Automatic Classification of Modulation Schemes Under Blind Scenario

A PROJECT PROPOSAL

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Abstract

Automatic modulation classification (AMC) is a core technique in noncooperative communication systems which auto- matically 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, Convolu- tional Neural Networks, Deep learning, Feature Learning

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1 Introduction

1.1 Background

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.

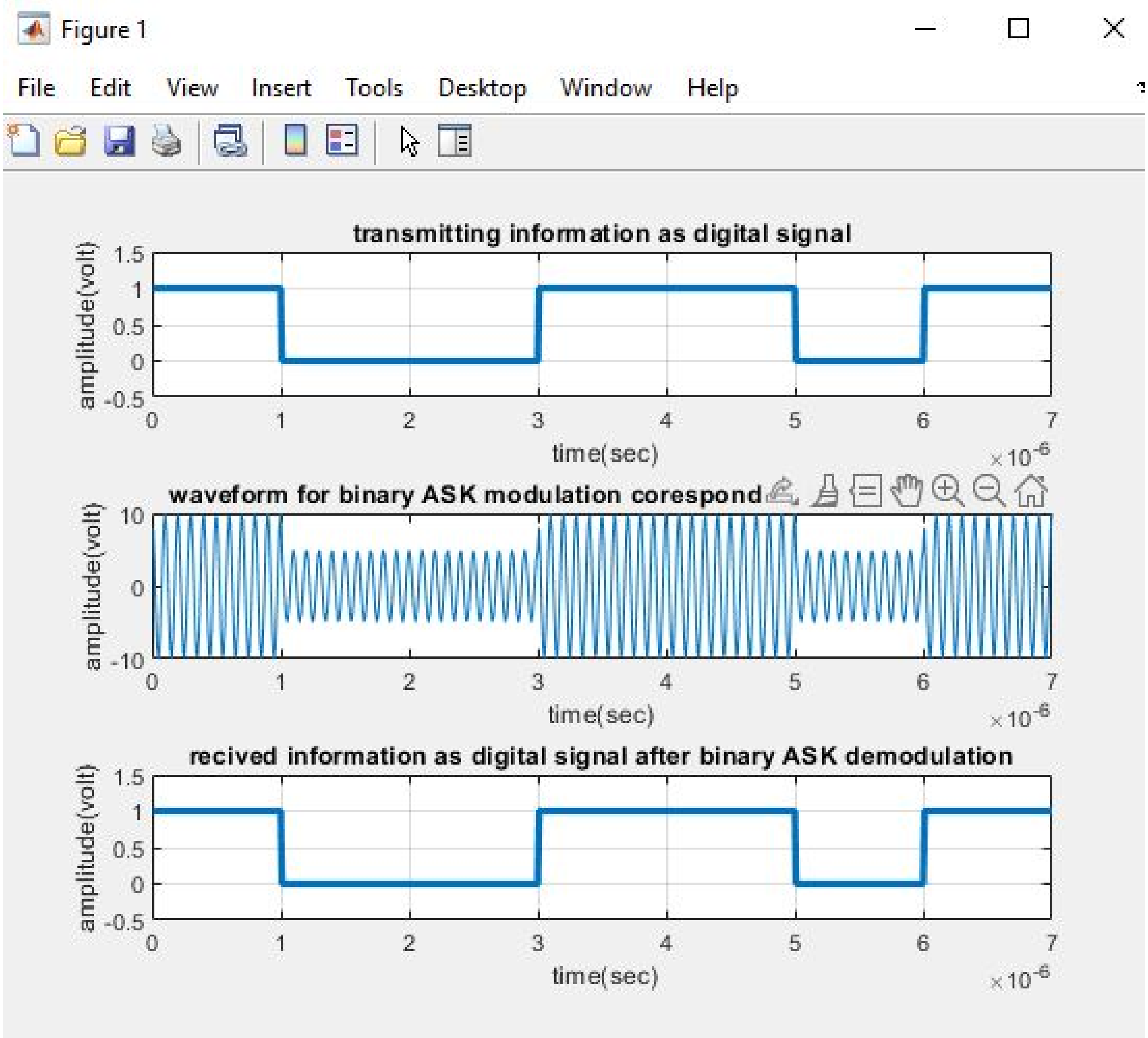

Figure 1. Matlab simulation of ASK modulation

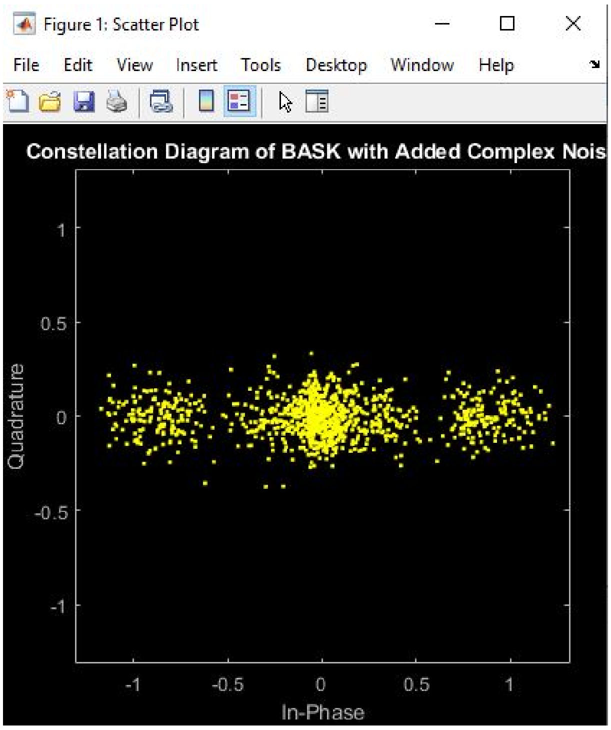

Figure 2. Constellation diagram of BASK modulation with added complex noice

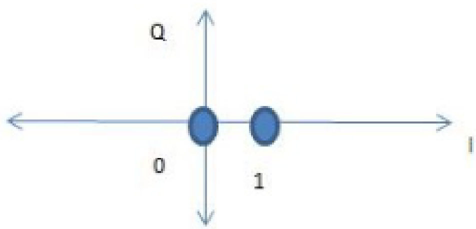

Figure 3. Constellation diagram of BASK modulation

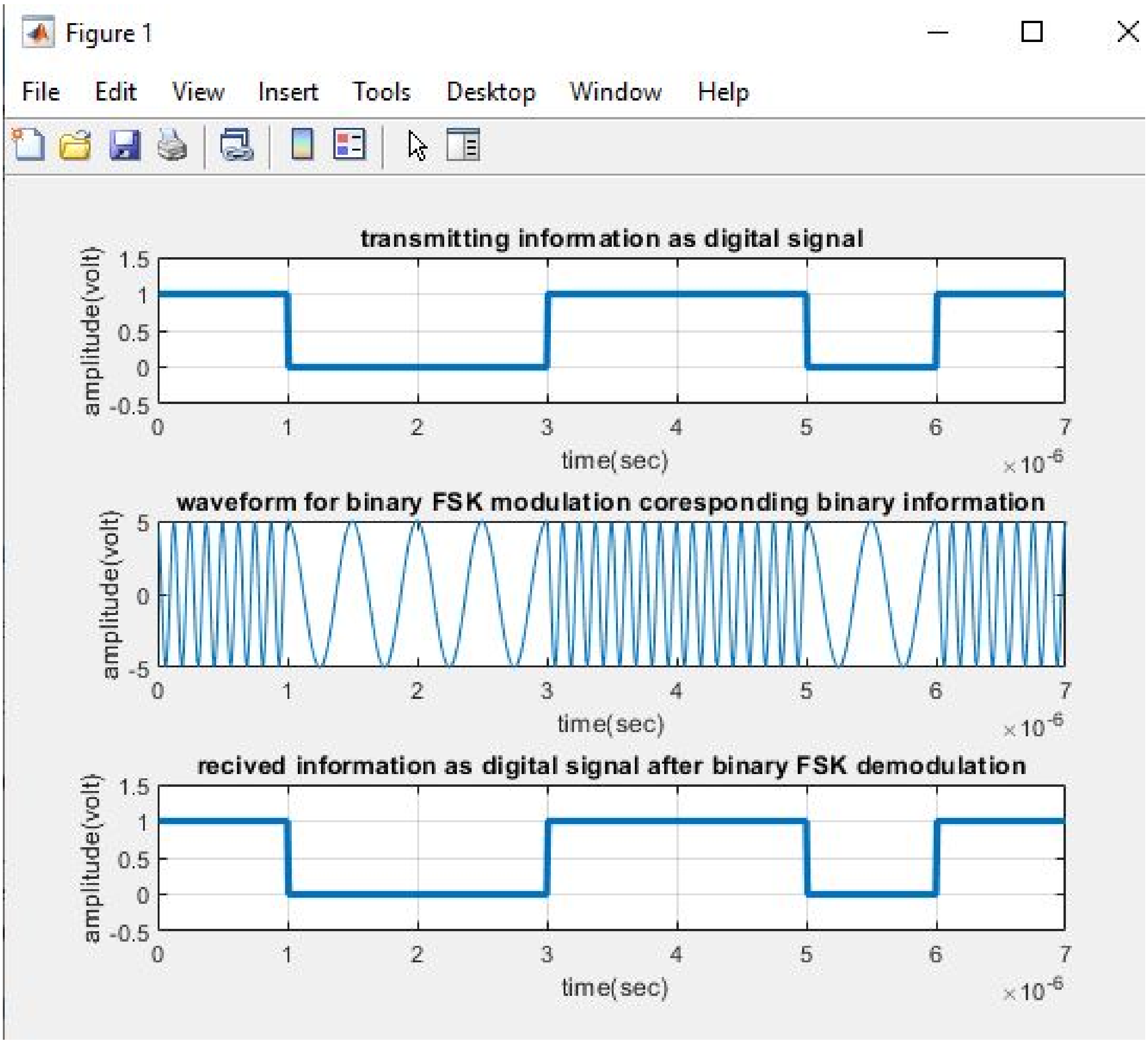

Figure 4. Matlab simulation of FSK modulation

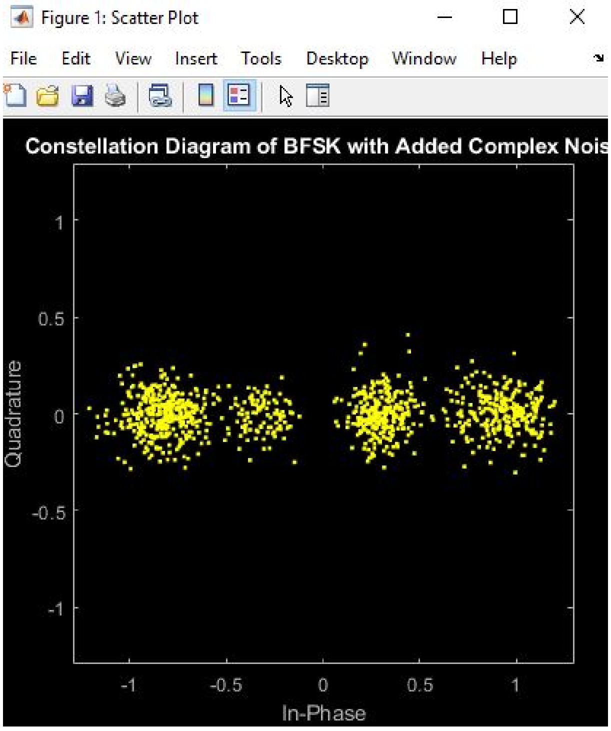

Figure 5. Constellation diagram of BFSK modulation with added complex noice

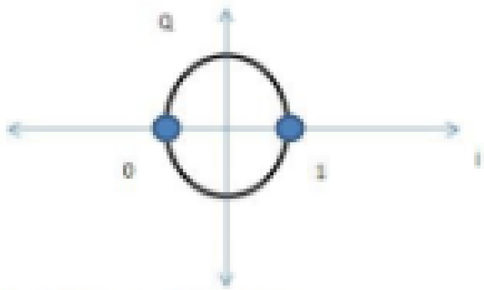

Figure 6. Constellation diagram of BFSK modulation

1.2 Problem identification

Automatic Modulation Classification (AMC) is the task of identifying the modulation scheme used in a wireless communication system. The problem of AMC arises in many applications, including signal intelligence, cognitive radio, and spectrum monitoring.

