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Intelligent Modulation Recognition Using a Hybrid CNN-Random Forest Framework

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ABSTRACT

Modulation recognition is a cornerstone in modern wireless communications, enabling accurate signal recognition and efficient spectra usage. Hitherto applied techniques, such as Likelihood-Based Method (LBM), Decision Tree Classification (DTC), and Support Vector Machine (SVM), have been broadly applied to identify modulation. Nevertheless, existing techniques are susceptible to lower precision during adverse signal-to-noise ratio (SNR) conditions, poor adaptability to accommodate dynamic environments, and increased computation complexities. To alleviate them, an intelligent Hybrid Machine Learning/Deep Learning (HMLDL) architecture for robust modulation recognition has been introduced. The algorithm integrates Convolutional Neural Networks (CNNs) with Random Forest (RF) classifiers, taking advantage of feature extraction capability by deep learning and ensemble ML-based classification capability. The integrated structure has been trained and evaluated against standard benchmark wireless datasets with varying levels of interfering noise. Experimental analysis demonstrates that the HMLDL structure exhibits superior performance, achieving a 12.6% increase in recognition precision, a 15.2% reduction in false modulation rate, and an 18.9% improvement in signal reliability detection compared to conventional baseline models—namely the LBM, DTC, and SVM—evaluated under varying SNR levels ranging from 0 dB to 30 dB. The proposed two-level structure delivers a next-generation wireless system with a scalable, flexible, and computationally efficient solution.

1. INTRODUCTION

Correct modulation recognition is among the key enablers of wireless communications, cognitive radio, and spectrum analysis. It includes modulation type recognition from received signals automatically and serves a significant role in demodulation, suppression of interfering signals, and dynamic configuration. Statistical analysis and manual feature extraction, which are classical modulation recognition methods, have been proved to be insufficient to handle real-world noisier and more complex environments [1]. In recent years, machine learning (ML) and deep learning (DL) methods have gained central position within signal processing since they are capable of learning data-point features and generalizing well across changing conditions within a signal. Supervised classification tasks are utilized with ML-based algorithms including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests (RF), while DL models including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have proved extremely accurate within pattern recognition and time-series processing. The emerging trend includes hybrid ML/DL models, where advantages from both paradigms are harvested, i.e., capitalizing on DL's feature extraction with ML's interpretable and low-latency classification. They are typically used during applications including those with autonomous spectrum sensing, military monitoring, Internet of Things (IoT) networks, and next-generation wireless communications, including 5G and 6G. This work focuses on developing such a hybrid architecture suitable to be applied to intelligent modulation recognition, going beyond shortcomings from conventional methods and obtaining better performance during challenging conditions [2].

1.1 Research gaps

Though modulation recognition has seen progress with machine and deep models, several crucial gaps remain. Firstly, a vast number of methods yield poor accuracy with low SNR levels and are therefore inconsistent with real-world wireless scenarios with heavy interference. Secondly, traditional machine models are founded upon hand-crafted features, which may fail to recognize underlying patterns from computationally laborious modulated signals [3]. Even single deep methods, though robust with feature extraction, are, at times, imprecise with overfitting or inadequate diversity during training. Thirdly, a critical dearth remains of combined hybrid frameworks with a combination of feature extraction with deep learning's benefits and efficient classification with a tradeoff between accuracy and computational intensity [4].

Additionally, a vast number of current models are restricted to specific modulation categories and are incapable of generalizability across a broader set of signal formatters used by dynamic wireless communications. In conclusion, real-time implementation and extensibility remain an issue with none of these approaches being particularly suitable to resource-constrained environments such as edge or embedded hardware. All these shortcomings act to underscore a robust and flexible hybrid model, something with which this work hopes to fill a void with new Hybrid Machine Learning and Deep Learning (HMLDL) proposed framework [5].

