

Article

Hierarchical Modulation Classification with Channel-Type-Guided Blind Preprocessing for High-Order QAM in Multipath Fading Channels

Sungsoo Park  and Gyuyeol Kong * 

Division of Mechanical and Electronics Engineering, Hansung University, Seoul 02876, Republic of Korea; sspark@hansung.ac.kr

* Correspondence: gykong@hansung.ac.kr

Featured Application

Non-cooperative spectrum monitoring and cognitive-radio receivers that require modulation awareness under flat and multipath fading conditions without pilot-aided channel equalization.

Abstract

Automatic modulation classification (AMC) becomes challenging in multipath fading channels, particularly for high-order quadrature amplitude modulation (QAM) signals whose constellation points are strongly distorted by inter-symbol interference, phase rotation, and fading. This paper presents a channel-type-guided hierarchical AMC framework that combines blind preprocessing with deep learning. In the first stage, the received in-phase and quadrature (IQ) signal is downsampled and preprocessed using blind signal processing techniques. Blind source separation (BSS) is used for additive white Gaussian noise (AWGN) and flat fading channels, whereas the constant modulus algorithm (CMA) followed by BSS is used for multipath fading channels. A convolutional neural network (CNN) then performs first-stage modulation classification and generates a QAM-family flag. If the first-stage output corresponds to a QAM-family signal, a second-stage refinement path is activated. In this path, a convolutional denoising autoencoder (CDAE) is applied to the original received signal to mitigate multipath-induced distortion, followed by BSS preprocessing and a dedicated CNN classifier for 16-QAM, 64-QAM, and 256-QAM. Simulation results over AWGN, flat fading, and multipath Rician fading channels show that the proposed hierarchy improves high-order QAM classification in the considered settings, especially for 64-QAM and 256-QAM under multipath fading with stronger time variation. Multi-frame Softmax averaging further improves decision stability. The results support the use of classical blind preprocessing and selective CDAE-based refinement as a practical, complementary front end for AMC in controlled multipath simulation scenarios, while real over-the-air validation and automatic channel-category detection remain future work.



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Keywords: automatic modulation classification (AMC); high-order quadrature amplitude modulation (QAM); multipath fading; blind preprocessing; blind source separation; constant modulus algorithm; convolutional denoising autoencoder; convolutional neural network

1. Introduction

Automatic modulation classification (AMC) is a key function in non-cooperative wireless receivers because it enables a receiver to infer the modulation format of an intercepted signal without access to transmitter-side signaling. It is important for spectrum monitoring, adaptive receivers, cognitive radio, radio-frequency situational awareness, and radar-communication coexistence [1,2]. As wireless systems become increasingly heterogeneous, modulation recognition must operate not only under additive white Gaussian noise (AWGN), but also under flat fading, frequency-selective multipath fading, Doppler shifts, and residual receiver impairments.

Deep learning has become the dominant approach for AMC because convolutional neural networks (CNNs), recurrent networks, residual networks, and transformer-based models can learn discriminative features from raw in-phase and quadrature (IQ) samples, time-frequency images, constellation diagrams, or multi-domain representations. Recent research has expanded the field toward larger and more realistic datasets, complex-valued or multi-stream networks, lightweight edge-oriented models, semi-supervised and contrastive representation learning, federated learning, and domain adaptation under channel variability [3–9]. These directions are important because practical AMC systems must address not only noise, but also limited labels, distribution shift, computational cost, and channel-induced distortion.

The opportunity addressed in this work lies between two dominant directions in the current state of the art. On the one hand, recent large neural backbones improve representation learning but can require broad channel coverage, large labeled datasets, and increased model complexity. On the other hand, classical blind signal-processing methods provide interpretable channel-distortion mitigation but are not sufficiently discriminative by themselves for fine-grained high-order QAM classification. This paper explores this intermediate design space by combining channel-type-guided blind preprocessing with selective neural restoration and hierarchical CNN classification.

Under stochastic multipath fading, AMC is affected by two related methodological issues: generalization and statistical stability. A received IQ frame can change substantially across independent channel realizations because of random path gains, delays, phase rotations, and Doppler-induced time selectivity. A purely end-to-end classifier may therefore learn channel-dependent nuisance patterns if the training data do not sufficiently cover the test channel distribution. This motivates the use of signal-processing priors that reduce channel-induced distribution shift before neural classification, while also requiring that simulation results be interpreted with finite-test-set uncertainty and model-generalization limitations in mind.

Despite these advances, high-order quadrature amplitude modulation (QAM) classification in multipath fading remains a practical challenge. In dense constellations, such as 64-QAM and 256-QAM, the distances between constellation points are small, and multipath-induced amplitude and phase distortion can significantly reduce class separability [10]. End-to-end deep networks may learn to compensate for part of this distortion if trained on sufficiently diverse data, but this can require large datasets and may not provide a clear engineering interpretation. Classical blind signal processing methods, such as the constant modulus algorithm (CMA) and blind source separation (BSS), offer useful signal-processing priors, whereas denoising autoencoders can learn nonlinear signal restoration. The question addressed in this paper is whether these tools can be organized into a simple hierarchical AMC pipeline that is practical for multipath environments and particularly helpful for high-order QAM classes.

This paper therefore does not aim to replace recent end-to-end AMC architectures, self-supervised representation learners, or domain-adversarial models. Instead, it investigates a complementary hybrid approach: classical blind preprocessing is used to reduce channel-induced distortion before CNN-based classification, and a convolutional denoising autoencoder (CDAE)-based refinement path is selectively activated only when the received signal is classified as belonging to the QAM family. This design is motivated by the observation that non-QAM classes and the QAM family can be separated more reliably than the fine-grained discrimination among 16-QAM, 64-QAM, and 256-QAM under multipath fading.

The study is guided by two hypotheses. First, channel-type-guided blind preprocessing can improve AMC performance by reducing channel-induced distortion without pilot symbols or explicit channel state information (CSI). Second, selective CDAE-based refinement can improve the fine-grained discrimination among high-order QAM classes under multipath fading while limiting the use of the computationally heavier restoration block to QAM-family candidates. The primary evaluation criterion is the probability of correct classification, denoted by P_{cc} , under the considered signal-to-noise ratio (SNR), channel, and modulation-class settings. A secondary criterion is the analytical complexity implication of conditional CDAE activation.

The main contributions of this paper are summarized as follows:

1. A channel-type-guided hybrid AMC framework is proposed, where BSS, CMA + BSS, and CDAE + BSS preprocessing are used according to AWGN/flat fading and multipath fading conditions without requiring pilot symbols or explicit channel state information (CSI) for equalization.
2. A two-stage hierarchical classifier is designed to classify non-QAM modulation types in the first stage and to activate a CDAE-assisted refinement stage only for high-order QAM signals. The hierarchy concentrates the computationally heavier restoration step on the modulation family that is most sensitive to multipath distortion.
3. Simulation results show that the proposed hierarchy improves the classification of 64-QAM and 256-QAM under the considered multipath Rician fading settings, and that multi-frame softmax averaging further stabilizes classification performance.

