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A Comprehensive Review on Optimized Comparative Analysis of Radio Modulation Techniques Using Machine Learning Approaches for 5G Services

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Abstract— Automatic modulation classification (AMC) has evolved significantly from traditional statistical methods to sophisticated machine learning approaches over the past two decades. This in-depth analysis explores the transition from likelihood-based and feature-based traditional techniques to recent deep learning architectures for radio signal modulation recognition. Traditional approaches, including Average Likelihood Ratio Test (ALRT), Generalized Likelihood Ratio Test (GLRT), and feature-based methods using statistical moments and spectral analysis, provided foundational understanding but suffered from computational complexity and manual feature engineering limitations. Machine learning, specifically deep learning, had transformed the area, with Convolution Neural Networks (CNNs) achieving 83.8% accuracy at high SNR, while advanced architectures such as ResNet (83.5%), DenseNet (86.6%), and Convolution Long Short-Term Deep Neural Networks (CLDNN) achieve state-of-the-art performance of 88.5% accuracy. Recent developments in transformer-based models and hybrid architectures show promising results for temporal modeling of radio signals. However, challenges remain in real- world deployment, including dataset domain gaps, computational constraints, and robustness under adverse conditions. This review synthesizes current methodologies, benchmarks, and identifies future research directions including federated learning, edge deployment optimization, and interpretability enhancement for critical communication systems.

Keywords— machine learning, deep learning, radio signal processing, wireless communication.

I. INTRODUCTION

Automatic modulation classification (AMC) is a vital element of current wireless communication systems, enabling intelligent spectrum management, cognitive radio operations, and electronic warfare applications [1]. The capacity to instinctively recognize the method of modulation of received radio signals despite having knowledge of transmission parameters has grown in importance as varied communication standards and dynamic spectrum access paradigms evolve [2], [3].

In current wireless communication systems, especially in circumstances requiring cognitive radio, electronic warfare, and spectrum monitoring, the receiver frequently functions in an uncooperative environment where the modulation type of the incoming signal is unknown. Automatic Modulation Classification (AMC) addresses this issue by detecting the modulation scheme of a received signal without any prior information. AMC is an important intermediary step between signal detection and demodulation, allowing the receiver to adjust its demodulation approach to properly retrieve the sent information. The importance of AMC has grown exponentially with the increasing density of wireless networks, the proliferation of diverse communication standards, and the need for dynamic spectrum access and interference management [4].

Traditionally, AMC techniques have been divided into a pair of groups: likelihood-based (LB) and feature-based (FB). LB techniques are theoretically ideal because they use empirical evidence for assessing signal received with each of potential modulation types.. However, their practical implementation is often hindered by high computational complexity and a strong dependence on accurate channel state information and signal parameters, which are rarely perfectly known in real-world scenarios. In contrast, FB methods aim to extract specific, discriminative features from the received signal, such as instantaneous amplitude, frequency, phase, higher-order cumulants, or cyclic statistics. These characteristics are then entered into a classifier, which identifies the modulation type. While often less computationally intensive and more robust to channel uncertainties than LB methods, effectiveness of FB approaches strongly depend on the proper selection and engineering of these characteristics, which sometimes requires extensive domain expertise. [4].The inherent limitations of traditional AMC methods, particularly their sensitivity to noise, channel impairments, and the need for manual feature engineering, have paved Machine learning and, in recent times, deep learning techniques have gained popularity. Data-driven strategies have the potential to automatically learn complicated patterns and characteristics from raw signal data, overcoming limitations in traditional methods. The parts below will explore how machine learning and deep learning have transformed radio modulation classification.

II. LITERATURE REVIEW

Automatic modulation classification (AMC) is important for efficient spectrum utilization and signal interception in complex electromagnetic environments. Traditional methods often struggle with accuracy and robustness, especially when dealing with various modulation types and signal-to-noise ratios (SNRs). More effective and robust AMC approaches are required to reliably detect modulation schemes under demanding settings. This research presents a revolutionary AMC technique that blends convolution neural networks (CNNs) and support vector machines (SVMs). The CNN is used for automatic feature extraction from raw signal data, taking use of its capacity to learn hierarchical representations. The collected characteristics are subsequently put into an SVM classifier, whereby computes the end result modulation classification. The study suggests that fusing CNN and SVM leads to more accurate modulation detection, particularly in low SNR situations, by combining deep learning characteristics with SVM-based classification. [1].

