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Automatic Modulation Classification: Convolutional Deep Learning Neural Networks Approaches

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Abstract— In this study, automatic modulation classification (AMC), a key part of both civilian and military applications, is looked at using a deep learning method .A lot of research has been done on feature-based (FB) AM algorithms in particular.
In this paper, a robust AMC strategy based on convolutional neural networks (CNN) is proposed to solve the issue that current FB AMC methods frequently target a small set of modulations and lack generalisation capability. In total, 11 different modulation types are taken into consideration. Conventional AMCs can be categorised into maximum likelihood (ML)-based (ML-AMC) and feature-based AMCs. This paper proposes a robust convolutional neural network (CNN)-based automatic modulation classification (AMC) technique. The recommended method may automatically identify the characteristics of the incoming signals and classify them without the need for feature extraction. A comparison study was done for the proposed CNN-based AMCs with two different optimizers at two different signal-to-noise ratios to select the best one of them based on performance.
Keywords: *Modulation classification, Deep learning, Convolutional neural network Wireless signal.*

1. INTRODUCTION

The civilian wireless communication system uses adaptive modulation techniques to achieve the best transmission rates while fully utilising time-varying channels.

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In these situations, the transmitter and receiver must exchange information about a particular modulation scheme utilised in a communication process via a network protocol at the expense of protocol overhead. When the receiver is capable of recognising modulation schemes, this overhead could be reduced. However, many military applications demand the automatic identification of the modulation techniques used by adversarial communications. Interception of signals and jamming are examples of such applications.
A crucial component of non-cooperative communication systems is automatic modulation classification (AMC), which determines the kind of modulation present in the received signal. Cognitive radio, adaptive communication, and electronic reconnaissance are just a few of the many civic and military applications that depend on the AMC. In these systems, the signal's modulation type can be arbitrarily chosen by the transmitters, but the receivers must be aware of the modulation type in order to successfully demodulate the signals. Without affecting spectrum efficiency, AMC is a good solution to handle this issue.

In the last 20 years, AMC algorithms have received a lot of research. Generally speaking, likelihood-based (LB) [1] and feature-based AMC algorithms fall into two groups (FB)[2]. While FB strategies rely on feature extraction and classifier building, LB approaches are founded on the probability function of the received signal. Although LB approaches can theoretically reach the ideal answer, they have a large computational complexity and demand previous knowledge from transmitters.
While FB approaches do not rely on past knowledge and have a significantly lower computational complexity, they can nevertheless produce inferior answers. Over the past two decades, academics have focused more on FB approaches because the prior information needed by LB methods is frequently not available in practise. Feature extraction and classifying are the two crucial components of FB techniques. AMC algorithms have explored and utilised a variety of feature types. In the time domain, for instance, instantaneous amplitude, frequency, and phase were used to determine instantaneous

properties[3]. Fourier and wavelet transforms were used to calculate features based on transformations [4]. Statistically significant are high-order cumulant (HOC) [5] properties characteristics that are derived from various orders of cumulants [6] from the received signals. The mathematical elimination of additive white Gaussian noise (AWGN) in HOC features is possible. On the spectral correlation function (SCF) derived from the Fourier transform of the cyclic autocorrelation function, cyclostationary features are based [7]. In order to train the classifiers, the cyclic domain profile selects the greatest SCF values for various cyclic frequencies. Maximum Likelihood (ML)-based AMC techniques are also examined in [1], where it has been demonstrated that they achieve the best results when used with situations including mathematical channel models. As an end-to-end module, ML-AMCs analyse the probability functions of all potential modulations in contrast to feature-based AMCs and select the modulation scheme with the highest likelihood value. However, real-time low-cost implementation is highly challenging due to the high computational complexity[8]. Additionally, in complicated contexts, it is challenging to attain the precise likelihoods in ML-AMC. The machine learning techniques in feature-based AMCs merely serve as a mapping function between features and many hypotheses. The deep learning approach[9] has been rapidly evolving in recent years, both in algorithm design and hardware implementation [10], and it can learn noticeably more complex functions than a shallow one. This ends feature engineering. Deep learning's quick progress has produced some effective communications applications[11], such as modulation classification. The eye map of the raw signal is employed in [12] as the input for a Lenet-5-based classifier[13] and gently links the issue of AMC with the well researched field of image recognition. The extracted feature set is the main factor that affects how well FB techniques operate. In other cases, features may not be feasible, and they must be manually developed to satisfy the proper set of modulation requirements and channel conditions. Additionally, careful thought must be put into finding useful features. These characteristics have led to the adoption of deep learning (DL) techniques, which can automatically extract features. Due to its superior categorization capabilities, DL, a subfield of machine learning, has had exceptional success. Many domains, including image classification [14] and natural language processing[15] , have used DL. Many common DL networks have been used in AMC, including deep belief networks[16], stacked auto encoders[17], and convolutional neural networks (CNN) [18] have been applied in AMC. Most modern DL techniques frequently use DL networks as classifiers.

