Automated Modulation Classification in Wireless Communication: A Deep Convolution Neural Network based Approach

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Abstract

This study conducts an empirical investigation focused on enhancing the performance of automatic modulation classification in wireless communication systems. We integrate a Customized CNN model with deep learning features. Initially, we employ pre-deep learning models to extract crucial features. These extracted features are then fed into a custom CNN classifier for precise modulation format categorization. To provide a comprehensive comparison of feature classification against pre-deep learning models, we find that our proposed model achieves superior classification results. We validate our approach using the publicly available RADIOML 2018.01A dataset. Our experiments reveal that our proposed scheme achieves an impressive accuracy of 95.16%, outperforming other state-of-the-art classification methods.

Keywords: CNN, Customized CNN, Deep Learning

1. Introduction

Due to the development of numerous modulation schemes for communication reasons, the wireless communication landscape is getting more complex [1]. The automatic modulation classification approach is essential for wireless communication signal analysis and signal processing [2]. This approach has uses in the business and military sectors alike. Rapid modulation type identification is essential in software-defined radio (SDR), where numerous communication streams are used [4, 5]. In these situations, it is clear that sophisticated automatic modulation categorization systems are necessary. Additionally, it is crucial to determine the source of received wireless signals [6, 7].

The two main subcategories of AMC are likelihood-based and feature-based techniques [8]. By contrasting the characteristic function of modulation with a predetermined pool of known modulations, the likelihood-based method [6] establishes the modulation type. It is helpful in situations involving several channels [9] where the modulation classification approach is used. However, when dealing with unknown elements like signal frequency, channel characteristics, and coding rates [10]. The received signal is put through a procedure in the feature-based method where its unique features are retrieved. After being extracted, these features are sent to a pattern recognition algorithm to detect the signal's modulation [11, 12]. Many conventional pattern recognition algorithms frequently manually retrieve asynchronous delay sampling features, higher-order statistics, time-frequency statistics, and other signal attributes [13].

Modulation classification has evolved significantly due to recent developments in artificial intelligence, including a striking rise in the processing power of individual computer processors [15, 16]. To achieve this classification, deep learning techniques have emerged as a crucial tool enabling information integration and recognition [17]. Multi-layer structures, which characterize deep architectures, allow for extracting additional signal features without requiring laborious manual data feature selection [18]. Currently, models like Residual Networks (ResNet-50), VGG-16, Convolutional Neural Networks (CNN), and Customized CNN have successfully been used to classify modulations.

This document's structure is described as follows: The related work is covered in Section 2, the planned work is presented in Section 3, the experimental findings and analysis are shown in Section 4, and the conclusion is provided in Section 5.

2. Related Work

Numerous automated CAD models that use different machine-learning techniques have proven to perform well in various applications [18–21]. For instance, Beura et al. [19] developed a CAD model that successfully classified data using a back-propagation neural network (BPNN) classifier and discrete wavelet transform (DWT) in combination with GLCM features. A different CAD approach was proposed in [22], which combines a KNN classifier with DWT and GLCM features. A model by Liu et al. [23] uses a support vector machine (SVM) classifier and principal component analysis (PCA) to condense DWT features. The development of a discrete curvelet transform (DCT) model in [25] produced admirable recognition rates by extracting pertinent features for a KNN classifier using Linear Discriminant Analysis (LDA). To achieve better classification with fewer features, Muduli et al. [20] proposed Lifting Wavelet Transform (LWT) features paired with PCA and LDA, along with an extreme learning machine (ELM) classifier tuned utilizing the moth flame optimization approach.In addition, Khan et al. [26] developed an improved CAD model based on a bank of Gabor filters, extracting relevant features using a support vector machine (SVM) as a fitness function in particle swarm optimization (PSO), and then improving accuracy by using an SVM classifier.

In medical image processing, features derived from convolutional neural networks (CNNs) based on deep learning have recently gained a key role. Many CNN models have proven their skill at feature extraction, including VGGNet [30], AlexNet [31], ResNet [32], GoogLeNet [33], and Inception [34]. Wang et al. [35] used a two-stage learning technique to create an automated CNN model for detecting Retinopathy of Prematurity (ROP), which produced better results. A hybrid CNN model with two phases that includes preprocessing and supervised learning was introduced by John et al. [38]. Through a sequence of nonlinear transformations, this model learns to represent visual content hierarchically from the raw pixel data of an image as its input.