The remainder of this paper is organized as follows. Section 2 positions the work with respect to recent AMC research. Section 3 presents the system model and modulation classes. Section 4 describes the proposed hierarchical AMC framework. Section 5 provides the simulation setup. Section 6 presents the results. Section 7 discusses the implications and limitations of the proposed approach, and Section 8 concludes the paper.

2. Related Work and Positioning

2.1. From General Classification to AMC

Automatic modulation classification belongs to a broader methodological tradition of pattern classification and clustering. Early statistical classification and grouping studies, including those by Driver and Kroeber, Zubin, and Tryon, established the idea that complex observations can be organized into meaningful classes when appropriate similarity measures and decision rules are defined [11–13]. Recent classification and clustering studies continue to address methodological issues such as uncertainty, incomplete labels, neighborhood structure, and class overlap. For example, neighborhood-based positive unlabeled learning using decision trees addresses uncertainty when only positive and unlabeled samples are available, and inversion-formula-based clustering provides an alternative way to separate overlapping data groups [14,15]. In AMC, analogous issues appear as class overlap among modulation constellations, channel-induced distribution shift, and uncertainty in non-cooperative observations. Classical AMC methods include

likelihood-based classifiers and feature-based approaches using expert-designed statistics, such as higher-order cumulants and cyclic features [16]. Although these methods can be interpretable, they often require reliable assumptions about channel parameters, noise variance, synchronization, or feature stability under fading. Early neural-network-based AMC relaxed some hand-crafted feature requirements, but practical multipath channels remain challenging because the classifier must separate modulation-specific structure from channel-induced nuisance variation [17].

2.2. Deep Learning-Based AMC

Deep learning shifted the focus toward feature learning from raw or transformed signal representations. Over-the-air deep learning-based radio signal classification demonstrated that neural networks can learn discriminative features from measured IQ signals [4]. Subsequent works explored CNNs, hybrid CNN and long short-term memory (LSTM) structures, residual networks, complex-valued networks, robust CNN-based AMC under multipath fading, spatiotemporal multi-channel learning, and multi-cue fusion [18–21]. More recent works address realistic data generation and practical system tasks, including RadioML 2022 (RML22) dataset generation, fast multi-loss AMC networks, and joint signal detection and modulation classification [5–7].

Recent AMC research has also moved beyond fully supervised CNN classification. Contrastive and semi-supervised learning frameworks seek to reduce the dependence on labeled signals and to learn modulation-invariant representations [8,22,23]. Domain-adversarial learning has been investigated to mitigate channel-induced distribution shift between training and deployment environments [24]. Federated learning has been applied to multipath AMC to exploit distributed data while reducing the need to centralize raw IQ signals [25]. Lightweight CNN and mobile/edge-oriented architectures have also been studied for practical deployment [26]. These trends emphasize generalization, label efficiency, and deployment feasibility.

2.3. Blind Preprocessing and Hierarchical Refinement

Blind preprocessing remains relevant because it can embed signal-processing priors into an AMC pipeline. Classical studies considered modulation classification in fading multipath channels and independent-component-analysis-based classification for multiple-input multiple-output orthogonal frequency-division multiplexing (MIMO-OFDM) signals [27,28]. The CMA is a well-established blind equalization method that exploits a constant-modulus criterion [29,30]. BSS and independent component analysis can reduce mixing and rotation effects under appropriate conditions [31–34]. Denoising autoencoders and their convolutional variants learn compact representations that can suppress noise and channel distortion [35].

Hierarchical classification has also been used when a subset of classes is particularly difficult to separate. In radar waveform recognition, time-frequency and CNN-based approaches have been studied for difficult waveform classes, and a two-stage deep learning architecture was used to distinguish confusing polyphase waveforms after denoising autoencoder-based blind equalization and time-frequency processing [36–39]. Related work in radar-communication coexistence and multicarrier signal classification has also considered blind preprocessing under multipath fading [40]. The present work adapts this hierarchical philosophy to single-carrier communication modulation classification and focuses on high-order QAM refinement rather than radar polyphase code discrimination.

2.4. Position of This Work

The proposed method is best viewed as an engineering-oriented hybrid AMC framework. It is not a general-purpose replacement for recent self-supervised, domain-adaptive,

federated, or large-scale transformer-based approaches. Its contribution is instead to show how known blind preprocessing tools and a selective CDAE restoration path can be combined with CNN classifiers to address the practical failure mode of high-order QAM classification under multipath fading. The method is blind with respect to pilot symbols, training equalization sequences, and explicit CSI. However, the channel category used for preprocessing selection is assumed to be available. Automatic channel-type detection is outside the scope of this paper and is discussed as future work.

Table 1 summarizes the position of this work relative to representative AMC research directions. The proposed method is not intended to claim state-of-the-art superiority over recent large neural backbones. Instead, it provides a signal-processing-guided front end and hierarchical QAM refinement strategy that can be combined with such backbones.

Table 1. Qualitative positioning of the proposed method relative to representative automatic modulation classification (AMC) research directions.

Method Family	Main Strength	Relation to This Work
Feature- or likelihood-based AMC	Interpretable signal models and hand-crafted features	Useful baseline philosophy, but often sensitive to unknown channel parameters or severe multipath distortion
Raw-IQ CNN/residual AMC	Strong end-to-end feature learning	Can be used as a backbone; the proposed preprocessing front end is complementary
Transformer and attention-based AMC	Long-range dependency modeling and expressive representation learning	Potential future classifier replacement; not the main focus of this paper
Contrastive or self-supervised AMC	Label-efficient representation learning and improved invariance	Complementary pretraining direction for the proposed front end
Domain-adaptive AMC	Explicit reduction of train–test channel shift	Complementary to channel-type-guided preprocessing; automatic domain adaptation is outside this paper’s scope
Federated AMC	Distributed learning without centralizing raw IQ data	System-level extension for multi-receiver spectrum monitoring
Proposed framework	Channel-type-guided blind preprocessing and selective CDAE-assisted QAM refinement	Focuses on a practical high-order QAM failure mode under controlled multipath simulation settings

Table 2 further compares representative recent works at the reference level and clarifies the specific gap addressed by the proposed framework. It should be noted that the comparison in Table 2 is intended to position the proposed framework rather than to claim numerical superiority over recent large neural backbones. A direct accuracy comparison with ResNet-, transformer-, contrastive-learning-, or domain-adaptive AMC models would require reimplementing these models under the same waveform generator, modulation set, channel models, SNR grid, frame length, and preprocessing assumptions. Because published AMC results are often obtained under different datasets, channel models, and training protocols, cross-paper numerical comparison can be misleading. Therefore, this study focuses on controlled internal comparisons among preprocessing and hierarchical-classification configurations, while direct benchmarking against recent large-scale AMC backbones is left for future work.

Table 2. Representative related works and the contribution of the proposed framework.

