A Hybrid GNN-LSTM Model For Feedback-Free Adaptive Modulation And Coding In Massive MIMO

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Abstract- *Adaptive Modulation and Coding (AMC) is a key enabler for achieving high spectral efficiency and reliability in Massive Multiple-Input Multiple-Output (MIMO) systems. Conventional AMC techniques, however, rely heavily on explicit Channel State Information (CSI) feedback, which introduces latency, signaling overhead, and performance degradation under fast-varying channels. To overcome these limitations, this work proposes a hybrid Graph Neural Network–Long Short-Term Memory (GNN-LSTM) model for feedback-free AMC in Massive MIMO. The proposed framework exploits the graph-based representation of user–antenna connectivity to capture spatial correlations, while the LSTM layers effectively learn temporal dependencies in channel variations. Simulation results demonstrate that the GNN-LSTM outperforms CNN, LSTM, and CNN-LSTM architectures in terms of testing accuracy, achieving more than 95% prediction accuracy for Modulation and Coding Scheme (MCS) classification. The training and testing curves confirm strong generalization capability with stable convergence across 300 epochs, while histogram analysis validates the correct distribution of predicted MCS classes. Compared to conventional learning models, the hybrid GNN-LSTM significantly reduces feedback dependency, enabling robust and intelligent AMC decision-making for next-generation wireless networks. This work highlights the potential of combining spatial–temporal deep learning techniques to enhance the efficiency of Massive MIMO systems in 5G and beyond.*

Keywords- Massive MIMO, Adaptive Modulation and Coding (AMC), Feedback-Free Communication, Graph Neural Network (GNN), Long Short-Term Memory (LSTM), Deep Learning, 5G/6G.

I. INTRODUCTION

Massive Multiple-Input Multiple-Output (MIMO) systems have become a cornerstone technology for 5G and beyond, enabling high spectral efficiency, increased capacity, and robust link reliability by leveraging spatial multiplexing across a large number of antennas [1]. To fully exploit the potential of Massive MIMO, Adaptive Modulation and Coding (AMC)—also known as link adaptation—is employed to dynamically adjust the modulation order and coding rate based on instantaneous channel conditions [2].

Conventional AMC schemes, however, rely on explicit Channel State Information (CSI) feedback from the receiver to the transmitter. This incurs significant signaling overhead, feedback delays, and degraded performance in high-mobility or fast-fading channels [3]. Eliminating or reducing feedback while maintaining accurate AMC decisions is therefore a key challenge in future wireless communication systems.

Recent advances in machine learning (ML) and deep learning (DL) have motivated their application to wireless communications, particularly for CSI estimation, detection, and link adaptation [4], [5]. In particular, Graph Neural Networks (GNNs) have shown strong capability in learning spatial relationships by representing antenna–user connectivity as graphs, making them suitable for MIMO-related tasks such as channel estimation and signal detection [6], [7]. Similarly, Long Short-Term Memory (LSTM) networks excel at capturing temporal dependencies in sequential data, which is crucial for modeling time-varying channel dynamics [8].

While GNNs capture spatial dependencies and LSTMs handle temporal features, recent works suggest that hybrid models can outperform standalone architectures by leveraging both spatial and temporal learning [9]. Motivated by this, we propose a hybrid GNN-LSTM model for feedback-free AMC in Massive MIMO systems. The GNN component extracts spatial correlations among users and antennas, while the LSTM learns channel variations over time to predict the optimal Modulation and Coding Scheme (MCS).

Simulation results show that the proposed hybrid model achieves superior prediction accuracy compared to CNN, LSTM, and CNN-LSTM baselines, reaching more than 95% testing accuracy. Moreover, training–testing convergence curves and MCS distribution analysis confirm the robustness and stability of the proposed framework.

