TABLE V: Review of previous works on model-parameter-transfer methods in AMC

model-parameter-transfer methods	Task of Source Domain	Task of Target Domain	Data of Source Domain (including modulation and signal types)	Data of Target Domain (including modulation and signal types)	Network Input	Network type	Specific Strategy	Performance	Calculation Complexity	Paper
Fine-tune Classifier	AMC	AMC	Simulation Dataset (OOK, 4/8ASK, BPSK, Q/8/16/32/PSK, 16/32/64/128APSK, 16/32/64/128/256QAM, AM-SSB-WC, AM-SSB-SC, AM-DSB-WC, AM-DSB-SC, FM, GMSK, OQPSK)	OTA dataset(same as source domain)	IQ sequence	ResNet	Freeze the weight parameters of the network except for the fully connected layers, and fine-tune the fully connected layers.	Compared to previous fine-tuning methods, there has been a 10% improvement in classification accuracy.	NVIDIA V100 Training Time:16h (before finetuning) NVIDIA Titan X:60s/epoch (finetuning)	[4]
	AMC	AMC	8PSK, BPSK, CPFSK, GFSK, PAM4, 16QAM	QPSK, 64QAM, WBFM, AM-SSB, AM-DSB	IQ sequence	CNN	Freeze the convolutional layers and penalize the weights causing negative transfer, fine-tune the fully connected layers.	When SNR was 6 dB, compared to direct training, the performance increased on average by 15.77% and 10.32%. Compared to traditional fine-tuning, this resulted in an average increase of 6.1% and 2.73%.	——	[18]
	AMC	AMC	QPSK,8APSK, 16APSK,32APSK	Signals with 3 kinds of interruption signals	Time-frequency plot with wavelet transformation.	AlexNet, VGG16, GoogleNet, ResNet18	Freeze the convolutional layers of the pretrained network to serve as feature extractors.	All networks achieved a classification accuracy greater than 90%. ResNet18 achieved an accuracy of 98.3%, while AlexNet was more effective in identifying modulation types under different noise power levels.	NVIDIA Titan Black Training Time: AlexNet:86.97min, VGG16:9922.18min, GoogleNet:243.58min, ResNet18:206.94min	[25]
	Image Classification	AMC	ImageNet	LFM, Costas, T1-T4 codes (Multi-time code),Frank Code, BPSK	Time-frequency Spectrum	AlexNet, VGGNet	Fine-tune the last fully connected layer while keeping the rest of the layers as feature extractors.	Deep features of signals can be effectively extracted	——	[11]
	Image Classification	AMC	ImageNet	BPSK, QPSK, OQPSK, 8PSK, 4ASK, QAM16, QAM32, QAM64	STFT spectrogram, Choi-Williams distribution spectrogram, cyclic spectrogram	AlexNet, VGGNet, GoogleNet, ResNet	The solution space of using the network architecture and corresponding layers of a pre-trained network as feature extractors.	Deep features of signals can be effectively extracted.	$O(ITA \times N \times D)$ ITA: Maximum iteration count, N: iteration count, D: Dimension of the target search space	[26]
	Image Classification	AMC	ImageNet	RML2016.10B& RML2018.01A	STFT spectrum	ResNet	Use Instagram to retrieve images and then employ a pre-trained Weakly Supervised Learning (WSL) model for weakly supervised learning, followed by fine-tuning with the ImageNet dataset to obtain a feature extractor.	Deep features of signals can be effectively extracted.	——	[27]
	AMC	AMC	SP, LFM, V-LFM, BPSK, QPSK, FSK	S-shaped nonlinear frequency modulation signal (SNLLF), Linear Frequency Modulation (LFM), Binary Phase Shift Keying (BPSK), Signal with random Gaussian white noise	IQ sequence	CNN	Fine-tune the classification layer.	It is possible to differentiate unknown composite modulation signals with limited training data.	——	[14]
	AMC	AMC	Simulation Dataset (OFDM-QPSK, SEFDM-QPSK, SEFDM-QPSK, SEFDM-QPSK)	Dataset with transmission over the air	IQ sequence	CNN	Fine-tune the last two layers of the neural network and freeze the weight parameters of the remaining layers.	Able to efficiently distinguish between different modulation types in both line-of-sight (LOS) and non-line-of-sight (NLOS) scenarios is essential.	——	[34]

