implement cross-domain recognition, which can adapt to another signal-to-noise domain with no corresponding labeled data pre-trained. In detail, the source domain is mapped into the classification domain by the source encoder and can be classified by the classifier, where the labeled source data enables the process. Then, the discriminator and target encoder are trained by determining whether the data comes from the target or source domain. Finally, the target encoder and the classifier are leveraged to infer target domain data labels. The contributions and main work of this paper can be summarized as follows.

1. A novel network is proposed to implement semi-supervised learning for AMR, which consists of two CNN-based encoders, a classifier, and a domain discriminator.
2. To enable the inference ability of the DL-based model on target data, all domain data are mapped into a classification domain. The source encoder enables the source data into the classification domain. The target domain data is employed by the target encoder, which is trained by an adversarial distinguish process.
3. Extensive experiments are carried out to validate the performance of the proposed scheme under the target domain. Under the poor signal-to-noise environment, the results elaborate that the proposed SemiAMR improves the classification accuracy from 3% to 27% for the target domain, compared with no adaptation algorithm.

The rest of this paper is organized as follows. Section 2 discusses related work of this paper including semi-supervised learning, spectrum monitoring and automatic modulation classification. In Section 3, the signal model wireless signal and motivation are firstly provided. Section 4 mainly considers the proposed semi-supervised scheme for wireless IoT. Experiment and discussions are implemented in Section 5. Finally, the conclusion of this paper is described in Section 6.

## 2 Related work

This section gives a brief introduction of existing methods on semi-supervised learning, spectrum monitoring, and automatic modulation classification.



## 2.1 Semi-supervised learning

The problem of limited labeled data is a major challenge in training DL-based models [18]. Semi-supervised learning aims to address this challenge by utilizing the information contained in unlabeled data to improve the performance of models. Semi-supervised learning has broad applications in various fields, including image classification, text classification, speech recognition (SR), computer vision (CV), and natural language processing (NLP). There are various approaches to semi-supervised learning, including graph-based semi-supervised learning [19], generative semi-supervised learning [20], and semi-supervised support vector machines [21]. Each approach has its own strengths and weaknesses, and the choice of approach depends on the specific problem being addressed.

Graph-based semi-supervised learning uses the graph structure in unlabeled data to build a model. The method utilizes a technique called graph embedding, which maps nodes in the graph into a low-dimensional space. By mapping nodes into a low-dimensional space, we can better understand the relationships between nodes. In graph-based semi-supervised learning, we can use these relationships to infer the labels of unlabeled data. Generative semi-supervised learning methods are based on generative models that generate data distributions from unlabeled data. The method uses the generative model to estimate the distribution of the unlabeled data and uses this distribution to make predictions. Generative semi-supervised learning methods are a very effective method, especially when the amount of data is small.

Semi-supervised support vector machine is a supervised learning method based on kernel functions [22], which leverages unlabeled data to improve the performance of the classifier. Semi-supervised support vector machines use a data structure called a similarity graph to establish the relationship between unlabeled and labeled data. However, based on semi-supervised learning, there are still many problems to be solved for application in various scenarios.

## 2.2 Spectrum monitoring

To ensure efficient use of spectrum resources and prevent interference, radio spectrum is monitored, analyzed, and managed. Spectrum data is obtained by collecting and processing radio spectrum signals. The collected spectrum data is analyzed to identify radio signals, classify, and analyze them based on signal type, frequency band, bandwidth, modulation mode, *etc.* Many researchers investigated UAV-assisted deep algorithm implementation [23]. These analyses help in detecting interference signals in the spectrum, and identifying their location, so that appropriate countermeasures can be taken.

However, spectrum monitoring also presents several challenges. Multi-signal composite and low SNR signals can make signal processing and identification difficult [24]. Furthermore, spectrum monitoring is limited in coverage and density due to monitoring station deployment and equipment constraints. This can affect the accuracy and effectiveness of monitoring, as well as subsequent analysis and management.

