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CLASSIFICATION OF MODULATION TECHNIQUES USING CONVOLUTIONAL NEURAL NETWORK: A REVIEW

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ABSTRACT

A method to classify the required modulations among the various kinds of distributed systems by using the Convolutional neural network (CNN). A supervised Machine learning (ML) algorithm, Support vector machine (SVM) is used to classify the required modulation among all the modulations due to its advantages of majorly low complexity. In this paper, different researchers' research work is studied and different problems are faced like CNNs are a regularised version of multilayer perceptrons that were motivated by the biological process of neuronal connection. They are efficiently used in a variety of classification problems because, in contrast to other classification methods, they require less preparation. The CNN is explained in simple terms with relevant mathematical analysis. For a better understanding of the classification of modulated techniques, some analog modulation techniques such as Binary phase shift keying (BPSK), Quadrature phase shift keying (QPSK), 8-ary phase shift keying (8-PSK), 16-ary Quadrature amplitude modulation (16-QAM), 64-ary Quadrature amplitude modulation (64-QAM), 4-ary pulse amplitude modulation (PAM4), Gaussian frequency shift keying (GFSK), Continuous phase frequency shift keying (CPFSK) and digital modulations such as Broadcast FM (B-FM), Double sideband amplitude modulation (DSB-AM), Single sideband amplitude modulation (SSB-AM) are considered for review.

Keywords: - Deep learning, Machine learning, Modulation classification, Multiclass classification, Wavelet transform

INTRODUCTION

Understanding the radio spectrum autonomously is important for a number of applications, including electronic warfare and threat analysis in military scenarios, dynamic spectrum access, spectrum interference detection, and monitoring in civil scenarios, and the rapid emergence of various advanced standards and technologies for wireless communications [Zhou, 2019]. However, a number of undesirable issues, such as co-channel interference and signal distortion over propagation channels, have been brought about by densely connected networks that aggressively utilize spectrum to accommodate the extremely high traffic in massive wireless communication systems. In addition, radio signals can be encoded by a variety of modulation formats from a predefined candidate pool using the non-cooperative configuration that is utilized in contemporary communication systems to achieve intelligent spectrum management (Fig. 1), in which the modulation format is chosen based on channel conditions and system specifications. The development of an effective algorithm for analog and digital modulation techniques have been incorporated into communication systems over the past few decades [Ma, 2022]. Using analog modulations like amplitude modulation (AM), phase modulation (PM), and frequency modulation

(FM), a transmission signal is encoded in analog communication systems. Modulation identification is the top priority in many software-defined radio-based communications because automatic identification of the modulation types of received signals enables the receiver to demodulate the signal. Signal processing and communication societies are increasingly paying attention to automatic modulation classification (AMC), a precursor to signal demodulation in the physical layer [Ahmed, 2022]. From an artificial intelligence (AI) perspective, the fundamental goal of AMC is to classify the modulation type of an incoming signal at the receiver. This typically functions as a multi-class decision-making task. Concisely, conventional feature engineering methods, such as feature extraction and selection, can be used to obtain the underlying radio characteristics, including information about the modulation type, in order to learn a classification model through supervised or unsupervised learning [Liu, 2018]. However, AMC must deal with a number of difficult issues [Elsagheer, 2022], such as the growing number of modulation formats, intra-class discrimination of higher order digital modulations, and strong channel impairments.

To strike a good balance between spectrum efficiency and transmission reliability, numerous advanced numerous advanced analog and digital modulation techniques have been incorporated into communication systems over the past few decades [Ma, 2022].

An analog baseband signal, also known as the source signal, is typically encoded using an analog modulation technique onto a high-frequency periodic waveform, also known as the carrier signal. Digital modulations are more suitable for use than analog modulations due to their stronger robustness against interference and improved coordination with digital data. As depicted in Fig., digital modulation-based communication systems 3, before being sent to a digital modulator, the source signal is first digitized through sampling and quantization. The resulting digital signal is then coded to increase data security and reduce transmission errors. Amplitude-shift keying (ASK), phase-shift keying (PSK), frequency-shift keying (FSK), pulse amplitude modulation (PAM), amplitude and phase-shift keying (APSK), and quadrature amplitude modulation (QAM) are a few of the most common digital modulations. Depending on the pre-defined modulation technique, various waveform characteristics of the carrier signal—like amplitude, frequency, phase, and a combination of amplitude and phase—can be altered during the modulation process. Using a learned AI model, an incoming signal's radio characteristics are inferred to determine the best modulation over propagation channels.

