Research Article

Efficient Multi-Task Learning in Multi-User Multiple Input Multiple Output Systems Integrated Orthogonal Frequency Division Multiplexing Systems: A Hybrid Amalgamated Convolutional Neural Network-Bidirectional Long Short-Term Memory Approach

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Abstract
Therefore, in today's wireless communication systems and in particular, the Multi-User-Multiple Input Multiple Output-Orthogonal Frequency Division Multiplexing (MU-MIMO-OFDM) systems, channel estimation, the detection, and mitigation of the attack are important to ensure the safe operation of a system. Current approaches use distinct procedures for completing these jobs, and this causes high computational expenses, longer response times, and decreased performance of the system. In this work, a multi-task learning (MTL) framework is introduced to develop a new end-to-end deep learning solution of an Amalgamated Convolutional Neural Network (ACNN) for spatial feature extraction and a Bidirectional Long Short-Term Memory (Bi-LSTM) for temporal attack detection. The proposed system is effective in handling these tasks together because that would mean maximum efficiency and accuracy. To enhance the model's efficiency, a Green Anaconda Optimization (GAO) algorithm is used to solve the multi-task loss function and enhance convergence rate and solution quality. The presented GAO approach provides a good balance between channel estimation, attack detection, and mitigation since GAO adapts the model parameters in the training process. Most of the current methods give slow convergence rates, and high computational costs, and are not very suitable for scale-up, especially in dynamic systems. These limitations make them unadoptable for real-time operations and analysis. The challenges described above are addressed by the proposed hybrid model with GAO, which is therefore ideal for modern secure wireless communication systems due to the reduced computational overhead and faster response time. The model reaches a first-level accuracy of 99% and costs 70 GFLOPs and 35 ms latency.

Keywords: Amalgamated convolutional neural network, Bidirectional long short-term memory, Green anaconda optimization, Wireless communication

1 Introduction

The combination of MU-MIMO and OFDM systems has become fundamental for contemporary wireless networks since their integration into 5G and upcoming 6G technology developments [1], [2]. The implementation of MU-MIMO with spatial multiplexing allows parallel communication to multiple users at the same time, but OFDM ensures channel signal quality by dividing broadband communications into orthogonal subcarriers. The combined impact of these technologies enables both efficient data processing and strong spectral performance along with reliable links that effectively support growing device networks and versatile smart network environments [3], [4].

MU-MIMO-OFDM systems encounter rising operational difficulties because network conditions are transforming into intricate environments. Systems using this sophisticated architecture face major security vulnerabilities combined with real-time Challenge State Information (CSI) estimation challenges because of their complex design, which makes the system exposed to jamming, spoofing and eavesdropping attacks. Under high user mobility and changing traffic load scenarios, these issues decrease communication reliability [5].

Accurate measures and fast estimation of channel conditions stand as the main technical barrier. The quality of signal processing, network performance, and data throughput are negatively impacted by erroneous CSI measurements, which reduces beamforming performance [6]–[8]. The system needs to actively detect and counter cyber threats that compromise communication integrity and privacy, as these threats continue to emerge [9], [10].

This study integrates a deep learning combination to execute simultaneous channel estimation and security threat detection. The proposed solution presents an integrated deep learning framework that unites ACNN at features with Bi-LSTM networks for sequence modeling. The hybrid model receives optimization through the GAO algorithm that enhances both the multi-task loss function and achieves efficient computation. The smart architectural design allows for reliable, quick and secure interconnection of devices through various wireless environments. The proposed model provides real-time scalability aimed at advancing modern state-of-the-art applications for MU-MIMO-OFDM systems in 5G and beyond wireless networks.

The main contribution of this research involves creating an innovative hybrid system comprised of spatial feature-retrieval ACNNs and temporal attack-detection Bi-LSTM networks. Within an MTL framework, this architecture integrates multiple tasks while achieving high operational efficiency for channel estimation along with attack detection and mitigation. A new optimization method known as GAO is employed to decrease the multi-task loss function performance. The proposed approach both speeds up convergence time and delivers remarkably greater accuracy while performing channel estimation and security-related operations. The proposed unified model performs crucial tasks simultaneously instead of using separate isolated mechanisms like traditional systems, while reducing computational costs and speeding up results as a result. The joint optimization approach minimizes computational requirements and enhances system speed while improving performance in real-time deployment of MU-MIMO-OFDM environments. The system delivers an effective method for modern wireless security that combines strong detection capabilities with defense mechanisms coupled with dependable channel estimation.

