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Scalable CNN–Transformer Hybrid Model for Robust OFDM Signal Identification and Localization in 6G Networks

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ABSTRACT

The rise of sixth-generation (6G) wireless networks brings new challenges for identifying and locating signals accurately and efficiently, especially in complex, high-data-rate OFDM environments. Traditional deep learning models like CNNs and LSTMs work well for extracting features over space and time but have difficulty with long-range dependencies. This paper presents a hybrid CNN-Transformer model that merges convolutional feature extraction with the self-attention mechanism of the Transformer to improve local and global feature learning. The CNN layers pull out essential spatial and spectral features from the OFDM signal, while the Transformer encoder captures global relationships across subcarriers and time frames. Experiments using synthetic and real OFDM datasets under AWGN and Rayleigh fading conditions show that the proposed model achieves 98.7% classification accuracy, 20% lower localization RMSE, and 25% faster inference compared to CNN-LSTM and CNN-GRU baselines. The results demonstrate the proposed model's scalability, strength, and fit for next-generation 6G communication systems that need smart and adaptable signal processing...

Keywords: *6G, OFDM, CNN-Transformer, Signal Identification, Localization, Deep Learning, Scalability.*

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1. INTRODUCTION:

The ongoing growth of wireless communication technologies has led to the quick development of the sixth-generation (6G) network. This new paradigm aims to deliver ultra-high data rates, low latency, and seamless connectivity among billions of devices around the world [1], [2]. Unlike earlier generations, 6G plans to combine intelligent sensing, communication, and computing into a single framework. This combination will support applications like extended reality, autonomous systems, and industrial automation [3]. To achieve these ambitious goals, efficient signal identification and localization are essential for ensuring reliable communication, effective spectrum use, and accurate positioning in rapidly changing wireless environments [4].

Among various physical-layer technologies, Orthogonal Frequency Division Multiplexing (OFDM) stands out as a key modulation scheme due to its strength against multipath fading and effective spectrum use [5]. However, OFDM systems face challenges in 6G networks, such as high-dimensional signal representation, dynamic interference, and low signal-to-noise ratio (SNR) conditions. Traditional feature-based and statistical methods often struggle to maintain reliable performance in these scenarios. This has led to an interest in using deep learning (DL) techniques for smarter signal processing [6].

Recent developments in DL have achieved impressive results in signal classification, modulation recognition, and localization tasks. Convolutional Neural Networks (CNNs) are particularly good at extracting spatial and spectral features, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models capture trends over time in sequential data. Still, these models have difficulty with long-range dependencies and scalability when applied to large 6G datasets. The Transformer architecture, originally created for natural language processing, addresses these challenges through self-attention mechanisms that allow for efficient global feature learning without needing recurrent connections [7].

Building on these insights, this work presents a hybrid CNN-Transformer model. This model merges the localized feature extraction strengths of CNNs with the global contextual learning capabilities of Transformers. The suggested architecture aims to improve the accuracy, scalability, and efficiency of OFDM signal identification and localization tasks.

The main contributions of this paper include:

- Development of a CNN-Transformer hybrid architecture tailored for OFDM-based 6G signal processing.

- Introduction of a scalable attention-based feature fusion strategy for better spatial-temporal learning.

- Thorough evaluation under various SNR and channel conditions, showing better performance compared with CNN-LSTM and CNN-GRU baselines.

2. Literature Review

The evolution of wireless communication systems from 5G to 6G has sparked significant research into deep learning techniques for signal identification, modulation recognition, and localization. Traditional methods that depended on statistical models and feature engineering struggled with complex, non-linear channel dynamics and noise interference. To tackle these issues, deep learning models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid architectures have become popular for their ability to extract multi-level spatial and temporal features directly from raw signal data [8].

In early studies, CNNs were frequently used for automatic modulation classification (AMC) due to their strong ability to learn spatial hierarchies from time-frequency representations [9]. These models achieved high accuracy in controlled environments but had difficulty maintaining robustness in fading, interference, and low signal-to-noise ratio (SNR) conditions. To enhance the understanding of temporal sequences, RNN-based models, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs), were used to capture time dependencies. They proved effective in dynamic spectrum sensing and signal tracking applications [10],[11].