In our research, we present a deep neural network (DNN) enabled AMC that can automatically learn to extract features from lengthy symbol-rate data at low SNR, and we use the convolution neural network (CNN) to achieve this AMC. While significantly increasing speed, the CNN-AMC can approximate the ML-AMC with little performance loss. Our suggested CNN-AMC compares to the ML-AMC, which can also produce training data under various conditions. These features enable a significant improvement in the generalisation capability of AMC under various SNR circumstances. The benefits and contributions of our suggested strategy are listed as follows in this paper:

- The modulations that were looked at in this study are more complicated and include a total of 11 different types. Most current methods, on the other hand, can only find a small number of modulation types.
- Even though the DL network at intermediate frequency (IF) handles incoming signals directly, most methods still require more processing or transformation before signals can be classified.
- Most current methods only work at a certain SNR level, but this method can give very accurate classifications over a wide range of SNR levels.
- While most DL approaches solely consider DL networks as potent classifiers, the CNN constructed in this paper also serves as a feature extractor. CNN's learned features are presented and examined. To further comprehend the feature learning process, the contributions of several convolutional kernels are also shown.

In this article, two CNN-based automatic modulation classifiers are introduced. Each CNN-based AMC architecture employs one of three proposed classification layers (CL), namely: Sum of Squared Errors-based (SSE) CL, and crossentropy-based CL. The performance of the proposed CNN-based AMCs will be investigated using optimization algorithm, namely: Adaptive Moment Estimation (Adam).

The remaining portions of the essay are structured as follows: Section 2 provides an explanation of the fundamental model and the specifics of our suggested methodology, while Section 3 provides the simulation results and a commentary. Section 4 serves as the paper's final conclusion.

2. SYSTEM MODEL

Between the receiver's signal detection and demodulation is the AMC. In

Fig **1** , the structure of our proposed AMC technique is contrasted with that of more conventional approaches.

In

Fig **1**, preprocessing is quantization and sampling of IF signals. The CNN in this case takes the place of the feature extraction, feature selection, and classifier processes inside the dashed frame. Before being used, the CNN is offline pre-trained with the appropriate number of samples. Additionally, if the SNR range of the communication channel is known, the CNN can learn the characteristics that adjust to the appropriate circumstance. Because of this characteristic, our method is not dependent on SNR estimation.

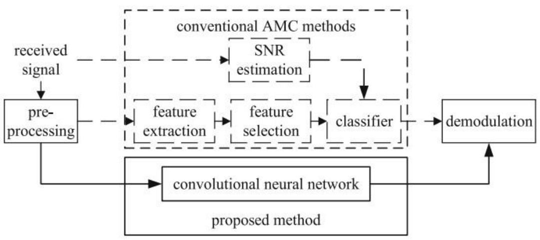


Fig 1: AMC method that is suggested and traditional methods are contrasted

2.1 Signal model

In this study, signals are distorted by AWGN while being processed in IF. The received signal can then be represented as

$$\mathbf{y(t) = x(t) + z(t)} \quad (1)$$

where $x(t)$ is the transmitted signal of different modulation types, $z(t)$ is AWGN, and SNR is defined as q_x/q_z (q_x is the power of signal and q_z is the power of noise). In this study, a set of modulations is examined that BPSK,QPSK,8-PSK,16-QAM,64-QAM,PAM4,GFSK,CPFSK,B-FM,DSB-AM,SSB-AM signals.$x(t)$ is expressed as

$$\boldsymbol{x(t) = A_m \sum_n a_n\, g(t - nT_s) \cos[2\pi(f_c + f_m)t + \varphi_0 + \varphi_m]} \quad \mathbf{(2)}$$

where A_m, a_n, T_S, f_c, f_m, φ_0, and φ_m are, in that order, the modulation amplitude, symbol order, symbol period, carrier frequency at IF, modulation frequency, starting phase, and modulation phase and $h(t)$ the gate function is shown as:

$$\mathbf{h(t)} = \begin{cases} \mathbf{1} & \mathbf{if 1 \le t \le T_s} \\ \mathbf{0} & \mathbf{other} \end{cases} \quad \mathbf{(3)}$$

