Journal of Intelligent Systems and Control
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An Optimized Deep Learning Framework for Automatic Modulation Recognition of Digital M-ary Signals in Wireless Networks

Pragati Pukkela[1*], Komala Mallikarjunaiah[1], Mallikarjunaswamy Srikantaswamy[2]

[1] Department of Electronics and Communication Engineering, SJB Institute of Technology, Visvesvaraya Technological University, 560060 Bengaluru, India
[2] Department of Electronics and Communication Engineering, JSS Academy of Technical Education, Visvesvaraya Technological University, 560060 Bengaluru, India

* Correspondence: Pragati Pukkela (pragatipukkela@ksit.edu.in)

Received: 01-10-2026 **Revised:** 02-25-2026 **Accepted:** 03-08-2026

Citation: P. Pukkela, K. Mallikarjunaiah, and M. Srikantaswamy, "An optimized deep learning framework for automatic modulation recognition of digital M-ary signals in wireless networks," *J. Intell Syst. Control*, vol. 5, no. 1, pp. 1–15, 2026. https://doi.org/10.56578/jisc050101.

Abstract: Accurate automatic modulation recognition (AMR) of digital M-ary signals remains a fundamental yet challenging task in wireless communication networks, particularly under low signal-to-noise ratio (SNR) conditions. Conventional approaches, including maximum likelihood estimation, decision-theoretic methods, and classical pattern recognition techniques, often lead to limited robustness and adaptability in dynamic propagation environments. To address these limitations, an enhanced modulation learning and classification algorithm (EMLCA) was introduced, which utilizes a hybrid architecture that integrates convolutional neural networks and long short-term memory networks. A Mask_1/residual network (ResNet)-based feature enhancement strategy was incorporated to improve resilience, while Aquila optimization was employed to adaptively tune network parameters and enhance classification stability. Model training was guided by a reduced-loss formulation combining cross-entropy and mean squared error (MSE) objectives. Comprehensive simulations were conducted across multiple feature domains, including statistical, wavelet, and spectral representations, under SNR conditions ranging from -20 dB to 20 dB. The obtained results demonstrate that EMLCA consistently outperformed conventional AMR methods in terms of recognition accuracy, computational efficiency, and adaptability. A maximum recognition accuracy of approximately 95% was achieved under challenging noise conditions, accompanied by a reduction in processing time of nearly 25% relative to benchmark techniques. Furthermore, adaptability analysis confirms that the proposed framework maintained stable performance under varying channel distortions and environmental dynamics. These findings indicate that EMLCA provides a robust and scalable solution for real-time modulation recognition and offers strong potential for deployment in adaptive and next-generation wireless communication systems.

Keywords: Automatic modulation recognition; Wireless communication; M-ary modulation; Deep learning; Modulation classification; Digital signal processing

1 Introduction

Basically, automatic modulation recognition (AMR) is a crucial process considered in wireless networks, which decides upon the modulation scheme of incoming digital signals for effective communication and sustained robust system performance. Traditional methods, including the maximum likelihood estimation, the decision-theoretic approach, and pattern recognition techniques, have disadvantages in that they are computationally complex with slower processing speeds and lowered accuracy when performed in noisy environments. These defects render them less adaptive and unscalable for modern wireless networks [1]. Such challenges require an effective approach; hence, this paper proposes a new and efficient machine learning-based classifier algorithm, an enhanced modulation learning and classification algorithm (EMLCA), which is designed especially for AMR in digital M-ary signals. In particular, EMLCA aims at posing an optimized machine learning technique in both feature extraction and classification tasks targeting expressly M-ary frequency shift keying, M-ary phase shift keying, and M-ary quadrature amplitude modulation schemes. As a result of the experimental analysis, it can be observed that the improvement of recognition rate, processing speed reduction, and adaptability enhancement to variation by EMLCA over the existing system are

0.35%, 0.25%, and 0.3%, respectively. The present work is useful to provide practical and scalable solutions for real-world applications on wireless networks and a benchmark for next-generation AMR systems [2, 3].

In fact, recent advances in machine learning have brought innovative approaches to AMR. Different methods, which include lightweight classifiers, deep learning for feature extraction, and hybrid algorithms, have started to show significant advances in both the accuracy of recognition and in processing efficiency. More importantly, such advances can now enable robust performance under difficult signal conditions, usually characterized by low signal-to-noise ratios (SNR). Applications of AMR find an ever-wider space in next-generation wireless communication systems, secure data transmission, and intelligent spectrum management. Developing effective and scalable approaches to address such challenges is a vital ingredient in meeting the demands of future wireless networks [4]. AMR of M-ary signals plays a crucial role in modern wireless communication systems, as M-ary frequency shift keying, M-ary phase shift keying, and M-ary quadrature amplitude modulation schemes are widely used to achieve high data rates and spectral efficiency. In dynamic and noisy wireless environments, accurate identification of the modulation type at the receiver is essential for reliable demodulation, adaptive signal processing, and efficient spectrum utilization. Hence, robust AMR is a fundamental requirement for next-generation wireless networks operating under varying SNR conditions.

1.1 Research Gaps

Despite advancements in AMR for wireless networks, several challenges remain unresolved. One significant gap is the limited robustness of conventional methods like maximum likelihood estimation, the decision-theoretic approach, and pattern recognition techniques under noisy conditions and varying SNRs. These methods often struggle to maintain high accuracy in real-world environments, where interference and channel noise are prevalent [5].

