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Deep Learning-Based Radio Signal Classification Using Convolutional LSTM-DNN (CLDNN)

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KEYWORDS

Automatic Modulation Classification, RadioML Dataset, Convolutional Neural Network (CNN), CLDNN, DenseNet, Deep Learning, Signal-to-Noise Ratio (SNR), Wireless Communication, Feature Extraction, Robust Classification

ABSTRACT

This paper presents a comparative analysis of deep learning models, namely CNN, CNN with DenseNet, CLDNN, and CLDNN with DenseNet, for automatic modulation classification using the RadioML dataset under varying signal-to-noise ratio (SNR) conditions. The performance is evaluated in terms of training, testing, and validation accuracies across SNR levels of 18 dB, 12 dB, 6 dB, and -2 dB. At high SNR of 18 dB, the CLDNN model achieves superior performance with a testing accuracy of 81.22%, while CLDNN with DenseNet further improves to 83.0%, outperforming CNN which yielded 70.77% and CNN with DenseNet resulting in 74.54%. At moderate SNR of 12 dB, CLDNN with DenseNet maintains robust performance with a testing accuracy of 80.00%, compared to CLDNN and CNN that achieved 70.90% and 61.04%. As the SNR decreases to 6 dB, CLDNN with DenseNet achieves the highest testing accuracy of 74.22%, followed by CLDNN of 65.31%, while CNN performance drops to 48.13%. At very low SNR (-2 dB), the proposed CLDNN with DenseNet model demonstrates strong robustness with a testing accuracy of 62.08%, outperforming CLDNN, CNN with DenseNet and CNN. The results confirm that integrating DenseNet with CLDNN significantly enhances feature extraction and classification robustness, particularly under noisy conditions, making it a reliable approach for practical wireless communication systems

I. INTRODUCTION

Automatic modulation classification is a vital technique in modern wireless communication systems, as it enables the identification of different signal modulation schemes used in communication networks. Traditional modulation classification methods primarily rely on manual feature extraction and conventional signal processing techniques, which often lead to lower classification accuracy and increased computational complexity, particularly under noisy environments and varying signal-to-noise ratio (SNR) conditions.

To address these limitations, deep learning–based approaches have recently gained attention due to their ability to perform automatic feature extraction and achieve improved classification performance. In this work, a deep learning–based classification approach is proposed using a Convolutional Long Short-Term Memory Deep Neural Network (CLDNN) to classify radio signal modulations. The model is trained and evaluated using the Radio ML 2016 dataset.

In this work, automatic modulation classification is performed using the CLDNN architecture. The organization of this paper is as follows: Section II presents the literature review, Section III describes the CLDNN model, dataset, and proposed methodology, Section IV discusses the proposed methodology, Section V presents results obtained at different SNR levels and Section VI provides the Conclusions.

II. LITERATURE REVIEW

Modulation classification has become a key research area in wireless communication, especially with the rise of cognitive radio and intelligent networks. Various machine learning and deep learning techniques have been proposed to improve recognition accuracy using datasets like RadioML.

Timothy J. O'Shea, Johnathan Corgan and T. Charles Clancy (2016)[1] introduced a CNN-based approach for automatic modulation classification using raw I/Q samples from the RadioML dataset. However, the model requires large datasets and high computational resources for training.

Pengfei Liu, Shengli Zhang and Pengfei Yu (2017)[2] proposed a CNN-based modulation recognition framework that extracts discriminative features directly from radio signals. The method improved classification performance compared to traditional techniques, but the accuracy decreases significantly at low SNR levels.

Timothy J. O'Shea, T. Roy and T. Charles Clancy (2018)[3] explored deep learning-based modulation classification in over-the-air communication environments. Their CNN model showed promising results in practical scenarios; however, performance is affected by channel noise and signal distortions.

S. Rajendran, W. Meert and D. Giustiniano (2018)[4] compared different deep learning architectures such as CNN, LSTM and CLDNN for modulation classification. Their study showed that hybrid architectures improve recognition accuracy but increase computational complexity and training time. Z. Wu, S. Zhou and Z. Yin (2019)[5] proposed a deep CNN architecture to extract features from radio signals for modulation classification. The method improved recognition accuracy across multiple modulation types, but requires large datasets and high computational resources.