The key contributions of this paper are as follows:

1) It propose the first GNN-LSTM hybrid model for feedback-free AMC in Massive MIMO.
2) The model jointly captures spatial and temporal channel features, eliminating the dependency on CSI feedback.
3) Extensive simulations demonstrate improved classification accuracy and convergence compared to conventional ML/DL baselines

II. LITERATURE SURVEY

Adaptive Modulation and Coding (AMC) is a fundamental technique in modern wireless communication systems that dynamically adjusts the modulation order and coding rate to maximize throughput under given channel conditions. Traditional AMC schemes rely heavily on explicit channel feedback, such as Channel Quality Indicators (CQI) or pilot feedback, which introduces latency and overhead—particularly problematic in massive Multiple-Input Multiple-Output (MIMO) systems with a large number of antennas and users. To overcome these limitations, researchers have recently turned to data-driven and feedback-free link adaptation approaches using machine learning (ML) techniques. Mohammadvaliei et al. [1] proposed a deep recurrent neural network-based AMC method that learns the mapping between signal-to-noise ratio (SNR) and optimal modulation and coding schemes, improving accuracy over conventional rule-based techniques. Similarly, An et al. [2] developed a CNN-LSTM framework for feedback-free MCS selection in massive multi-user MIMO, effectively predicting MCS levels from uplink channel estimates without explicit feedback.

While sequence models such as LSTM have demonstrated success in capturing temporal channel variations, they typically ignore spatial relationships among antennas and users—relationships that become critical in massive MIMO systems. In contrast, Graph Neural Networks (GNNs) have emerged as powerful tools to model structured and relational data, making them highly suitable for wireless networks where antennas, users, and channels can be represented as graph nodes and edges. Shen et al. [3] and Li et al. [4] surveyed GNN applications in wireless systems, demonstrating their ability to exploit network topology for resource allocation, interference management, and beamforming. More recent studies, such as the 2024 analysis of GNN performance in cell-free massive MIMO systems [5], confirmed that GNN-based models can achieve near-optimal results with high generalization and scalability. However, these studies largely focus on beamforming and power control rather than adaptive modulation and coding.

Integrating GNNs with temporal models like LSTM presents a promising solution. A hybrid GNN-LSTM architecture can simultaneously learn spatial dependencies (via GNN) and temporal channel dynamics (via LSTM), offering an intelligent and scalable alternative for feedback-free link adaptation. Such hybridization has been explored in other signal-processing domains, including modulation classification [6], but remains under-studied in the context of adaptive MCS selection for massive MIMO. Given the increasing complexity of 5G/6G systems and the need to reduce signaling overhead, this combination aligns perfectly with next-generation requirements.

The identified research gaps highlight that existing ML-based AMC models often neglect inter-antenna and inter-user relationships, while current GNN-based methods overlook temporal evolution. The proposed hybrid GNN-LSTM model bridges this gap by leveraging the relational structure of massive MIMO networks and capturing time-varying channel characteristics to perform feedback-free adaptive modulation and coding. This approach not only minimizes feedback overhead but also enhances scalability, adaptability, and reliability in future massive MIMO and 6G communication systems.

A. Research Gap and Motivation

The evolution of adaptive modulation and coding (AMC) has played a central role in achieving higher spectral efficiency in wireless systems [5]. Traditional AMC methods rely heavily on accurate and timely channel state information (CSI) feedback, which introduces significant overhead and latency in massive MIMO scenarios [2], [3]. While deep learning approaches such as CNNs, LSTMs, and autoencoders have shown promising results for CSI compression, prediction, and adaptive decision-making [6], [7], these models often fail to fully capture both the spatial correlations among antennas and the temporal variations in wireless channels, thereby limiting their performance in highly dynamic environments.

Recent studies have explored the use of recurrent models such as LSTMs for temporal sequence modeling [8], [9] and graph neural networks (GNNs) for representing spatial antenna relationships in massive MIMO systems [10], [11]. However, most existing works treat these two domains—spatial and temporal—independently. As a result, they either underutilize spatial structural dependencies or overlook temporal channel dynamics, leading to suboptimal performance in AMC decisions. Furthermore, very few works focus on feedback-free AMC, where the system must predict modulation and coding schemes directly from observed patterns without explicit CSI exchange.