Another CNN-based CAD model was also developed by [39], and it made use of several predefined CNN architectures, including ResNet50 [32], InceptionV3 [34], and VGG16 [30]. These models produced better results when tested on the INbreast dataset [41] after being trained on the DDSM dataset [40]. A CNN model built on the YOLO detector, as given by [42], assessed various learning classifiers on a common dataset, including FFCNN, ResNet-50, and InceptionResnet-V2. More recently, [43] proposed a multi-scale CNN model that included global and local information to create feature maps while utilizing DensNet and MobileNet for feature extraction.[44] provided another CNN model that combined features from multiple established CNN models and was tested on the DDSM dataset. This CNN model was centred on in-depth feature extraction. A CNN model built using textural information from local binary patterns (LBP) was also introduced by [45]. A modified deep CNN model using InceptionV3 [34] and ResNet50 [32] was created by Rahman et al. [46]. A deep feature-based CNN model was proposed by Dhungel et al. [47] in which features were extracted using CNN and then classified using a random forest (RF) classifier. Chougrad et al. [48] investigated the best methods for fine-tuning several deep CNN models while highlighting the importance of transfer learning.

CNN has a wide range of applications, mainly because of its inherent feature extraction and dimensionality reduction advantages. Inspiring by this, we present a CNN-based strategy.

3. Proposed Work

The authors of this study provide a robust, tailored CNN model for automatically classifying modulations. They offer a preprocessing step where the signal is converted into the picture domain using newly proposed polar features rather than directly processing the received data using deep learning algorithms. This change can improve prediction accuracy significantly and strengthen the model's robustness.

3.1. Customized CNN Deep Learning Model

This is a deep learning-focused variation of a convolutional neural network (CNN or ConvNet) that can learn directly from data without requiring manual feature extraction. CNNs are excellent at identifying patterns in images, allowing them to identify objects, faces, and sceneries with remarkably high accuracy. The proposed work is experimented with and RADIOML 2018.01Adataset, where each {modulation class, SNR} pair has 4096 training examples [50]. This means that for each combination of modulation class and SNR level, we have 4096 I/Q time-series samples. Since each sample represents an I/Q time-series, we have decided how long these time-series are. The length of these time-series has been considered as input size. The dataset contains I/Q time-series, which typically means two channels: one for the in-phase component and one for the quadrature component. We have mentioned that there are 24 modulation classes. The input shape for the proposed model is$128\times4096\times2$ (batch size is 128, 4096 number of samples, channel size is 2). The 'customized CNN' deep learning model employs several layers to accomplish its objectives. It consists of one fully connected layer and four convolutional layers. The first layer, designated as "CON_1," uses 64 filters, each 7x7 in size. Then, a max-pooling layer, ReLU activation, and batch normalization are used. To shrink the size of the feature map, the pooling layer uses a 2x2 filter and a stride of 2. In a similar vein, the second convolutional layer, "CON_2," is made up of 64 filters that are each 3x3 in size. The following layers, 'CON_3,' 'CON_4,' and 'CON_7,' use 32, 16, and 8 filters, respectively, and are all 3x3 in size. They all have the same structure as the first convolutional layer. The model uses the softmax layer to determine if the news is real or fraudulent once the deep-learned characteristics are combined into a single vector within the fully connected layer.The block diagram of the custom CNN model is depicted in Figure 1, and the model's setup is detailed in Table 1.

