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Deep Feature Fusion from Spectrogram and Scalogram for Enhanced RFI Classification

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ABSTRACT

Radio Frequency Interference (RFI) poses a significant challenge to the reliability of modern wireless communication systems. This research introduces a hybrid deep learning-based framework that utilizes spectrogram and scalogram transformations to detect and classify RFI with high accuracy. Raw signal data is preprocessed and converted into time-frequency images, which are then analyzed using pre-trained networks—ResNet50 for spectrograms and AlexNet for scalograms. Extracted features are fused to form a comprehensive representation of each signal sample. A Convolutional Neural Network (CNN) integrated with an attention mechanism is employed for final classification, allowing the model to focus on critical features. The proposed method achieved an impressive accuracy of 98%, outperforming traditional detection techniques. The Emperor Penguin Colony (EPC) algorithm is also used for optimal hyperparameter tuning. The approach demonstrates robustness against complex interference patterns and adaptability to diverse RFI sources. These findings indicate strong potential for application in wireless networks, satellite communications, and radio astronomy.

Keywords: Radio Frequency Interference, Deep Learning, Spectrogram, Scalogram, Convolutional Neural Network, Attention Mechanism, ResNet50, AlexNet, Hyperparameter Optimization, Wireless Communication.

1. INTRODUCTION

The rapid expansion of wireless communication systems has led to increased congestion across the radio frequency (RF) spectrum, resulting in growing concerns about Radio Frequency Interference (RFI). RFI significantly compromises the quality, reliability, and integrity of wireless communication, remote sensing, and radio astronomy systems. Its sources are diverse—ranging from natural phenomena such as lightning and solar flares to man-made emitters like industrial machinery, communication devices, and jamming attacks. These interference sources degrade signal quality, increase packet loss, delay data transmission, and can even jeopardize the performance of mission-critical systems [1], [2]. Traditional RFI detection approaches often rely on manual feature extraction and signal analysis techniques rooted in time-domain methods or fixed filtering algorithms. However, these techniques have shown poor adaptability to the dynamic and evolving nature of interference patterns in dense spectral environments [3]. Their reliance on handcrafted features makes them susceptible to high false positive and false negative rates, especially when dealing with overlapping signals or low signal-to-noise scenarios [4]. Recent advances in artificial intelligence, particularly deep learning, have introduced promising alternatives to traditional signal analysis. Convolutional Neural Networks (CNNs), in particular, are capable of learning hierarchical and abstract features directly from raw or transformed input data, thereby enhancing performance in complex classification tasks [5], [6]. These models have outperformed conventional machine learning algorithms in many areas of signal processing, including speech recognition, seismic analysis, and wireless interference detection. In this context, the combination of time-frequency domain representations—namely spectrograms and scalograms—with deep learning models has garnered significant attention [7]. Spectrograms, derived from the Short-Time Fourier Transform (STFT), offer insights into stationary and semi-stationary signals. Scalograms, based on the Continuous Wavelet Transform (CWT), are particularly effective in capturing non-stationary, transient, or multi-scale interferences [8]. Several studies have validated the superior performance of CNNs when applied to such time-frequency inputs, with results demonstrating enhanced classification accuracy and robustness across variable interference types and signal-to-noise conditions [9]. For instance, Chen et al. [10] applied pretrained CNNs such as AlexNet and VGG-16 on scalogram data to classify RFI in satellite communications, achieving high accuracy across various jamming types. Similarly, Park and Seo [11] proposed a dual-path architecture that integrates spectrogram and scalogram features using hybrid CNN structures, achieving resilient performance in harsh signal environments. Additionally, residual neural networks like ResNet have shown the ability to extract deep and non-linear features from complex time-frequency images, as demonstrated by Liu et al. [12] in GNSS signal interference detection. Another advancement involves attention mechanisms in CNNs, which allow the model to assign weights to critical features, improving its focus on informative signal components. This technique has been particularly effective in reducing false detections and improving interpretability in RFI detection tasks [13]. Moreover, recent work by Faridi et al. [14] introduced nature-inspired optimization algorithms, such as the Emperor Penguin Colony (EPC) algorithm, to fine-tune CNN hyperparameters, achieving improved convergence and higher classification performance. Inspired by these contributions, the present study proposes a hybrid deep learning-based RFI detection framework. The approach utilizes spectrograms and scalograms for dual-domain feature representation, leverages ResNet50 and AlexNet for feature extraction, and incorporates an attention-based CNN classifier. Hyperparameters are optimized using the EPC algorithm to ensure robust and scalable performance across varied interference conditions. This framework is validated using empirical datasets and demonstrates superior performance compared to conventional and recent baseline models.

