# Performance Analysis of Automatic Modulation Recognition Using Convolutional Neural Network

**N. Venkateswara Rao and B. T. Krishna**

**Abstract** In recent trends, automatic modulation recognition (AMR) has become a primary candidate in cognitive radio (CR). Modulation recognition using deep learning (DL) drawn attention of users in recent times due to its capability of performing in blind scenarios. In this article, convolutional neural network (CNN) model has been preferred for modulation classification purpose. This model learns from the features of modulation schemes present in the training data. CNN classifier operates in all adverse channel conditions. MPSK and MQAM modulation schemes are chosen in this paper. Total 7 modulation classes is trained in CNN with different training rates at different SNR. In this paper, proposed approach is compared with traditional models. Simulation results shows that proposed model performs well at different SNR.

**Keywords** AMR · CNN · DL · CR

## 1 Introduction

Future wireless applications demand continuous growth in certain aspects like mobility and quality of service. In telecommunication field, several challenges still need to be covered like providing encrypted wireless communication, accurate channel estimation and upgrading the QoS of the wireless methodologies used [1]. AMR can be an ultimate solution to the challenges which are stated above. AMR is used as a primary module in cognitive radio, which identifies the modulation class in presence of noise [2]. AMR is having a large research scope in wireless communication. It is used for spectrum management and interference rejection in civilian applications. It is used for jamming and demodulation of the signal in battlefield scenarios. It has been extended to various fields like radar [3, 4] and medical. Al-

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Qatab et al. proposed a framework that incorporates feature selection and acoustic features that will be helpful in speech classification, depending on the levels of deterioration [5].

In the last few years, various algorithms are proposed for AMR in the literature [6]. In general, signal parameter detection methods are usually classified into likelihood ratio-based (LB) approach and feature-based (FB) approaches [7]. LB approach is formulated as a hypothesis problem [8]. It is computed by setting a specific threshold value; later, it will compare the likelihood ratio with that threshold value [9]. Zhu et al. selected the modulation type based on probability distribution that increases the loglikelihood function [10]. In LB approach, some prior probability information is required, and it is selected at the expense of high computational complexity. FB approaches have dominance in practical implementations due to their low complexity. FB approach makes decisions based on extracted features. For feature extraction characteristics like cyclic statistics [11], wavelet transform [12] and high-order cumulants [13, 14] are used. ML algorithms like ANN [11], KNN [15] and SVM [16] have been widely used for classification. But these methods were developed such that it can be operated in limited environments. Feature extraction and classification both are independent processes. Due to their mismatch, the performance will be degraded for the above approaches.

With the recent advances in wireless technologies, a new paradigm based on DL is adopted for AMR. In [17–20], high performance is achieved, which decreases human participation. DL mainly focuses on the network models, which includes CNN and recurrent neural network (RNN) for AMR. DL has numerous applications in natural language understanding [21], speech recognition and image recognition. DL has been considered as important tool in many areas such as IoT detection [22, 23], MIMO detection [24, 25], radio control [26–28] and channel estimation [29, 30].

Recently, CNNs have created a big impact in computer vision [31–33]. With this success, it is now playing a lead role in AMR [34]. Initial design model of CNN was developed by O'Shea et al. for classification [35], which gave better performances compared to previous approaches, and it is more robust for different kind of signals. Authors at [36] developed a model cascading two CNN in their work. Out of these two, first CNN utilized in-phase and quadrature (IQ) components and the second one made use of the constellation diagrams. Long-term dependency is better handled by RNN. Karpathy et al. [37] combined RNN and CNN for image classification problem, in which CNN is used for feature extraction, and RNN is used for modeling temporal dependencies.

This paper is presented as follows. Section 2 provides a brief introduction of proposed model. Section 3 gives an overview of experimental setup. Section 4 shows the results and comparison tables with traditional approaches. Concluding remarks are presented in Sect. 5.

## 2 Proposed Model

CNN model is preferred in this article for modulation recognition. Almost all CNN models comprise various layers like convolutional layer, batch normalization layer, rectification layer (ReLU), max pooling layer, fully connected layer, Softmax layer and output layer. Convolution layer is utilized for extracting features from input data, and these are processed to next stage. Excluding input layer, remaining layers needs an activation function. It is provided by ReLU and parametric ReLU. Pooling layer is mainly used to improve the performance. It is also used to reduce the dimensions of feature to overcome overfitting. In CNN model, fully connected layer will be used as a classifier. For better classification, fully connected layer makes use of results from previous layers. Softmax layer utilizes Softmax activation function for mapping the output data. It is preferred for multi-classification problem.