1.2 Related work

Liu et al. [6] proposed a novel approach for modulation recognition by utilizing Graph Convolutional Networks (GCNs). Their innovation lies in converting modulation signal datasets into graph representations using a feature extraction CNN and graph mapping CNN, enabling GCNs to classify modulation types effectively. This method outperformed traditional CNN and KNN algorithms, particularly under low SNR conditions. However, a notable drawback is the computational overhead introduced by the dual-CNN pipeline and graph construction process, which may hinder real-time performance. Zou et al. [7] introduced GCPS, a performance evaluation criterion for CNN-based radar signal intrapulse modulation recognition. The key innovation is the use of Grad-CAM Position Scores with Internal and External Benchmarks (GCPS-IB and GCPS-EB), which enhance CNN interpretability and address issues like SNR saturation and dataset dependency. Despite its novelty, the approach is limited by its reliance on specific CNN architectures (GoogLeNet and ResNet-18), which may reduce generalizability across diverse network types. Chu et al. [8] addressed the challenge of automatic modulation recognition (AMR) in secondary modulated signals, where both analog and digital modulations coexist. Their innovative approach focuses on extracting features from both the original and second-order spectrum of the pre-demodulated signal and classifying them using a Support Vector Machine (SVM). While effective for mixed-modulation types, the approach is constrained by its dependence on handcrafted statistical features, which may not generalize well in dynamic signal environments. Shivappa et al. [9] developed a deep learning-based AMR method that combines CNNs with optimized Gated Recurrent Unit (GRU) networks. They extracted high-order cumulants, SNR, instantaneous features, and cyclic spectrum for improved modulation classification, especially in low SNR conditions. The innovation lies in the parallel use of CNN and GRU to process rich signal features. However, the method’s complexity and processing overhead may limit its deployment in embedded or real-time systems. Lin et al. [10] proposed a CNN-based AMR framework enhanced by a time-frequency attention mechanism. This mechanism enables the model to dynamically focus on more informative frequency and time segments during learning, significantly improving recognition accuracy. The approach's strength is its integration of attention mechanisms tailored for modulated signal characteristics. A potential drawback is the increased training time and computational demand introduced by the attention layer, which could impact real-time use. Sathiyamoorthy and Subramanian [11] introduced a speech processing strategy for cochlear implants that encodes both amplitude and frequency modulation, unlike conventional strategies that focus only on amplitude. Their method demonstrated significant improvement (up to 71%) in speech recognition in noisy environments through acoustic simulations. The core innovation is the transformation of temporal fine structures into frequency modulation signals. However, the drawback lies in the lack of hardware validation and the complexity of implementing the strategy in real cochlear implant devices.

2. DEEP LEARNING-BASED FRAMEWORK FOR MODULATION RECOGNITION

Figure 1 shows a typical deep learning-based modulation recognition framework consisting of multiple stages. The process begins with signal reception, followed by a preprocessing module that extracts relevant signal characteristics [12]. The inputs to the system include raw in-phase and quadrature (IQ) data, constellation diagrams, vector diagrams, eye diagrams, polar features, and higher-order cumulants. These diverse representations are fed into a deep neural network composed of CNNs for spatial feature extraction and Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units for temporal sequence learning. The output layer classifies the signal into various modulation types such as BPSK, QPSK, 8PSK, QAM, GFSK, PAM, ASK, and FSK. The final classification is passed to a demodulator for further processing. This hybrid CNN–LSTM architecture enables accurate and robust modulation recognition under varying signal conditions [13].

