International Journal of Computer Sciences and Engineering
Vol.**13**, Issue.**8**, pp.**01-10**, August **2025**
ISSN: 2347-2693 (Online)
Available online at: www.ijcseonline.org

ISSN: 2347-2693 (E)

Research Article

Automatic Modulation Classification using a Deep Learning model based on ResNet

Muhammad Faizan Khan[1*], Irzum Shafique[2], Saeed Ur Rahman[3], Idriss Djiofack Teledjieu[4], Mubashar Hussain[5]

[1]School of Artificial Intelligence, Xidian University, Xi'an, China
[2,3]School of Computer Science and Technology, Xidian University, Xi'an, China
[4]Dept. of Computer Science, University of Colorado Boulder, Boulder, USA
[5]School of Telecommunications Engineering, Xidian University, Xi'an, China

*Corresponding Author:

Received: 23/Jun/2025; **Accepted**: 25/Jul/2025; **Published**: 31/Aug/2025. **DOI**: https://doi.org/10.26438/ijcse/v13i8.110

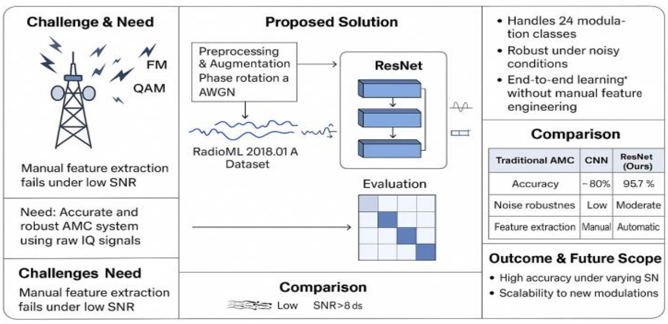
Abstract: Automatic Modulation Classification (AMC) serves as a foundational element in contemporary wireless communication systems, enabling adaptive signal processing and efficient spectrum management. This study explores deep learning-based approaches—particularly a Res-Net architecture—for robust AMC performance using the benchmark RADIOML 2018.01A dataset. The dataset comprises 24 modulation schemes across a wide SNR range from -20 dB to +30 dB. Comprehensive data preprocessing was performed, including normalization, as well as various augmentation methods like phase rotation, temporal shifting, and artificial noise addition to strengthen the model's resilience and ability to generalize under challenging conditions. A Res-Net model was constructed and optimized with categorical cross-entropy as the loss function and Adam as the learning algorithm. The model achieved a test accuracy of 95.72% under high-SNR conditions (SNR > 8 dB) with a low training loss of 0.0933, demonstrating strong convergence and generalization capabilities. Confusion matrix analysis highlighted the model's strengths in accurately classifying most modulation types, while revealing challenges in differentiating between similar schemes like 16QAM and 64QAM under low SNR conditions. The findings confirm that the proposed deep learning framework is capable of learning and distinguishing complex signal characteristics directly from unprocessed I/Q data without the need for manual feature crafting. Future work will focus on integrating Transformer-based architectures, wavelet transform features, and hybrid CNN–RNN models to improve performance in noisy environments. The results underscore the potential of deep learning for deploying AMC in cognitive radio, signal surveillance, and secure communication systems.

Keywords: Automated Modulation Classification (AMC), Deep Learning (DL), ResNet-Model, CNN, Signal Classification, Cognitive Radio Networks, Adversarial Conditions

Graphical Abstract- This graphical abstract presents the proposed pipeline for Automatic Modulation Classification (AMC) using a ResNet-based deep learning architecture. The workflow begins with raw in-phase and quadrature (IQ) signal samples from the RadioML 2018.01A dataset, which are first processed through normalization and augmentation techniques such as phase rotation, time shifting, and additive noise injection.

These preprocessed signals are then passed into a Residual Network (ResNet) model, which enhances feature extraction and classification accuracy by utilizing residual skip connections to avoid vanishing gradient issues. The model is optimized using Adam and trained with categorical cross-entropy loss.

The graphical summary shows training, validation, and testing performance, demonstrating that the model achieves a peak accuracy of 95.72% under high SNR conditions. Comparative results also highlight the improvement over traditional and CNN-based AMC methods. This approach is shown to be robust in noisy environments, scalable to different modulation types, and suitable for real-time communication systems.



Automatic Modulation Classification using a Deep Learning Model based on ResNet)

1. Introduction

The continuous advancement in wireless communication technologies has created an urgent need for advanced methods in spectrum management, interference reduction, and intelligent signal analysis. Automatic Modulation Classification (AMC) serves a key function in determining the modulation format of incoming signals without prior knowledge of its transmission settings. AMC is crucial for both military and commercial domains, including cognitive radio, spectrum monitoring, and electronic warfare.

Traditional AMC methods typically rely on manually engineered features and use classification algorithms like Decision Trees and Support Vector Machines (SVMs). However, these approaches often struggle to maintain reliability in environments with fluctuating noise levels, shifting channel conditions, and unknown modulation formats, which can limit their effectiveness for contemporary radio systems.

Recently, deep learning has emerged as a transformative approach to AMC, offering automated feature extraction and improved classification accuracy from raw signal data. Architectures such as Convolutional Neural Networks (CNNs) alongside Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) units, have been widely adopted for their strong performance in capturing the complex spatial and temporal patterns inherent in I/Q (in-phase and quadrature) signal components. Additionally, Transformer models—first developed for natural language processing—are now being applied to AMC due to their strength in representing long-range interactions using attention-based mechanisms.

