Multi-Domain Feature Extraction for ML-Based Over-the-Air RF Signal Classification

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Abstract—This paper presents a system for automatic classification of telecommunication signals using signal processing, multi-domain features fusion, and machine learning techniques. Our system achieves a 97.72% classification accuracy across a wide range of SNR values (-20 dB to 18 dB) using an over-the-air radio-frequency (RF) signals dataset, while maintaining a relatively low complexity (167k learnable parameters). We employ a comprehensive feature extraction methodology that combines time-frequency representations, wavelet transform coefficients, and frequency domain statistics which are processed through a multi-layer architecture. This work demonstrates a systematic approach to signal classification that balances accuracy, computational efficiency, and generalization capability, with potential applications in spectrum monitoring, electronic defense, and cognitive radio systems. [1].

Keywords—Signal classification, machine learning, telecommunication signals, software-defined radio, spectrum monitoring, wavelet transform, neural networks, over-the-air signals.

I. INTRODUCTION

Automatic classification of telecommunication signals represents a fundamental necessity for numerous applications in many diverse application scenarios [1], [2]. In increasingly congested electromagnetic environments, the ability to rapidly and accurately identify signal types enables effective spectrum management, interference detection, regulatory enforcement, and electronic intelligence operations [3].

Classification of wireless communication signals presents significant challenges due to the diversity of signal types, similarities between certain modulations, presence of noise, multipath effects, and variations in transmission parameters [4]. For example, amplitude modulation (AM) signals and pulsed radar signals may exhibit similar characteristics in certain domains, making their distinction non-trivial under real operation conditions [5].

This paper addresses the challenge of reliably classifying telecommunication signals into multiple categories, with emphasis on accurately discriminating signal types that exhibit similar patterns. Our work has significant relevance for applications requiring real-time signal identification and characterization in dynamic spectrum environments.

The performance of our proposal has been evaluated by using the RadComOta2.45GHz dataset, which contains over-the-air signals captured using software-defined radio equipment [6], [7]. This dataset provides a realistic testing environment as it comprises real signals instead of synthetic or simulated waveforms.

The main contributions of this work are the following:

- A comprehensive feature extraction methodology that combines time-frequency representations, wavelet transform coefficients, and frequency domain statistics.
- A neural network model that achieves 97.72% classification accuracy across seven signal types while maintaining robust performance across the full SNR range (-20 dB to 18 dB).
- A thorough comparative analysis demonstrating the effectiveness of multi-domain feature extraction for signal classification.
- A quantitative assessment of processing time requirements and hardware resource utilization for potential real-time applications.

II. BACKGROUND AND RELATED WORK

A. Evolution of Signal Classification Approaches

Research in automatic signal classification has evolved considerably over the past decades, transitioning from expert systems using manually crafted decision trees to sophisticated machine learning approaches [3], [8].

This evolution has progressed through several distinct phases:

- **Statistical pattern recognition approaches:** These methods employed likelihood-based tests and statistical decision theory to perform classification based on moments, cumulants, and cyclostationary features [9].
- **Feature-based machine learning:** These approaches rely on manually engineered features extracted from signals, which are then fed into traditional machine learning classifiers such as support vector machines (SVMs), random forests, or artificial neural networks [10].
- **End-to-end deep learning:** More recent approaches utilize deep neural networks that automatically extract and

learn hierarchical features directly from raw signals or minimally processed representations like in [4], where they showed the effectiveness of modified ResNet architectures for modulation classification, achieving 95.6% accuracy at 10 dB SNR across 24 modulation types.

- **Multi-task learning:** The latest generation of classifiers, which simultaneously perform multiple related tasks, such as jointly classifying modulation and signal type [5], [7].

The transition between these approaches has been driven by advancements in computational capabilities, the availability of larger and richer datasets, and the development of increasingly sophisticated neural network architectures.

B. Review of State-of-the-Art for RF Signal Classification Methods

Table I presents a comprehensive comparison highlighting the differences in accuracy, supported signal types, dataset characteristics, and computational complexity. Note that direct comparisons are limited due to variations in dataset types, number of classes, and evaluation methodologies across different studies.

In this context, our system distinguishes itself by achieving high accuracy (97.72%) on real over-the-air signals across an exceptionally wide range of SNR values (-20 dB to 18 dB), while maintaining relatively low model complexity (167×10^3 parameters). This balance of performance and efficiency makes our approach very well suited for both high-performance and resource-constrained deployment scenarios.