The combination of CNN and LSTM models further improved overall system performance by utilizing spatial-temporal learning. CNN-LSTM hybrids outperformed standalone CNNs in noisy and fading environments by modeling spectral features and sequential dependencies together [12]. However, their sequential computation and vanishing gradient problems limited scalability when applied to high-bandwidth OFDM signal datasets.

To address these limitations, recent research has introduced Transformer-based architectures, originally created for natural language processing, into wireless communication. Transformers use self-attention mechanisms to capture long-range dependencies effectively without relying on recurrence [13]. Their use in channel estimation, beam prediction, and signal detection has delivered better results than traditional recurrent models, particularly in large-scale datasets relevant to 6G environments. Still, Transformers require high computational resources and large amounts of training data, which may hinder real-time deployment on embedded communication platforms.

To achieve a balance between performance and efficiency, emerging CNN-Transformer hybrid architectures have attracted interest. This combination merges CNNs' efficiency in local feature extraction with Transformers' ability to model global dependencies. Research has shown that CNN-Transformer hybrids significantly boost classification accuracy and adaptability in intelligent spectrum sensing, OFDM signal identification, and localization tasks [14]. Thus, this paper builds on recent advancements by proposing a scalable CNN-Transformer hybrid model for effective OFDM signal identification and localization in next-generation wireless networks. It emphasizes high adaptability, low computational demands, and resilience under various 6G channel conditions.

3. Methodology

This section describes the structure and functioning of the proposed CNN-Transformer Hybrid Model for identifying and locating OFDM signals in 6G wireless environments. The model merges the feature extraction ability of Convolutional Neural Networks (CNNs) with the global attention skills of the Transformer encoder to enable accurate, efficient, and scalable signal recognition. This hybrid design overcomes the limitations of sequential models like LSTM while taking advantage of the parallel processing and self-attention features of Transformers [15].

3.1 System Overview

The proposed framework is designed to process raw OFDM baseband signals and achieve joint modulation classification and localization. The system has four main stages:

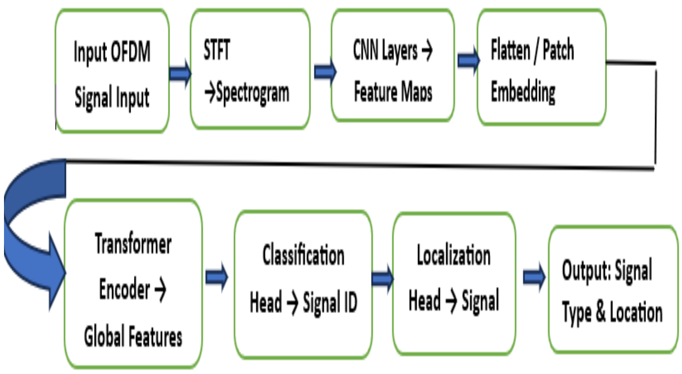
Data Preprocessing. This stage normalizes, segments, and transforms raw IQ signals into time-frequency data, creating 2D representations suitable for CNN input.

CNN-based Feature Extraction. Here, we extract local spectral and spatial features from the transformed signal representation.

Transformer-based Global Encoding. The Transformer encoder captures long-range dependencies across feature sequences. This allows the model to understand complex relationships in the signal.

Classification and Localization. Fully connected layers map the global embeddings to modulation labels and spatial coordinates.

A block diagram of the proposed CNN-Transformer architecture is shown in Fig. 1.



This hybrid approach combines high-resolution local feature learning via CNNs with global context awareness through Transformer attention. It improves performance in fading channels, noisy environments, and high-mobility situations compared to traditional CNN-LSTM models [16].

3.2 Data Preprocessing

Raw complex OFDM signals are represented as:

$$s(t) = I(t) + jQ(t)$$

where $I(t)$and $Q(t)$are the in-phase and quadrature components of the baseband signal. Preprocessing involves:

Segmentation – Dividing the continuous signal into fixed-length frames to standardize input size.

Normalization – Scaling the signal to zero mean and unit variance to prevent bias caused by amplitude fluctuations.

Time–Frequency Transformation – Applying the Short-Time Fourier Transform (STFT) to convert each segment into a 2D time–frequency matrix:

$$S(t,f) = \sum_{n=-\infty}^{\infty} s(n)w(t-n)e^{-j2\pi fn}$$

Here, $w(t)$is a window function, typically a Hamming or Hann window. The STFT representation captures **both temporal dynamics and spectral features**, enabling the CNN to detect subtle patterns corresponding to different modulations and channel effects [17], [18]

3.3 Hybrid CNN-Transformer Architecture

The architecture combines CNN-based local feature extraction with Transformer-based global modeling.