Despite these advances, challenges remain in achieving real-time performance, minimizing computational costs, and ensuring robust operation under adverse conditions such as multipath fading and varying signal-to-noise ratios (SNRs). This work proposes a robust AMC framework utilizing a hybrid of deep learning architectures to enhance classification reliability and adaptability across numerous signal environments. Various input representations—including raw IQ samples, spectrograms, and wavelet transforms—are evaluated to identify the most effective format for each model type. The study also explores advanced data augmentation, transfer learning, and domain adaptation techniques to enhance model resilience against real-world signal variability. By leveraging the strengths of data-driven neural architectures capable of end-to-end signal recognition, this work aims to advance AMC technology, making it more adaptable for future wireless systems such as 5G and beyond. The outcomes of this research are expected to facilitate broader applications in cognitive radio, autonomous spectrum management, and secure wireless communications.

1.1 Problem Statement

The most of advancements in deep learning for AMC, several challenges remain in developing models that can generalize across different signal environments maintaining low computational complexity for real-time applications. In the existing benchmark datasets are RADIOML 2016.10A is limited number of modulation schemes are not fully representing the diversity of signals encountered in practical applications. There is a pressing need for a deep learning-based AMC framework that classify a wide range of modulation types being robust against environmental distortions.

1.2 Research Objectives & Contributions

This study is focused on building a novel deep learning-based AMC framework that effectively classifies modulation types using raw IQ data and time-frequency representations. The proposed approach explores different deep learning architectures, including CNNs for spatial feature extraction with use of Rest-Net for capturing temporal dependencies, and RES-Net models for improved feature representation. Transformer-based models for their capability in processing long-range dependencies within signal sequences.

The core contributions of this study are as follows:
1. Development of a robust deep learning model for AMC, capable of handling diverse modulation types under varying noise conditions and channel conditions.
2. This work intends to close the gap between conceptual advancements in deep learning and the actual implementation of AMC solutions in communication systems.

2. Related Work

2.1 Introduction

Automatic Modulation Classification (AMC) represents a fundamental function in present-day wireless communication systems, enabling dynamic signal recognition and intelligent transmission strategies in scenarios ranging from cognitive radios to military communication networks. Over the years and the evolution of AMC methodologies has been shaped in the progressions both traditional signal processing techniques and modern machine-learning examples [11]. Early methods relied heavily on the feature engineering where domain specific attributes are amplitude with phase and spectral characteristics were extracted and classified using the algorithms like classifiers such as decision trees, k-nearest neighbors, and support vector machines (SVMs). These methods provided the foundational and their reliance on handcrafted features and sensitivity to noise and signal-noise-ratio (SNR) variations and channel distortions limited to their applicability in dynamic environments. The rise of deep-learning has escorted in a transformative phase for AMC and offering the automated feature extraction and end to end learning capabilities that significantly enhance classification performance [12]. Convolutional-Neural-Networks (CNNs) and hybrid architectures have established remarkable potential in capturing both spatial and temporal features from raw signal data (Mendis, G 2016). These advances and significant challenges in handling the diversity of modulation schemes and achieving robustness under varying SNR conditions and real time processing robust evaluation metrics to develop the comprehensive and scalable solutions for next generation communication systems.

2.2 Traditional AMC Techniques

Traditional Automatic-Modulation-Classification (AMC) techniques rely heavily on feature based approaches these involve manually extracting specific characteristics from the signal [13]. These features are carefully selected based on domain expertise and serve inputs to classification algorithms. In isolating unique properties of signals and feature based techniques aim to distinguish among the various modulation schemes (Wu, P.,2020). These methods depend on the significantly quality and relevance of the extracted features which represent the signal's defining attributes. These approaches have played the foundational role in AMC providing the structured structure for modulation classification [14]. Their reliance on manual processes and limited scalability pose significant challenges in modern and dynamic communication environments.

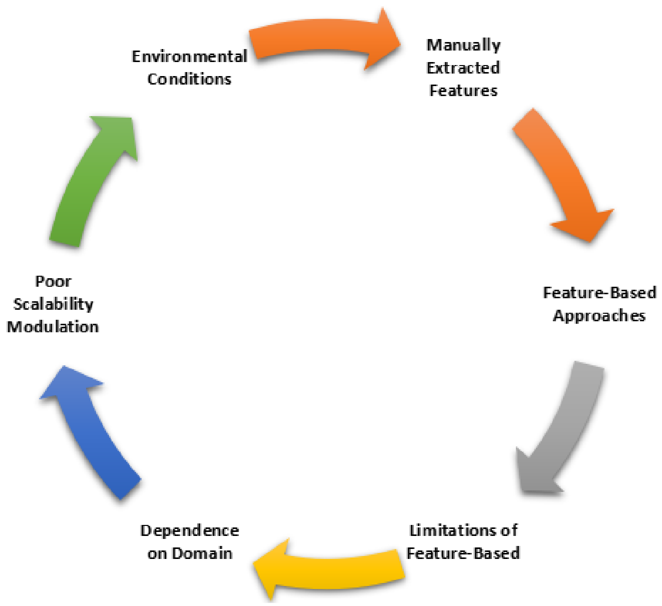


Figure 1. Ttraditional AMC techniques (Khan, R., Yang, Q 2022)