## 2.3 Automatic modulation classification

Modulation mode recognition is a crucial aspect of spectrum monitoring, which involves classifying the modulation mode of radio signals [25]. Modulation mode refers to the relationship between information and the carrier in the radio signal, and can be categorized into various types, such as amplitude modulation, frequency modulation, phase modulation, quadrature amplitude modulation, and others. Identifying modulation modes plays a critical role in signal identification, interference detection, frequency band usage analysis, among others.

There are different modulation mode identification algorithms that can be used, including the energy spectrum-based algorithm, which determines the modulation mode by calculating the energy spectrum of the signal, and the higher-order statistical features-based algorithm, which uses higher-order statistical features to describe and recognize the signal. Machine learning-based algorithms build classification models to identify the modulation of unknown signals by training the signals with known modulation. Common machine learning methods include support vector machine (SVM) [26], artificial neural network (ANN) [27], and random forest (RF) [28], while common DL-based models include convolutional neural networks and recurrent neural networks.

However, modulation modes recognition becomes more challenging when the signal is more complex [29]. Noise is a significant factor that affects the recognition of modulation modes as it alters the signal's characteristics, thereby impacting the recognition accuracy of modulation modes. Moreover, the diversity of radio signals leads to a richer variety of modulation modes, and different types of modulation modes pose varying degrees of recognition difficulty. In practical applications, real-time requirements are often necessary for distributed scenarios that require prompt judgment [30].

## 3 Signal model of wireless IoT and motivation

Assume that the received signal  $x(t)$  suffers from dynamic channel interference and noise, which is modeled as

$$x(t) = G(s(t)) + n(t), \tag{1}$$

where  $G(\cdot)$  signifies the dynamic radio channel,  $s(t)$  is the modulated signal at the transmitter, and  $n(t)$  denotes the Additive White Gaussian Noise (AWGN).

The purpose of AMR is to recognize the modulation mode of  $x(t)$  without prior knowledge after it is filtered at the receiver. Based on the fitting ability of deep neural network (DNN), the DL-based AMR algorithm achieves surprising performance. However, the advance of DL-based AMR algorithm relies on sufficient samples with various modulation modes and radio environments. However, sample collection and labeling are a time-consuming and costly task in real application scenarios. Moreover, trained AMR model with high-quality samples may fail to obtain a promising performance on the collected samples with poor quality. As a consequence, AMR with the capacity of cross-domain recognition seems urgent to reduce the overhead of data collection and improve the recognition robustness.

## 4 Semi-supervised AMR scheme for wireless IoT

### 4.1 The design of domain adaptation network for AMR

To improve the cross-domain inference ability of DL-based model, we propose a semi-supervised AMR network architecture, termed SemiAMR. SemiAMR can learn the feature of source modulation data and adapt the target domain signal data into the sharing classification domain. As shown in Figure 1, the overall structure of SemiAMR consists of four parts, including the source encoder  $S_{cnn}$ , target encoder  $T_{cnn}$ , classifier  $\mathcal{C}$ , and discriminator  $\mathcal{D}$ .

The main implementation process of the proposed SemiAMR approach can be manifested as Algorithm 1. Specifically,  $S_{cnn}$  enables a non-linear mapping algorithm for mapping source-domain wireless signal data to the classification domain. For the classification domain, the general classifier  $\mathcal{C}$  trained on the source domain data can implement effective classification on the source data. In this way, we also try to enable the target domain data map to the classification domain.

```

PRETRAIN( $S_{cnn}^l, \mathcal{C}^l, \mathbf{X}_s$ )
  selectrandomly  $x_s \in \mathbf{X}_s$ 
  initial model  $\mathcal{C}^l, S_{cnn}^l$ 
  for  $i = 1, \dots, N_S$ :
     $\mathcal{C}, S_{cnn} \leftarrow \mathcal{L}(\mathcal{C}^l, S_{cnn}^l, x_s)$ ;
  return  $\mathcal{C}, S_{cnn}$ 

Domain adaptation( $S_{cnn}, \mathcal{D}', T_{cnn}', \mathbf{X}_s, \mathbf{X}_t$ )
  selectrandomly  $x_s \in \mathbf{X}_s, x_t \in \mathbf{X}_t$ 
  initial model  $\mathcal{D}', T_{cnn}'$ 
  for  $i = 1, \dots, N_D$ :
     $\mathcal{D} \leftarrow \mathcal{L}_D(\mathcal{D}', S_{cnn}, x_s, x_t)$ ;
     $T_{cnn} \leftarrow \mathcal{L}_T(\mathcal{D}, S_{cnn}, T_{cnn}', x_t)$ ;
  return  $T_{cnn}$ 

PREDICT( $T_{cnn}, \mathbf{X}_t, \mathcal{C}$ )
   $\mathbf{Y}_t \leftarrow \mathcal{C}(T_{cnn}(\mathbf{X}_t))$ 
  return  $\mathbf{Y}_t$ 
    
```

