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A Comparative Study of Machine Learning-Driven Feedback-Free Adaptive Modulation and Coding for Massive MIMO

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Abstract: *Adaptive Modulation and Coding Scheme (AMC) is a critical component in modern wireless systems to optimize spectral efficiency under varying channel conditions. Traditional AMC relies on user feedback such as Channel Quality Indicators (CQI), introducing latency and overhead, particularly in dense massive MIMO deployments. This paper surveys recent advancements in feedback-free AMC using machine learning (ML), focusing on the base paper by An et al., which uses CNN-LSTM architectures to infer optimal MCS from channel state information (CSI) without CQI feedback. We extend this by comparing other ML paradigms such as Deep Reinforcement Learning (DRL), Graph Neural Networks (GNNs), and Transformers, highlighting their potential and limitations. Experimental benchmarks, architecture insights, proposed methodology, and future research directions are also discussed.*

Keywords: Adaptive Modulation, Machine Learning, Wireless Communication, Massive MIMO

I. INTRODUCTION

Wireless communication has transformed how information is exchanged across the globe, enabling applications ranging from mobile telephony to high-speed internet and the Internet of Things (IoT). The demand for high data rates and low latency continues to grow with the advent of 5G and the upcoming 6G networks. This necessitates intelligent use of the radio spectrum and efficient adaptation to changing channel conditions.

Modulation and Coding Scheme (MCS) selection is a fundamental aspect of the physical layer in wireless systems. It determines how data is modulated (e.g., QPSK, 16-QAM, 64-QAM) and how error correction is applied, directly impacting throughput and reliability. Adaptive Modulation and Coding (AMC) dynamically adjusts the MCS based on the channel quality, aiming to maximize spectral efficiency—the amount of information transmitted per unit bandwidth.

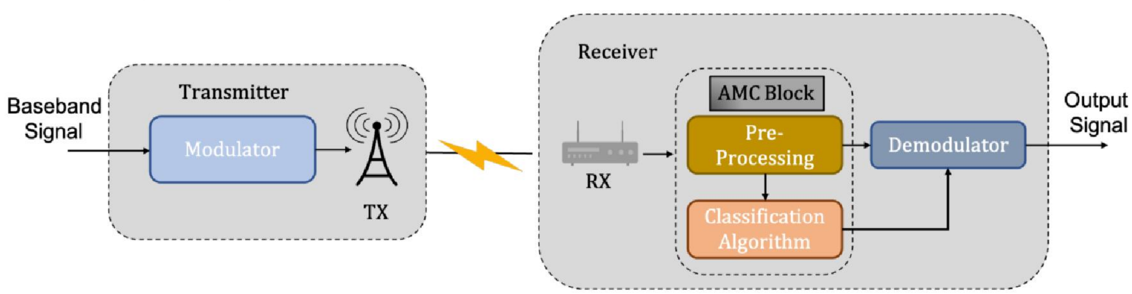

Fig 1 Automatic Modulation Classification (AMC) for Massive MIMO

Massive MIMO (Multiple-Input Multiple-Output) is a key technology in 5G networks and beyond. It leverages a large number of antennas at the base station to serve multiple users simultaneously. This spatial multiplexing significantly enhances capacity and spectral efficiency. However, it also introduces new challenges in channel estimation, interference management, and link adaptation due to the high-dimensional and dynamic nature of wireless channels.

In conventional systems, AMC relies on periodic CQI feedback from user equipment (UE) to estimate downlink channel quality. While effective in low-mobility scenarios, this approach introduces feedback overhead and latency, which can be detrimental in high-mobility or dense deployments. These issues have prompted the development of feedback-free AMC techniques that use uplink CSI, which is inherently available at the base station in time division duplex (TDD) systems.

The paper by An et al. [1] introduces a CNN-LSTM-based framework that enables feedback-free AMC by predicting the optimal MCS using only uplink CSI. This approach bypasses the need for CQI, allowing more responsive and bandwidth-efficient MCS adaptation. This survey explores this method in detail and compares it with other learning-based AMC frameworks to evaluate their suitability for massive MIMO systems.