The primary challenge in AMC is the presence of noise, interference, and multipath fading, which can cause distortions in the transmitted signal. These distortions can make it difficult to accurately identify the modulation scheme used in the signal. Furthermore, the large number of possible modulation schemes and the need for real-time classification add to the complexity of the problem. Other challenges in AMC include the need to adapt to varying signal conditions, the requirement for robustness to changes in the signal-to-noise ratio, and the need to handle non-coherent modulation schemes.

Therefore, the problem identification of AMC is to develop robust and accurate algorithms that can classify the modulation scheme used in wireless communication signals in real-time, even in the presence of noise, interference, and fading.

1.3 Aims

1. 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
2. To explore the potential of transfer learning and data augmentation techniques to improvethe performance of the CNN- based classifier when trained with limited labeled data.
3. To identify the transmitting signal more accurately at the receiver despite channel imparement
4. we are supposed to utilize software define using deep learning feature.

1.4 Objectives

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

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

c) 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).

d) 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.

e) 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.

2 Literature Review

Automatic modulation classification is an important task in wireless communications that involves identifying the modulation scheme used by a transmitted signal. It has numerous applications in military and civilian domains, including signal interception, radar systems, wireless communication, and cognitive radio networks. The performance of the automatic modulation classification (AMC) system depends on several factors, such as the quality of the received signal, the choice of features, and the classification algorithm. In this literature review, we explore some of the recent developments in AMC, including feature extraction techniques, machine learning algorithms, and deep learning-based methods.

Feature extraction is an important step in AMC, as it involves transforming the raw signal into a set of informative features that can be used for classification. Several feature extraction techniques have been proposed in the literature, including statistical moments, wavelet transforms, and spectral analysis. Statistical moments, such as mean, variance, and skewness, can provide useful information about the signal's amplitude distribution. Wavelet transforms can decompose the signal into different frequency subbands, allowing the identification of modulation-related features. Spectral analysis techniques, such as periodogram and spectrogram, can provide valuable information about the signal's frequency content.

Machine learning algorithms have been extensively used for AMC due to their ability to learn complex patterns in data. Some of the popular machine learning algorithms used for AMC include Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests (RF). SVM is a binary classifier that separates different classes using a hyperplane in a high-dimensional feature space. K-NN is a non-parametric algorithm that classifies a test sample based on its proximity to the nearest k training samples. RF is an ensemble learning algorithm that combines multiple decision trees to improve classification accuracy.

Deep learning-based methods have shown promising results in AMC due to their ability to learn complex representations from raw data. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are two popular deep learning architectures used for AMC. CNNs use convolutional layers to extract local features from the input signal, while RNNs use recurrent connections to model temporal dependencies in the signal. Several variations of CNNs and RNNs have been proposed in the literature, such as ResNet, DenseNet, LSTM, and GRU.