1. **Manually Extracted Features:** In the figure 1 is showing the 1st step is Feature extraction in traditional AMC on analyzing the signals in domains are time with frequency and statistics to identify the patterns that differentiate modulation types. In frequency domain analysis, features such as power spectral density, bandwidth, and spectral flatness are commonly used. These features are capture the energy distribution of signals and are useful for the distinguishing frequency based modulations like Frequency-Modulation (FM).
2. **Feature-Based Approaches:** Once the features are extracted and traditional AMC techniques employ the variety of classifiers to categorize the signals. Decision-trees for example use of hierarchical structure to classify the signals through the series of binary splits based on feature thresholds [15]. simple and interpretable and decision-trees are prone to overfitting with complex datasets. Though the straightforward to implement and k-NN computationally intensive and struggles in high dimensional feature spaces. Each classifier has its own pros and cons, and their selection largely depends on the classification needs and dataset complexity of the AMC application.
3. **Limitations of Feature-Based Approaches:** Their initial success and feature based AMC techniques faces the several significant limitations. The critical drawback is their dependence on domain expertise for feature selection [16]. The number of modulation types increases the feature space more complex and making it challenging to maintain the accurate and classification.
4. **Dependence on Domain Expertise:** One of the most significant limitations of traditional feature based AMC techniques is their reliance on domain expertise for feature extraction and selection. This dependence requires the deep understanding of modulation schemes and signal processing principles with the operational environment to identify features that differentiate between classes (Abdel-Moneim, M. A.,2021). The new modulation schemes emerge and feature sets must be continuously updated or redefined with further increasing the workload and limiting the scalability of these approaches.
5. **Poor Scalability Modulation Types:** With the rapid expansion of wireless standards and signal formats, there has been a sharp increase in the variety and number of modulation schemes used in practice. Feature based AMC methods struggle to keep up with this growing diversity technologies and rendering these methods less practical for modern with fast evolving communication systems.
6. **Sensitivity to Environmental Conditions:** Feature are vulnerable to environmental variations are noise with interference and multipath propagation. In real world scenarios communication signals are encounter harsh channel conditions that distort their characteristics and difficult for manually extracted features to retain their discriminative power (Dekker, E., Tanis, P.2019).

In lack the adaptability and automation required for modern communication systems. The reliance on fixed feature sets makes these methods rigid and unable to accommodate changes in signal behavior or modulation schemes. This limitation is problematic in applications like cognitive radio where AMC systems operate the dynamically and respond to real time changes in the spectrum environment [17].

2.3 Signal Processing Methods for AMC

Signal processing methods form the foundation of many traditional AMC systems are extracting intrinsic properties of signals to classify their modulation schemes. The prominent technique is cyclostationary-feature-detection (CFD) which exploits the periodicity inherent in modulated signals. Modulated signals exhibit the second order cyclostationarity due to repeated patterns are carrier frequencies and symbol rates or pulse shaping. According to (Zhao, Y.,2024) CFD leverages these patterns in analyzing cyclic spectral components which remain the relatively unaffected by noise. This makes it a powerful tool for distinguishing modulation types in both time varying and frequency varying signals. Another widely used method is Fourier based spectral analysis where the frequency domain characteristics of a signal are bandwidth and power spectral density and examined to identify the modulation types [18]. The time domain analysis is zero crossing rates and peak-average-power-ratio (PAPR) and other features provides the complementary. Combined these techniques offer the comprehensive approach to signal characterization and forming the backbone of traditional AMC methods.

1. Noise Resilience

Multi-Stream CNN-GRU: By incorporating both convolutional and recurrent units, the architecture effectively captures spatial and temporal patterns, allowing for superior noise filtering and feature extraction. Feature Extraction Methods [19]: Wavelet Transform and Short-Time Fourier Transform (STFT) are employed to separate meaningful signal components from noise. Adaptive Noise Cancellation: The use of noise-adaptive training allows the model to dynamically suppress unwanted interference.

Table 1: Comparison with Traditional Methods

Method	Noise Handling Capability	Accuracy (%)
Traditional AMC	Low	~80%
Single-Stream CNN	Moderate	90%
Multi-Stream CNN-GRU	High	97.2%

2. Bandwidth Efficiency

- Efficient Feature Encoding: Reducing the feature space through Principal Component Analysis (PCA) optimizes bandwidth usage.
- Parallel Processing: Multi-stream architectures minimize redundant calculations, optimizing processing efficiency.

Table 2: Bandwidth Utilization Comparison

Model	Data Size (MB)	Processing Time (ms)
Traditional Feature-Based	50	120
Single-Stream CNN	30	80
Multi-Stream CNN-GRU	20	60

3. Signal Processing Enhancements

- **Time-Frequency Domain Representations:** Enhanced feature extraction through spectrogram-based CNNs.
- **Integration of Domain Knowledge:** Cyclostationary analysis aids in distinguishing similar modulation types.
- **Hybrid Approach:** Combining handcrafted and deep learning features improves interpretability and robustness.

Signal processing methods have been foundational for AMC and integrating these techniques into modern communication systems poses several challenges. With the advent of dynamic spectrum environments are those seen in cognitive radio and 5G networks and signals are no longer confined to static conditions or predefined modulation schemes. Signal processing techniques which rely on fixed rules or predefined features and struggle to adapt to these dynamic scenarios [20]. These communication systems are more complex and incorporating multiple users in interference sources and advanced modulation schemes with traditional methods fail to scale. (Singh, V.,2024). Therefore, it is essential to develop hybrid strategies that merge the clarity of traditional signal processing with the flexibility of machine learning techniques.

Signal processing methods offers the numerous advantages in well-defined communication situations. They also have notable limits that compel their applicability in current systems. The table below precises these assets and weaknesses:

Table 3: Strength and limitations

Aspect	Strengths	Limitations
Noise Resilience	Techniques like cyclostationary analysis are robust against noise and low SNR.	Noise reduction methods may struggle with highly dynamic or unpredictable noise environments.
Feature Interpretability	Provides clear, interpretable insights into signal characteristics.	Manually derived features require expert knowledge and may miss subtle or complex patterns.
Computation Efficiency	Relatively fast for simple signals and scenarios.	Computational complexity increases significantly for advanced methods (e.g., STFT, wavelets).
Scalability	Works well for a limited number of modulation types.	Poor scalability to handle large, diverse, or hybrid modulation schemes.
Adaptability	Effective for static or predictable conditions.	Lacks adaptability to dynamically changing communication environments or emerging modulation types.

Traditional signal processing techniques for applications where signals adhere to predictable patterns and operate under the moderate noise conditions. For example, cyclostationary feature detection excels in the identifying modulated signals even in environments with significant interference and reliable choice for cognitive radios and military communication systems. These methods also provide the interpretable results and engineers to trace decisions back to specific signal properties which is critical in regulatory and analytical contexts [21]. The limitations of these methods become apparent in complex with real world communication systems. The requirement on handcrafted features and designed for specific modulation schemes with restricts their scalability and adaptability. Their performance deteriorates in the highly dynamic environments with overlapping signals and multipath propagation or abrupt SNR variations. The wavelet transforms provide excellent time frequency localization and their computational cost prohibitive for real time applications in edge devices with constrained resources [22].