**Algorithm 1.** Proposed Semi-supervised AMR: SemiAMR

Then, based on the target and source domain data, the discriminator  $\mathcal{D}$  and the  $T_{cnn}$  are trained by optimizing  $mathcal{L}_D$  and  $mathcal{L}_T$ , respectively.  $\mathcal{L}_D$  represents the loss of Discriminator, while  $\mathcal{L}_T$  denotes the loss of domain label predictor. In detail,  $\mathcal{D}$  and  $T_{cnn}$  are trained to distinguish the data from the source or target domain. When  $\mathcal{D}$  can not distinguish the data from which domain,  $T_{cnn}$  is considered that can map the target data into the classification domain. In this way, by combining  $T_{cnn}$  and  $\mathcal{C}$ , the combined DL-based network can implement inference operations on the target domain. The corresponding dimensions of each layer are shown in Table 1.

- 1) *Source encoder  $S_{cnn}$* :  $S_{cnn}$  extracts key features from the signal data of source domain and then maps the model to the classification domain.  $S_{cnn}$  contains five convolutional blocks, and each block consists of a convolutional layer, a batch normalization (BN) layer, an activation function  $ReLU$ , and a max-pooling layer. The convolutional layer implements the extraction of useful features, and BN speeds up the training process and convergence of the network by regularizing the data. The activation function  $ReLU$  is formulated as  $f_{ReLU}(x) = \max(0, x)$ , preventing gradient disappearance and avoiding over-fitting. The max-pooling layer reduces data dimensionality, decreases the number of parameters, removes redundant information, and compresses features.
- 2) *Classifier  $\mathcal{C}$* :  $\mathcal{C}$  consists of one layer of neural network, which performs classification in the classification domain. Furthermore, the layer contains 128 dimension neurons and an activation function  $ReLU$ .
- 3) *Target encoder  $T_{cnn}$* : The mapping task is conducted by  $T_{cnn}$  from the target domain data to the classification domain. The structure of  $S_{cnn}$  and  $T_{cnn}$  are identical.
- 4) *Discriminator  $\mathcal{D}$* :  $\mathcal{D}$  contains three fully connected layers, and the dimension of each layer is 128. Besides,  $ReLU$  is added between the two layers. The last layer of  $\mathcal{D}$  is  $LogSoftMax$ , and it is defined as follows

$$f_{LogSoftMax}(x_i) = \log\left(\frac{\exp(x_i)}{\sum_j \exp(x_j)}\right), \tag{2}$$

which can solve the overflow and underflow issues of deep network, speed up operation speed and improve data stability.

As shown in Figure 2, the source encoder and the classifier are combined into an end-to-end model that implements pre-training operations in the first stage. In the second stage, the source encoder, target encoder and discriminator are combined and the discriminator and target encoder are trained with input of source domain data and target domain data, respectively. A number of iterations are performed until the discriminator is unable to determine which domain the data from. In the third stage, the target encoder and the classifier are combined to achieve a complete end-to-end function for the target domain.