Several studies have been conducted to compare the performance of different feature extraction techniques and classification algorithms in AMC. For instance, in a study by A. Khaldi et al., the authors compared the performance of different feature extraction techniques, such as wavelet packet decomposition, and statistical moments, in conjunction with different machine learning algorithms, such as SVM, k-NN, and RF. The results showed that wavelet packet decomposition with SVM achieved the highest classification accuracy. In another study by Y. Li et al., the authors proposed a deep learning-based approach for AMC using a hybrid CNN-RNN architecture. The proposed method outperformed several state-of-the-art methods, achieving an accuracy of 98.9

In conclusion, automatic modulation classification is an important task in wireless communications that has numerous applications in military and civilian domains. The performance of AMC systems depends on several factors, such as the quality of the received signal, the choice of features, and the classification algorithm. Feature extraction techniques, machine learning algorithms, and deep learning-based methods have been extensively used in AMC, with promising results. Several studies have compared the performance of different techniques and algorithms, providing insights into the strengths and limitations of different approaches. Overall, AMC is a challenging

3 Methodology and Implementation

3.1 Methodology

3.1.1 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 5”. Preprocessing in “Figure 5” 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.

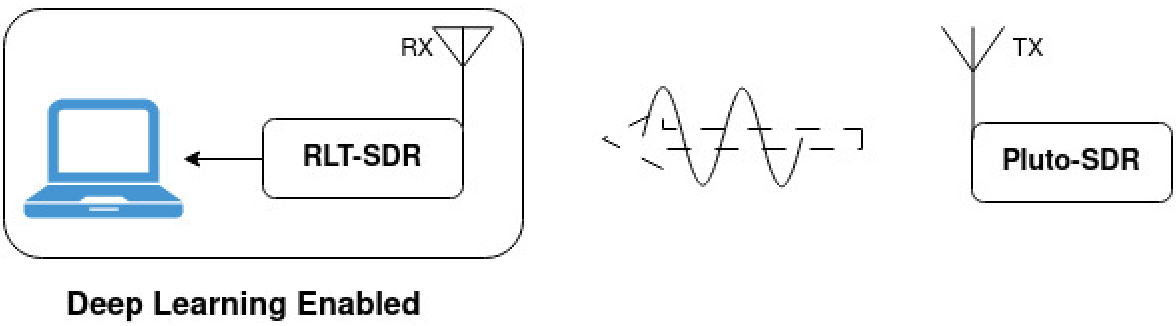

Figure 7. The proposed AMC method.

3.1.2 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

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

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

3.1.3 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.

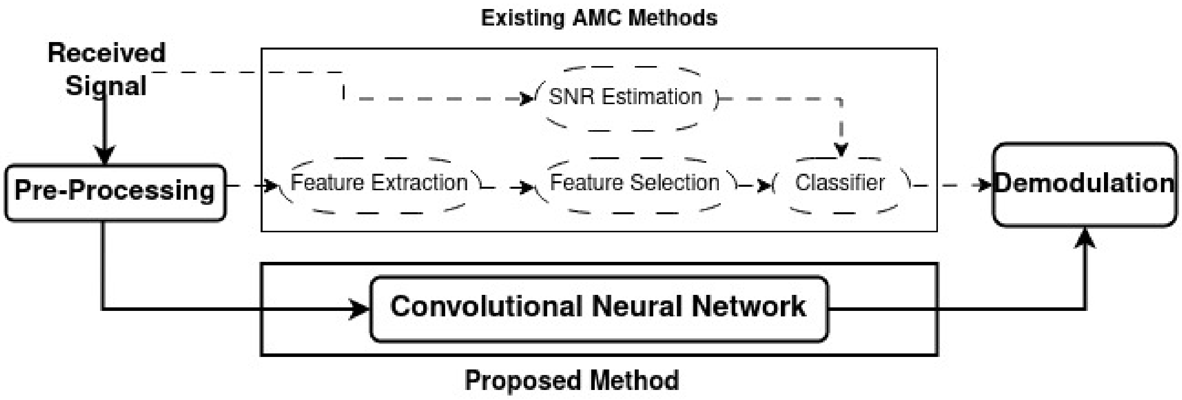

Figure 8. Block Diagram of Classification with CNN.