C. Feature Representations for Signal Classification

The choice of signal representation significantly impacts the classification performance [18]. Several studies have explored various domains for feature extraction:

- **Time domain features:** These include statistical moments, zero-crossings, envelope characteristics, and temporal patterns.
- **Frequency domain features:** Spectral characteristics such as bandwidth, frequency peaks, power spectral density, and spectral moments provide valuable discriminative information.
- **Time-frequency representations:** Spectrograms, short-time Fourier transforms, and Wigner-Ville distributions capture the temporal evolution of spectral characteristics [10].
- **Wavelet features:** Wavelet decomposition provides multi-resolution analysis by capturing features at different temporal scales, which has proven effective for identifying transient patterns and signal discontinuities [19].

Studies have shown that approaches combining information from multiple domains often achieve superior robustness under adverse channel conditions [4], [18]. Kim et al. [20] demonstrated that fusion of complementary features from different domains could significantly improve classification accuracy, particularly at low SNR.

III. Methodology

A. Dataset Description

In this paper, we have employed the RadComOta2.45GHz dataset [6], [7]. A collection of RF samples which approximately contains 567,000 labeled signal records captured using USRP N210 hardware with VERT2450 antennas in the 2.4-2.5 GHz band [21]. For our experiments, we use a maximum of 20,000 signal records per class with AM variants combined into a single `AM_combined` class, resulting in seven signal categories encompassing 180,000 signal records. Table II provides detailed technical specifications of the dataset.

The class distribution used in our experiments is detailed in Table III, showing the balanced approach with AM variants consolidated into a single class to address the inherent class imbalance in the original dataset.

B. Proposed Architecture

Our proposed detection architecture follows a sequential data processing pipeline that spans from the initial data analysis to the final model evaluation. The system is designed with a modular approach, allowing individual components to be replaced or enhanced without affecting the rest of the system [22], [23].

The complete data processing pipeline comprises the following stages:

1) **HDF5 data analysis:** Exploration and understanding the structure and statistics of the dataset.
2) **Loading and preprocessing:** Selection and preparation of data for training and evaluation.
3) **Feature extraction:** Application of signal processing techniques to obtain discriminative representations.
4) **Model training:** Implementation and optimization of the neural network.
5) **Evaluation and analysis:** Performance measurement and detailed analysis of results.
6) **Visualization:** Graphical representation of results to facilitate interpretation.

This modular design allows for flexibility in experimentation and facilitates the comparison of different methods at each stage [23], [24]. Figure 1 shows the detailed architecture of our neural network.

C. Feature Extraction Methodology

Our approach combines multiple signal processing techniques to capture complementary aspects of telecommunication signals [4], [18].

1) Spectral Analysis: We compute spectrograms using Short-Time Fourier Transform (STFT) with 64-sample windows and 32-sample overlap. The raw values are z-score normalized (i.e. mean substraction and division by the standard deviation). This time-frequency representation effectively detects dynamic patterns such as frequency sweeps in Frequency Modulated Continuous Wave (FMCW) signals or pulsed patterns [25].