Automatic Modulation Classification (AMC) is a key element of current communication systems, allowing intelligent receivers to adapt to new signal environments. However, current AMC systems frequently suffer from excessive computing complication and insufficient precision, especially in real-time applications. There is a need for fast and accurate AMC systems that can efficiently use deep learning techniques. A fast and precise AMC system called DL-AMC, which makes use of deep learning techniques. DL-AMC uses convolution neural networks (CNNs) to extract features from raw IQ data. The architecture is optimized for efficiency and accuracy, with the goal of minimizing computational overhead while maintaining good classification efficiency. The suggested method outperforms previous AMC approaches in terms of speed and accuracy, making it appropriate for real-time applications in dynamic communication contexts. [2].

Automatic modulation classification (AMC) is an essential technology in ineffective communication systems. However, present deep learning-based AMC models are frequently computationally complex and demand large hardware resources, rendering them inappropriate for implementation on devices with limited capacity. There is a need for lightweight AMC models that can achieve high accuracy with minimal computing cost, such as an ultra-lightweight neural network for automated modulation classification. The design suggestion is intended to reduce the quantity of variables and computational operations while yet retaining excellent precision for classification. This is accomplished using effective network design methods such as depth-wise separable convolutions and optimized layer configurations. The model's lightweight design makes it suited for placement on embedded devices and other resource-limited platforms, allowing real-time AMC in many applications. [3].

In radar and electronic warfare systems, intra-pulse modulation recognition is crucial for determining the modulation scheme contained inside a single pulse. Complex modulation types and noisy situations frequently pose challenges for traditional approaches. The advent of transformer architectures, noted for their capacity to detect broad interdependence, represents a viable path for boosting recognition accuracy. This study investigates the use of transformer-based models for intra-pulse modulation. The suggested approach uses transformer mechanism for self-attention to efficiently detect time - dependent variables and patterns inside the radar pulse. The algorithm used receives instruction on a dataset containing several intra-pulse modulation schemes, proving its capacity to correctly categorize complicated modulations even in the presence of noise. The transformer architecture's inherent power to process sequential data makes it well-suited for this purpose, giving better performance than conventional techniques. [4].

Automatic modulation classification (AMC) is an important problem in wireless communication, especially in complex electromagnetic environments. While deep learning models have shown promise, achieving high accuracy with efficient model size remains a challenge. There is a need for AMC models that can effectively balance performance and computational resources. It presents a Multi-Channel Convolution Distilled Transformer for Automatic Modulation Classification. The suggested architecture combines the advantages of convolution neural networks (CNNs) for local feature extraction with transformer networks for capturing long-range dependencies. Distilling information is a technique used to move information from a bigger, more complex instructor model to a smaller, better-performing student model, lowering model size while retaining high precision. This approach seeks to [5].

Deep learning-based Automatic Modulation Recognition (AMR) systems are subject to hostile attacks, in which slight, undetected modifications to input signals cause misclassification. This vulnerability jeopardizes wireless communication systems' dependability and security. Robust AMR models must be developed to withstand such attacks. It presents a transformer-based modulation recognition model that is resilient against adversarial attacks. The transformer's self-attention mechanism enables it to solely concentrate on global dependencies rather than local perturbations, making it more robust against adversarial noise. To improve the model's robustness, it is trained using adversarial cases. Experiments show that a suggested transformer-based model greatly improves existing deep learning models on the basis of adversarial robustness while maintaining good classification accuracy [6].

Traditional deep learning models for wireless communication often process real-valued signals, neglecting the inherent complex-valued nature of radio frequency (RF) signals. This might result in data loss and inferior outcomes in tasks such as modulation classification. This study examines the use of complex-valued transformers in wireless communications to effectively utilize the complex-valued features of RF signals Investigates the capabilities of complex-valued transformers in wireless communications. The suggested method extends the transformer design to directly handle complex-valued IQ signals while keeping the phase and amplitude information required for RF signal analyses. This enables the model to acquire more detailed descriptions of the signals, resulting in better performance in tasks like modulation categorization and signal identification. The complex-valued transformer outperforms its real-valued counterparts, demonstrating the advantages of introducing complex arithmetic into deep learning models for wireless applications. [7].