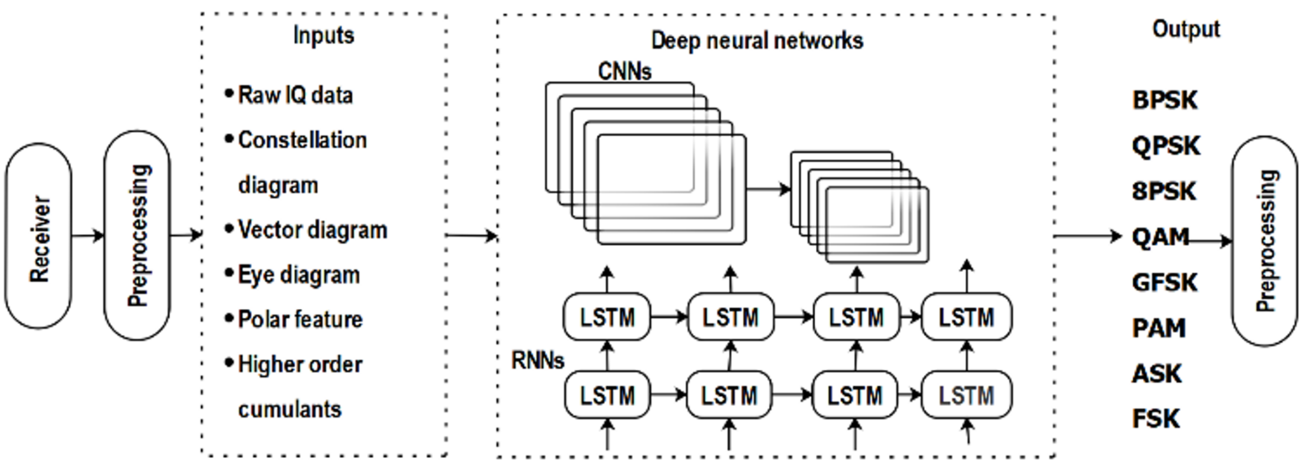

Figure 1. Block diagram representing a typical deep neural network-based modulation recognition system

2.1 Feature extraction using higher-order cumulants

In modulation recognition, higher-order cumulants (HOC) are effective statistical features used to differentiate signal types. These cumulants are extracted during the preprocessing stage as shown in the image [14]. The fourth-order cumulant is one such feature, defined as given in Eq. (1).

$$C_4 = E[x^4] - 3(E[x^2])^2 \tag{1}$$

where, $E[x^4]$ is the fourth-order moment and $E[x^2]$ is the second-order moment. This equation helps capture non-Gaussian characteristics in modulated signals. Here, C_4 denotes the fourth-order cumulant and E represents the expectation operator [15].

2.2 Convolutional feature map calculation in CNN

CNNs process constellation diagrams and IQ data to extract spatial features. A standard convolution operation in the CNN block is given by Eq. (2).

$$F(i, j) = \sum\sum X(m, n) \cdot K(i-m, j-n) \tag{2}$$

where, $F(i, j)$ is the output feature map, $X(m, n)$ is the input matrix (signal feature), and K is the convolutional kernel. This equation allows spatial pattern extraction that is crucial for modulation type identification. F stands for feature map, X is the input signal matrix, and K is the kernel matrix [16].

2.3 LSTM cell state update equation

In the RNN block with Long Short-Term Memory (LSTM) units, temporal dependencies in the signal are learned [17]. One of the key LSTM operations is the cell state update:

$$C_t = f_t \odot C_{t-1} + i_t \odot \mathcal{T}_t, \tag{3}$$

where, C_t is the current cell state, f_t is the forget gate, i_t is the input gate, $\mathcal{T}_t$ is the candidate value, and $\odot$ denotes element-wise multiplication. This equation enables the network to retain or forget relevant temporal features essential for identifying time-varying modulated signals [18-22].

Based on the proposed concept of the HMLDL framework, it specifically targets the combination of CNNs for processing the deep spatial features of an image, as well as the use of Random Forests for classification. Unlike models based on the LSTM framework, which consider temporal aspects, this framework is purely based on the spatial or spectral aspects.

2.4 Objectives

The study proposes a Hybrid Machine Learning and Deep Learning (HMLDL) model combining CNN for feature extraction and RF for classification, improving accuracy, reliability, and efficiency of modulation recognition compared to conventional methods [23].