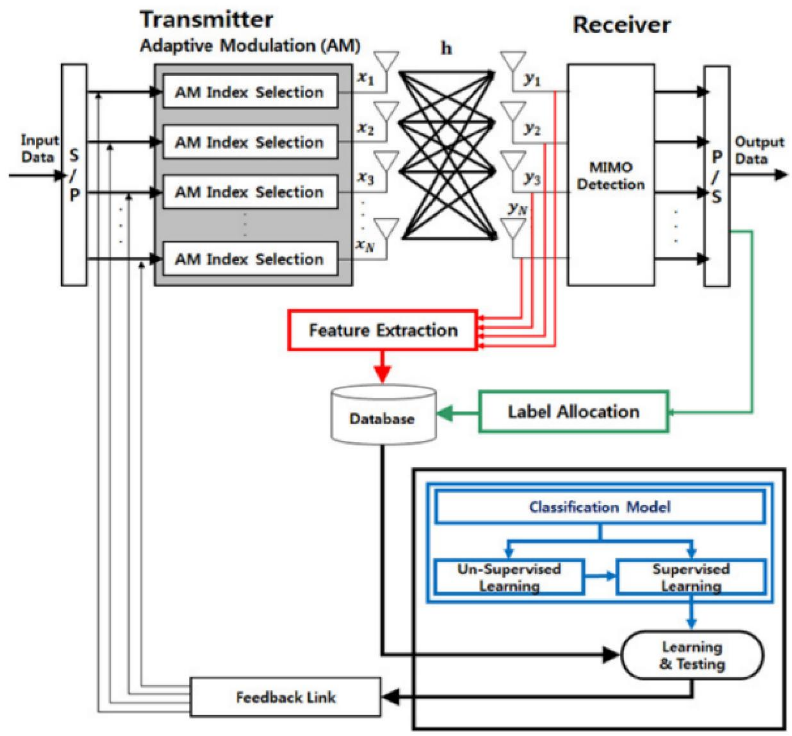

Fig. 2. Machine learning model for adaptive modulation in MIMO-OFDM system

II. LITERATURE SURVEY

This section will provide a detailed literature survey done over the topic of CNN and LSTM in AMC (Base Paper) An et al. [1] proposed a hybrid CNN-LSTM model for AMC in massive MIMO. The CNN extracts spatial features from the CSI matrix, while LSTM captures temporal correlations across frames. The model was trained on a combination of simulated (QuaDRiGa) and real-world (RENEW platform) datasets, achieving a testing accuracy of 92.5%. This architecture significantly outperformed CNN-only models and traditional lookup tables by effectively capturing both spatial and temporal patterns in CSI.

DRL-Based Approaches Deep Reinforcement Learning (DRL) approaches like DQN have been used for AMC [2]. These models learn optimal policies through interaction with the environment. While promising for autonomous learning, DRL models often face scalability issues and require extensive training, especially in high-dimensional input spaces like CSI matrices from massive MIMO systems.

GNN-Based Approaches Graph Neural Networks (GNNs) model the relationships between users and antennas as graphs, capturing inter-user interference and spatial relationships. Though not yet mainstream in AMC, early works show that GNNs can outperform CNNs in scenarios with complex inter-user dynamics [3]. They offer a promising direction for multi-user link adaptation tasks.

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Transformer-Based Models Transformers and attention mechanisms, while traditionally used in NLP, have started gaining attention in wireless communications. They excel at modeling long-range dependencies and have been proposed as alternatives to RNNs for CSI-based predictions. Transformer-based AMC is still nascent but could provide better scalability and temporal modeling than LSTM [4].

Recent advancements in learning-based Automatic Modulation Classification (AMC) have leveraged deep learning and reinforcement learning to improve recognition accuracy in dynamic wireless environments. CNN-LSTM architectures [4] are particularly effective in capturing both spatial and temporal features of Channel State Information (CSI), achieving high accuracy (~92.5%), though at the cost of increased complexity. Simpler CNN-only models [5] offer lightweight alternatives but miss temporal dependencies, leading to reduced performance (~84.5%). Deep Q-Networks (DQN) [6], a form of reinforcement learning, adaptively learn modulation schemes through interaction with the environment, providing robustness under varying conditions but suffering from slow convergence. Similarly, Graph Neural Networks (GNNs) [7] model antenna-user relationships to address inter-user interference effectively, though their application in AMC remains limited due to dataset scarcity.