Representative Work	Main Approach	Evaluated Signal/Channel Setting	Remaining Gap Relative to This Paper	Role in Positioning This Work
O’Shea et al. [4]	Raw-IQ deep learning for over-the-air radio signals	Measured radio signals with practical impairments	Does not focus on channel-type-guided blind preprocessing or selective QAM refinement	Establishes deep-learning-based AMC as a practical direction
Tekbıyık et al. [18]	CNN-based AMC under multipath fading	Multipath fading channels	Uses a neural classifier but does not explicitly allocate a CDAE-based refinement stage only to high-order QAM	Closely related multipath AMC baseline direction
Kong et al. [22] and Xiao et al. [23]	Transformer/contrastive representation learning	Semi-supervised or contrastive AMC settings	Improves representation learning but does not study the proposed blind preprocessing and QAM-family gating mechanism	Complementary learning backbones that could replace the CNN classifier
Shahriar [24]	Domain-adversarial adaptation	Channel variability and domain shift	Addresses source-target domain mismatch rather than channel-type-guided blind equalization	Complementary domain-adaptation direction
Bhardwaj et al. [25]	Federated AMC	Distributed multipath channels	Focuses on distributed training rather than receiver-side selective QAM restoration	System-level extension for multi-receiver monitoring
Kong et al. [39]	DAE-assisted hierarchical waveform recognition	Radar waveform recognition in multipath fading	Targets radar waveforms and polyphase-code discrimination, not single-carrier high-order QAM classes	Motivates hierarchical treatment of difficult signal classes
This work	Channel-type-guided blind preprocessing + selective CDAE-assisted QAM refinement	AWGN, flat fading, and multipath Rician fading for seven single-carrier modulations	Assumes channel category and uses controlled simulation settings	Provides an engineering-oriented hybrid front end for high-order QAM failure modes under multipath fading

3. System Model and Modulation Classes

We consider a non-cooperative receiver that observes a complex baseband communication signal transmitted over AWGN, flat fading, or frequency-selective multipath fading channels. Let $s(t)$ denote the complex transmitted signal and $n(t)$ denote complex AWGN with variance σ_n^2 . The continuous-time received-signal model used throughout the paper is given in Equation (1).

$$y(t) = \sum_{n=0}^{\ell-1} \alpha_n(t)s(t - \tau_n) + n(t), \quad (1)$$

where ℓ is the number of propagation paths, $\alpha_n(t)$ is the complex channel coefficient of the n -th path, and τ_n is the corresponding path delay. The maximum Doppler frequency is denoted by f_D .

The received signal is sampled at Lf_s , where L is the oversampling factor and f_s is the symbol rate. The sampled complex signal is represented as $[y[0], \dots, y[M-1]]^T$, where M is the number of time-domain samples. In this paper, $M = 4096$ and $L = 8$. The real-valued

input to the classification system is organized as a 2×4096 array by stacking the in-phase and quadrature components.

Seven single-carrier modulation types are considered: Gaussian minimum shift keying (GMSK), Gaussian frequency shift keying (GFSK), quadrature phase shift keying (QPSK), eight phase shift keying (8PSK), and Q -ary QAM for $Q = 16, 64$, and 256 . The objective is to classify the modulation type of the received signal under the considered channel conditions.

These modulation classes were selected to cover representative signal families with different envelope and constellation properties. GMSK and GFSK represent continuous-phase frequency modulation with nearly constant-envelope behavior, which is common in low-power and robust wireless links. QPSK and 8PSK represent phase-shift keying classes with constant-envelope constellation structures. The 16-QAM, 64-QAM, and 256-QAM classes represent high-order amplitude-phase modulation, where both amplitude and phase carry information and where the constellation spacing becomes increasingly dense as Q increases. This class set therefore allows the proposed framework to be evaluated across frequency-modulated, phase-modulated, and high-order amplitude-phase-modulated signals, with particular emphasis on the QAM classes that are most vulnerable to multipath-induced amplitude and phase distortion.

Table 3 summarizes the signal family, envelope property, discriminative feature, and reason for including each modulation class.

Table 3. Characteristics of the modulation classes evaluated in this study.

Class	Signal Family	Envelope/Constellation Property	Main Discriminative Feature	Reason for Inclusion
GMSK	Continuous-phase frequency modulation	Nearly constant envelope	Smooth phase/frequency trajectory	Represents robust non-QAM frequency-modulated signals
GFSK	Frequency-shift keying	Nearly constant envelope	Frequency deviation pattern	Provides a second non-QAM frequency-modulated class
QPSK	Phase-shift keying	Constant-envelope four-state phase constellation	Phase-state transitions	Represents low-order phase modulation
8PSK	Phase-shift keying	Constant-envelope denser phase constellation	Finer phase-state separation	Represents a more difficult PSK class
16-QAM	Amplitude-phase modulation	Non-constant-envelope QAM constellation	Amplitude and phase levels	Lower-order QAM reference class
64-QAM	High-order amplitude-phase modulation	Dense non-constant-envelope constellation	Fine amplitude/phase separation	Multipath-sensitive high-order QAM class
256-QAM	High-order amplitude-phase modulation	Very dense non-constant-envelope constellation	Very fine constellation separation	Most challenging QAM class in the considered set

4. Proposed Hierarchical AMC Framework

4.1. Overview

Figure 1 shows the proposed hierarchical AMC framework. The first stage performs downsampling, blind preprocessing, and CNN-based classification. The first-stage classifier first estimates the modulation label among the seven considered classes. Its output is then

converted into a QAM-family flag indicating whether the predicted label is one of 16-QAM, 64-QAM, or 256-QAM. If the flag is not activated, the final decision is made at this stage. If the signal is identified as QAM-family, a second-stage refinement path is activated. The second stage applies CDAE-based blind equalization to the original 2×4096 received signal, then performs downsampling, BSS preprocessing, and CNN-based classification among 16-QAM, 64-QAM, and 256-QAM.

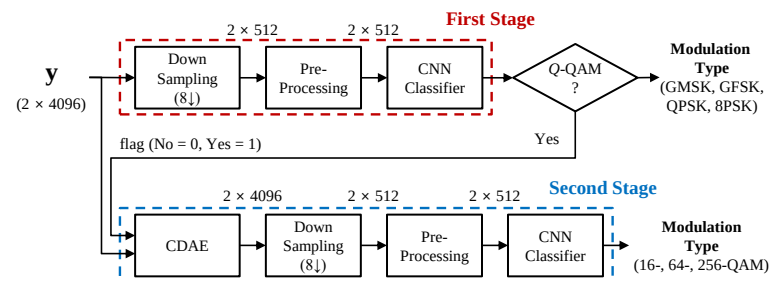


Figure 1. Proposed two-stage hierarchical AMC framework.

The hierarchy is motivated by the fact that high-order QAM classes are more sensitive to multipath-induced amplitude and phase distortion than lower-order or constant-envelope modulation families. Therefore, the CDAE is used selectively rather than being applied to every modulation class.