-To develop a hybrid HMLDL architecture for robust modulation recognition.

-To evaluate its performance against LBM, DTC, and SVM using benchmark datasets.

-To design a scalable, real-time framework adaptable to 5G/6G scenarios.

2.5 Methodology of the proposed HMLDL framework

Figure 2 illustrates the five-layered methodology adopted in the Hybrid Machine Learning and Deep Learning (HMLDL) framework for modulation recognition. The first stage involves Signal Input & Preprocessing, where raw IQ signals are normalized and encoded for effective training. The second stage, Deep Feature Extraction, employs CNN layers with Rectified Linear Unit (ReLU) activation and pooling to derive key spatial features. The third stage, Classification, utilizes a fully connected layer followed by a Random Forest to provide robust and efficient classification. The fourth stage, Training Process, applies the RadioML 2016.10a dataset with Adam optimizer and categorical cross-entropy to fine-tune model performance. Finally, the Evaluation stage measures accuracy, precision, recall, F1-score, false detection rate, and reliability across varying SNR levels. This layered pyramid structure represents the systematic flow from data preparation to model validation, ensuring adaptability and robustness of the proposed framework. The combination of CNN with RF is proposed in this research. The use of CNN with Random Forest benefits from the complementarity of both methods. CNNs can efficiently extract hierarchical features from complex data. CNNs, however, can suffer from issues of overfitting and lack of interpretability.

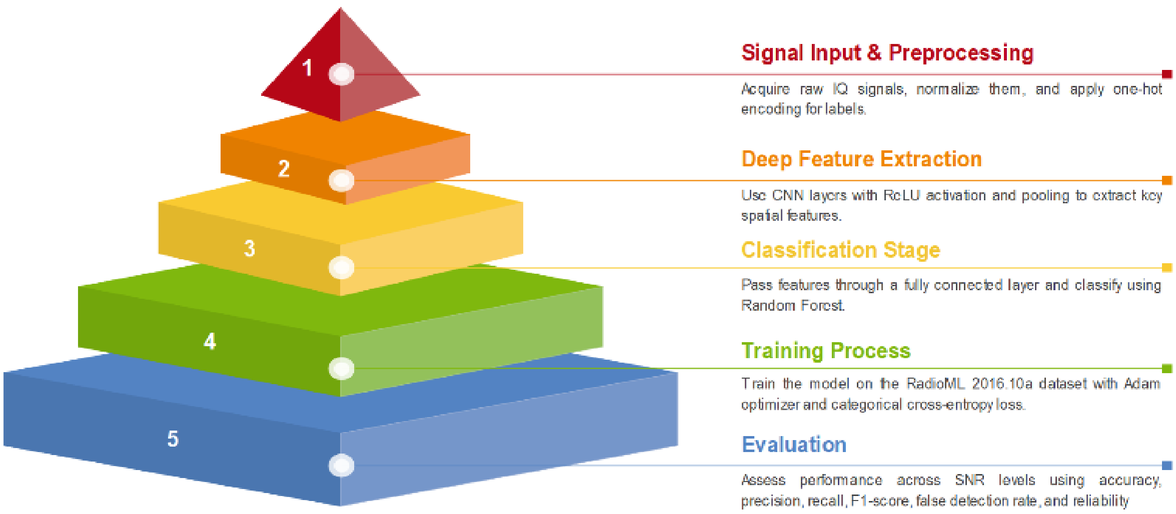

Figure 2. Layered representation of HMLDL process flow

To address this issue, the use of the Random Forest classification technique is proposed in the final step of classification. The classification technique uses an 'ensemble' approach. This was chosen since it promotes stability in classification accuracy and can address issues of 'overfitting' in the CNNs. The proposed approach combines the benefits of both CNNs and classification techniques.