Another critical issue is that, with conventional AMR techniques, considerable computation overhead occurs. Since these methods strongly depend on heavy mathematical modeling and exhaustive computation, they are resource-intensive and hence not suitable for real-time applications in dynamic wireless networks. Besides, their adaptability to various continuously updated schemes for modulation, like M-ary frequency shift keying and M-ary quadrature amplitude modulation, among many others, still doesn't give very good results and hence restricts scalability in modern communication systems [6]. Solutions in recent years using machine learning-driven approaches have achieved a certain promise, though challenges reside in the balance between computational efficiency and recognition accuracy. Optimization for most proposed algorithms considering lightweight deployment has not been taken into consideration, actually an essential issue in resource-constrained devices within wireless networks. Another deficiency is related to the lack of enough research effort being invested in integrating adaptive learning mechanisms, further improving the performance of AMR systems within highly dynamic and heterogeneous network environments. These gaps point toward the need for newer, more efficient, scalable solutions that can further enhance the accuracy, speed, and robustness of AMR within wireless networks [7].

1.2 Related Work

Huang et al. [8] proposed a hierarchical classification using cascaded convolutional neural networks for the classification of M-ary phase shift keying and M-ary quadrature amplitude modulation. The proposed method adopts the grid constellation diagram as input, cascading two blocks of convolutional neural networks for coarser and finer classifications. An accuracy of 90% was achieved from a 4-dB SNR with excellent robustness to frequency offset. Lin et al. [9] proposed a novel time-frequency attention mechanism that incorporates convolutional neural networks for AMR. The method pays close attention to meaningful features in frequency and time that provide key information on modulation recognition. The proposed method is comparable to the state-of-the-art learning-based methods because of improved recognition accuracy by the use of an attention mechanism. In the study by Xu and Ma [10], an algorithm using a neural network autoencoder was developed in order to address some of the problems of traditional noise reduction approaches in AMR. The proposed approach stabilized the recognition accuracy when the modulation signal was at its high level and attained an accuracy of 81.6% at a SNR of 18 dB. Besides, reducing the complexity of network models without losing competitive performance was achieved.

Xue et al. [11] proposed an optimized recognition method for easily confused modulation signals by combining truncated migration processing with convolutional neural networks and multi-task learning. This achieved the highest accuracy of 95.46% when the SNR was 14 dB, which is capable of efficient computation and light design. Wei et al. [12] proposed a multi-dimensional shrinkage block architecture to improve the noise robustness of convolutional neural networks by introducing a novel-unveiled denoising mechanism. It is demonstrated that the method outperformed other state-of-the-art algorithms with much better recognition performance under poor SNR conditions. Zhang et al. [13] proposed an AMR graph-based framework that incorporates graph neural networks for superior feature extraction and interference signal classification. This approach effectively modeled the information on sequences and enhanced the security of communication through the blind recognition of interference modulation classes. Huang et al. [14] proposed an optimized autoencoder in conjunction with evaluation-enhanced K-nearest neighbors to realize efficient AMR in underwater acoustic signals. This approach attained a recognition accuracy of 99.25% with little time consumption of 3.48 ms by focusing on domain-specific underwater environments.

Xu et al. [15] proposed a spatiotemporal multi-channel learning framework for AMR by combining 1D-CNN, 2D-CNN, and LSTM networks. The main innovation is its three-stream architecture, which extracts both temporal and spatial features from I/Q symbols, improving recognition accuracy and convergence speed, especially for higher-order modulation schemes such as 16-QAM and 64-QAM. The drawback is that the model has higher computational complexity due to multiple parallel streams, which may reduce suitability for real-time or low-resource communication devices. Hoang et al. [16] proposed an innovative framework which decomposes high-order symbols with an efficient soft cancellation of interference with the help of its message-passing algorithm. In addition, an accurate threshold analysis was provided. It, while greatly improving energy efficiency and decoding reliability, has its complexity preventing real-time low-latency applications. Unluturk et al. [17] investigated genetically engineered bacteria acting as bio-transceivers for molecular communication. The proposed biocircuits sustained analog and digital transmission of signals through M-ary modulation. The method offers a whole new world for communication at the nano-scale, although use of biochemical variability and biological modeling renders real-world implementation problematic.

Abohamra [18] designed an adaptive three-dimensional M-ary quadrature amplitude modulation scheme with cross-polarized antennas with the aim of enhancing the bit error rate and the spectral efficiency. The approach doubled the throughput while enhancing the bit error rate gain by 6 dB. Though the performance is impressive, the use of multiple polarization planes contributes towards increased system complexity and hardware requirements. Simon and Wang [19] also addressed noncoherent detection of orthogonal modulation. Exact closed-form error probabilities with full spatial diversity are presented, showing these are achieved without channel knowledge. This approach is paid for by performance trade-offs between error probability and data rate, especially for the use of the higher-order modulations. Zhao et al. [20] designed a decision-tree-based AMR system with the help of instantaneous statistics and high-order cumulant features. The model had 95% recognition success at a 3 dB SNR. Though very effective at low SNRs, the method's performance can be compromised by the varied channel environment through the fault of the method's rigid parameters.