The rapid advancements in deep learning have led to a proliferation of research in radio signal modulation recognition. However, the wide diversity of suggested deep learning architectures and approaches makes it difficult to grasp the present situation of field and identify promising further study routes. A thorough overview is required to synthesize existing knowledge and identify relevant trends. It presents a thorough overview of deep learning applications in radio signal modulation recognition. It categorizes and analyses several deep learning architectures, such as CNNs, RNNs, as well as hybrid models, examining their strengths, shortcomings, and applicability for specific modulation recognition tasks. The survey also looks at common datasets, evaluation measures, and obstacles in the field, providing insights into the existing landscape and future possibilities of deep learning-based radio signal modulation detection. [8].

Automatic Modulation Classification (AMC) is a critical step in non-cooperative communication systems. While classic deep learning models have had tremendous success, their ability to capture long-range correlations in signal sequences is restricted. Transformer networks, with their self-attention mechanism, present a viable solution for dealing with this restriction. For the first time in this paper, the Transformer Network (TRN) is applied to the automated modulation categorization (AMC) problem. The suggested model uses the self-attention mechanism to capture global dependencies inside the signal sequence, allowing it to learn complicated patterns over time. Experimental results show that the TRN-based model achieves good classification accuracy, particularly for modulation schemes with intricate temporal characteristics, demonstrating transformers' promise in signal modulation classification. [9].

Intelligent receivers in non-cooperative communication systems rely heavily on automatic modulation classification (AMC). However, previous approaches frequently struggle with low accuracy, particularly at low signal-to-noise ratios (SNRs), and may be vulnerable to a variety of channel impairments. This work offers an efficient automatic modulation classification algorithm that utilizes an innovative convolution neural network (CNN) architecture. To extract more meaningful characteristics from raw I/Q sequences, the model uses asymmetric kernels organized in parallel combinations. To avoid vanishing gradient issues, these components are linked together via skip connections. The suggested approach works effectively in identifying nine various techniques for modulation that were created through simulation considering typical wireless channel defects such as AWGN, Rician multipath fading, and clock offset. It enhances the efficiency of classification at low SNRs, obtaining 86.1% at −2 dB SNR and 99.8% at 10 dB SNR, displaying high feature extraction capability for demanding modulation methods such as 16QAM and 64QAM. [10].

TABLE I. COMPARISON OF AMC STUDIES IN ML

Paper No.	Year	Modalities	Purpose	Approach	Result
[11]	2024	Multi-channel signals	Automatic Modulation Classification (AMC)	Multi-Channel Convolution Distilled Transformer	Improved accuracy in modulation recognition

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Paper No.	Year	Modalities	Purpose	Approach	Result
[12]	2025	Wireless signals	Defense against adversarial attacks in modulation recognition	Transformer-based model	Enhanced robustness against adversarial perturbations
[13]	2025	Complex-valued signals	Wireless communications signal processing	Complex-valued Transformers	Better handling of complex signal representations
[14]	2023	Various signal types	Survey of deep learning in modulation recognition	Review of CNN, RNN, and Transformer methods	Comprehensive overview of state-of-the-art techniques
[15]	2022	RF signals	Signal modulation classification	Transformer Network	Competitive performance compared to CNNs
[16]	2023	Cognitive radio signals	AMC for cognitive radio networks	Robust CNN architecture	High accuracy in noisy environments
[17]	2025	Wireless signals	Improved AMC with deep learning	Deep learning with additive attention	Better feature extraction and classification
[18]	2025	Neuro-signals (EEG/ERP)	Decoding event-related brain potentials	Transformer model	Improved neural signal decoding
[19]	2022	Radio signals	Modulation classification	Deep Residual Neural Networks (ResNet)	High classification accuracy
[20]	2024	Cognitive radio signals	AMC with attention mechanism	CNN with probabilistic attention	Enhanced focus on relevant signal features
[21]	2024	Time-frequency signals	AMC under fading channels	Deep learning with time-frequency features	Robust performance in dynamic channel conditions
[22]	2024	Wireless signals	Robust modulation classification	Deep Hybrid Transformer Network	High resilience to noise and interference
[23]	2024	Wireless signals	Efficient AMC with attention mechanisms	Pruned LSTM-GRU with Multi-Head Attention	Reduced computational cost while maintaining accuracy
[24]	2023	Spatial cognitive radio signals	Multi-domain fusion for AMC	Multi-domain-fusion deep learning	Improved recognition in spatial signal processing
[25]	2024	IoT wireless signals	Lightweight AMC for IoT devices	Lightweight deep learning architecture	Efficient deployment on resource-constrained devices