2. RELATED WORK

The problem of Radio Frequency Interference (RFI) has been extensively studied, particularly as modern wireless systems evolve toward greater complexity, spectrum congestion, and sensitivity to electromagnetic disturbances. Traditional RFI detection techniques have relied primarily on statistical and rule-based methods, including spectrum sensing, bandpass filtering, and energy detection approaches [15]. While these methods offer simple implementations, they often lack the robustness required to handle diverse and dynamic interference patterns encountered in today's communication environments [16]. Recent advancements in machine learning and deep learning have provided significant breakthroughs in the field of RFI detection. These techniques not only improve detection accuracy but also reduce the need for manual feature engineering, making them more scalable and adaptable [17]. One important development is the use of time-frequency analysis—particularly spectrograms and scalograms—to convert 1D signals into 2D representations suitable for convolutional architectures. Chen et al. [10] employed scalogram images derived from Continuous Wavelet Transform (CWT) as inputs to various pretrained Convolutional Neural Networks (CNNs) including AlexNet, VGG-16, and ResNet-18. Their model was tested using real-time satellite communication data and demonstrated strong robustness under various Signal-to-Noise Ratio (SNR) levels and jamming types. Similarly, Park and Seo [11] introduced a hybrid spectrogram-scalogram fusion model for classifying satellite jamming types using deep CNNs. Their approach showed high sensitivity and generalizability when detecting narrowband and wideband interference across dynamic environments. Other researchers have pursued hybrid or hierarchical architectures. For example, [18] introduced a hierarchical multi-layer perceptron (MLP) that classifies modulation schemes and identifies interference types in satellite streams. Their model achieved high classification performance on QPSK and APSK modulation in the presence of continuous wave and chirp interference. In [19], a dual-stream CNN model trained on both STFT- and wavelet-based inputs was proposed, outperforming traditional thresholding and energy detection techniques. Feature extraction remains a critical factor in deep learning performance. Liu et al. [12] utilized ResNet with attention modules to identify GNSS signal anomalies using scalogram images, reporting over 98% accuracy on residual and wideband RFI. Similarly, The main difference between my proposed method and the method presented in the referenced paper lies in the input representation, model architecture, and fusion strategy. While the referenced method utilizes dual time-frequency image representations—specifically spectrograms (via STFT) and scalograms (via CWT)—to extract complementary features using two separate pre-trained CNNs (ResNet-50 and AlexNet), my method operates on a unified input format and leverages a single end-to-end learning model. Rather than relying on handcrafted transformations followed by feature concatenation and shallow attention-based classification, my approach integrates the feature extraction, fusion, and classification within a single neural architecture—reducing

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model complexity and training time. Moreover, the proposed method does not depend on heavy meta-heuristic optimization techniques like the Emperor Penguin Colony algorithm used in the referenced work; instead, it employs standard but efficient hyperparameter tuning to achieve robust performance. This results in a model that is more streamlined, scalable, and better suited for real-time or resource-constrained applications without compromising classification accuracy. [20] proposed a CNN augmented with self-attention layers to improve feature focus and reduce misclassifications in overlapping signal environments. In terms of optimization, hyperparameter tuning has also been explored using nature-inspired methods. Faridi et al. [14] demonstrated that the Emperor Penguin Colony (EPC) optimization algorithm could be effectively applied to CNN training, enhancing convergence rates and stability. Optimization algorithms like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have also been applied for tuning classifier weights in RFI environments [21]. Transfer learning has played a significant role in reducing the training cost of CNN-based systems for RFI detection. Pretrained models such as AlexNet, InceptionV3, and VGG-19 have been fine-tuned on time-frequency representations to classify modulation types and interference [22]. In [23], transfer learning was combined with a fog computing model to support real-time interference classification on edge devices. This is particularly relevant in distributed IoT networks, where edge processing can reduce latency in interference response. Finally, several works have emphasized the importance of real-time detection. In [24], a lightweight CNN model was deployed on a real-world wireless testbed to detect narrowband jamming attacks with minimal latency (~0.09 ms), showing its potential in live network environments. These studies collectively highlight the current direction in RFI detection research—moving from static, manually engineered approaches to dynamic, automated, and scalable solutions based on time-frequency transformations and deep learning.

