Accuracy Enhancement of Automatic Modulation Recognition Using Deep Learning Paradigm

Salah Ayad Jassim and Ibrahim Khider
Sudan University of Science and Technology, College of Engineering, Dept of Electronics, Sudan
Email: Salahayadvip@gmail.com; Ibrahim_khider@hotmail.com

Abstract —Communication systems consist of advanced system performance that enables signal reception at the destination. In such a system, the difficult problem is to restore the original transmission. In this study, Automatic Modulation Recognition (AMR) is used to improve the precision of modulation recognition. This method is essential for advanced communication systems that require a minimal delay, such as Realtime broadcasting. Using paradigms of deep learning, the modulation approach of a received signal is identified. Feed-forward neural network with Particle Swarm Optimization (PSO) integration is proposed for this purpose. The suggested model exhibits optimal recognition accuracy of 97.3 percent, as reported.

Index Terms—Modulation, Automatic Modulation Classification (AMC), Particle Swarm Optimization (PSO), FFNN, Convolutional Neural Network (CNN), AWGN (Additive White Gaussian Noise), deep learning

I. Introduction

The demand for digital modulation identification is being fueled by the proliferation of digital communications on a variety of scales, such as mobile networks, and the emergence of new digital technologies, such as cognitive radio. The same concept is referred to as “automated recognition of signals,” which focuses on identifying the modulation methods that were applied to the signal during transmission to execute the appropriate procedure for original data and signal recovery. Automatic signal recognition is of interest in numerous applications, such as spectrum management, surveillance, noise elimination, signal processing, and monitoring systems, among others. Accessible potential implementation strategies for automatic modulation include analytically based recognition [1] and pattern recognition [2]. The first technique employs probabilistic rules based on hypotheses to detect the signal. It is rumored that this method is difficult to implement due to its high computational cost and complexity. In contrast, pattern recognition is utilized as a dependable and cost-effective alternative to signal identification in numerous relevant investigations. This is accomplished by applying a computerized mining algorithm to the classification of signals according to their initial race. In contrast, the second strategy, such as automated recognition, employs machine learning, which includes both supervised and unsupervised learning. This facilitates the categorization of signals. Pattern recognition may make errors when making decisions, with the extent of these errors depending on the learning quality of the particular algorithm employed for categorization purposes. Pattern recognition is typically superior to analytical recognition in terms of both performance and ease of implementation. Utilizing computerized algorithms for pattern recognition is a viable implementation alternative (deep learning and machine learning). Consequently, the structure of these systems can be broken down into two subsystems, namely feature extraction and classification. In the process of feature extraction, the signal's pertinent properties are first extracted, and then those extracted attributes are used to represent the signal in the next step. Feature extraction from a communication signal requires locating the following information in a modulated signal: zero-crossing, phase angle with signal amplitude, the shape of constellation [3]-[5], signal Kurtosis, signal approximation using wavelet transform [6], and signal representation in the frequency domain [7]. In contrast, the subsequent method involves signal categorization using well-known classification strategies such as random forest [8], k-nearest neighbor [9], neural network, etc.

However, as previously mentioned, the automated recognition of modulation can be expanded to include a wide range of industries beyond communication; for instance, it can be implemented in electric transmissions, measurement devices, power systems, medical applications, and so on. In this paper, modulation recognition is initiated through the use of deep learning and big data for learning purposes. Utilizing the particle swarm optimization algorithm, the accuracy of modulation recognition is improved (PSO).

II. Automatic Modulation Classification

AMC (Automatic Modulation Classification) is widely used in a variety of technological applications. However, chaotic sequences are used to code the features of the said modulated signals to block unauthorized receivers. When the AMC technique is used to classify the chaotic MPSK (Multi Pre-Shared Key) signal at high SNR, the identification rate of the said signals is nearly zero, compared to 90% when no chaotic sequences are used [10]. AMC is used to estimate the SNR in None Data Aided (NDA) estimation of wireless networks by utilizing three features, namely bit-rate, modulation

