

# FSOS-AMC: Few-Shot Open-Set Learning for Automatic Modulation Classification

Hao Zhang<sup>§</sup>, Fuhui Zhou<sup>§</sup>, Qihui Wu<sup>§</sup>, and Chau Yuen<sup>†</sup>

<sup>§</sup>Nanjing University of Aeronautics and Astronautics, China;

<sup>†</sup>Nanyang Technological University, Singapore, Singapore

Email: haozhangcn@nuaa.edu.cn, zhoufuhui@ieee.org, wuqihui2014@sina.com, and chau.yuen@ntu.edu.sg

**Abstract**—Automatic modulation classification (AMC) is essential for the advancement and efficiency of future wireless communication networks. Deep learning (DL)-based AMC frameworks have garnered extensive attention for their impressive classification performance. However, existing DL-based AMC frameworks rely on two assumptions, large-scale training data and the same class pool between the training and testing data, which are not suitable for *few-shot and open-set* scenarios. To address this issue, a novel few-shot open-set automatic modulation classification (FSOS-AMC) framework is proposed by exploiting a multi-scale attention network, meta-prototype training, and a modular open-set classifier. The multi-scale attention network is used to extract the features from the input signal, the meta-prototype training is adopted to train the feature extractor and the modular open-set classifier can be utilized to classify the testing data into one of the known modulations or potential unknown modulations. Extensive simulation results demonstrate that the proposed FSOS-AMC framework can achieve higher classification accuracy than the state-of-the-art methods for known modulations and unknown modulations in terms of accuracy and area under the receiver operating characteristic curve (AUROC). Moreover, the performance of the proposed FSOS-AMC framework under low signal-to-noise ratio (SNR) conditions is much better than the compared schemes.

**Index Terms**—Automatic modulation classification, few-shot open-set, multi-scale attention network, meta-prototype training, modular open-set classifier.

## I. INTRODUCTION

Automatic modulation classification (AMC) is crucial for future wireless communication systems because it facilitates a range of applications including cognitive radio and intelligent spectrum management. AMC is the process of identifying the modulation scheme of a received signal, which is essential for both civilian and military applications. In civilian applications, AMC can be used for identifying unauthorized signals by detecting the modulation schemes, while in military applications, AMC facilitates abnormal signal detection and interference detection. With the further development of next-generation wireless communication systems, such as 6G, the AMC problem becomes more challenging due to the increasing number

of modulation schemes and the dynamic wireless environment. Thus, it is essential to develop efficient and robust AMC frameworks.

Traditional AMC schemes include likelihood-based (LB) schemes and feature-based (FB) schemes [1], [2]. The LB schemes formulate AMC as a hypothesis testing problem, which requires known signal-to-noise ratio (SNR) and frequency offsets [3]. The FB methods are computationally expensive and require human-expert feature extraction [4]. Both methods are intricate and time-intensive, and they lack the flexibility required to adapt to the dynamic nature of wireless environments. In response to the rapid advancements in artificial intelligence [5]–[7], deep learning (DL)-based AMC frameworks have been proposed, which are capable of autonomously learning features directly from raw signals [8]. For example, the authors in [9] first developed a RadioML dataset and proposed a convolutional neural network (CNN)-based AMC framework for solving the AMC problem, achieving a high classification accuracy. Later, a large-scale dataset was proposed in [10] and a ResNet-based AMC framework was proposed for solving the AMC problem. However, the existing deep learning-based AMC methods relied on two dataset assumptions, large-scale training datasets and the same class pool between the training and testing data, *i.e.* a closed-set scenario. These assumptions failed under two scenarios, 1) *few-shot conditions*, where it is hard to collect enough labeled data and 2) *open-set scenarios*, where the testing classes do not appear during training.

**Closed-set AMC frameworks:** Closed-set is the most common scenario in AMC, where the training and testing data are from the same set of modulation schemes. Various deep learning-based AMC frameworks have been proposed, such as CNN-based [1], recurrent neural network (RNN)-based [11], and hybrid frameworks. The works [9] and [10] introduced the RadioML datasets, which are widely used for AMC research. Zhang *et al.* [1] proposed a novel multi-scale convolutional neural network-based AMC framework, which can achieve high classification accuracy. The authors in [11] exploited an RNN-based AMC framework, demonstrating that the RNN-based classifier is robust to uncertain noise conditions. In summary, while CNNs and RNNs have driven initial wireless deep learning research, a key limitation that remains is their reliance on large labeled datasets for training.