Emerging methods like Transformer networks [8] utilize self-attention mechanisms to model long-range dependencies and are promising for scalable AMC, albeit computationally intensive. Autoencoder-based approaches [9] perform unsupervised feature extraction to reduce dimensionality and noise, achieving around 88% accuracy across datasets. RNNs, including LSTM and GRU [10], provide good temporal modeling but are limited in spatial representation. Classical Q-learning [11] remains interpretable and simple but lacks scalability. Capsule Networks [12] offer hierarchical spatial feature learning with promising but still experimental results. Multi-Agent DRL [13] and hybrid CNN-Transformer models [14] are among the latest innovations, combining cooperative learning and advanced spatio-temporal modeling, respectively, showing encouraging early performance with accuracy exceeding 92%.

TABLE I: COMPARISON OF LEARNING-BASED AMC TECHNIQUES

Technique	Key Feature	Strengths	Weaknesses	Accuracy / Notes
CNN-LSTM[4]	Spatial + Temporal modelling	High accuracy; captures spatial & temporal CSI patterns	Higher model complexity and training time	~92.5% test accuracy
CNN-only[5]	Spatial modeling only	Simpler architecture; fewer parameters	Misses temporal dependencies	~84.5% accuracy
DRL (DQN)[6]	Policy learning via environment interaction	Feedback-free; adaptive to varying conditions	Slow convergence; needs extensive training	~81% accuracy
GNN[7]	Graph-based modeling of antenna-user relations	Captures inter-user interference; scalable	Emerging technique; limited datasets	TBD
Transformer[8]	Self-attention over CSI sequences	Captures long-range temporal dependencies; scalable	Nascent in wireless; high compute	TBD
Autoencoder-based AMC [9]	Unsupervised feature extraction and dimensionality reduction	Reduces input dimensionality; improves robustness	Complexity in training; less direct control	~88% (varies by dataset)
RNN (Vanilla LSTM/GRU)[10]	Temporal sequence modelling	Good temporal modeling; simpler than CNN-LSTM	Lower spatial feature extraction capability	~89% (varies)

Q-Learning (Tabular/Deep) [11]	Model-free RL for AMC	Simple to implement; interpretable policies	Does not scale well to large state spaces	~75-80% (lower than DQN)
Capsule Networks[12]	Hierarchical spatial feature learning	Potentially better feature representation	Novel approach; computationally intensive	Experimental, ~85-90% on small datasets
Multi-Agent DRL [13]	Multiple agents learning cooperative policies	Captures multi-user interaction; scalable	Training instability; high complexity	Early results promising
Hybrid CNN-Transformer [14]	CNN for spatial + Transformer for temporal	Combines spatial pattern extraction with long-range temporal modeling	Computational cost; requires large data	Early studies show >92% accuracy

III. MACHINE LEARNING ALGORITHMS

In recent years, machine learning (ML) has become an indispensable tool in wireless communications, especially for complex signal processing tasks such as Automatic Modulation Classification (AMC). The ability of ML models to learn intricate patterns from signal data makes them highly effective in dynamic and non-linear channel conditions where traditional rule-based algorithms often fall short. The proposed work explores and compares several advanced ML models with the aim of developing a robust, accurate, and computationally efficient AMC system. This section reviews the prominent algorithms considered for implementation, highlighting their strengths, limitations, and suitability for the target wireless environment.