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format, and SNR-related features in Asynchronous Delay-Tap Plots (ADTPs), with 99.12% accuracy [11]. Satellite transmissions involved the use of a variety of modulation standards, including linear modulation techniques such as MPSK for greater robustness against hardware non-linearity. Nonlinear modulations, such as Gaussian minimum shift keying (GMSK), can improve spectrum efficiency. Furthermore, offset-QPSK (OQPSK) reduces out-of-band interferences. This sparked a debate about how broadcasting companies should use technology. AMC (i.e. Bayesian classifiers) have shown promising results in allowing modulation diversity over satellite transmission by recognizing different signal races [12]. An ANN classifier was used in a software-defined radios application to recognize M-APSK and DVB-S2X modulations using Higher Order Spectra Features (HOSF) at SNR=0 dB [13]. Learning filters are a new signal processing technology that allows digital filters to learn from different experiences using artificial intelligence to address the challenges of weak signal detection in Unmanned Aerial Vehicle (UAV) communication [14]. Principal Component Analysis (PCA) is used to classify information extracted from digital mammograms using the Block-Based Discrete Wavelet Packet Transform (BDWPT) [15]. The European 868 MHz AMC has been used to improve short-range communication by using the Random Forest algorithm (RFA)-based classification [16]. In military applications, AMC is used during the deployment of a Cognitive Radio Network (CRN). Because the receiver has no knowledge of the modulation type of the incoming signals in CRN, conventional Higher-Order Statistics (HOS) features were extracted from the signal to allow the classifier to learn the behaviors of various signals for efficient spectrum sensing [17].

III. Proposed System

As previously described, the system consists of two primary stages: a machine learning-based emotional classifier/recognizer and an automatic emotional classifier/recognizer. Each section's overview is discussed here.

A. *Dataset Explanation*

The Radio ML dataset is widely used in modulation classification research and is a widely accepted dataset. To demonstrate the robustness of our proposed Convolutional Neural Network (CNN) model, we also evaluate its performance on the RadioML dataset. This section utilizes the RadioML2016.10a dataset. It consists of ten types of modulation applied to synthetic signals. The dataset includes the following modulation types: AM–DSB, WBFM, GFSK, CPFSK, 4– PAM, BPSK, QPSK, 8–PSK, 16–QAM, and 64–QAM. [15] contains information regarding the generation and packaging of the dataset. In this instance, the dataset is divided into two parts (training and test) containing an equal number of signals. Following the training procedure, the models are evaluated with the remaining signals. According to test results, the performance of the proposed CNN model is superior to that of the CLDNN model at SNR levels greater than -2dB. CNN performs slightly worse than LSTM. The CLDNN is capable of achieving a maximum accuracy of 88.5%. In contrast, the proposed CNN model achieves a maximum accuracy of 90.7% despite not being designed specifically for the RadioML2016.10a dataset. Although LSTM achieves a maximum accuracy of 92,3 %, its computational complexity is extremely high.

B. *Empirical Stage A*

Features can be extracted from images using a signal stage Convolutional Neural Network (CNN) with the existing parameters (VGG-19 pretrained model); the model can be used for feature extraction, and the resulting scores can be used to train a critical neural network Artificial Neural Network (ANN) model that will be used for classification.

Before Artificial Neural Network (ANN) training, dimension reduction of the features will be accomplished using principal component analysis. Using the Enhanced Mutation Genetic algorithm it is possible to optimize the ANN (EMGA). This can be compared to SCI-learning-based methods like Support Vector Machine (SVM), Rando Forest (RF), Logical Regression (LR), etc.

1. Using the PCA (principle component analysis) technique, features discovered by CNN are further processed for dimensionality reduction.
2. Using the dimension-reduced features provided, an Artificial Neural Network (ANN) is employed for classification in the following.
3. The weight coefficients of the ANN will be updated using a genetic approach for optimization.
4. The resultant score of the aforementioned system will be compared to other machine learning-based classifiers, including Random Forest (RF), Support Vector Machine (SVM), Principal Component Analysis (PCA), KNN, and Bagging. Fig. 1 demonstrates the overall system design of subsection A.

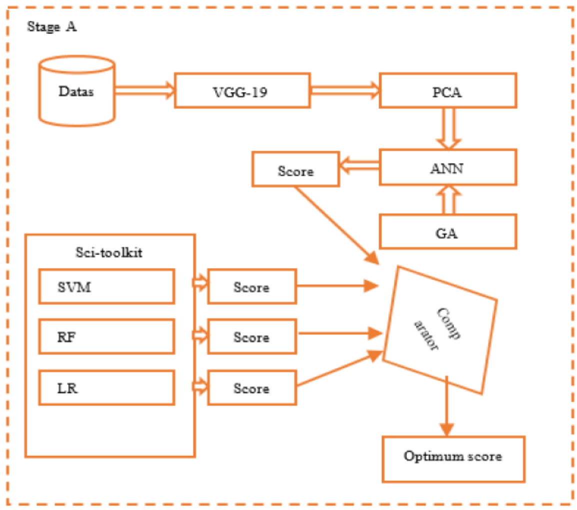

Fig. 1. Machine learning-based emotional classifier.