**Few-shot AMC frameworks:** few-shot AMC is a scenario

This work was supported by the National Natural Science Foundation of China under Grant 62222107, the Fundamental Research Funds for the Central Universities under Grant 56XIA22003, and Grant 3082023NQ2023004, the China Scholarship Council under Grant 202306830108, the Postgraduate Research & Practice Innovation Program of Jiangsu Province under Grant KYCX23\_0380, and the Interdisciplinary Innovation Fund for Doctoral Students of Nanjing University of Aeronautics and Astronautics under Grant KXKCXJJ202302.

where the model is trained with a few samples of each modulation scheme. Recent works can be categorized into three categories, namely, few-sample-based methods, support-data-based methods, and synthetic-data-based methods. Li *et al.* [12] introduced an AMR-CapsNet for AMC that achieves high accuracy under limited training data. The authors in [2] proposed a novel few-shot AMC framework by using semi-supervised learning, which can achieve high classification accuracy with a small number of samples. Existing few-shot AMC frameworks focused on the few-shot learning problem under the closed-set scenario, without considering the open-set recognition problem.

*Open-set AMC frameworks:* Open-set recognition (OSR) is a scenario where the model is trained with a set of modulation schemes, but the testing data may contain modulation schemes that are not seen during training. Bendale *et al.* [13] proposed the OpenMax model, replacing the softmax layer in the deep network with the OpenMax layer for OSR. Chen *et al.* [14] proposed a metric-based OSR framework, which can achieve high classification accuracy. The authors in [15] exploited a feature space singularity-based framework, which can improve discrimination between in-distribution and out-of-distribution features by promoting compact classification boundaries and reducing feature overlap. However, the existing open-set AMC frameworks still rely on large-scale training data.

Motivated by the challenge of the few-shot open-set AMC, we propose a novel few-shot open-set automatic modulation classification (FSOS-AMC) framework. The FSOS-AMC framework consists of three main parts, a multi-scale attention network, the meta-prototype training, and a modular open-set classifier. The multi-scale attention network can learn the multi-scale features of the input signal, the meta-prototype training is used to train the feature extractor in a few-shot learning manner, and the modular open-set classifier can classify the testing data into one of the known or potential unknown modulations. Simulation results demonstrate that the proposed FSOS-AMC framework can achieve high classification accuracy for known and unknown modulations compared to state-of-the-art methods. Moreover, the proposed FSOS-AMC framework can achieve high classification accuracy under low SNR conditions with less confusion between known and unknown modulations.

The structure of this paper is organized as follows. Section II introduces the preliminaries. Section III details our proposed FSOS-AMC framework. Section IV discusses the simulation results. The paper concludes in Section V.

## II. PRELIMINARIES

### A. Signal Model

Assume that the wireless communication system is equipped with a single transmitter, a channel and a receiver. The transmitter modulates the information bits into a signal, which is transmitted through the channel and received by the receiver. The received signal  $x(n)$  can be denoted as

$$x(n) = s(n) * h(n) + w(n), n = 0, 1, \dots, N, \quad (1)$$

where  $s(n)$  is the transmitted signal,  $h(n)$  is the channel impulse response,  $w(n)$  is the additive white Gaussian noise (AWGN), and  $N$  is the number of samples.

The received signal  $x(n)$  can be transferred into an in-phase and quadrature (I/Q) signal  $\mathbf{x}_{IQ}(n)$  as a vector, given as

$$\mathbf{x}_{IQ}(n) = \begin{bmatrix} \Re\{x(1), x(2), \dots, x(N)\} \\ \Im\{x(1), x(2), \dots, x(N)\} \end{bmatrix}, \quad (2)$$

where  $\Re\{\cdot\}$  and  $\Im\{\cdot\}$  denote the operators of the real and imaginary parts of the complex signal, respectively.

### B. Problem Formulation

The AMC problem can be formulated as a multi-class classification problem. Given a set of  $N$  modulation schemes, the goal is to classify the received signal into one of the  $N$  classes. For closed-set AMC, the training data and testing data are from the same set of modulation schemes. It can be formulated as

$$\hat{y} = \arg \max_y p(y|\mathbf{x}_{IQ}), \quad (3)$$

where  $\hat{y}$  is the predicted modulation scheme,  $p(y|\mathbf{x}_{IQ})$  is the probability distribution of the modulation schemes given the received signal  $\mathbf{x}_{IQ}$ .