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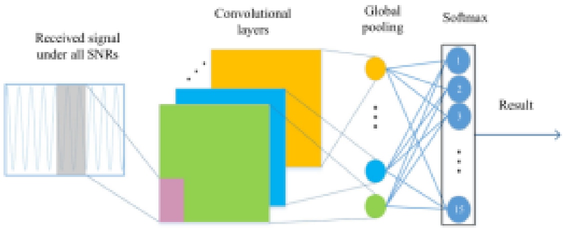

Figure 9. Classification with Deep CNN.

3.2 Implementation

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.

3.2.1 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 6”. We are tring to generate 20000 training samples and 1000 testing samples for each modulation type at every SNR level.

3.2.2 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.

4 Project Management Mechanism

4.1 Estimated project expenditure

Component	quantity	price
RTL-SDR blog V3	1	Rs 13750
ADALM-Pluto SDR	1	Rs 107000
Total		Rs 120750

Table 1. Estimated project expenditure.

5 Abbreviations

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 2. Summary of Abbreviations.

5.1 Task Allocation

Task	Responsible person
Plotting constellation diagram for ASK/FSK/PSK	Ahamed,Vishwa
Obtaining BER for ASK/FSK using matlab simulation	Ahamed,Vishwa
Purchasing electronic components	Ahamed,Vishwa
Implementation	Ahamed,Vishwa
Testing the system	Ahamed,Vishwa
Report Draft Preparation	Ahamed,Vishwa
3min Presentation preparation	ahamed,Vishwa
Project Report preparation	Ahamed,Vishwa

Table 3. Task allocation.

5.2 Workplan

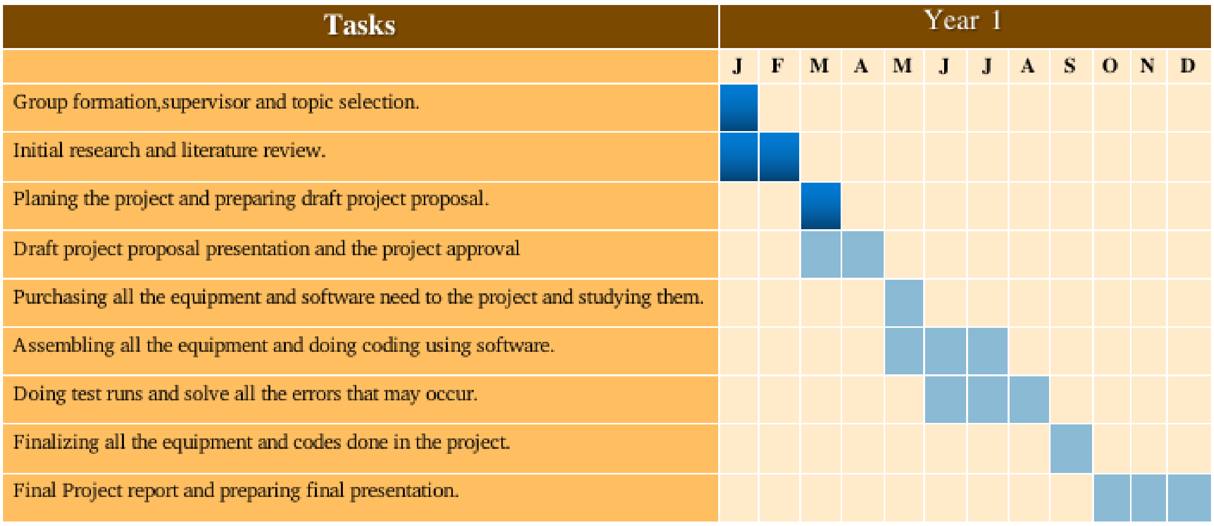

Figure 10. Gantt Chart.

6 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.

7 References

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