M. L. Xue et al. (2021)[6] proposed MICNet, a CNN–Inception model for multi-scale feature extraction that improves accuracy but degrades at low SNR. Tianpe Xu and Ying Ma (2023)[7] introduced an autoencoder-based model that reduces complexity and enhances feature extraction, though performance drops in noisy conditions.

Hany S. Hussein (2023)[8] developed CNN-based models showing improved performance with proper optimization, but with high training time and computational cost. Saeed Mohsen et al. (2024)[9] proposed CNN-based modulation classification using the RadioML dataset, achieving automatic feature learning but with relatively lower accuracy and limited real-world generalization.

Wang Jiang et al. (2025)[10] proposed a multi-scale CNN architecture integrated with attention mechanisms for modulation recognition improving feature learning and classification performance, but the multi-scale design increases computational complexity.

Yixuan Chen (2025)[11] proposed a hybrid modulation recognition model combining phase transformation with a ResCNN–BiLSTM architecture. The method captures both spatial and temporal signal features effectively, but the hybrid architecture introduces higher computational cost.

III. METHODOLOGY

Convolutional Long Short Term Memory Deep Neural Network(CLDNN)

The Convolutional Long Short-Term Memory Deep Neural Network (CLDNN) is a hybrid deep learning architecture that combines convolutional, recurrent, and fully connected networks to effectively model complex data. This architecture was first introduced by Tara N. Sainath et al.[12] in their work titled Convolutional, Long Short-Term Memory, Fully Connected Deep Neural Networks. The working of CLDNN begins with convolutional (CNN) layers that extract local and hierarchical feature representations from the input data as shown in Figure 1. These layers perform convolution and pooling operations to capture spatial patterns and reduce dimensionality while preserving important structural information.

