Automatic Classification of Modulation Types in Digital Communication Signals with Probabilistic Neural Networks

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***Abstract*—In recent days, the Automatic Classification of Modulations (ACM) is one of the major considerable research attention techniques in Digital Communication (DC) signals, which is used to design the intelligent transceivers. Previous researchers have suggested various traditional feature-based methods including Higher-Order Cumulants (HOC) have been utilized for ACM due to low computational complexity but these are sensitive to noise and interference. To overcome these issues, Probabilistic Neural Network (PNN) is proposed due to faster adaptability. Initially, the data is considered from Real-world Wireless Communication (RWC) Dataset and further preprocessed with Spectral Subtraction (SS). The SS preprocessing technique effectively reduces the stationary noise without significantly destructing the signal. After that, Mel-Frequency Cepstral Coefficients (MFCCs) extracts features from the preprocessed signals by mel-frequency wrapping to represent the signals spectral characteristics. Finally, the classification of modulations is performed with proposed PNN by computing distance between input signals and modulation patterns to select modulation type with highest probability. From the results, the proposed PNN established better results when compared to existing threshold autoencoder denoiser convolutional neural network (TADCNN) by providing accuracy as 88.90% respectively.**

Keywords—automatic classification of modulations, spectral subtraction, mel-frequency cepstral coefficients, probabilistic neural network, digital communication.

I. INTRODUCTION

Digital communication systems are developing the efficiency of radio spectrum usage. The range of modulation schemes used in wireless communication is increasing, creating a more complex communication landscape [1]. As wireless communication technology continues to develop, the need for rapid and automatic detection then analysis of communication signals is becoming increasingly important [2]. Modulating the transmitted signals is a key step in the transmission process of wireless communication systems [3]. The modulation type is adjusted in each transmission to improve Bit Error Rate (BER) work. Modulation classification is a crucial part of the receiver process in various wireless communication applications, such as electronic surveillance systems and electronic warfare [4]. In adaptive modulation systems, the Automatic Modulation Classification (AMC) plays a key role in detecting and demodulating telecommunication signals. AMC has gained significant attention due to its broad range of applications. In military contexts, AMC is used in electronic warfare (EW) systems to detect and counteract threats [5].

In civilian settings, it finds use in software-defined radios, frequency management, transmitter monitoring, and network traffic control [6]. AMC generally consists of two main stages such as signal preprocessing and classifier selection [7]. There are two primary methods for implementing AMC. The first is decision-theoretic, which involves high computational complexity and struggles with parameter ambiguity [8]. The second method uses statistical pattern recognition, or feature-based pattern recognition, where specific features of the signal are extracted first, and decisions are made based on these features. The second approach is less complex and easier to implement, making it more suitable for practical systems [9]. Traditional modulation classification methods often rely on a separate control channel and require prior knowledge of the signal and transmission parameters. As a result, AMC is essential for wireless communication systems, where modulation schemes can change frequently due to environmental factors. This led to the development of new techniques for detecting and classifying modulation schemes [10]. The contribution of the paper discussed below:

- In this research, the Probabilistic Neural Network (PNN) is proposed by computing distance between input signals and modulation patterns to select modulation type with highest probability.
- He Real-World Wireless Communication (RWC) dataset is collection of Radio Frequency (RF) signal acts as input to the proposed PNN. The collected signals given to the pre-processed Signal Subtraction (SS) for improve the quality of signals.
- The pre-processed signals used to extract the significant information by using Mel-Frequency Cepstral Coefficients (MFCCs) wrapping to represent the signals spectral characteristics. Atlast, PNN is used

for differentiate the modulation types with high probability.

The remaining part of portion is arranged in the succeed way: Section 2 illustrates literature review of existing papers that related for AMC to select the modulation types. Section 3 shows proposed methodology. Section 4 illustrates discussion and results. Section 5 shows conclusion of paper.

II. Literature Review

In this section, existing models that are related for AMC to select the modulation type is discussed along with their advantages and limitations below.

To Truong An et al. [11] developed Threshold Autoencoder Denoiser Convolutional Neural Network (TADCNN) used to classify the modulation type and improve the accuracy of the classification. The TADCNN divided into three parts such as CNN, Fully Connected (FC) part, TAD denoiser. The TAD denoiser used for reduce an unnecessary feature into zeros and helps for remove noise from signal that improve classification accuracy. The CNN part consists one Conv2D, one linear combination, three ResNet blocks which avoid vanishing gradients. FC part consists of three dense layers that integrate with the CNN output to perform the final modulation classification. The TAD denoiser helps in reducing noise and occurring of residual noise it affects the performance especially in low-SNR (Signal-to-Noise-Ratio).