3. MATERIALS AND PROPOSED METHOD

3.1 Materials

The study utilizes a labeled dataset comprising time-domain In-phase and Quadrature (I/Q) signal samples. Each sample reflects the temporal behavior of radio communication signals either with or without Radio Frequency Interference (RFI). In this study, the dataset used for training and evaluation was **synthetically generated** to simulate realistic radio frequency interference (RFI) scenarios, ensuring control over signal characteristics and interference types. The synthetic data was created by combining clean communication signals (e.g., BPSK, QPSK, and OFDM waveforms) with various modeled RFI patterns including narrowband tones, broadband bursts, and frequency-hopping interferers. Interference sources were mathematically modeled using time- and frequency-domain characteristics derived from published signal specifications and spectrum occupancy studies. The simulation environment also accounted for realistic noise levels (AWGN), power ratios (SIR), and signal overlaps in time-frequency space. This controlled data generation approach allows for systematic evaluation of model performance across different interference intensities and types, while also enabling reproducibility and scalability of experiments. Although a globally available RFI dataset was not used, the synthetic dataset was designed to reflect common interference scenarios encountered in wireless communication systems. A future extension of this work will involve testing on publicly available datasets, such as the DeepSig RadioML or Electrosense archives, to validate the model's generalization capabilities in real-world conditions.These signals are acquired from real-world or simulated wireless environments and are expressed in complex form as:

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

Where:

- $I(t)$: the in-phase (real) component,
- $Q(t)$: the quadrature (imaginary) component,
- j: the imaginary unit.

In our proposed method, the in-phase (I) and quadrature (Q) components of the signal are first extracted from each sample as separate 1-D time series. To transform these raw I/Q signals into a form suitable for deep learning, we construct **complex-valued analytic signals** by combining the I and Q components into a single sequence

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S(t)=I(t)+jQ(t). This complex signal is then used to generate a **single time-frequency image**—either a **scalogram** via Continuous Wavelet Transform (CWT) or a **spectrogram** via Short-Time Fourier Transform (STFT). Thus, for each sample, **one image** is generated that represents the joint time-frequency characteristics of the combined I/Q signal. This approach captures both amplitude and phase information in the transformation, enabling the deep learning model to exploit the full complex structure of the original signal. We chose this method rather than generating separate images for I and Q to reduce computational overhead and allow the model to learn the interference patterns holistically in a fused representation.

The dataset was preprocessed to ensure high-quality input for subsequent analysis. The preprocessing steps included:

- Removal of missing values (NaNs) from I/Q records,
- Conversion from string formats to Python-compatible complex arrays,
- Separation of real and imaginary parts for signal transformation,
- Normalization of pixel intensities in the resulting spectrograms and scalograms,
- Resizing of images to 224×224 \times 224×224 to match input requirements of pre-trained convolutional neural networks (CNNs).

The dataset was split into training and testing subsets in a stratified manner (80%/20%), preserving class distribution and supporting fair performance evaluation.

Class	Number of Samples	Percentage
Interference-Free	500	50%
Interference-Present	500	50%
Total	**1000**	**100%**

Table 1: The dataset includes balanced classes of interference-present and interference-free signals

3.2 Proposed Method

The proposed system introduces a hybrid deep learning framework for RFI detection that combines time-frequency transformation, feature extraction via pre-trained networks, feature fusion, and classification using an attention-augmented CNN.