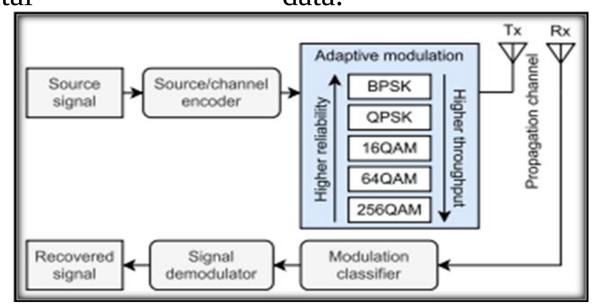

Figure 1: Communication system with an adaptive modulation [Huynh, 2021]

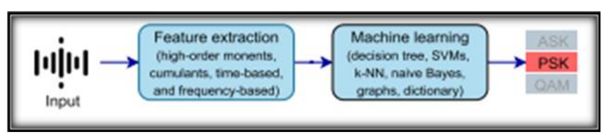

Figure 2: Overall processing flow of feature-based AMC approaches [Huynh, 2021]

Automatic modulation classification (AMC) that identifies the modulation type of the received signal is an essential part of non-cooperative communication systems. The AMC plays an important role in many civil and military applications such as cognitive radio, adaptive communication, and electronic reconnaissance.

In these systems, transmitters can freely choose the modulation type of signals; however, the knowledge of modulation type is necessary for the receivers to demodulate the signals so that the transmission can be successful. AMC is a sufficient way to solve this problem with no effects on spectrum efficiency

AMC algorithms have been widely studied in the past 20 years. In general, conventional AMC algorithms can be divided into two categories:

- Likelihood-based (LB) [Zhou, 2019] and
- Feature-based (FB) [P G, 2022].

LB methods are based on the likelihood function of the received signal, and FB methods depend on feature extraction and classifier design.

Although LB methods can theoretically achieve the optimal solution, they suffer from high computational complexity and require prior information from transmitters. In contrast, FB methods can obtain suboptimal solutions with much smaller computational complexity and do not depend on prior information.

Since the prior information required by LB methods is often unavailable in practice, researchers have paid more attention to FB methods over the past two decades. The two most important parts of FB methods are feature extraction and classifier. Various types of features have been studied and used in AMC algorithms. For example, instantaneous features [Yang, 2020 - Essai, 2023] were extracted from the instantaneous amplitude, frequency, and phase in the time domain. Transformation-based features were calculated from Fourier and wavelet transforms [Ahmed, 2022 – Liu, 2011]. The high-order cumulant (HOC) features are statistical features obtained from different orders of cumulants from the received signals. Additive white Gaussian noise (AWGN) can be completely mathematically eliminated in HOC features. Cyclostationary features are based on the spectral correlation function (SCF) derived from the Fourier transform of the cyclic autocorrelation function [Kharbech - 2014, 18]. The highest values of SCF for different cyclic frequencies are taken by the cyclic domain profile and used to train the classifiers.

The classifier is another important part of FB methods. The decision tree [Yang, 2020] is the most widely applied linear classifier in the early years. Linear classifiers are notably easy to implement but not feasible for linearly inseparable problems. Many nonlinear classifiers are applied in AMC, e.g., K nearest neighbor [Zhou, 2019], neural networks [P G, 2022], and support vector machine (SVM) with kernels [Yang, 2020]. SVM is considered to have advantages when the number of samples is limited and can provide better generalization ability at the same time. Thus, SVM has become the most useful classifier for AMC problems in recent years.