For open-set AMC, the model is trained with a set of modulation schemes, but the testing data may contain modulation schemes that are not seen during training. Given a set of training data  $D_{tr} = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$  with  $n$  labeled instances and  $N$  known classes,  $y_i \in 1, 2, \dots, N$  denotes the label of the  $i$ -th instance. The goal of open-set AMC is to classify the testing data  $D_{te} = \{x_1, x_2, \dots, x_m\}$  with  $m$  instances into one of the  $N$  known classes or potential unknown classes, denoted as  $N + 1$ . It should be noted that the unknowns may belong to various classes, and their specific classifications are not the primary focus of the open-set recognition task.

## III. PROPOSED FSOS-AMC FRAMEWORK

The proposed few-shot open-set automatic modulation classification (FSOS-AMC) framework is shown in Fig. 2. The FSOS-AMC framework consists of three main parts, multi-scale attention feature extractor, meta-prototype training, and modular open-set classifier. The multi-scale attention feature extractor is used to extract the features from the input signal by using a combination of a multi-scale module and a channel attention module. The meta-prototype training can train the feature extractor in a few-shot learning manner, which can learn the features from a small number of samples. Finally, the modular open-set classifier can classify the testing data into one of the known or potential unknown modulations.

### A. Multi-Scale Attention Feature Extractor

Multi-scale module has been demonstrated useful for signal recognition tasks [1], [16], [17]. In this work, we introduce a multi-scale attention network (MSANet) to further enhance the feature representation. The MSANet consists of two layers of multi-scale attention modules, which are composed of a

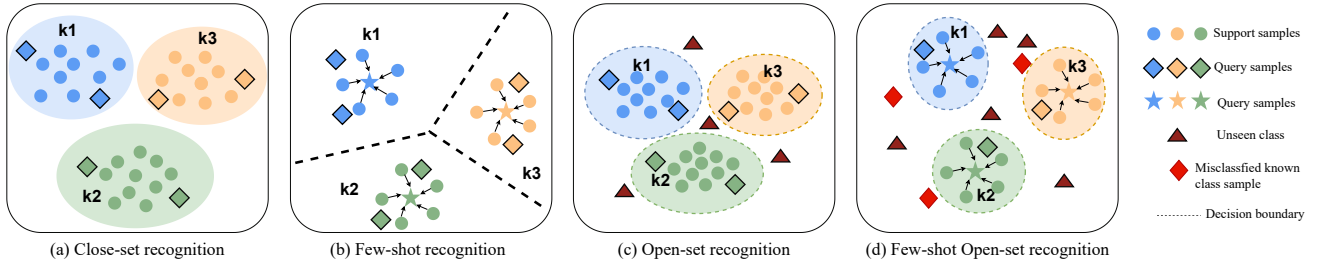


Fig. 1. Illustration of the few-shot open-set recognition compared to (a) closed-set recognition, (b) few-shot recognition, and (c) open-set recognition.

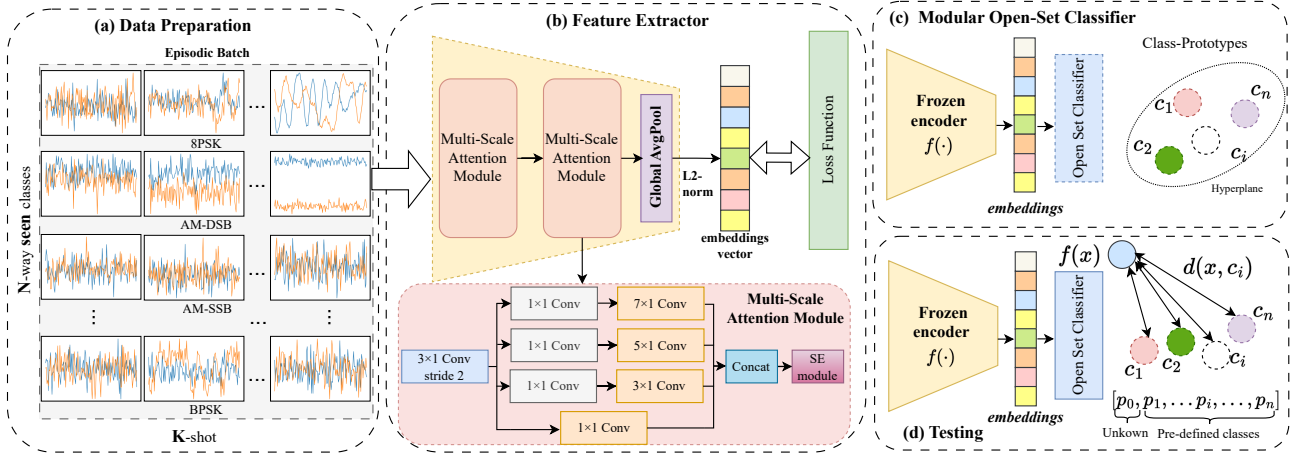


Fig. 2. Overview of the proposed few-shot open-set automatic modulation classification (FSOS-AMC) framework.

multi-scale module and a channel attention module. The multi-scale module is designed to capture the multi-scale features of the input signal, learning more separable features. Moreover, the channel attention mechanism is introduced to model the channel-wise dependencies and enhance the important features. Finally, a global average pooling layer is used to aggregate the feature maps and a  $L_2$  normalization layer is used to normalize the feature vectors.