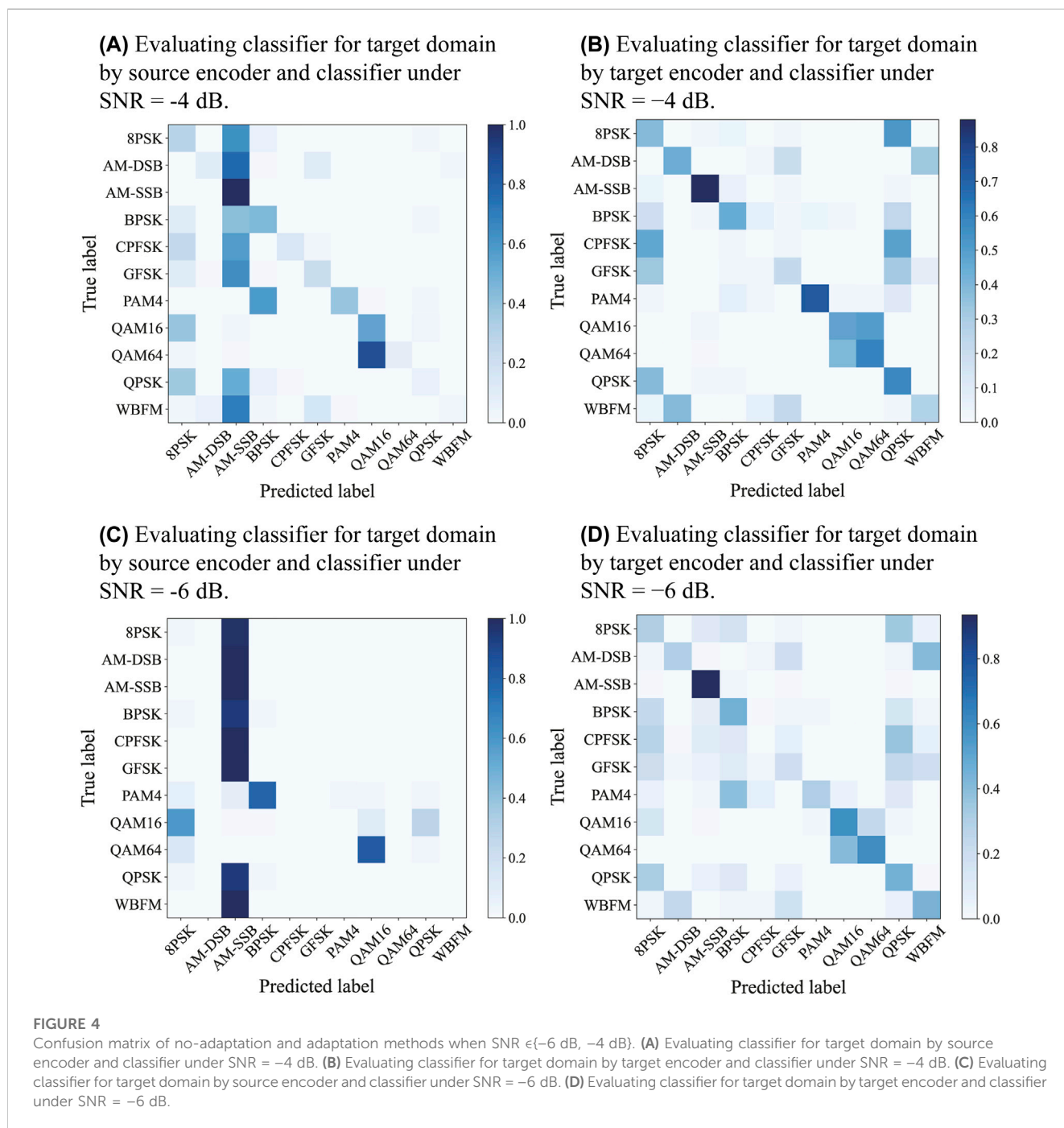
### 4.2 Loss function

In this work, to improve the generation of the CNN-based AMR scheme,  $S_{cnn}$  and  $\mathcal{C}$  are pre-trained on the source data firstly. Cross entropy is leveraged as the loss function of the pre-train process,