The performance of FB methods primarily depends on the extracted feature set. Features must be manually designed to accommodate the corresponding set of modulation and channel environments and may not be feasible in all conditions. Moreover, looking for effective features requires great consideration. Considering these factors, deep learning (DL) methods, which can automatically extract features, have been adopted. DL is a branch of machine learning and has achieved remarkable success because of its excellent classification ability. DL has been applied in many fields such as image classification [Essai, 2023] and natural language processing [Ahmed, 2022]. Several typical DL networks such as a deep belief network [Liu, 2018], stacked autoencoder [Elsagheer, 2022] and convolutional neural network (CNN) [Ma, 2022] have been applied in AMC. DL networks are commonly deployed as classifiers in most current DL methods. They address different aforementioned features. The classification accuracy of DL methods has proven to be higher than other classifiers, particularly when the signal-to-noise ratio (SNR) is low. The existing methods are all based on the assumption that the SNRs of training and testing are equal. However, the result of SNR estimation is often inaccurate in practice, the actual channel SNR may also be unstable or rapidly varying under certain conditions. In this case, current schemes often lack generalization ability. To solve this problem, a CNN-SVM model for AMC is proposed in this paper. Considering the advantages of the powerful capability of feature learning for deep learning networks, CNN is deployed to explore new features that are suitable for classification under various SNRs. CNN directly handles the received signals at mid-frequency from − 10 to 20 dB, and can create new features robust to SNR variation. The generalization ability of AMC under varying SNR conditions can be significantly improved by these features. The advantages and contributions of this method in this paper are stated as follows:

- Most current methods identify a limited set of modulation types, whereas the set of modulations considered in this paper is more complicated and contains 15 different types in total.
- Received signals are directly handled by the DL network at intermediate frequency (IF); however, most existing methods still require extra processing or transformation before classifying signals.
- The method can provide outstanding classification accuracy under a large SNR range; however, most existing method is only feasible under a certain SNR level.
- The CNN built in this paper plays the role of the feature extractor, whereas most DL methods only regard DL networks as powerful classifiers. The features learned by the CNN are displayed and analyzed. The contribution of different convolutional kernels is also visualized to better understand the feature learning process.

METHODS

The likelihood-based and feature-based AMC approaches, in which conventional feature extraction and classification algorithms are utilized to learn modulation patterns, are first reviewed in this work. The fundamental ideas of various deep architectures, from basic layers to advanced processing units, are systematically presented under the DL techniques umbrella. Then, we look at the most recent AMC techniques that use DL as their core technology to boost modulation classification's overall efficiency. Last but not least, we draw attention to a number of difficult issues and potential directions for future research on AMC. In a nutshell, the following summarizes the primary contributions of this paper:

- The underlying concept of likelihood-based and feature-based approaches is presented in a brief overview of conventional AMC methods. As a result, their inherent flaws are brought up for discussion.
- The fundamental ideas behind the FFNN, RNN, LSTM, and CNN architectures are discussed. Its remarkable how thoroughly the various processing units and layers' operating principles are described.
- We look at revolutionary AMC methods that use a variety of deep models as classifiers to not only get around the drawbacks of traditional AMC methods but also improve their accuracy and complexity. For the purpose of knowledge enlightenment, several intricately designed networks with attached architectural diagrams stand out.
- We identify a number of real obstacles and suggest possible ways to increase AMC's accuracy and complexity efficiency.

A. State-of-the-Art Approaches

Numerous AMC methods have been proposed to assist dynamic spectrum access and intelligent spectrum management. This section briefly reviews the existing traditional AMC methods, where most of them are basically categorized into the likelihood-based (LB) and feature-based (FB) approaches with the general processing flow illustrated in Fig.

1) *Older Methods*

A lot of the AMC methods in this group use probabilistic frameworks in likelihood-based methods and old machine learning frameworks in feature-based methods. Under the circumstances of both known and unknown channel information, likelihood-based approaches typically employ probability theories and hypothesis models to solve modulation identification problems [Kharbech, 2018]. Even though likelihood-based methods can achieve the best classification accuracy with perfect knowledge of the signal model and channel model—which is impossible in the real world—estimating model parameters is computationally complex [Kharbech - 2014, 2018]. Due to their relatively simple implementation and low complexity, feature-based approaches for classification tasks that adhere to a standard machine learning (ML) framework are more suitable for deployment in practical systems than likelihood-based approaches [P G, 2022]. The feature-based approaches have a number of major drawbacks, despite being adaptable to various channel models: limited ability to learn traditional classification algorithms and a limited discriminative experience with handcrafted features [Yang, 2020] – [Ahmed, 2022].