Compared with a uniform preprocessing pipeline, this hierarchy has two intended effects. First, it avoids applying the nonlinear restoration path to non-QAM signals whose discriminative features may not require CDAE-based reconstruction. Second, it reserves the second-stage restoration and dedicated classifier for the subset where the first-stage confusion analysis indicates the main performance bottleneck, namely 64-QAM and 256-QAM under multipath fading. The complete processing procedure of the proposed hierarchical AMC framework is summarized in Algorithm 1.

Algorithm 1 Algorithmic procedure of the proposed hierarchical AMC framework.

Require: Received IQ frame y and channel category c .

Ensure: Estimated modulation label $\hat{m}$.

- 1: Downsample y by the factor 8 to obtain a 2×512 frame.
 - 2: **if** c is AWGN or flat fading **then**
 - 3: Apply BSS preprocessing to the downsampled frame.
 - 4: **else**
 - 5: Apply CMA followed by BSS preprocessing to the downsampled frame.
 - 6: **end if**
 - 7: Feed the preprocessed frame to the first-stage CNN.
 - 8: Obtain the first-stage label and the QAM-family flag.
 - 9: **if** the QAM-family flag is not activated **then**
 - 10: Output the first-stage label as $\hat{m}$.
 - 11: **else**
 - 12: Apply the CDAE to the original 2×4096 received frame.
 - 13: Downsample the CDAE output by the factor 8.
 - 14: Apply BSS preprocessing and feed the result to the second-stage CNN.
 - 15: Output $\hat{m} \in \{16\text{-QAM}, 64\text{-QAM}, 256\text{-QAM}\}$.
 - 16: **end if**
 - 17: If multiple frames are available, average Softmax outputs before the final decision.
-

4.2. Channel-Type-Guided Blind Preprocessing

The preprocessing step is designed to mitigate channel-induced distortion without pilot-aided channel estimation. In this paper, the channel type is assumed to be known, and preprocessing selection is performed according to the channel category. This assumption

allows us to focus on the effect of blind preprocessing on modulation classification. The automatic selection or estimation of channel type is not considered in this work.

The term “blind” is used in a restricted signal-processing sense. The proposed preprocessing does not use pilot symbols, known training sequences, or explicit estimates of the path gains and delays in (1). Nevertheless, the framework is channel-category-guided because it assumes that the receiver can distinguish broad channel categories, such as AWGN/flat fading and multipath fading, before selecting the preprocessing branch. In practical non-cooperative receivers, such a category could be estimated using indicators such as delay-spread measures, Doppler-spread estimates, covariance eigenvalue spread, or a lightweight channel classifier. If the channel category is misdetected, the wrong preprocessing branch may be selected; for example, treating a multipath channel as flat fading may leave residual inter-symbol interference, whereas treating a flat channel as multipath may introduce unnecessary equalization. The effect of channel-category detection errors is not evaluated in this paper and is identified as future work.

For AWGN and flat fading channels, BSS is used as preprocessing. BSS transforms the in-phase and quadrature components of the received signal so that they become as statistically independent as possible. In flat fading channels, this can reduce the effect of phase rotation and improve CNN classification. In multipath fading channels, the CMA is first used to mitigate inter-symbol interference by enforcing a constant modulus criterion, and BSS is then applied to compensate for the arbitrary phase rotation introduced by the CMA. Thus, CMA + BSS is used in the first stage for multipath fading channels. In the second stage, after CDAE-based restoration of QAM signals, BSS is applied before the dedicated QAM classifier.

The role of the preprocessing block is not to solve equalization perfectly, but to transform the received signal into a representation that is more suitable for CNN classification. This hybrid design combines classical blind signal processing with learned classification, thereby reducing the burden on the CNN to learn all channel compensation solely from raw IQ samples.

4.3. CDAE-Based Blind Equalization for QAM Refinement

Figure 2 shows the CDAE structure used in the second stage. The CDAE is applied only when the first-stage classifier activates the QAM flag. It takes the original 2×4096 received signal as input and outputs an estimated 2×4096 signal. The use of the original-length input preserves information before the second-stage downsampling operation.

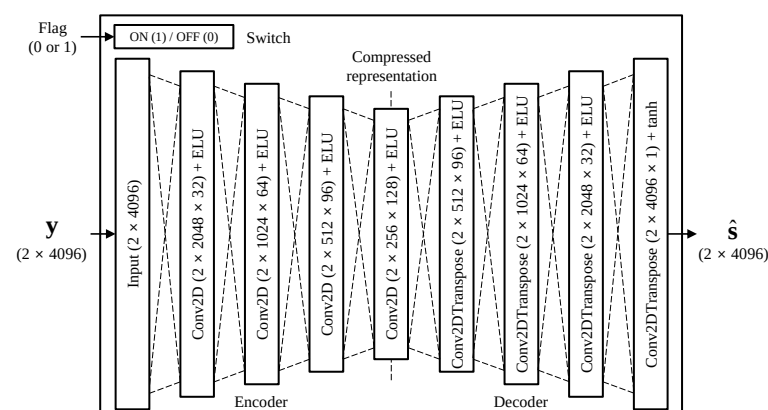


Figure 2. CDAE structure for second-stage QAM refinement.

The CDAE consists of an input layer, four two-dimensional convolutional layers in the encoder, and four two-dimensional transposed convolutional layers in the decoder. The encoder uses filter numbers of 32, 64, 96, and 128 with a 1×8 filter size, stride size 2,

and zero padding. The decoder uses filter numbers of 96, 64, 32, and 1 with the same filter size and stride. The exponential linear unit (ELU) is used in the encoder and decoder [41], except for the final transposed convolutional layer, where the hyperbolic tangent activation function is used to constrain the output to the range $[-1, 1]$.

Unlike a CDAE that directly maps the received signal to the ideal transmitted constellation, the CDAE in this paper is trained to target a signal corresponding to dominant-path flat fading and the desired QAM signal. This target is easier to learn than a fully de-rotated ideal constellation and is compatible with the subsequent BSS preprocessing. The CDAE therefore acts as a learned blind equalizer that reduces severe multipath distortion before the dedicated QAM classifier.

4.4. CNN Classifier and Multi-Frame Decision Rule

The first and second stages use the same CNN structure except for the output layer. The first-stage classifier has seven output nodes corresponding to GMSK, GFSK, QPSK, 8PSK, 16-QAM, 64-QAM, and 256-QAM, while the second-stage classifier has three output nodes corresponding to 16-QAM, 64-QAM, and 256-QAM. In the hierarchical decision, first-stage QAM outputs activate the second-stage path.

Table 4 summarizes the CNN architecture. The CNN input is a 2×512 signal after downsampling and preprocessing. The network uses four convolutional layers, four batch-normalization layers [42], four pooling layers, two fully connected (FC) layers, dropout, and a Softmax output layer. ELU is used as the activation function except in the output layer.

Table 4. Structure of the employed convolutional neural network (CNN) for the modulation classification problem. ELU denotes exponential linear unit, and FC denotes fully connected.