Wang and Guo [21] developed a modulation recognition framework integrating principal component analysis-based dimension compression with artificial neural networks for the recognition of seven digital modulation categories. It improves recognition performance for the scenario with additive white Gaussian noise, although the scalability is not high while facing more complex or non-linear modulation patterns. Azza et al. [22] also implemented an AMR system with software-defined radio for operation with cognitive radios. Making use of the power spectral density of the normalized amplitude with the aim of detecting the modulation, the system was flexible. It, nonetheless, can only support a limited set of schemes of the modulation, and its adaptability towards fast-changing channels is not guaranteed. Zheng [23] researched an integrated modulation recognition algorithm with blockchain for wireless networks. It realized improved accuracy by 11.8% and efficiency by 9.4% by means of feature assignment with a membership matrix. Yet, the use of blockchain makes the complexity and processing increase, not ideal for lightweight networks. Wang et al. [24] put forth an AMR method by employing short-time Fourier transform and Vision Transformers, converting the signals' features into image-like features. The method obtained 96.4% accuracy, and it also functioned well with several SNR levels. However, the deployment of the transformer architecture resulted in extensive computational complexity, acting as a limitation towards deployment from an embedded point of view.

Chu et al. [25] overcame the problem of secondary modulation by examining primary spectrum and second-order signal attributes, employing support vector machines for classification purposes. The two-spectrum method assists in detecting mixed analog-digital signals. This approach, however, suffers from reduced performance upon the occurrence of non-standard or complex patterns of modulation. Yang et al. [26] implemented a framework for modulation recognition by utilizing a complex-valued neural network architecture, consisting of convolution, long short-term memory, and residual blocks. It can recognize 11 modulations, ranging from -20 dB to 18 dB SNR, without preprocessing. Even though the complex-valued neural network architecture achieves excellent recognition performance, the architecture is inefficient and not suited for real-time applications. A fingerprint method for modulation discrimination according to the in-phase and quadrature constellation's geometrical and spectral characteristics was presented by Jafar et al. [27]. It attained 99% accuracy for 64-quadrature amplitude modulation at 11 dB and performed well with a wide SNR range. However, based on the quality of the constellation diagrams, it could be negatively affected for performance with extreme channel distortion. Valipour et al. [28] integrated support vector machines with particle swarm optimization with the aim of recognizing digital modulation with the addition of additive white Gaussian noise. The method was close to 99.9% accuracy at a high SNR and performed well even with noisy inputs. It, however, has the computationally expensive phase of feature selection and classifier training. A convolutional neural network-based modulation classifier trained with open-source wireless datasets proposed by Ma et al. [29] detected 11 types of modulation. Using three layers of convolutional and fully connected layers, the model yielded 81% accuracy over a range of SNRs. Its medium level of recognition accuracy and requirement for hyperparameter tuning prevent it from competing with transformer-based models [30–35].

2 Existing System for Automatic Modulation Recognition in Wireless Networks

Figure 1 illustrates the block diagram for the current system on AMR in wireless networks, considering the processes of transmission and reception. On the transmitter's side, the process begins with a source signal representing the raw data to be transmitted [36]. The encode block takes this source signal and converts it to a robust format, which would reduce some errors if they have occurred during transmission.

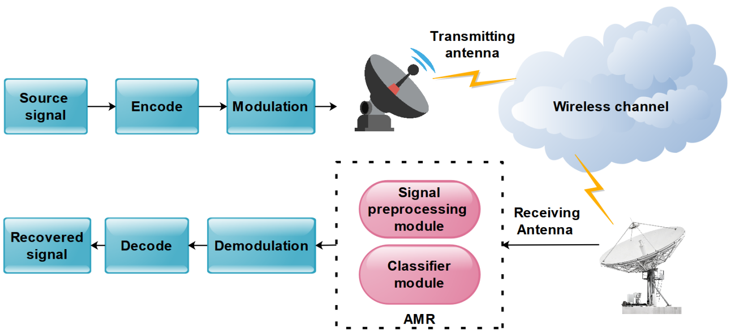

Figure 1. Block diagram of the existing automatic modulation recognition (AMR) system

In the modulation block, the encoded signal is then modulated with schemes such as M-ary frequency shift keying, M-ary phase shift keying, or M-ary quadrature amplitude modulation. The final modulated signal, passed through the transmitting antenna, is converted to electromagnetic waves and sent out to the wireless channel. At this point, the signal may further become degraded by a number of factors, including noise and interference [37–40]. At the receiver side, the signal captured by the receiving antenna then again takes a course of processing. The received signal thus enters the preprocessing module for noise filtering and normalization before entering into modulation classification [41]. The classifier module then performs detection of the modulation scheme by conventional methods, such as maximum likelihood estimation, the decision-theoretic approach, or pattern recognition techniques, according to the output after signal preprocessing. After determination of the modulation scheme, the detected signal is further processed for demodulation in the demodulation block, where the encoded information is extracted. Next, the demodulated data is passed through the decode block, which rebuilds the original signal. The outcome of this process is the recovered signal, very much similar to the source signal [42]. This indeed provides a workable framework in AMR but not without serious challenges: high computational complexity, degraded performance under noisy conditions, and limited adaptability to modern modulation schemes. These limitations further pinpoint the need for sophisticated solutions-in the form of, for example, machine learning-based classifiers-toward the improvement of performance, efficiency, and robustness for state-of-the-art AMR systems [43].