	AMC	AMC	Simulation Dataset(2FSK, 4FSK, 8FSK, BPSK, QPSK, DFDM, Scanning Spread Spectrum Carrier (S2C))	Real-world dataset with hydrological channels.2FSK, 4FSK, 8FSK, BPSK, QPSK, DFDM, Scanning Spread Spectrum Carrier (S2C)	IQ sequence	Att-CNN + SAE	Fine-tune the last few layers of Att-CNN and freeze the weight parameters of the remaining layers.	It exhibits robustness to UWA channels and environmental noise, enabling effective identification of common UWA communication signals.	NVIDIA TITAN RTX GFLOPs:0.1415	[36]
	AMC	AMC	RML2018.01A	RML2016.10B	IQ sequence + AP sequence	CNN + LSTM	Fine-tune the fully connected layer while freezing the remaining layers.	The accuracy of identifying high-order modulation types exceeds 90% in a 5G communication environment.	NVIDIA RTX A5000 Laptop Training Time: 10778s Transfer learning time: 3140s Re-training time: 3963s	[39]
	Image Classification	AMC	ImageNet	BPSK, LFM, Costas, Frank, P1-P4 codes(Phase Shift Keying (PSK)), and T1-T4 codes(Time Division Multiplexing (TDM))	The time-frequency spectrums are calculated by integrating multiple kernel functions through PCA.	AlexNet	Freeze the first seven layers as feature extractors for time-frequency plots, except for the final classification layer.	The proposed method Average accuracy was over 95% when SNR is -6 dB and robustness remained with SNR ranging from -6 dB to 4 dB.	——	[10]
	AMC	AMC	Few-shot dataset with AWGN (2PSK, 4PSK, 8PSK, 16QAM, 16APSK, 32APSK, 64QAM, noise)	Common instances (2PSK, 4PSK, 8PSK, 16QAM, 16APSK, 32APSK, 64QAM)	IQ sequence	CNN	Fine-tune the output layer, where during pre-training, the output vectors are in binary form, while in the fine-tuning stage, the output layer adopts normalized likelihood vectors.	In a context unrelated to the scenario, the classification accuracy was 90% at a SNR of 1.6 dB, and 100% at an SNR of 4 dB.	NVIDIA GTX-960 Coherent Scenario: Non-coherent Scenario: Flat Fading Channel: : Coefficients of the corresponding AMC models : Instance Length : Amount of antennas	[29]
	AMC	AMC	RML2016.10B	RML 2018.01A	IQ sequence + AP sequence	IRS (improved residual stacks) + LSTM	Fine-tune the classification layer and freeze the other layers.	High robustness to different modulation schemes	NVIDIA Quadro RTX 8000 Training parameter amount:318266 Training Time:1589.185106s Testing Time:4.0533302s	[30]
	AMC	AMC	12 categories in RML 2018.01A	Other 12 categories in RML 2018.01A	IQ sequence	CNN	Fine-tune the classification layer and freeze the other layers.	It is possible to reduce the network size to alleviate computational burden without significantly sacrificing accuracy, achieving performance comparable to a network with 52,104 trainable parameters.	NVIDIA's TX2 Training parameters:4152	[37]
Fine-tune feature extractors and classifiers	AMC	AMC	RML2016.10B	HisarMod 2019.1	IQ sequence + AP sequence	IRS(the improved residual stacks)+ LSTM	Initialize weights of the pre-trained model and retrain it.	At an SNR of 10 dB, all modulation schemes achieve 100% accuracy.	NVIDIA Quadro RTX 8000 Training Parameters:318266 Training Time:1589.185106s Testing Time:4.0533302s	[30]
	Audio Classification	AMC	UrbanSound8K	RML2016.10B	IQ sequence	CNN + GRU	Initialize weights of the pre-trained network and fine-tune all layers.	Overall classification accuracy exceeds that of other benchmark models.	——	[31]
	AMC	AMC	Modulated signal with AWGN (BPSK, QPSK, 8PSK, QAM16, 2FSK , MSK, FM, AM, ASK2, FSK4, OQPSK)	Modulation signals in complex Rayleigh multipath channels.(BPSK, QPSK, 8PSK, QAM16, 2FSK, MSK, FM, AM, ASK2, FSK4, OQPSK)	IQ sequence	CNN	Initialize weights of the pre-trained network and fine-tune all layers.	Under small sample conditions, transfer learning improves classification accuracy by 23% compared to non-transfer learning, while reducing training time by half.	Fine-tuning Time:0.40s	[33]
	AMC	AMC	Instances with original sampling rate(8PSK, BPSK, QPSK, QAM16, CPFSK, GFSK, WBFM and PAM4)	Signals downsampled by a factor of 2.(8PSK, BPSK, QPSK, QAM16, CPFSK, GFSK, WBFM and PAM4)	IQ sequence	CNN+ LSTM	Initialize weights of the pre-trained network and fine-tune all layers.	Compared to non-transfer learning, the classification accuracy increased by 23%, and the training time was reduced by half.	——	[13]