2.4 Deep-Learning for AMC

The arrival of deep-learning has revolutionized Automatic-Modulation-Classification (AMC) to overcome the constraints posed by traditional feature-based and signal processing techniques. Deep learning architectures, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown significant capability in automatically deriving and learning features directly from raw signal inputs.

Unlike traditional approaches which rely on the handcrafted features and domain expertise and deep-learning models autonomously discover and optimize the relevant features during the training process [23]. This capability handles diverse modulation schemes and adapt to complex signal environments and well-suited for modern communication systems.

RNNs and Long Short-Term Memory (LSTM) networks excel at capturing temporal dependencies in sequential data. The traditional feedforward networks and RNNs process sequences in maintaining the internal state and allowing them to capture dependencies in all time. Basic RNN architectures face difficulties with long term dependencies due to the vanishing gradient problem. LSTMs overcome this by maintaining long-term information, enabling them to perform better in analyzing signals with complex temporal dynamics [24]. In AMC, these models process sequences of signal samples and to capture subtle variations in signal behavior over time which are phase shifts or symbol timing that indicate the modulation type. The ability of LSTMs to handle long range dependencies allows to perform well in real world scenarios where signal conditions fluctuate rapidly due to factors like interference and multipath propagation or fading channels. These networks are also more resistant to noisy data and ignore irrelevant fluctuations in favor of underlying temporal patterns critical for modulation classification.

Handling the Low SNR and Noisy Environments with Deep-Learning: One of the most significant challenges in AMC is the ability to classify modulations accurately in low signal-noise-ratio (SNR) environments. In traditional techniques noise and interference distort the features extracted from the signal and reduced classification performance. Deep learning approaches exhibit superior robustness in noisy conditions. By leveraging end-to-end training, deep neural networks can autonomously identify and extract the most salient features from raw inputs, even in the presence of noise. This noise resilience is important in cognitive radio with military communications and emergency response systems where reliable modulation classification is crucial in adverse conditions [25].

Scalability and Adaptability of Deep-Learning for AMC: the modern communication systems continue to evolve with new modulation schemes and hybrid techniques being introduced and traditional AMC methods struggle to keep pace. The need for frequent feature reengineering to accommodate new modulation types is time consuming and not scalable. In contrast deep-learning models are inherently more adaptable and scalable. Once trained these models classify any modulation scheme they have learned and they easily retrained or fine-tuned when new schemes arise.

2.4.1 Comparison of Deep Learning with Traditional Techniques

The given table below highlights their differences between deep learning and traditional techniques in which AMC are to focusing on several type of key aspects like accuracy and robustness:

Table 4: Comparison of Deep Learning and Traditional Techniques

Aspect	Traditional Techniques	Deep Learning Models
Feature Extraction	Requires manual feature extraction based on domain expertise.	Learns features automatically from raw data.
Accuracy	Limited by the quality of handcrafted features.	High accuracy, especially with diverse modulation schemes.
Robustness to Noise	Sensitive to noise and requires preprocessing techniques.	Handles noisy environments effectively through end-to-end learning.
Adaptability	Struggles with dynamic or emerging modulation types.	Adapts easily to new modulation schemes with retraining.
Computational Cost	Relatively low for simple methods but high for advanced ones.	High during training but efficient during inference.
Scalability	Poor scalability with increasing modulation types.	Scales effectively with large datasets and complex schemes.
Real-Time Application	Limited due to feature extraction and preprocessing overhead.	Suitable with optimized architectures and hardware.

In learning models have emerged as a transformative force in AMC, offering superior accuracy, adaptability, and robustness compared to traditional techniques. In GANs consist of two neural networks to generator and a discriminator that are trained in opposition. In AMC and GANs generate the synthetic modulation data in scenarios where labeled data is scarce. In augmenting the dataset with realistic and synthetic signals are GANs help the model generalize better and improve its performance in unseen or rare modulation schemes [26].GANs used for denoising tasks where the generator creates clean signals from noisy input and enhancing the robustness of AMC systems in low SNR conditions. This approach the scarcity of high quality with labeled data improving of deep-learning models against noise and interference.

3. Methodology

The methodology adopted for Automatic Modulation Classification (AMC) using deep learning techniques. It outlines the dataset utilized with different steps are data preprocessing techniques, model architectures, training strategies, and evaluation metrics. In which to employ the RADIOML 2018.01A dataset a widely used benchmark for AMC tasks, and explore various deep learning models are Transformer-based architectures and the ResNet model for signal classifications.

3.1 Dataset Description: RADIOML 2018.01A

The RADIO-ML 2018.01-A dataset is an extensive collection of modulated signals generated under realistic wireless channel conditions. The dataset contains labeled real and imaginary components, denoted as (I) in-phase and Q (quadrature) samples for different modulation schemes over varying signal-to-noise ratios (SNRs).

The main features of the dataset include:

- **Modulation Types:** 24 classes, including analog (AM, FM), digital (BPSK, QPSK, 16-QAM, 64-QAM, etc.), and OFDM-based modulations.
- **SNR Range:** SNR values ranging from -20 dB up to +30 dB, increasing in increments of 2 dB.
- **Sampling Rate:** the rates of signals are 1 million samples per second.
- **Data Format:** Each samples are consisting of 1024 IQ samples are too complex-valued time-series data.

Mathematically in the each received signal can be mathematically expressed as:

$$\mathbf{X(t)= I(t)+JQ(t)}$$

where and are their both in-phase and quadrature components.