III. METHODOLOGY

III.I Traditional Machine Learning Methods

Traditional machine learning techniques, which mostly relied on precisely designed features, were widely utilized for AMC prior to the development of deep learning. Usually, these techniques consist of two primary steps: Classification and feature extraction.

These methods employ the incoming signal to extract particular statistical or deterministic properties that are then utilized for developing a classifier. Common features include instantaneous amplitude, frequency, and phase as well as higher order cumulants (HOCs) and cyclic statistics. HOCs for instance, are effective in distinguishing between different modulations schemes due to their sensitivity to the non-Gaussian nature of modulated signals. Cyclic statistics, derived from cyclostationarity of modulated signals, can capture periodicities related to carrier frequency and symbol rate. Once these features are extracted, various classical ML algorithms can be employed for classification, such as Support Vector Machines (SVMs), K-Nearest Neighbors (KNN), Decision Trees, and Artificial Neural Networks (ANNs). While these methods offer lower computational complexity compared to likelihood-based approaches, the caliber and applicability of hand crafted characteristics have a significant impact on the way they perform, often requiring extensive domain knowledge and careful selection to achieve optimal results.

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III.II Deep Learning Methods

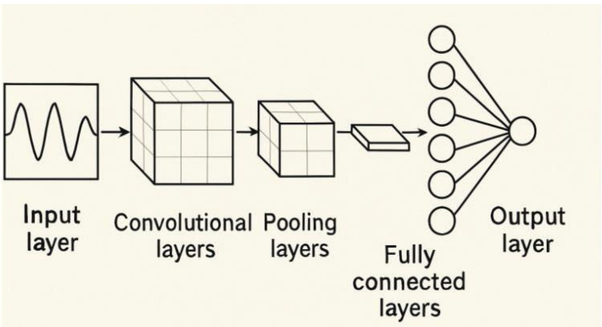
Because deep learning (DL) is capable of automatically developing complicated patterns and hierarchical representations from raw or little pre-processed signal data, it has become a dominating framework in AMC. By eliminating the demand for human feature engineering, this capability makes DL models extremely flexible and resilient to many modulation types and signal conditions. Convolution neural networks (CNNs), Recurrent neural networks (RNNs), and their hybrid combinations, together with more contemporary Transformer-based models, are the most common DL architectures utilized in AMC.

III.II.A CNN Architecture

After several convolution layers, fully connected layers usually make up the basic CNN architecture for modulation classification. Research has demonstrated that four convolution layer architecture with 256*1 filters in the first layer and 802*3 filters in subsequent layers achieves optimal performance. This configuration reaches approximately 83.8% accuracy at high SNR conditions, representing a significant improvement over traditional methods.

The convolution layer performs feature extraction through learnable filters that capture modulation-specific patterns in the signal representation. Each convolution layer applies multiple filters to generate feature maps, followed by activation functions and pooling operations to reduce dimensionality and enhance translation invariance.

Fig 1 : Illustration of basic CNN architecture showing convolution layers



III.III Advanced Deep Learning Architectures

III.III.A Residual Networks (ResNet)

By allowing direct exchange of data between non-adjacent layers using disconnected connections, residual networks solve the problem of gradients disappearing in deep neural networks. For modulation classification, ResNet architectures with four convolution layers achieve approximately 83.5% accuracy at high SNR

The residual connection allows information to bypass intermediate layers through identity mappings, represented scientifically as:

$$y = F(x, \{W\_i\}) + x \qquad (1)$$

Where F (x, {W_ i}) represents the left-over organizing and x is the input. This architecture enables training of deeper networks without performance degradation, though optimal depth for modulation classification appears limited to four convolution layers.

