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CNN/LSTM Based AMR with Custom Dataset

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ABSTRACT
Automatic Modulation Recognition (AMR) is a pivotal algorithm to recognize several types of signal modulations prior to demodulation in modern wireless communication systems and is essential for adaptive modulation and cognitive radio networks. Traditional AMR approaches rely heavily on manual feature extraction, which is often complex and lack of adaptability. The recent proliferation of Machine Learning (ML) and Deep Learning (DL) practices that has opened new avenues for automating and improving AMR performance. This manuscript conveys a ample analysis of the ML and DL practices used in AMR, highlighting their strengths, limitations, and potential future developments. Availability dataset of various modulation schemes is challenge, here, dataset is simulated using python. CNN and LSTM based AMR are implemented, tested on custom dataset. Comparison in between CNN based AMR and LSTM based AMR is presented. For small dataset, CNN based AMR outperform in comparison with LSTM based AMR. Challenges related to model complexity, computational requirements, and real-time adaptability were also examined, thereby providing a roadmap for future research.

Index Terms— *AMR (Automatic Modulation Recognition), CNN (Convolutional Neural Network), (DL) Deep Learning, LSTM (Long Short Term Memory), Federated Machine Learning.*

INTRODUCTION

Modern communication systems depend on Automatic Modulation Recognition (AMR) to adapt to changing signal types and maximize data transmission. This technology allows devices to recognize modulation schemes without prior knowledge, a critical feature for efficient and flexible networks. In literature, the existing AMR methods relied on manual feature selection, which was slow and limited, ML and DL have automated this process. By using CNNs and LSTMs, systems can now automatically identify and classify complex signal patterns, even in noisy or crowded environments. This allows for better spectrum management, especially in technologies like 5G and military applications. The ability to quickly recognize and adapt to different modulation types ensures reliable communication in dynamic environments, and ongoing research is refining these techniques for even greater efficiency [1-8].

Automatic Modulation Recognition (AMR) is essential for deciphering unknown signals in various applications, from military electronic warfare to civilian spectrum analysis. While traditional methods like likelihood-based and feature-based approaches have been used, deep learning (DL) has become a promising alternative because of its ability to automatically excel its features. However, a significant drawback of current DL-based AMR systems is their limited ability to handle varying signal-to-noise ratios (SNRs). Most existing convolutional neural networks (CNNs) are trained on datasets with a single SNR, resulting in poor performance when faced with different SNR conditions. This necessitates the development of more adaptable CNN models that can generalize across a range of SNR scenarios for practical deployment [9-18].

LITERATURE SURVEY

Motivation

Deep learning (DL) has significantly advanced Automatic Modulation Recognition (AMR) by leveraging its robust capabilities for training, learning, and classifying modulation types. Specifically, DNNs (Deep

Neural Networks), CNNs, and (DBNs) Deep Belief Networks have demonstrated high recognition accuracy and low false-alarm rates, primarily owing to their inherent skill to inevitably extract and classify complex signal characteristics.

Despite these advantages, DL-AMR techniques encounter several challenges that hinder their practical implementation. These include: the opaque nature of deep learning models hinders interpretability, complicating the understanding of their decision-making process; prolonged training and testing periods, which limit real-time applicability; the requirement for extensive training datasets, which may not always be readily available; and sensitivity to noise, which degrades performance in real-world wireless environments.

To address interpretability concerns, researchers have examined alternatives like substituting CNNs with dense, fully connected neural networks. This substitution has shown promise in significantly reducing training and testing durations by up to a factor of ten, while maintaining comparable levels of recognition accuracy. Balancing computational efficiency and performance is essential for the real-world deployment of DL-AMR in wireless communications. Researchers are actively enhancing Deep Learning-based Automatic Modulation Recognition (DL-AMR) by focusing on adaptability, efficiency, and robustness. Exploring latent space analysis, phase estimation with optimized networks, and Temporal Convolutional Networks (TCNs) for real-time applications are advised. Novel architectures like multi-network fusion, and capsule networks are being investigated to improve performance with fewer resources. To combat noise and frequency offsets, multi-feature fusion and specialized constellation diagram extraction methods are being developed.

These advancements aim to address the limitations of DL-AMR, including complexity, data requirements, and real-time constraints. The goal is to create more adaptable and robust systems for diverse applications, from military communications to IoT edge devices. By combining innovative architectures and feature extraction techniques, researchers are striving to improve accuracy and efficiency in challenging communication environments, paving the way for practical DL-AMR implementations.