Layer	Dimension	Parameters	Activation
Input	(2, 512)	-	-
Convolution 1D	(2, 512, 16)	272	-
Batch Normalization	(2, 512, 16)	16	ELU
Max Pooling 1D	(2, 256, 16)	-	-
Convolution 1D	(2, 256, 32)	4128	-
Batch Normalization	(2, 256, 32)	32	ELU
Max Pooling 1D	(2, 128, 32)	-	-
Convolution 1D	(2, 128, 48)	12,336	-
Batch Normalization	(2, 128, 48)	48	ELU
Max Pooling 1D	(2, 64, 48)	-	-
Convolution 1D	(2, 64, 64)	24,640	-
Batch Normalization	(2, 64, 64)	64	ELU
Avg Pooling 1D	(2, 32, 64)	-	-
Flatten	-	-	-
FC1 (Dense)	(4096)	524,416	ELU
Dropout (0.5)	-	-	-
FC2 (Dense)	(128)	(903 or 387)	ELU
Dropout (0.5)	-	-	-
Dense	(7 or 3)	-	Softmax

For multi-frame classification, the Softmax outputs of multiple received frames are averaged before making the final decision. This decision smoothing does not change the network structure, but it reduces the variance of individual frame decisions and is useful in spectrum monitoring scenarios where several consecutive observations are available.

4.5. Analytical Complexity of Conditional CDAE Activation

The selective second-stage design also changes the expected inference cost. Let C_{stage1} denote the cost of the first-stage downsampling, preprocessing, and CNN classification;

C_{CDAE} denote the CDAE restoration cost; and C_{stage2} denote the second-stage downsampling, BSS preprocessing, and QAM CNN classification cost. The expected cost per frame is expressed in Equation (2):

$$C_{\text{avg}} = C_{\text{stage1}} + P_{\text{QAM}}(C_{\text{CDAE}} + C_{\text{stage2}}), \quad (2)$$

where P_{QAM} is the probability that the first-stage output activates the QAM-family flag.

In addition to the conditional-cost expression, the trainable model size can be estimated from the network structures. Based on the parameters listed in Table 4, the first-stage seven-class CNN has approximately 5.67×10^5 trainable parameters, whereas the second-stage three-class CNN has approximately 5.66×10^5 trainable parameters. The CDAE contains approximately 3.29×10^5 trainable parameters under the implemented convolutional structure, where the 2×4096 IQ matrix is treated as a single-channel two-dimensional input. Thus, the total loaded model size is approximately 1.46×10^6 trainable parameters.

The conditional structure affects inference cost rather than only model storage. Under a uniform class prior and assuming that the first-stage QAM-family flag follows the true QAM-family occurrence, $P_{\text{QAM}} \approx 3/7 \approx 0.429$. Therefore, the CDAE and second-stage QAM classifier are activated for approximately 42.9% of input frames under the uniform-class assumption. Equivalently, compared with a hypothetical all-CDAE pipeline that applies the restoration block to every received frame, the proposed hierarchy avoids CDAE execution for approximately $1 - P_{\text{QAM}} = 4/7 \approx 57.1\%$ of the input frames.

This analysis does not replace hardware latency measurement, but it clarifies the conditional computational advantage of the architecture.

5. Simulation Setup

The modulation classification performance is evaluated over AWGN, flat fading, and multipath fading channels, following standard communication-system simulation practice [43]. Three channel conditions are considered: Rician flat fading with $f_D = 100$ Hz (Channel 1), multipath Rician fading with $f_D = 100$ Hz (Channel 2), and multipath Rician fading with $f_D = 1000$ Hz (Channel 3). The symbol rate is set to $f_s = 1.92$ MHz. Table 5 summarizes the evaluated instances and simulation settings used in this study.

Table 5. Evaluated instances and simulation settings.

Item	Setting
Modulation classes	GMSK, GFSK, QPSK, 8PSK, 16-QAM, 64-QAM, 256-QAM
Number of classes	Seven total classes; three QAM-family classes
Input frame size	2×4096 real-valued IQ samples
Downsampled frame size	2×512
Oversampling factor	$L = 8$
Symbol rate	$f_s = 1.92$ MHz
SNR values	10, 15, 20, 25, and 30 dB
Channel conditions	Channel 1: Rician flat fading with $f_D = 100$ Hz; Channel 2: multipath Rician fading with $f_D = 100$ Hz; Channel 3: multipath Rician fading with $f_D = 1000$ Hz
Training/validation frames	15,000 frames per modulation class, split into 80% training and 20% validation
Test frames	10,000 frames per modulation class
Primary metric	Probability of correct classification P_{cc}

The parameter choices are intended to focus on moderate-to-high SNR regimes where high-order QAM is practically meaningful and where multipath distortion, rather than

noise alone, is a major source of class confusion. The SNR range of 10–30 dB was therefore selected to evaluate the regime in which 16-QAM, 64-QAM, and 256-QAM are relevant candidates for classification. Channel 2 and Channel 3 share the multipath Rician fading setting but differ in maximum Doppler frequency. This allows the effect of stronger time selectivity to be discussed separately from the presence of multipath fading. The selected modulation classes cover continuous-phase frequency modulation, phase modulation, and high-order amplitude-phase modulation, as discussed in Section 3.

For the training and validation processes of the CDAE and CNN, 15,000 signals are generated for each of the seven modulation types. The signal-to-noise ratio (SNR) ranges from 10 dB to 30 dB with a step size of 5 dB. For each modulation type, 80% of the generated signals are used for training and 20% are used for validation. For testing, 10,000 signals are generated for each modulation type. The SNR definition used in all simulations is given in Equation (3).

$$\text{SNR(dB)} = 10 \log_{10} \left(\frac{E_s}{\sigma_n^2} \right), \quad (3)$$

where E_s is the signal power. The probability of correct classification, denoted by P_{cc} , is used as the main evaluation metric.

The signal generation procedure is as follows. First, random binary sequences are generated independently for each frame and modulation class. Second, the bit sequence is mapped to the corresponding single-carrier modulation symbols. Third, the baseband waveform is oversampled by the factor $L = 8$ and a frame of $M = 4096$ complex samples is formed. Fourth, the frame is passed through the selected channel model: AWGN, Rician flat fading, or multipath Rician fading. Fifth, complex AWGN is added to satisfy the target SNR. Finally, the complex received signal is represented as a 2×4096 real-valued tensor by stacking the in-phase and quadrature components. The training, validation, and test sets are generated independently to avoid data leakage. The signal-generation procedure is summarized in Algorithm 2.

Algorithm 2 Algorithmic procedure for generating the evaluated signal instances.

Require: Modulation class m , SNR value, and channel condition.

Ensure: Real-valued received frame $\mathbf{y} \in \mathbb{R}^{2 \times 4096}$.