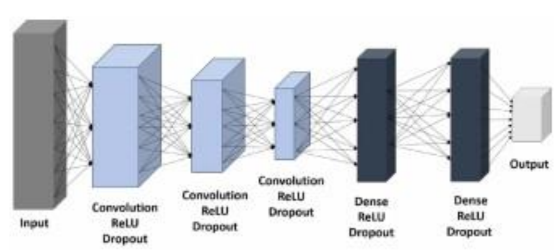
2.2 Convolutional neural network

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. A convolutional neural network condenses the input to the crucial elements that aid in identifying the input. Convolutional, pooling, and fully connected layers make up the three types of layers seen in typical CNN systems. In supervised learning, the last layer of the CNN uses an extra softmax regression layer as the classifier [19].

- **Convolution Layer**: The convolution layer performs the convolution between the filter and the input map. The underlying input is altered after the filter is applied in such a way that particular aspects of the input are highlighted.
- **Pooling Layer**: The output of the convolution layer must be compressed for some applications. By down sampling the feature map, pooling allows for the summary of the features. This makes the features for position changes more robust. The pooling method and the maximum pooling method are the most popular pooling techniques.
- **Fully connected layer**: Dense layers are used for the classification task, and each neuron in each layer is normally connected to every other neuron in the layer below with some weights and activations.
- **Output Layer**: The final layer, known as the output layer, uses a certain activation function to ascertain the probability response.

This image displays a typical CNN architecture. **Fig 2 and Table 1**

Fig 2: Convolutional Neural Network



layer number	layer type	output dimension	layer number	layer type	output dimension
1	Input Layer	(1×1024×1)	9	Max Pooling4	(1×64×48)
2	CNN 1	(1×1024×16)	10	CNN 5	(1×64×64)
3	MaxPooling1	(1×512×16)	11	Max Pooling5	(1×32×64)
4	CNN 2	(1×512×24)	12	CNN 6	(1×32×96)
5	Max Pooling2	(1×256×24)	13	Average Pooling 6	(1×1×96)
6	CNN3	(1×256×32)	14	Fully connected	(1×1×11)
7	Max Pooling3	(1×128×32)	15	Soft Max	(1×1×11)
8	CNN 4	(1×128×48)	16	Classification layer out put	

Table 1: **CNN's Organization**

3. Numerical results and discussion

The dataset used in this study was initially created. The dataset contains 10,000 frames for each investigated modulation type. The dataset is split into three sections: The proposed DNN-based AMCs are trained with 80% of the frames, validated with 10%, and tested with the remaining 10%. During the DNN training phase, training and validation frames are employed.

Test frames are used to determine the final classification accuracy. Each frame has 1024 samples and runs at a rate of 200 kHz. Eight samples constitute a symbol in digital modulation types. Each decision is made by the network based on a single frame rather than numerous consecutive frames. Assume that the digital and analogue modulation types have a centre frequency of 900 MHz and 100 MHz, respectively. The parameters of modulation are shown in Table 2

Parameter	Symbol	Value
Samples per symbol	SPS	8
Samples per frame	SPF	1024
Center frequencies	f_c	[900e6 100e6]
Sample rate	f_s	200e3

Table 2: Modulation Parameter

In this section, a comparative study will be conducted for the three proposed CNN-based AMCs. The three classifiers have the same architecture except for the final classification layer. Each classification layer is based on a different loss function. The adopted CLs are novel sum of squared errors-based CLs and crossentropy-based CLs, which are the most commonly used. The loss function can be expressed as follows[20]

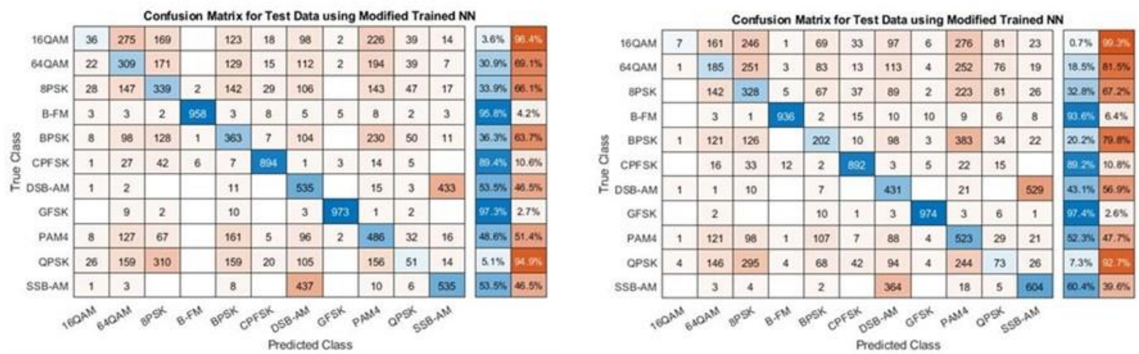
$$crossentropyex = -\sum_{i=1}^{N}\sum_{j=1}^{c} x_{ij}(k)\log(\widehat{X_{ij}}(k)) \tag{4}$$