2) *Revolutionary Methods*

A few years ago, inspired by the unprecedented success of deep learning (DL) in a variety of fields, including computer vision [Liu, 2018], [Elsagheer, 2022], and communications [Ma, 2022], [Kharbech, 2018], a number of revolutionary methods have utilized a variety of DL architectures, including deep neural networks (DNNs), recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and convolutional neural networks (CNNs or CovNets), in order to significantly Higher-order modulation formats' classification accuracy under synthetic channel deterioration is improved by DL's automatic feature extraction and high learning capacity, which outperform conventional machine learning [Kharbech, 2014 - Hassan, 2011]. In addition, DL can be used for modulation classification in Internet-of-Things (IoT) systems [Yang, 2020], where edge devices generate a large amount of data, by effectively processing big data.

In recent decades, very few surveys have been carried out regarding AMC. Along with a summary of numerical results and a discussion of research trends, provides an extensive overview of likelihood-based and feature-based approaches. In contrast to [Elsagheer, 2022], the work [Essai, 2023] provided a more up-to-date overview of DL-based AMC methods after first outlining the fundamentals of deep networks. The insightful analysis and discussion of deep architectures, on the other hand, were omitted from [Essai, 2023]. As a result, the advantages and disadvantages of deep networks for particular channel conditions were not adequately discussed. Recently, broad evaluations of DL for a variety of difficult wireless communications tasks have been carried out. Mao and others looked at how DL was used for a variety of physical layer tasks like alignment of interference, resistance to jamming, physical coding, and classification of modulation. Liu [2018] gave a brief overview of how DL-enabled wireless signal identification and modulation recognition can be used for intelligent spectrum management and monitoring in IoT and fifth-generation (5G) networks. The study that was carried out by Jdid et al. [Elsagheer, 2022] primarily focused on the communication side of using DL for AMC in single-antenna and multi-antenna systems. A recent survey [Ma, 2022] covered modulation classification, signal detection, beamforming, and channel estimation as four fundamental aspects of intelligent radio signal processing. Although the aforementioned surveys came to the conclusion that DL can improve the performance of modulation classification in order to achieve high reliability in communication systems, they did not provide a comprehensive analysis of deep architectures and did not highlight the ways in which intricately designed deep networks can increase accuracy while maintaining an acceptable level of complexity.

B. The Modulation Recognition Approach Based on Deep Learning

Deep learning is a powerful artificial intelligence technique that can fit nonlinear networks and learn features from a lot of data. As a result, it is used extensively in computer vision, natural language processing, and speech recognition and has been extremely successful. Relevant researchers have applied deep learning to the field of communication [Ahmed, 2022] in light of the fact that mobile communication networks are capable of rapidly generating large quantities of various types of data. This presents opportunities for the advancement of communication technologies. In wireless communication, for instance, deep learning techniques can be used to identify signal modulation. Deep learning-based modulation identification methods are more accurate and robust than traditional AMR methods. The deep learning-based modulation recognition algorithm is essentially a feature-based recognition technique that must extract the signal's features. However, deep learning can automatically extract and classify the features of signals, displacing traditional recognition algorithms' steps of relying on expert experience to identify features. The recognition accuracy is also improved. Figure is a visual representation of the deep learning-based modulation recognition model.

In deep learning, there are numerous excellent neural networks like CNN, RNN, and others.

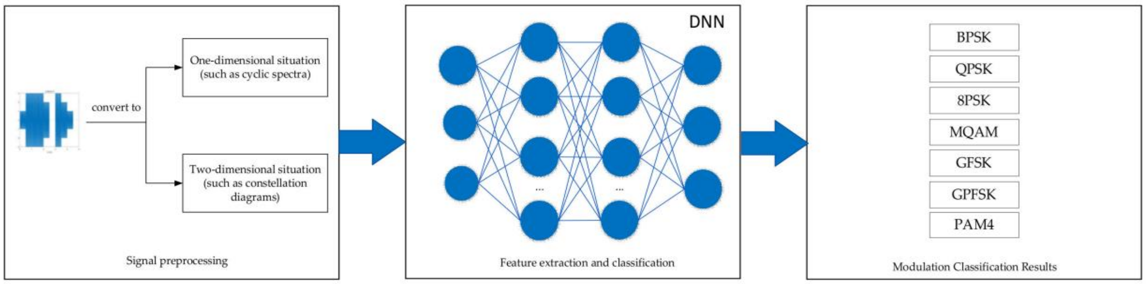

Figure 3: Deep learning-based modulation recognition model [Xiao, 2022]