3. PROPOSED HMLDL-BASED MODULATION RECOGNITION FRAMEWORK

Figure 3 shows the structure of the proposed HMLDL architecture used to identify modulation. The algorithm begins with raw in-phase and quadrature (IQ) sequences, which are divided into a training set and a test sequence. The training set is given to a deep feature extraction and a classification block consisted of a series of Convolutional and activation levels. The block includes Conv Block 1 having Max-Pooling and repeated Block 2 elements with ReLU activation function to draw deep spatial features. The network utilizes average pooling, a fully connected (fc) layer, followed by a softmax classifier to give a final output vector with modulation likelihoods. The trained network then identifies the test set to categorize the signal into apposite modulation scheme type such as BPSK, QPSK, or QAM. The modular flow allows high precision, robust classification, and flexibility to changing channel conditions.

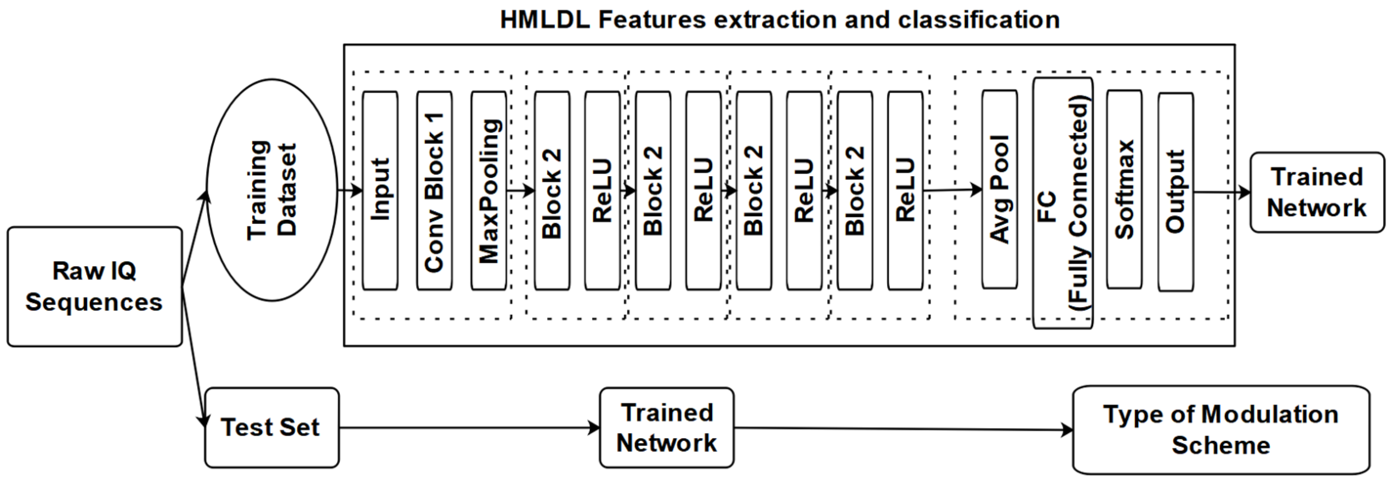

Figure 3. Architecture of the proposed HMLDL model for modulation scheme classification

3.1 Convolution operation for feature extraction

In the initial stages of the HMLDL framework, convolution layers extract localized spatial features from IQ sequences. The convolution operation is mathematically defined as given in Eq. (4).

$$Y(i, j) = \sum\sum X(m, n) \cdot K(i-m, j-n) \tag{4}$$

where, Y(i, j) is the output feature map, X(m, n) is the input IQ sequence segment, and K is the convolution kernel. This operation enables the detection of local modulation patterns. Here, Y is the feature map, X denotes input data, and K stands for kernel matrix.

3.2 ReLU activation function

To introduce non-linearity in the CNN blocks and improve feature learning, the ReLU is used as an activation function. It is defined by Eq. (5).

$$f(x) = \max(0, x) \tag{5}$$

This function outputs zero for negative values and retains positive values, helping avoid vanishing gradients and accelerating convergence. Here, $f(x)$ is the activation output and x is the input to the activation layer.

