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RESEARCH ARTICLE

Automatic Modulation Classification: Convolutional Deep Learning Neural Networks Approaches

HANY S. HUSSEIN[1,2], (Senior Member, IEEE), **MOHAMED HASSAN ESSAI ALI**[3], **MOHAMMED ISMEIL**[1,4], (Member, IEEE), **MOHAMED N. SHAABAN**[3], **MONA LOTFY MOHAMED**[5], AND **HANY A. ATALLAH**[4]

[1]Electrical Engineering Department, Faculty of Engineering, King Khalid University, Abha 61411, Saudi Arabia
[2]Electrical Engineering Department, Faculty of Engineering, Aswan University, Aswan 81528, Egypt
[3]Electrical Engineering Department, Faculty of Engineering, Al-Azhar University, Qena 83523, Egypt
[4]Electrical Engineering Department, Faculty of Engineering, South Valley University, Qena 83523, Egypt
[5]Electrical Engineering Department, International Maritime Science Academy, Hurghada 1971307, Egypt

Corresponding author: Mohamed Hassan Essai Ali (mhessai@azhar.edu.eg)

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ABSTRACT This study proposes robust convolutional neural network (CNN)-based automatic modulation classification (AMC) techniques. Traditional AMCs may be classified into two types: those that rely on ML (maximum likelihood-based AMCs) and those that rely on features. Numerous studies have been conducted on feature-based automatic modulation classification techniques. The current feature-based AMCs lack generalization capability and frequently target a small group of modulation techniques. The current paper develops three different CNN-based AMCs, each with a different classification layer (CL). The adopted classification layers are mean absolute error-based CL, a sum of squared errors-based CL, and crossentropy-based CL. The developed techniques can classify the received signals without feature extraction, where they can learn the features from the transmitted signals automatically during the offline training process, thus eliminating the necessity for feature extraction. A comparison study was done for the proposed CNN-based AMCs with three optimization algorithms at two signal-to-noise ratios. The proposed AMCs attain a true classification accuracy of up to 100% depending on the optimizer and loss function-base CL.

INDEX TERMS Modulation classification, deep learning, convolutional neural network, wireless signal.

I. INTRODUCTION

Signal modulation is an essential process in wireless communication systems. Modulation recognition tasks are frequently used in signal detection and demodulation. Appropriate demodulation of the received signal is essential for its subsequent processing. However, as wireless communication methods develop and more sophisticated needs emerge, the number of modulation schemes and parameters used in wireless communication systems increases dramatically. Therefore, the difficulty of correctly identifying and categorizing modulation techniques is growing. Recognizing the type of modulation used in transmitted signals is essential for demodulating and recovering the originally sent signals, which is what automatic modulation classifier (AMC) is all about [1]. Therefore, studying modulation recognition is crucial in studying receiver technologies for non-cooperative communication networks. Modulation classification is often a crucial communication problem in civilian and military applications such as spectrum management, signal identification, electronic warfare, and threat analysis. To create highly efficient jamming signals, it is critical in military communication systems to detect the modulation type [2].

Traditional modulation classification techniques frequently require a separate control channel since they rely on the user's prior knowledge of signal and transmission channel

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parameters [3]. Therefore, automatic modulation classification is necessary for wireless communication systems, where modulation schemes are likely to shift often due to environmental changes. For this reason, innovative techniques for detecting and classifying the modulation scheme are under consideration.

Likelihood-based (LB) [4], [5] and feature-based (FB) [6] algorithms are the two main types of conventional AMC methods. Theoretically, LB-based AMC techniques can find the optimal solution, but they are computationally intensive and necessitate background knowledge from transmitters. However, FB-based AMC techniques [7] do not require prior knowledge and can generate subpar solutions with significantly lower processing costs. The two most crucial components of FB methods are the feature extractor and the classifier. Traditionally the features extractor and classifier are separately built for an AMC system. For example, the envelope amplitude of the signal, the power spectral variance of the signal, and the mean of absolute value signal frequency were extracted in [8] to describe a signal from several different aspects. Yang and Soliman used the phase probability density function for AMC [9]. Meanwhile, traditional methods usually combine instantaneous and statistical features. Shermeh used the fusion of high-order moments and cumulants with instantaneous features for AMC [10]. The features can describe the signals using both absolute and relative levels. In addition, the high-order features can eliminate the effects of noise. The eighth statistic is widely used in several methods. Panagiotou et al. considered AMC as a multiple-hypothesis test problem and used decision theory to obtain the results [11]. They assumed that the phase of AWGN was random and dealt with the signals as random variables with a known probability distribution. Finally, the generalized or average likelihood ratio test was used to obtain the classification results by the threshold. The classifiers were then used in the AMC system. In [12], shallow neural networks and SVM were used as classifiers. In [13], modulation modes were classified using CNNs with high-level abstract learning capabilities. However, the traditional classifiers are let down either by their capacity for feature representation or by requiring complete prior knowledge, e.g., clock frequency offset. This approach has led to negative influences on the classification performance. Many different aspects have been investigated and implemented in AMC algorithms. For instance, in a time domain, instantaneous amplitude, frequency, and phase were utilized to extract instantaneous characteristics [14], [15]. Transformation-based feature extraction was computed using Fourier and wavelet transforms [16], [17]. Several types of nonlinear classifiers are utilized in AMC, such as neural networks [18] and support vector machines (SVM) with kernels [19]. SVM is believed to offer advantages and can also provide improved generalization capability when the number of samples is limited [20]. Therefore, in recent years, SVM has become the preferred classifier for AMC problems. Standard signal processing, sophisticated signal processing [21], and a machine learning approach [22] were all used to address AMC.

An intelligent communication concept has been proposed recently. It is envisaged that a smart receiver can decode the message data and locate the appropriate signal for every given application [23]. Deep Learning Neural Networks (DLNNs) are a successful type of machine learning due to their superior categorization abilities [24]. There are several fields where DLNNs have been put to use, including image classification [25], [26] and natural language processing [27]. DLNNs are used in communications systems because they have many benefits. First of all, communications systems have the big data that DLNNs require because there are so many communications devices with very high data rates [28]. Second, DLNNs can extract features independently, avoiding the time-consuming effort of manual feature selection. Third, because DL is continuously developing, it has excellent potential in communications fields.