- 1: Generate a random binary sequence independently for the frame.
 - 2: Map the bits to symbols according to the selected modulation class m .
 - 3: Oversample the baseband waveform by the factor $L = 8$.
 - 4: Extract or form an $M = 4096$ complex-sample frame.
 - 5: Pass the frame through the selected channel model.
 - 6: Add complex AWGN according to the target SNR in Equation (3).
 - 7: Stack the in-phase and quadrature components to form the final 2×4096 input tensor.
 - 8: Assign the generated frame to the training, validation, or test set while keeping the sets independent.
-

The CDAE and CNN are trained for 50 epochs using the Adam optimizer [44] with an initial learning rate of 10^{-3} . The mini-batch size is 64. The same training configuration is used for all compared preprocessing and classification settings so that performance differences are not caused by different hyperparameter choices. Adam is used because it provides stable first-order optimization for neural-network training with mini-batches. No claim is made that this hyperparameter set is globally optimal; rather, it provides a fixed training protocol for controlled comparison. Table 6 lists the evaluated preprocessing and classification configurations.

Table 7 reports the hardware and software environment used for the experiments.

Table 6. Configuration of the evaluated preprocessing and classification methods.

Configuration	Channel Condition	Preprocessing	CDAE	Classifier Output	Purpose
No preprocessing + CNN	Channel 1/2	None	No	Seven classes	Raw baseline for first-stage evaluation
BSS + CNN	AWGN/flat fading	BSS	No	Seven classes	First-stage preprocessing for AWGN/flat fading
CMA + CNN	Multipath fading	CMA	No	Seven classes	Blind equalization baseline under multipath
CMA + BSS + CNN	Multipath fading	CMA followed by BSS	No	Seven classes	First-stage preprocessing for multipath fading
One-stage with five-frame averaging	Multipath fading	CMA + BSS	No	Seven classes	Decision-smoothing baseline
Proposed two-stage hierarchy	Multipath fading and QAM-family flag	First stage: CMA + BSS; second stage: CDAE + BSS	Yes, QAM only	Seven-class first stage and three-class QAM second stage	Selective high-order QAM refinement

Table 7. Hardware and software environment used for the experiments.

Item	Specification
CPU	Intel Core i9-13900K
GPU	NVIDIA GeForce RTX 4080
Memory	64 GB RAM
Operating system	Windows 11 Pro 64-bit
Programming environment	MATLAB R2024b
Deep-learning library/toolbox	MATLAB Deep Learning Toolbox
Acceleration libraries	CUDA 12.x/cuDNN 8.x
Randomness control	Training, validation, and test frames were generated independently; repeated retraining with different random initializations was not included.

Each reported test point is computed from independently generated test frames. For class-wise results, each modulation class uses 10,000 test frames; for overall seven-class accuracy, the estimate aggregates 70,000 test frames. To quantify finite-test-set uncertainty, we use the approximate binomial confidence interval

$$\hat{p} \pm 1.96 \sqrt{\frac{\hat{p}(1 - \hat{p})}{N}}, \quad (4)$$

where $\hat{p}$ is the measured classification probability and N is the number of test frames. Around $\hat{p} = 0.9$, the 95% interval is approximately $\pm 0.59\%$ for class-wise accuracy with $N = 10,000$ and approximately $\pm 0.22\%$ for overall seven-class accuracy with $N = 70,000$. These intervals quantify finite-test-set sampling uncertainty only. They do not capture training variability due to independent network retraining with different random initializations, which is acknowledged in Section 7.

To provide an additional non-parametric finite-test-set check without introducing additional channel simulations, a bootstrap resampling procedure was applied to the binary correctness indicators of the existing test outputs. For a pair of methods evaluated on the same test setting, the frame-level correctness difference was resampled with replacement, and the distribution of the difference in P_{cc} was obtained. A comparison was interpreted as supported by the finite-test-set evidence when the 95% bootstrap interval of the difference did not include zero. When the improvement was small or channel/SNR-dependent, the text describes the result as a trend rather than as a categorical conclusion. This resampling analysis does not replace repeated retraining with different random initializations, which remains a limitation.

6. Results

Unless otherwise stated, the reported differences are interpreted as performance trends under the considered simulation settings. When performance differences are several percentage points, they exceed the finite-test-set uncertainty quantified by the confidence interval in Equation (4) and were further examined using the non-parametric bootstrap procedure described in Section 5. However, the results should not be interpreted as repeated-training statistical significance because multiple independent retraining runs are not included.

6.1. First-Stage Preprocessing Performance

Figure 3 shows the overall classification performance in the first stage as a function of SNR for Channel 1 and Channel 2. On Channel 1, BSS provides better overall classification performance than no preprocessing, whereas CMA and CMA + BSS degrade performance. On Channel 2, the multipath channel produces stronger distortion, and CMA + BSS achieves better overall classification performance than BSS or CMA alone. At an SNR of 30 dB, BSS improves the overall classification performance by more than 4% compared with no preprocessing on Channel 1, while CMA + BSS improves the overall classification performance by more than 12% compared with no preprocessing on Channel 2. These results support the use of BSS for AWGN/flat fading conditions and CMA + BSS for multipath fading conditions.

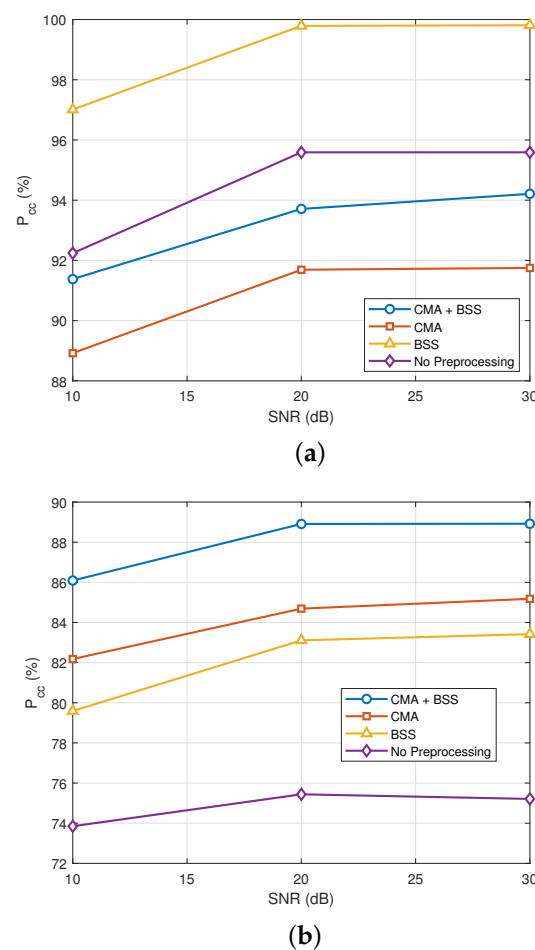


Figure 3. Overall first-stage classification performance versus SNR for (a) Channel 1 and (b) Channel 2.

Table 8 shows the confusion matrix of the first-stage classifier with BSS preprocessing at an SNR of 20 dB on Channel 1. The overall classification rate is 99.8%, and all modulation classes are clearly separated. In this condition, the second-stage QAM refinement path is not necessary because QAM classes are already well classified.