Yang Peng et al. [12] designed a Deep Residual neural network with Masked Modeling (DRMM) used to solve a problem of AMC. DRMM divided into three parts such as autoencoder classifier, masked modelling and training process. The autoencoder classifier extracts important features from masked signals and predicts the ground truth labels for those signals. The masked modeling selects the masked parts of the signal and designs an objective function to guide the autoencoder in reconstructing the masked portions. The masked signals are then fed into the autoencoder to extract features and classify the ground truth label during the forward propagation. If the model is not trained on a diverse range of modulations, DRMM's ability to generalize to new, unseen modulation types may be limited, even if it performs well on the training data.

Anand Kumar et al. [13] implemented an AMC for adaptive Orthogonal Frequency Division Multiplexing (OFDM) systems through CNN by Residual Learning (RL). The AMC helps to identify format of received OFDM signal by various subcarriers. The input network was divided into 2-dimensional signal that contains the IQ sample which helps to differentiate real and imaginary samples of complex baseband received OFDM signal. The combination of CNN with RL improved the model's ability to classify modulation format of received signal accurately, even with complex OFDM signals. The CNN model had lack of training data or new, unseen data it leads to overfitting.

Tianpei Xu and Ying Ma [14] produced a Long Short-Time Memory (LSTM) network for signal AMC and recognition. The input data was pre-processed using the normalization and LSTM network extracts the time domain features of signal. The LSTM helps to address the problem of accuracy loss, which is often caused by traditional noise reduction algorithms that can damage the original signal during the noise removal process, thereby reducing recognition accuracy. The LSTM network effectively capture time-domain features of the signal, enhanced the accuracy of modulation classification and recognition. If the input signal data was poor quality or heavily corrupted by noise, the model might still struggle, even though it is more robust than traditional methods.

Dong Wang et al. [15] introduced a CNN-Transformer Graph Neural Network (CTGNet) to classify the modulation types and simplify the complex representations in signal data. A sliding window pre-processing technique is used for convert novel signals into structured data. The CTGNet then maps the pre-processed signals into graph structures and employs Graph Neural Network (GNN), depends on GraphSAGE and DMoNPool for classification. The use of CNN and transformer networks, combined with GNN, enables efficient mapping of signal data into graph structures, improving feature extraction for classification. The sliding window technique for pre-processing must be carefully tuned, as improper configuration lead to inefficient feature extraction or loss of important signal information.

III. Proposed Methodology

The proposed methodology are follows in four steps like dataset, data pre-processing, feature extraction, classification. The RWC dataset are the collection of RF signals that provided as input to the proposed method. First, the input data is given for pre-processing such as SS. The pre-processed data applied for the MFCC to feature extraction. The PNN is used for classification phase to improve the accuracy of classification. Fig. 1 represents workflow for proposed system.

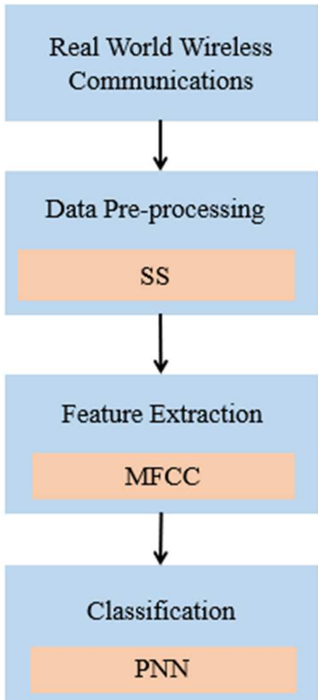

Fig. 1. Workflow for proposed method.

A. Dataset

The RWC dataset [16] is an input to the proposed PNN method that collection of RF signals from three main wireless technologies such as Wi-Fi (IEEE 802.11 ax), LTE and 5G. The data is used to advance the support research in spectrum analysis, identifying the inference and enhancing the wireless communication. The signals were captured under various conditions of real time scenarios like helps to cover the different modulation types, channel scenarios and data speed. This dataset assists a standard resource for developers, researchers and professionals working on Wi-Fi, LTE and 5G. The RWC dataset is widely used in the applications of signal processing, reducing the interference and classifying the signals etc. The input dataset is acts as input to the proposed method.

B. Data Pre-processing

The collected real world RF signals are input to the proposed PNN method. The SS is a pre-processing technique that used to improve the quality of the signals and helps to reduce the noise. The SS is a common method used to reduce the audio noise helps to remove the particular frequency components from noise audio part that attain a cleaned and improved recording. The basic principle of creating a noise profile from the recorded audio, which is effective for short recordings and where background noise remains steady. For example, in the year of 2016, researchers used SS to improve frog call classification in 44-second recordings of 26 frog species. However, this method is less effective for long recordings with quickly changing background noise and works best for shorter, event-based recordings. To extract the significant audio signals, pre-processed signals are provided.