In the multi-scale module, a convolutional layer with kernel  $3 \times 1$ , stride 2 is used to downsample the input signal, labeling as  $C_{\text{down}}$ . Then, the downsampled signal is fed into four parallel convolutional layers with different kernel sizes. The four parallel convolutional layers consist of  $1 \times 1$ ,  $3 \times 1$ ,  $5 \times 1$ , and  $7 \times 1$  kernels, respectively, and the convolutional operation is represented as  $\text{Conv}_1, \text{Conv}_3, \text{Conv}_5, \text{Conv}_7$ . At the beginning of the  $\text{Conv}_3, \text{Conv}_5, \text{Conv}_7$  layers, a  $1 \times 1$  convolutional layer is used to reduce the channel dimension, denoting as  $C_1$ . All the convolutional layers are followed by a batch normalization layer and a ReLU activation function. The output feature maps of the four convolutional layers are concatenated along the channel dimension. The multi-scale module can be formulated as

$$\mathbf{X}_{\text{multi}} = \text{Concat}(\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3, \mathbf{X}_4), \quad (4)$$

where  $\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3$ , and  $\mathbf{X}_4$  are the output feature maps of

the four convolutional layers, given as

$$\mathbf{X}_1 = \text{Conv}_1(C_{\text{down}}(\mathbf{X})), \quad (5a)$$

$$\mathbf{X}_2 = \text{Conv}_3(C_1(C_{\text{down}}(\mathbf{X}))), \quad (5b)$$

$$\mathbf{X}_3 = \text{Conv}_5(C_1(C_{\text{down}}(\mathbf{X}))), \quad (5c)$$

$$\mathbf{X}_4 = \text{Conv}_7(C_1(C_{\text{down}}(\mathbf{X}))). \quad (5d)$$

To further enhance the feature representation, we introduce the channel attention mechanism into the feature extraction module. The channel attention mechanism can capture the inter-channel dependencies and enhance the important features. The squeeze-and-excitation (SE) module [18] is adopted to model the channel-wise dependencies. As shown in Fig. 3, the SE module consists of two operations, namely, squeeze and excitation. The goal of the squeeze operation is to aggregate spatial information within each channel to produce a channel descriptor. This is typically achieved through global average pooling, which reduces the spatial dimensions (height and width) of each channel, retaining only the channel dimension. Mathematically, for an input feature map  $\mathbf{X} \in \mathbb{R}^{H \times W \times C}$ , the squeeze operation can be expressed as

$$z_c = \text{GAP}(\mathbf{X}) = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W \mathbf{x}_{i,j}^c, \quad (6)$$

where  $z_c$  is the feature obtained by performing global average pooling over the  $c$ -th channel, and  $\mathbf{x}_{i,j}^c$  is the value of the  $c$ -th channel at position  $(i, j)$ .

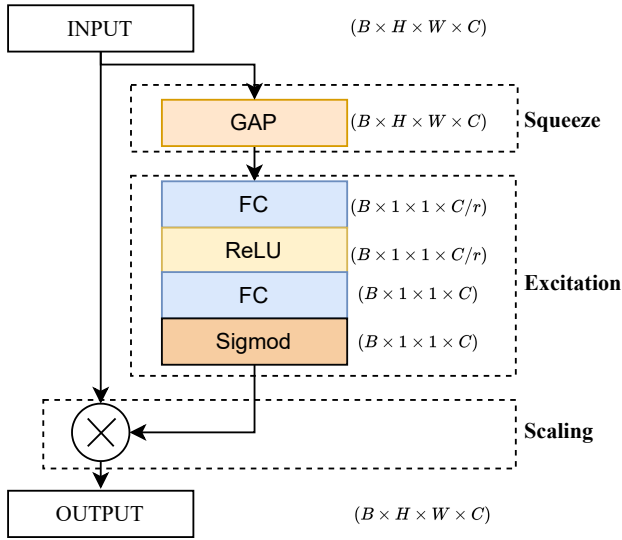


Fig. 3. Squeeze-and-Excitation Module.