The proposed CNN model comprises image input layer, convolution 2D layer, batch normalization layer, ReLU layer and max pooling 2D layer. The following layers are repeated in 6 stages. In the last stage, average pooling 2D layer is used rather than max pooling 2D layer. Finally, fully connected layer is utilized followed by Softmax layer and classification output layer. The proposed CNN model is shown in Fig. 1.

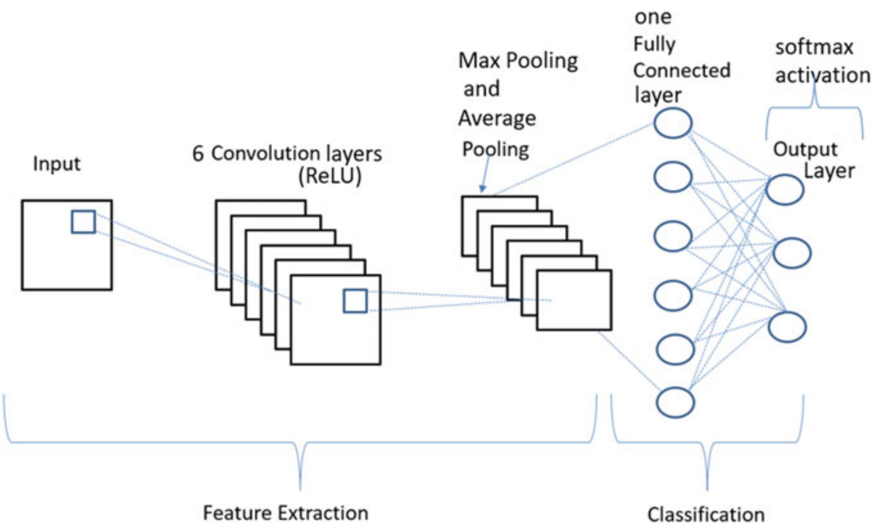


**Fig. 1** Proposed CNN model

## 3 Experimental Setup

For modulation recognition, 7 modulation classes are considered, i.e., 64QAM, 16QAM, CPFSK, GFSK, QPSK, BPSK and 8PSK. For each modulation class, several frames are generated for effective training, where 80% of the features are used for training, and 10% of them is utilized for testing phase. In the network training stage, 10% of features are used for validation. Parameters chosen for waveform generation are samples per frame is 1024 samples, samples per symbol is 8, sample rate ($f_s$) is 200 kHz and center frequency is chosen as 902MHzfor digital signal modulation types and 100 MHz foe analog signal modulation types. Figure 2 represents the real and imaginary parts of different modulation classes considered for simulation.

Spectrograms of modulated signals are generated with the help of short-time Fourier transform (STFT).

Figure 3 represents the spectrograms of different modulation classes at 20 dB SNR. Each frame in the channel passes through different channel conditions like AWGN and Rician multipath fading.

CNN model makes use of 1024 samples for training. Based on training, it accurately finds out the type of modulation. CNN model is given training with different training rates and different timings. Parameters chosen for training are batch size, epochs and learning rate. The learning rate and epochs are varied based on training.