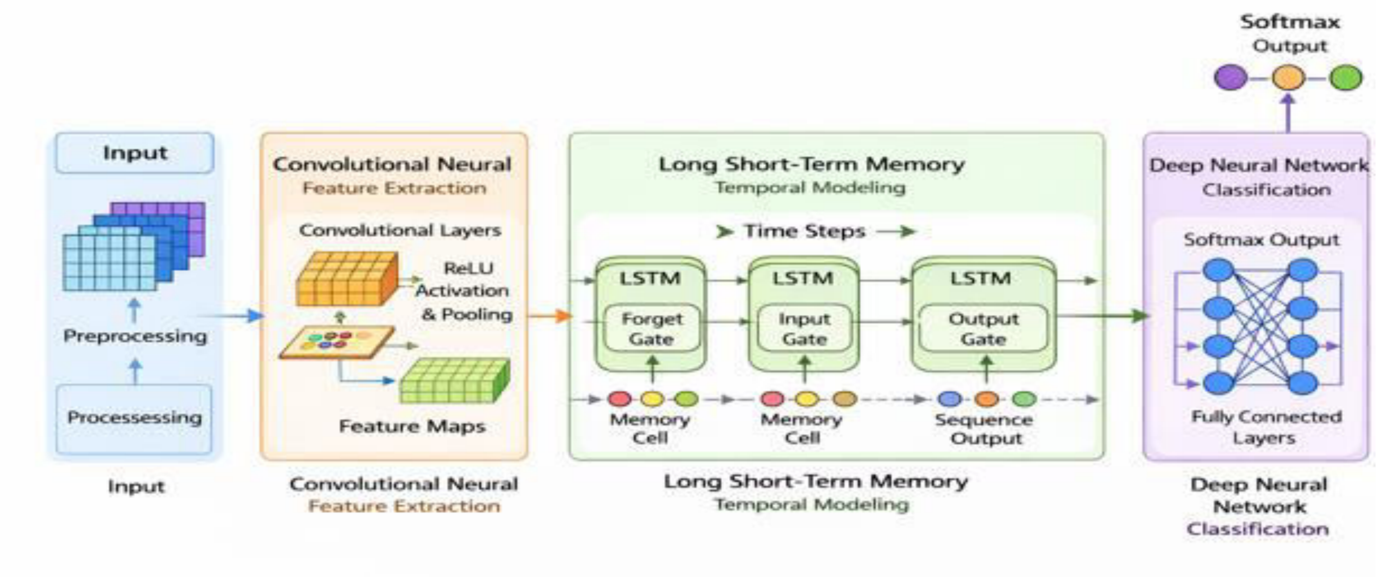

Figure 1: Architecture of Convolution Long Short Term Memory Deep Neural Network

The feature maps generated by the CNN layers are then passed to Long Short-Term Memory (LSTM) layers, which model temporal dependencies and sequential relationships in the data. The LSTM network uses memory cells and gating mechanisms to retain relevant information over time and discard redundant features, enabling effective sequence learning. Finally, the processed features are fed into fully connected deep neural network (DNN) layers, which perform high-level abstraction and classification. The output layer typically employs a Softmax activation function to generate class probabilities. This integrated architecture allows CLDNN to simultaneously learn spatial and temporal features, making it highly effective for a wide range of sequence-based applications.

Dataset :

The experiments in the present work use the DeepSig RadioML 2016.10A dataset[13], a standard benchmark for automatic modulation classification. Generated using GNU Radio, it contains complex baseband I/Q samples representing various digital and analog modulation schemes under different noise conditions. Each sample consists of 128 time-domain values with separate I and Q channels.

The dataset includes 11 modulation types such as BPSK, QPSK, 8PSK, QAM, and AM variants, commonly used in wireless systems. It covers SNR levels from −20 dB to +18 dB in steps of 2 dB, allowing evaluation under diverse channel conditions. For each modulation–SNR pair, 1000 samples are provided, totaling around 220,000 instances, and the dataset is available in .pkl format.

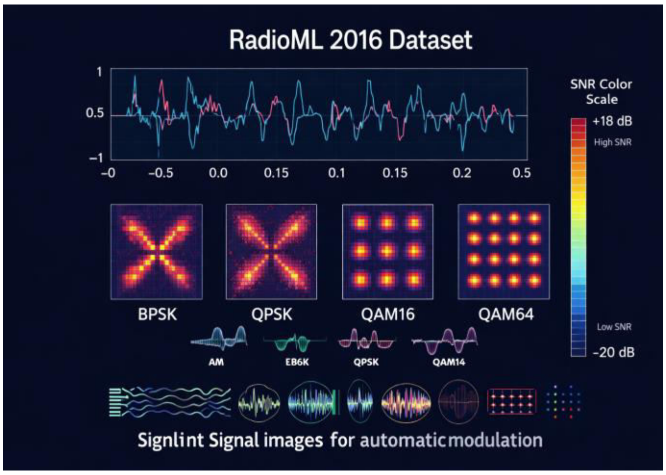

Figure 2 : Representation of the RadioML Dataset

IV. PROPOSED METHODOLOGY

The proposed methodology employs a Convolutional

Long Short-Term Memory Deep Neural Network (CLDNN) for effective classification of signal data by integrating spatial feature extraction, temporal modeling, and classification within a unified framework. Initially, the input data is preprocessed and normalized to ensure stable training, and the labels are encoded using one-hot representation. The processed data is then fed into convolutional layers, where local features are extracted using one-dimensional convolution operations followed by activation and pooling. Mathematically, the convolutional operation at layer l is expressed as:

$$y_i^{(l)} = \sigma\left(\sum_{k=1}^{K} w_k^{(l)} * x_{i+k-1}^{(l-1)} + b^{(l)}\right)\ldots\ldots\ldots\ldots(1)$$

where $x^{(l-1)}$ is the input, $w_k^{(l)}$ represents the convolution kernel, $b^{(l)}$ is the bias, and $\sigma(\cdot)$ denotes the activation function. These layers enable the model to learn robust local patterns and reduce noise in the input data.

The extracted feature maps are then passed to the LSTM layer to capture temporal dependencies in the sequential data. The LSTM operates using gating mechanisms defined as:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right), i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)\ldots\ldots(2)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, h_t = o_t \odot \tanh\,(C_t)\ldots\ldots\ldots\ldots(3)$$

where f_t, i_t, and o_t denote forget, input, and output gates, respectively.