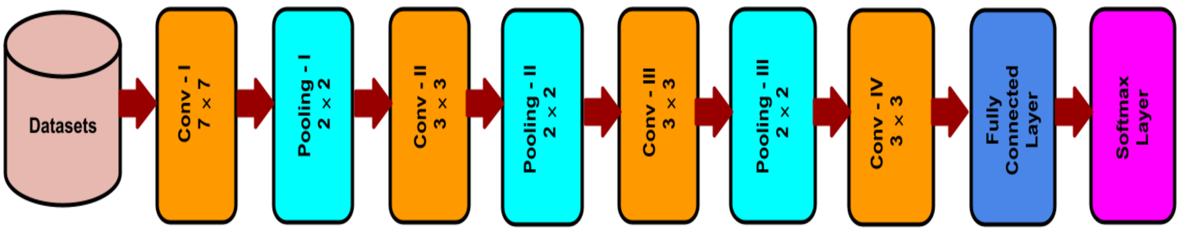

Fig 1 Block Diagram of Proposed method

Table 1 displays the suggested configuration of the specially built CNN structure.

L_a	S_z	F_s	N_f	Stride
I_N	128×4096×2			
Con_1	$C_L + B_N + R_E L_U$	7 × 7	6	1 × 1
$M_{PL\_}1$		2 × 2	4	2 × 2
Con_2	$C_L + B_N + R_E L_U$	3 × 3	6	1 × 1
$M_{PL\_}2$		2 × 2	4	2 × 2
Con_3	$C_L + B_N + R_E L_U$	3 × 3	3	1 × 1
$M_{PL\_}3$		2 × 2	2	2 × 2
Con_4	$C_L + B_N + R_E L_U$	3 × 3	1	1 × 1
$M_{PL\_}4$		2 × 2	6	2 × 2
Con_5	$C_L + B_N + R_E L_U$	3 × 3	8	1 × 1
Fully Connected	Op Size = 24			
OP	Classification layer	Soft Max		

- ❖ $L_a = Layer$, $S_z = Size$, $I_N = Input$, $F_s = Filter\ Size$, $N_f = Number\ of\ Filter$ $C_L = Convolution$, $B_N = Batch\ Normalization$, $R_E L_U = Relu$, $M_{PL\_} = \max - pooling\ layers$, OP= output

3.1.1. Convolution Neural network

Convolution neural network (CNN) have revolutionized computer vision tasks, achieving state-of-the-art results in image classification, object detection, segmentation, and more. Ongoing research focuses on improving efficiency, interpretability, and adaptability to various domains and data types, making CNNs a pivotal area of study in deep learning. Researchers continue to explore novel architectures and techniques to further advance the field [49].

3.1.2. Convolution Layer

In CNN structures, convolutional layers are assembled to construct deep networks, enabling the automatic acquisition of hierarchical features from unprocessed data. As you delve deeper into the network, these acquired features become progressively more sophisticated and abstract, facilitating the effective execution of tasks such as image classification, object detection, and segmentation by CNNs[49].

3.1.3 Pooling Layer

After convolution, pooling layers down sample feature maps to reduce computational complexity and make the network translation-invariant. Max-pooling and average-pooling are common techniques. Pooling layers making the network more robust to variations in the input[49].

3.1.4 Activation Function

Activation functions are crucial to give the model non-linear features and enable it to capture intricate interactions between input and output data. The choice of activation function depends on the specific task and network architecture. ReLU is a common default choice due to its simplicity and effectiveness in training deep networks, but it's important to experiment with different activation functions to find the one that works best for your problem. Activation functions play a critical role in enabling CNNs to learn complex representations and make them capable of handling a wide range of tasks.This encourages output sparsity while simultaneously introducing non-linearity.

Activation functions are crucial to give the model non-linear features and enable it to capture intricate interactions between input and output data. We have used the Rectified Linear Unit (ReLU) activation function in this instance. ReLU is the preferred option for activation in CNNs because it substitutes zeros for all negative output values. This encourages output sparsity while simultaneously introducing non-linearity [49].

3.1.5 Stride

Stride is an important hyperparameter to consider when designing a CNN architecture, as it influences the network's receptive field, computational efficiency, and the ability to capture different scales of features. The choice of stride should align with the specific requirements of the task at hand and the architectural design goals [49].

3.1.6 Fully Connected Layer

Fully connected layers are typically found at the end of a CNN architecture, after several convolutional and pooling layers. They play a crucial role in mapping the learned features to the final output, making them suitable for tasks like image classification, where the network needs to make a decision based on the extracted features. However, for some tasks and architectures, fully connected layers may be replaced or supplemented with other types of layers, such as Global Average Pooling or attention mechanisms [49].