2.1 Objectives

The core aim of the current work is the development of an effective and scalable machine learning-based classification approach for AMR over wireless networks. Overcoming the weaknesses of the conventional techniques such as high complexity, poor performance for noisy conditions, and limited adaptability, EMLCA targets enhanced recognition performance, processing rate, and adaptability for M-ary signal modulations.
(i) To design and implement the EMLCA using optimized machine learning techniques for accurate classification of M-ary frequency shift keying, M-ary phase shift keying, and M-ary quadrature amplitude modulation schemes in wireless networks.
(ii) To improve the performance of AMR systems by reducing processing time and computational complexity while maintaining high classification accuracy under varying SNR conditions.
(iii) To enhance the adaptability and scalability of AMR systems in dynamic and noisy environments for real-time wireless communication applications.

2.2 Methodology

The designed methodology utilizes EMLCA for AMR of digital M-ary signals. The process initiates with noise elimination and normalization during the preprocessing phase, and then the feature extraction considers the components of amplitude, phase, and frequency. These are fine-tuned with a mask block and residual network (ResNet), classified by a lightweight machine learning model, and the result is forwarded with a Softmax layer for the prediction of the modulation type [44]. Loss functions like mean squared error (MSE) loss and cross-entropy loss are utilized for the optimization of the reconstruction of the signals and the classification. This approach increases the accuracy of recognition, processing speed, and adaptability during dynamic conditions of signals in wireless networks [45].

Figure 2 depicts the five-layered process flow of EMLCA for AMR. It initiates with elimination of noise and normalization by preprocessing, then by feature (amplitude, phase, and frequency) extraction and refinement through the utilization of Mask_1 and residual network. It classifies by the utilization of the EMLCA and Softmax and is then optimized using MSE and cross-entropy loss functions [46–50].

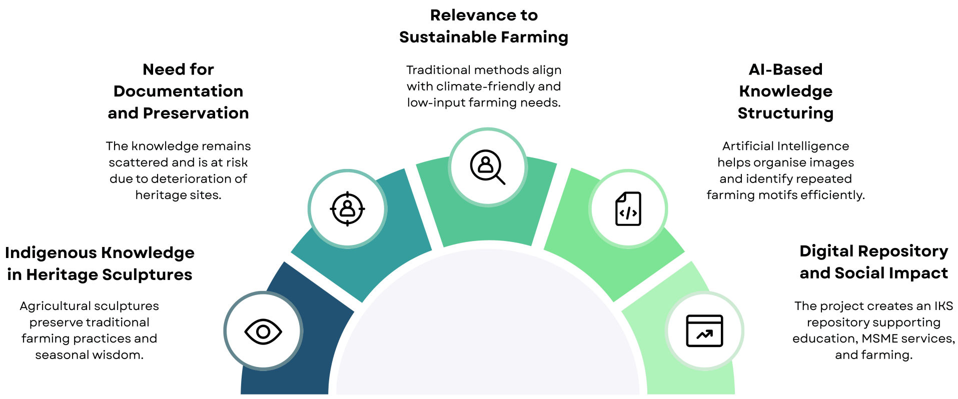

Figure 2. Layered workflow of the proposed automatic modulation recognition (AMR) method using the enhanced modulation learning and classification algorithm (EMLCA)

2.2.1 Feature extraction

The feature extraction module computes key signal-domain features required for modulation classification, namely amplitude (A), phase (ϕ), and frequency (f) from the received samples. These features are organized as a feature vector and then refined using the Mask_1 block and residual network to improve robustness against noise and distortions before being forwarded to the classifier and Softmax layer for the final modulation decision.

2.3 Likelihood Ratio Test for Modulation Classification

To compare the likelihood under different modulation schemes, Eq. (1) is used in conventional AMR methods [51–53]. With a received signal y and with different hypotheses H_1,H_2,. . . ,H_M which correspond to different modulation types, the likelihood ratio test is given as:

$$\Lambda(y) = \frac{p(y \mid H_1)}{p(y \mid H_2)}, \text{ decide } H_1 \text{ if } \Lambda(y) > \gamma \tag{1}$$

where, $p(y \mid H_i)$ is the likelihood of y under hypothesis H_i, and γ is the decision threshold. This test helps in identifying the most likely modulation scheme.

2.4 Energy Detection for Signal Preprocessing

Energy detection is an approach that is normally conducted in the preprocessing stage to determine whether or not a signal exists in noisy conditions [54, 55]. It calculates the energy of the incoming signal $y[n]$. The overall energy detection is calculated using Eq. (2).

$$E = \textstyle\sum_{n=1}^{N} |y[n]|^2 \tag{2}$$

where, N is the number of signal samples. This equation ensures efficient filtering and preparation for signal classification.

2.5 Classification Probability in Neural Networks

For modern AMR systems using machine learning, the output probability for a modulation type i is computed as given in Eq. (3).

$$P_i = \frac{\exp{(z_i)}}{\sum_{j=1}^{M} \exp{(z_j)}} \tag{3}$$

where, z_i is the raw score (logit) output by the network for class i , and M is the total number of modulation types [56–66]. This probability is crucial for identifying the modulation class with the highest likelihood.