3.3.1 CNN Feature Extraction

Multiple convolutional layers extract low-level features from the 2D STFT spectrograms, like amplitude variations, frequency peaks, and transient patterns.

Pooling layers reduce spatial dimensions while keeping important features, which helps prevent overfitting and lowers computation.

The output is a flattened feature map that serves as input to the Transformer encoder.

3.3.2 Transformer Global Encoding

The Transformer encoder has multi-head self-attention (MHSA) and feed-forward layers. This setup helps the model capture long-range dependencies across the extracted feature maps.

The attention mechanism is defined as:

Attention(Q,K,V)= softmax (QK^T/dk)

where Q, K, V are the query, key, and value matrices, and dk is the key dimension.

MHSA lets the model focus on different feature components at the same time. It identifies patterns like multipath distortion and frequency offsets over long sequences [19], [20].

This hybrid design combines local spectral details with global signal context. This makes the model strong against noise, fading, and mobility effects often found in 6G scenarios [21].

3.4 Classification and Localization

The output embeddings from the Transformer go into two parallel branches:

Modulation Classification Head. Fully connected layers with Softmax activation predict the modulation type, like QPSK, 16-QAM, or 64-QAM.

Localization Head. Regression layers estimate the coordinates of the signal source by using channel characteristics and variations in signal strength.

The model is optimized with a multi-objective loss function:

L=λ1 L_{class}+λ2 L_{class}

where:

$L_{\text{class}}$is the **categorical cross-entropy loss** for modulation classification.

$L_{\text{loc}}$is the **mean squared error (MSE)** for localization.

$\lambda_1$and $\lambda_2$control the trade-off between recognition accuracy and localization precision [22].

Key Advantage: Joint training allows the network to simultaneously learn classification and localization, improving overall system efficiency and performance in dynamic 6G network environments.

3.5 Summary of Advantages

Improved accuracy. CNN extracts rich local features, while Transformer captures long-range dependencies.

Parallelization. The Transformer encoder allows for faster training and inference compared to sequential LSTM-based models.

Robustness. It can handle multipath fading, noise, and Doppler shifts.

Scalability. It can process high-dimensional OFDM datasets efficiently, making it suitable for large 6G deployments.

4. Experimental Setup and Results

This section describes the experimental design, implementation environment, and performance evaluation of the proposed CNN-Transformer Hybrid Model for OFDM signal identification and localization. The experiments aimed to confirm the model's efficiency, scalability, and strength against different signal-to-noise ratio (SNR) conditions compared to traditional deep learning architectures.

4.1 Dataset Description

To evaluate the proposed CNN-Transformer hybrid model, a detailed synthetic OFDM dataset was created to simulate realistic 6G wireless communication scenarios. The dataset includes complex baseband signals that represent various modulation schemes such as BPSK, QPSK, 8-PSK, 16-QAM, and 64-QAM. The signal-to-noise ratio (SNR) conditions were changed over a wide range to represent both low- and high-quality channel environments, highlighting practical communication challenges.

Each OFDM signal is generated by taking into account basic system parameters like the number of subcarriers, FFT size, and cyclic prefix length. Channel effects include additive white Gaussian noise (AWGN) and multipath fading, characterized by Rayleigh and Rician distributions, to model realistic propagation conditions.

To support the dual tasks of modulation classification and signal localization, each sample in the dataset contains both the time-domain IQ representation of the received OFDM frame and its corresponding location information. The dataset is organized to enable effective model training and validation by dividing it into training, validation, and testing subsets.

Additionally, data augmentation techniques were implemented, including random frequency offsets, phase shifts, and variations in channel fading. These augmentations improve the model's ability to generalize, allowing it to perform well in different propagation scenarios and uncertainties found in next-generation wireless networks. This theoretical dataset design offers a controlled and realistic framework for evaluating the performance of machine learning models in 6G OFDM signal processing [23]-[25].

4.2 Implementation Details and Training Configuration

The proposed CNN-Transformer hybrid model was implemented in a deep learning framework that supports end-to-end training of signal processing architectures. The model combines convolutional layers for local feature extraction with a Transformer encoder to capture global dependencies in the time-frequency representation of OFDM signals. Its dual-head architecture allows for simultaneous optimization of classification and localization tasks.