3.1.7 Soft Max Layer

The softmax layer is a critical component in CNNs for tasks involving multiple classes. It transforms the network's output into a meaningful probability distribution, allowing the model to make informed decisions about which class the input belongs to. During training, the network learns to adjust its parameters to produce the correct class probabilities that match the true labels in the training data [49].

3.2. Data Sets

In this initial phase, the authors evaluate the modulation recognition challenge employing a distinct dataset, and RADIOML 2018.01A, encompassing 24 modulation scheme classes [50]. The aim is to conduct a comparative analysis between the proposed research and existing methodologies utilizing these datasets. The datasets were generated through the utilization of GNU Radio, encompassing both analogue and digital modulation techniques.In the dataset, there are 24 different modulation classes observed across 26 signal-to-noise ratio (SNR) levels. These SNR levels span from -20dB to +30dB, increasing in steps of 2dB. Each combination of modulation class and SNR level is represented by 4096 training examples. Consequently, the entire dataset contains a grand total of 2.56 million labeled I/Q time-series examples.The 24 modulation categories encompass a wide variety of modulation styles, and you can find specific information about them in Table 2.

Table 2 . Dataset description of the proposed model

Deepsig.io RADIOML 2018.01A		
Class	Signal	SNR
24 Modulations	➢ Number of Modulation 24 ➢ Samples as floating In phase and Quadrature phase (1024,2) frame shape ➢ Total number of signal 2,555,904	26 SNR/Modulation

4. Result and Discussion

From the experimental evaluation, we have observed that the proposed customized CNN model provides better classification results than existing models.It has also been observed that compared to traditional models. The hyperparameters for different classifiers have been described in Table 3. The classification result of the proposed model-based accuracy and loss concerning a number of epochs is shown in Figure 2 – 3.During the experiment, the proposed customized CNN Model simulation ondetails performance with other pre-trained models, such as VGG 16. Resnet 50, Inception V3 by using different classifiers such as Extreme Learning Machine (ELM), Support Vector Machine (SVM), and K-Nearest Based Neighbours (K-NN). From the experiment outcomes, it is evident that the Customized CNN model delivers superior accuracy at 95.16 % compared to other pre-existing models shown in Table 4.

Table 3. Hyperparameters of proposed Customized CNN model

Hyperparameters	Values
Learning Rate	0.001
Batch Size	128
Number of Epochs	100
Optimizer	SGD
Loss Function	CatagoricalCross-entropy
Dropout Rate	0.2
Activation Function	ReLU