$$\mathrm{SSE} = \sum_{i=1}^{N}\sum_{j=1}^{c}(X_{ij}(k) - \widehat{X_{ij}}(k))^2 \tag{5}$$

Where N is the sample number, c is the class number, X_{ij} is the i^{th} transmitted data sample for the j^{th} class and $\widehat{X_{ij}}$ is the CNN-based AMC response for sample i for class j. For the purpose of identifying the most robust CNN-based AMC, The performance of the proposed CNN-based AMCs will be investigated in terms of the classification accuracy using the optimizer Adaptive Moment Estimation (Adam). This experiment will be conducted at SNRs of 0 dB and 20 dB.

3.1 At SNR = 0dB

At SNR=0dB, the suggested CNN-based AMCs are used to directly classify signals (**Fig 3**) show the normalized classification accuracies of each modulated signal including16QAM, 64QAM, 8PSK, B-FM, BPSK, CPFSK, DSB-AM, GFSK, PAM4, QPSK, SSB-AM using the 11 CNN-based AMCs at SNR=0dB. The y-axis represents the true class of the modulated signals, and the x-axis represents the predicted class gotten from the examined CNN-based AMCs. The diagonal values represent the true classification accuracies. **Table 3** collects all classification accuracies for more comfort tracking.



crossentropyex SSE

Fig 3: Confusion matrixes for CNN-based AMCs using Adam optimizer and at SNR=0dB (Crossentropyex –SSE based CL)

Optimizer		ADAM										
Modulation Type		16QAM	64QAM	8PSK	B-FM	BPSK	CPFSK	DSB-AM	GFSK	PAM4	QPSK	SSB-AM
Loss Function	Crossentropyex	3.6	30.9	33.9	95.8	36.3	89.4	53.5	97.3	48.6	5.1	53.5
	SSE	0.7	18.5	32.8	93.6	20.2	89.2	43.1	97.4	52.3	7.3	60.4

Table 3: Classification accuracies for all investigated CNN-based AMCs using Optimizer (ADAM) and loss functions-based CLs (crossentropyex-SSE) at SNR =0dB

For **16QAM** modulation method, **64QAM** modulation method, 8PSK modulation method ,BPSK modulation method and QPSK modulation method, CNN $_{(ADAM,crossentropyex,SSE)}$ failed to correctly classify modulated signal.For **B-FM** modulation method, CNN $_{(ADAM,\ Crossentropyex)}$ achieves accuracy95.8% also CNN $_{(Adam,\ SSE)}$ provides a reasonable classification with 93.6% accuracy. For **CPFSK** modulation method, all examined classifiers provide a competitive classification performance of accuracies 89%.For DSB-AM modulation method ,PAM4 nodulation method and SSB-AM modulation method all examined classifiers provide a competitive classification performance of accuracies in range 43% to 60.4%. For **GFSK** modulation method,
CNN $_{(ADAM,\ crossentropyex,\ SSE)}$ achieve the highest accuracy 97.5%classification.

3.2 At SNR =20dB

At SNR=20dB, the suggested CNN-based AMCs are used to directly classify signals (Fig 4: **Confusion matrixes for CNN-based AMCs using Adam optimizer and at SNR=20dB (Crossentropyex –SSE based CL)**
) show the normalized classification accuracies of each modulated signal including16QAM, 64QAM, 8PSK, B-FM, BPSK, CPFSK, DSB-AM, GFSK, PAM4, QPSK, SSB-AM using the 11 CNN-based AMCs at SNR=20dB. The

y-axis represents the true class
of the modulated signals, and the x-axis represents the predicted class gotten from the examined CNN-based AMCs. The diagonal values represent the true classification accuracies.