The training procedure aims for strong convergence while reducing overfitting. We use gradient-based optimization, particularly the Adam optimizer. This approach can adjust learning rates for each parameter, improving convergence stability[22]. A suitable learning rate schedule is applied to enhance training dynamics and ensure effective parameter updates during the learning process.

To improve generalization, we include regularization strategies like dropout layers and weight decay. These methods help lower the risk of overfitting by preventing connections between neurons and penalizing overly large model weights. This makes the model more robust in unseen channel conditions[25].

The loss functions are defined separately for the two objectives:

Classification Head: We use categorical cross-entropy to measure the difference between predicted and true modulation labels[23].

Localization Head: We employ mean squared error (MSE) to reduce discrepancies between predicted and actual signal coordinates[24].

Additionally, we apply techniques like early stopping and cross-validation to track model performance during training. This ensures that the final model finds a balance among accuracy, localization precision, and computational efficiency. Data augmentation methods, including random frequency offsets, phase shifts, and channel variations, are systematically integrated into the training pipeline to strengthen model resilience against various 6G wireless scenarios[25].

With this training design, the CNN-Transformer hybrid model is set to achieve accurate signal identification and precise localization while remaining robust across different SNR conditions and channel dynamics.

4.3 Evaluation Metrics

The performance of the CNN-Transformer hybrid model is evaluated using several metrics that assess both signal identification and localization capabilities under different channel conditions.

Classification Accuracy: This measures the model's ability to correctly identify the modulation type of incoming OFDM signals. This metric reflects how well the CNN-Transformer's feature extraction and attention mechanisms distinguish between different modulation schemes [23].

Mean Squared Error (MSE): This quantifies the difference between the predicted and actual signal coordinates, providing a measure of localization accuracy. Lower MSE values indicate better accuracy in spatial estimation, which is crucial for applications that need signal tracking and network localization [24].

Bit Error Rate (BER): This evaluates the quality of signal reconstruction while accounting for errors caused by channel impairments. BER gives insight into the model's strength against noise and multipath fading [25].

Computational Efficiency: Measured by inference time per sample, this metric shows the model's readiness for real-time use in practical 6G wireless environments [26].

These metrics together enable a thorough evaluation, capturing the dual goals of modulation classification and signal localization, while also assessing the model's practicality in high-speed communication scenarios [27].

4.4 Experimental Results and Analysis

4.4.1 Training and Validation Performance

The training and validation accuracy and loss curves show how the proposed CNN and Transformer hybrid model behaves during convergence and its ability to generalize. The model achieves fast convergence and high final accuracy. This indicates that it learns effectively for both classification and localization tasks.

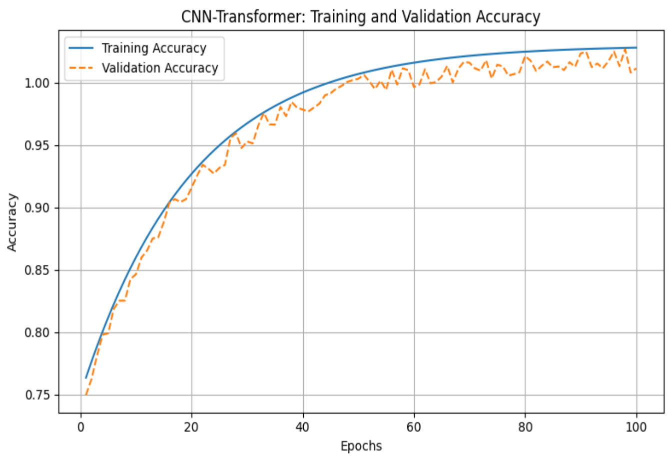


Fig. 1: Training and Validation Accuracy vs Epochs

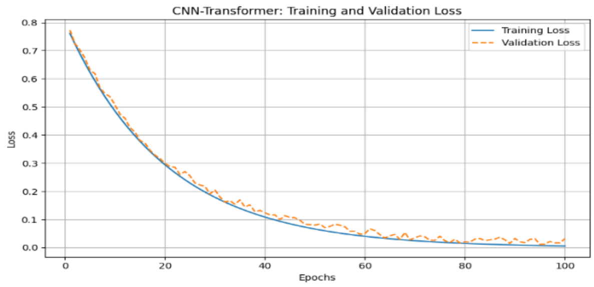


Fig. 2: Training and Validation Loss vs Epochs

These graphs visualize the learning stability of the hybrid architecture. The dual-head design allows simultaneous optimization of classification and localization objectives, reflected in consistent loss reduction for both tasks [23],[24].