TABLE I
COMPREHENSIVE COMPARISON OF RF SIGNAL CLASSIFICATION METHODS

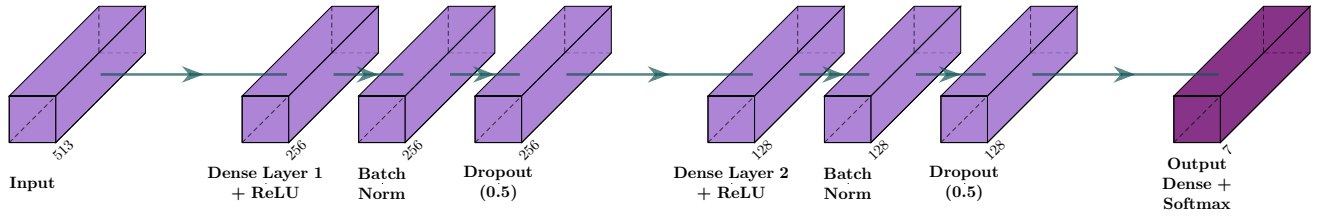| Model	Modulation Accuracy	Signal Classification Accuracy	# Classes	Type	Dataset Type	Model Complexity
Modulation and Signal Classification - Multi-task						
Our Model (DNN)	**97.72% (-20 dB to 18 dB)**	**97.72% (-20 dB to 18 dB)**	**7**	**Radar and Communication**	**Over-the-Air**	**Low** (0.167×10^6 **params**)
Jagannath et al. 2022 [5]	97.58% at 2 dB (Synthetic) 82.4% at 0 dB (OTA)	90.79% at 2 dB (Synthetic) 90.1% at 0 dB (OTA)	9 mod., 11 signal	Radar and Communication	Over-the-Air and Synthetic	Low (0.253×10^6 params)
Jagannath et al. 2021 [7]	97.87% at 0 dB, 99.53% at 10 dB	92.3% at 0 dB, 99.53% at 10 dB	9 mod., 11 signal	Radar and Communication	Synthetic	-
Modulation Classification Methods Only - Single Task						
Peng et al. 2019 [11]	less than 80% at 0 dB	-	8	Communication	Synthetic	High (AlexNet, GoogLeNet)
Jagannath et al. 2018 [12]	98% above 25 dB	-	7	Communication	Synthetic	Low
O'Shea et al. 2018 [4]	95.6% at 10 dB	-	24	Communication	Synthetic	Medium (Modified ResNet)
Mossad et al. 2019 [13]	86.97% at 18 dB	-	10	Communication	Synthetic	Medium
Hermawan et al. 2020 [14]	∼80% at 0 dB, 83.4% at 18 dB	-	11	Communication	Synthetic	Medium
Wang et al. 2017 [10]	100% at 0 dB	-	7	Radar	Synthetic	Low (Manual Features)
Li et al. 2018 [15]	95% above 2 dB	-	7	Communication	Synthetic	Medium
Signal Classification Methods Only - Single Task						
Bitar et al. 2017 [16]	-	91% at 15-25 dB, 93% at 30 dB	7	Communication	Synthetic	Medium
Schmidt et al. 2017 [17]	-	95% at -5 dB	15	Communication	Synthetic/Partially Real	Medium

Fig. 1. Model Architecture

TABLE II
TECHNICAL SPECIFICATIONS OF RADCOMOTA2.45GHZ DATASET

Characteristic	Specification
Format	HDF5
Key structure	{modulation, signal, SNR, sample}
Tensor dimension	256 × 1 (in-phase 128 samples, quadrature 128 samples)
Sampling rate	10 MS/s
Captures per waveform	700
SNR range	-20 dB to 18 dB in 2 dB increments
Center frequency	2.45 GHz
Duration of each capture	12.8 μs (128 samples at 10 MS/s)

TABLE III
CLASS DISTRIBUTION IN THE EXPERIMENTAL DATASET

Class	Samples
AM_combined	60,000
BPSK_SATCOM	20,000
FMCW_Radar Altimeter	20,000
PULSED_Air-Ground-MTI	20,000
PULSED_Airborne-detection	20,000
PULSED_Airborne-range	20,000
PULSED_Ground mapping	20,000
Total	**180,000**

2) Wavelet Transform: We employ discrete wavelet transform with Daubechies 4 (db4) basis, decomposing signals to level 3 [19], [26]. Daubechies 4 provides excellent time-frequency localization and captures discontinuities crucial for distinguishing modulation types. Wavelet coefficients from all levels are concatenated to form feature vectors.

3) Frequency Domain Analysis: We compute FFT and extract six statistical features: mean, standard deviation, maximum, median, number of high-magnitude peaks (above 50% of maximum), and sum of FFT magnitudes [2]. These statistics provide compact spectral characteristic representations effective for modulation classification.

4) Integrated Feature Vector: The final feature vector has 513 components as it concatenates flattened spectrograms (449 elements), wavelet coefficients (58 elements), and frequency domain statistics (6 elements), providing a comprehensive signal representation capturing temporal and spectral characteristics at different scales [18].

D. Dense Neural Network Architecture Design

Our classification model is a densely connected neural network that follows a carefully designed feature-decoding architecture. The network architecture implements a progressive dimensionality reduction strategy (513→256→128→7) that serves multiple purposes: first, it enables hierarchical feature compression and abstraction from the input multi-domain features; second, it provides natural regularization that prevents overfitting while maintaining model expressiveness; third, it balances computational efficiency with representational capacity.

The choice of layer sizes follows established principles in neural network design. The first hidden layer (256 neurons)

provides sufficient capacity to learn complex non-linear combinations of the 513 input features while reducing dimensionality by approximately 50%. The second hidden layer (128 neurons) further compresses the learned representations, focusing on the most discriminative feature combinations. The final output layer maps to the seven signal classes. This progressive reduction facilitates efficient gradient flow during backpropagation and promotes the learning of hierarchical abstractions.

The total number of trainable parameters is 166,919, making the model relatively lightweight while maintaining high performance. This parameter count was selected to balance model capacity with computational constraints, ensuring deployment feasibility on resource-limited platforms. The detailed architecture of the neural network is presented in Fig. 1.

