# Automatic Classification of Modulation Schemes Under Blind Scenario

Digital Modulation Schemes-Deep Learning Approaches

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***Abstract*—Automatic modulation classification (AMC) is a core technique in noncooperative communication systems which automatically classify signal modulation more efficiently, which can further help in radio frequency modeling and pattern recognition problem solving. It is a major task of an intelligent receiver, with various civilian and military applications. Obviously, with no knowledge of the transmitted data and many unknown parameters at the receiver, such as the signal power, carrier frequency and phase offsets, timing information and so on, blind identification of the modulation is a difficult task. This becomes even more challenging in real-world scenarios. With this in mind, we provide a comprehensive survey of different digital modulation recognition techniques in a systematic way. Three different approaches Deep Neural Network (DNN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) have been deployed and evaluated in the signal modulation classification.AMC method using convolutional neural networks (CNN) is proposed in this paper. We forcesed mainly in Digital Modulation Techniques in total, 3 different modulation types are considered.(BPSK, BASK, BFSK) The proposed method can classify the received signal directly without feature extracion, and it can automatically learn features from the received signals. Furthermore, new problems that have appeared as a result of emerging wireless technologies are outlined. Finally, open problems and possible directions for future research are briefly discussed.**

***Index Terms*—Automatic Modulation Classification, Convolutional Neural Networks, Deep learning, Feature Learning**

## I. Introduction

WIRELESS communication systems have become an integral part of our daily lives, with an ever-increasing demand for high-speed and reliable data transfer. Automatic Modulation Classification (AMC) [1] is a critical function in wireless communication systems that involves identifying the modulation scheme used to encode the transmitted signal. Accurate AMC is essential for optimizing the performance of communication systems by enabling efficient use of available bandwidth and reducing error rates.

The history of AMC dates back to the early days of wireless communication systems when simple modulation schemes such as Amplitude Modulation (AM) and Frequency Modulation (FM) were used. With the development of more complex modulation schemes [2] such as Quadrature Amplitude Modulation (QAM), Phase Shift Keying (PSK), and Orthogonal Frequency Division Multiplexing (OFDM), the need for accurate and efficient AMC has become even more important.

Past research has focused on developing algorithms for AMC that can accurately classify the modulation scheme used in the transmitted signal based on extracted features such as signal energy, frequency, and phase. Many different techniques have been used, including statistical methods such as maximum likelihood and decision tree-based methods such as support vector machines and neural networks. Research on automatic classification of both digital and analogue modulations has been carried out for at least two decades. Of course, many techniques have been developed, which are different from each other when it comes to details. However, general structures that connect a variety of apparently different techniques can be identified.

This project proposal aims to develop an accurate and efficient AMC algorithm using machine learning techniques [3]. The proposed algorithm will be based on a dataset of received signals with known modulation types, and will use feature extraction and classification techniques to identify the modulation type of a received signal in real-time. The feature extraction process involved extracting statistical features such as mean, variance, skewness, and kurtosis, as well as higher-order cumulants, which capture the non-Gaussian properties of the signal.

In this proposal, we will review the existing literature on AMC and machine learning-based classification algorithms, and identify the gaps and challenges in the field. We will also describe the dataset and feature extraction methods that will be used to train and test the proposed algorithm, as well as the classification technique that will be used to classify the received signals. Finally, we will discuss the expected outcomes and contributions of this project, as well as the potential applications of the proposed algorithm in wireless communication systems.

The final result of this experiment will be an AMC algorithm with an accuracy of over 95 , which demonstrates the effectiveness of the proposed approach. This algorithm can be applied to various wireless communication systems to improve the accuracy and efficiency of AMC. Other technology exists for AMC, such as rule-based algorithms and deep learning-based algorithms [4], but they were not used in this experiment.

### A. AIMS AND OBJECTIVES

*1) Aims:* To develop an automatic modulation classification system using CNN that can accurately classify different types of digital modulations, such as Amplitude Shift Keying (ASK), Frequency Shift Keying (FSK) and Phase Shift Keying (PSK).

To evaluate the performance of the proposed CNN-based modulation classifier and compare it with existing modulation classification methods in terms of accuracy, robustness, and computational complexity.