Deep learning has recently emerged as a novel area of application in the realm of wireless communication systems. One of the most used DLNN architectures, the Convolutional Neural Network (CNN), is used to classify different modulation types.

Recently, accompanied by a probabilistic-based output layer, sparse autoencoders based on deep neural networks (DNNs) were introduced for AMC [29]. These methods showed the promising potential of the deep learning model for the AMC task. The advantage of CNNs is achieved with local connections and tied weights followed by some form of pooling which results in translation-invariant features. Furthermore, another benefit is that they have fewer parameters than fully connected networks with the same number of hidden units. In [30], Oshea et al. created a dataset with 24 different types of modulation, known as RadioML 2018.01A, and achieved high classification performance using convolutional neural networks specifically using residual connections within the network (ResNet). In [31], the authors treated the communication signal as 2-dimensional data, similar to an image, and took it as a matrix to a narrow 2D CNN for AMC. They also studied the adaptation of CNN to the time domain in-phase and quadrature (IQ) data. A 3D CNN was used to process video information in [32]. The result showed that CNN multi-frames were considerably more suitable than a single-frame network for video cognition. Recently, Zhang et al. applied a one-two-one network to compression artifact reduction in remote sensing [33]. This motivates us to solve the AMC problem. CNN is fed modulated signals by converting them into grid-like topological data, such as images of constellation diagrams [34], [35], [36]. Then the trained CNN is used to recognize radio modulation [37].

This article presents three automatic modulation classifiers based on convolutional neural networks. Each CNN-based AMC architecture employs one of three proposed

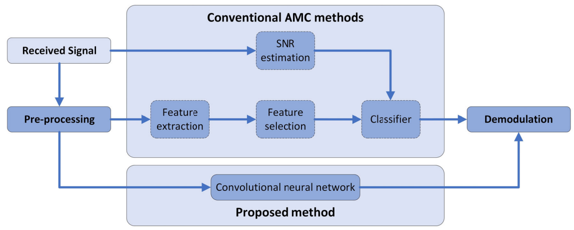

FIGURE 1. The block structure of the suggested receiver system.

classification layers (CL): mean absolute error-based CL, sum of squared errors-based CL, and crossentropyex-based CL. The performance of the proposed CNN-based AMCs will be investigated using three optimization algorithms, namely: Stochastic Gradient Descent with Momentum (SGdm), Adaptive Moment Estimation (Adam), and Root Mean Square Propagation (RMSProp).

The primary contributions of this paper can be summarized as follows:

1- The paper briefly reviews traditional AMC methods, where the underlying idea of likelihood-based and feature-based approaches is presented. Accordingly, their inherent drawbacks are pointed out for discussion.

2- The paper presents three automatic modulation classifiers based on convolutional neural networks. Each CNN-based AMC architecture employs one of three proposed classification layers (CL): mean absolute error-based CL, sum of squared errors-based CL, and crossentropyex-based CL.

3- The collection of modulations studied in this paper is more intricate and includes a total of 11 different types, in contrast to most current approaches, which only identify a small number of modulation types.

4- The proposed AMCs achieve true classification accuracy that reaches 100% depending on the optimizer and loss function-base CL.

5- The numerical results show that the true classification accuracy increases as the SNR increases.

6- The presented results demonstrate the importance of studying the effect of using different optimizers and loss functions on the performance of CNN-based AMCs.

7- Finally, the paper highlights several challenging issues and future research directions on the topic of AMC.

The article continues as follows. Section II details the model's foundations and our proposed methodology, while Section III presents simulation results and discussion. Then, the paper is summarized and afterward concluded in Section IV.

II. METHODS

AMC is a process performed by the receiver between signal detection and demodulation. Figure 1 illustrates the entire structure of the proposed AMC technique compared to the conventional AMC approach.

As depicted in Figure 1, the intermediate frequency (IF) signals are sampled and quantized during the pre-processing stage. The techniques within the dashed frame, such as feature extraction, feature selection, and classifier, are substituted by the mentioned CNN. Prior to implementation, CNNs are pre-trained offline using a sufficient sample size. Moreover, CNN has the ability to learn features that adjust to the situation as long as the SNR range of the communication channel is known.

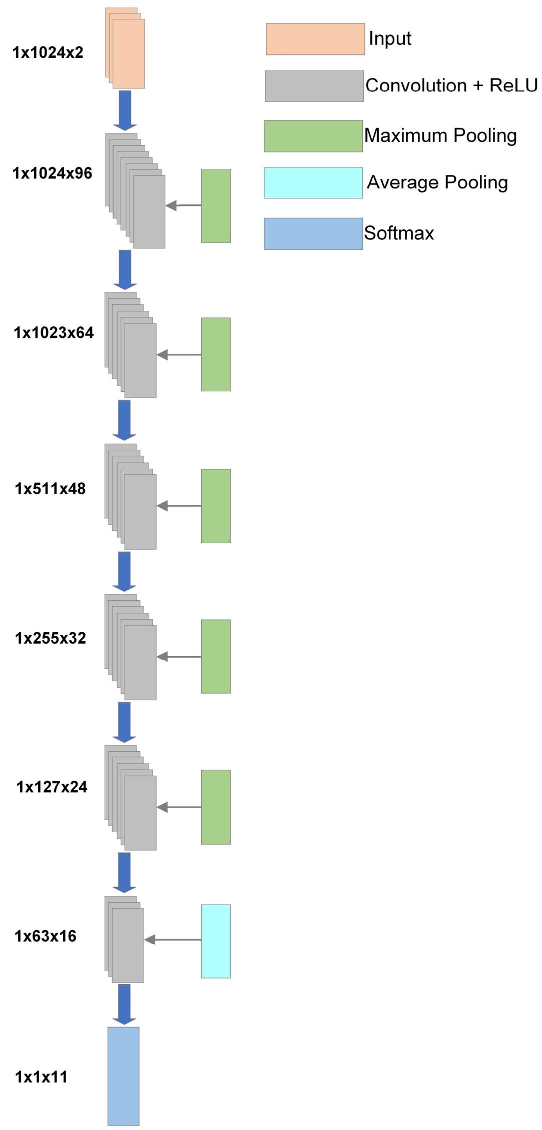

FIGURE 2. A CNN-based modulation classifier's architecture.