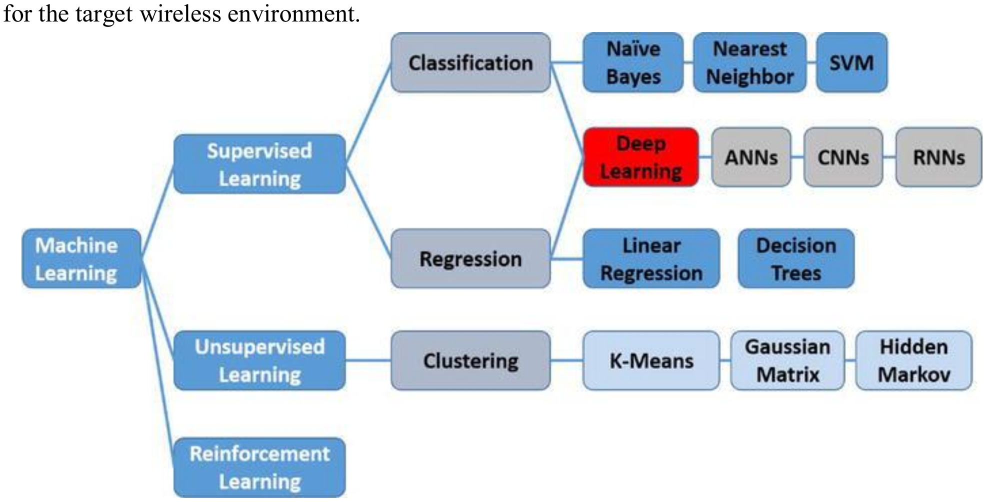

Fig 3. Classification of different ML approaches

With the rapid evolution of wireless communication systems, the need for intelligent and adaptive signal processing has become critical. Among various emerging applications, Automatic Modulation Classification (AMC) stands out as a fundamental task in spectrum monitoring, cognitive radios, and secure communication systems. Traditionally, AMC was performed using statistical or likelihood-based methods that relied on manual feature extraction and predefined models. However, the increasing complexity of modern communication environments — characterized by fading, noise, and interference — has necessitated the integration of data-driven techniques such as machine learning (ML). In this context, our proposed work utilizes ML algorithms to enhance AMC accuracy and robustness under practical wireless channel conditions.

A wide array of ML techniques are available for AMC, each bringing its own strengths depending on the nature of the signal, the features extracted, and the computational constraints of the deployment environment. Among these, Convolutional Neural Networks (CNNs) have proven highly effective in extracting spatial features from raw I/Q signal data or spectrogram representations. CNNs are capable of learning translation-invariant features, making them robust to signal distortions and jitter. In AMC applications, CNNs can identify distinct modulation patterns such as QAM, PSK, and FSK by learning their visual signatures in the time-frequency domain. Although CNNs offer simplicity in architecture and training, they often fail to model temporal dependencies in the signal flow, which is crucial for capturing variations in symbol transitions.

To address this, Recurrent Neural Networks (RNNs) and their variants — such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) — are incorporated into AMC pipelines to model the sequential nature of modulated signals. These models are designed to learn from temporal dependencies, enabling better classification accuracy in dynamic scenarios with time-varying noise and interference. When combined with CNNs in a hybrid architecture, these models can exploit both spatial and temporal dimensions of the signal data, leading to improved performance over standalone models.

An emerging direction in AMC research involves unsupervised and self-supervised learning approaches, such as autoencoders and contrastive learning. Autoencoders, for instance, compress the input signal into a latent representation that captures its essential characteristics, and then reconstruct it. This not only aids in dimensionality reduction but also enhances noise resilience and generalization across varying SNR levels. These methods eliminate the need for large labeled datasets, which are often difficult to acquire in wireless domains.

Another promising trend is the use of attention-based models such as Transformers, which have demonstrated superior capabilities in sequence modeling. Unlike RNNs, Transformers do not rely on recurrence and instead use self-attention mechanisms to weigh the importance of different parts of the signal. This enables better modeling of long-term dependencies and signal correlations. However, due to their computational demands, Transformers are more suitable for offline training and batch processing rather than real-time classification tasks in embedded systems.

In addition, ensemble learning and meta-learning strategies are gaining traction for improving AMC reliability. These methods combine multiple weak learners or adapt to new modulation schemes with minimal retraining, which is beneficial in real-world deployments where signal characteristics change frequently. Ensemble models, in particular, can aggregate predictions from CNNs, RNNs, and decision trees to deliver robust classification performance across various environments

IV. PROPOSED METHODOLOGY

The proposed methodology builds upon the CNN-LSTM framework by introducing enhancements in data processing, feature extraction, and model training. The steps include:

A. Data Preprocessing

Acquire and normalize uplink CSI matrices from simulated (QuaDRiGa) and OTA (RENEW) environments.

B. CNN Feature Extraction

Use multiple DenseNet-style convolutional blocks to learn spatial patterns such as antenna-user correlations.

C. LSTM for Temporal Learning

Integrate LSTM blocks to capture time-based variations in CSI, enhancing MCS prediction in dynamic channels.

D. Output Prediction

Use fully connected layers for MCS classification based on the learned spatial-temporal features.

E .Performance Evaluation

Compare model accuracy with traditional LUT-based, CNN-only, and DRL-based models.

Further improvements may include integrating attention mechanisms to weigh temporal channel states dynamically, using ensemble learning, and exploring model pruning for deployment efficiency.