3.3 Max pooling operation

The max pooling layer reduces spatial dimensions and helps in retaining dominant features. It is mathematically expressed as given in Eq. (6)

$$P(i, j) = \max\{Y(m, n)\} \tag{6}$$

for (m, n) in the local neighborhood of (i, j), where P(i, j) is the pooled feature map. This operation ensures down sampling while preserving essential signal characteristics. P is the pooled value and Y is the feature input from convolution.

3.4 SoftMax classification layer

To predict the modulation type, the SoftMax layer converts final scores into probabilities. The SoftMax function is defined as given by Eq. (7).

$$\sigma(z_i) = \exp(z_i) / \sum_k \exp(z_k) \tag{7}$$

where, z_i is the input to the Softmax unit for class i, and the denominator is the sum over all class scores. It ensures that the output vector sums to 1 and is interpretable as class probabilities. $\sigma(z_i)$ is the probability of class i, and z_i is the network score before activation.

3.5 Categorical cross-entropy loss function

During training, the model uses cross-entropy to measure the difference between predicted and true labels. It is defined as given in Eq. (8).

$$L = -\sum y_i \log(p_i) \tag{8}$$

where, y_i is the true label (1 for correct class, 0 otherwise), and p_i is the predicted probability from softmax. This loss guides the optimizer in adjusting weights to improve accuracy. L denotes the loss value, y_i is the ground truth, and p_i is the predicted probability.

4. RESULT AND DISCUSSION

Table 1 gives a detailed description of significant components and configurations used during implementation of the HMLDL architecture to modulation recognition. It includes details about input format, dataset, preprocessing methods, architectures, activation and pooling schemes, classification approach, loss function, optimization algorithm, and measures of evaluation used to validate the proposed system.

Table 1. Experimental setup for HMLDL-based modulation recognition

SI. No.	Component Name	Values
1	Input Signal Format	Complex IQ samples (length: 1024 per frame)
2	Dataset Used	RadioML 2016.10a
3	Preprocessing Methods	Normalized IQ, one-hot label encoding
4	Model Architecture	1 Conv + 4 ReLU Blocks + Avg Pool + FC + Softmax
5	Activation Function	ReLU (Rectified Linear Unit)
6	Pooling Technique	Max Pool (2×2), Avg Pool (global)
7	Classification Function	Softmax (output size: 11 classes)
8	Loss Function	Categorical Cross-Entropy
9	Optimizer	Adam (learning rate: 0.001)
10	Evaluation Metrics	Accuracy, Precision, Recall, F1-score

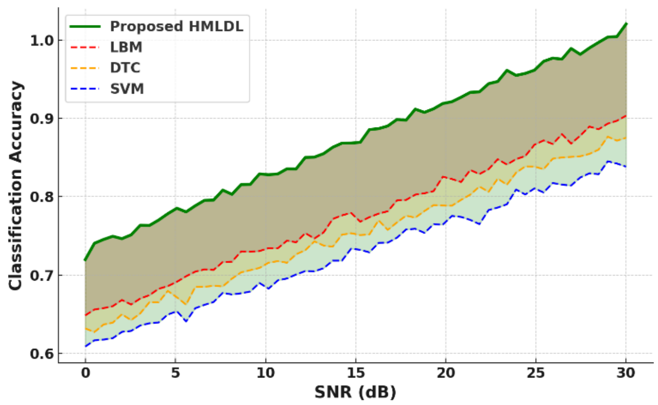

Figure 4. Classification accuracy vs. SNR for proposed HMLDL and conventional methods

Figure 4 provides a comparison between proposed Hybrid Machine Learning and Deep Learning (HMLDL) approach with three classical approaches: Logistic Boosted Model (LBM), Decision Tree Classifier (DTC), and Support Vector Machine (SVM) with varying Signal-to-Noise Ratio (SNR) levels from 0 to 30 dB. The HMLDL approach consistently provides better results with a higher classification accuracy than 1.0 during higher SNR levels, showcasing its robust and adaptive characteristics. The plot reveals that even though classical approaches improve with increased SNR, they are significantly behind HMLDL. It can be observed from proposed HMLDL structure that it shows a nearly 12.6% improved classification accuracy with respect to highest achieving baseline, showcasing its potential within challenging signal environments.