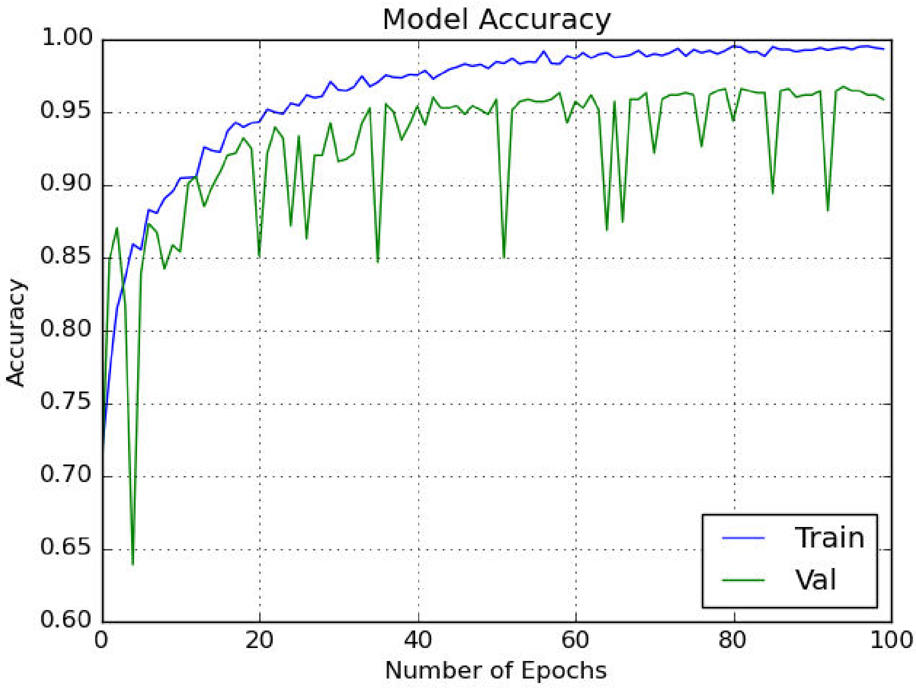

Fig 2 Accuracy Model of Customized CNN

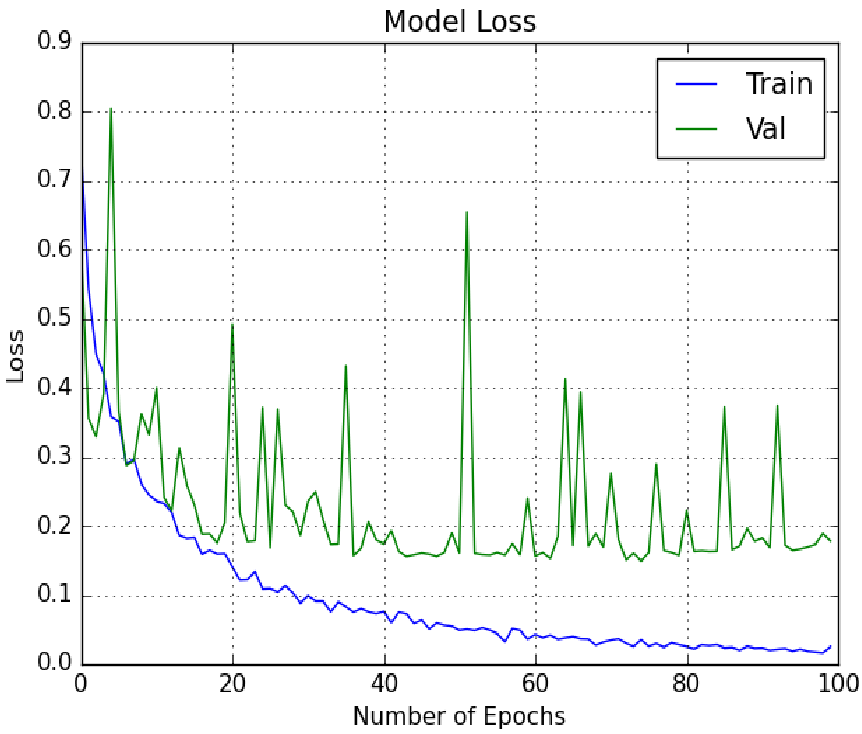

Fig 3. Loss Model of Customized CNN

Table 2 Performance Analysis of proposed model with existing models.

Classification Method			Accuracy
MCNet +stochastic gradient descent optimizer [30]			58.8
CLDNN +LSTM [31]			46.4
ResNet +SVM [32]			59.4
VGG16	KNN	Existing method	74.22
	SVM		79.42
	BPNN		88.26
	MFOP-ELM		91.70
Resnet 50	KNN	Existing method	76.52
	SVM		78.42
	BPNN		89.56
	MFOP-ELM		93.65
Inception V3	KNN	Existing method	86.54
	SVM		88.36
	BPNN		92.38
	MFOP-ELM		94.19
Customized CNN	**CNN**	**Proposed method**	**95.16**

4. Conclusion

This paper presents a novel hybrid model designed to facilitate efficient and accurate modulation classification in wireless communication. Leveraging established deep learning architectures like the Customized CNN, we meticulously fine-tune model parameters, including input weights and biases, to achieve optimal performance. Our experimental results, conducted on widely recognized benchmark dataset, demonstrate promising outcomes, with the proposed model achieving an impressive accuracy rate of 95.16%. Moving forward, our research agenda aims to explore innovative deep learning techniques to further enhance the model's capabilities, while also delving into alternative optimization methods for continued refinement.

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