Classification of RF Signal Using Deep Learning

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Abstract

Automatic Modulation Classification (AMC) is a fundamental component of intelligent wireless communication systems that guarantees robust recognition of modulation types in complex Radio Frequency (RF) channels. This research proposes an end-to-end RF communication model based on a Convolutional Long Short-Term Memory Deep Neural Network (CLDNN) for AMC and communication performance estimation. The RadioML 2016.10a dataset including eleven modulation types was normalized and trained via a novel hybrid CLDNN network which consists of feature extraction module using convolution and temporal sequences learning model. The proposed framework implements not only the classical classification procedure but also synthesis of I/Q signals, their transmission through the TCP channel, and receiver performance evaluation via Bit Error Rate (BER). The obtained experimental results showed 62.48% validation accuracy at 10 dB SNR, while signal reconstruction guaranteed the real-world application of the proposed approach.

Keywords: Automatic Modulation Classification (AMC), Convolutional Long Short-Term Memory Deep Neural Network (CLDNN), Radio Frequency Signal Classification, In-Phase and Quadrature (I/Q) Signals, Bit Error Rate (BER), Intelligent Wireless Communication Systems.

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1. Introduction

The exponential growth of wireless communication technologies has led to increase in the need for intelligent RF signal analysis. Automatic Modulation Classification (AMC) has emerged as an important element in areas like cognitive radio, spectrum sensing, electronic warfare, software-defined radio, and adaptive wireless network communications. Traditional methods of modulation classification are predominantly based on the design of hand-crafted features and expert-designed decision-making rules. This renders these methods heavily dependent on human experience and not very effective when applied to complex channel environments and diverse signals. With the advancement in wireless communication systems and diversification of signals being transmitted through the channels, there is an urgent need for more automated and intelligence-driven solutions for modulation classification.

The recent advancements in machine learning and deep learning techniques have contributed greatly to RF signal classification in that they allow for automatic feature learning using I/Q signal representations. Convolutional neural networks have proven their ability to extract good spatial features, while recurrent networks have shown effectiveness in temporal pattern recognition within sequential RF signals. The performance of classification tasks can also be enhanced through hybrid models of deep learning that combine different deep learning architectures in order to leverage their different abilities. However, the current methods of classification still suffer from difficulties associated with feature generalization, discrimination of spectrally close signals, computational complexity, and practical implementation in end-to-end communication systems. Most of the existing research works concentrate only on solving the problem of modulation recognition without testing the viability of the predicted modulation type in a communication system.

To address with these issues, the proposed CLDNN-based framework that classifies RF signals along with communication-oriented validation is introduced. This framework utilizes the combination of convolutional and long short-term memory networks in order to learn the spatial-temporal characteristics from raw I/Q signals, which allows for the accurate classification of automatic modulation. In addition to the task of modulation classification, the proposed framework includes synthetic signal generation, communication through transmission pipeline, and transmission quality estimation with bit error rate evaluation. Thus, it expands the range of tasks that can be accomplished within the framework of the standard AMC systems to communication validation. Such integrated approach enhances the applicability of deep learning-based AMC to the intelligent wireless environment by combining the process of signal recognition with communication. The experimental evaluation confirms the effectiveness and feasibility of the proposed framework for RF signal processing and analysis.

2. Literature Review

The techniques for automatic classification have evolved from classical feature engineering to deep learning methodologies that enable automatic feature learning from the data. Early researchers have recognized the drawbacks of conventional classification algorithms in dealing with complex and noisy environments and the requirement for an adaptive learning system [1]. The introduction of deep neural network models has greatly advanced the performance of classification algorithms through hierarchical feature learning without depending on manual feature selection [2]. Improved techniques show the capability of more accurate and robust classification using deeper models and better feature learning [3].

Hybrid deep learning architectures have received significant attention because of their capacity to model local and global characteristics. Comparative studies between CNN, LSTM, and hybrid CNN-LSTM networks revealed that hybrid models tend to perform better than separate networks since they combine spatial learning and sequential learning [4]. Likewise, CLDNN network models, which are hybrid architectures combining convolutional, recurrent, and fully connected layers, have proven effective in modeling high-dimensional data sets [5].