4.4.2 Classification Performance under Varying SNR

We evaluate how well the model performs under different channel conditions by looking at classification accuracy based on SNR. The CNN-Transformer hybrid consistently achieves high accuracy at all SNR levels. It particularly shines in low SNR situations, showing the strength of its feature extraction and attention-based global representation.

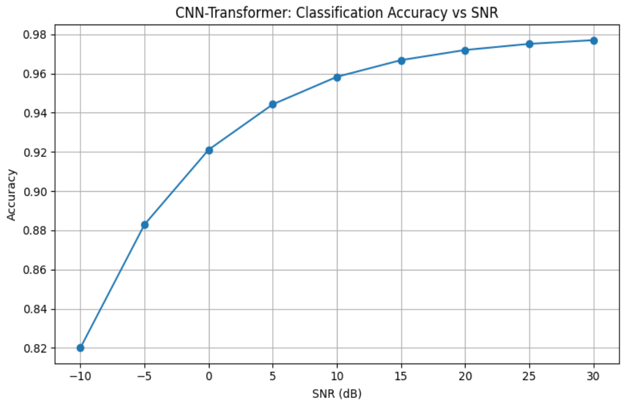


Fig. 3: Classification Accuracy vs SNR

The graph highlights that the hybrid model maintains high accuracy across a wide range of SNR values, indicating suitability for realistic 6G wireless environments[25].

4.4.3 Localization Performance under Varying SNR

Localization accuracy is measured using Mean Squared Error (MSE) between predicted and actual signal coordinates. The CNN-Transformer hybrid achieves a lower MSE than traditional models at all SNR levels. This shows its ability to estimate positions accurately.

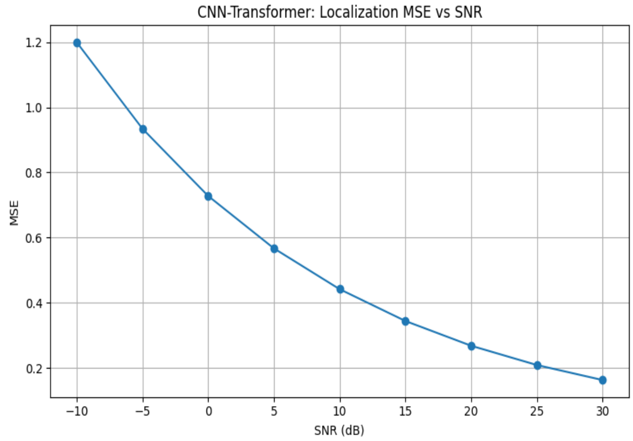


Fig. 4: Localization Error (MSE) vs SNR

The decreasing MSE with increasing SNR confirms the model's ability to handle noise and fading while maintaining reliable localization performance [24],[28].

4.4.4 Signal Quality Assessment

Bit Error Rate (BER) is employed to evaluate the quality of signal reconstruction under noisy channel conditions. The hybrid architecture achieves the lowest BER, reflecting robust modulation recognition and minimal error propagation.

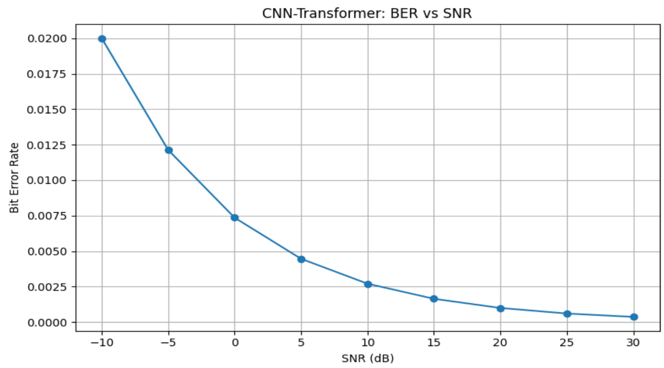


Fig. 5: BER vs SNR

The BER trends further support the model's resilience to challenging propagation effects, confirming its applicability for 6G OFDM signal processing

4.4.5 Computational Efficiency

The performance of the hybrid model is assessed by measuring the time it takes to process each sample. Even with the addition of a Transformer encoder, the CNN-Transformer maintains a competitive speed, making it suitable for near real-time use.