A. MODEL OF THE SIGNAL

In this article, signals are processed in IF and are corrupted by AWGN [38]. The received signal is then written by.

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

where $r(t)$ is the received signal, $s(t)$ is the transmitted signal of different modulation types, n(t) is AWGN, and SNR is defined as q_n/q_s (q_s stands for the signal power and q_n stands for the noise power). This study's modulation set consists of the following: BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, 4-PAM, GFSK, CPFSK, B-FM, DSB-AM, SSB-AM signals.

B. CONVOLUTIONAL NEURAL NETWORK

In simple terms, a CNN is a type of neural network in which at least one layer conducts a convolution instead of a matrix multiplication. The typical CNN structure includes three types of layers: convolutional, pooling, and fully connected. A supplementary softmax regression layer also serves as a classifier in the final CNN layer, specifically used for supervised learning purposes. [39].

1) CONVOLUTIONAL LAYER

In this research, a CNN is introduced, comprising six convolutional layers and one fully connected layer [40]. Except for the last, each convolution layer is preceded by a batch normalization layer, a rectified linear unit (ReLU) activation layer [41], and a max pooling layer. However, in the final convolution layer, an average pooling layer is employed instead of the max pooling layer, and the output layer is activated using the softmax function.

2) MAX-POOLING AND GLOBAL AVERAGE POOLING

The pooling layer is an integral part of CNN and holds significant importance. As mentioned earlier, the convolutional layer conducts multiple convolutions to produce a sequence of outputs. Subsequently, each of these outputs undergoes processing by a nonlinear activation function (ReLU) defined as:

$$Z_{out} = \Gamma_{max}(0, \omega Z_{in} + \gamma) \tag{2}$$

In this equation, Z_{in}, Z_{out}, ω, and γ represent the input and output of the function, weight, and bias, respectively. After this activation step, the layer's output undergoes further adjustments through a pooling function.

A pooling function substitutes the output at a specific position in the network with a summary statistic derived from related outputs [42]. In this research, the pooling technique utilized is max pooling, which selects the highest output within a pooling window. Following the last convolutional layer, global average pooling [43] is employed. This method calculates the average of each feature map, and the resulting output vector is directly fed into the softmax layer.

3) BATCH NORMALIZATION

The batch normalization (BN) layer expedites the training of deep networks by mitigating the issue of internal co-variate shift [44], [45]. In training, the internal co-variate shift refers to the alterations in the distribution of each layer's output, often induced by imbalanced nonlinear mapping (e.g., ReLU activation).

4) SOFTMAX REGRESSION

In the context of supervised learning, the last layer of a CNN is a softmax regression layer. Illustrated in Figure 2 and detailed in Table 1, the softmax regression serves as a multi-class classifier, operating similarly to logistic regression and providing probability distributions for the different classes.

III. NUMERICAL RESULTS AND DISCUSSION

The data set that was used in this study was initially created. The data set has 10,000 frames for each type of modulation that is studied. The data set is split into three parts: The proposed DNN-based AMCs utilize 80% of frames for training, 10% for validation, and the remaining 10% for testing. During the training phase of DNN, the training and validation frames are used. Test frames are used to figure out the accuracy of the final classification. Each frame has 1024 samples and runs at a rate of 200 kHz. In digital modulation types, one symbol is composed of eight samples. The network makes decisions based on a single frame instead of a series of frames. Assume that the center frequency of the digital and analogue types of modulation is 900 MHz and 100 MHz, respectively. The parameters of modulation are shown in Table 2

In this section, a comparative study will be conducted for the three proposed CNN-based AMCs. The architecture of the three classifiers is the same, except for the final classification layer. Each classification layer is based on a different loss function. The adopted CLs are novel mean absolute error-based CL, a sum of squared errors-based CL; and the most used crossentropyex-based CL. The loss function can be expressed as follows [46]:

$$crossentropyex = -\sum_{i=1}^{N}\sum_{j=1}^{c} x_{ij}(k) log(\widehat{X_{ij}}(k)) \tag{3}$$

$$SSE = \sum_{i=1}^{N}\sum_{j=1}^{c}(X_{ij}(k) - \widehat{X_{ij}}(k))^2 \tag{4}$$

$$MAE = \sum_{i=1}^{N}\sum_{j=1}^{c}\left\| X_{ij}(k) - \widehat{X_{ij}}(k)\right\| /N \tag{5}$$

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. In order to figure out which CNN-based AMC is the strongest. Using three optimizers, the performance of the proposed CNN-based AMCs will be investigated in terms of classification accuracy. Stochastic Gradient Descent with Momentum (SGdm), Adaptive Moment Estimation (Adam), and Root Mean Square Propagation are these optimizers (RMSProp). This experiment will be conducted at SNRs of 10 dB and 30 dB. In the scope of results analysis, we have used:

1- Confusion matrices for CNN-based AMCs using different optimizers, and loss functions-based classification layers.

2- Classification accuracy for all investigated CNN-based AMCs using different optimizers and loss functions-based classification layers. While in the scope of the validation of the results we have followed:

1-Accuracy validation curves obtained during the training process.

TABLE 1. CNN's organization.

Layer number	Layer type	Output dimension	Layer number	Layer type	Output dimension
1	Input Layer	$(1\times1024\times1)$	9	Max Pooling4	$(1\times64\times48)$
2	CNN 1	$(1\times1024\times16)$	10	CNN 5	$(1\times64\times64)$
3	MaxPooling1	$(1\times512\times16)$	11	Max Pooling5	$(1\times32\times64)$
4	CNN 2	$(1\times512\times24)$	12	CNN 6	$(1\times32\times96)$
5	Max Pooling2	$(1\times256\times24)$	13	Average Pooling 6	$(1\times1\times96)$
6	CNN3	$(1\times256\times32)$	14	Fully connected	$(1\times1\times11)$
7	Max Pooling3	$(1\times128\times32)$	15	Soft Max	$(1\times1\times11)$
8	CNN 4	$(1\times128\times48)$	16	Classification layer output	

TABLE 2. Modulation parameter.