Recent research efforts have concentrated on the development of end-to-end learning algorithms that integrate both feature extraction and classification processes, which help improve the discriminative ability and system performance [6], [7]. Besides, there has been the design of lightweight deep learning algorithms in order to minimize computation while maintaining comparable accuracy levels, making them applicable in large-scale applications [8]. There has also been the high performance of deep learning algorithms in performing object detection and classification in different environments, together with the robustness of adaptive learning algorithms [9], [10].

Despite the achievements of the existing deep learning frameworks for classification and recognition tasks, there are still some issues when it comes to heritage point cloud segmentation. Most of the classical techniques mainly concentrate on one of two ways, either local geometric features or global context description, neglecting the complicated relations between elements in the heritage object. Current state-of-the-art CNN-based models are weak in capturing the irregular topology of the point cloud data, whereas the graph-based models may fail in refining the local features of the data. Moreover, the current models cannot appropriately combine the kernel-based feature extraction and graph representation, resulting in low performance in segmenting fine architectural parts, damage, and culture-specific structures within the data. The heritage point clouds are known for their geometric complexity, density variation, occlusion, and noise, which makes semantic segmentation difficult. For that reason, it is necessary to design the Hybrid Graph-Kernel Fusion Network for exploiting both neighborhood relations using graph representation and local features using kernels.

3. Methodology

The proposed approach provides a comprehensive RF communication framework for achieving intelligent modulation classification, generation of synthetic signals, reliable data transfer and assessment of communication performance.

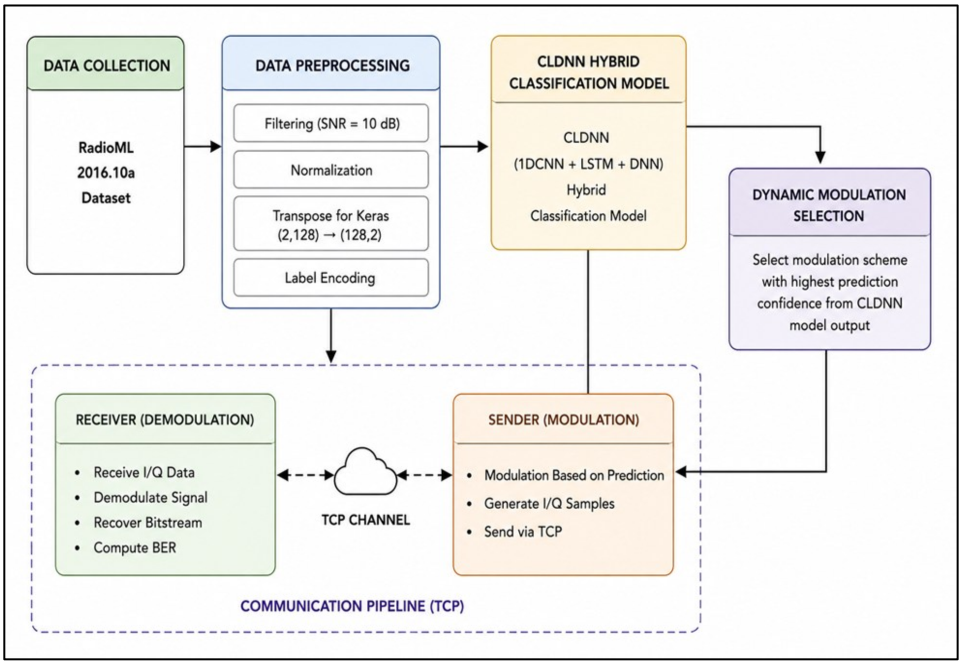

Figure 1. Proposed end-to-end CLDNN-based RF signal classification

The complete workflow is illustrated in Figure 1. The whole system includes four main components are preprocessing of the input data, CLDNN-based modulation classification, generation of synthetic I/Q signals with their TCP-based transfer and demodulation at the receiver end along with assessment of the Bit Error Rate (BER).