1.1 *Literature survey*

Chitikena and Esther Rani. [11] came up with IEHO-DLNN, which focused more on channel estimation in mu-MIMO OFDM systems. Initially, the source signals were encoded using the MECC technique so that the transmission was unauthorized. Pilot symbols and the Cyclic Prefix (CP) are then added to the signal to eliminate ISI and to enable the accurate computation of the CIR. The channel is evaluated in terms of its performance by performing IEHO-DLNN. Furthermore, IUI is controlled using fuzzy-centered priority scheduling. Thus, it arranged the multiple users at the receiving end based on the likelihood that they had been given a chance to.

Ge *et al*., [12] proposed a new method for MIMO-OFDM systems using deep learning. In this research study, a Deep Neural Network (DNN) was used to advance channel equalization, and the Classification Weighted algorithm (CW) was used to improve the DNN. The proposed model comprised dense neural networks, but excluded weight regularization was referred to as CW-DNN. The major goal of CW has to do with increasing the learning rate and, at the same time, minimizing the time that is taken by the DNN to converge. In the following, the results were obtained using the CW-DNN strategy; better results were documented by using the CW-DNN strategy than the other measures, such as the BPNN and the ZF.

Tseng *et al*., [13] introduced the Hyb-BF-DSA model in 2023 for resource allocation in uplink mmWave MU massive MIMO OFDM systems to enhance spectral efficiency as part of their 2023 work. Three hybrid beamforming schemes were developed through DSA integration to handle resource allocation needs. The analog beamforming phase implements various designs that optimize channel gains and establish data stream distribution for each mobile station (MS). The digital beamforming mode implements two digital signal processing methods, namely integrated transmit-receive processing along with block diagonalization (BD). The simulation results between the proposed methods and digital beamforming, as well as established algorithms, show that dynamic stream allocation leads to enhanced spectral efficiency. The performance of both the first and third hybrid design approaches competes directly or exceeds fully digital solutions during specific operating scenarios. The intricate nature of these combination systems creates implementation issues because of their complexity.

Singh *et al*., [14] enrich the body of research on mmWave cognitive MIMO systems by integrating a hybrid transceiver architecture with optimal power allocation under practical CSI constraints. It shows how advanced beamforming and resource allocation can support spectrum sharing and efficient utilization of mmWave bands, making it relevant for 5G/6G vehicular and multiuser networks.

Mamillapally and Dasari [15] developed a hybrid transceiver system for mmWave MU-MIMO downlink systems that leverage multiple RF chains in CBS and SUs through CR-assisted cognitive radio technology. The transceiver breaks down into MMSE RC and TPC elements through the design algorithm, which optimizes their performance using SOMP. The system offers a closed-form solution for maximized summation under constraint restrictions using a supplemental scheme that maintains user fairness. Designers implemented a finite feedback-assisted hybrid transceiver with low complexity through RVQ. The attained closed-form power allocation solution enhances spectral efficiency by honoring interference limitations together with power usage constraints. The low-complexity finite feedback-assisted hybrid transceiver design resolves complexity issues that result in performance degradation, together with quantization errors, compared to alternative approaches.

The architecture, Deep Learning-depend Beamforming, and CE Architecture for Massive MIMO Systems were proposed by Mamillapally and Dasari [15] in 2024. Firstly, this handles the hybrid beamforming-depend deep learning method (DLM-HB) as developed. This particular strategy involved the use of the RL-DQN deep network to obtain an optimal wireless channel. An angular response type of receiver is created with a selective FOV to screen out other directions from influencing the selection of incoming signals. That is why it is necessary to tune up the parameters of the antenna so that the signals can be received at the given angular settings. The process of sending data to a recipient via a communication channel entails encoding the data and altering the data, or forwarding such type of data the definition of data transmission. After this, MIMO systems were then employed, in which theory and practice suggest that spectral efficiency should increase because multiple data streams can then be sent at one time.