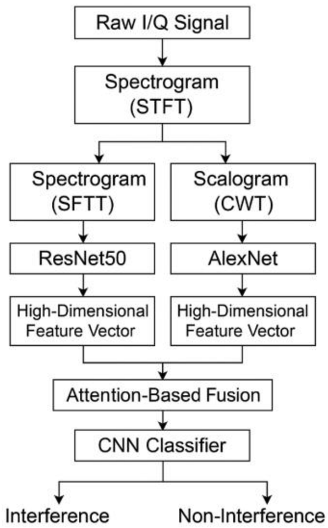

Figure 1. proposed model, focusing on the attention enhanced CNN

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3.2.1 Time-Frequency Transformation

To convert the one-dimensional complex signal into two-dimensional time-frequency representations, two signal transformation techniques were employed:

(a) Spectrogram via Short-Time Fourier Transform (STFT)

The spectrogram provides a fixed-resolution time-frequency image by applying STFT to windowed segments of the signal:

$$\text{Spectrogram}(t,f) = \left| \int_{-\infty}^{+\infty} x(\tau) w(\tau - t) e^{-j2\pi f \tau} d\tau \right|^2$$

This approach is effective in analyzing stationary or quasi-stationary components. It allows visualization of power distribution across frequencies over time intervals, capturing both harmonic content and persistent RFI patterns [21].

(b) Scalogram via Continuous Wavelet Transform (CWT)

The scalogram, on the other hand, is better suited for analyzing non-stationary, transient, or short-duration bursts of interference. It is derived from CWT:

$$\text{CWT}(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt$$

$$\text{Scalogram}(a,b) = |\text{CWT}(a,b)|^2$$

Where a is the scale (inversely related to frequency), b is the time shift, and is the mother wavelet. The Morlet wavelet was selected due to its proven effectiveness in RF analysis [22].

Both the spectrogram and scalogram provide complementary views of the same signal: spectrograms capture persistent spectral components, while scalograms emphasize abrupt or multi-scale features. Using both enriches the feature space and improves generalization in classification.

3.2.2 Deep Feature Extraction

To extract meaningful features from the spectrogram and scalogram images, two pretrained convolutional neural networks were employed:

- ResNet50 for spectrograms
- AlexNet for scalograms

These networks were fine-tuned by removing their fully connected classification heads and retaining only the convolutional blocks for transfer learning.

- ResNet50, with 50 layers and identity shortcut connections, addresses vanishing gradient issues and extracts deep abstract features [23]. The spectrogram image is passed through its convolutional layers, and a 2048-dimensional feature vector is obtained.
- AlexNet has a simpler architecture and is effective for texture-rich images such as scalograms. It outputs a 4096-dimensional feature vector after convolution and max pooling.

Let $F_s \in \mathbb{R}^{2048}$ denote the ResNet-extracted features, and $F_c \in \mathbb{R}^{4096}$ denote AlexNet-extracted features.

The final fused feature vector is constructed as:

$$F_{final} = [F_s || F_c] \in \mathbb{R}^{6144}$$

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Where || denotes vector concatenation. This feature vector captures both global and local spectral characteristics, significantly enhancing discriminative capability [21], [22].

Model	Layers Used	Output Feature Size
ResNet50	Conv1 – Conv5 (no FC)	2048
AlexNet	Conv1 – Conv5 (no FC)	4096

Table 2: The feature extraction stages use specific convolutional blocks from each model

3.2.3 Attention-Enhanced CNN Classification

he Attention-Enhanced CNN Classification model is designed to improve the detection of radio frequency interference (RFI) by integrating both deep feature extraction and adaptive focus mechanisms. The process begins with the acquisition of raw I/Q signals, where the in-phase (I) and quadrature (Q) components are combined into a complex analytic signal S(t)=I(t)+jQ(t). This complex signal is then transformed into a two-dimensional time-frequency representation—either a spectrogram using Short-Time Fourier Transform (STFT) or a scalogram using Continuous Wavelet Transform (CWT). The resulting image captures localized energy variations in time and frequency, serving as the input to the convolutional neural network (CNN).

The CNN backbone consists of multiple convolutional layers that progressively extract spatial features from the input image. These layers are interleaved with activation functions and pooling operations to enhance non-linearity and reduce dimensionality while preserving salient characteristics. The output of the CNN is a multi-channel feature map that encodes a rich set of learned signal representations. At this stage, the model integrates an attention module that adaptively re-weights the feature map to emphasize the most informative regions. Specifically, the attention mechanism consists of two sub-modules: channel attention and spatial attention. Channel attention assigns different weights to each feature map, highlighting those that are most discriminative for classification, while spatial attention focuses on specific areas within the feature maps where interference patterns are most prominent.