C. Empirical Stage B

A modified Convolutional Neural Network (CNN) is proposed for modulation recognition, with the proposed methodology aiming to address the aforementioned issues by completing the phases outlined below:

1. Classification using VGG-16 as a pretrained CNN model. Using the proposed model, however, the performance of the described classifier can be enhanced in terms of training time and computing cost.
2. The proposed improvement to the classifier can be implemented by modifying the number of filters in the existing VGG-16 model.
3. Multi-stage CNN (the proposed paradigm) can be utilized to increase the learning process. The photos can be run through a CNN bank where each CNN unit's classification scores are unique. Eventually, score maximization can be accomplished with the use of a pooling layer in each CNN unit. In conclusion, the results from each classifier unit can be added together. Fig. 2 illustrates this phase.

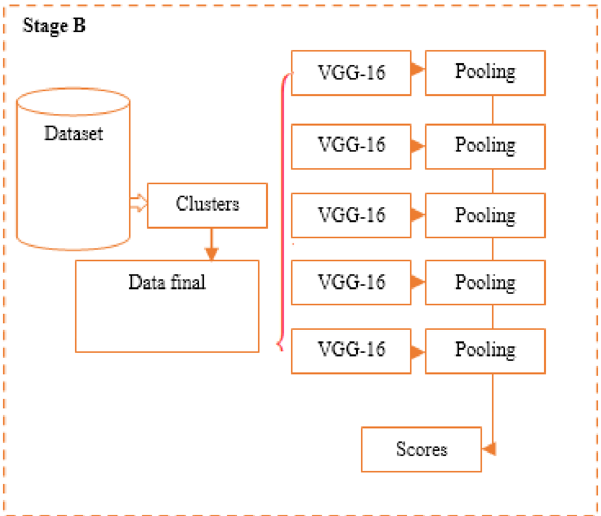

Fig. 2. Automatic emotional classifier.

D. PSO-FFNN Model

Particle Swarm Optimization (PSO) algorithm has a noteworthy performance in tackling multidimensional problems in engineering and sciences. The heuristic approach of the PSO algorithm is inspired by birds' social and biological actions while they search for food [16]. The standard PSO or SPSO works for evaluating the best particle in a swarm of particles by updating the position and velocity of a particle in multiple iterations. Let the swarm be located at y_{axis} and composed of a large number of particles (N particles). m_i is denoting the i^{th} particle in the swarm and hence, p_i denoted the position of the particle m_i in the swarm. So, particle position in the swarm moving on y-dimensional can be expressed as:

$$p_i = \left(p_{i1,}\, p_{i2,...,}\, p_{iy}\right) \tag{1}$$

The article m_i is varying its position by moving on the swarm domain by velocity s_i which is given as the following vector:

$$s_i = \left(s_{i1,}\, s_{i2,}\, s_{i3,...,}\, s_{iy}\right) \tag{2}$$

Hence, SPSO may attempt to evaluate the best positions of a particle m_i in a swarm and yield that in a vector as in Eq. (3):

$$u_i = \left(u_{i1,}\, u_{i2,}\, u_{i3,...,}\, u_{iy}\right) \tag{3}$$

Some other terminologies are used in PSO more likely, the social and cognitive acceleration constants $(c_2 \; and \; c_1)$ as well as the weight of inertia (*W*) [14]. To express the other PSO parameters mathematically, firstly weight of inertia is expressed as:

$$W = W_{min} + \left[\frac{k}{K} \times r_3 \times \left(-W_{min} + W_{max}\right)\right] \tag{4}$$

$$s_{ix}^{k+1} = r_1^k c_1 \left(u_{iy} - p_{iy}^k\right) + r_2^k c_2 \left(u_{gy}^k - p_{iy}^k\right) + s_{iy}^k W \tag{5}$$