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

2- Loss validation curves obtained during the training process.

A. RESULTS AT SNR = 10 dB

At SNR = 10 dB, the suggested CNN-based AMCs are used to directly classify signals. Figures 3-5, show the normalized classification accuracy of each modulated signal including 16QAM, 64QAM, 8PSK, B-FM, BPSK, CPFSK, DSB-AM, GFSK, PAM4, QPSK, SSB-AM using the 9 CNN-based AMCs at SNR = 10 dB. 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 true classification accuracy is indicated by the diagonal values. Table 3 collects all classification accuracy for more comfort tracking.

For 16-QAM modulation, $CNN_{(SGdm,MAE)}$ achieves a classification accuracy of 86.5% while $CNN_{(Adam,MAE)}$, $CNN_{(RMSProp,MAE)}$ and other CNN-based automatic modulation classifiers (AMCs) failed to classify 16-QAM modulated signal correctly. For 64-QAM modulation, $CNN_{(RMSProp,MAE)}$ achieves accuracy of 94.0%, also $CNN_{(Adam,MAE)}$ provides a reasonable classification with 86.1% accuracy, but $CNN_{(SGdm,MAE)}$ failed to classify correctly the 64-QAM modulated signal. For 8-PSK modulation, $CNN_{(Adam,Crossentropyex)}$ achieves an accuracy of 74.4%. For B-FM modulation, $CNN_{(SGdm,Crossentropyex)}$, $CNN_{(Adam,Crossentropyex)}$, and $CNN_{(RMSProp,Crossentropyex)}$ provide classification accuracy of 99.7%, 99.5%, and 99.3% respectively. Also, the rest of investigated CNN-based AMCs provide satisfactory performance. For BPSK modulation, $CNN_{(RMSProp,MAE)}$, $CNN_{(Adam,Crossentropyex)}$, and $CNN_{(RMSProp,Crossentropyex)}$ achieve classification accuracy of 90.7%, 90.4% and 90.0% respectively. For CPFSK modulation, all examined classifiers provide a competitive classification performance of accuracy in the range of 89% to 98.2%. For DSB-AM modulation $CNN_{(SGdm,MAE)}$ and $CNN_{(Adam,MAE)}$ failed to correctly classify, while $CNN_{(RMSProp,MAE)}$ peaks all 100% accuracy. For GFSK

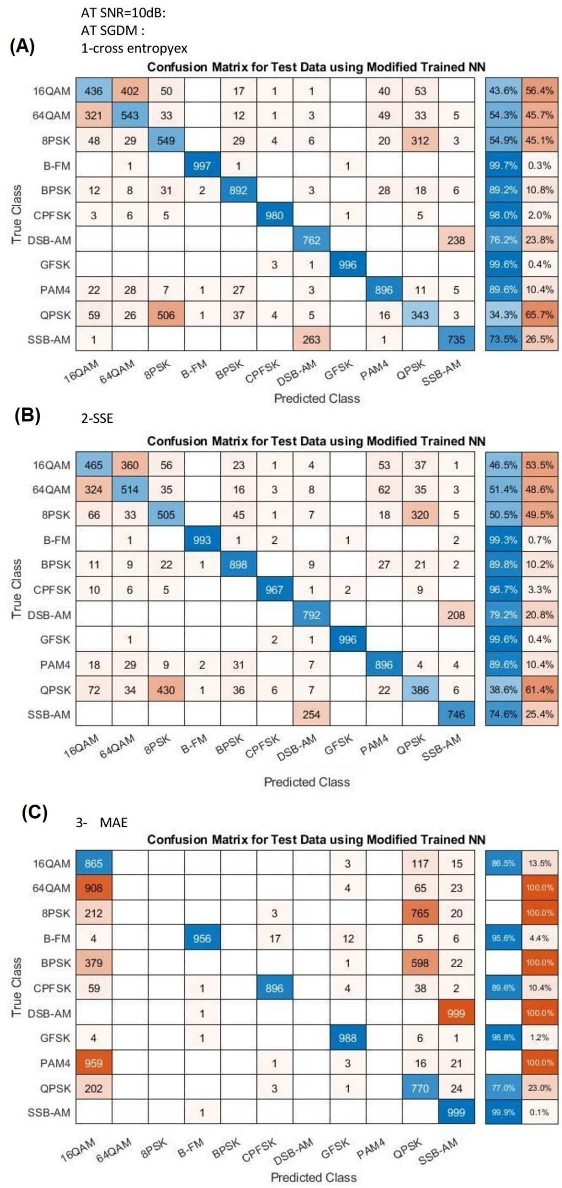

FIGURE 3. Confusion matrices for CNN-based AMCs using SGdm optimizer and at SNR = 10dB: (A) crossentropyex-based CL, (B) Steady-state Embedding (SSE)-basedCL and (C) Mean absolute error (MAE)-based CL.

modulation, all examined classifiers provide approximately 99% classification accuracy. For PAM4 modulation, $CNN_{(RMSProp,MAE)}$ and $CNN_{(SGdm,MAE)}$ failed to classify correctly, while its peers provide competitive performances

TABLE 3. Classification accuracy for all investigated CNN-based AMCs using different optimizers and loss functions-based CLs at SNR = 10dB.