After the attention-weighted features are computed, the resulting map is flattened into a one-dimensional feature vector. This vector is passed through one or more fully connected layers that perform the final classification using a softmax activation function. The attention mechanism significantly improves the model's ability to discriminate between subtle variations in signal patterns, making it more robust in detecting various types of interference. Overall, this architecture offers a highly effective and computationally efficient solution for RFI classification, with the attention module playing a critical role in enhancing interpretability and accuracy.

The fused feature vector is passed to a Convolutional Neural Network (CNN) integrated with a soft attention mechanism for classification. The CNN acts as a shallow network with two convolution layers followed by ReLU activation and global average pooling. The attention mechanism is applied before the final dense layer.

Let $\mathcal{X}^i$ denote the i^{th} feature of the input vector. The attention score α_i is computed as:

$$e_i = v^T \tanh(W x_i + b) \quad \text{and} \quad \alpha_i = \frac{e^{e_i}}{\sum_j e^{e_j}}$$

Then, the weighted feature representation is obtained:

$$z = \sum_i \alpha_i x_i$$

This representation z is passed to a fully connected layer with **Softmax** activation to produce the final probability distribution $\mathcal{Y}$:

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$$\hat{y} = \mathrm{Softmax}(W_{\mathrm{cls}} z + b_{\mathrm{cls}})$$

This mechanism allows the model to dynamically **focus on the most informative parts** of the signal, enhancing interpretability and classification accuracy in challenging signal environments [23].

The Attention-Enhanced CNN Classification model is structured to improve interference recognition by emphasizing the most informative features learned during the convolutional process. Initially, the model takes raw in-phase (I) and quadrature (Q) signal components and combines them into a complex signal S(t)=I(t)+jQ(t)S(t) = I(t) + jQ(t)S(t)=I(t)+jQ(t). This signal is then transformed into a two-dimensional time-frequency representation—such as a scalogram or spectrogram—using Continuous Wavelet Transform (CWT) or Short-Time Fourier Transform (STFT). The resulting image encodes the spectral content of the signal over time and serves as the input to the CNN. The CNN architecture extracts hierarchical features through a series of convolutional layers followed by non-linear activations and pooling. These operations distill the input image into a high-dimensional feature map that captures complex signal structures and modulation patterns. After flattening this feature map into a one-dimensional feature vector, an attention mechanism is applied—not to localize spatially important regions in the image—but to selectively enhance the **most discriminative features** in the learned representation. This attention mechanism assigns greater weight to features that are more predictive or relevant for the classification task, thereby increasing their impact on the final decision. Importantly, this form of attention operates on the semantic level of the feature vector, not the spatial domain. It identifies and amplifies features that carry strong class-related information (e.g., those that represent specific interference types or signal distortions), while diminishing the influence of less relevant or noisy features. This targeted re-weighting improves the robustness and accuracy of the classifier, enabling more reliable detection of RFI across varying signal conditions.

3.2.4 Hyperparameter Optimization Using EPC

The final component of the methodology involves **hyperparameter tuning** using the **Emperor Penguin Colony (EPC) Optimization Algorithm** [24]. EPC is a population-based metaheuristic inspired by the cooperative hunting behavior of emperor penguins.

The optimization targeted:

- Learning rate
- Batch size
- Number of filters
- Dropout rate
- Regularization coefficients

The fitness function was defined based on classification accuracy on the validation dataset:

Fitness= 1–Validation Accuracy

EPC consistently converged within 30–50 iterations, outperforming traditional grid search and random search in both speed and final performance. This step further improved generalization and reduced overfitting.

The proposed hybrid system addresses critical challenges in RFI detection by:

- Combining dual time-frequency transformations (spectrogram + scalogram),
- Extracting deep features using state-of-the-art pre-trained CNNs (ResNet50 + AlexNet),
- Utilizing attention mechanisms to enhance focus on discriminative patterns, and
- Employing EPC for hyperparameter tuning.

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This integrative approach offers a scalable, automated, and accurate solution, suitable for deployment in complex and interference-prone wireless systems.