Traditional Machine Learning Approaches

Automatic Modulation Recognition (AMR) has evolved significantly, transitioning from traditional methods reliant on manual feature extraction and algorithms like SVMs, to deep learning (DL) approaches. Traditional systems struggled with real-world complexities and novel modulations, highlighting the need for more adaptable solutions. DL revolutionized AMR by automating feature extraction, improving accuracy, and handling diverse signal conditions. CNNs analyze spectral data, LSTMs capture temporal patterns, and hybrid models combine both, enhancing robustness.

DL-based AMR impacts signal processing and communication systems by enabling adaptive modulation, crucial for cognitive radio and next-generation wireless networks. The improved efficiency and reliability of modulation classification support robust and flexible communication protocols. This shift signifies a major advancement, pushing the boundaries of wireless communication and signal processing by addressing the limitations of traditional methods and fostering more sophisticated and adaptable systems.

Deep Learning Techniques

Deep Learning (DL) has revolutionized Automatic Modulation Recognition (AMR) by automating feature extraction, a significant improvement over traditional methods requiring manual design. CNNs are effective for spectral feature extraction, while LSTMs specialize in capturing temporal relationships. Hybrid CNN-LSTM models combine these strengths, enhancing accuracy and robustness in challenging environments by simultaneously processing frequency and time-domain signal characteristics. This DL-based approach improves versatility in dynamic communication systems, crucial for adaptive modulation and cognitive radio. By automating feature learning and leveraging hybrid architectures, DL-AMR enhances recognition accuracy and efficiency, paving the way for advanced wireless communication technologies that utilize spectrum more efficiently and adapt to changing signal conditions.

Methodology

Hybrid CNN-LSTM models represent a significant advancement in Automatic Modulation Recognition (AMR), leveraging the strengths of both network types. CNNs excel at extracting spatial features from signal representations like constellations and spectrograms, while LSTMs capture temporal dependencies in sequential data. This combination enhances robustness, enabling accurate modulation classification across diverse signal-to-noise ratios (SNRs) and channel conditions.

These hybrid architectures offer adaptability and efficiency. The flexible nature allows for modifications to accommodate evolving modulation techniques and communication standards, ensuring relevance in dynamic wireless environments.

The integration of CNNs for efficient feature extraction and LSTMs for sequential processing helps reduce computational complexity, making the approach well-suited for real-time and resource-constrained applications.

Furthermore, these models can be fine-tuned for specific applications and environments, such as cognitive radio or military use, by adjusting network parameters. Their potential extends beyond classification, encompassing signal detection, channel estimation, and interference mitigation. Ongoing research focuses on incorporating attention mechanisms, improving training efficiency, and utilizing transfer learning to further enhance performance.

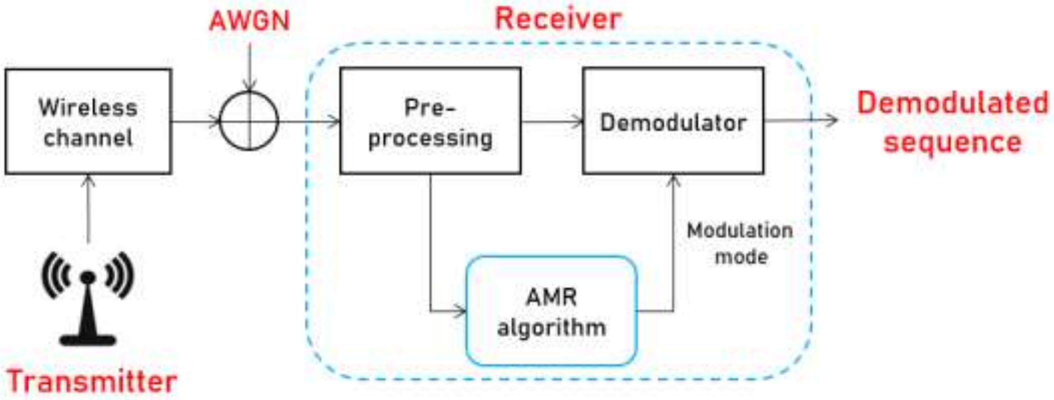

Fig.1 Block level representation of AMR process

The block diagram shown in Figure.1 is the communication system that utilizes an AMR algorithm to intelligently decode signals transmitted across a noisy wireless channel. The transmitter encodes information using a modulation scheme, embedding it onto a carrier wave for transmission. Signal transmission through the channel introduces impairments like AWGN, which degrade the signal and hinder accurate recovery.