The LSTM output is then passed through fully connected layers for classification, given by

$$z = Wh + b\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

and the final prediction is obtained using the Softmax function

$$\hat{y}_i = \frac{e^{z_i}}{\sum_j e^{z_j}}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

The model is trained using categorical cross-entropy loss,

$$L = -\sum y_i \log\,(\hat{y}_i)\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

and optimized using the Adam optimizer. This integrated approach enables the model to effectively learn both spatial and temporal features, resulting in improved classification performance of RadioML dataset.

V. RESULTS AND DISCUSSION

The performance comparison of different deep learning models on the RadioML dataset shows a clear dependence on Signal-to-Noise Ratio (SNR). At higher SNR levels (18 dB), all models achieve relatively strong performance, with CLDNN and CLDNN with DenseNet outperforming the basic CNN architecture. This improvement is mainly due to the hybrid nature of CLDNN, which combines convolutional layers for spatial feature extraction with recurrent layers for temporal dependency learning. The addition of DenseNet further enhances feature propagation and reuse, resulting in better generalization as shown in Table I. In contrast, the standalone CNN model exhibits comparatively lower accuracy, indicating its limitation in capturing temporal characteristics of modulation signals.

Table I : Performance Comparison of Deep Learning Models for RadioML Modulation Classification at different SNR Levels

Deep Learning Models	SNR at 18dB			SNR at 12 dB			SNR at 6dB			SNR at -2dB		
	Training Accuracy	Testing Accuracy	Validation Accuracy	Training Accuracy	Testing Accuracy	Validation Accuracy	Training Accuracy	Testing Accuracy	Validation Accuracy	Training Accuracy	Testing Accuracy	Validation Accuracy
CNN	76.53%	69..09%	70.5%	63.45%	61.04%	58.52%	49.78%	48.13%	51.63%	35.72%	32.40%	31.8%
CNN with Densenet	81.64%	74.54%	73.75%	80.14%	69.51%	70.66%	84.28%	61.93%	59.93%	78.98%	58.24%	59.63%
CLDNN	88.60%	81.22%	82.38%	71.81%	70.90%	68.40%	79.18%	65.31%	67.61%	55.10%	61.90%	63.30%
CLDNN with Densenet	87.64%	83.18%	83.40%	80.37%	80.00%	79.15%	73.07%	74.22%	73.18%	81.89%	62.08%	63.52%

However, models incorporating DenseNet, particularly CNN with DenseNet and CLDNN with DenseNet, demonstrate better robustness under noisy conditions, maintaining relatively higher testing and validation accuracies compared to their counterparts. Notably, at very low SNR (-2 dB), CLDNN with

DenseNet achieves the most stable performance, highlighting its superior ability to extract meaningful features even in adverse conditions. Overall, the results emphasize that hybrid architecture with dense connectivity are more effective for modulation classification in low SNR environments, while simpler CNN models are less reliable as noise increases.

The results presented in Table II indicate that all models achieve high classification performance under high SNR conditions due to clear signal characteristics. Among the models, CLDNN and CLDNN with DenseNet consistently outperform CNN-based architectures, achieving higher precision, recall, and F1-scores across most modulation schemes. The hybrid CLDNN architecture effectively captures both spatial and temporal features, while the integration of DenseNet further enhances feature propagation and reuse. This is particularly evident in complex modulation schemes such as QAM16 and QAM64, where CNN-based models show relatively lower F1-scores compared to CLDNN variants. Overall, Table II demonstrates that advanced architecture provides more reliable and balanced performance when noise levels are minimal.

As the SNR decreases to 12 dB and 6 dB as shown in Tables III and IV, the impact of noise becomes more prominent, leading to degradation in performance across all models. This degradation is especially significant for higher-order modulation schemes like QAM16 and QAM64, where precision and recall values drop noticeably due to increased inter-class confusion. However,

CLDNN with DenseNet maintains comparatively better robustness, preserving higher F1-scores and recall values than CNN and CNN with DenseNet. While CNN with DenseNet shows improvement over the baseline CNN, it still struggles to maintain consistent performance under moderate noise. Modulations such as AM-SSB, CPFSK, and GFSK remain relatively stable across all models, indicating their distinct feature characteristics that are less sensitive to noise.