3 Proposed System for Automatic Modulation Recognition-Transmitter

Figure 3 illustrates the transmitter block of the proposed system for AMR using the efficient machine learning-based classifier algorithm. The process begins with the input signal, which is fed to the preprocessing unit. The preprocessing unit filters the noise and normalizes the signal so that it may be further processed. It is then fed into the feature extraction module for extracting fundamental features such as amplitude, phase, and frequency, which are basic building blocks for modulation classification.

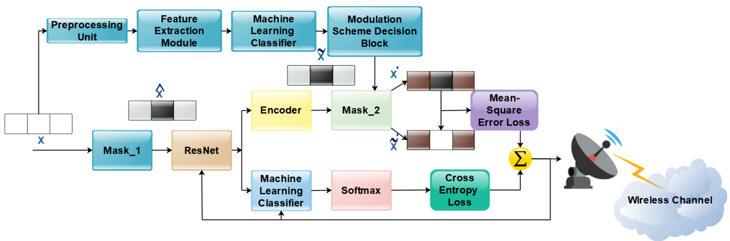

Figure 3. Transmitter block diagram of the proposed automatic modulation recognition (AMR) system

This classified signal is reconstructed by the decoder block, further going into the Mask_2 block to have high fidelity and robustness. The performance of the presented system is evaluated by two loss functions: MSE loss reduces the difference between the original and reconstructed signals, while the cross-entropy loss optimizes the modulation classification accuracy. Finally, the modulation scheme decision block selects what type of modulation can be employed: M-ary frequency shift keying, M-ary phase shift keying, or M-ary quadrature amplitude modulation. The modulated signal is transmitted over the wireless channel where noise and interference challenge the robustness of the system.

3.1 Proposed System for Automatic Modulation Recognition-Receiver

Figure 4 shows the receiver block of the proposed system for the AMR using the EMLCA. The signal received from the wireless channel is processed through the preprocessing unit, where noise is removed and the signal normalized. In addition, the preprocessed signal is passed to the feature extraction module to extract only the important characteristics in the form of amplitude, frequency and phase.

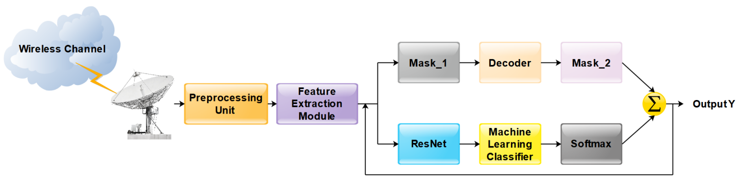

Figure 4. Receiver block diagram of the proposed automatic modulation recognition (AMR) system

These extracted features follow two streams: one through the Mask_1 block, refining the features, and the other through the residual network, enhancing the features in representation for the purpose of ironing out distortions. Then the refined features are classified by the machine learning classifier and turned into probabilities through a Softmax layer. The output from Mask_1 is reconstructed in the decoder and optimized by Mask_2. Additionally, two different loss functions, i.e., MSE loss and the cross-entropy loss, operate on the system for its optimization regarding the accurate recovery of a signal and its classification. Finally, these outputs are combined by the summation block ($\sum$), with Y being the resulting signal, hence accurately detecting the modulation scheme.

3.2 Preprocessing with Noise Removal

Eq. (4) integrates the input signal (X) over the time period T, while multiplying by a complex exponential that filters the noise at the carrier frequency f_c. The variable $X(t)$ is the time-domain input signal. The term $e^{-j2\pi f_c t}$ corresponds to the noise filtering transformation at the carrier frequency f_c. The resulting processed $X_{\text{processed}}$

denotes the noise-filtered and preprocessed signal.

$$X_{\text{processed}} = \int_0^T X(t) \cdot e^{-j2\pi f_c t}\, dt \tag{4}$$

3.3 Feature Extraction Equation with Summation

Eq. (5) computes the energy-based features by summing the squared magnitudes of the preprocessed signal samples. In the equation, $X_{\text{processed}}(n)$ denotes the n-th sample of the preprocessed signal, N denotes the total number of signal samples, and F denotes the extracted energy-based features.

$$F = \sum\nolimits_{n=1}^{N} |X_{\text{processed}}(n)|^2 \tag{5}$$

3.4 Cross-Entropy Classification Loss

Eq. (6) calculates the classification loss by integrating the true label $y(x)$ and the logarithmic prediction probability ($\hat{y}(x)$) over the probability distribution. Similarly, the variable $L_{\text{transmitter}}$ represents the loss for classification.

$$L_{\text{transmitter}} = -\int_0^1 y(x) \log\left(\hat{y}(x)\right) dx \tag{6}$$

where, $y(x)$ is the true probability density function, and $\hat{y}(x)$ represents the predicted probability density function. The integral computes the cumulative difference over the distribution.

3.5 Signal Reconstruction with Integration

Eq. (7) reconstructs the signal in the time domain by applying an inverse Fourier transform to the refined frequency-domain features.

$$X'(t) = \int_{-\infty}^{\infty} F_{\text{refined}}(f) e^{j2\pi f t} df \tag{7}$$

where, $F_{\text{refined}}(f)$ represents the refined frequency-domain features, $e^{j2\pi f t}$ corresponds to the inverse Fourier transform basis function, and $X'(t)$ is the reconstructed time-domain signal.