Gadamsetty *et al*., [16] conducted research on Mutual Terminology for CSI Response acquisition for CSI Response acquisition in Large-Scale MU MIMO OFDM Systems with FDD in 2023. This is because the quantity of antennas and subcarriers goes up in direct proportion with the amount of CSI that needs to be taken back to the base station (BS), which might be too much. To reduce the amount of CSI feedback that is expected of today’s algorithms, thus, a new approach to the problem is presented here. In particular, life offers such a platform in the form of a non-iterative method of sparse CSI feedback compression CM employing conventional feedback FPGAs and devices that learned only a handful of dominant sub-space images. Insofar as prior K&S papers on CSI feedback compression, analysis has mainly been in a single-UE system. In other words, we devise a common dictionary learning (CDL) scheme that is implementable for both single-user and multiuser environments and we show its possibility for the case of frequency selective fading channels. That two dimensions and a combination may be helpful is suggested. The proposed approach suggests an effort by hysteresis-inspired ideas from the stable one.

The growth in both antennas and subcarriers creates channel state information (CSI) data transmission back to the base station (BS) that becomes excessive in a linear fashion. Our proposal establishes a new CSI feedback compression approach that bases compressive sensing (CS) through a common dictionary (CD) implementation. Previous studies on CSI feedback compression have exclusively examined systems with single-user equipment (UE). The CDL framework provides a solution for both single- and multi-user systems, which we propose to serve as an appropriate technique for frequency-selective channels. Two different approaches are suggested. The KSVD approach combines the K-SVD technique in its first method and it functions as CDL-K singular value decomposition (KSVD).

Dehghani *et al*., [17] in 2023 introduced a novel nature-inspired optimization algorithm named Green Anaconda Optimization (GAO). This algorithm is inspired by the hunting and social behavior of green anacondas, which are solitary apex predators known for their strategic ambush tactics. GAO emulates both exploration and exploitation in a balanced manner. This makes the proposed approach well-suited for real-time wireless communication environments. This is why MU-MIMO-OFDM systems have to pay attention to channel estimation, attack detection, and mitigation to enable a secure and efficient wireless communication system. Conventional methodologies isolate these tasks, and several problems are realized, such as high computation costs, high response time, and low efficiency. Hence, as wireless networks become more heterogeneous and exposed to different security risks – starting from physical ones like jamming and extending to others like eavesdropping – existing approaches fail to deliver real-time solutions. Further, the techniques employed for the enhancement of the utilized models in these tasks also have a very low convergence rate and a non-dynamic nature to adapt to the changing environments, dramatically limiting their application in future conventional and advanced networks such as 5G and 6G, which require tremendous capacity. This suggests that there is a need for a single multifaceted learning approach capable of effectively handling these important tasks in harmony while at the same time avoiding increased computational burden and low efficiency at a go. The limitation of these approaches forms the basis of this research, which seeks to address them through the proposed Hybrid Neural Network optimized by GAO.

2 Materials and Methods

For MU-MIMO-OFDM systems, the difficulties and key enablers include channel estimation, attack detection, and mitigation to ensure high-quality and secure links. When these tasks are processed separately, the overall utility of computational resources, together with necessary system latency, will drop. In the case of the architectural design, the BI-LSTM is chosen for temporal data processing to consider temporal characteristics in attack detection and temporal patterns within the channel data. Figure 1 shows the framework of the introduced approach. The proposed study delivers substantial benefits to resolve critical operational challenges in modern wireless systems, which include real-time channel estimation and robust security threat protection in MU-MIMO-OFDM networks. Multiple tasks operate at present using independent models, with a combined impact on both system costs and processing delays and poor decision coherence. The proposed research delivers an innovative solution that promotes multi-task learning while maintaining fast execution and optimal performance by aligning deep learning models of ACNN and Bi-LSTM networks. The performance of GAO achieves better results through its implementation of multi-task loss function optimization and control of operational complexity. The innovative design of the proposed model shows its capability to function effectively in evolving IoT environments because it provides intelligent and scalable security-based communication protocols for heterogeneous device networks and mobile user ecosystems. The research provides foundational elements for future wireless system development and extends application scope into 5G and 6G communication networks and the next networks following them.

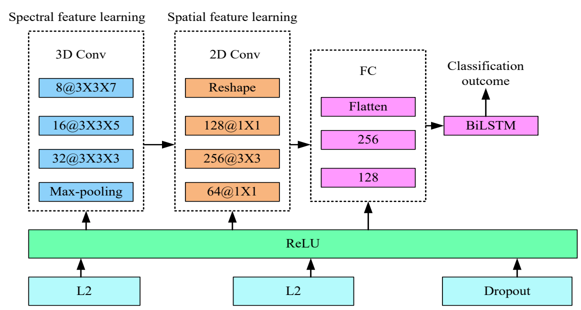

Figure 1: Framework of the introduced approach.