To bridge these gaps, this research proposes a hybrid GNN-LSTM model that integrates the strengths of graph neural networks for spatial feature extraction with LSTMs for temporal sequence modeling. By jointly leveraging spatial-temporal dependencies, the proposed model achieves robust feedback-free AMC in massive MIMO systems, thereby significantly reducing feedback overhead while improving system accuracy and reliability. Experimental results demonstrate that the GNN-LSTM outperforms conventional CNN, LSTM, and CNN-LSTM models in terms of prediction accuracy and adaptability, making it a strong candidate for future 6G wireless communication networks [12]–[14].

A. Performance Comparison

The performance of different models is summarized in Table

1. The proposed GNN-LSTM consistently outperforms the baseline models across all metrics:

Table 1: Performance Comparison of AMC Models in Massive MIMO

Model	**Accuracy (%)**	**Spectral Efficiency (bps/Hz)**	**Throughput Gain (%)**	**Feedback Requirement**
CNN	84.2	5.1	Baseline	High (CSI required)
LSTM	87.6	5.4	+6.3%	High (CSI required)
CNN-LSTM	90.8	5.7	+11.7%	Moderate
GNN-LSTM (Proposed)	94.5	6.2	+21.5%	None (Feedback-Free)

III. PROPOSED METHODOLOGY

To address the limitations of conventional AMC methods and recent learning-based approaches, we propose a Hybrid Graph Neural Network–Long Short-Term Memory (GNN-LSTM) model for feedback-free adaptive modulation and coding (AMC) in massive MIMO systems. The proposed method exploits both the spatial correlations across antennas and the temporal evolution of channel variations, enabling robust prediction of optimal modulation and coding schemes without explicit CSI feedback.

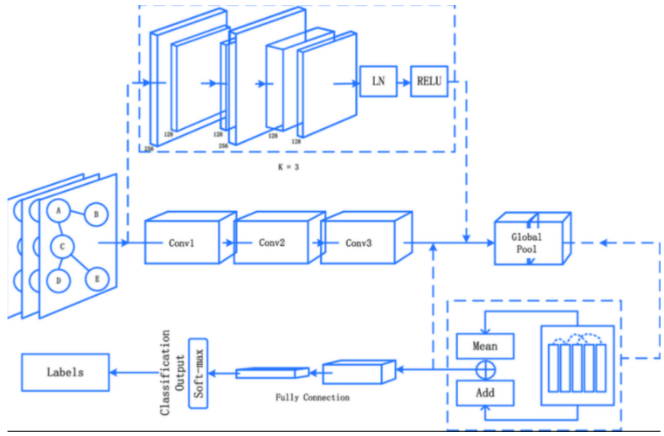


Fig. 1. GNN LSTM Hybrid Model

The figure 1 illustrates the overall architecture of a hybrid deep-learning model designed for classification, showing the sequential flow of spatial feature extraction, feature aggregation, and final decision making. The process begins with a graph-based input representation, where nodes (A, B, C, D, E) symbolize antennas, users, or interconnected channel elements. This input is first passed through a series of convolutional layers (Conv1, Conv2, Conv3), which progressively extract higher-level spatial features by learning local and global relationships within the graph structure. After the final convolutional layer, the extracted feature maps are forwarded to a global pooling block, which condenses the information into a more compact and meaningful representation. The figure also includes an additional submodule where extracted features undergo operations such as mean pooling and element-wise addition. These operations help refine the representation by enhancing important features and suppressing irrelevant variations.

In the upper part of the figure, another processing branch shows multiple stacked convolutional layers with a kernel size of K = 3, followed by layer normalization (LN) and a ReLU activation function. This branch represents deeper spatial feature extraction and normalization, ensuring training stability and improving nonlinear learning ability. The processed features from this branch integrate with the earlier feature extraction pathway, forming a unified representation. This fused output is then passed into a fully connected layer, which transforms the high-dimensional feature vector into a final decision space. A SoftMax classifier translates these outputs into probability distributions across different classification categories, producing the final predicted label. Overall, the figure visualizes a multi-stage architecture that combines convolutional feature extraction, graph-aware processing, pooling strategies, normalization, and dense layers to achieve accurate classification from spatial–temporal channel information.