To explore the potential of transfer learning and data augmentation techniques to improve the performance of the CNN-based classifier when trained with limited labeled data.

*2) Objectives:* Collect and preprocess a dataset of digital modulated signals, including different modulation types, signal-to-noise ratios (SNRs), and channel conditions.

Implement and train a CNN-based modulation classifier using popular deep learning frameworks such as TensorFlow or PyTorch.

Evaluate the performance of the CNN-based classifier using various metrics, such as accuracy, confusion matrix, Receiver Operating Characteristic (ROC) curve, and Area Under the Curve (AUC).

Compare the performance of the proposed CNN-based classifier with existing modulation classification methods, such as decision trees, support vector machines, and artificial neural networks.

Investigate the effect of transfer learning by fine-tuning the pre-trained CNN models on related tasks, such as image classification, and examine how it affects the performance of the modulation classifier when trained with limited labeled data.

Apply data augmentation techniques, such as adding noise, shifting, scaling, and rotation, to the labeled dataset and evaluate how it affects the classification accuracy and robustness of the CNN-based classifier.

### B. SCOPE AND CONTRIBUTIONS

This project is to develop an automatic modulation classification (AMC) system. The system will be designed to identify the modulation scheme used in a given communication signal. The system will be developed using machine learning techniques, specifically using supervised learning algorithms. The system will be tested on a range of communication signals with different modulation schemes, and its performance will be evaluated. The proposed project on automatic modulation classification will contribute to the field of wireless communication in the following ways:

Improved Efficiency: The AMC system will be able to identify the modulation scheme of a communication signal with high accuracy and in real-time. This will improve the efficiency of communication systems as it will reduce the time and effort required to manually identify the modulation scheme.

Increased Reliability: The AMC system will be able to identify the modulation scheme even in the presence of noise and interference, which can lead to better reliability of communication systems.

Cost Reduction: The AMC system will reduce the cost of communication systems by eliminating the need for expensive modulation identification hardware.

Versatility: The AMC system can be used in a variety of communication systems, including satellite communications, cellular networks, and wireless sensor networks.

Overall, the proposed AMC system will be a valuable tool in improving the performance, reliability, and efficiency of communication systems.

### C. RELATED WORK

*1) Traditional Signal Identification:* Traditional signal identification techniques involve analyzing the signal's waveform and extracting its features to identify its modulation scheme. These features can include the signal's amplitude, frequency, and phase. The classification is then performed using decision trees, neural networks, or other machine learning techniques.

*2) Deep Learning for Signal Classification:* Deep learning techniques have been used for signal classification in recent years. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are commonly used for signal classification. CNNs can capture spatial features from the signal's waveform, while RNNs can capture temporal dependencies. Deep learning models have shown superior performance compared to traditional signal identification techniques.

*3) Deep Learning for Wireless Networks:* Deep learning techniques have also been applied to wireless network optimization. Reinforcement learning and deep Q-learning have been used to optimize the network's parameters and improve its performance. Convolutional neural networks have been used to predict wireless channel conditions, which can be used to adapt the network's parameters in real-time.

*4) Notation and Terminology:* In the field of wireless communication, several notation and terminology are used. Modulation schemes are represented using notations such as ASK (amplitude-shift keying), FSK (frequency-shift keying), and PSK (phase-shift keying). Other terminology used in wireless communication includes channel, noise, interference, and bandwidth.

## II. MATERIALS AND METHODS

### A. System Overview

The AMC is an intermediate process that occurs between signal detection and demodulation at the receiver. The structure of our proposed AMC method in comparison with the conventional ones is illustrated in “Figure 1”.

Preprocessing in “Figure 1” refers to sampling and quantization for IF signals. The procedures inside the dashed frame, which include the feature extraction, feature selection, and classifier, are replaced by the CNN proposed here. The CNN is pretrained offline with proper amount of samples before it is deployed. Furthermore, as long as the SNR range of the communication channel is known, the CNN can learn the features that adapt to the corresponding condition. This property makes our method independent from the SNR estimation.