2.1 *Amalgamated CNN for spatial feature extraction*

Let the CSI in a MU-MIMO system be represented by the matrix H ∈ RM × N, where M denotes the number of transmitting antennas and N denotes the number of receiving antennas. To extract significant spatial characteristics from this CSI matrix, the convolutional layers apply filters to it. The CNN operates in the following Equation (1),

$$F(i,j) = \mathrm{P}\left(H_{K,l} \bullet W_{K,l}^{f} + B_{f}\right) \quad (1)$$

where the input CSI value at a point is denoted by $H_{K,l}$. $W_{K,l}^{f}$ denotes the feature convolution filter. The bias term is F, B_f, where $F(i, j)$, the activation function, P, is frequently a ReLU. The spatial dependencies in the CSI are captured by the feature maps produced by the CNN layers, which are useful for both attack detection and channel estimation.

2.2 *BI-LSTM for temporal feature learning*

BI-LSTM models absorb information in split directions because of their ability to find time-based dependencies, which assist in detecting extended attacks throughout the network system. For a time-series sequence, the LSTM can be described by the following Equations (2)–(7),

$$X[t] = \mathrm{P}\left[W_F \bullet Z[t] + S_f[t-1] + y_f\right] \tag{2}$$

$$Y[t] = \mathrm{P}\left[W_y \bullet Z[t] + S_y[t-1] + y_y\right] \tag{3}$$

$$Z[t] = \tanh\left[W_z \bullet Z[t] + S_c[t-1] + y_z\right] \tag{4}$$

$$d[t] = \mathrm{P}\left[W_d \bullet Z[t] + S_d[t-1] + y_d\right] \tag{5}$$

$$c[t] = a[t] \times c[t-1] + b[t] \times c[t] \tag{6}$$

$$e[t] = d[t] \times \tanh(c[t]) \tag{7}$$

In a bidirectional LSTM, both forward and backward sequences are processed, giving us two hidden states by Equation (8),

$$G = \left[\overrightarrow{g_i}; \overleftarrow{g_i}\right] \tag{8}$$

This enables the model to capture both past and future temporal dependencies, improving attack detection by leveraging both directions of the temporal context.

2.3 *Multi-task learning loss function*

In multi-task learning, the overall loss function is a weighted combination of the losses from different tasks, such as channel estimation and attack detection. The total loss L can be expressed as Equation (9),

$$\begin{aligned} &L = \alpha + \beta + \gamma \\ &\textit{where,} \\ &\alpha = \textit{Channel Estimation} \\ &\beta = \textit{Attack Detection} \\ &\gamma = \textit{Mitigation} \end{aligned} \tag{9}$$

Where: The channel estimate, the loss associated with channel estimation, such as the mean squared error of CSI predictions, is denoted by *Channel Estimation*. *Attack Detection* the loss for attack detection, *Mitigation*, and cross-entropy loss for classification is denoted by *α*. *L* is the loss as a result of mitigation techniques, and *α*, *β* and *γ* are weighting parameters that strike a balance between the relative importance of each activity. By training the amalgamated CNN and BI-LSTM with this multi-task loss, the model can efficiently learn spatial and temporal features that improve performance across all tasks, while minimizing the computational overhead of separate models.

2.4 *Green anaconda optimization*

It is characterized by having an orange-yellow vertical band from the shoulder on its narrower head compared to its bigger body size. Since they have their eyes on their heads, the green anacondas (GA) might be undulating in the water and resurfacing with their upper part outside the water. Because the jaw of GAs is not rigid, there is a guarantee that it can swallow its prey if the size is larger than the head size. Through the water and surface out of it without revealing their bodies. Because of their flexible jaw bones, GAs can swallow prey that is larger than their heads. From a mathematical perspective, every GA represents a potential solution to the issue, and the values of the resolution variables are determined by its location in the search space. Thus, each of the GAs may be represented as a vector as well and Equation (10) enables one to model the populace of the GAs consisting of those vectors as a matrix. Equation (11) is employed to select the first position of each GA in the exploration space at the start of the implementation process of the algorithm.