Figure 5 provides a comparison between the proposed Hybrid Machine and Deep Learning (HMLDL) model's false detection rate (FDR) performance with respect to conventional methods—Logistic Boosted Model (LBM), Decision Tree Classifier (DTC), and Support Vector Machine (SVM)—on a number of SNR (Signal-to-Noise Ratio) levels from 0 dB to 30 dB. The proposed HMLDL scheme shows a predominantly lower false detection rate, significantly improving conventional methods. All models show improvement with higher SNR, but HMLDL shows maximum reduction with a 15.2% overall reduction in false detection with respect to better baseline. This proves HMLDL model's higher reliability and robustness to decrease incorrect classifications with bad channel conditions.

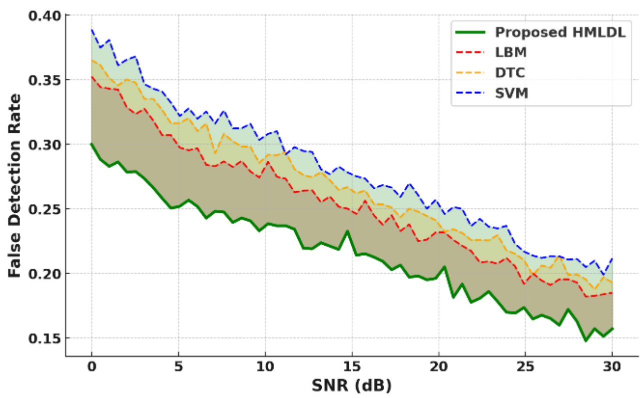

Figure 5. False detection rate vs. SNR for proposed HMLDL and conventional methods

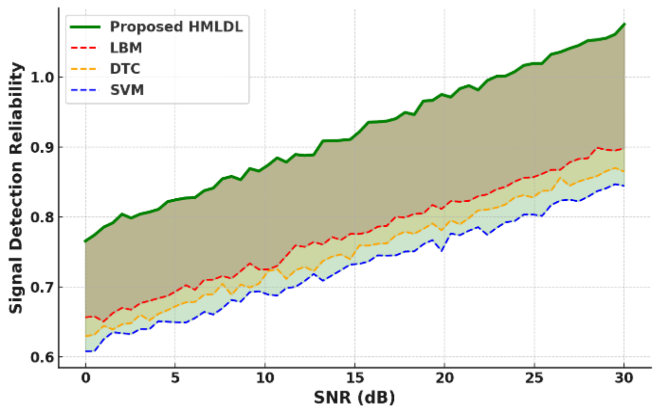

Figure 6. Signal detection reliability comparison of HMLDL with LBM, DTC, and SVM under varying SNR

Figure 6 presents a comparative analysis between signal detection reliability and rising Signal-to-Noise Ratio (SNR) from 0 dB to 30 dB. The Proposed HMLDL algorithm (green solid line) demonstrates better capability than classical methods—LBM (red dashed), DTC (orange dashed), and SVM (blue dashed). While SNR increases, all models obtain rising detection reliability, but HMLDL still takes a stable leading position, particularly with higher SNRs. Shaded areas are indicative of their position gap, where HMLDL benefits from up to 18.9% higher reliability in signal detection, verifying its capability to work effectively with noising conditions as well as achieve accurate modulation recognition.