The excitation operation utilizes the channel descriptors generated in the squeeze operation to learn a channel-specific weight vector. This is typically implemented using a simple fully connected layer, including a ReLU activation followed by a Sigmoid activation to generate the weights. Mathematically, the excitation function can be represented as

$$s = \sigma(\mathbf{W}_2 \delta(\mathbf{W}_1 z)), \quad (7)$$

where  $\sigma$  and  $\delta$  are the Sigmoid and ReLU activation functions, respectively.  $\mathbf{W}_1 \in \mathbb{R}^{\frac{C}{r} \times C}$  and  $\mathbf{W}_2 \in \mathbb{R}^{C \times \frac{C}{r}}$  are the weights of the fully connected layers, and  $r$  is the reduction ratio.

Finally, the obtained weights  $s$  are used to scale the original input feature map  $\mathbf{X}$  across channels by performing channel-wise multiplication

$$\mathbf{X}_{SE} = \mathbf{X} \cdot s, \quad (8)$$

where  $\mathbf{X}_{SE}$  is the output feature map after the SE module.

### B. Meta-Prototype Training

As shown in Fig. 2, the feature extractor is trained using a supervised, episode-based methodology. The feature encoder MSANet, denoted as  $f(\cdot)$ , is systematically trained utilizing a supervised, episode-based methodology. Each episode commences with the data loader introducing a batch of training data procured from the main dataset. This batch is distinctively composed, ensuring an equal representation of samples from  $N$  distinct classes.

Considering an episodic batch that includes  $S$  support samples  $\{x_{i,j}^S\}_{i=1}^S$  and  $Q$  query samples  $\{x_{i,j}^Q\}_{i=1}^Q$  from  $N$  classes, for a total of  $(S+Q) \times N$  support and query samples per batch. At every episode, a set of prototypes  $c = \{c_j\}_{j=1}^N$  is firstly computed, given as

$$c_j = \frac{1}{S} \sum_{i=1}^S f(x_{i,j}^S). \quad (9)$$

During the training process, a triplet loss is used to minimize the distance between the query sample and the correct class prototype, while maximizing the distance between the query sample and the incorrect class prototypes. The triplet loss can be formulated as

$$\mathcal{L} = \frac{1}{N_t} \sum_{i=1}^{N_t} \max(0, \mathbf{d}(x_{i,j}^{Q+}, c_j) - \mathbf{d}(x_{i,j}^{Q-}, c_k) + m), \quad (10)$$

where  $x_{i,j}^{Q+}$  and  $x_{i,j}^{Q-}$  are the query samples from the correct and incorrect classes, respectively.  $m$  is the margin parameter, and  $N_t$  is the number of triplets.  $\mathbf{d}$  is the distance function, given as

$$\mathbf{d}(x, j) = -d_{L2}(f(x), c_j), \quad (11)$$

and  $-d_{L2}$  is the euclidean distance function.

### C. Modular Open-Set Classifier

At inference time, the FSOS-AMC pipeline receives  $K$  enrollment samples for every user-defined modulation scheme. After computing the embeddings of the  $K$ -shot samples using the trained encoder, a classifier computes Eq. 9 and stores the class prototypes.

When a new test sample is fed to the pipeline, the open-set classifier returns a probability score vector  $P = \{p_i\}_{i=0}^N$  based on the current prototype set. Specifically,  $p_0$  is the prediction score for the unknown class and  $p_i$  is the probability of the  $i$ -th class, which assumes the highest value if the distance score of Eq. 11 is the lowest. The final class prediction  $y$  is

$$y = \begin{cases} \arg \max p_i, & \text{if } p_i \geq \gamma \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

where  $y = 0$  denotes the unknown class and  $\gamma$  is a manually tunable parameter to tradeoff between the classifier's precision and recall.

In this work, the Nearest Class Mean (NCM) classifier [19] is adopted as the open set classifier, which computes the distance between the query sample and the class prototypes. A simple open-set variant estimates the  $c_0$  prototype for the unknown class using  $K$  random samples taken from the target domain but not belonging to the pre-defined classes. The probability score is computed by applying the SoftMax on the  $(N+1)$ -sized distance vector obtained from Eq. 11.