RNN is good at processing sequence signals, while CNN is good at processing image data. In AMR, CNN and RNN are frequently used.

1) *Convolutional Neural Networks (CNN)*

The CNN is a well-known and widely used deep learning structure that addresses some of the challenges that existed in the early stages of artificial intelligence [Elsagheer, 2022]. In the fields of image processing, video recognition, and others, significant advancements were made, which may have contributed to the current boom in deep learning. The CNN's structure is depicted in the figure. A deep neural network and a convolution structure make up CNN. Convolution structure can reduce the number of network parameters to alleviate the model problem. A crucial component of convolution neural networks are their hidden layers. In most cases, the input, convolution, fully connected, pooling, and output layers of common CNN architectures are present. Convolution and pooling layers make up the majority of CNN. The learning convolution kernel is used to complete the convolution process in the feature mapping of the layer before it. Converting the kernel to a convolution layer is absolutely necessary.

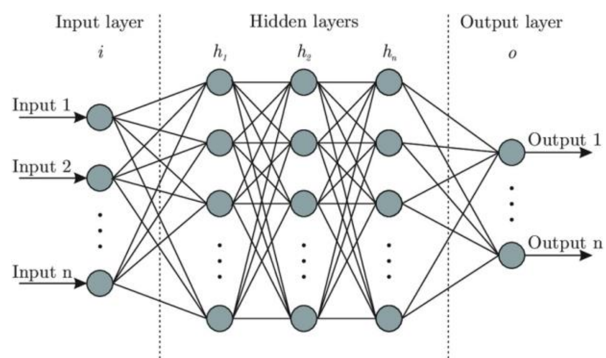

Figure 4: Typical convolutional neural network [Bre, 2018]

The core of the convolution kernel is the functional extractor. The automatic extraction of the deep data from the input signal is its primary function. The functional map of this layer, which is referred to as the functional extraction layer, is produced by the activation function when the output of the convolution result produces the neurons of this layer. The local receptive zone of the previous layer is connected to the input of each neuron in order to extract the local area properties. The final layer of the network is the fully connected layer. Most of the time, the ReLU (rectified linear unit) function is the activation function of each neuron in all of the linked layers. SoftMax activation might be used by the final output layer to achieve the classification function.

Understanding the precise mathematical connection between input and output, current networks are able to learn a great deal about input-output mapping. In actual applications, there are significantly more unlabeled data than labeled data. Manual data labeling also requires a lot of effort simultaneously. However, in order to fully train the supervised CNN and have higher generalizing capacities, a number of labeled training data are required, which limits the practical application of CNN to a certain extent. One of the most well-liked and successful deep learning architectures is the convolutional neural network (CNN), which has a structure diagram in Figure and consists of multiple convolutional, pooling, and fully connected layers. The pooling layer can downscale high-dimensional features after convolution to speed up computation, the fully connected layer can combine previously extracted local features into global features, and finally, the convolutional layer can complete the classification according to the features. Because it can precisely extract feature information from images through convolution, CNN is ideal for image processing. Therefore, scholars typically process the modulated signal into two-dimensional images like constellation diagrams and time-frequency diagrams before utilizing convolutional layers to extract the features of the signal from the image and the fully connected layer to classify the signal. On the other hand, CNN is frequently used to extract features directly from signals because it is also widely used in text and signals.