The receiver employs a sophisticated AMR algorithm to overcome this challenge. First, it preprocesses the received signal to enhance its quality, using techniques like filtering and amplification. Then, the AMR algorithm, powered by a combination of CNNs and LSTMs, analyzes the signal. CNNs extract spatial characteristics, identifying patterns in the signal's structure, while LSTMs capture temporal dependencies, recognizing how the signal evolves over time.

Based on this analysis, the AMR algorithm accurately identifies the modulation scheme used by the transmitter. This information guides the demodulator, which then extracts the original information from the received signal. This adaptive approach ensures robust communication even when the transmitter's modulation scheme is unknown or dynamically changing, crucial in modern wireless systems.

Table.1: Comparison of Techniques

Aspect	Deep Learning (DL)	Traditional Machine Learning using SVMs
Feature Mapping	By learning features from raw data, CNNs remove the reliance on manually designed features.	Requires manual feature mapping.
Hierarchical Representation Learning	Hierarchical representations with increasing abstraction at each layer	Focuses on pre-defined feature spaces.
Adaptability	Adaptable transfer learning and fine-tuning.	Less adaptable
End-to-End Training	Supports end-to-end training and optimize the entire process	Involves separate steps for feature extraction and classification.
Computational Requirements	High computational power needed for training and inference.	Lower computational power.
Training and Inference Time	Slower due to complex architectures and training processes.	Faster training and inference.
Memory Footprint	Large memory requirements	Smaller memory footprint
Interpretability	Less interpretable due to the 'black box' nature of neural networks.	More interpretable decision-making processes
Performance with Datasets	Requires large datasets for optimal performance.	Performs well with smaller datasets.
Robustness to Overfitting	More prone to overfitting, without regularization or adequate data.	More robust to overfitting, appropriate regularization is used.
Theoretical Guarantees	Lacks strong theoretical guarantees for generalization.	Provides strong theoretical guarantees.

As per the comparison table shown in Table.1, Deep learning models, are exemplified by CNNs, and conventional machine learning with Support Vector Machines (SVMs) differ significantly in their approach to learning and data representation. CNNs automatically extract hierarchical features from raw data, which eliminates the need for manual feature engineering and helps them recognize complex patterns. Their adaptability and end-to-end learning make them highly versatile, though they require significant computational resources, have longer training times, and may suffer from excessive fitting. In contrast, SVMs rely on pre-defined feature spaces and require careful feature engineering. While computationally efficient and less prone to overfitting, SVMs may struggle to capture complicated relationships in data. Their interpretability and strong theoretical foundation make them valuable in specific applications. Ultimately, the choice between DL and conventional methods depends on the specific role, accessible data, and computational constraints.

CNN & LSTM BASED AMR

Mathematical representations for AMR using CNNs and LSTMs for the core concepts and provide simplified representations as shown below:

A. Convolutional Neural Networks (CNNs) for AMR:

i) Brief Introduction

Convolutional Layer:

A convolutional layer relates filters (kernels) to the input to extract its features. Let W be the filter weights, b be the bias, and * denote the convolution operation.

The outcome of a convolutional layer, C, can be observed as:

$$C = f(X * W + b) \quad (1)$$

Where f is the activation function (e.g., ReLU).

Pooling Layer:
By reducing the spatial dimensions of feature maps, pooling layers simplify the model and improve its robustness.

Max pooling is a standard pooling method that picks the highest value within a given window.

Mathematically max pooling layer is represented as:

$$P(i,j) = \max(C[m,n]) \qquad (2)$$

where m,n are inside of the pooling window centered in i,j.

Fully Connected Layers:
After the convolutional and pooling layers, the resulting output is flattened and input into the fully connected layers. The output from a fully connected layer, Y, is expressed as:

$$Y = f(WC + b) \qquad (3)$$

Where W signifies the weight matrix, b denotes the bias vector, and f implies an activation function.

Output Layer:
The output layer uses a softmax function to produce probabilities for each modulation class, represented as:

$$Output = softmax(Y) \qquad (4)$$

ii) Proposed CNN Architecture
Figure 2 shows a CNN architecture that starts with a convolutional layer, followed by max pooling, then another convolutional layer and pooling, and a third convolutional and pooling layer.