## IV. EXPERIMENTS AND RESULTS

### A. Evaluation Metrics

Open set recognition is a challenging problem in DL-based recognition tasks. To better understand the difficulty of the open set recognition problem, the *openness* [20] metric is defined as

$$openness = 1 - \sqrt{\frac{2 \times N_{tr}}{N_{tr} + N_{te}}}, \quad (13)$$

where  $N_{tr}$  represents the number of known modulation schemes in the training set, and  $N_{te}$  is the number of known modulation schemes in the testing set. Typically, the openness value is between 0 and 1. A higher openness value indicates

TABLE I  
DATASET CONFIGURATION FOR FEW-SHOT OPEN-SET AMC USING  
RADIOML 2016.10A DATASET.

	Training	Testing
Classes	AM-DSB, QAM64, CPFSK,GFSK, 8PSK, PAM4	AM-DSB, QAM64, CPFSK,GFSK, 8PSK, PAM4, unknown: $\{AM-SSB, BPSK,$ $QAM16, QPSK, WBFM\}$
Numbers	5-way 10-shot	14,000 samples
<i>openness</i>	15.98%	

a more challenging open set recognition problem.  $N_{tr} \leq N_{te}$ . When  $N_{tr} = N_{te}$ , the value of *openness* is 0 and it is closed set recognition.

To evaluate the performance of the proposed FSOS-AMC framework, classification accuracy is used to evaluate the performance of the proposed FSOS-AMC framework for known classes. Moreover, to evaluate the performance of the proposed FSOS-AMC framework for unknown classes, two metrics, *AUROC* (Area Under the Receiver Operating Characteristic curve), and *FRR* (False Reject Rate) are used. The larger the *AUROC* value, the better the performance of the open set recognition, and the smaller the *FRR* value, the better the performance.

### B. Experimental Setup

To evaluate the performance of our proposed FSOS-AMC framework, we conduct experiments on the RadioML 2016.10a dataset [9], which is a widely used dataset for AMC. The dataset contains 11 modulation schemes, including 8 digital modulation schemes and 3 analog modulation schemes at varying signal-to-noise ratios from  $-20$  dB to  $18$  dB with a step of 2. The digital modulation schemes include 8PSK, BPSK, CPFSK, GFSK, PAM4, QAM16, QAM64, QPSK. The analog modulation schemes include AM-DSB, AM-SSB, and WBFM. The dataset is generated by GNU Radio and is available on the web. By the specifications outlined in [2], we opt for a signal-to-noise ratio (SNR) range of  $-6$  dB to  $12$  dB with an interval of 2 dB in our experiment, with total 110,000 samples. The proportion of the training set and testing set is 80% and 20%, respectively. To perform open set recognition, we randomly select 6 modulation schemes (AM-DSB, QAM64, CPFSK, GFSK, 8PSK, PAM4) as the training set and all 11 modulation schemes as the testing set, where 5 modulation schemes are unknown during testing. For this setting, the *openness* value is 15.98%. The dataset configuration is shown in Table I, the compared methods and the proposed FSOS-AMC framework are first trained on the 5 known modulation schemes using a 5-way 10-shot learning manner, and then tested on the 11 modulation schemes.

Experiments are conducted on a workstation with an AMD Ryzen 9 7900X3D CPU, 64GB RAM, and an NVIDIA GeForce RTX 4070 Ti GPU, and the system is running Ubuntu 22.04. Code is implemented in Python and the PyTorch

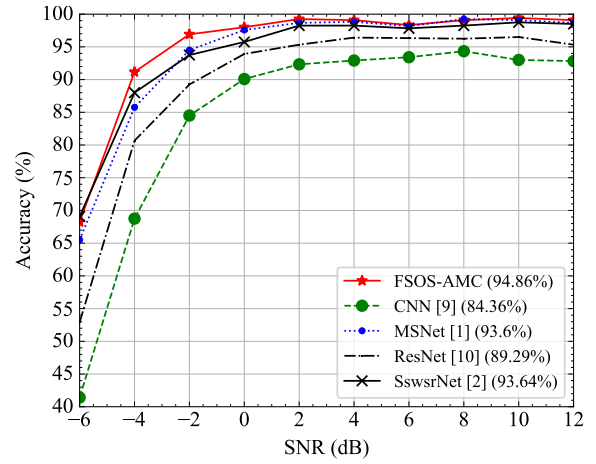


Fig. 4. Classification performance comparison of the proposed FSOS-AMC framework with the state-of-the-art methods, including CNN [9], ResNet [10], MSNet [1], and SSwsrNet [2] under various signal-to-noise ratio (SNR).

deep learning framework. To train our proposed FSOS-AMC framework, we employ the Adam optimization algorithm with an initial learning rate of 0.001 over 50 training epochs. During each training epoch, 200 episodes of 5 modulation schemes with 10 samples from each modulation scheme are selected.