Table II : Comparative Analysis of CNN and CLDNN Models with DenseNet for Modulation Classification at SNR level of 18dB

Modulation	SNR at 18dB															
	CNN				CNN with DenseNet				CLDNN				CLDNN with DenseNet			
	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
8PSK	0.876	0.530	0.933	0.676	0.883	0.667	0.533	0.593	0.964	0.965	0.894	0.928	0.981	0.915	0.935	0.925
AM-DSB	0.939	0.564	0.760	0.648	0.931	0.680	0.340	0.453	0.978	0.589	0.934	0.722	0.938	0.573	0.965	0.718
AM-SSB	0.982	0.978	0.893	0.934	0.998	0.962	1.000	0.980	0.997	0.952	0.989	0.970	1.000	0.957	1.000	0.978
BPSK	0.959	0.792	0.887	0.836	0.987	0.943	0.953	0.948	0.993	0.976	0.964	0.970	0.996	0.975	0.965	0.970
CPFSK	0.999	0.993	1.000	0.997	0.995	0.987	0.967	0.977	0.999	0.971	1.000	0.985	1.000	1.000	1.000	1.000
GFSK	0.987	0.928	0.940	0.934	1.000	0.920	1.000	0.958	0.996	0.942	0.966	0.954	0.999	0.990	1.000	0.995
PAM4	0.966	0.965	0.733	0.833	0.988	0.955	0.953	0.954	0.997	0.981	0.978	0.979	0.996	0.980	0.980	0.980
QAM16	0.918	0.552	0.387	0.455	0.909	0.368	0.187	0.247	0.946	0.502	0.664	0.572	0.954	0.491	0.855	0.624
QAM64	0.917	0.531	0.507	0.519	0.903	0.441	0.880	0.588	0.930	0.387	0.336	0.360	0.935	0.400	0.105	0.167
QPSK	0.954	0.833	0.600	0.698	0.962	0.710	0.627	0.666	0.987	0.927	0.955	0.941	0.989	0.936	0.950	0.943
WBFM	0.926	0.557	0.393	0.461	0.936	0.535	0.760	0.627	0.953	0.824	0.284	0.422	0.929	0.885	0.270	0.414

Table III : Comparative Analysis of CNN and CLDNN Models with DenseNet for Modulation Classification at SNR level of 12dB

Modulation	SNR at 12dB															
	CNN				CNN with DenseNet				CLDNN				CLDNN with DenseNnet			
	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score

8PSK	0.902	0.359	0.140	0.201	0.888	0.589	0.220	0.320	0.903	0.467	0.485	0.476	0.948	0.769	0.795	0.782
AM-DSB	0.909	0.587	0.487	0.532	0.915	0.688	0.526	0.596	0.980	0.602	0.925	0.730	0.963	0.626	0.730	0.674
AM-SSB	0.999	0.939	1.000	0.969	0.999	0.968	1.000	0.984	0.999	0.969	1.000	0.984	0.999	0.952	1.000	0.976
BPSK	0.948	0.607	0.726	0.661	0.982	0.973	0.960	0.966	0.988	0.864	0.930	0.896	0.996	0.985	0.985	0.985
CPFSK	0.987	0.839	0.985	0.906	0.965	0.991	0.747	0.852	0.992	0.908	0.967	0.937	1.000	1.000	1.000	1.000
GFSK	0.979	0.820	0.934	0.873	0.998	0.964	0.993	0.978	0.991	0.900	0.945	0.922	0.998	0.939	0.990	0.964
PAM4	0.962	0.826	0.744	0.783	0.995	0.917	0.993	0.954	0.984	0.873	0.910	0.891	0.997	0.988	0.985	0.986
QAM16	0.893	0.341	0.551	0.421	0.923	0.239	0.360	0.287	0.924	0.243	0.165	0.196	0.941	0.436	0.185	0.259
QAM64	0.876	0.256	0.155	0.193	0.903	0.271	0.429	0.332	0.905	0.377	0.636	0.474	0.958	0.534	0.830	0.651
QPSK	0.931	0.345	0.439	0.387	0.942	0.573	0.553	0.563	0.951	0.516	0.451	0.482	0.970	0.795	0.800	0.797
WBFM	0.922	0.552	0.480	0.513	0.938	0.626	0.720	0.670	0.931	0.711	0.245	0.364	0.959	0.641	0.500	0.562