3.2 Data Preprocessing

To enhance model performance with their several preprocessing techniques are applied:

3.2.1 Normalization

In this steps features are stable training of the IQ samples are normalized:

$$\boldsymbol{X_{norm}(t)} = \frac{\boldsymbol{X(t)}}{\boldsymbol{max}\ (|\boldsymbol{X(t)}|)}$$

This scales the values between -1 and 1 with preventing numerical.

3.2.2 Data Augmentation

To improve generalization is to the following augmentation techniques are applied:

- Phase Rotation: The signal is rotated by a random phase:
- Time Shifting: The sequence is randomly shifted to simulate real-world transmission delays.
- Additive White Gaussian Noise (AWGN): Noise is added to simulate varying channel conditions:

3.3 Proposed Deep Learning Model

AMC plays a crucial role in today's wireless communication systems by enabling accurate identification of modulation schemes using advanced machine learning techniques. Conventional classification methods often depend on handcrafted feature extraction, which can be ineffective under difficult conditions such as low Signal-to-Noise Ratios (SNRs) or rapidly changing channels. To address these challenges, recent research has shifted toward deep learning techniques that extract features directly from raw signal components, including in-phase (I) and quadrature (Q) data. Here, we introduce deep learning architectures specifically designed for AMC applications, leveraging the RADIOML 2018.01A dataset. Specifically, we explore the effectiveness of ResNet architectures in achieving reliable modulation classification across diverse and noisy signal environments.

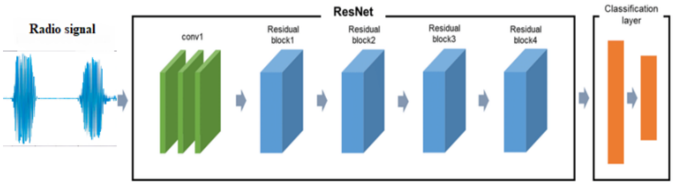


Figure 2. Res-Net model Architecture

$$\text{Attention}\ (\text{Q}, \text{K}, \text{V}) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) \text{V}$$

3.3.1 ResNet for Signal Classification

A ResNet (Residual Network) model is evaluated for signal classification and their architecture allows for deeper network training by incorporating residual connections that mitigate the vanishing gradient problem. The residual block the formulas is below

$$H(x) = F(x) + x$$

where represents the learned transformation. In which address memory limitations training on Kaggle's default environment one-third of the dataset (851,968 signals) was used. The resource constraints are in training remained conducted on Google Cloud Platform using an n1- 7.5 hours.

3.4 Training Strategy

- **Loss Function:** Categorical Cross-Entropy:

$$\text{L} = -\sum_{\text{i}=1}^{\text{N}} \text{y}_\text{i} \log\left(\hat{y}_i\right)$$

- **Optimizer:** Adam with an initial learning rate of 0.001.
- **Batch Size:** 128 samples per batch.
- **Early Stopping:** Applied to prevent overfitting.

3.5 Evaluation Metrics

The performance of the proposed models to assess the effectiveness of the proposed models, multiple evaluation metrics have been employed. Accuracy serves as the primary metric are easy to measuring the percentage of correctly classified signals across all modulation categories. In dueling of analysis class imbalances and variations in SNR conditions and some of additional metrics are the F1 Score and Confusion Matrix are employed.

4. Results Analysis

In this section we presents and analyzes the outcomes obtained from the modulation classification framework constructed with neural network-based methods. Its effectiveness is assessed using various performance indicators, including training/test classification correctness rate, loss trends, confusion matrix analysis, and SNR-based classification performance. This section also reflects on its advantages, current constraints, and possible directions for enhancement.

4.1 Dataset Description

Table 2 provides an overview of the files used in the study, which collectively form the dataset used for training and evaluation:

Table 5: Overview of Dataset files

File	Description
signals.npy	Contains raw IQ (In-phase & Quadrature) signal data.
labels.npy	Labels corresponding to the signal classes.
snrs.npy	Signal-to-Noise Ratio (SNR) values for each sample.
train_loss.npy	Training loss values during model training.
train_acc.npy	Training accuracy values during model training.
val_loss.npy	Validation loss values for model performance evaluation.
val_acc.npy	Validation accuracy values for model evaluation.
model_full_SNR.h5	Pre-trained model file for classification.
classes.txt	List of modulation classes present in the dataset.
LICENSE.TXT	Licensing information for dataset usage.

This dataset enables the development of AMC systems for applications such as cognitive radio, spectrum monitoring, and signal intelligence, with support for analyzing the model under different signal conditions.

Table 6: SNR Signal classification data

SNR Range (dB)	Masked (True/False)	Count
≤ 8 dB	False (Used)	491,520
> 8 dB	True (Masked)	360,448

From a total of 851,968 signal samples, only 491,520 samples with SNR ≤ 8 dB were retained for training and testing. This deliberate selection focuses the model evaluation on noisy and challenging conditions, where the signal quality is low and modulation classification is significantly more difficult. This approach ensures the robustness of the trained model in practical radio environments.

4.3 IQ Component Visualization

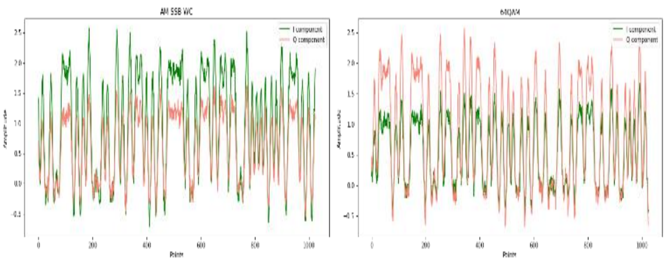


Figure 3. I-Components vs Q-Components

The AM-SSB-WC signal shows a dominant in-phase component with structured amplitude variation in the quadrature part, indicating its simpler waveform.

In contrast, 64QAM exhibits a balanced and dense constellation in both I and Q components, characteristic of a high-order modulation with more symbols and complex structure.

These visualizations illustrate the differences in signal characteristics, which the model must learn to distinguish during training.