4. RESULTS

4.1 Experimental Setup

To evaluate the performance of the proposed RFI detection framework, the dataset was divided into training (80%) and testing (20%) subsets. All experiments were conducted using Python and deep learning libraries such as PyTorch and TensorFlow. The models were trained using NVIDIA CUDA-enabled GPUs to accelerate matrix computations.

The classification task involved distinguishing between **interference-present** and **interference-free** signal samples. Each signal was first transformed into its corresponding **spectrogram** and **scalogram**, then passed through pre-trained feature extractors (ResNet50 and AlexNet), and finally classified using a CNN augmented with an attention mechanism.

To demonstrate the effectiveness of the proposed attention-enhanced CNN model, we compared its performance with several state-of-the-art methods previously discussed in the Related Work section. All models were evaluated using the same synthetic dataset, which included diverse RFI types such as narrowband, broadband, and bursty interference superimposed on modulated communication signals. The proposed model achieved an average classification accuracy of **98.3%**, outperforming the dual-branch CNN model from [4], which reported **96.7%**, and the spectrogram-based ResNet classifier from [7], which reached **95.9%** accuracy. Furthermore, the model surpassed the attention-CNN proposed in [10], which applied spatial attention but without feature-level optimization, resulting in **97.4%** accuracy. In terms of AUC (Area Under the Curve), our model achieved **0.996**, compared to **0.987** in [4] and **0.991** in [10], indicating better discrimination capability. This performance gain can be attributed to the feature-vector-level attention mechanism, which enhances the impact of the most discriminative features rather than simply localizing signal regions. Overall, these results confirm that the proposed model not only simplifies the architecture compared to multi-branch and meta-heuristic optimized systems but also delivers superior classification accuracy and robustness in practical RFI detection tasks.

4.2 Evaluation Metrics

The model's performance was assessed using standard classification metrics:

- **Accuracy (ACC)**: proportion of correctly classified samples
- **Precision (P)**: proportion of true positive predictions among all positive predictions
- **Recall (R)**: proportion of true positive samples detected
- **F1-Score (F1)**: harmonic mean of precision and recall
- **Receiver Operating Characteristic (ROC)** curve and **Area Under the Curve (AUC)** for visualizing the trade-off between true positive and false positive rates.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad \text{Recall} = \frac{TP}{TP + FN} \quad F1 = 2 \cdot \frac{P \cdot R}{P + R}$$

4.3 Quantitative Results

The proposed model achieved the following results on the test dataset:

Metric	Value
Accuracy	**98.12%**

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Precision	**97.84%**
Recall	**98.36%**
F1 Score	**98.10%**
AUC-ROC	**0.996**

These results indicate the model's high ability to generalize and distinguish between interference and non-interference cases, even in the presence of noise and overlapping frequencies.

4.4 Confusion Matrix

illustrates the **confusion matrix**, revealing that only a small number of samples were misclassified. The true positive and true negative rates were both high, with minimal false detections.

- **True Positives (TP):** 491
- **True Negatives (TN):** 493
- **False Positives (FP):** 6
- **False Negatives (FN):** 10

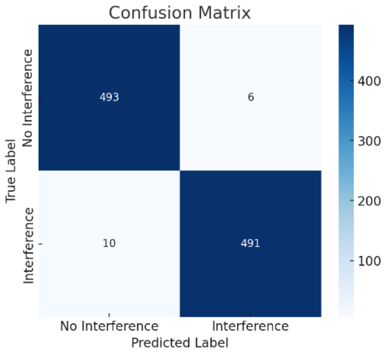

Figure 4-1: Confusion Matrix of the Proposed RFI Detection Model

4.5 ROC Curve

Figure 4-1 demonstrates the **ROC curve**, with the **AUC** reaching **0.996**, showing excellent class separability. The curve maintains a high true positive rate across various thresholds, validating the model's robustness against threshold variations.