(
Table 4**)** collects all classification accuracies for more comfort tracking**.**

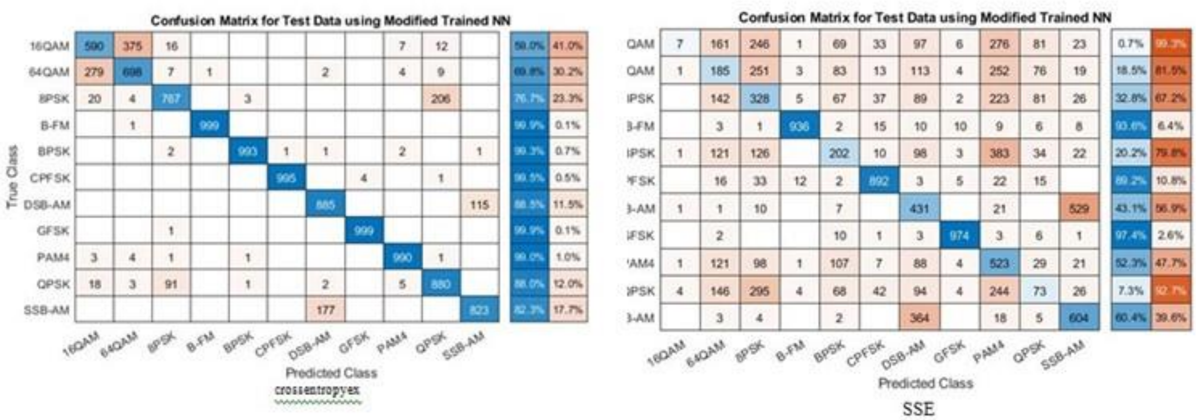


Fig 4: **Confusion matrixes for CNN-based AMCs using Adam optimizer and at SNR=20dB (Crossentropyex –SSE based CL)**

Optimizer		ADAM										
Modulation Type		16QAM	64QAM	8PSK	B-FM	BPSK	CPFSK	DSB-AM	GFSK	PAM4	QPSK	SSB-AM
Loss Function	Crossentropyex	59.0	69.8	76.6	99.9	99.3	99.5	88.5	99.9	99.0	88.0	82.3
	SSE	67.0	76.8	83.7	98.7	98.7	98.6	80.8	99.9	97.9	81.5	85.8

Table 4: **Classification accuracies for all investigated CNN-based AMCs using Optimizer (ADAM) and loss functions-based CLs (crossentropyex-SSE) at SNR =20dB**

For **16QAM**modulation method, $CNN_{(ADAM,Crossentropyex)}$achieves accuracy of 59% and $CNN_{(ADAM,SSE)}$ achieves accuracy of 67%. For **64QAM** modulation method, CNN $_{(ADAM, Crossentropyex)}$ achieves accuracy of 69.8% and $CNN_{(ADAM,SSE)}$ achieves accuracy of76.8% . For **8PSK** modulation method, CNN $_{(Adam, crossentropyex)}$ achieves accuracy of 76.6%. For **B-FM** modulation method ,BPSK modulation method ,CPFSK modulation method ,GFSK modulation method and PAM4 modulation method all examined classifiers provide a competitive classification performance of accuracies in range 98.6% to 99.9%.

For DSB-AM modulation method, QPSK modulation method and SSB-AM modulation method all examined classifiers provide a competitive classification performance of accuracies in range 80% to 80.5%

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4. CONCLUSION

In this paper, deep learning CNN-based AMCs have been proposed and new loss functions-based classification layers have been adopted to be used as the last layer. Finally, the developed classifiers' performance has been studied using optimizers: Adam. In total, 11 different modulation types have been used to train and test the proposed classifiers at SNR = 0, and 20 dB.The numerical results show that the true classification accuracy increases as the SNR increases. Also, the proposed AMCs achieve true classification accuracy that reaches 99.9% depending on the optimizer and loss function-base CL.The highest true classification accuracies (in range of 90%-99.9%) at SNR=10dB have achieved by CNN(ADAM Crossentropyex, SSE). The presented study demonstrates the importance of studying the effect of using optimizer (ADAM) and loss functions (crossentropyex-SSE) on the performance of CNN-based AMCs.

For future studies, the performance of proposed AMC can be investigated using other optimization algorithms such as Adaptive Gradient (AdaGrad), Stochastic Gradient Descent momentum and nesterov (SGDm+n), Adaptive Delta (Adadelta), and Nesterov-accelerated Adaptive Moment Estimation (Nadam), and loss functions-based classification layers.

ABBREVIATIONS

AMC: Automatic modulation classification
SNR: Signal to noise ratio.
FB: Feature Based
LB: Likelihood Based
IF: Intermediate frequency
AWGN: Additive white Gaussian noise
CNN: Convolutional neural network
DL: Deep learning
RELU: Rectified linear unit

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