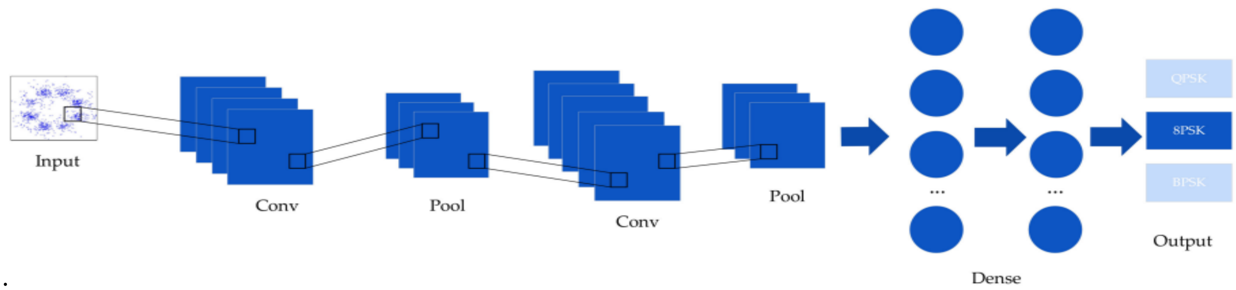

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Figure 5: Convolutional neural network structure [Xiao, 2022]

2) *Deep Neural Network (DNN) Overview*

A particular layered structure of Artificial Neural Networks (ANNs) serves as the foundation for the design of DL models. The human brain's biological neural network serves as a model for the design of ANN. A basic ANN's structure is depicted in the figure. The input layer, which receives the input data, is the first layer, and the output layer, which returns the output data, is the rightmost layer. Because their values aren't visible in the training set, the layers between these two perform mathematical calculations on the input data. These layers are called hidden layers. An ANN with multiple hidden layers is typically referred to as a DNN, and the deeper it is, the more hidden layers it has. There are several nodes, or neurons, in each layer. A neural network's fundamental component is the neuron. It processes an input x before producing an output. This output will either be sent to other neurons via weighted connections for further processing or it will be the final output. A particular weight Wi is associated with each connection between these neurons. These loads are haphazardly introduced and are refreshed during the model preparation process. The significance of the associated input value is determined by each weight. Additionally, the input is subjected to the bias bi linear component. The bias function alters the weight multiplied input's range.

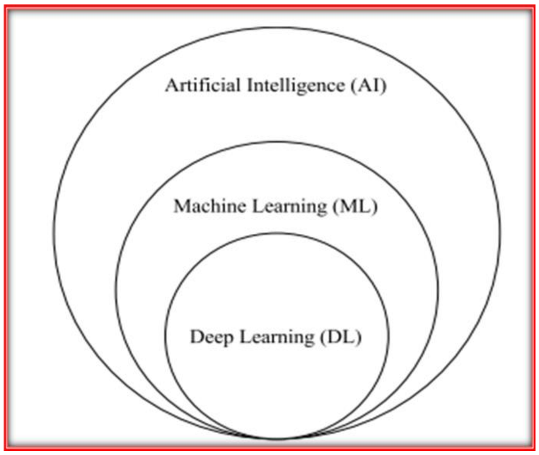

Figure 6: The taxonomy of AI as the broader umbrella for both ML and DL, and DL as a sub-branch of ML [Bachir, 2021]

The final linear component is, as can be seen:

$$L_i = x_i \times W_i + b_i$$

However, the primary objective of training a DNN is to reduce prediction error and improve prediction accuracy. As a result, this error ought to be measured and dealt with using a cost or loss function. In addition, rather than sending the entire input at once, the neural network should be trained on random batches of equal size. Additionally, regularization and optimization methods like dropout regularization and gradient descent optimization algorithms can be used. It is important to note that DNN can have loops, whereas Multi-Layer Perceptron (MLP) is always feed-forward