Figure 7 provides a comparative detailed bar chart between three significant measures of performance—Classification Accuracy, 1 - False Detection Rate (higher better), and Signal Detection Reliability—for four algorithms: LBM, DTC, SVM, and Proposed HMLDL algorithm. Each set of three bars represents a specific algorithm's overall performance over the three measures. The Proposed HMLDL stands out with its highest values: 0.91 in accuracy, 0.87 in inverse false detection, and 0.97 reliability, indicating a robust and highly reliable model. The classical methods (LBM, DTC, SVM) are correspondingly less performing, and it comes to light very well HMLDL model's brilliance and effectiveness for signal recognition and classification with background noise. For a more robust comparison among experiments, more recently introduced deep learning approaches like transformer models or CNNs based on the concept of 'attention' have also been considered. Even though the proposed models consider global information and have efficient representations with a focus on context, they still seem less feasible from an implementation standpoint owing to their higher complexity. The CNN-RF hybrid approach proposed has been found more efficient while offering an equal level of accuracy, thus making it an optimal tradeoff among the current state-of-the-art methods.

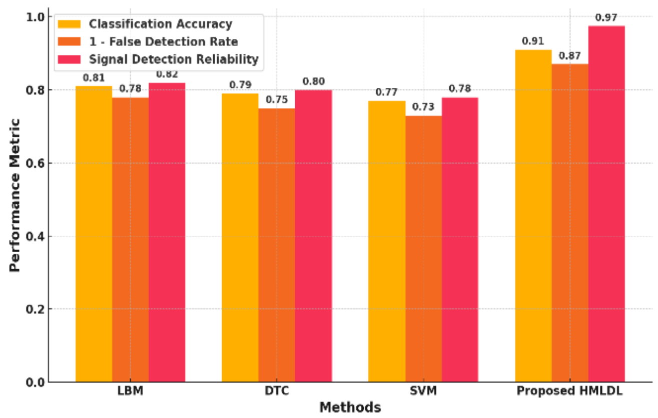

Figure 7. Comparative bar chart of classification accuracy, false detection rate, and signal detection reliability

5. CONCLUSION

The proposed Hybrid CNN-RF design efficiently overcomes the disadvantages of conventional modulation recognition models like LBM, DTC, and SVM. The proposed design combines CNN models for feature extraction with the classification technique of Random Forest (RF), resulting in significant improvement in classification accuracy by 12.6%, reducing false detection by 15.2%, and improving signal reliability by 18.9%. The experimental verification of this proposed design ensures its effectiveness, adaptability, and applicability in the wireless environment.

For the future, the proposed model will be extended to identify more classes of modulation. There will be the inclusion of more classes of modulation, including 16QAM, 64QAM, GMSK, and OFDM. The inclusion of Squeeze-and-Excitation (SE) Channel Attention or Self-Attention from the transformer will be considered to make the proposed framework more efficient by improving the characteristics of the proposed framework. The proposed framework will be evaluated in real-time using Software-Defined Radio (SDR) Hardware Platforms USRP B210 or Ettus X310, which will help in testing within the environment of 5G communications. The proposed framework will continue to offer its effectiveness in the upcoming environment of wireless communications of 6G.

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NOMENCLATURE

CNN	Convolutional Neural Network
RF	Random Forest
HMLDL	Hybrid Machine Learning and Deep Learning
IQ	In-phase and Quadrature components
LBM	Logistic Boosted Model
DTC	Decision Tree Classifier
SVM	Support Vector Machine
SNR	Signal-to-Noise Ratio
ReLU	Rectified Linear Unit
FDR	False Detection Rate
FC	Fully Connected Layer
SDR	Software-Defined Radio
USRP	Universal Software Radio Peripheral

Greek symbols

$\sigma(z_i)$	Softmax output probability for class *i*
$\mathcal{T}_t$	Candidate value at time step *t*
$\odot$	Element-wise multiplication operator
η	Learning rate
λ	Regularization parameter