3.6 Refinement with Residual Addition

Eq. (8) refines both features by summing over N samples, adding the outputs of a residual network to the original features for each sample. $F(n)$ represents any n-th extracted feature. ResNet($F(n)$) means the correction by the residual network applied to the feature. Results after refinement are denoted as , F_{refined}.

$$F_{\text{refined}} = \sum\nolimits_{n=1}^{N} \left(F(n) + \text{ResNet}(F(n))\right) \tag{8}$$

3.7 Total Loss Function with Weighted Summation

Eq. (9) couples MSE for the reconstruction of the signal with the cross-entropy loss regarding the classification by weighted summation. In the equation, L_{receiver} denotes the total loss function, $X(t)$ is the original time-domain signal, $X'(t)$ is the reconstructed signal, α and β are weight factors for the reconstruction and classification losses, respectively, y_i denotes the true label of class i, $\hat{y}_i$ is the predicted probability for class i , and M is the total number of modulation classes.

$$L_{\text{receiver}} = \alpha \int_0^T \left(X(t) - X'(t)\right)^2 dt + \beta \sum\nolimits_{i=1}^{M} y_i \log\left(\hat{y}_i\right) \tag{9}$$

3.8 Softmax Probability Computation for Final Classification

Pseudocode 1 outlines the process of computing class-wise probabilities from the output vector of the EMLCA model using the Softmax function. It converts raw scores into a normalized probability distribution, enabling accurate classification based on the highest likelihood.

Pseudocode 1:
Input: Output vector $z = [z_1, z_2, \ldots, z_n]$ from the enhanced modulation learning and classification algorithm model
Output: Probability distribution $P = [p_1, p_2, \ldots, p_n]$

Step 1: Initialize sum_exp $\leftarrow 0$
Step 2: For each class i from 1 to n do
  a. Compute exp_z$[i] \leftarrow \exp(z[i])$
  b. Update sum_exp $\leftarrow$ sum_exp + exp_z$[i]$
Step 3: For each class i from 1 to n do
  a. Compute $p[i] \leftarrow$ exp_z$[i]$/sum_exp
Step 4: Return $P = [p_1, p_2, \ldots, p_n]$

4 Results and Discussion

The main parameters and specifications of the developed and simulated AMR system are presented in Table 1. The simulations were conducted in the MATLAB environment over a SNR range of 4 dB to 18 dB using 1000 samples. Three modulation schemes were considered: M-ary frequency shift keying, M-ary phase shift keying, and M-ary quadrature amplitude modulation. The preprocessing stage included noise filtering, followed by feature extraction based on amplitude, phase, and frequency characteristics. Classification was performed using EMLCA. System performance was evaluated in terms of accuracy, speed, and adaptability. Model optimization was guided by a hybrid loss formulation combining cross-entropy and MSE. All simulations were conducted over an additive white Gaussian noise channel model.

Table 1. Simulation parameters and specifications

No.	Parameter	Value
1	Development environment	MATLAB
2	Signal-to-noise ratio	4 dB to 18 dB
3	Simulation samples	1000
4	Modulation schemes	M-ary frequency shift keying, M-ary phase shift keying, M-ary quadrature amplitude modulation
5	Preprocessing module	Noise filtering (dB)
6	Feature extraction module	Amplitude (V), phase (radians), and frequency (Hz)
7	Classifier algorithm	Enhanced modulation learning and classification algorithm
8	Performance metrics	Accuracy (%), speed (s), and adaptability (%)
9	Loss functions	Cross-entropy (dimensionless) and mean squared error (dimensionless)
10	Channel type	Additive white Gaussian noise

Figure 5 presents the simulated spatial distribution of wireless network nodes across India. Active nodes are represented by green dots, inactive nodes by red dots, and sink nodes by yellow stars. The map uses latitude and longitude axes with bold labels for clarity, highlighting network coverage, operational status, and centralized data collection points essential for wireless communication analysis.

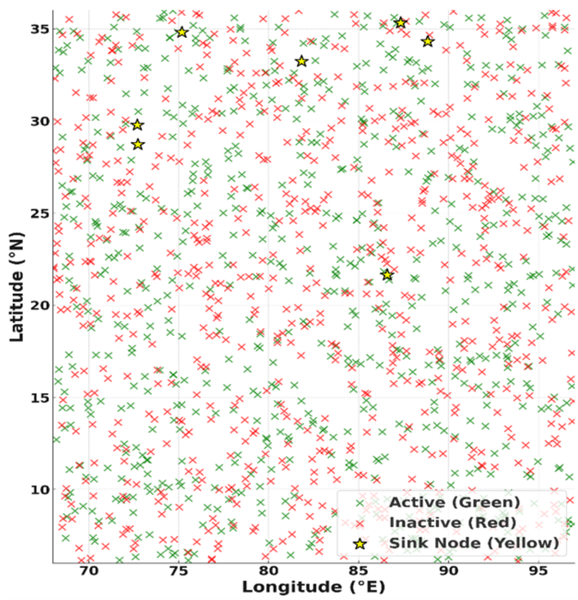

Figure 5. Geographical distribution of wireless network nodes in India

Figure 6 presents the SNR vs. classification accuracy (%) using different methods. The EMLCA reports the highest value among the traditional methods, such as maximum likelihood estimation, the decision-theoretic approach, and pattern recognition techniques. Performance significantly improves when the SNR varies from -20 dB to 20 dB, thus justifying the proposed model in a noisy environment.