Table 8. Confusion matrix of modulation classification with blind source separation (BSS) preprocessing in the first stage at a signal-to-noise ratio (SNR) of 20 dB on Channel 1. The overall classification rate is 99.8%.

	GMSK	GFSK	QPSK	8PSK	16-QAM	64-QAM	256-QAM
GMSK	100	0	0	0	0	0	0
GFSK	0	100	0	0	0	0	0
QPSK	0	0	100	0	0	0	0
8PSK	0	0	0	100	0	0	0
16-QAM	0	0	0	0	100	0	0
64-QAM	0	0	0	0	0	98.7	1.3
256-QAM	0	0	0	0	0	0.3	99.7

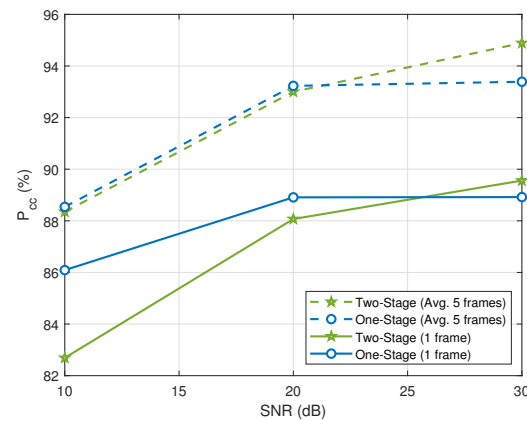
Table 9 shows the confusion matrix of the first-stage classifier with CMA + BSS preprocessing at an SNR of 20 dB on Channel 2. GMSK, GFSK, QPSK, 8PSK, and the QAM family are classified reliably, but the discrimination among 16-QAM, 64-QAM, and 256-QAM is difficult. The 64-QAM class is particularly confused with 256-QAM, showing the need for stronger signal restoration and a dedicated QAM refinement stage.

Table 9. Confusion matrix of modulation classification with constant modulus algorithm (CMA) and blind source separation (BSS) preprocessing in the first stage at a signal-to-noise ratio (SNR) of 20 dB on Channel 2. The overall classification rate is 88.9%.

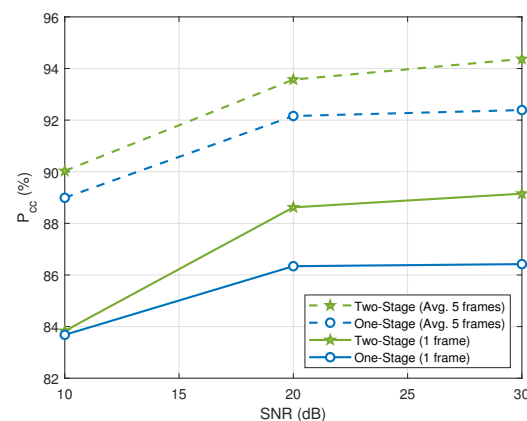
	GMSK	GFSK	QPSK	8PSK	16-QAM	64-QAM	256-QAM
GMSK	100	0	0	0	0	0	0
GFSK	0	100	0	0	0	0	0
QPSK	0	0	99.4	0.4	0.1	0	0.1
8PSK	0	0	0.2	98.9	0.3	0.2	0.4
16-QAM	0	0	0	0.4	88.8	3.0	7.8
64-QAM	0	0	0	0.4	2.7	62.5	34.4
256-QAM	0	0	0	0.3	2.6	24.3	72.8

6.2. Hierarchical Classification Performance

Figure 4 shows the overall classification performance of one-stage and two-stage classification on Channel 2 and Channel 3. In the first stage, CMA + BSS is used as preprocessing for multipath fading, and in the second stage, CDAE + BSS is used for QAM refinement. On Channel 2, the two-stage classifier improves the overall classification performance at an SNR of 30 dB, while the one-stage classifier performs better when the SNR is below 20 dB. On Channel 3, where the Doppler effect is larger and the channel is more time-selective, the two-stage classifier achieves better overall classification performance when the SNR is higher than 10 dB. These results show that the benefit of the second stage is channel- and SNR-dependent, and is most evident when the high-order QAM classes experience stronger residual amplitude and phase variation.



(a)



(b)

Figure 4. Overall one-stage and two-stage classification performance versus SNR for (a) Channel 2 and (b) Channel 3.

Multi-frame Softmax averaging further improves the performance. When five frames are used for classification, the overall classification performance improves by more than 5% compared with one-frame classification in both one-stage and two-stage settings. This indicates that multi-frame decision smoothing is a useful practical addition when the receiver can observe multiple consecutive frames.

6.3. High-Order QAM Classification Performance

Figure 5 shows the classification performance of QAM signals on Channel 3. The two-stage classifier improves the classification of 64-QAM and 256-QAM compared with the one-stage classifier, while the effect on 16-QAM is relatively small. The improvement increases as the QAM order increases, which is consistent with the intuition that denser constellations are more sensitive to multipath-induced distortion. For QAM signals, the two-stage classification improves the overall classification probability by approximately 5% compared with the one-stage classification when the SNR is higher than 20 dB. With five-frame averaging, the overall QAM classification probability improves by more than 10% compared with one-frame classification.

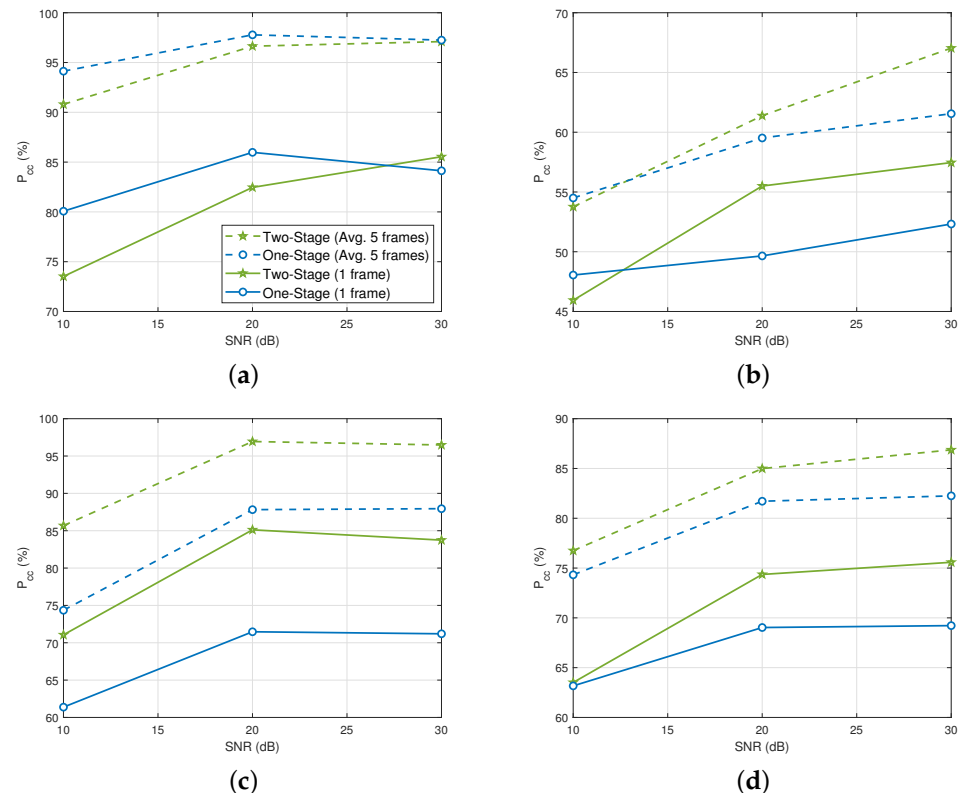


Figure 5. QAM classification performance on Channel 3 versus SNR: (a) 16-QAM, (b) 64-QAM, (c) 256-QAM, and (d) overall.