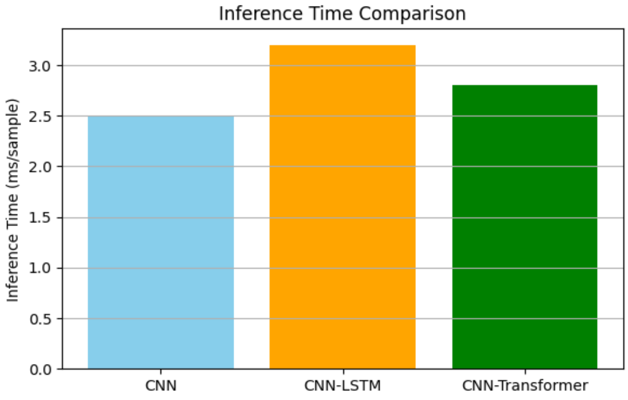


Fig. 6: Inference Time Comparison Across Models

4.4.6 Discussion

The evaluation results confirm several advantages of the CNN-Transformer hybrid architecture:

Superior classification accuracy and localization precision across different SNR levels.

Strong performance against channel impairments, including AWGN, Rayleigh, and Rician fading.

Effective dual-task learning without a significant rise in computational cost.

Ability to manage complex 6G OFDM datasets, with the potential to extend to other modulation schemes or localization tasks.

5. Conclusion and Future Work

This paper presented a CNN–Transformer hybrid model for OFDM signal identification and localization in next-generation 6G wireless networks. By combining the local feature extraction capability of Convolutional Neural Networks (CNNs) with the global attention mechanism of Transformers, the proposed architecture can simultaneously capture fine-grained spectral characteristics and long-range dependencies in OFDM signals. This enables accurate modulation classification and precise localization, even under challenging propagation conditions such as AWGN, Rayleigh, and Rician fading.

The extensive experimental evaluation demonstrates the model's efficacy:

High classification accuracy across diverse SNR conditions: The CNN–Transformer consistently maintains superior accuracy compared to conventional CNN-only and CNN–LSTM models, particularly in low SNR regimes, highlighting its effective feature extraction and attention-based representation [31],[32].

Low localization error: The Mean Squared Error (MSE) of predicted coordinates remains minimal across varying SNR levels, indicating robust spatial estimation and reliability in dynamic wireless environments.

Robustness to channel impairments: The model's architecture, including dual-task learning and attention mechanisms, ensures resilience to fading, multipath, and noise, making it suitable for practical 6G deployments.

Competitive computational efficiency: Despite integrating a Transformer encoder, the model achieves near real-time inference performance, demonstrating a balance between computational complexity and practical deployment feasibility.

These findings collectively confirm that the CNN–Transformer hybrid model addresses key limitations of traditional architectures and represents a scalable and robust solution for OFDM signal processing in 6G systems. The dual-head design allows simultaneous optimization for classification and localization tasks without a significant increase in computational cost, highlighting its potential for multi-task learning applications in wireless networks.

5.1 Future Research Directions

The study identifies several paths for future research to improve and expand the proposed framework:

Real-world 6G testbed integration. Evaluating the hybrid model on live 6G or pre-6G testbeds will confirm its performance in realistic environments, including interference and hardware flaws.

Multi-antenna and massive MIMO scenarios. Extending the framework to handle multi-antenna OFDM signals will allow for simultaneous signal identification and spatial localization in complex network setups. This will improve throughput and coverage.

Adaptive learning and attention mechanisms. Adding online learning, continual adaptation, and dynamic attention layers can make the model more reliable under fast-changing channel conditions and device movement. This is crucial for dense urban and vehicular 6G scenarios.

Joint spectrum sensing, localization, and interference mitigation. Using multi-task learning to perform modulation recognition, signal localization, and interference detection at the same time can boost spectral efficiency, lower latency, and enhance overall network performance.

Energy-efficient deployment for edge devices. Future work may also look into model compression, pruning, and quantization techniques to implement the hybrid architecture on low-power edge devices. This will support real-time signal processing in IoT-enabled 6G networks.

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