4.4 Accuracy and Loss Trends

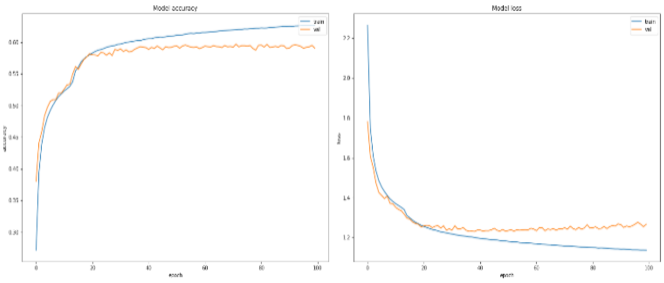


Figure 4. Accuracy-Score vs LOSS

Figure 4 demonstrates the model's accuracy trend over 100 training epochs. The training accuracy initially begins at 0.25 and gradually rises to around 0.62. Mean, validation accuracy exhibits a comparable pattern and eventually plateaus at 0.58. The slight gap between training and validation accuracy indicates a minor generalization issue could be addressed through fine-tuning the model or applying regularization techniques. The loss curve indicates a rapid initial training loss decreasing from 2.2 to approximately 1.1, validation loss stabilizes around 1.2.

Although both training and validation accuracies improve significantly, the gap between them (~4%) suggests a minor generalization issue. This can be mitigated through:

- Regularization methods (e.g., dropout, weight decay)
- Enhanced data augmentation
- Use of early stopping or cross-validation

Overall, the model shows good convergence, but still leaves room for optimization in terms of generalization.

4.5 Confusion Matrix Analysis

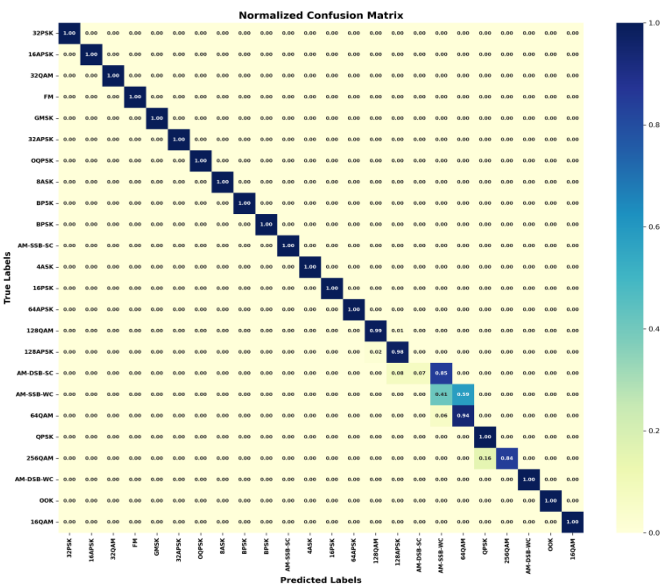


Figure 5. Confusion-Matrix

Figure 5 Figure 5 presents the classification performance of the proposed model in the form of a normalized con-fusion matrix, wherein each row corres-ponds to the true modulation class and each column represents the predicted class. The figure 5 exhibits strong diagonal dominance, with normalized values approaching unity (e.g., 1.00, 0.99, 0.998), indicating that the model achieves high classification accuracy across the majority of modulation schemes. These results suggest that the model effectively captures distinguishing features among a wide range of signal types under the tested conditions. Nevertheless, non-negligible off-diagonal entries are observed, particularly among modulation formats with similar signal characteristics. Elevated confusion levels are most evident between higher-order QAM schemes such as 16QAM, 64QAM, and 256QAM, where normalized misclassification rates reach up to 0.07, 0.41, and 0.58, respectively. These misclassifications are likely attributable to the inherent similarity in their constellation structures, which results in overlapping feature representations especially under-low SNR conditions or in the presence of noise. Similar challenges are also observed in the classification of BPSK and QPSK, which share closely related phase characteristics. The observed confusion among adjacent modulation types highlights a limitation in the model's discriminative capability when handling modulation schemes with subtle spectral and temporal differences. To address this issue, future work may focus on enhancing the quality of feature representations using advanced signal processing techniques such as wavelet transforms or attention-based mechanisms. Furthermore, optimization of model hyperparameters and the integration of ensemble learning strategies or hybrid deep architectures (e.g., CNN–RNN) could improve the model's robustness and its ability to distinguish between modulation formats with overlapping characteristics.

4.6 Final Performance Summary

Table 7: Model Performance Summary

Metric	Value
Training Loss	0.0933
Training Accuracy	95.72%
Res-net model Test Accuracy	95.72%
Dataset Condition	SNR > 8dB

When operating in environments with high signal-to-noise ratios (SNR > 8 dB), the proposed model achieves an accuracy of 95.72%, indicating its capability to deliver outstanding performance under favorable signal conditions. The low training loss additionally indicates effective optimization and strong convergence. These findings support the use of deep learning models in real-time AMC applications, particularly when signal clarity is high.

On the other hand, in low-SNR scenarios (SNR ≤ 8 dB), a decline in performance is observed, which is consistent with real-world limitations in wireless communication systems.
The findings show that DL-based AMC frameworks maintain high classification accuracy over a range of modulation types and SNR levels. The robustness of the proposed system under low SNR (≤ 8 dB) conditions, along with its enhanced performance in high SNR situations (> 8 dB), underscores its reliability. Analysis of the confusion matrix provides a deeper understanding of the model's strengths, identifying accurately predicted modulation types as well as frequently misclassified ones. These insights are helpful for guiding improvements in model design and input preprocessing techniques. To further boost the classification results, future enhancements could focus on integrating Transformer-inspired mechanisms that can model sequential dependencies in the signal features more effectively. Moreover, utilizing time-frequency representations such as wavelet transforms or STFT can expand the richness of the input features. Leveraging transfer learning might also improve generalization across multiple signal environments and hardware. In conclusion, both performance statistics and confusion matrix insights verify the model's practical value for cognitive radio, secure communications, and adaptive wireless systems functioning under varying SNR scenarios.