$$p_{iy}^{k+1} = p_{iy}^k + v_{iy}^{k+1} \tag{6}$$

where K is maximum iterations and r_1, r_2, r_3 are random number having values in the range of [0,1] [17]. PSO optimization may begin with swarm generation or population generation. To execute the PSO algorithm; parameters such as several populations (swarm) (N), social and cognitive coefficients (c1, c2), random distributed numbers e (r1, r2), inertia weight coefficient (W) as well as the global best (GP) are required to be set. PSO works to search the weight (particle) to ensure the best approximation of the fitness function. Hence, in PTS-based ACO-OFDM transmission, PSO is used to search the type of modulation according to the data inputs provided into the neural network. In this work, we have enhanced the PSO performance by tuning up the velocity coefficient using the Artificial Neural Network (ANN)as a third-party predictor. The number of velocities in PSO depends on the number of positions of a particle in the swarm (solutions in search space). The velocity of i^{th} the particle is to be updated to reach the best position. Let s^i is the velocity of i^{th} a particle at $t = t_0$; hence the velocity at $t = t_1$ can be expressed in Eq. (7).

$$s_i^{t1} = W \times s_i^{t0} + c_1 \times R \times p_i^{diff} + c_2 \times R \times p_i^{diff} \tag{7}$$

$$p_{diff} = p_i - p_i^b \tag{8}$$

where R is a random variable and p_i^b is the best position of i^{th} the particle. To find the best velocity, ANN is used for guessing the s_i^{t1}. The proposes of PSO-FFNN are illustrated in the Figure below.

IV. Results and Discussions

The suggested approaches' performance is evaluated using four performance metrics: accuracy, mean square error (MSE), mean absolute error (MAE), and training time (seconds). The approaches are validated using a 10-fold cross-validation algorithm, in which the dataset is divided into ten folds, with each fold including two subsets, namely training and testing subsets. The results will be classified in the following sections based on the metrics that were used.

The average accuracy taken for all ten folds is given in Table I below:

TABLE I: THE MODULATION RECOGNITION AVERAGE ACCURACY TAKEN FOR THE TEN FOLDS CROSS-VALIDATION ALGORITHM OUTPUTS.

Method	Accuracy
CNN	89.2
LSTM	89.76
PSO-FFNN	97.122
SVM	73.92
RF	76.16
KNN	64.761

The average folds accuracy is given in Fig. 3 below:

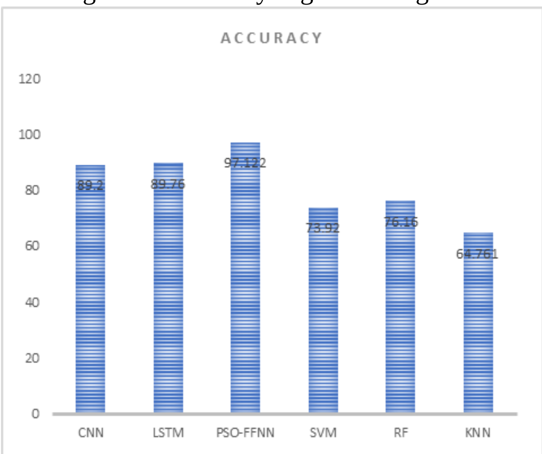

Fig. 3. Graphical representation of the modulation recognition average accuracy taken for the ten-fold cross-validation algorithm outputs.

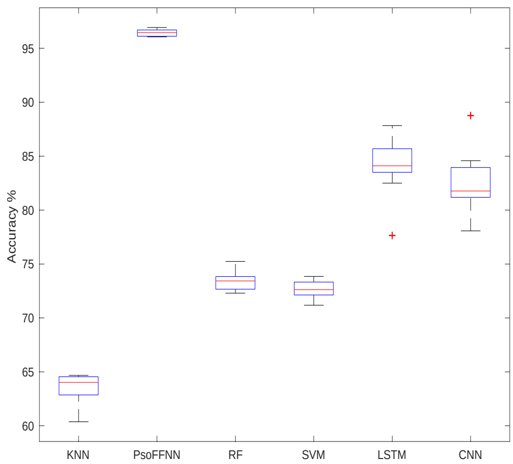

Fig. 4. Box-plot representation of the all accuracies of modulation recognition obtained using the all proposed tools.