Table IV : Comparative Analysis of CNN and CLDNN Models with DenseNet for Modulation Classification at SNR levels of 6dB

Modulation	SNR at 6dB															
	CNN				CNN with DenseNet				CLDNN				CLDNN with DenseNet			
	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
8PSK	0.890	0.237	0.812	0.367	0.903	0.430	0.127	0.196	0.902	0.229	0.040	0.068	0.909	0.000	0.000	0.000
AM-DSB	0.873	0.000	0.000	0.000	0.945	0.754	0.613	0.676	0.972	0.570	0.898	0.698	0.914	0.677	0.555	0.610
AM-SSB	0.998	0.951	0.989	0.970	0.999	0.968	1.000	0.984	0.987	0.925	0.835	0.878	0.999	0.968	1.000	0.984
BPSK	0.955	0.411	0.722	0.524	0.930	0.500	0.467	0.483	0.981	0.833	0.935	0.881	0.995	0.975	0.970	0.972
CPFSK	0.992	0.729	0.981	0.836	0.944	1.000	0.469	0.639	0.919	0.631	0.390	0.482	1.000	1.000	1.000	1.000
GFSK	0.992	0.573	0.971	0.721	0.991	0.858	0.980	0.915	0.964	0.874	0.727	0.794	0.998	0.956	0.985	0.970
PAM4	0.975	0.000	0.000	0.000	0.995	0.897	0.993	0.943	0.995	0.974	0.960	0.967	0.997	0.995	0.990	0.992
QAM16	0.865	0.000	0.000	0.000	0.905	0.162	0.273	0.203	0.964	0.581	0.970	0.726	0.999	0.995	1.000	0.998
QAM64	0.869	0.000	0.000	0.000	0.903	0.366	0.800	0.502	0.941	0.281	0.225	0.250	0.998	0.975	0.985	0.980
QPSK	0.907	0.365	0.115	0.175	0.924	0.505	0.427	0.463	0.972	0.379	0.895	0.533	0.999	0.503	0.990	0.668
WBFM	0.948	0.510	0.665	0.577	0.955	0.621	0.633	0.627	0.934	0.553	0.210	0.304	0.963	0.608	0.690	0.647

Table V : Comparative Analysis of CNN and CLDNN Models with DenseNet for Modulation Classification at SNR level of -2dB

Modulation	SNR at -2dB															
	CNN				CNN with DenseNet				CLDNN				CLDNN with DenseNet			
	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
8PSK	0.964	0.960	0.893	0.925	0.882	0.183	0.080	0.111	0.903	0.321	0.045	0.079	0.893	0.364	0.195	0.253
AM-DSB	0.956	0.823	0.780	0.801	0.906	0.602	0.469	0.527	0.964	0.576	0.825	0.678	0.962	0.540	0.881	0.669
AM-SSB	0.965	0.818	0.788	0.803	0.977	0.674	0.972	0.796	0.998	0.933	0.980	0.956	0.989	0.942	0.944	0.943
BPSK	0.970	0.818	0.781	0.799	0.889	0.265	0.474	0.340	0.927	0.667	0.560	0.609	0.942	0.506	0.765	0.610
CPFSK	0.990	0.974	0.938	0.956	0.885	0.228	0.365	0.280	0.910	0.352	0.165	0.225	0.919	0.620	0.566	0.592

GFSK	0.989	0.856	0.905	0.880	0.908	0.445	0.403	0.423	0.938	0.674	0.690	0.682	0.941	0.630	0.745	0.683
PAM4	0.942	0.589	0.537	0.562	0.990	0.799	0.905	0.849	0.990	0.915	0.860	0.887	0.989	0.901	0.905	0.903
QAM16	0.952	0.600	0.563	0.581	0.948	0.684	0.725	0.704	0.980	0.776	0.895	0.831	0.955	0.690	0.270	0.388
QAM64	0.964	0.737	0.747	0.742	0.987	0.984	0.890	0.935	0.981	0.939	0.775	0.850	0.987	0.913	0.900	0.906
QPSK	0.975	0.767	0.829	0.797	0.889	0.000	0.000	0.000	0.942	0.342	0.775	0.474	0.904	0.533	0.391	0.451
WBFM	0.958	0.708	0.873	0.782	0.918	0.466	0.505	0.485	0.925	0.607	0.240	0.344	0.925	0.418	0.205	0.275

At very low SNR conditions, as shown in Table V (-2 dB), the classification task becomes highly challenging, and performance drops significantly for all models. CNN-based models exhibit considerable degradation, with some modulation classes showing very low precision and recall, indicating failure in accurate classification.