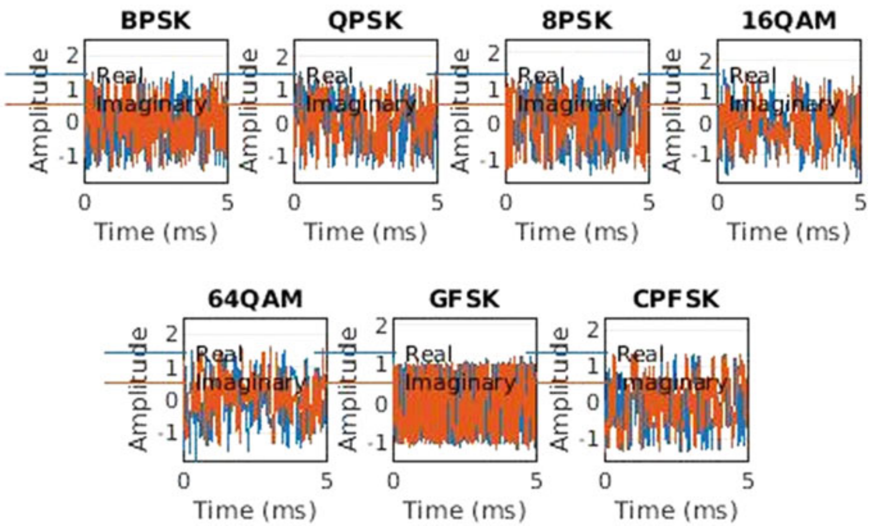


**Fig. 2** Real and imaginary parts of the signal frames

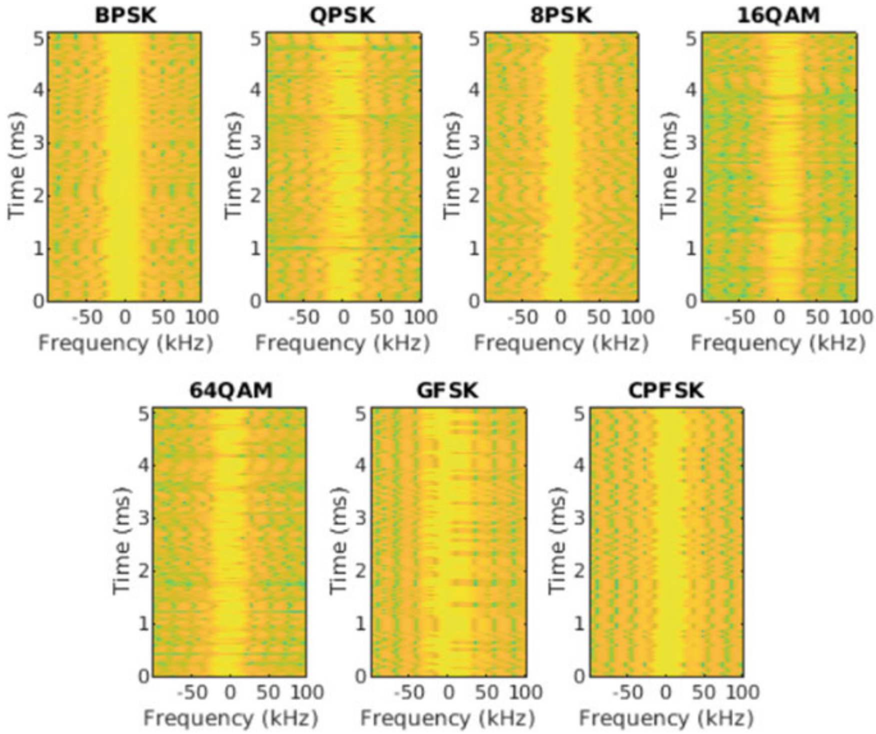


**Fig. 3** Spectrograms of seven modulation classes

## 4 Simulation Results

QPSK, BPSK, 8PSK, CPFSK, GFSK, 16QAM and 64QAM signals are considered for training to check the performance of CNN at non-ideal channel conditions with SNR = (0,10,20 and 30) dB. CNN model is trained with different training rates at (80, 70, 60 and 50) and different testing times at (10, 20, 30 and 40). The confusion matrices of proposed CNN in terms of true class and prediction class at 20 dB SNR are shown in Fig. 4. For 80% training, performance reached is 93.14%. The performance levels at 70, 60 and 50% are 92.71, 92.71 and 92.43%.

Table 1 summarizes the accuracy of each modulation class at different training rates and SNR values. And Table 2 summarizes the test accuracies of CNN model for AMR with different SNR and different training rates. Table 3 shows the performance comparison of the proposed approach with other existing approaches.

From the simulations, it is clear that event at 50% training rate, the proposed classifier performance better in classification of modulations for SNR 10 dB and above.