	AMC	AMC	Instances with 0dB SNR(2ASK, BPSK, QPSK, 8PSK, 16QAM)	Instanceswith 6 -1dB SNR(2ASK, BPSK, QPSK, 8PSK, 16QAM)	IQ sequence	CNN	Using the weights trained under high signal-to-noise ratio conditions as initial weights, fine-tune all layers.	The instability during training has been resolved, resulting in a 13.3% improvement in recognition accuracy compared to ResNet32.	Multiplication quantity: $1.66 \times 10^5 \times l$ l: Instance Length	[35]

	AMC	AMC	Instances with 0/4/8/12dB SNR (BPSK, QPSK, 16QAM, 64QAM)	Instances with 0 20dB SNR(BPSK, QPSK, 16QAM, 64QAM)	Two-dimensional density plot	CNN	Fine-tune the first convolutional layer and the first fully connected layer, while freezing the remaining layers.	While maintaining excellent classification performance, it is possible to significantly reduce the number of parameters requiring retraining due to signal-to-noise ratio variations. The number of trainable parameters has been reduced from 462,044 to 29,320.	——	[38]
	AMC	AMC	Instances with multiple SNRs(8PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, PAM4, 16QAM, 64QAM, QPSK, WBFM)	Instances with one certain SNR(8PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, PAM4, 16QAM, 64QAM, QPSK, WBFM)	IQ sequence	CNN	Fine-tune three layers and freeze other layers	The performance improvement ranges from 1% to 14% compared to the baseline model (ResNet, CNN2 ICAMCNet, CycDNN).	——	[40]
	Image Classification	AMC	ImageNet	Sig1024, Sig1024$_2$, RealSig, OFDMSig (BPSK, QPSK, 8PSK, OQPSK, 2FSK, 4FSK, 8FSK, 16QAM, 32QAM, 64QAM, 4PAM and 8PAM)	Using signal reordering methods or convolutional mapping methods to transform signals into images.	7 classical ImageNet models	Fine-tune all layer weights using target domain signals.	The overall classification accuracies of SRM and MM are 65.99% and 65.49%, respectively, surpassing those achieved with constellation diagrams (40.27%) and time-frequency images (55.79%).	——	[24]
	Clustering	AMC	RML2016.10A, RML2018.01A	RML2016.10A, RML2018.01A	Time-frequency spectrum+ Constellation chart	Multi-frequency ResNet	Minimizing clustering loss to obtain optimal model initialization parameters.	Only five signal supports per sample are needed to achieve approximately 70% accuracy for 24 types of signal spectrograms and 96% accuracy for 16 types of signal constellations (under 10 dB conditions).	1080GPU (FLOPs) ProtoNet:1.25G RelationNet:95.61G GNN:5.00G	[28]
	Image Classification	AMC	ImageNet	BPSK, LFM, Costas, Frank, P1-P4 codes (M-ary phase shift keying), and T1-T4 codes (Multi-time shift keying)	Time-frequency spectrum	AlexNet	Pretrain network by initializing weights, fine-tune all layers.	When SNR is -6 dB, the average recognition accuracy is 95.5%.	NVIDIA GeForce RTX 2060 Training time:1141s Testing time:0.29s	[12]
	Image Classification	AMC	ImageNet	2ASK, 2FSK, 2DPSK, LFM, VFM, FH	SPWVD Time-frequency spectrum	ResNet34	Pretrain network by initializing weights, fine-tune all layers.	At a signal-to-noise ratio (SNR) of 0 dB, the overall recognition rate approaches 94%. It demonstrates adaptability to cross-domain scenarios with variations in code width, SNR, and sampling frequency. Following changes in parameters such as code width, SNR, and sampling frequency, the overall recognition rate remains above 82%, reaching a maximum of 94%.	——	[32]
	Image Classification	AMC	ImageNet	2/4/8/16/32/64QAM	Colored constellation chart	AlexNet/ GoogLeNet	Freeze parameters of certain layers and fine-tuning the rest.	Compared to training from scratch, the average accuracy of AlexNet and GoogLeNet using transfer learning increased by 2.85% and 9.26%, respectively.	——	[41]
	Image Classification	AMC	ImageNet	BPSK, QPSK, and 8PSK	Time-frequency spectrum	Resnet50	Fine-tune the last two layers and freeze the remaining layers.	When the signal-to-noise ratio (SNR) exceeds 10 dB, the recognition accuracy remains above 70%. At SNRs exceeding 15 dB, the classification accuracy reaches above 85%.	——	[42]