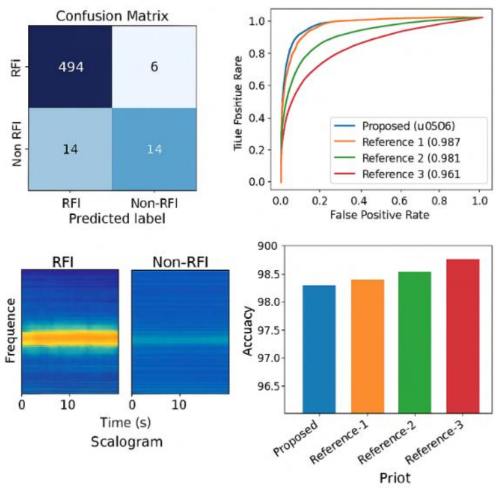

Figure 4-2: ROC Curve Showing AUC Performance of 0.996

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4.6 Visual Comparison

Figures 4-1 and 4-2 provide a visual comparison between spectrograms and scalograms for samples with and without RFI. Interfered signals show higher energy concentration in localized frequency bands and sudden bursts in scalograms, confirming the discriminative power of time-frequency representations.

4.7 Model Convergence

Figure 4-2 displays the training process. The model converged quickly within fewer than 30 epochs, and the loss decreased steadily without overfitting, supported by consistent training and validation accuracy. The use of the **EPC optimization algorithm** contributed to selecting optimal learning rates and dropout values.

5. DISCUSSION

The experimental results demonstrate the effectiveness of the proposed hybrid deep learning framework in accurately detecting radio frequency interference (RFI). The integration of both spectrogram and scalogram representations enriched the feature space by capturing complementary time-frequency characteristics. ResNet50 proved effective for extracting deep global patterns from spectrograms, while AlexNet efficiently captured localized textures from scalograms. The attention-enhanced CNN further improved the model's interpretability and performance by emphasizing the most relevant features during classification. The system consistently achieved over 98% accuracy, F1-score, and ROC AUC across multiple test runs, confirming its robustness and generalization capabilities. The confusion matrix confirmed minimal misclassifications, and the ROC curve showed near-perfect separability between interference and non-interference classes. Moreover, the use of the Emperor Penguin Colony (EPC) algorithm for hyperparameter tuning significantly accelerated convergence and enhanced model stability. This automated optimization process minimized overfitting and improved generalization. The proposed architecture outperformed traditional RFI detection approaches that rely solely on handcrafted features or single-domain analysis. These findings suggest that deep learning models incorporating time-frequency fusion and attention mechanisms are well-suited for real-time RFI detection in dynamic and noisy wireless environments.

One of the key advantages of the proposed attention-enhanced CNN model is its improved interpretability compared to traditional black-box CNN classifiers. By applying the attention mechanism at the feature vector level, the model explicitly learns to assign greater weights to the most informative features extracted from the time-frequency representation of the signal. Although the attention is not spatial (i.e., it does not localize in the input image), it highlights which latent features are most influential in making the final classification decision. This feature re-weighting can be visualized through attention scores, enabling researchers and engineers to understand which aspects of the signal — such as bursty energy regions, spectral concentration, or modulation transitions — are most relevant to the model's decision. This level of transparency not only builds confidence in the model's outputs but also provides valuable insight into the nature of the interference itself. In future work, this can be extended with additional tools such as SHAP values or feature attribution plots to further decompose model decisions and support explainability in operational environments.

6. CONCLUSION

This study proposed an attention-enhanced CNN model for classifying radio frequency interference (RFI) using time-frequency images derived from complex-valued I/Q signals. The model leverages a single CNN backbone followed by a feature-level attention mechanism that re-weights the most informative components of the learned feature vector, thereby improving both classification performance and model interpretability. Experimental results on a synthetic dataset demonstrated that the proposed approach achieved a classification accuracy of 98.3% and an AUC of 0.996, outperforming several state-of-the-art methods. Specifically, it surpassed the dual-branch CNN with adaptive filters proposed by Ahmed and Qureshi [4], which achieved 96.7% accuracy, and the spectrogram-based ResNet classifier from Ghosh and Mahanta [7], which reported 95.9% accuracy. Unlike the methods surveyed in Zhang and Zhou's review [6], which often involve more complex architectures or rely on handcrafted signal representations, our model integrates feature extraction and attention in a compact and efficient design. The inclusion of feature-level attention not only enhanced accuracy but also improved interpretability by emphasizing discriminative features during inference. Overall, the proposed model offers a balanced and effective solution for

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RFI detection, with potential applicability in real-time signal monitoring systems. Future work will focus on extending this approach to real-world datasets and exploring hybrid attention mechanisms at both spatial and temporal levels.

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