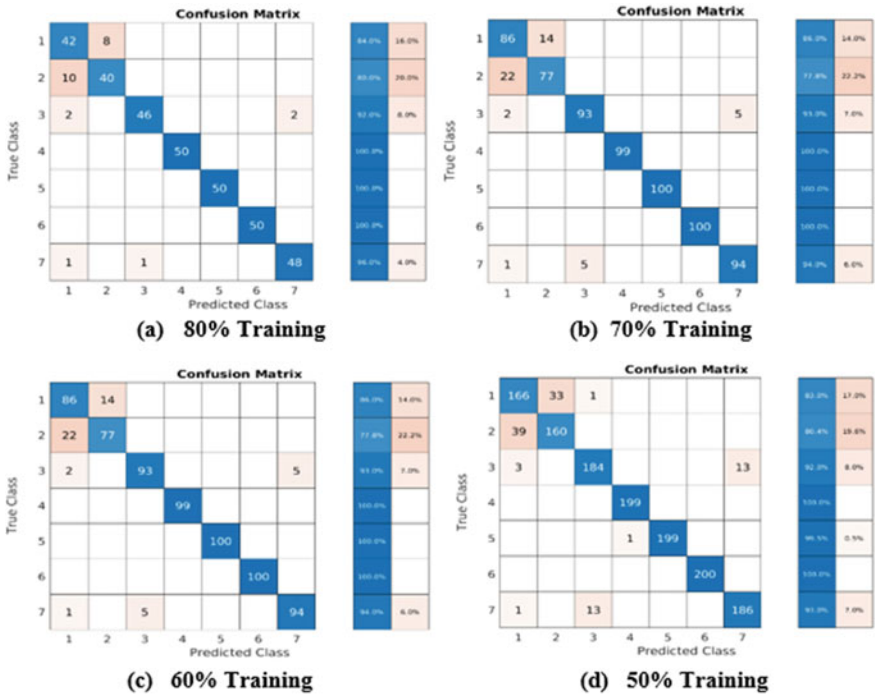


**Fig. 4** Confusion matrix at 20 dB SNR

## 5 Conclusion

This paper presented CNN model approach for AMR of digitally modulated signals. From the simulation results, it is proven that CNN works in non-ideal channel conditions. It achieved an accuracy of 94% at 30 dB SNR. The proposed classifier outperformed all existing approaches. In future, this model can be applied to different signal classification problems in all adverse conditions.

**Table 1** Accuracy of each class at different training rates and SNR

| Class/training rate | Accuracy (%) | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SNR 30 dB | | | | SNR 20 dB | | | | SNR 10 dB | | | | SNR 0 dB | | | |
| | 80 | 70 | 60 | 50 | 80 | 70 | 60 | 50 | 80 | 70 | 60 | 50 | 80 | 70 | 60 | 50 |
| 1 | 78 | 81 | 79.3 | 80 | 84 | 86 | 86 | 83 | 89.8 | 90.9 | 85.9 | 84.8 | 48.1 | 40.7 | 41.8 | 42.2 |
| 2 | 88 | 85.9 | 85.9 | 86.9 | 80 | 77.8 | 77.8 | 80.4 | 57.4 | 48.9 | 48.6 | 49.5 | 20 | 15.4 | 14.9 | 19 |
| 3 | 96 | 93 | 90.7 | 92 | 92 | 93 | 93 | 92 | 89.8 | 87.9 | 82.6 | 82.4 | 43.8 | 38.7 | 40 | 39.2 |
| 4 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 99.5 | 92.1 | 89.2 | 88.5 | 88.6 |
| 5 | 100 | 100 | 99.3 | 99.5 | 100 | 100 | 100 | 99.5 | 100 | 100 | 99.3 | 99.5 | 87.5 | 90.3 | 89.5 | 90.2 |
| 6 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 93.9 | 93.9 | 91.9 | 92.9 |
| 7 | 96 | 93 | 91.3 | 92 | 96 | 94 | 94 | 93 | 76 | 80 | 75.2 | 76.3 | 63.3 | 63.2 | 59.8 | 58 |

**Table 2** Summary of test accuracies for different SNR/training rates

| **SNR** (dB) | **Accuracy (%) at training rate of** | | | |
|---|---|---|---|---|
| | **80** | **70** | **60** | **50** |
| 30 | 94 | 93.14 | 92.29 | 92.86 |
| 20 | 93.14 | 92.71 | 92.71 | 92.43 |
| 10 | 86.57 | 85.86 | 83.62 | 83.79 |
| 0 | 50 | 46.43 | 45.91 | 46.36 |

**Table 3** Comparison of proposed approach with existing approach

| Reference no | Approach | Features | Modulation classes | Accuracy |
|---|---|---|---|---|
| [38] | MTL-CNN | Signal samples | 9 | 86.97 |
| [39] | LSTM | Time domain Amplitude and Phase | 11 | 90 |
| [40] | CNN and LSTM | I, Q and HOC | 11 | 88 |
| [41] | RNN | Signal samples | 4 | 92 |
| Proposed model | CNN | Spectrograms | 7 | 94% |

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