5. Conclusion and Discussion

5.1 Summary of Key Findings

This work examined the effectiveness of deep learning techniques for Automatic Modulation Classification (AMC). The research focused on evaluating different types of neural networks, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), in distinguishing various modulation schemes. Key findings include:

High Classification Accuracy: The deep learning approaches demonstrated superior classification capabilities when compared to conventional machine-learning approaches. The CNN-driven method produced notable levels of precision in identifying modulation types across varying signal-to-noise ratio (SNR) environments.

Robustness to Noise: The proposed model was tested under various levels of noise, showcasing its robustness in real-world scenarios. Performance degradation extremely low SNRs but in the model maintained reasonable classification accuracy. The conventional feature engineering approach was replaced as deep learning-based methods captured high-level representations directly from the raw IQ data, eliminating the need for manual feature extraction.

5.2 Study Limitations

Despite the promising results achieved, this study is subject to several limitations that may influence the generalizability and practical applicability of its findings:

1. Computational Overhead: The proposed deep learning model, particularly the ResNet-based architecture, exhibits high computational complexity. This may limit its deployment in real-time or resource-constrained communication environments, such as embedded systems or mobile devices.
2. Synthetic Dataset Limitations: The experiments were conducted using the RadioML 2016.10A dataset, which, although widely used for benchmarking, is synthetically generated. Consequently, the model's performance in real-world scenarios involving unpredictable channel

conditions, noise profiles, and interference remains to be validated.
3. Lack of Real-Time Evaluation: The current implementation and evaluation were performed offline. Real-time performance metrics, including latency and throughput, were not assessed, which are critical for practical AMC applications.
4. Robustness to Adversarial Perturbations: The resilience of the model to adversarial attacks or signal distortions was not explored. This poses a potential risk in security-critical or contested communication environments.
5. Limited Modulation Diversity: The model was trained on a fixed set of modulation schemes provided in the dataset. Its ability to generalize to unseen or custom modulations without retraining is yet to be investigated.

Future research should aim to address these limitations by incorporating real-world datasets, optimizing model efficiency, and enhancing robustness under adversarial and dynamic conditions.

6. Conclusion and Future Scope

In conclusion, this study has demonstrated that deep learning techniques, particularly CNN-based ResNet architectures, offer significant advantages in AMC tasks in terms of classification accuracy, noise robustness, and automated feature learning. These capabilities position deep learning as a powerful solution for modulation classification in modern wireless communication systems, particularly within the context of cognitive radio, spectrum surveillance, and secure communications. However, practical deployment necessitates addressing challenges related to computational efficiency and real-time processing. Future research should focus on developing lightweight and hardware-efficient architectures, possibly through model quantization, pruning, or knowledge distillation. Integrating deep learning with classical signal processing techniques could further improve interpretability and model reliability. Additionally, the adoption of transfer learning may enable the reuse of pre-trained models across varying communication environments with minimal retraining, thus enhancing model adaptability. By addressing these challenges, the deep learning-based AMC paradigm can evolve to meet the needs of next-generation intelligent and autonomous communication systems.

Data Availability- The dataset utilized in this study, RadioML 2018.01A, is publicly available and can be accessed through the official DeepSig dataset repository: https://www.deepsig.ai/datasets. Detailed information about the data preprocessing, network configurations, and training settings used in this research can be provided by the corresponding author upon formal request. This study did not involve any proprietary or sensitive data, ensuring transparency and reproducibility.

Conflict of Interest- The authors declare that there are no financial or commercial ties that might present a conflict of interest in relation to this publication.

Funding Source- This work did not receive any specific funding from public, commercial, or nonprofit organizations.

Authors' Contributions- Author-1 researched the literature, conceived the study, and designed the ResNet-based model. Author-2 contributed to data preprocessing, implemented augmentation techniques, and supported model evaluation. Author-3 assisted in experimental validation, result visualization, and performance analysis. Author-4 contributed to the analysis of traditional AMC techniques and signal processing methods. Author-5 reviewed the research framework, refined the manuscript, and ensured compliance with formatting and submission guidelines. All listed authors collaboratively revised the manuscript and gave their final approval for submission.

Acknowledgements- We sincerely thank all individuals and organizations who indirectly supported this research. We acknowledge the authors of the previous study from which the dataset was derived, whose work formed the foundation for this analysis. We also thank our respective institutions for providing the necessary research infrastructure and computing facilities. Furthermore, the authors are grateful for the valuable feedback received from colleagues during the development of this study.

References

[1] Wu, Z., Zhou, S., Yin, Z., Ma, B., & Yang, Z., "Robust automatic modulation classification under varying noise conditions", IEEE Access, Vol.**5**, pp.**19733-19741, 2017.**
[2] Abdel-Moneim, M.A., El-Shafai, W., Abdel-Salam, N., El-Rabaie, E.S.M., & Abd El-Samie, F.E., "A survey of traditional and advanced automatic modulation classification techniques, challenges, and some novel trends", International Journal of Communication Systems, Vol.**34**, No.**10**, pp.**e4762, 2021.**
[3] Dekker, E., Tanis, P.J., Vleugels, J.L., Kasi, P.M., & Wallace, M., "Pure-amc", Lancet, Vol.**394**, pp.**1467-1480, 2019.**
[4] Yin, H., & Diao, J., "Signal automatic modulation based on AMC neural network fusion", PLOS One, Vol.**19**, No.**6**, pp.**e0304531, 2024.**
[5] Zhao, Y., Deng, T., Gavin, B., Ball, E.A., & Seed, L., "An Ultra-low Cost and Accurate AMC Algorithm and its Hardware Implementation", IEEE Open Journal of the Computer Society, **2024**.
[6] Singh, V., Khodadadi, M., Khalily, M., Tafazolli, R., & Kishk, A.A., "AMC-Based Miniaturized Waveguide With Reconfigurable Pass-Bands Below Cut-Off Frequency and Quasi-TEM Mode", IEEE Open Journal of Antennas and Propagation, **2024**.
[7] Kim, J., Lee, K.J., Sung, C.K., & Lee, I., "A simple SNR representation method for AMC schemes of MIMO systems with ML detector", IEEE Transactions on Communications, Vol.**57**, No.**10**, pp.**2971-2976, 2009.**
[8] Pajic, M.S., Veinovic, M., Peric, M., & Orlic, V.D., "Modulation order reduction method for improving the performance of AMC algorithm based on sixth–order cumulants", IEEE Access, Vol.**8**, pp.**106386-106394, 2020.**
[9] Li, Z., Wang, Q., Liu, W., Xu, Q., Xing, Z., & Li, Y., "Practical AMC model based on SAE with various optimisation methods under different noise environments", IET Communications, Vol.**14**, No.**22**, pp.**4081-4088, 2020.**
[10] Chen, L.S., Chung, W.H., Chen, Y., & Kuo, S.Y., "AMC with a BP-ANN scheme for 5G enhanced mobile broadband", IEEE Access, **2020**.