A fully connected dense layer is applied next, followed by a dropout layer with a 0.5 rate. The output layer uses the 'softmax' activation for prediction. The number of neurons at each stage is detailed in Figure 2.

B. Long Short-Term Memory (LSTMs) for AMR:

i) Brief introduction

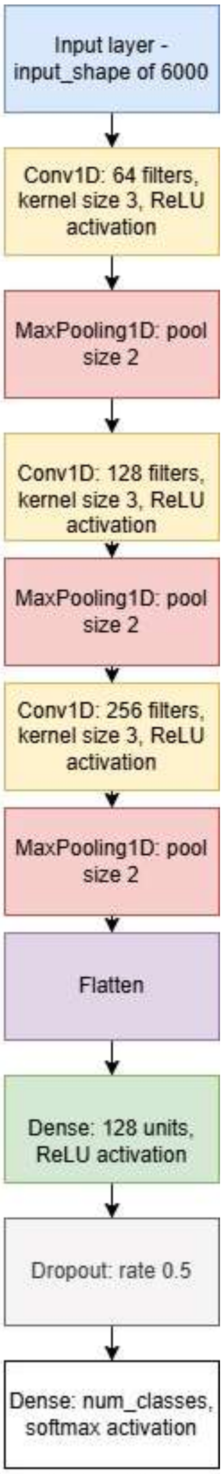

Fig 2. CNN Architecture

A specific kind of recurrent neural network (RNN) structure called Long Short-Term Memory (LSTM) is made to efficiently model and learn from sequential data, especially when long-term dependencies are involved. Because LSTMs solve the vanishing gradient issue, they can retain information for longer than regular RNNs.

Three fundamental gates—the input gate, forget gate, and output gate—as well as a specific memory cell help them accomplish this. Together, these gates control information flow and retention, which makes LSTMs ideal for tasks such as speech recognition, natural language processing, and the time-series prediction.

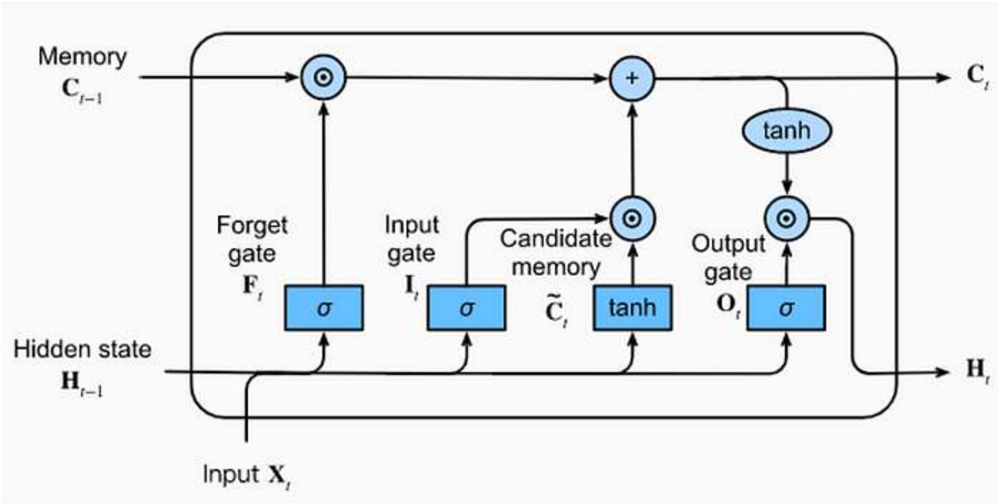

Fig. 3: Architecture of a LSTM Unit ([12])

From the Figure 3, the LSTM architecture consists the components as follows

1. **Forget Gate (f)**: Specifies the information to eliminate from the previous cell state (C(t-1)). Uses a sigmoid function (0 to 1).
2. **Input Gate (i)**: Stipulates the new information to add to the cell state. Also utilizes a sigmoid function.
3. **Candidate (g)**: Computes potential new information to be added, processed through a Tanh function (-1 to 1).
4. **Cell State (C(t))**: The "memory" of the network, updated as

$$C(t) = f * C(t\text{-}1) + i * g \qquad (5)$$

5. **Output Gate (o)**: Controls the updated cell state and produce as the hidden state h(t). Uses sigmoid function.
6. **Hidden State (h(t))**: The final output at time t, analysed as

$$h(t) = o * \mathrm{Tanh}(C(t)) \qquad (6)$$

ii) Proposed LSTM structure

Figure 4 illustrates the LSTM architecture, starting with three LSTM layers, followed by a convolutional layer with a 'ReLU' activation function. A fully connected dense layer with a 'ReLU' activation is applied next, followed by a dropout layer (rate = 0.5). The output layer uses the 'Softmax' activation function for prediction. The number of neurons at each stage is provided in the figure.