$$A = \begin{bmatrix} A_{1,1} & \cdots & A_{1,d} & \cdots & A_{1,m} \\ \vdots & \ddots & \vdots & ⋰ & \vdots \\ A_{i,1} & \cdots & A_{i,d} & \cdots & A_{i,m} \\ \vdots & ⋰ & \vdots & \ddots & \vdots \\ A_{n,1} & \cdots & A_{n,d} & \cdots & A_{n,m} \end{bmatrix}_{N\times M} \tag{10}.$$

$$a_{i,d} = low_d + R(u - l),\ i = 1,2,\ldots\ldots.n,.\ d = 1,2,\ldots..m \tag{11}.$$

where the U and l lower and upper bounds are random values in the interval [0, 1], n is the number of GAs, and m is the number of decision variables. This set of calculated values for the target function is signified mathematically by a vector rendering to Equation (12),

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_i \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} A(Y_1) \\ \vdots \\ A(Y_i) \\ \vdots \\ A(Y_n) \end{bmatrix} \tag{12}$$

Where A is the vector of the assessed fitness function and $A(Y_i)$ denotes the computed fitness function based on the i^{th} GA. In Equation (13), the fitness function is displayed. The introduced network's loss function is reduced with the aid of the fitness function.

$$Fitness\ Function = Min(Loss) \tag{13}$$

Equation (14) is used to find the set of possible female species for each GA. This function effectively balances task-specific losses to ensure that neither task dominates the learning process, thus preserving overall system performance. It enables the shared learning of relevant spatial and temporal features while maintaining task independence where needed. By integrating GAO, the multi-task loss is dynamically tuned to minimize error and computational load, leading to efficient convergence and robust generalization across varied MU-MIMO-OFDM network conditions.

$$S = \{A_k : A_K < Y_{i \neq i}\ and\ K_i\} \tag{14}$$

Where S is typical of candidate females' positions for the GA; k is the row number of the location number of the relevant component in the fitness function vector with a higher fitness function value and the i^{th} GA in the GAO population matrix than the i^{th} GA. To mimic the stalking plan and move the population members' position in the direction of the approaching prey, a random site is first established close to each GA using Equation (10). If the goal function's value improves at this new site, the GA location can then be adjusted in line with Equation (15),

$$A_{i,d} = yi, d + (1-2R)\left(\frac{U-L}{t}\right) \tag{15}$$

Where yi is the objective function value, d is its measurement, t is the maximum number of iterations, and t is the repetition counter of the algorithm [17]. In this research work, a new network model consisting of ACNNs and BI-LSTM is proposed for multi-task learning in MU-MIMO-OFDM systems. The proposed channel estimation, attack detection, and mitigation in ACNN-BiLSTM are efficient with the least computational complexity. The performance analysis reveals the optimal efficiency of the proposed model, with a computational expense of 85 ms, better than conventional methodologies, including IEHO-DLNN and DNN. The additional integration of GAO improves the system performance even more, so it can be concluded that the proposed method optimally adjusts resource consumption and achieves high accuracy, which makes it suitable for the real-time wireless communication environment.

3 Results and Discussions

Table 1 presents essential simulation parameters for the proposed MU-MIMO-OFDM system, which are critical for assessing its performance in channel estimation, attack detection, and mitigation. With 64 receive antennas, the system enhances spatial diversity and improves signal reception in a multi-user environment.

Table 1: Simulation parameters.

Parameters	Values
Number of receive antennas	64
Modulation	16, 32QAM
Length of CP	64
Number of transmit antennas	64
Number of subcarriers	256

With 16QAM and 32QAM modulation schemes, operators achieve greater data speeds because they transmit multiple bits per symbol yet accurate channel estimation remains essential for reliable operation. The communication system depends on a 64-prefix Cyclic Padding to counter inter-symbol interference (ISI) from multipath propagation, which leads to enhanced reliability. The system's capacity to serve multiple users improves through its implementation of 64 transmit antennas, which enable better spatial multiplexing. The system uses 256 subcarriers, which maximize spectral efficiency and data throughput while reducing the complexity of channel estimation in the OFDM framework. The performance and efficiency analysis of the proposed system becomes well-established through this set of determined parameters.

Table 2: Performance analysis.