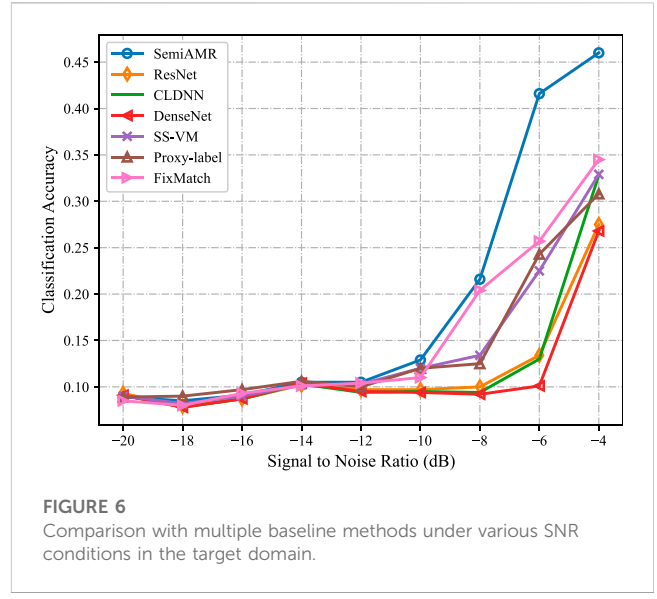
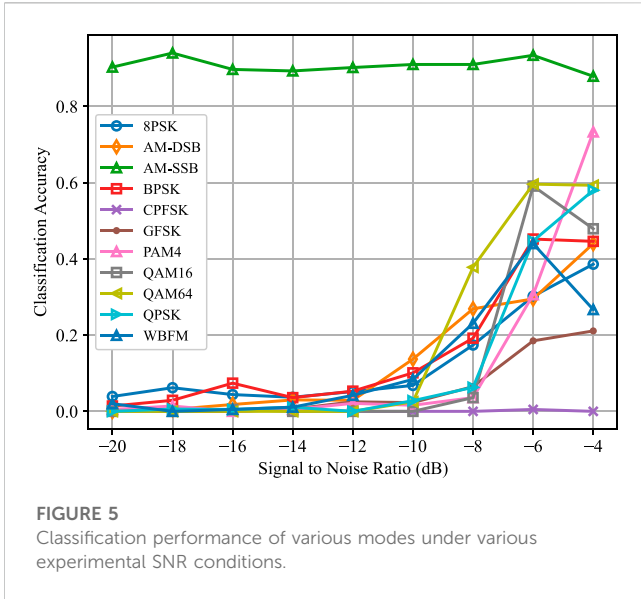
**TABLE 3** Performance comparison of different encoder layers under various SNR conditions.

Settings	-20 dB	-18 dB	-16 dB	-14 dB	-12 dB	-10 dB	-8 dB	-6 dB	-4 dB
Encoder 4 Layers	0.090	0.087	0.092	0.103	0.105	0.131	0.213	0.406	0.443
Encoder 5 Layers	0.089	0.085	0.091	0.105	0.105	0.129	0.216	0.416	0.460
Encoder 6 Layers	0.091	0.089	0.099	0.108	0.125	0.143	0.238	0.426	0.463
Encoder 7 Layers	0.089	0.089	0.090	0.101	0.100	0.117	0.210	0.409	0.452



**FIGURE 4**

Confusion matrix of no-adaptation and adaptation methods when SNR  $\in$  {-6 dB, -4 dB}. (A) Evaluating classifier for target domain by source encoder and classifier under SNR = -4 dB. (B) Evaluating classifier for target domain by target encoder and classifier under SNR = -4 dB. (C) Evaluating classifier for target domain by source encoder and classifier under SNR = -6 dB. (D) Evaluating classifier for target domain by target encoder and classifier under SNR = -6 dB.



$$\mathcal{L}_C = -E_{x_s}[\log \mathcal{C}(S_{cm}(x_s))], \tag{3}$$

where  $x_s$  denotes the source data, and  $E(\cdot)$  represents the mathematical expectation operation.