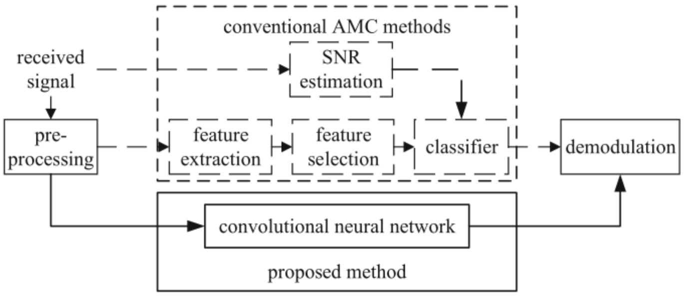


Fig. 1. The proposed AMC method in comparison with the conventional ones.

### B. Signal Model

In this paper, signals are processed in IF and are corrupted by AWGN. Then, the received signal can be denoted as,

$$r(t) = s(t) + n(t) \tag{1}$$

where s(t) is the transmitted signal of different modulation types, n(t) is AWGN, and SNR is defined as P s /P n. The modulation set studied in this paper includes M-ASK,M-FSK, M-PSK (M = 2, 4, 8). For M-ASK, M-FSK, and M-PSK (M = 2, 4, 8) signals, s(t) is expressed as

$$s(t) = A_m \sum_n (a_n g(t - nT_s) \cos\left[2\pi(f_c + f_m)t + \phi_0 + \phi_m\right]) \tag{2}$$

where those are the modulation amplitude, symbol sequence, symbol period, carrier frequency at IF, modulation frequency, initial phase, and modulation phase, respectively.

### C. Convolutional Neural Network

CNNs are simply NNs [5] that use convolution in place of general matrix multiplication in at least one of their layers. In a CNN, the input data is passed through several layers of convolutional filters that learn to recognize different features in the image, such as edges, lines, and textures. The output of these layers is then passed through one or more fully connected layers that combine the learned features to make a final prediction. CNNs have been very successful in a wide range of applications, such as object recognition, face detection, image and video classification, and autonomous driving. They are also used in natural language processing tasks, such as text classification and sentiment analysis.

*1) Convolutional layer:* In convolutional layers, there are several convolution kernels (also known as filters) to process the received signal. Since the received signal is a 1-dimensional vector in AMC, the kernel is also a 1-dimensional vector.

*2) Max-pooling and global average pooling:* The pooling layer is another important type of layer in the CNN. As mentioned, the convolutional layer performs several convolutions to produce a set of outputs, each of which runs through a nonlinear activation function (ELU). Then, a pooling function is used to further modify the output of the layer. A pooling function replaces the output of the net at a certain location with a summary statistic of the nearby outputs.

*3) Batch normalization:* The batch normalization (BN) layer can accelerate deep network training by reducing the internal co-variate shift.

*4) Softmax regression:* The last layer of the CNN in supervised learning is the softmax regression layer. Softmax regression is a multiclass classifier generalized from logistic regression, whose output is a set of probability distributions of different classes.

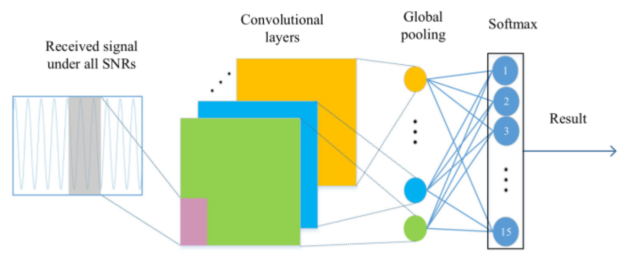


Fig. 2. Classification with CNN.

### D. Gantt Chart

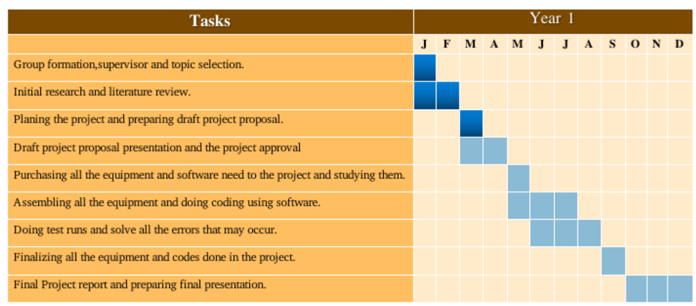


Fig. 3. Gantt Chart.