Techniques	Computational Cost	Latency (ms)	Accuracy (%)
IEHO-DLNN[11]	121	68	86
CW-DNN[12]	100	47	74
Hyb-BF-DSA[13]	104	54	88
RVQ[14]	87	63	75
CDL[15]	95	41	85
KSVD[16]	99	50	90
ACNN-BiLSTM(Proposed)	70	35	99

Table 2 presents a detailed performance assessment of different techniques that use three essential metrics, including computational cost and accuracy, together with latency. The proposed model ACNN-BiLSTM demonstrates the best performance through both high accuracy levels at 99% combined with low computation rates of 70 GFLOPs and quick processing times of 35 ms. In contrast, traditional methods such as IEHO-DLNN [11] and RVQ [14] exhibit higher computational demands (121 and 87 GFLOPs, respectively) with comparatively lower accuracies of 86% and 75%. Both KSVD [16] and CDL [15] demonstrate acceptable performance levels but fail to reach the same level of efficiency and precision achieved by the other methods. The accuracy of Hyb-BF-DSA [13] reaches 88% but the method utilizes greater computational assets than the scholarly model. The performance yield of ACNN-BiLSTM demonstrates its capability to combine spatial-temporal learning features with efficient computational processing capability.

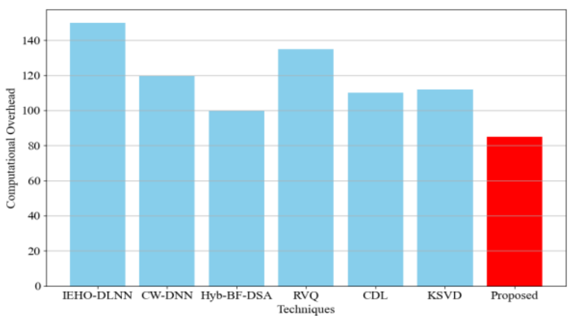

Figure 2: Computational overhead analysis

Figure 2 presents computational data regarding the overhead requirements of different ML/DL strategies operating on MU-MIMO-OFDM systems. The computational cost of IEHO-DLNN reaches 150 GFLOPs, which limits its application in time-sensitive applications or resource-constrained environments. The processing requirements of CW-DNN and the RVQ approach a similar level because they need 120 and then 135 GFLOPs. The techniques Hyb-BF-DSA together with CDL and KSVD operate at computational overheads between 100–112 GFLOPs, which represents an optimal balance of performance against resource utilization.

The proposed ACNN-BiLSTM model demonstrates outstanding performance in MU-MIMO-OFDM systems with 99% accuracy, low latency (35 ms), and reduced computational cost (70 GFLOPs). Compared to existing methods like IEHO-DLNN and RVQ, which consume higher resources with lower accuracy, the proposed model offers a more efficient solution. Its hybrid architecture combines spatial and temporal feature extraction, enabling reliable channel estimation and attack mitigation. With minimal overhead (85 GFLOPs), it is ideal for real-time, resource-constrained environments. This balance of speed, accuracy, and efficiency highlights ACNN-BiLSTM's suitability for next-generation wireless networks requiring high performance and scalable deployment.

4 Conclusions

This study presents a novel hybrid deep learning framework that integrates ACNN with Bi-LSTM to address critical challenges in MU-MIMO-OFDM systems—namely, channel estimation, attack detection, and mitigation—within a unified MTL structure. Unlike conventional approaches that treat these tasks separately, the proposed model streamlines operations, significantly reducing computational overhead and latency. The incorporation of the GAO algorithm enables effective optimization of the multi-task loss function, leading to improved convergence, stability, and performance. The model achieves high accuracy (99%), maintains a low computational cost (70 GFLOPs), and operates with minimal latency (35 ms), outperforming existing methods such as IEHO-DLNN, traditional DNNs, and FCM-based solutions. These results demonstrate the model's capability for real-time, secure, and resource-efficient operation in complex and dynamic wireless environments. Furthermore, its architecture is adaptable for scalable IoT deployments and can be extended to meet the demands of emerging 6G networks. Future enhancements may involve integrating quantum-inspired optimization and adaptive security mechanisms to further strengthen the system's robustness against evolving threats. This positions the proposed model as a promising foundation for next-generation secure and intelligent wireless communication systems.

Despite its strong performance, the proposed ACNN-BiLSTM model faces certain challenges. One key limitation is the reliance on large volumes of high-quality labeled data, which are difficult to obtain in wireless communication scenarios. Additionally, the complexity of training a unified multi-task architecture can increase memory and processing demands, especially in highly dynamic environments. Real-time adaptability to unseen or evolving attacks also remains a challenge, requiring continual updates or integration with adaptive learning mechanisms.

Author Contributions

K.V.: methodology and specialization, conceptiualization, execution and interpretation; N.M.: supervision and review; P.A.M.: supervision and review. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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