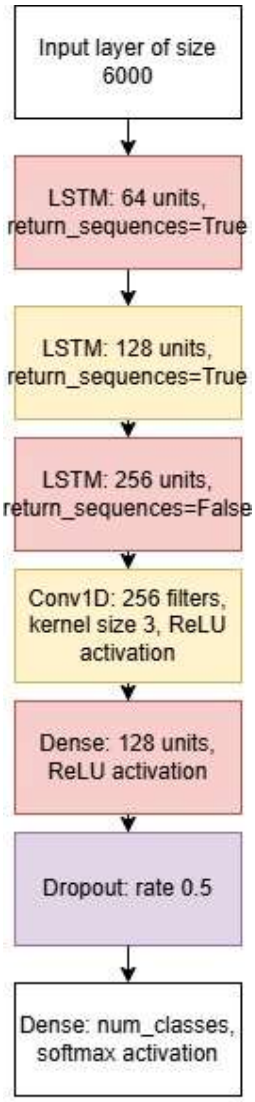

Fig 4. LSTM structure

RESULTS AND COMPARISON

Data source:

In M-ary based PSK systems, the phase of the carrier accepts one of M possible values $\theta_i = \frac{2i\pi}{M}$, where i = 1,2,..., M. Length of bit stream is 60, bit duration is T_b, carrier frequency is 10 Hz, and the variance of noise is 0.1. During each signaling interval of duration T, one of the M possible signals is represented as shown in Equation (7):

$$s_i(t) = \sqrt{\frac{2E}{T}} \cos\left(2\pi f_c t + \frac{2i\pi}{M}\right), i = 1,2,\ldots,M \qquad (7)$$

is transmitted, where E is the signal energy per symbol. The carrier frequency $f_c = \frac{n_c}{T}$ for some fixed integer n_c. Excel file is created, consisting of 100 signals for each of these modulation schemes as given in Table 1.

Table 1: Modulation schemes dataset details

Modulation	M value	Sampling rate	Symbol duration
BPSK	2	100	$1T_b$

QPSK	4	200	**2 T_b**
8-PSK	8	300	**3 T_b**
16-PSK	16	400	**4 T_b**
32-PSK	32	500	**5 T_b**

AMR process is verified with respect to different parameters such as Accuracy, Epoch and Loss. The graph presented in Figure 5 is the changing of Accuracy vs Epoch in terms of training and validation for the techniques CNN and LSTM. For the AMR process 98% of accuracy is obtained using CNN model. Whereas Figure 6 is the graph representing the change of loss vs epoch in training and validation using CNN and LSTM methods. From the graph it is observed that CNN technique produces very less loss of 0.1% as compared to the LSTM technique. Figure 7 represents the performance metric comparison, changing of score and metrics using CNN and LSTM methods. From the graph it is concluded that CNN produces more accuracy, high precision, recall and F1-score values. Hence it is concluded that by combining CNN and LSTM methods for AMR better results can be achieved. Similarly, the comparison table shown in Table 2 also reflects the parameters, training accuracy, test accuracy, precision, recall and F1-score. Efficiency of AMR can be determined by these parameters.