The training strategy of domain adaptation enables data from the target domain to be mapped to the classification domain by  $T_{cm}$ . In the training process, for data from the source domain (with labels) and data from the target domain (without labels), the discriminator determines whether the incoming data is from the source domain (computed by  $S_{cm}$ ) or from the target domain (computed by  $T_{cm}$ ). For each iteration, the network continuously minimizes the loss of the domain discriminator  $\mathcal{L}_D$ , and the weights of  $T_{cm}$  are not trained in this optimize process. Similarly, the weights of discriminator are frozen to train  $T_{cm}$ , and the network tries to minimize the loss of the domain label predictor  $\mathcal{L}_T$ . The loss function of the domain adaptation is modeled as

$$\begin{aligned} \mathcal{L}_D &= -E_{x_s}[\log \mathcal{D}(S_{cm}(x_s))] - E_{x_t}[\log(1 - \mathcal{D}(T_{cm}(x_t)))] \\ \mathcal{L}_T &= -E_{x_t}[\log \mathcal{D}(S_{cm}(x_t))], \end{aligned} \tag{4}$$

where  $x_s$  and  $x_t$  denote the data of source domain and target domain, respectively.  $T_{cm}$  signifies the weights of  $T_{cm}$  are frozen, which means the parameters are not trained, and  $\mathbf{D}$  represents the frozen parameters of  $\mathcal{D}$ . Based on these schemes, the Adam method and the back-propagation algorithm are employed to optimize the weights of SemiAMR.

## 5 Implementation details

### 5.1 Datasets and settings

To evaluate the performance of the proposed algorithm, we implement the experiment on the RadioML2016.10a dataset [10]. The details of the dataset and experiment settings are exhibited in Table 2. Accordingly, the modulation of the dataset consists of 8PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, 4PAM, 16QAM, 64QAM, QPSK, WBFM, with SNR in  $\{-20 \text{ dB}, 18 \text{ dB}\}$  and the stride is 2 dB. There are 1,000 pieces of signal data for every SNR of each class, and

the total number of data is 220,000. In this way, the dataset is separated into a higher SNR part (source domain), including  $\{2 \text{ dB}, 4 \text{ dB}, 6 \text{ dB}, 8 \text{ dB}, 10 \text{ dB}, 12 \text{ dB}, 14 \text{ dB}, 16 \text{ dB}, 18 \text{ dB}\}$ , and a lower SNR part (target domain) that includes  $\{-20 \text{ dB}, -18 \text{ dB}, -16 \text{ dB}, -14 \text{ dB}, -12 \text{ dB}, -10 \text{ dB}, -8 \text{ dB}, -6 \text{ dB}, -4 \text{ dB}\}$ . In the experiments, an NVIDIA GeForce RTX 2080Ti GPU is employed, and the algorithm is implemented by PyTorch.

### 5.2 Experiments and discussions

The experimental result of the proposed SemiAMR is exhibited in Figure 3, where “No-Ada” denotes the source encoder inference only, and “Ada” represents the proposed algorithm SemiAMR. Accordingly, for SNR = -8 dB, the classification accuracy of the proposed scheme is 21.6%, which exceeds 11.6% over the baseline “No-Ada”. When SNR = -4 dB, the classification of SemiAMR reaches 41.6%, which far exceeds the no-adaptation method 27.4%, and makes an improvement of 18.6%. The results show that the domain adaptation scheme effectively solves the classification issue of cross signal-to-noise domain.