3.1 Data Preparation and Preprocessing

The RadioML 2016.10a [11] dataset has been used for acquiring RF signals for training and testing purposes. The data consists of eleven different types of modulation signals which are characterized by complex in-phase and quadrature signal samples with different levels of Signal-to-Noise Ratio (SNR). In order to guarantee that the SNR level is consistent throughout the process of training and reduce the effects of noise as much as possible, only signal samples with an SNR level of 10 dB were selected. This SNR ratio provide a balance between the signal and the channel effects, enabling the model to efficiently learn the features of modulation discrimination.

Each signal is made up of two channels corresponding to I and Q channels that have 128 temporal observations. Normalization of the signals was done before the training of the model in order to remove any amplitude variations in the signal. The normalization technique is expressed as (1).

$$\hat{Y}_{i,j} = \frac{(X_{i,j} - \mu_i)}{(\sigma_i + \varepsilon)}, \qquad i \in \{I, Q\},\ j = 1, 2, \ldots, 128 \tag{1}$$

where,

- $X_{i,j}$: represents the original signal value
- μ_i: denotes the mean of channel i
- σ_i: denotes the standard deviation of channel i
- ε: is a small constant added to prevent division by zero
- $i \in \{I,Q\}$ indicates the in-phase and quadrature signal channels.
- $j = 1,2,\ldots,128$ represents the temporal sample index.

3.2 CLDNN-based Modulation Classification

The hybrid Convolutional Long Short-Term Memory Deep Neural Network (CLDNN) is developed for the classification of RF modulation techniques based on normalized in-phase (I) and quadrature (Q) signal samples. The proposed structure incorporates the layers of the convolutional neural network for hierarchical spatial feature extraction along with the LSTM layer for modeling temporal dependencies to facilitate the learning process. Figure 2 shows the architectural design of the proposed CLDNN model.

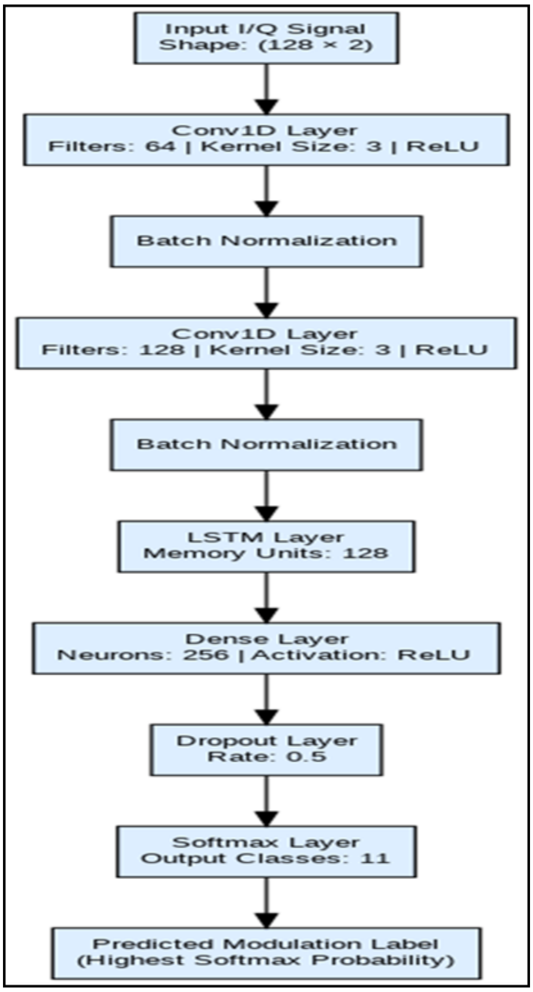

Figure 2. Layer-wise architecture of the proposed CLDNN model

As shown in Figure 2, the input signal with dimensions 128 x 2 first undergoes processing through two consecutive Conv1D layers with 64 and 128 filters, respectively, each having a kernel size of 3 with ReLU activation function. A Batch Normalization layer is added after every convolutional layer in order to improve the convergence of the model and stabilize the feature distributions. Next, the extracted features maps are fed to an LSTM layer with 128 memory units that learn the sequence properties of RF signals. The subsequent Dense layer with 256 neurons and ReLU activation function learns high-level features, followed by the Dropout layer with rate of 0.5 in order to avoid overfitting. Lastly, the Softmax layer produces probability values for 11 modulation classes, and the class with maximum probability value is selected as the prediction.