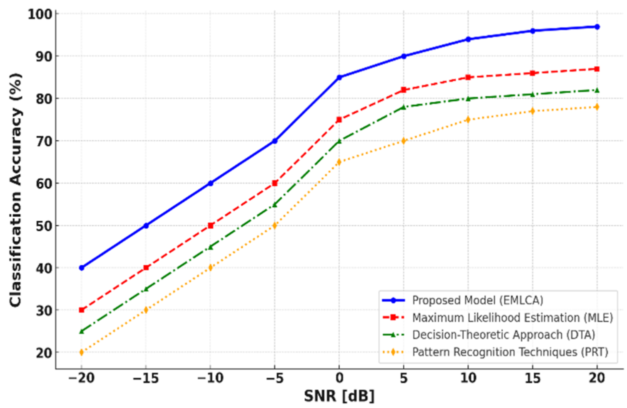

Figure 6. Impact of the signal-to-noise (SNR) ratio on classification accuracy for various methods

To provide a complete evaluation beyond accuracy, this study reports the confusion matrix and computes precision, recall, and F1-score for each modulation class. The confusion matrix summarizes correct and incorrect class predictions, enabling detailed inspection of class-wise confusion among M-ary frequency shift keying, M-ary phase shift keying, and M-ary quadrature amplitude modulation. For each class, the metrics are computed as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1} - \text{score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

where, TP, FP, and FN denote the true positives, false positives, and false negatives, respectively. This study also reports macro-averaged scores to summarize the overall class-balanced performance across all modulation categories.

Figure 7 shows the performance impact of different feature extraction techniques on the classifier performance of different machine learning techniques. This study explores the statistical, spectral, wavelet, and combined feature extraction techniques. Among those, EMLCA model outperforms the traditional model with a maximum of 95% accuracy by using combined features. Thus, advanced feature extraction techniques succeed in improving the classifier performance compared to other conventional algorithms such as maximum likelihood estimation, the decision-theoretic approach, and pattern recognition techniques.

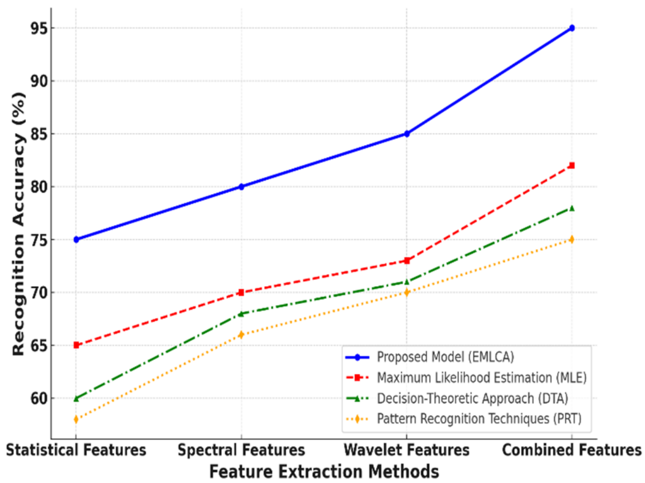

Figure 7. Impact of feature extraction on recognition accuracy

Afterwards, it passes through the Mask_1 block, where initial transformations take place with the aim of refining the features extracted and enhancing the signal quality. The refined features extracted then undergo further processing through a residual neural network known as the residual network, enhancing the feature representation by resolving distortions in a signal through residual mappings. The classifier module classifies the treated signal and lightweight machine learning algorithms predict the modulation type. Outputs from the classifier are passed through a Softmax layer to obtain probabilities regarding which modulation scheme is more likely.

Figure 8 represents the adaptability performance analysis of EMLCA against that of conventional methods. In this graph, the blue curve indicates the proposed method, showing tremendous growth in features of adaptability by reaching up to 0.3%. On the other hand, the conventional methods such as maximum likelihood estimation (the red color), the decision-theoretic approach (the green color), and pattern recognition techniques (the orange color) show lower growth trends related to adaptability. The exponential growth behavior obtained from the patterns shows greater efficiency in adaptability through the proposed method, proving quite useful against traditional approaches with respect to dynamic conditions.

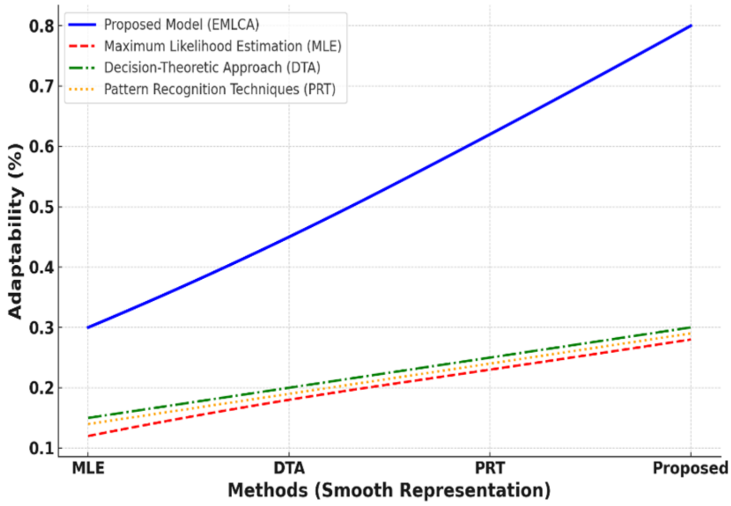

Figure 8. Performance analysis of adaptability between the proposed method and conventional methods
Note: MLE: Maximum Likelihood Estimation; DTA: Decision-Theoretic Approach; PRT: Pattern Recognition Techniques