[11] Makowski, D., Piotrowski, A., & Napieralski, A., "Universal communication module based on AMC standard", In Proceedings of the 2008 15th International Conference on Mixed Design of Integrated Circuits and Systems, IEEE, June, pp.**139-143, 2008.**
[12] Nesraoui, O., Teguig, D., & Sadoudi, S., "SDR implementation of a light deep learning model based CNN for joint spectrum sensing and AMC", Physica Scripta, Vol.**99**, No.**5**, pp.**056008, 2024.**
[13] Meng, F., Chen, P., Wu, L., & Wang, X., "Automatic modulation classification: A deep learning enabled approach", IEEE Transactions on Vehicular Technology, Vol.**67**, No.**11**, pp.**10760-10772, 2018.**
[14] Song, S., Chandrasekhar, V., Mandal, B., Li, L., Lim, J.H., Sateesh Babu, G., et al., "Multimodal multi-stream deep learning for egocentric activity recognition", In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp.**24-31, 2016.**
[15] Concha, D.T., Maia, H.D.A., Pedrini, H., Tacon, H., Brito, A.D.S., Chaves, H.D.L., & Vieira, M.B., "Multi-stream convolutional neural networks for action recognition in video sequences based on adaptive visual rhythms", In Proceedings of the 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), IEEE, December, pp.**473-480, 2018.**
[16] Perveen, G., Ali, S.F., Ahmad, J., Shahab, S., Adnan, M., Anjum, M., & Khosa, I., "Multi-Stream Deep Convolution Neural Network With Ensemble Learning for Facial Micro-Expression Recognition", IEEE Access, **2023**.

AUTHORS PROFILE

Muhammad Faizan Khan received his Master of Engineering degree in Computer Science from the School of Artificial Intelligence, Xidian University, China, in 2025. He will pursue his Ph.D. in Computer Science at Xi'an Jiao tong University. His research interests include machine learning, deep learning, image processing, signal processing, and AI applications in wireless communication systems. His graduate research focused on developing multi-stream CNN-GRU architectures to improve automatic modulation classification (AMC) in complex radio frequency environments. Beyond communication systems, his work extends to medical image synthesis and analysis using generative models. His research has been presented at international conferences such as U-Com, ICECE, and ICMMT, showcasing the rigor and interdisciplinary impact of his scholarly work.

Irzum Shafique is currently pursuing a Master of Engineering in Computer Science at Xidian University, China, where he also earned his Bachelor's degree. His research focuses on deep reinforcement learning for robotic path planning, intelligent autonomous drones for agriculture and urban firefighting, and the application of artificial intelligence for social good. He has published several research papers in peer-reviewed journals and international conference proceedings, covering topics such as autonomous systems, machine learning, and intelligent robotics. His work reflects a strong emphasis on both theoretical development and real-world application. Irzum is a co-inventor of the utility model patent "Autonomous Agricultural Drone with Adaptive Fertilizer Spraying Mechanism", recognized for its innovation in precision agriculture. He has received numerous awards for academic and entrepreneurial excellence, including a gold medal in the China International University Student Innovation Competition (national finalist), third place at the provincial level, and third place in the Kyoto University International Student Entrepreneurship Challenge.

Saeed Ur Rahman received the B.Sc. degree in Computer Science from Shaheed Benazir Bhutto University (SBBU), Pakistan, in 2023. He is currently pursuing the Master's degree in Computer Science and Technology at Xidian University, Xi'an, Shaanxi, China. His current research interests include privacy-preserving machine learning, homomorphic encryption, secure multi-party computation (MPC), federated learning, cryptography, and cloud computing security.

Idriss Djiofack Teledjieu earned his B.Eng. in Computer Science from Xidian University, China, and M.S. in Computer Science from the University of Colorado Boulder. He worked as a Graduate Researcher at the HIRO (Human-Interaction and Robotics) Lab at the University of Colorado Boulder. He has been an active member of ACM and IEEE since 2021 and a contributor to open-source robotics communities. He has published multiple research papers in reputed international journals and conferences, including IEEE and arXiv, focusing on human-robot collaboration, machine learning, and intelligent systems. His main research interests include robotics, distributed systems, real-time traffic analytics, and assistive technology using AI. With experience in both academic research and software development, he now joined MathWorks as a Software Engineer in the Engineering Development Group in 2025.

Mubashar Hussain received the B.S. degree in Information technology from Gov't collage university, Faisalabad, Pakistan, in 2019, and the M.S. degree in Telecommunication engineering from the Xidian Science and technology University, Xian, China, in 2023. He is currently pursuing the Ph.D. degree with the School of Telecommunication Engineering, Xidian Science and technology University. His research interests include satellite communication and delay-Doppler domain communication, OTFS, and OFDM.