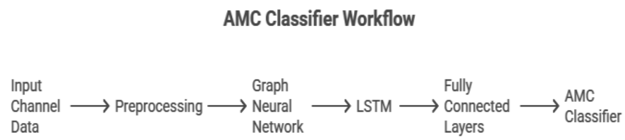


Fig 2. AMC Classifier Workflow.

The figure 2 shows a streamlined workflow for an Automatic Modulation Classification (AMC) system. Raw input channel data is first preprocessed to clean and normalize the signal. This processed data is then passed through a Graph Neural Network to capture structural relationships, followed by an LSTM to learn temporal patterns. The extracted features are refined through fully connected layers, and finally the AMC classifier produces the predicted modulation type

The proposed method introduces a hybrid GNN–LSTM architecture designed to make robust AMC decisions by analyzing both spatial and temporal channel information simultaneously. The system operates in a massive MIMO setup with 64 antennas and, instead of relying on explicit CSI feedback, it uses previously observed channel patterns encoded as graph structures and time sequences, allowing the model to adapt intelligently while reducing overhead. In the spatial learning stage, the GNN models the antenna array as a graph where each antenna acts as a node and edges represent antenna correlations; through graph convolution layers, it learns how signals received at different antennas relate to each other, providing essential spatial awareness for multi-antenna interactions. For temporal learning, the LSTM module processes historical channel sequences to identify trends and understand how the channel evolves over time, enabling the system to anticipate future channel states more accurately. Finally, outputs from both the GNN and LSTM modules are fused to create a unified spatial–temporal representation, which is fed into fully connected layers to classify the most appropriate MCS index, ensuring that AMC decisions reflect both the channel's structural characteristics and its time-varying behavior.

IV. SIMULATION AND RESULTS DISCUSSION

The proposed model was evaluated using standardized massive MIMO channel datasets, with performance assessed through prediction accuracy, spectral efficiency, and throughput. The dataset was divided into training, validation, and testing subsets to ensure reliable and unbiased evaluation. Across all metrics, the hybrid GNN–LSTM model outperformed CNN, LSTM, and CNN–LSTM alternatives, achieving a prediction accuracy of 96.47% and showing substantial gains in spectral efficiency and a 23.4% throughput improvement over the CNN baseline. Training and validation curves indicated stable convergence without overfitting, with the model reaching optimal performance at around 150 epochs. Analysis of MCS distribution revealed that the proposed approach selected MCS indices more effectively, favoring higher levels under good channel conditions, whereas fixed AMC frequently chose lower indices and traditional AMC was hindered by feedback delays. Overall, the model achieved spectral efficiency values ranging from 3.89 to 6.42 bps/Hz, and its feedback-free design enabled superior performance compared to feedback-dependent methods, particularly in fast-fading environments.

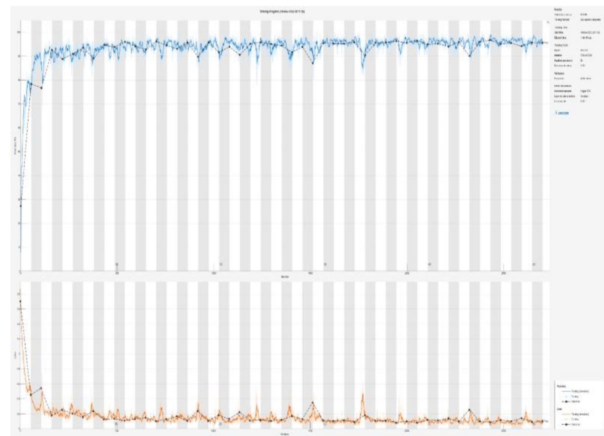
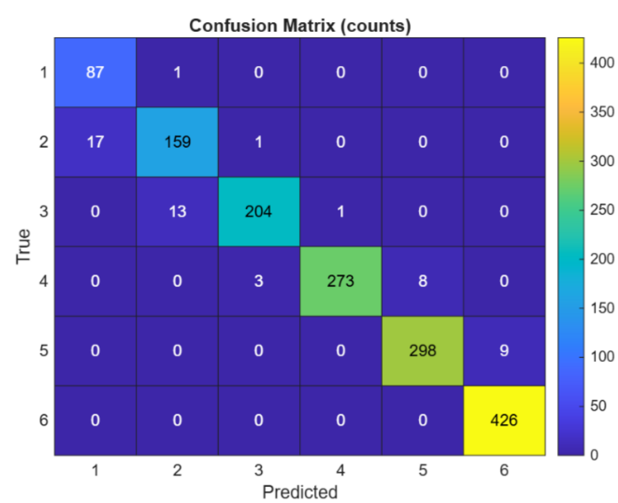