III.III.B Densely Connected Networks (DenseNet)

DenseNet topologies improve information flow by dense connection patterns, with each layer receiving data coming from all prior levels.. This connectivity pattern is expressed as:

$$x\_l = H\_l([x\_0, x\_1, \ldots\ldots, x\_\{l-1\}]) \qquad (2)$$

where [x_0, x_1,……..,x_{l---1}] reflects a collection of maps of characteristics from preceding layers. DenseNet achieves 86.8% accuracy at high SNR for modulation classification, demonstrating superior performance compared to both basic CNN and ResNet architectures.

The dense connections facilitate feature reuse and strengthen feature propagation throughout the network, leading to improved classification performance with fewer parameters compared to traditional architectures.

III.III.C Convolution Long Short-Term Deep Neural Networks (CLDNN)

By merging convolution and recurrent neural network components, CLDNN, the most advanced architecture for modulation classification, achieves a precision of 88.5% at high SNR. CNN layers are used in the hybrid architecture for regional feature recognition, while LSTM layers are used for sequential time analysis.

The CLDNN architecture consists of four convolution layers for feature extraction, followed by an LSTM layer with memory cells for temporal modeling, and concludes with fully connected layers for classification. The LSTM component captures long term dependencies in signal sequences, which proves particularly beneficial for time domain radio signal analysis.

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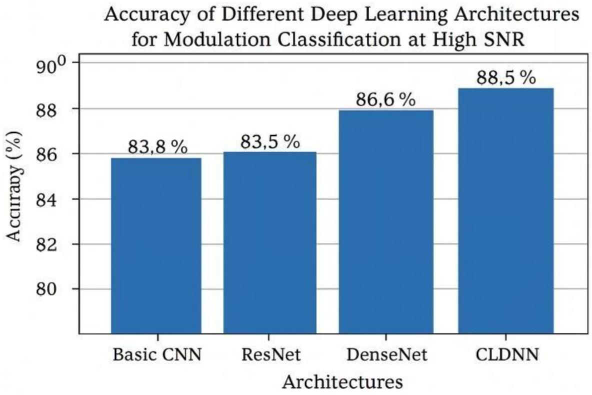
Fig 2 : Performance comparison of different deep learning architectures for modulation classification showing Accuracy Vs SNR curves



III.IV Modern Deep Learning Approaches

Transformer-Based Models

Transformer designs self-attention processes, which identify inter-dependence across time in signal series, have recently drawn interest for modulation categorization. MC Former architecture adapts transformer blocks specifically for modulation recognition tasks, demonstrating competitive performance against CNN and RNN-based methods. Global context awareness is made possible by the self-attention mechanism, which calculates attention weights between each place in the input sequence:

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T/\sqrt{d\_k})V \quad (3)$$

where Q, K, and V represent query, key, and value matrices respectively. Transformer-based models show particular promise for handling variable-length signal sequences and capturing complex temporal patterns.

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IV. CONCLUSION

The field of automatic modulation classification (AMC) has experienced significant change, moving from conventional analytical techniques for signal analysis to advanced machine learning and deep learning approaches. This comprehensive review has traced this progression, highlighting the foundational contributions of likelihood-based and feature-based methods, while also emphasizing their inherent limitations in terms of performance deterioration in low signal-to-noise ratio (SNR) settings, difficulty in computation, and dependence on manual feature engineering.

Deep learning's introduction has completely changed the AMC scenario by making automatic feature extraction possible and greatly increasing the classification accuracy. In radio signal modulation recognition, architectures like Convolution Neural Networks (CNNs), Residual Networks (ResNets), Densely Connected Networks (DenseNets), and especially Convolution Long Short-Term Deep Neural Networks (CLDNNs) have demonstrated innovative work that pushes the envelope of what's technically feasible.

Improved stability and adaptation are likewise promised by ongoing development of contemporary deep learning techniques, such as transformer-based models and different hybrid architectures.

Notwithstanding these advancements, actual implementation of AMC systems continues to encounter major difficulties. The domain gap between idealized training datasets and complex real-world radio environments, computational constraints for edge deployment, and the need for improved robustness under adverse conditions remain critical hurdles. Furthermore, in order to foster confidence and facilitate their use in sensitive applications, continuous study into interpretability and explanation is required due to the "black box" nature of deep learning models.

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