3.3 Model Training and Optimization

CLDNN was trained on the categorical cross-entropy loss, which is generally applied in classification problems that involve more than two classes. The optimization process seeks to minimize the difference between the predicted probabilities and the correct class labels (2).

$$L = -\Sigma_{\mathrm{i}}{}^{=111} y_{\mathrm{i}} \times log(\hat{\mathrm{y}}_{\mathrm{i}}) \tag{2}$$

where,

- y_{i}: represents the ground-truth label
- $\hat{\mathrm{y}}_{\mathrm{i}}$: denotes the predicted probability for class i

The optimization process was based on the Adam technique because of the adaptiveness of its learning rate and efficient convergence. The Adam optimizer uses momentum along with adaptive gradient approximation in order to minimize the training loss. Early stopping was used as an approach to avoid overfitting.

3.4 Synthetic Signal Generation and TCP-based Communication

Following modulation classification, synthetic I/Q signals correspond to the identified modulation format were created to replicate actual RF transmission situations. The signals were created from ideal constellation mappings pertaining to the modulation formats including BPSK, QPSK, 8PSK, 16QAM, and 64QAM. The artificial signals also had the same dimensionality as those in the original database, making their use easy in the communication system. To determine the feasibility of deployment, the I/Q samples that had been created were sent via a Transmission Control Protocol (TCP) communication channel. This is due to the nature of the TCP protocol, which features reliable, ordered, and controlled delivery of data. The payload of the transmitted information included the prediction of the modulation type, the original binary sequence, and the I/Q signal matrix.

3.5 Receiver Processing and BER Evaluation

At the receiver, the I/Q signal was demodulated based on the transmitted modulation scheme. After that, the received bit stream was compared to the transmitted one in order to measure the accuracy of communication. System performance was measured in terms of Bit Error Rate (BER), given as (3)

$$BER = \frac{(Number\ of\ Error\ Bits)}{(Total\ Number\ of\ Transmitted\ Bits)} \tag{3}$$

where,

- $Number\ of\ Error\ Bits$: the count of bits that were received incorrectly
- $Total\ Number\ of\ Transmitted\ Bits$: the total count of bits sent

The lower value of the Bit Error Rate corresponds to higher accuracy of communication and correct prediction of modulation. The obtained values of BER, together with signal visualization and modulation data were presented via Graphical User Interface (GUI). Such a testing approach makes it possible to conduct an overall evaluation of classification and communication performance of the suggested CLDNN-based RF communication system.

4. Results and Discussion

4.1 CLDNN Model Performance Analysis

The proposed CLDNN model is trained by using RadioML 2016.10a dataset, which includes eleven types of modulation at the 10 dB SNR level. In total, training was performed up to a maximum number of 50 epochs, but due to overfitting concerns and the application of the early stopping technique, the procedure was stopped at epoch number 18.