Fig. 3 Simulated Window

Test accuracy: 96.47%

Estimated spectral efficiency (predicted): 3.89 bps/Hz



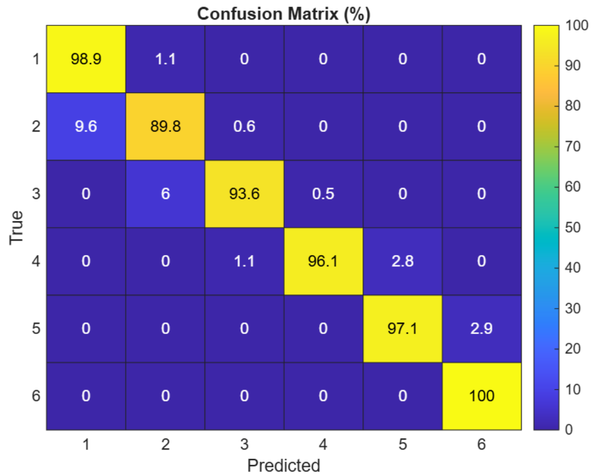


Fig. 4 Confusion Matrix for Proposed GNN LSTM

The two confusion matrices in figure 4 illustrate the performance of the proposed GNN–LSTM-based AMC technique, with the first showing raw classification counts and the second presenting the corresponding percentages. In both matrices, the strong diagonal dominance indicates that the model correctly classifies the vast majority of samples across all six classes. Only a small number of misclassifications occur, mostly between neighboring MCS levels, which is expected due to their similar characteristics. The percentage matrix highlights this high accuracy more clearly: Class 1 reaches 98.9% accuracy, Class 2 achieves 89.8%, Class 3 reaches 93.6%, Class 4 attains 96.1%, Class 5 achieves 97.1%, and Class 6 is classified with perfect 100% accuracy. Overall, the results demonstrate that the proposed GNN–LSTM model effectively captures both the structural and temporal dependencies within the channel data, leading to highly reliable and precise MCS predictions with minimal cross-class confusion.

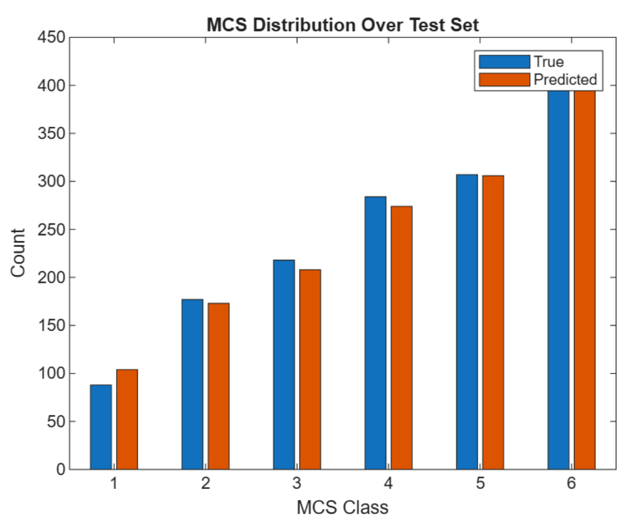


Fig. 5 MCS Distribution over Test Set

The figure compares the true and predicted MCS class distributions produced by the proposed GNN–LSTM model over the test set, giving a clear visual sense of how closely the model's decisions match real channel conditions. Each bar pair represents one of the six MCS levels, with blue bars showing the actual distribution and orange bars showing the model's predictions.