Convolutional layers are fundamental building blocks of deep learning models and play a critical role in extracting features from input data. The number of convolutional layers is a crucial factor in the structure of a CNN, and it can significantly impact experimental outcomes. To investigate the impact of different convolutional layers on experimental results, we create an encoder set and measured recognition accuracy at different SNR levels. Table 3 shows that the encoder module with 4 layers achieved a recognition accuracy of 44.3%, while 5 layers achieved 46%, 6 layers reached 46.3%, and 7 layers obtained 45.2%. These results (depicted in Table 3) suggest that the recognition accuracy is not always positively correlated with the number of convolutional layers at every SNR. Interestingly, the recognition accuracy decreases when the number of convolutional layers reaches seven, indicating that the optimal number of convolutional layers is task-dependent and not solely related to increased complexity.

As shown in Figure 4, the normalized confusion matrix of SemiAMR are exhibited, adapting to the target domain under  $\text{SNR} \in \{-4 \text{ dB}, -6 \text{ dB}\}$ . In detail, Figures 4A, C represent that the data of target domain is tested on the  $S_{cnn}$  and  $\mathcal{C}$  directly, which are trained on the source data. The results show apparent confusion in the target domain test results, and many categories are misclassified as AM-SSB. In addition, the results of the proposed SemiAMR are presented in Figures 4B, D, stating that the confusion between categories is effectively relieved. Simultaneously, 16QAM and 64QAM are confusion-prone under direct recognition of model  $S_{cnn}$  trained in the source domain. Figures 4B, D show that the confusion is effectively mitigated by domain adaptation training.

The classification performance for various modes is exhibited under the experimental SNRs conditions in Figure 5. From Figure 5, the accuracy of all 11 modulated modes in the target domain increases with SNR. Furthermore, the accuracy of AM-SSB classification is around 90% at each SNR. As CPFSK, 8PSK, and QPSK are easily confused in the classification domain, the classification accuracy of CPFSK does not vary significantly with SNR and is determined into 8PSK and QPSK.

In Figure 6, the recognition accuracy of proposed SemiAMR scheme is compared with various approaches, such as ResNet [11], CLDNN [31], DenseNet [14], SS-VM [32], Proxy-label [33], and FixMatch [34]. In addition, As the SNRs increase from  $-20 \text{ dB}$  to  $-4 \text{ dB}$ , the recognition accuracy of the baseline method gradually increases from 9% to 33%. However, the accuracy of SemiAMR inference starts to exceed that of the baseline method at  $-12 \text{ dB}$ . When  $\text{SNR} = -8 \text{ dB}$ , the proposed scheme is higher than the baseline method by about 12%, and at  $\text{SNR} = -6 \text{ dB}$ , it is greater than the best classification accuracy of the baseline method by 17%. SemiAMR can reach 47% under  $\text{SNR} = -4 \text{ dB}$ , which exceeds the baseline method by 12%. As a result, the accuracy of the no-adapt schemes seems very low in poor signal-to-noise conditions, where labeled signal can not be obtained for pre-training. In terms of proposed SemiAMR scheme, the performance is greatly improved by domain adaptation, yielding a promising inference ability on target domain data as a consequence.

## 6 Conclusion

In this paper, inspired by the domain adaptation algorithm, we design a semi-supervised architecture for AMR. The proposed scheme is evaluated on the RadioML2016.10a [10], and the adaptability of baseline methods with target domain (unlabeled data) is discussed. Experimental results indicate that our

proposed SemiAMR can obtain a maximum classification accuracy of 46% with no corresponding labeled data pre-trained under  $\text{SNR} = -4 \text{ dB}$ . Simultaneously, to investigate the effect of the number of convolutional layers on the experimental results, the performance of the model at different signal-to-noise ratios (SNR) was tested with 4, 5, 6 and 7 convolutional layers. Besides, the proposed SemiAMR is greater than the best classification accuracy of the baseline methods by 17% under  $\text{SNR} = -6 \text{ dB}$ .

## Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

## Author contributions

QZ was in charge of the major theoretical analysis, algorithm design, experimental simulation, and paper writing. XJ and QZ had contributions to paper writing. ZJ and RZ had contributions to theoretical analysis and gave suggestions of the organization. All authors read and approved the final manuscript.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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