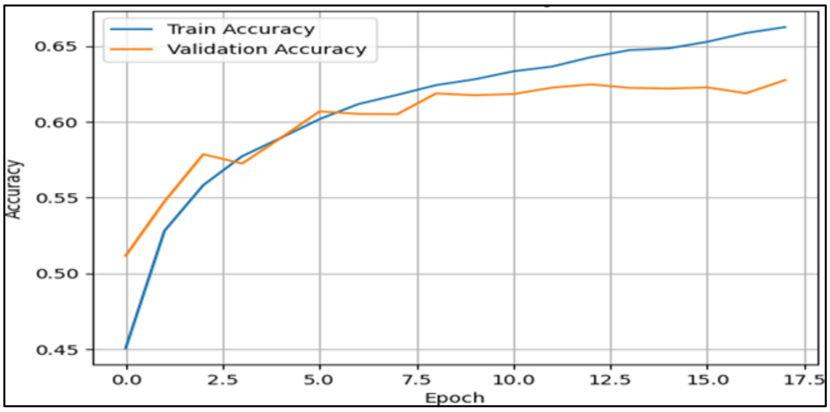

Figure 3. Training and validation accuracy of the proposed CLDNN model

As illustrated Figure 3, both the training and validation accuracy curves increase steadily at the beginning of the process, implying efficient feature learning and stable optimization. In addition, the validation accuracy curve converges to around 62.48%, implying successful extraction of modulation-based attributes from the I/Q sample data. The slight difference between the training and validation curves implies minimal overfitting, hence confirming the efficiency of the use of batch normalization and dropout regularizations. The behavior during convergence also confirms the appropriateness of the CLDNN design in extracting local and temporal features of the signals.

Table 1. Classification performance of the proposed CLDNN model

Parameter	Value
Dataset	RadioML 2016.10a [11]
Number of Classes	11
Selected SNR	10 dB
Maximum Epochs	50
Early Stopping Epoch	18
Validation Accuracy	62.48%
Optimizer	Adam
Loss Function	Categorical Cross-Entropy

From Table 1, CLDNN architecture attained a validation accuracy of 62.48% when employing categorical cross-entropy loss function along with Adam optimization. The early stop criterion stopped the learning process after 18 epochs, which denotes that the model converged within the defined training period. These findings reveal that the proposed architecture possesses the potential for discriminating various modulation formats in actual channel conditions. While there exists an overlap among some modulation classes, the overall classification accuracy remains acceptable.

4.2 Confusion Matrix and Class-Wise Performance Analysis

The confusion matrix shown in Figure 4 illustrates the demonstration of the classification capability of the proposed CLDNN model for the 11 classes of modulations.

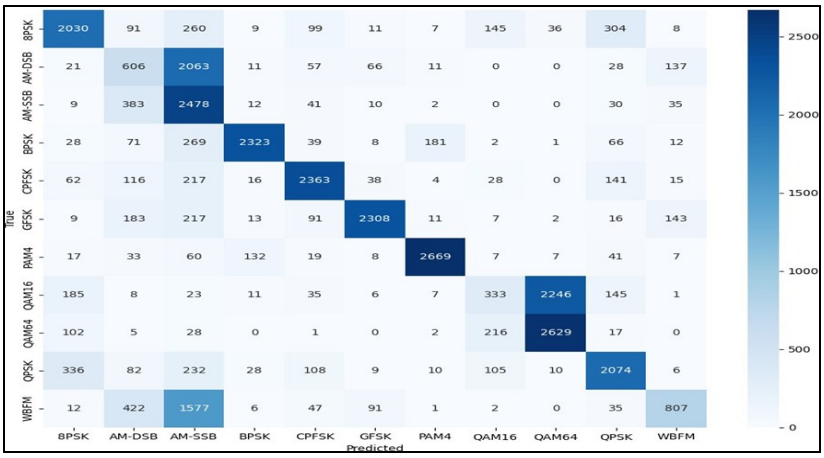

Figure 4. Confusion matrix for multi-class RF modulation classification

Almost all types of modulations are classified correctly as demonstrated by the prominent diagonal terms in the confusion matrix, and thus the CLDNN model is able to extract discriminative spatial-temporal features from the I/Q signal samples. The misclassification instances of the modulations occur mostly between modulations with similar constellation characteristics, especially those of higher order digital and analog modulations.

4.3 CLDNN Classification Output Analysis

The classification results produced by the CLDNN model are shown in Table 2 and include precision, recall, F1-score, and support for each modulation class. Metrics in question are used to assess the prediction capabilities of the model by means of calculating accuracy, completeness, and overall performance of the classification process for particular modulation types. The higher precision and recall rates signify that respective modulation types have been accurately identified while lower rates suggest that the differences between modulation schemes are more difficult to detect due to their similar signal properties. Class-wise classification performance proves that CLDNN is capable of learning representative features for the I/Q signals thus ensuring reliable modulation classification for eleven modulation types. In general, numerical results obtained for the classifier can be seen in Table 2 and prove the effectiveness of the proposed architecture.