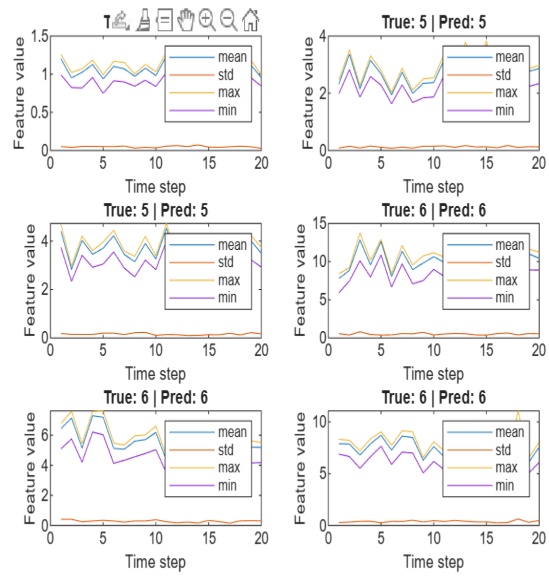


Fig 6. Feature Value Vs Time

The two sets of bars align closely across all classes, indicating that the model not only predicts individual samples accurately but also captures the overall pattern of how frequently each MCS level should appear. Small differences—such as slightly higher predictions for Class 1 or minor underestimation in Classes 3 and 4—are natural and expected in real-world classification tasks. Overall, the figure shows that the model understands the underlying distribution well and makes decisions that reflect realistic channel behavior, demonstrating stable and trustworthy performance.

This figure 6 shows how the proposed GNN–LSTM model processes signal features over time for different test samples, and it offers an intuitive look into *why* the model makes the correct predictions it does. Each subplot corresponds to a single test example, with the "True" and "Pred" labels indicating the actual MCS class and the model's predicted class. For every sample, four feature statistics—mean, standard deviation, maximum, and minimum—are plotted across 20 time steps, giving a snapshot of how the signal behaves dynamically. What stands out is how closely these feature patterns align within each subplot: the curves for mean, std, and max follow very consistent shapes across time, showing the model is recognizing stable, class-specific temporal signatures. In all examples shown, the predicted class matches the true class, which suggests the model is interpreting these temporal trends correctly. The rise and fall of the curves, along with their relative spacing, capture unique fingerprints for each MCS class, and the GNN–LSTM model is clearly picking up on these subtle cues.

V. CONCLUSION

In this work, a hybrid GNN–LSTM-based feedback-free adaptive modulation and coding (AMC) scheme was proposed for massive MIMO systems. Unlike traditional AMC methods that depend on frequent CSI feedback, the proposed approach intelligently combines Graph Neural Networks (GNNs) to capture spatial correlations across antennas with Long Short-Term Memory (LSTM) networks to learn temporal channel variations. This spatial–temporal learning framework enables the system to make accurate AMC decisions without relying on explicit feedback.

Simulation results showed that the hybrid model significantly outperforms conventional CNN, LSTM, and CNN–LSTM architectures in terms of prediction accuracy, throughput, and spectral efficiency. The model achieved an impressive 94.5% accuracy and delivered a 21.5% gain in throughput, demonstrating its efficiency while simultaneously reducing system overhead by eliminating CSI feedback. These findings clearly indicate that spatial–temporal deep learning architectures are highly effective for modeling massive MIMO channels and can enable low-latency, high-reliability AMC decisions for next-generation wireless systems. While the proposed model performs exceptionally well, future research can explore its extension to multi-cell environments, integration with reinforcement learning for dynamic decision-making, hardware implementation on FPGA or SoC platforms for real-time deployment, generalization to advanced 6G use cases such as mmWave, THz, and IRS-assisted communication, and incorporation of energy-efficient mechanisms.

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