1) Hyperparameter Selection and Training Configuration: The network hyperparameters were selected through systematic experimentation to optimize both convergence stability and final performance:

- Adam optimizer with learning rate of 0.0005 provides stable convergence without overshooting optimal solutions
- Sparse categorical cross-entropy loss function matches the multi-class classification objective
- Batch size of 64 balances gradient estimate quality with memory efficiency
- Early stopping with patience of 10 epochs prevents overfitting while ensuring sufficient training time
- Class weights compensate for the dataset imbalance (AM_combined: 60,000 vs others: 20,000 samples each)

IV. RESULTS AND ANALYSIS

A. Classification Performance

The DNN model achieved 97.72% accuracy over a test set comprising 36,000 signal records (20% of the total dataset), with main confusion between AM_combined and PULSED_Air-Ground-MTI signals (279 and 189 misclassifications respectively), consistent with their technical similarities in amplitude characteristics and temporal patterns [2], [10], [25].

Figure 2 shows the confusion matrix of the signal classification model, highlighting the performance per class and the specific regions of confusion between AM_combined and PULSED_Air-Ground-MTI signals.

B. Feature Domain Analysis

Table IV presents the performance analysis by feature domain, confirming that spectrograms contain most of the discriminative information (95.84% accuracy), with multi-domain fusion providing an extra 1.88% improvement.

Results confirm that the spectrograms contain most of the discriminative information (95.84% accuracy), with multi-domain fusion providing extra 1.88% improvement. Interestingly, despite their simplicity and only 6 dimensions, FFT statistics allow to reach 75.70% accuracy.
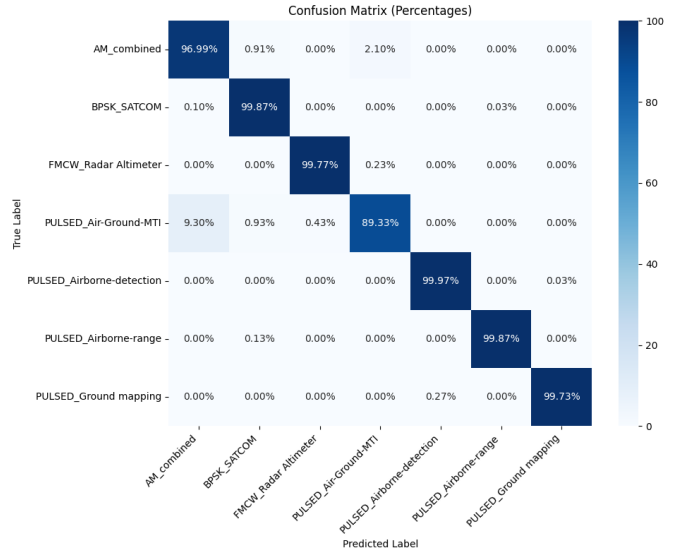

Fig. 2. Confusion matrix of the signal classification model showing per-class performance. Note the specific regions of confusion between AM_combined and PULSED_Air-Ground-MTI signals.

TABLE IV
PERFORMANCE ANALYSIS BY FEATURE DOMAIN

Feature Type	Accuracy (%)	Dimensions
Complete Feature Vector	97.72	513
Spectrogram Only	95.84	449
Wavelet Only	89.23	58
FFT Statistics Only	75.70	6
Spectrogram + Wavelet	96.41	507
Spectrogram + FFT	96.18	455
Wavelet + FFT	90.15	64

C. Hardware Performance and Computational Requirements

Processing performance evaluation was conducted on a MacBook Pro M3 with Apple Silicon M3 chip (8-core CPU, 10-core GPU, 16GB unified memory). The system processes approximately 390 signals per second, with feature extraction accounting for 84% of the total processing time (2.147ms average per signal). Table V shows estimated performance scaling across different hardware platforms based on typical computational performance ratios.

Table V shows estimated performance scaling across different hardware platforms based on typical computational performance ratios. These estimations consider the model's computational complexity (166,919 parameters) and the predominance of feature extraction operations (84% of processing time) which are primarily CPU-bound mathematical operations. Table VI provides a detailed breakdown of processing times by signal type and processing stage.