7. Discussion

7.1. Interpretation of the Channel-Type-Guided Preprocessing

The first-stage results show that no single blind preprocessing method is uniformly effective across all channel conditions. BSS is suitable for AWGN and flat fading channels because it can reduce the effect of phase rotation without imposing a constant-modulus constraint that may be harmful for non-constant-envelope signals. In multipath fading channels, CMA becomes useful because it partially compensates for inter-symbol interference, but its arbitrary phase rotation can make CNN classification more difficult. Applying BSS after CMA helps reduce this effect. This explains why CMA + BSS is effective in Channel 2, while BSS alone is preferred in Channel 1.

This interpretation also clarifies the meaning of “blind” in the proposed method. The preprocessing does not require pilot symbols, training equalization sequences, or explicit CSI. However, the selection of the preprocessing branch is guided by the channel category, which is assumed to be available in this study. Therefore, the method should be understood as channel-type-guided blind preprocessing rather than fully autonomous channel-adaptive preprocessing.

7.2. Why High-Order QAM Benefits from Second-Stage Refinement

The confusion matrix for Channel 2 shows that the main weakness of the first-stage classifier is not the separation of all modulation families, but the fine-grained discrimination among high-order QAM classes. In particular, 64-QAM and 256-QAM are strongly confused under multipath fading. This is expected because these classes have denser constellation structures and are more sensitive to residual amplitude and phase distortion. The second-stage CDAE path therefore focuses on the most difficult subset of the classification problem. This selective use of CDAE is important because applying a restoration network to all modulation types may be unnecessary and may even distort features of non-QAM signals.

7.3. Multipath and Doppler Effects

Channel 2 and Channel 3 both include multipath Rician fading, but Channel 3 uses a larger maximum Doppler frequency. The comparison therefore suggests how stronger time selectivity affects the hierarchical classifier. Multipath primarily creates delayed signal replicas and inter-symbol interference, which distort the constellation geometry and reduce the separability of dense QAM classes. Doppler makes the channel vary more rapidly over time, which can increase residual amplitude and phase variation within the observation window. The results suggest that the second-stage refinement becomes more useful when the channel is more time-selective. However, the present results do not isolate the internal compensation mechanism of the CDAE; a more detailed analysis of Doppler compensation remains future work.

7.4. Computational Performance

The proposed hierarchy is intended to limit the use of the computationally heavier CDAE block. The main CNN classifier in Table 4 uses a compact four-convolutional-layer structure, while the CDAE is activated only when the first-stage output belongs to the QAM family. The parameter-count analysis in Section 4.5 shows that the first-stage CNN, second-stage CNN, and CDAE contain approximately 5.67×10^5 , 5.66×10^5 , and 3.29×10^5 trainable parameters, respectively. Under the uniform-class assumption, the CDAE is conditionally executed for approximately 42.9% of input frames and avoided for approximately 57.1% of frames compared with a hypothetical all-CDAE pipeline. This does not prove real-time hardware feasibility, but it supports the architectural rationale for selective restoration.

7.5. Practical Implications and Limitations

The proposed framework is relevant to spectrum monitoring and non-cooperative receiver scenarios where the receiver can operate without pilot-aided equalization but can obtain or assume coarse channel condition information. Multi-frame averaging provides an additional reliability mechanism when multiple signal observations are available. Nevertheless, the results should be interpreted as controlled simulation evidence rather than real-world deployment validation. The channel category is assumed to be known; automatic channel-category detection and the effect of branch-selection errors are not quantified. The reported confidence intervals reflect finite-test-set uncertainty, but repeated retraining with different random initializations was not performed. The study also does not provide quantitative benchmarks against recent ResNet-, transformer-, contrastive-, or domain-adaptive AMC architectures. In particular, the present comparison with recent ResNet-, transformer-, contrastive-, and domain-adaptive AMC methods is qualitative rather than experimental; a fair quantitative benchmark requires reimplementing of these models under the same simulated channel and dataset settings. Finally, latency and power consumption were not measured on a hardware platform. Future work should therefore investigate automatic channel-category estimation, real over-the-air datasets, retraining variability, hardware latency, and integration of the proposed preprocessing front end with recent representation-learning backbones.

8. Conclusions

This paper presented a hierarchical hybrid AMC framework that combines channel-type-guided blind preprocessing with deep learning. In the first stage, BSS is used for AWGN/flat fading channels and CMA + BSS is used for multipath fading channels before CNN classification. When a QAM-family signal is detected, the second stage applies CDAE-based blind equalization followed by BSS preprocessing and a dedicated CNN

classifier for 16-QAM, 64-QAM, and 256-QAM. The results indicate that the proposed framework is useful for high-order QAM classification in the considered multipath Rician fading scenarios, where the first-stage classifier has difficulty discriminating among dense QAM constellations. Multi-frame Softmax averaging further improves decision stability. The proposed method is best understood as a practical, engineering-oriented hybrid AMC framework that complements recent end-to-end and representation-learning-based approaches by explicitly incorporating blind signal-processing priors and selective QAM refinement. The revised analysis also clarifies the evaluated instances, method configurations, algorithmic processing steps, model-size and conditional-complexity estimates, finite-test-set confidence intervals, non-parametric bootstrap interpretation, and experimental hardware/software reporting. Real over-the-air validation, automatic channel-category detection, repeated-retraining variability, hardware latency measurement, and quantitative comparison with recent large-scale AMC backbones remain important directions for future work.

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Abbreviations

The following abbreviations are used in this manuscript:

AMC	Automatic modulation classification
AWGN	Additive white Gaussian noise
BSS	Blind source separation
CDAE	Convolutional denoising autoencoder
CI	Confidence interval
CMA	Constant modulus algorithm
CNN	Convolutional neural network
CSI	Channel state information
ELU	Exponential linear unit
FC	Fully connected
GFSK	Gaussian frequency shift keying
GMSK	Gaussian minimum shift keying
IQ	In-phase and quadrature
LSTM	Long short-term memory
MIMO-OFDM	Multiple-input multiple-output orthogonal frequency-division multiplexing
NPULUD	Neighborhood-based positive unlabeled learning using decision tree
QAM	Quadrature amplitude modulation
QPSK	Quadrature phase shift keying
SNR	Signal-to-noise ratio

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