	Optimizers	SGdm			Adam			RMSProp		
	Loss Functions	MAE	SSE	Cross.	MAE	SSE	Cross.	MAE	SSE	Cross.
Modulation Types	16QAM	86.5	46.5	43.6	0	31	27.9	0	36.9	33.7
	64QAM	0	51.4	54.3	86.1	63.6	69	94	55.2	61.9
	8PSK	0	50.5	54.9	0	63.6	74.4	0	52.1	55.8
	B-FM	95.6	99.3	99.7	96	97.9	99.5	96.6	98.6	99.3
	BPSK	0	89.8	89.2	86.2	89.9	90.4	90.7	84.6	90
	CPFSK	89.6	96.7	98	95.4	97	98.2	94.5	97	96.9
	DSB-AM	0	79.2	76.2	0	68.7	70.3	100	84	46.5
	GFSK	98.8	99.6	99.6	99.2	99.5	99.8	99.1	99.9	99.6
	PAM4	0	89.6	89.6	84.6	87.5	88.9	0	84.1	89.3
	QPSK	77	38.6	34.3	78.3	23.9	14	0	35.4	34.9
	SSB-AM	99.9	74.6	73.5	100	75.2	66	0	65.1	65.1

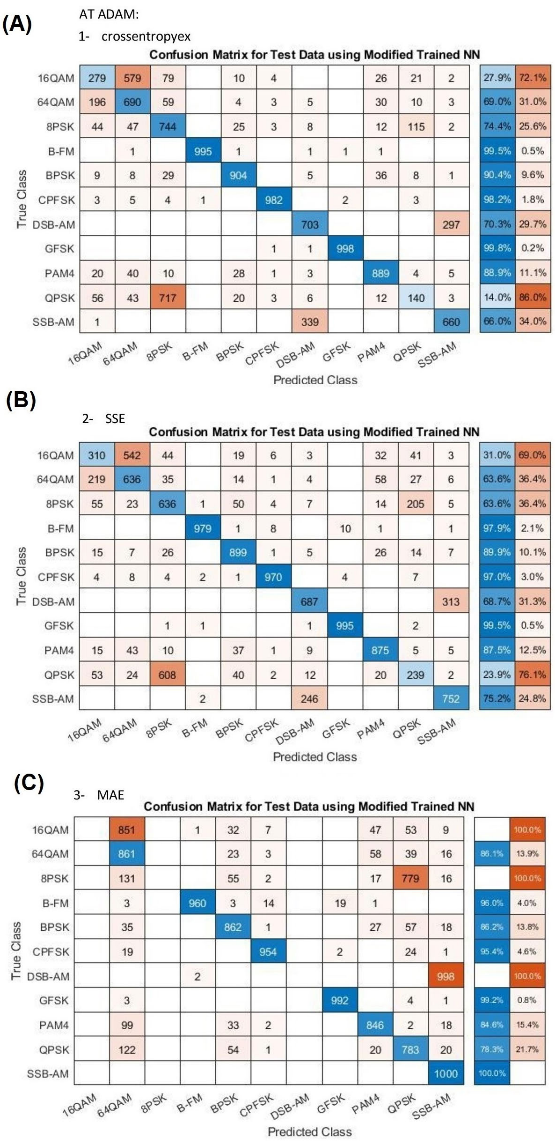

FIGURE 4. Confusion matrices for CNN-based AMCs using Adam optimizer and at SNR = 10dB: (A) crossentropyex-based CL, (B) SSE-based CL and (C)MAE-based CL.

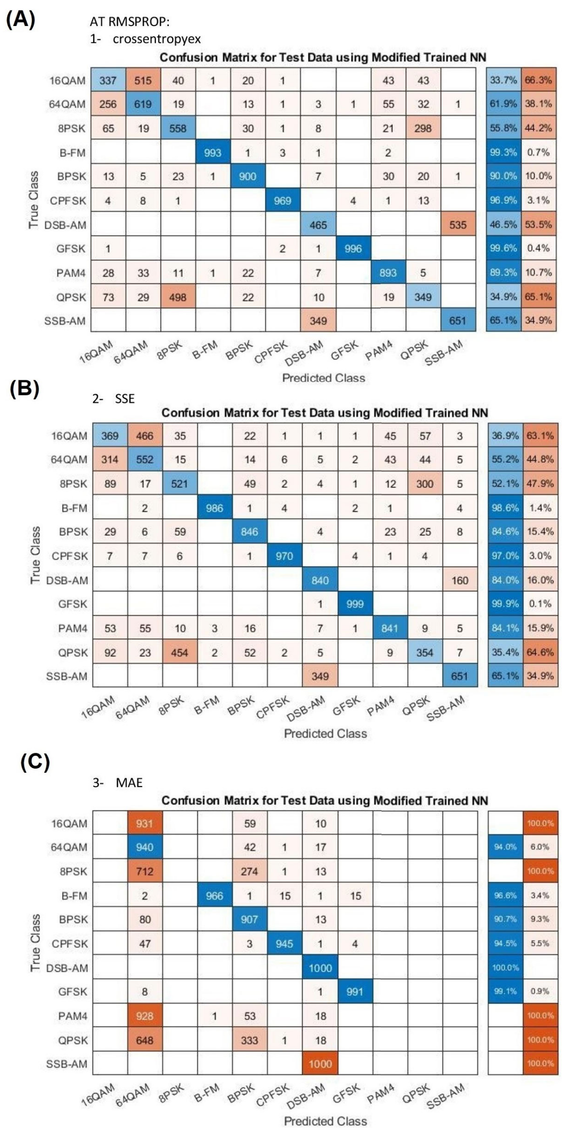

FIGURE 5. Confusion matrices for CNN-based AMCs using RMSProp optimizer and at SNR = 10dB: (A) crossentropyex-based CL, (B)SSE-based CL, and (C)MAE-based CL.

of accuracy in the range of 84.1% to 89.6%. For QPSK modulation $CNN_{(SGdm,MAE)}$ and $CNN_{(SGdm,MAE)}$ achieve modulation accuracies of 77.0% and 78.3%, respectively. For SSB-AM modulation, $CNN_{(RMSProp,MAE)}$ failed to correctly classify, while $CNN_{(SGdm,MAE)}$ and $CNN_{(Adam,MAE)}$ achieve modulation accuracies of 99.9% and 100%, respectively.

TABLE 4. Classification accuracy for all investigated CNN-based AMCs using different optimizers and loss functions-based CLs at SNR = 30dB.