Table 2. Class-wise performance metrics of the proposed CLDNN model

Modulation	Precision	Recall	F1-Score
8PSK	0.72	0.68	0.70
AM-DSB	0.30	0.20	0.24
AM-SSB	0.33	0.83	0.48
BPSK	0.91	0.77	0.84
CPFSK	0.81	0.79	0.80
GFSK	0.90	0.77	0.83
PAM4	0.92	0.89	0.90
QAM16	0.39	0.11	0.17
QAM64	0.53	0.88	0.66
QPSK	0.72	0.69	0.70
WBFM	0.69	0.27	0.39

4.4 Communication Performance Evaluation

The proposed framework is verified by performing a real-time communication experiment using the modulations predicted by the trained CLDNN model. Initially, an arbitrary RF signal was classified, and the prediction by the model indicated 8PSK as the modulated signal. Following this, synthetic I/Q samples of the predicted modulation were generated and transmitted through the TCP communication channel. Figure 5 displays the generated 8PSK signal constellation plot. There is clear evidence of eight phases in the points of the constellation as expected.

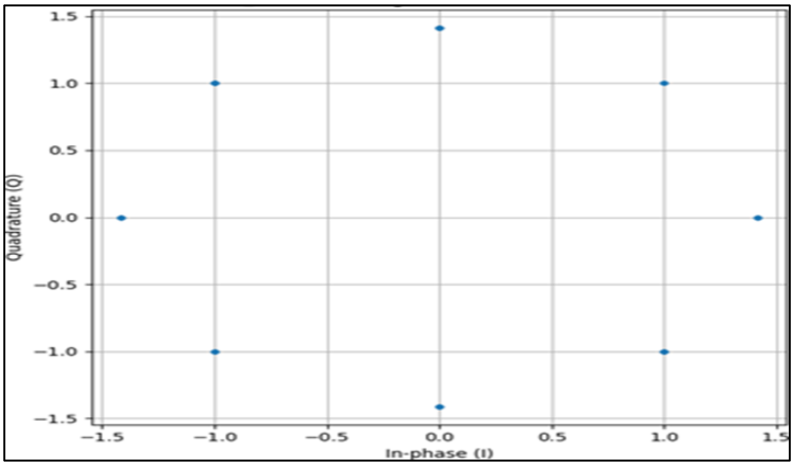

Figure 5. Generated 8PSK constellation for signal transmission

At the receiving end, the signal was received and demodulated based on the expected modulation format. Figure 6 displays the visualization of the received signal.

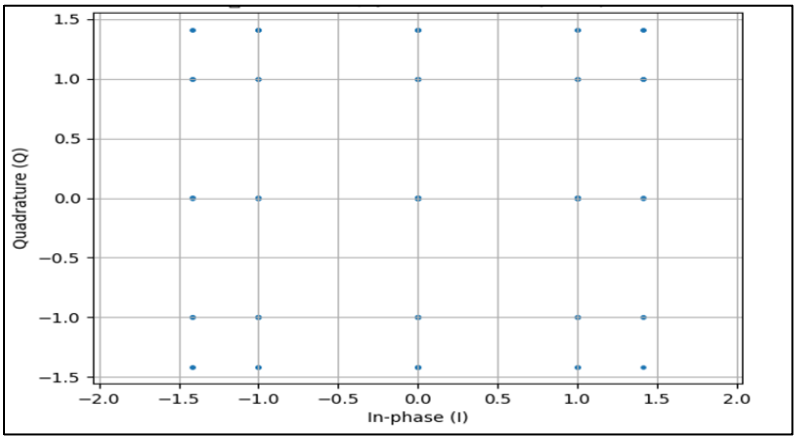

Figure 6. Receiver-side signal reconstruction following TCP transmission

The received signal appears similar to the transmitted signal wave, which proves the efficient communication process and proper signal reception. The value of the Bit Error Rate (BER) for the received signal was found to be 0.4805. To explore the importance of selecting an intelligent modulation technique, a mismatched experiment was performed using BPSK modulation instead of the predicted 8PSK modulation. The constellation diagram is shown in Figure 7.