### C. Results and Analysis

To demonstrate the performance of the proposed FSOS-AMC framework for known classes, we first evaluate the accuracy of the proposed FSOS-AMC framework and the compared methods on the 5 known modulation schemes. As shown in Fig. 4, the performance comparison of the proposed FSOS-AMC framework with the state-of-the-art methods, including CNN [9], ResNet [10], MSNet [1], and SSwsrNet [2] in terms of accuracy with respect to the SNR. It can be observed that the proposed FSOS-AMC framework outperforms the compared methods in terms of accuracy, achieving the highest accuracy over 95% across all SNR values. Moreover, the proposed FSOS-AMC framework can achieve an accuracy over 90% when the SNR is larger than 0 dB, which is 2 dB more sensitive than the recent SSwsrNet, and MSNet. The recent SSwsrNet and MSNet achieve a similar performance of 93.6%, which is about 1.5% lower than the proposed FSOS-AMC framework.

To demonstrate the performance of the proposed FSOS-AMC framework for unknown classes, we evaluate the *AUROC*, and *FRR* of the proposed FSOS-AMC framework and the compared methods on the 5 unknown modulation schemes. As shown in Fig. 5, the performance comparison of the proposed FSOS-AMC framework with the state-of-the-art methods, including CNN [9], ResNet [10], MSNet [1], and SSwsrNet [2] in terms of *AUROC*, and *FRR*. It can be seen that the proposed FSOS-AMC framework achieves the highest *AUROC* of 54.25%, which is about 0.8% higher than the recent SSwsrNet. Moreover, the proposed FSOS-AMC framework achieves a lower *FRR* compared to other methods.

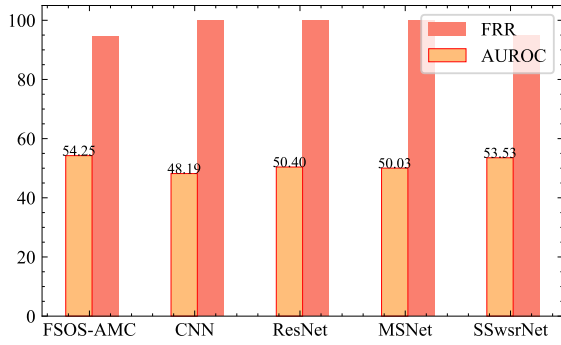


Fig. 5. Performance comparison in terms of AUROC and FRR.

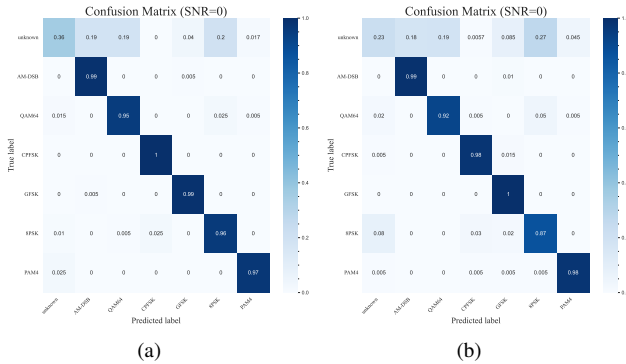


Fig. 6. Confusion matrix of the proposed (a) FSOS-AMC framework and (b) SSwsrNet [2] under SNR = 0 dB.

To further demonstrate the effectiveness of the proposed FSOS-AMC framework under open-seg scenarios, we present the confusion matrix of the proposed FSOS-AMC framework and the recent SSwsrNet [2] under SNR = 0dB. It can be found that the proposed FSOS-AMC framework can achieve over 95% classification accuracy for known classes and 36% classification accuracy for unknown classes, which is superior to the recent SSwsrNet. Moreover, compared to the performance of the recent SSwsrNet on unknown classes, the proposed FSOS-AMC framework can achieve a gain of 13% classification accuracy under low SNR conditions.

## V. CONCLUSION

A novel few-shot open-set automatic modulation classification (FSOS-AMC) framework is proposed in this paper. The FSOS-AMC framework consists of three main parts, a multi-scale attention feature extractor (MSANet), a meta-prototype training strategy, and a modular open-set classifier. The MSANet is exploited to extract the features from the input signal, and the meta-prototype training strategy is utilized to train the feature extractor using a supervised, episode-based methodology. The modular open-set classifier is adopted to classify the testing data into one of the pre-defined known modulations or potential unknown modulations. Simulation results demonstrate that the proposed FSOS-AMC framework can achieve a high classification accuracy for known

modulations and unknown modulations. The proposed FSOS-AMC framework outperforms the recent advanced methods in terms of accuracy, AUROC, and FRR under few-shot open-set scenarios.