	Optimizers	SGdm			Adam			RMSProp		
	Loss Functions	MAE	SSE	Cross.	MAE	SSE	Cross.	MAE	SSE	Cross.
Modulation Types	16QAM	97.8	75.8	71.5	0	84.8	82.9	99.4	79.5	80.1
	64QAM	0	76.1	72.5	98.8	85	85.5	0	80.9	86.6
	8PSK	0	84.8	87.1	96	93.9	93.9	93.5	87.6	90.5
	B-FM	96.6	99.7	99.9	98.7	98.9	99.9	97	98.5	99.7
	BPSK	96.1	99.5	99.8	0	99.9	100	99.8	99.2	99.7
	CPFSK	99	99.6	99.6	99.5	99.6	99.7	99.3	99.2	99.8
	DSB-AM	92.5	96.2	94.4	90.2	93.8	94.2	86.7	95.2	96.3
	GFSK	99.9	99.7	99.9	99.9	100	100	99.9	99.9	100
	PAM4	96.9	99.4	99.8	95.7	99.7	100	0	97.9	99.5
	QPSK	90.1	84.7	87.6	0	93.1	93.3	0	87.6	89.2
	SSB-AM	90	94.6	93.6	90.4	93.5	92.8	93.6	91	92.8

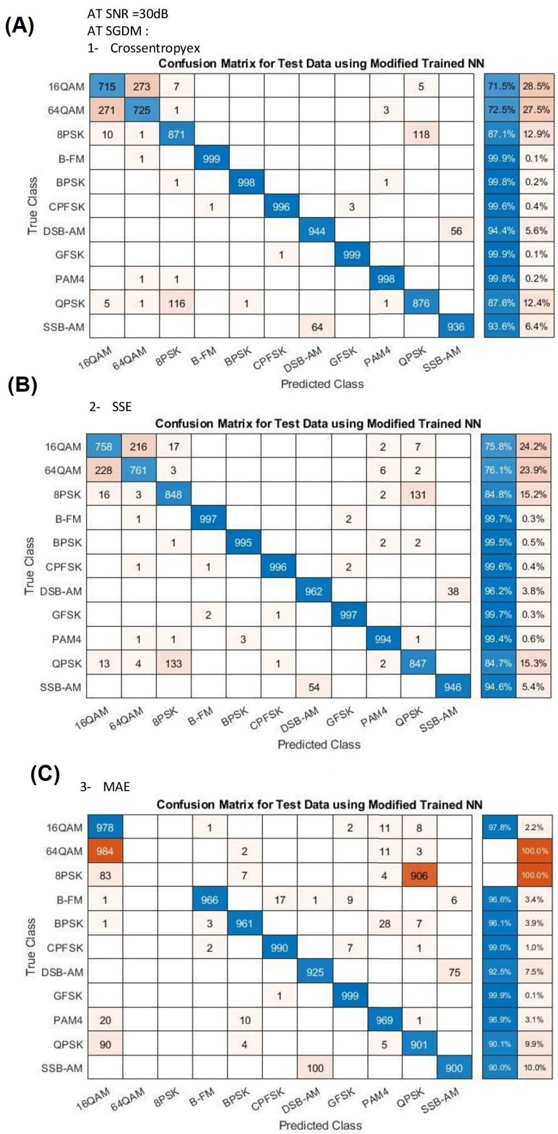

FIGURE 6. Confusion matrices for CNN-based AMCs using SGdm optimizer and at SNR = 10dB: (A) crossentropyex-based CL, (B) SSE-based CL, and (C) MAE-based CL.

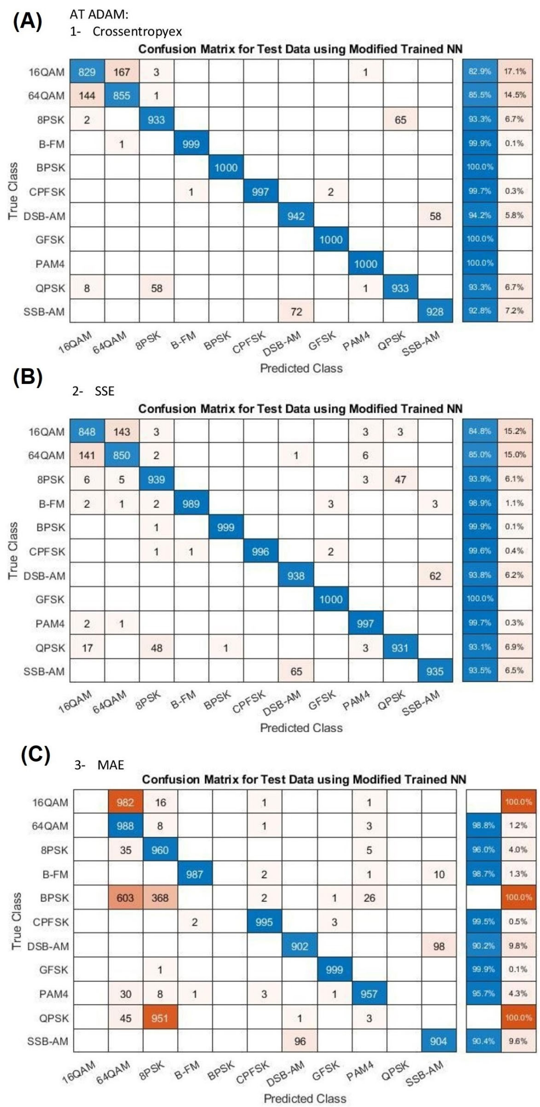

FIGURE 7. Confusion matrices for CNN-based AMCs using Adam optimizer and at SNR = 10dB: (A) crossentropyex-based CL, (B) SSE-based CL and (C) MAE-based CL.

B. RESULTS AT SNR = 30 dB

In this subsection, signals are directly classified by proposed CNN-based AMCs, at SNR = 30 dB. Figures 6-8 show the normalized classification for each modulated signals using the developed CNN-based AMCs. Table 4, lists all true classification accuracies at SNR = 30dB.

For 16-QAM modulation, $CNN_{(RMSProp,MAE)}$, $CNN_{(SGdm,MAE)}$ provides classification accuracies of 99.4%

TABLE 5. Advantages and disadvantages of proposed CNN-based AMCs in comparison to the traditional all AMCs.