In contrast, CLDNN with DenseNet demonstrates the highest resilience, maintaining relatively better performance even under severe noise conditions. This highlights the effectiveness of combining temporal feature learning with dense connectivity for robust modulation classification. Overall, the results across Tables II–V confirm that CLDNN with DenseNet is the most reliable model across varying SNR levels, making it highly suitable for real-world wireless communication scenarios where noise conditions can vary significantly.

Figure 3: Graphs of Training, Testing and Vaildation accuracy using Deep Learning models at SNR level of 18dB

Figure 3a Training Accuracy using CNN at SNR level of 18dB

Figure 3b Training Accuracy using CNN with Densenet at SNR level of 18dB

Figure 3c Training Accuracy using CLDNN at SNR level of 18dB

Figure 3d Training Accuracy using CLDNN with Densenet at SNR level of 18dB

The graphs in Figure 3 illustrate the training, testing, and validation accuracies for different models (CNN, CNN with DenseNet, CLDNN, and CLDNN with DenseNet) at an SNR level of 18 dB for the RadioML dataset. In Figure 3a, the CNN model shows a steady increase in training accuracy, reaching around 0.80–0.85, while validation accuracy stabilizes slightly lower. The testing accuracy initially starts low but gradually improves and converges close to the validation curve, indicating reasonable generalization with minimal overfitting. However, minor fluctuations in validation accuracy suggest sensitivity to feature variations. In Figure 3b, the CNN with DenseNet architecture demonstrates improved feature extraction capability, with training accuracy approaching higher values compared to the basic CNN. Although validation accuracy follows a similar upward trend, the testing accuracy exhibits noticeable fluctuations before stabilizing near 0.70–0.75. This indicates that while DenseNet enhances representation learning, the model may require further regularization to reduce variance between training and testing performance.

Figures 3c and 3d highlight the performance of CLDNN-based models. The CLDNN model (Figure 3c) achieves higher and more stable training accuracy (around 0.85–0.90), with validation accuracy closely tracking the training curve, suggesting better temporal feature learning and reduced overfitting. The testing accuracy shows a sharp improvement after initial epochs, eventually aligning with validation performance. The combined CLDNN with DenseNet model (Figure 3d) delivers the best overall performance, with training, validation, and testing accuracies all converging near 0.90 or above. This indicates strong generalization capability and effective learning of both spatial and temporal features, making it the most robust model among the evaluated architectures for RF signal classification at high SNR.

VI. CONCLUSION

The experimental results of this study demonstrate that deep learning models significantly improve radio signal classification performance on the RadioML dataset, particularly at higher SNR levels. Among the evaluated models, the baseline CNN achieved a training accuracy of 74.2%, testing accuracy of 70.77%, and validation accuracy of 72.2% at 18 dB SNR, while CNN with DenseNet improved the performance to 81.64% training, 74.54% testing, and 73.75% validation accuracy. The proposed CLDNN model further enhanced classification capability, achieving 88.60% training, 81.22% testing, and 82.38% validation accuracy, highlighting the importance of incorporating temporal feature learning along with spatial feature extraction.

The best performance was obtained using the CLDNN with DenseNet model, which achieved 87.64% training accuracy, 83.18% testing accuracy, and 83.40% validation accuracy at high SNR conditions. This demonstrates that the integration of DenseNet improves feature reuse and strengthens generalization capability. Furthermore, the convergence of training, testing, and validation accuracies indicates reduced overfitting and robust model behavior. Overall, the results confirm that hybrid architectures combining convolutional, recurrent, and dense connectivity mechanisms provide superior classification performance and robustness.

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Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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