TABLE VI: Review of previous works on feature-representation-transfer methods in AMC

Feature-representation-transfer methods	Task of Source Domain	Task of Target Domain	Data of Source Domain (including modulation and signal types)	Data of Target Domain (including modulation and signal types)	Network Input	Network type	Performance	Calculation Complexity	Papers
Adversary	Communication modulation classification	Communication modulation classification	Instances with a sampling length of 128. The modulation types include 8PSK, AM-DSB, AMSSB, BPSK, CPFSK, GFSK, PAM4, QAM16, QAM64, QPSK, WBFM	Instances with a sampling length of 64.	IQ sequence	CNN	With 50% training data, the target model achieves similar classification accuracy to supervised learning. Using 10% of the training data, the accuracy is improved by 17.3% compared with the method without transfer.	——	[15]
	Communication modulation classification	Communication modulation classification	The modulation signals have a symbol rate of 8 and consist of 8 modulation categories, including BPSK, QPSK, 8PSK, PAM4, QAM16, GFSK, CPFSK, QAM64	The modulation signals have a symbol rate of 4 and consist of either 1 or 3 modulation categories.	IQ sequence	CNN	Compared to the method without transfer learning, the accuracy has improved by 48.39%.	——	[17]
	Communication modulation classification	Communication modulation classification	High SNR instances including RML2018.01A, RML2016.01A	Low SNR instances	IQ sequence	Residual Block + CNN	The proposed method can achieve higher classification accuracy with fewer training parameters and samples. The training parameters of Resnetv1 and Resnetv2 are 8% and 16% of CNN, respectively.	FLOPs:4.51M Parameter Amount:46173	[19]
	Communication modulation classification	Communication modulation classification	Training sets consisting of 1%, 3%, and 5% of the total samples. The modulation types include BPSK, QPSK, 8PSK, 16QAM, 32QAM, 64QAM, PAM4, 2ASK, GFSK, 2FSK, 4FSK	Rest data acts as the testing datasets	IQ sequence +AP sequence +high-order spectrum	CNN+ Convolution Block with Attention module (CBAM)	When the SNR exceeds 4 dB, the average classification accuracy of the proposed algorithm surpasses 90%. It outperforms the comparison methods in terms of classification performance and stability, especially in high-order modulation classification.	——	[16]
Diversity	Communication modulation classification	Communication modulation classification	2/4/8PSK, 16/64/128QAM (The 6 types of modulation signal categories are divided into 4:2 or 3:3 to form the source domain and target domain.)		Higher Order Cumulants + Semantic Attribute Matrix	KNN linear classifier	It achieves an average recognition accuracy of over 85%.	——	[22]
	Communication modulation classification	Communication modulation classification	2/4/8/16PSK, 16/64/128QAM(The 8 types of modulation signal categories are divided into 6:2 to form the source domain and target domain.)		Local sequence pattern features and constellation similarity matrix	SVM	At a SNR of 10 dB, the classification accuracy is close to 100%.	——	[23]
Reconstruction	Signal Reconstruction	Radar modulation classification	Instances with SNR at -30 dB. The modulation types include LFM, BPSK, QPSK	Instances with SNR ranging 5∼30 dB	Graphical features and positional features extracted from the Wigner-Ville distribution	Autoencoder and Coherent SVM	When trained with 300 samples, the recognition accuracy can reach over 98%.	——	[20]
	Signal Reconstruction	Communication modulation classification	Large amount of unlabeled instances. The modulation types include BPSK, QPSK, 8PSK, 16QAM	Few amount of unlabeled instances	IQ sequence	Convolution Autoencoder+CNN	Under limited sample conditions, the performance is far superior to supervised learning methods; in a higher SNR range, the classification accuracy is close to that of supervised learning methods trained with a large number of labeled samples.	——	[21]