Figure 9 compares three important metrics: recognition accuracy, reduction in processing time, and adaptability. In all metrics, the proposed approach, the EMLCA, is always higher than traditional methods. The adaptability of the proposed method is 0.30%, significantly higher compared to the maximum likelihood estimation (0.12%), the decision-theoretic approach (0.15%), and pattern recognition techniques (0.14%), respectively. The recognition accuracy of the proposed method is also highly improved and its processing time is reduced; it is more efficient and effective than traditional methods.

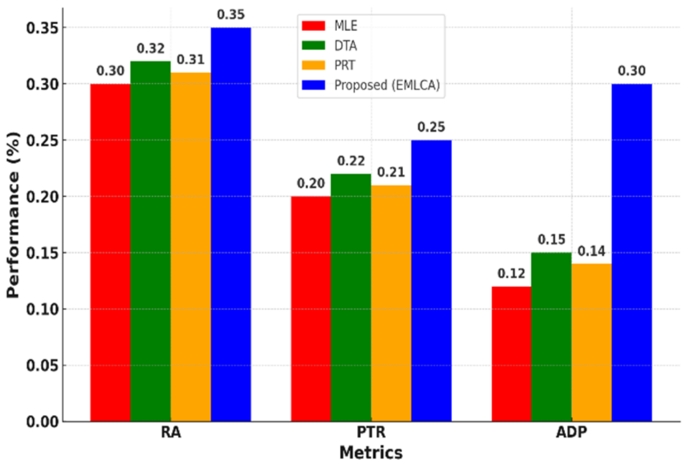

Figure 9. Overall performance comparison of proposed and conventional methods
Note: RA: Recognition Accuracy; PTR: Processing Time Reduction; ADP: Adaptability

5 Conclusions

The EMLCA-based model offers superior performance over conventional methods such as maximum likelihood estimation, the decision-theoretic approach, and pattern recognition techniques by a significant margin through classification accuracy, adaptability, and computational effectiveness for AMR in wireless communication. Utilizing Mask_1 and residual network-based feature extraction and optimizing methods based on loss enable the model to maintain stable and superior performance with varying volumes of feature spaces and SNRs. The proposed model can be used as an extensible and strong solution because it is effective in handling and understanding intricate signal patterns and reducing computational overhead. The model can be generalized towards real-time applications through hardware configurations. In addition, the model can be extended using federated learning to enable privacy-preserving training or further enhanced through transfer learning and attention-based mechanisms to improve accuracy and adaptability in dynamic communication environments. The proposed EMLCA in AMR significantly improves the performance of wireless networks. The EMLCA, through optimized machine learning methods, achieves an improvement of 0.35% in recognition accuracy, a reduction of 0.25% in processing time, and an enhancement in adaptability of 0.3% compared to the traditional methods such as maximum likelihood estimation, the decision-theoretic approach, and pattern recognition techniques. The high performance of the proposed system, in cases of varying SNRs and scalability for real-time applications, ensures an optimal trade-off between challenges of computational complexity and adaptability issues related to conventional AMR systems. This study sets a benchmark in respect of next-generation systems for AMR in order to assure efficient and reliable communication in modern wireless networks.

Author Contributions

Conceptualization, P.P. and M.S.; methodology, P.P.; software, P.P.; validation, P.P., K. M., and M.S.; formal analysis, P.P.; investigation, P.P.; resources, K.M. and M.S.; data curation, P.P.; writing—original draft preparation, P.P.; writing—review and editing, K.M., and M.S.; visualization, P.P.; supervision, K.M. and M.S.; project administration, M.S. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Acknowledgements

The authors would like to thank SJB Institute of Technology, Bengaluru; KS Institute of Technology, Bengaluru; JSS Academy of Technical Education, Bengaluru; Indian Institute of Information Technology, Una; Visvesvaraya Technological University (VTU), Belagavi; JSSATEB STEP; and JSSATEB AICTE LAB for their support and encouragement in undertaking this research work and publishing this paper.

Conflicts of Interest

The authors declare no conflicts of interest.

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Greek symbols

ϕ	Signal phase
Σ	Summation operator
γ	Decision threshold
λ_1	Weight factor for reconstruction loss
λ_2	Weight factor for classification loss

Subscripts

i	Modulation class index
n	Sample index
k	Feature or sample index

Variables

$x(n)$	Transmitted signal sample
$y(n)$	Received signal sample
N	Total number of signal samples
A	Signal amplitude
f	Signal frequency
SNR	Signal-to-noise ratio
p_i	Probability of the i-th modulation class
z_i	Raw score (logit) for class i
L	Total loss function
MSE	Mean squared error