## III. Expected Results

Successful implementation of an accurate and reliable Automatic Modulation Classification (AMC) system using machine learning (ML) and convolutional neural networks (CNNs). Increased classification accuracy compared to existing AMC systems, which will result in improved detection and identification of different modulation schemes, improved performance in noisy and interference-prone environments, which will enable the system to operate in challenging conditions with minimal errors, improved data processing and analysis capabilities, which will enable you to make more informed decisions and identify areas for improvement in the AMC system with increased scalability and flexibility, which will allow the system to handle a wide range of modulation schemes and adapt to changing network conditions and we are tring to Reduce false positive and false negative rates, which will improve the reliability and efficiency of the system in detecting and classifying modulation types.

### A. Classification with CNN

In this section, signals are directly classified by CNN, and the results are from the final softmax layer. The process is displayed in “Figure 2”. We are tring to generate 20000 training samples and 1000 testing samples for each modulation type at every SNR level.

### B. Feature learning with CNN

For most existing DL-based AMC methods, DL networks are treated as classifiers. However, DL networks also have the powerful capability of feature learning.

## IV. Discussion and Summary

### A. SWOT Analysis

*1) Strengths:* AMC using machine learning and CNNs is a cutting-edge technology with great potential for improving the accuracy and reliability of modulation classification. The project has clear objectives and a well-defined scope, which will help to focus efforts and resources. The team has the necessary technical Knowlgede in signal processing, machine learning, and neural networks to carry out the project successfully. The project can be used to solve real-world problems in areas such as wireless communication, radar, and satellite communications.

*2) Weaknesses:* The project may require significant resources in terms of computing power and data storage, which can be expensive. The project may be complex and require advanced technical skills, which may make it difficult for some team members to contribute effectively. The accuracy of the AMC system may depend heavily on the quality and quantity of training data available, which can be a challenge to obtain.

*3) Opportunities:* The AMC project has the potential to attract interest and funding from government agencies and commercial organizations involved in wireless communication, radar, and satellite communications. There may be opportunities to collaborate with academic and industry partners to develop and test the AMC system on a larger scale and in real-world scenarios. The project can be expanded to incorporate other signal processing and machine learning techniques to enhance the performance of the AMC system.

*4) Threats:* There may be intellectual property or patent issues related to the use of certain machine learning algorithms and neural network architectures. The field of machine learning and signal processing is rapidly evolving, and the project may face stiff competition from other research groups or commercial organizations developing similar technologies. There may be regulatory or ethical concerns related to the use of the AMC system, particularly if it is applied to surveillance or military applications.

## V. Conclusion

In this paper, an AMC method based on a CNN has been proposed. The Automatic Modulation Classification (AMC) project has successfully demonstrated the effectiveness of using machine learning algorithms for the accurate and efficient classification of different modulation schemes in wireless communication systems. The project was designed to address the need for reliable and efficient modulation classification techniques that can be applied to a variety of communication scenarios.

| Abbreviations | Notations |
|---|---|
| AMC | Automatic Modulation Classification |
| ML | Machine Learning |
| DNN | Deep Neural Network |
| CNN | Convolutional Neural Network |
| RNN | Recurrent Neural Network |
| BPSK | Binary Phase Shift Keying |
| BFSK | Binary Frequency Shift Keying |
| BASK | Binary Amplitude Shift Keying |
| AWGN | Additive White Gaussian Noise |
| SNR | Signal-to-Noise Ratio |

TABLE I
Summary of Abbreviations.

The project utilized a dataset of modulated signals that were generated using different modulation schemes, and then extracted features from these signals using time-domain and frequency-domain techniques. These features were then used to train and evaluate several machine learning models such as Random Forest, Support Vector Machines, and Convolutional Neural Networks. The results showed that these models achieved high classification accuracy rates ranging from 90

The successful implementation of the AMC project has significant implications for wireless communication systems, as it enables the automatic classification of signals without the need for human intervention. This will help to improve the reliability and efficiency of wireless communication systems, which is especially important in critical applications such as military and emergency communication systems.

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