	Advantages	Disadvantages
Traditional AMCs	1- Simple to apply. 2- Once a maximum-likelihood estimator is derived, the general theory of maximum -likelihood estimation provides standard errors, statistical tests, and other results useful for statistical inference. 3- The method is statistically well understood.	1- Computationally intensive and so extremely slow (though this is becoming much less of an issue). 2- Frequently requires strong assumptions about the structure of the data. 3- The estimates that are obtained using this method are often biased. That is, they contain a systematic error of estimation.
CNN-based AMCs	1- No human supervision is required. 2- Automatic feature extraction. 3- Highly accurate at image recognition and classification. 4- Weight sharing and Minimizes computation. 5- Ability to handle large datasets.	1- High computational requirements. 2- Training takes a long time.

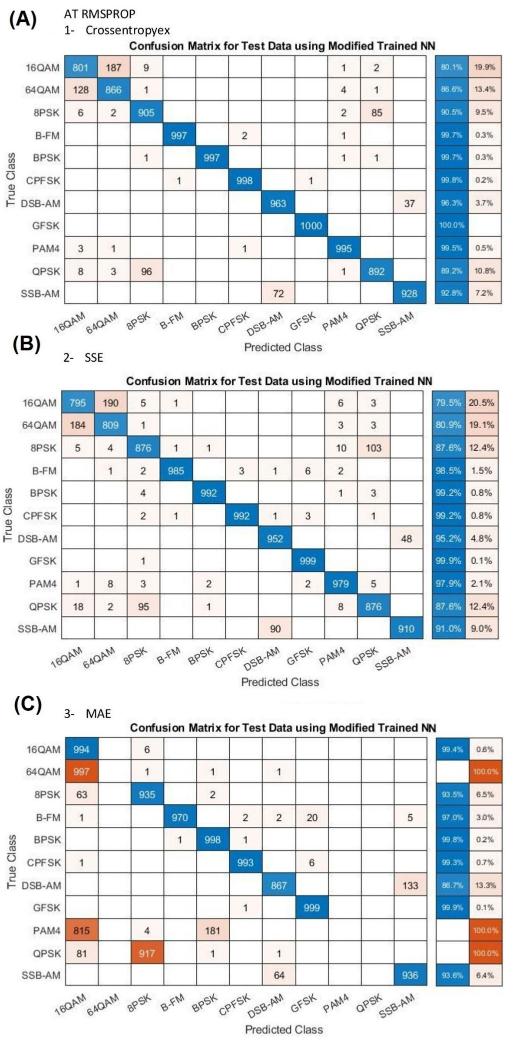

FIGURE 8. Confusion matrices for CNN-based AMCs using RMSProp optimizer and at SNR = 10dB: (A) crossentropyex-based CL, (B) SSE-based CL, and (C) MAE-based CL.

and 97.8%, respectively. For 64-QAM modulation, $CNN_{(Adam,MAE)}$ achieves an accuracy of 98.8%. For 8-PSK modulation, $CNN_{(Adam,MAE)}$ achieves an accuracy of 96%. For B-FM modulation, all examined classifiers provide a competitive performance while $CNN_{(SGdm,Crossentropyex)}$ and $CNN_{(Adam,Crossentropyex)}$ peak all with a classification accuracy of 99.9%. For BPSK modulation, $CNN_{(Adam,MAE)}$ failed to classify correctly, while the rest of investigated classifiers provide competitive classification performance and $CNN_{(Adam,Crossentropyex)}$ outperforms all at 100% accuracy. For CPFSK modulation, all examined classifiers provide a competitive classification performance of accuracies in the range of 99% to 99.8%. For DSB-AM modulation, all examined classifiers provide a competitive classification performance of accuracies in the range of 86.7% to 96.3%. For GFSK modulation, all examined classifiers provide approximately 100% classification accuracy. For PAM4 modulation, $CNN_{(RMSProp,MAE)}$ failed to classify correctly, while its peers provide competitive performances and $CNN_{(Adam,Crossentropyex)}$ peaks all at 100% accuracy. For QPSK modulation, $CNN_{(Adam,SSE)}$ and $CNN_{(Adam,Crossentropyex)}$ achieve classification accuracies of 93.1% and 93.3%, respectively. For SSB-AM modulation, all presented classifiers provide reasonable performances in the range of 90% - 94.6% by $CNN_{(SGdm,SSE)}$. At SNR = 10 dB, $CNN_{(Optimizer,MAE)}$ failed to classify the modulated signals of 16-QAM, 64-QAM, 8PSK, BPSK, PAM4, QPSK, DSB-AM, and SSB-AM. At SNR = 30 dB, $CNN_{(Optimizer,MAE)}$ failed to classify the modulated signals of 16-QAM, 64-QAM, 8PSK, BPSK, PAM4, and QPSK.

In traditional machine learning techniques such as a simple artificial neural network, most of the applied features need to be identified by a domain expert to reduce the complexity of the data and make patterns more visible for learning algorithms to work. The biggest advantage of deep learning algorithms is that they try to learn high-level features from data in an incremental manner. This eliminates the need for domain expertise and hard-core feature extraction. Finally, we will make a comparison between the proposed AMC models and the more traditional peers in terms of advantages and disadvantages as shown in Table 5.

IV. CONCLUSION

In this paper, deep learning CNN-based AMCs have been proposed and two 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 three different optimizers: SGdm, Adam, and RMSProp. In total, 11 different modulation types have been used to train and test the proposed classifiers at SNR $= 10$ and 30 dB. The numerical results show that the true classification accuracy increases as the SNR increases. Furthermore, the proposed AMCs achieve a true classification accuracy that reaches 100% depending on the optimizer and loss function-base CL. The highest true classification accuracy (in the range of 90%-100%) at SNR $= 10$ dB, and 30 dB have been achieved by $CNN_{(RMSProp, MAE, Crossentropyex, SSE)}$, and $CNN_{(Adam, Crossentropyex, SSE, MAE)}$, respectively. The current study highlights the significance of investigating using various optimizers and loss functions and their effects on the performance of CNN-based AMCs. In subsequent research endeavors, the performance of the 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.