C. Feature Extraction

To extract the significant audio signals, pre-processed signals are provided. The MFCC is a feature extraction technique that used extract the signals.

1) Mel-Frequency Cepstral Coefficients: The MFCC is an extraction technique that used for extract audio signals from the pre-processed signal data. The use of R package 'tuneR' helps to analyze the MFCCs with default settings, except for adjusting frequency range among 0.4 and 1.6 kHz. A default setting used to analyze a 12 MFCC for every 25-ms time frame. The gibbon calls differ between 9.1- 27.3 seconds and Machine Learning (ML) models involve feature vectors of equal distance to every call, through this calculate mean and standard deviation of every MFCC across all time frames. At last, this provide a 24-element feature vector (12 means and 12 standard deviations) for each gibbon call. The extracted signals are provided as classification to select the modulation type with high probability.

D. Classification

The PNN is used for classification phase to select the modulation type with high probability from the extracted audio signals. The PNN classification is explained in below discussion.

1) Probabilistic Neural Network: The PNN is a type of Artificial Neural Network (ANN) depends on the concept of gradient steepest descent. This approach helps minimize errors between the actual and predicted outputs by fine-tuning network's weights. PNN uses a statistical algorithm inspired by Bayesian networks, specifically kernel Fisher discriminant analysis (FDA) and consists of four layers such as initial layer is input layer that every neuron shows a predictor variable and inputs pass for next layer. The second layer is pattern layer that calculates the distance between input vector and the training data vectors to find the closest match. Thirdly, the summation layer is used for contributions of each class to the input and creates a probability vector for multiple classes. Finally, decision layer classifies the input into one of the predefined classes by selecting the class with the highest probability. The PNN structure is shown in Fig. 2.

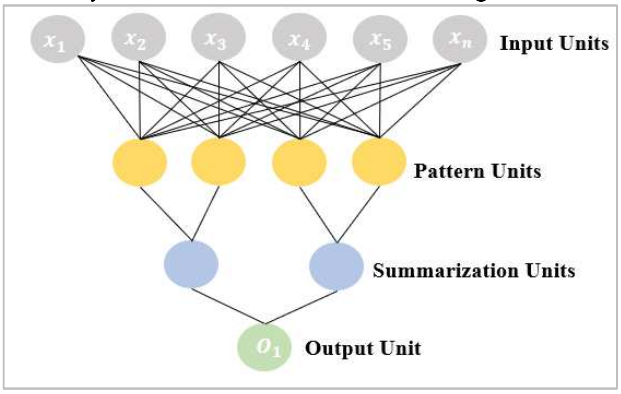

Fig. 2. Structure of PNN

The PNN is faster and more accurate than various other neural network methods, making it highly effective for classification tasks. However, it is slower when processing new inputs and requires significant memory to store results.

a) Input Layer: Every neuron in input layer signifies a predictor variable. These neurons don't perform any calculations; they just pass the input data on to neurons in hidden layer.

b) Pattern unit: This layer has one neuron for each case in training dataset. Each neuron calculates a product of input vector x and weight vector w_i, signifying for $z_i = x.w_i^t$. After that, a nonlinear operation is applied, as shown in equation (1).

$$exp\left[\frac{-(w_i-x).(w_i-x)^T}{2\sigma^2}\right] \tag{1}$$

c) Summation unit: Each node connected for specific class, the inputs are added from pattern unit that matches the chosen class, as shown in equation (2).

$$\sum_i exp\left[\frac{-(w_i-x).(w_i-x)^T}{2\sigma^2}\right] \tag{2}$$

d) Output unit: The output layer compares weighted votes for every target class collected from pattern layer and selects highest vote for determine decision classes Ωr and Ωs, $r \neq s$, $r, s = 1,2, \dots q$ according to the classification criteria are shown in equation (3).

$$\sum_i exp\left[\frac{-(w_i-x).(w_i-x)^T}{2\sigma^2}\right] > \sum_j exp\left[\frac{-(w_i-x).(w_i-x)^T}{2\sigma^2}\right] \tag{3}$$

These nodes each have a single weight, C denotes priori membership probabilities and number of training samples in every class, is determined by cost parameter, as shown in equation (4).

$$C = -\frac{h_s l_s}{h_r l_r} \cdot \frac{n_r}{n_s} \tag{4}$$

Where h_s signifies previous prospect, Group n, and c_n represents misclassification cost.