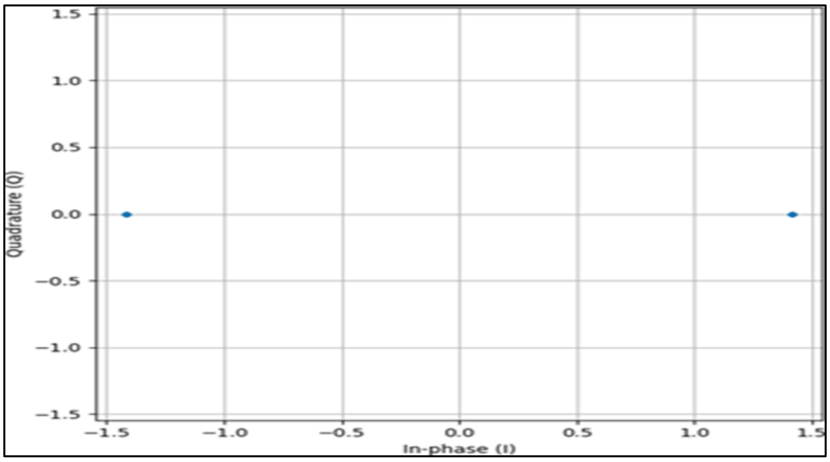

Figure 7. BPSK constellation used for modulation mismatch analysis

In this incorrect modulation setting, the BER reached up to 0.5000, indicate the degraded transmission performance. The higher BER demonstrates the importance of modulation detection in providing effective transmission characteristics.

Table 3. BER Comparison for different transmission conditions

Transmission Scenario	BER
Predicted 8PSK	0.4805
Forced BPSK Mismatch	0.5000

As shown in Table 3, the transmission approach based on the modulation obtained from the CLDNN model showed a smaller BER than forced modulation mismatching. Even though the difference between these two values is not significant, it can be concluded that modulation-aware transmission leads to higher decoding performance of errors in communication systems.

4.5 Discussion

The experimental results confirm the efficacy of the proposed CLDNN architecture for automatic modulation classification and RF signal processing tasks. The combination of convolutional layers and LSTM nodes allows us to obtain comprehensive information regarding both spatial and temporal properties of I/Q signals, which makes it possible to discriminate several modulation types successfully. The recognition of modulation types characterized by unique signal features is especially high in the proposed framework, while the classes with similar spectral and temporal features show comparatively low recognition results due to the complexity of the classification process itself. The inclusion of the steps of artificial signal generation, transmission, reception, and estimation of bit error rate allows us to highlight the practical applicability of the suggested CLDNN framework. Thus, the proposed CLDNN-based framework not only supports the automatic modulation classification but also includes the entire process of communication and can be viewed as an evolution of the classical automatic modulation classification technique.

5. Conclusion and Future Work

In this research, a complete Automatic Modulation Classification (AMC) framework for intelligence-based RF communication is developed based on CLDNN for the classification of eleven modulation schemes from the RadioML 2016.10a dataset. Combining the use of convolutional and LSTM layers for spatial and temporal information respectively, the designed model can perform effective classification of modulations. The use of I/Q data synthesis, TCP-based transfer, receiver-side demodulation, and BER estimation proved the potential for implementing the modulation classification process to the complete communication scenario. From the experimental results, conclude that the designed AMC framework performs modulation recognition while providing an end-to-end evaluation of communication performance in dynamic RF environment. In the future work, we are going to improve classification results by using attention mechanisms and transformer architectures, test the proposed framework for multiple Signal-to-Noise Ratio (SNR) and RF datasets, and validate the approach for real-time scenarios based on Software-Defined Radio (SDR) platforms.

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