## REFERENCES

- [1] H. Zhang, F. Zhou, Q. Wu, W. Wu, and R. Q. Hu, "A novel automatic modulation classification scheme based on multi-scale networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 8, no. 1, pp. 97–110, 2021.
- [2] H. Zhang, F. Zhou, Q. Wu, and N. Al-Dhahir, "Sswsrnet: A semi-supervised few-shot learning framework for wireless signal recognition," *IEEE Transactions on Communications*, 2024.
- [3] F. Hameed, O. A. Dobre, and D. C. Popescu, "On the likelihood-based approach to modulation classification," *IEEE transactions on wireless communications*, vol. 8, no. 12, pp. 5884–5892, 2009.
- [4] A. Hazza, M. Shoaib, S. A. Alshebeili, and A. Fahad, "An overview of feature-based methods for digital modulation classification," in *2013 1st international conference on communications, signal processing, and their applications (ICCSIPA)*. IEEE, 2013, pp. 1–6.
- [5] H. Zhang, J.-J. Xu, H.-W. Cui, L. Li, Y. Yang, C.-S. Tang, and N. Boers, "When geoscience meets foundation models: Towards general geoscience artificial intelligence system," *arXiv preprint arXiv:2309.06799*, 2023.
- [6] J.-J. Xu, H. Zhang, C.-S. Tang, Q. Cheng, B. Liu, and B. Shi, "Automatic soil desiccation crack recognition using deep learning," *Geotechnique*, vol. 72, no. 4, pp. 337–349, 2022.
- [7] J.-J. Xu, H. Zhang, C.-S. Tang, Q. Cheng, B.-g. Tian, B. Liu, and B. Shi, "Automatic soil crack recognition under uneven illumination condition with the application of artificial intelligence," *Engineering geology*, vol. 296, p. 106495, 2022.
- [8] H. Zhang, L. Yuan, G. Wu, F. Zhou, and Q. Wu, "Automatic modulation classification using involution enabled residual networks," *IEEE Wireless Communications Letters*, vol. 10, no. 11, pp. 2417–2420, 2021.
- [9] T. J. O'Shea, J. Corgan, and T. C. Clancy, "Convolutional radio modulation recognition networks," in *International Conference on Engineering Applications of Neural Networks*. Springer, 2016, pp. 213–226.
- [10] T. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-air deep learning based radio signal classification," *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 168–179, 2018.
- [11] S. Hu, Y. Pei, P. P. Liang, and Y.-C. Liang, "Deep neural network for robust modulation classification under uncertain noise conditions," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 564–577, 2019.
- [12] L. Li, J. Huang, Q. Cheng, H. Meng, and Z. Han, "Automatic modulation recognition: A few-shot learning method based on the capsule network," *IEEE Wireless Communications Letters*, vol. 10, no. 3, pp. 474–477, 2020.
- [13] A. Bendale and T. E. Boult, "Towards open set deep networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 1563–1572.
- [14] Y. Chen, X. Xu, and X. Qin, "An open-set modulation recognition scheme with deep representation learning," *IEEE Communications Letters*, vol. 27, no. 3, pp. 851–855, 2023.
- [15] Y. Chen, L. Zhu, C. Jin, J. Zhang, C. Yao, and Y. Gu, "Boosting open-set rf signal recognition under low snr condition in feature space," *IEEE Communications Letters*, 2024.
- [16] L. Yuan, H. Zhang, M. Xu, F. Zhou, and Q. Wu, "A multiscale cnn framework for wireless technique classification in internet of things," *IEEE Internet of Things Journal*, vol. 9, no. 12, pp. 10366–10367, 2021.
- [17] R. Ding, H. Zhang, F. Zhou, Q. Wu, and Z. Han, "Data-and-knowledge dual-driven automatic modulation recognition for wireless communication networks," in *ICC 2022-IEEE international conference on communications*. IEEE, 2022, pp. 1962–1967.
- [18] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 7132–7141.
- [19] T. L. Hayes and C. Kanan, "Online continual learning for embedded devices," *arXiv preprint arXiv:2203.10681*, 2022.
- [20] W. J. Scheirer, A. de Rezende Rocha, A. Sapkota, and T. E. Boult, "Toward open set recognition," *IEEE transactions on pattern analysis and machine intelligence*, vol. 35, no. 7, pp. 1757–1772, 2012.