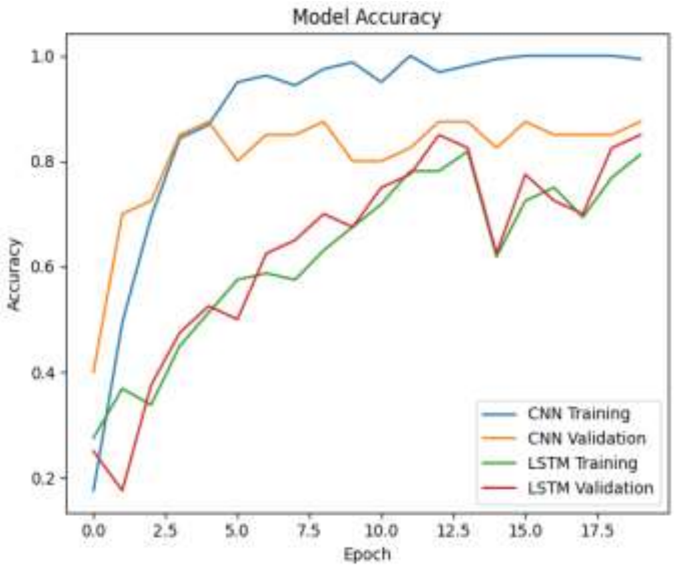

Fig. 5 Changing of accuracy and Epoch in training and validation for CNN Vs LSTM

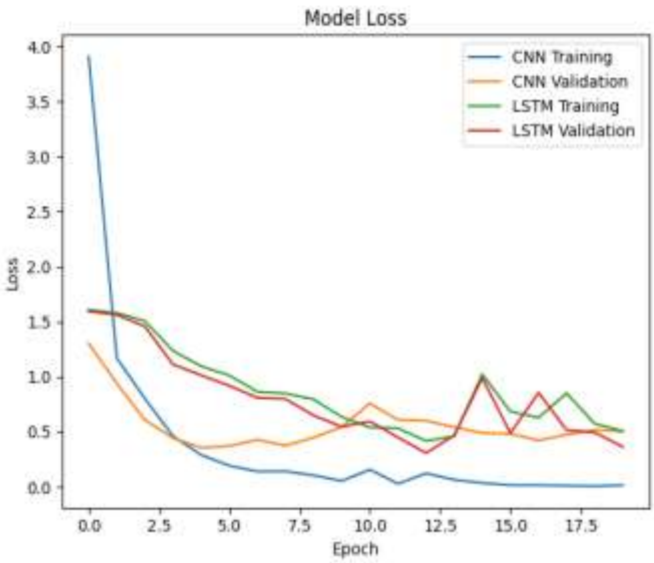

Fig. 6 Changing of Loss and Epoch in training and validation for CNN Vs LSTM

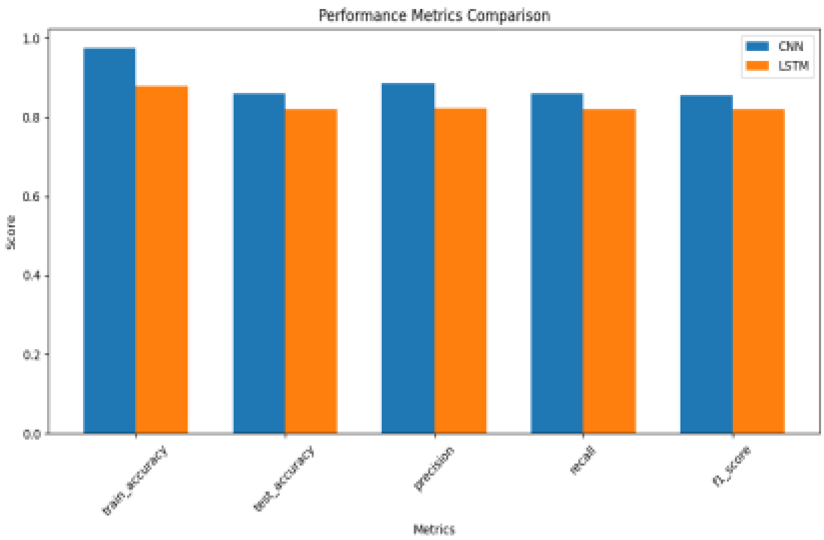

Fig. 7 Performance metric comparison, changing of score and metrics for CNN Vs LSTM

Table 2: Comparison of CNN and LSTM techniques in various parameters.

Model Type	Train accuracy	Test Accuracy	Precision	Recall	F1_score
CNN	0.97	0.86	0.89	0.86	0.85
LSTM	0.88	0.82	0.82	0.82	0.82

CONCLUSIONS

Machine and deep learning (ML/DL) significantly enhance Automatic Modulation Recognition (AMR) by enabling real-time adaptation to changing channel conditions and optimizing resource allocation. Techniques like neural networks, SVMs, and reinforcement learning have been explored, with ongoing research focusing on CNN based AMR and LSTM based AMR. These advancements promise to revolutionize wireless communication by improving spectrum allocation and resource management. It is observed that CNN based AMR outperformed in comparison with LSTM based AMR against small dataset. On the other hand, large dataset, LSTM based AMR dominates than that of CNN based AMR.

Future research should prioritize developing efficient and scalable ML/DL algorithms for AMR like integration of CNN and LSTM networks, Federated learning, etc, addressing challenges related to model complexity and computational overhead.

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