DECLARATIONS

A. CONFLICT OF INTEREST/COMPETING INTERESTS

The authors declare that they have no competing interests.

B. ETHICS APPROVAL

Not applicable.

C. CONSENT TO PARTICIPATE

Not applicable.

D. CONSENT FOR PUBLICATION

All authors have agreed and given their consent for submission of this article to Wireless Networks.

E. AVAILABILITY OF DATA AND MATERIALS

Not applicable.

F. CODE AVAILABILITY

Not applicable.

G. AUTHORS CONTRIBUTIONS

Mohamed Hassan Essai Ali and Hany S. Hussein: conceptualization; Mohamed Hassan Essai Ali, Mohamed N. Shaaban, and Mona Lotfy Mohamed: formal analysis and funding acquisition; Mohamed N. Shaaban and Mona Lotfy Mohamed: investigation, writing-original draft, and provided resources and software; Mohamed Hassan Essai Ali, Hany A. Atallah, and Mohammed Ismeil: methodology; Mohamed Hassan Essai, Hany S. Hussein, Mohammed Ismeil, and Hany A. Atallah: project administration, supervision, and writing-review editing. All authors read and approved the final manuscript.

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HANY S. HUSSEIN (Senior Member, IEEE) received the B.Sc. degree in electrical engineering and the M.Sc. degree in communication and electronics from South Valley University, Egypt, in 2004 and 2009, respectively, and the Ph.D. degree in communication and electronics engineering from the Egypt–Japan University of Science and Technology (E-JUST), in 2013. In 2012, he was a Special Researcher Student with Kyushu University, Japan. He has been an Associate Professor with the Faculty of Engineering, Aswan University, since 2019. He is currently an Assistant Professor with the College of Engineering, King Khalid University, Saudi Arabia. His research interests include digital signal processing for communications, multimedia, image, and video coding; low-power wireless communications; and one-bit ADC.

MOHAMED HASSAN ESSAI ALI was born in El-Balyana, Sohag, Egypt, in 1978. He received the B.S. degree in electrical engineering from Al-Azhar University, Egypt, in 2001, the M.S. degree in electrical engineering from Assiut University, Egypt, in 2007, and the Ph.D. degree in mechanical engineering from Novosibirsk State Technical University, Novosibirsk, Russia, in 2012. From 2001 to 2008, he was a Demonstrator and a Lecturer Assistant with Al-Azhar University, where he was an Assistant Professor, from 2012 to 2018. From April 2014 to December 2014, he was a Guest Researcher with Novosibirsk State Technical University. Since 2018, he has been an Associate Professor with the Department of Electrical Engineering, Faculty of Engineering, Al-Azhar University. He is the author of five textbooks and more than 43 articles. His research interests include theory and applications of robust statistics, wireless communication, channel estimation of signals in terms of a priori uncertainty for the problems of telecommunications, optical wireless communication, artificial intelligence-based signal processing applications, and FPGA-based applications.

MOHAMMED ISMEIL (Member, IEEE) was born in Qena, Egypt, in October 1977. He received the B.Sc. and M.Sc. degrees in electrical engineering from South Valley University, in 2002 and 2008, respectively, and the Ph.D. degree from the Department of Electrical Drive Systems and Power Electronics, Technical University of Munich (TUM), Germany, and the Channel System Program, Aswan University, in April 2014. From April 2014 to September 2018, he was an Assistance Professor with the Faculty of Engineering, Aswan University. Since October 2018, he has been an Associate Professor with the Qena Faculty of Engineering, South Valley University. From March 2020 to November 2022, he was the Head of the Electrical Department, Qena Faculty of Engineering, and since November 2002. He is currently an Associate Professor with the College of Engineering, King Khalid University, Saudi Arabia. His current research interests focus on power electronics applications in wind energy conversion systems, PV interface with the utility, smart grid technologies, and digital control applications (PIC, FPGA, and DSP).

MOHAMED N. SHAABAN was born in Sharqiya, Egypt, in July 1983. He received the B.Sc. and M.Sc. degrees in electrical engineering (electronics and communications) from Al-Azhar University, in 2007 and 2014, respectively. From October 2015 to September 2020, he was a Ph.D. Student with the Department for Radio-Electronic and Telecommunication Systems, Kazan National Research Technical University, named after A. N. Tupolev—KAI, Russia, as a Governmental Study Mission. From 2009 to 2020, he was a Demonstrator and a Lecturer Assistant with Al-Azhar University, where he has been an Academic Lecturer with the Faculty of Engineering—Qena, since March 2021. He is the author of 16 articles, including one patent entitled: Millimeter Wave Antenna (RU2694156C1). His current research interests focus on antenna design and there applications, digital control systems, wireless communication and FPGA-based applications, and dialectic waveguide antennas.

MONA LOTFY MOHAMED received the B.Sc. degree in electronics and communications engineering from Assuit University, Egypt, in 2011. She is currently pursuing the M.Sc. degree in communication engineering with Qena University. Since 2019, she has been an Engineer with the International Maritime Science Academy, Red Sea, Egypt. Her research interests include artificial intelligence, deep learning, machine learning, convolutional neural networks, and modulation classification.

HANY A. ATALLAH was born in Qena, Egypt. He received the B.Sc. and M.Sc. degrees in electrical engineering and electronics and communications from South Valley University, Egypt, in 2007 and 2012, respectively, and the Ph.D. degree in antennas and microwave engineering from Egypt–Japan University for Science and Technology (E-JUST). He is currently an Associate Professor with the Electrical Engineering Department, Faculty of Engineering, South Valley University. He was a Visiting Researcher with the E-JUST Laboratory, School of Information Science and Electrical Engineering, Kyushu University, Japan, from September 2015 to July 2016. His research interests include antenna design, dielectric resonators, metamaterials, reconfigurable antennas, antenna arrays, microwave filters, and FDTD. His current research interests include cognitive radio (CR) antennas, wireless power transfer (WPT) for biomedical implants, electric vehicles, electronic devices, breast cancer detection, smart meters, artificial intelligence, neural networks, and the Internet of Things (IoT).