IV. Experimental Results

The configuration of the system required for the implementation of the PNN proposed methodology in Python 3.9, RAM 16GB, intel i5 processor and windows OS-10. The proposed PNN model is tested and experimented through utilizing the RWC dataset. The proposed method is validated through using different assessment metrices such as accuracy, recall, precision and F1-score. A formulation of metric is expressed in equation (5) to (8) as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

$$F1-Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{8}$$

Where, TN - True Negative, TP - True Positive, FN- False Negative, FP-False Positive.

A. *Performance analysis*

The qualitative and quantitative analysis of proposed PNN is validated in this section by using the RWC dataset. The performance of the feature extraction technique such as MFCC is used in this research that shown in metrics. Table I represents the performance analysis of various feature extraction with MFCC.

TABLE I. Performance Analysis of Various Feature Extraction

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CF	81.05	82.31	80.91	81.60
STFI	84.82	83.36	81.13	82.23
LPC	85.06	84.48	82.89	83.68
MFCC	88.90	86.02	87.56	86.78

Table I shows the various feature extraction with proposed method helps to classify the emotion recognition. The existing feature extraction such as CF, STFI and LPC are compared and estimated with the proposed MFCC methods. As compared to these individual approaches, the classifier provides a comprehensive view of analysis of classifiers, leads for enhance the classification accuracy. The feature extraction techniques such as MFCC attains the accuracy of 87.46% for RWC dataset respectively.

An achievement of proposed PNN is estimated with various existing methods. Table II represents the analysis of different classification results with RWC dataset.

TABLE II. Analysis of Different Classifiers with Datasets

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RBNN	82.78	81.89	80.82	81.35
GRNN	84.05	83.11	82.83	82.97
FNN	86.90	85.49	84.41	84.95
Proposed PNN	88.90	86.02	87.56	86.78

Table II represents various classifiers with PNN helps for select the modulation type with high probability. The existing classifiers such as RBNN, GRNN and FNN are compared and estimated with the proposed PNN methods. The PNN classifier attains the accuracy of 88.90% for RWC dataset respectively.

B. *Comparative analysis*

In this research, existing methods are compared with the proposed method depends on RWC. The existing approaches TADCNN [11], CNN [13], LSTM [14] are compared with proposed PNN approach by using various performance metrices. As compared to these existing methods, the proposed PNN approach has the capability to process data in both directions allow to select the modulation type for enhance a classification accuracy. Table III depicts the comparative analysis of existing AMC system with performance metrics.

TABLE III. Comparative Analysis of Existing Emotion Recognition

Methods	Accuracy (%)
TADCNN [11]	66.64
CNN [13]	56.00
LSTM [14]	76.00
Proposed PNN	88.90

C. *Discussion*

In this research, the PNN is proposed to select the modulation type with high probability. The existing works are related to AMC with limitations are discussed in following discussions. The TAD denoiser helps in reducing noise and occurring of residual noise it affects the performance [11]. If the model is not trained on a diverse range of modulations, DRMM's ability to generalize to new, unseen modulation types may be limited, even if it performs well on the training data [12]. The CNN model had lack of training data or new, unseen data it leads to overfitting [13]. If the input signal data was poor quality or heavily corrupted by noise, the model might still struggle, even though it is more robust than traditional methods [14]. The sliding window technique for pre-processing must be carefully tuned, as improper configuration lead to inefficient feature extraction or loss of important signal information [15]. To overcome these limitations, the PNN is proposed. The RWC is a collection of RF signals dataset acts as input to the proposed PNN method. The collected dataset is fed into the pre-processed method for improve the quality of the signals and helps to reduce the noise. The pre-processed signals given to feature extraction phase to extract the signals. The extracted signals are passed to classification phase and PNN is a classifier used to select the modulation type with high probability. The use of PNN, classification accuracy is widely enhanced. The performance metrics such as accuracy of 88.90% are used to evaluate a performance of the PNN model respectively.

V. Conclusion

In this research, PNN is proposed to select the modulation types with high probability. AMC plays a key role in detecting and demodulating telecommunication signals. AMC has gained significant attention due to its broad range of applications. The RWC is a collection of RF signals dataset acts as input to the proposed PNN method. The collected dataset is fed into the pre-processed method for improve the quality of the signals and helps to reduce the noise. The pre-processed signals given to feature extraction phase to extract the signals. The extracted signals are passed to classification phase and PNN is a classifier used to select the modulation type with high probability. From the results, the proposed PNN established better results when compared to existing TADCNN by providing accuracy as 88.90% respectively. The future work of the research aims to use to effective feature extraction techniques to improve the performance of the model.

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