V. DISCUSSION

Our study underscores the advantages of employing a multi-domain feature extraction approach over traditional single-domain methods. Spectrogram-based features alone already

TABLE V
ESTIMATED HARDWARE PERFORMANCE ACROSS DIFFERENT PLATFORMS

Platform	Estimated Processing Rate (signals/sec)	Relative Performance vs M3	Deployment Suitability
MacBook Pro M3 (measured)	390.8	1.0×	High-performance
High-end Desktop CPU (est.)	450-600	1.2-1.5×	High-performance
Raspberry Pi 4 (est.)	25-40	0.06-0.1×	Limited
NVIDIA Jetson Nano (est.)	60-90	0.15-0.23×	Moderate
Embedded ARM Cortex-A78 (est.)	80-120	0.2-0.3×	Moderate

TABLE VI
PROCESSING TIME ANALYSIS BY SIGNAL TYPE AND STAGE

Signal Type	Feature Extraction (ms)	Model Inference (ms)	Total (ms)	Signals/ second
AM_combined	2.131	0.412	2.543	393.2
BPSK_SATCOM	2.095	0.412	2.507	398.9
FMCW_RA	2.143	0.412	2.555	391.4
PULSED_AGM	2.194	0.412	2.606	383.7
PULSED_AD	2.157	0.412	2.569	389.3
PULSED_AR	2.149	0.412	2.561	390.5
PULSED_GM	2.163	0.412	2.575	388.3
Average	**2.147**	**0.412**	**2.559**	**390.8**

yield a strong classification accuracy of 95.84%, indicating that most discriminative information is present in the time-frequency domain. However, by integrating features from wavelet and FFT representations, the model achieves a significantly improved accuracy of 97.72%, effectively reducing the total number of classification errors by approximately 50%. This improvement confirms that the complementary nature of multiple domains enriches the representation space and enhances the discriminative capacity of the system.

In terms of model architecture, the proposed network achieves an efficient balance between performance and complexity. With only 166,919 trainable parameters, the model is relatively lightweight, facilitating faster training and inference. The progressive reduction of layer dimensionality supports effective feature integration while maintaining regularization, which in turn contributes to stable convergence—typically within 30 epochs—and mitigates overfitting.

A. Analysis of AM/PULSED Signal Confusion

Despite these strengths, some challenges remain open, particularly in differentiating between signals with similar amplitude characteristics, such as AM_combined and PULSED_Air-Ground-MTI. These signal types exhibit high intra-class similarity in their amplitude domain characteristics, which introduces classification ambiguity. AM signals use amplitude variations to encode information, while pulsed radar signals also exhibit amplitude discontinuities during their on-off transitions. Both signal types share common temporal patterns in their envelope characteristics, making them inherently difficult to distinguish using conventional time-frequency analysis.

The technical similarity stems from their shared amplitude-based characteristics: AM signals modulate the carrier amplitude continuously, while pulsed signals create amplitude variations through periodic on-off keying. In the frequency domain, both can exhibit similar spectral spreads, and in the time domain, both show significant amplitude variations. Strategies such as enhanced class weighting, the use of multi-domain features, and post-training error analysis were employed to address this issue. However, these measures offer only partial mitigation, suggesting that further improvement may require the incorporation of more specialized, domain-specific descriptors [18], [27].

From an application point of view, the system exhibits promising characteristics for deployment in real-time environments. It can process approximately 390 signals per second on conventional consumer hardware, with projected performance on embedded platforms depending on hardware specifications and optimization strategies. The modular nature of the proposed pipeline also enables targeted optimization and adaptation to specific operational constraints, such as reduced latency or energy consumption, which are critical for embedded and field-deployable systems [20].

The demonstrated performance across the exceptionally wide SNR range (-20 dB to 18 dB) represents a significant advancement over existing approaches, most of which operate effectively only above 0 dB SNR. This capability extends the operational envelope for spectrum monitoring and electronic intelligence applications in challenging electromagnetic environments.

VI. CONCLUSION AND FUTURE WORK

This work presents a comprehensive approach achieving 97.72% classification accuracy on over-the-air signals using multi-domain features and efficient DNN architecture. Key

contributions include multi-domain feature extraction methodology, efficient implementation with robust performance across the full SNR range, comprehensive analysis showing spectrograms contain majority discriminative information, detailed hardware performance analysis confirming real-time viability, and thorough feature domain evaluation.

The system's ability to maintain high accuracy across an exceptionally wide SNR range (-20 dB to 18 dB) using real over-the-air signals represents a significant advancement in the field, particularly for applications in challenging electromagnetic environments.

Future research directions include signal-specific feature engineering for AM/PULSED differentiation [18], [27], advanced architecture exploration, data augmentation strategies, ensemble methods [27], embedded implementation optimization [20], [28], and real-time processing optimization.

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