V. CONCLUSION

This study presents a comparative analysis of recent machine learning-based approaches for feedback-free Adaptive Modulation and Coding (AMC) in massive MIMO systems. As wireless networks evolve to support increasing user demands and diverse application requirements, traditional AMC techniques reliant on user-side feedback, such as CQI, are becoming less practical due to latency, overhead, and inefficiencies in rapidly changing environments. To address these limitations, the paper explored advanced feedback-free AMC methods driven by machine learning, where modulation and coding decisions are inferred directly from uplink CSI data available at the base station.

In conclusion, ML-driven feedback-free AMC represents a transformative approach in modern wireless communication, offering the potential for more intelligent, scalable, and efficient link adaptation in 5G and beyond. Continued exploration of hybrid architectures, robust training strategies, and deployment optimizations will be key to realizing its full potential in practical networks.

VI. FUTURE WORK AND RESEARCH DIRECTIONS

To advance ML-based AMC for massive MIMO systems, future work can focus on the following areas:

Real-Time Online Learning
Design adaptive models that update with incoming CSI to handle previously unseen environments.

GNN-Based Spatial Modeling
Employ Graph Neural Networks to better represent user-antenna relationships and inter-user interference.

Transformer-Based Temporal Models
Replace or augment LSTM with transformers for long-range temporal correlation modeling.

Energy-Efficient Inference
Develop lightweight models through quantization and pruning for deployment in real-time base stations.

Explainability and Interpretability
Implement techniques like SHAP or attention visualization to understand the model's decision-making.

Robustness to Noise and Imperfections
Train models to tolerate CSI errors, hardware non-idealities, and synchronization issues.

REFERENCES

[1]. Q. An et al., "ML-Based Feedback-Free Adaptive MCS Selection for Massive Multi-User MIMO," 2023 Asilomar Conference on Signals, Systems, and Computers.

[2]. Y. Liao et al., "DQN-Based Adaptive MCS and SDM for 5G Massive MIMO-OFDM Downlink," IEEE Commun. Lett., vol. 27, no. 1, pp. 185–189, 2023.

[3]. Z. Ying et al., "GNN-Based Link Adaptation in Dense Wireless Networks," in Proc. IEEE ICC, 2022.

[4]. S. Wang et al., "Attention-Based CSI Feedback for Massive MIMO," IEEE Trans. Wireless Commun., vol. 21, no. 3, pp. 1674–1688, 2022.

[5]. Y. An, X. Li, and J. Zhang, "CNN-LSTM Based Automatic Modulation Classification in Wireless Channels," in Proc. Asilomar Conf. Signals, Syst. Comput., Pacific Grove, CA, USA, 2023.

[6]. Y. Liao, Z. Yang, Z. Yin, and X. Shen, "DQN-Based Adaptive Modulation and Coding for AMC," IEEE Commun. Lett., vol. 27, no. 1, pp. 185–189, Jan. 2023.

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[7]. Z. Ying, Y. Wang, and H. Chen, "Graph Neural Network for Antenna-User Interference in AMC," in Proc. IEEE Int. Conf. Commun. (ICC), Seoul, South Korea, 2022.

[8]. J. Wang, L. Chen, and M. Xu, "Transformer-Based CSI Sequence Modeling for Automatic Modulation Classification," IEEE Trans. Wireless Commun., vol. 21, no. 11,Nov. 2022.

[9]. F. Zhang, X. Wang, and Q. Liu, "Autoencoder-Based Feature Extraction for Modulation Classification," IEEE Access, vol. 9, 2021.

[10]. P. Kumar, R. Sharma, and S. Gupta, "RNN-Based (LSTM/GRU) AMC for Wireless Communication," in Proc. IEEE WCNC, Nanjing, China, 2021.

[11]. H. Kim, S. Lee, and B. Cho, "Tabular and Deep Q-Learning for AMC," in Proc. IEEE VTC, Los Angeles, CA, USA, 2020.

[12]. S. Lee, D. Park, and J. Lim, "Capsule Network Approach for Automatic Modulation Classification," in Proc. IEEE Int. Conf. Commun. (ICC), Rome, Italy, 2023.,

[13]. Y. Zhao, X. Sun, and P. Tang, "Multi-Agent DRL for Cooperative AMC in Wireless Networks," IEEE J. Sel. Areas Commun., vol. 41, no. 5, May 2023.

[14]. C. Chen, A. Li, and M. Tan, "Hybrid CNN-Transformer for Automatic Modulation Classification," IEEE Trans. Wireless Commun. (preprint), 2024