RELATED WORK

Paper	Channel	Modulation Pool	Results
[Kharbech, 2018]	Frequency flat time varying MIMO	{BPSK, QPSK, 8PSK} and {BPSK, QPSK, 8PSK, 4ASK, 8ASK, 16QAM}	ANNs classifier with antennas no. 2 × 6, 3 ×6 ($N_t \times N_r \in$) was used. Main feature was HOMs (higher order moments) up to eight order and HOCs (higher order cumulants) upto six order. It's recognition accuracy with mobility is less than 97% and for SNR its less than 5dB.
[Kharbech, 2014]	Frequency flat time selective MIMO	{BPSK, QPSK, 8PSK} and {BPSK, QPSK, 8PSK, 4ASK, 8ASK, 16QAM, 64QAM}	ANNs classifier with antennas no. 2 × 6, 3 ×6 ($N_t \times N_r \in$) was used. Main feature was HOMs (higher order moments) up to eight order and HOCs (higher order cumulants) upto six order.
[Hassan, 2011]	Frequency flat spatially correlated block fading MIMO	{BPSK, QPSK, 8PSK} and (BPSK, QPSK, 8PSK, 4ASK, 8ASK, 16QAM, 64QAM}	ANNs classifier with antennas no. N_t=2, N_r =4 was used. Main feature was HOMs (higher order moments) and HOCs (higher order cumulants) upto sixth order.
[Liu, 2017]	Time invariant and frequency flat MIMO	{BPSK, QPSK,8PSK} and {16QAM,64QAM}	Two ELMs classifier with antennas no. $N_t \in$ (2,4), N_r=4 was used. Main feature was HOMs (higher order moments) and HOCs (higher order cumulants) upto sixth order. It's recognition accuracy for 2x4 antennas is 95% for SNR less than 4dB.
[Guner, 2019]	Additive white Gaussian Noise (AWGN)	{BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM and 4-ASK}	ELM classifier with antennas no. N_t=1, N_r =1 was used. Main feature was LBP histogram features. It's recognition accuracy for 2048 symbols is 95% for SNR less than 2dB.
[Shah, 2019]	AWGN and Raleigh fading	{QPSK, 16PSK, 64PSK, BFSK, 4FSK, 16FSK, QAM, 16QAM and 64QAM}	ELM classifier with antennas no. N_t=1, N_r =1 was used. Main features are Shift c, scale σ, modulation parameters f and weight w. It's recognition accuracy for SNR is 0dB similar to 99.7% and similar to 100% at 512 samples and 1024 samples, respectively.
[Almohamad, 2018]	Multiple fading	{2ASK, QPSK and 16 QAM}	SVM classifier with antennas no. N_t=1, N_r =1 was used. Main feature was Histogram feature. Its recognition accuracy is similar to 99.83 % by employing all features.
[Yang, 2018]	AWGN	{2PSK, 4PSK, 8PSK and 16QAM, 32QAM and 64QAM}	SVM classifier with antennas no. N_t=1, N_r =1 was used. Main feature was characteristic parameters: T2, T4, T8, T16, T32. Its recognition accuracy is similar to 59% for SNR it's less than 2dB.
[Huang, 2011]	Multiple fading channels	{4QAM, 16QAM, 64QAM} and {8ASK, 16QAM, 64QAM, BPSK}	SVM classifier with antennas no. N_t=1, N_r =1 was used. Main feature was higher-order cyclic cumulants (CCs). Its recognition accuracy is less than 90% for SNR it's less than 10dB.
[Xie, 2017]	AWGN Channel	{2ASK, 4ASK, 8ASK, 16QAM, 2FSK, 4FSK, 88FSK, 2PSK, 4PSK, 8PSK}	SVM classifier with antennas no. N_t=1, N_r =1 was used. Main feature was 8 instantaneous feature, 7 HOCs, 5 wavelet feature, and 5 cyclostationary features. Its recognition accuracy is similar to 95% for SNR less then 5dB and similar to 97% for SNR it's less than 10dB.

CONCLUSION

The rapid development of information and wireless communication technologies, together with the large increase in the number of end-users, have made the radio spectrum more crowded than ever. Besides, providing a stable and reliable service is challenging, as electromagnetic environments are evolving and becoming more sophisticated. Accordingly, there is an urgent need for more reliable and intelligent communication systems that can improve the efficiency of the spectrum and the quality of service by providing agile management of network resources, so as to better meet the needs of future wireless users. Machine learning and deep learning are becoming increasingly popular in the automatic modulation recognition domain. Research in this area is still in its infancy, but it has shown outstanding results. In this article, a comprehensive survey of recent work lying at the junction of automatic modulation recognition, machine learning, and deep learning is studied, and it will be implemented in the future with the help of modulation techniques.

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