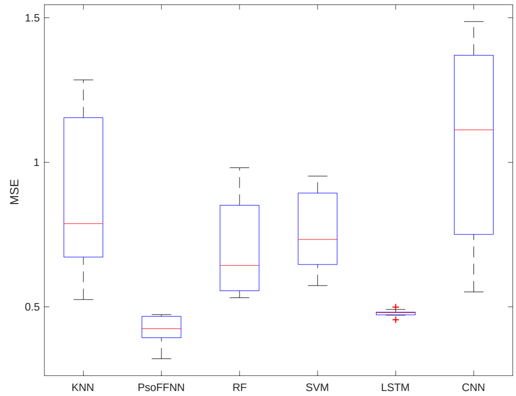

Fig. 5. Box-plot representation of the all MSEs of modulation recognition obtained using the all proposed tools.

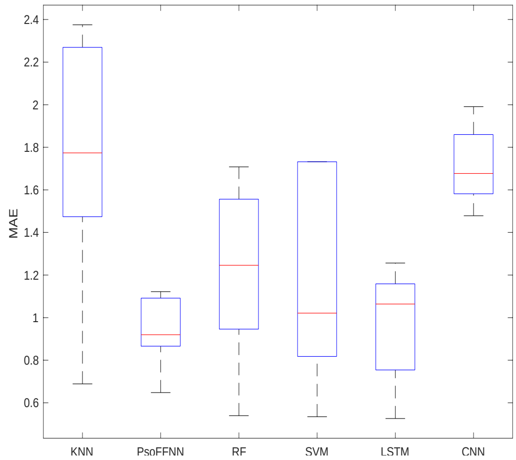

Fig. 6. Box-plot representation of the all MAEs of modulation recognition obtained using all proposed tools.

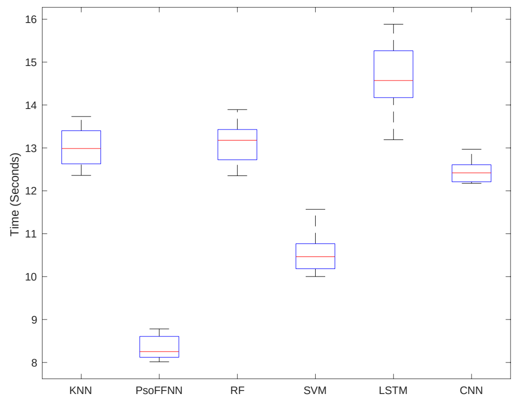

Fig. 7. Box-plot representation of all Training times of modulation recognition obtained using all proposed tools.

The following observations are made based on the findings of the accuracy metric for the 10 folds:

The proposed prototype, a particle swarm optimization-based feed-forward neural network, achieves maximum accuracy. It can be shown that the modulation recognition accuracy is more than 97 percent (see Figures 4 through 7). The accuracy boxplot also shows that the accuracy of all folds is around or more than 95%. That is, the proposed methodology had the highest recognition accuracy across all folds.

The long short-term memory neural network then achieves good accuracy in the 80 to 85 percent range.

The proposed convolutional neural network obtained modulation recognition accuracy of 75 to 85 percent. The other tools, Random Forest, Support vector machine, and K-nearest neighbor, all achieved recognition accuracy of modulation up to 76 percent, with k-nearest neighbor achieving the lowest recognition accuracy of modulation at 60 percent.

V. Conclusion

As noted previously, automatic recognition of modulation may be expanded to include various industries in addition to communication. It can be used in electric translators, measuring devices, power systems, and medical applications, among other things. The AMC system is built using Deep Learning concepts. The results are evaluated, and the proposed prototype, a particle swarm optimization-based feed-forward neural network, produces results with greater than 97 percent accuracy. The other metrics, mean absolute error and mean square error, are proportional to the degree of accuracy, with the tool with the highest level of accuracy having the lowest mean square error and mean absolute error. Due to the simplicity of the model structure in comparison to other models such as LSTM and CNN, the proposed pso-ffnn method achieved the required recognition accuracy in the shortest training time. The length of training is then calculated for each of the algorithms involved in this process. It implies that the proposed model requires significantly fewer processing resources than the other models to complete the required task.

Conflict of Interest

The authors have no conflict of interest.

Author Contributions

Salah Ayad Jassim has prepared and analyzed the data, reviewed the research, and proofread the English language; Ibrahim Khider has modified the paper's organization and outline. All authors had approved the final version.

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Salah A Jassim was born in Ramadi, Iraq, in 1990. He received the B.S. degree from Al-Anbar University, Electrical department, Ramadi in 2013 and M.S. degree from the University of Technology, Baghdad, in 2016. He is currently pursuing the Ph.D. degree with the Department of Electrical and Electronic Engineering, Sudan University for Science and Technology.