Lightweight and Interpretable DL Model Using Convolutional RFF for AMC

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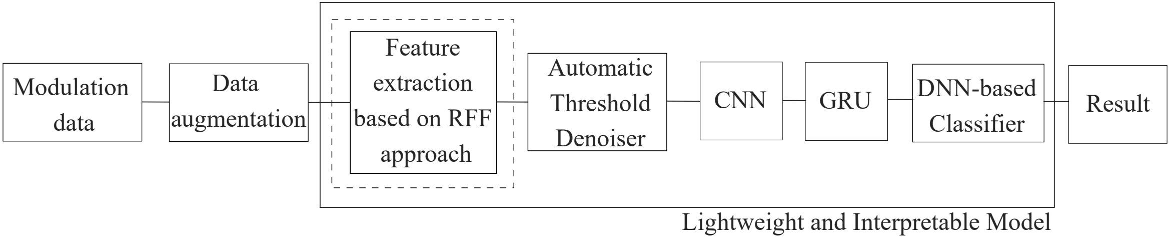
Convolutional RFF Threshold Denoiser Network



We introduce a **lightweight**, **interpretable** deep learning architecture for AMC featuring a 2D convolutional random Fourier feature layer that improves data representation, accuracy, and model simplicity.

Simplifying Kernel Computations

Kernel methods, critical for large datasets, typically require extensive computations.
Rahimi and Recht's approach [?] simplifies this with an efficient approximation:

$$k(x, y) \approx z(x)^T z(y), \tag{1}$$

enabling scalable computations in $\mathbb{R}^D$ with reduced complexity.
Their embedding, based on the Fourier transform:

$$\tilde{z}(x) := \sqrt{\frac{2}{D}} \left[\sin(\omega_1^T x) \quad \cos(\omega_1^T x) \right]^T, \tag{2}$$

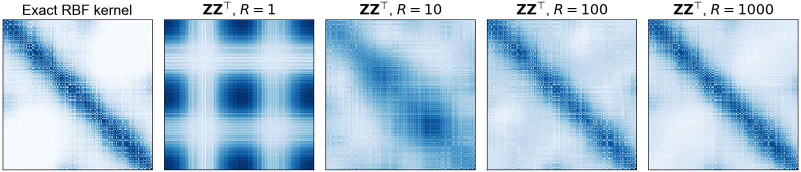
streamlines kernel calculations for high-dimensional data.

Enhanced Kernel Embeddings for Practical Applications

The second embedding introduces phase shifts for enhanced robustness:

$$\hat{z}(x) := \sqrt{\frac{2}{D}} \left[\cos(\omega_1^T x + b_1) \quad \dots \quad \cos(\omega_D^T x + b_D) \right]^T, \tag{3}$$

where $b_i \sim \mathrm{Unif}[0, 2\pi]$.



Convolutional Form

This approach improves noise resilience and adaptability, making it ideal for complex applications like I/Q signal processing in communication systems.
Adapting to convolutional settings, this embedding optimizes spatial data processing:

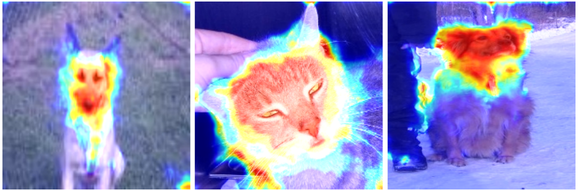
$$F_l = \sqrt{\frac{2}{D}} \left[\sin(W_l^{(\sin)} \otimes F_{l-1}) + \cos(W_l^{(\cos)} \otimes F_{l-1}) \right], \tag{4}$$

where $W_l^{(\sin)}$ and $W_l^{(\cos)}$ are convolutional kernels, enhancing data fidelity and processing efficiency.

Grad-CAM++ for CNN Decision Visualization

Grad-CAM++ provides a visual interpretation of decision-making areas in convolutional neural networks (CNNs) [?]. It computes class-specific importance weights for each feature map in a CNN, creating heatmaps that highlight decision-critical regions:

$$L^{c}_{\text{Grad-CAM++}} = \mathrm{ReLU}\left(\sum_{k} \alpha_k \sum_{i,j} \mathrm{ReLU}\left(\frac{\partial Y^c}{\partial A^k_{ij}}\right) A^k_{ij}\right) \tag{5}$$



These heatmaps enhance the understanding of model decisions, particularly in applications requiring trust and clarity.

Efficient Signal Denoising Using RSBU Architecture

- **Feature Reduction:** Global Average Pooling (GAP) reduces the feature map to a one-dimensional vector, minimizing complexity.
- **Threshold Adjustment:**

$$\gamma(c) = \frac{1}{1 + \exp^{-z(c)}} \cdot \text{GAP}(\text{abs}(A))$$

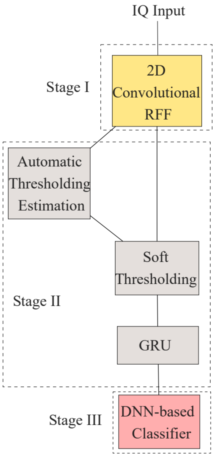
  This formula calculates adaptive thresholds $\gamma(c)$, enhancing signal-to-noise ratio.

- **Noise Removal:** Soft thresholding applies adaptive cut-offs to cleanse the signal:

$$\delta(\omega) = \begin{cases} 0, & |\omega| < \gamma(c) \\ (|\omega - \gamma(c)|) \cdot \text{sgn}(\omega), & |\omega| \geq \gamma(c) \end{cases}$$

Post-denoising, signals undergo convolutional and GRU processing to detect modulation patterns, readying them for accurate classification.

Proposed Architecture



Key Components:

I . **2D Convolutional RFF:** Utilizes random Fourier features in a convolutional layer to extract complex spatial patterns from signal data effectively.

II . **Automatic Thresholding:** Implements dynamic thresholding to enhance signal clarity by distinguishing significant features from noise.

III . **Classification:** Employs a neural network with softmax activation to accurately classify signal modulation types based on extracted features.

Study Dataset Overview

Utilization of RadioML 2016.10A Dataset:

- **220,000 signals** across **20 SNR levels**, from **-20dB to +18dB**.
- **1,000 signals per SNR** for each modulation type.
- **11 modulation types**: 8 digital (e.g., BPSK, QPSK, 16-QAM) and 3 analog (e.g., AM-DSB).
- Comprehensive SNR range and modulation variety allow for **extensive testing and comparison** of AMC methods.

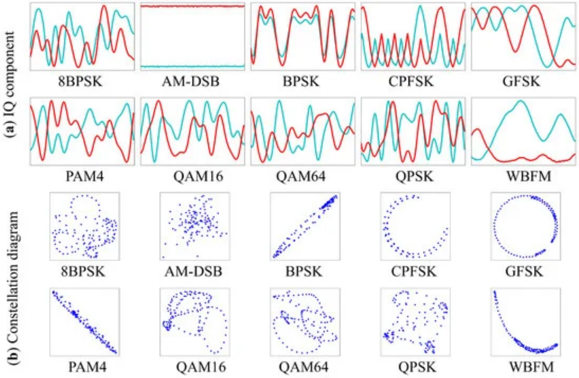


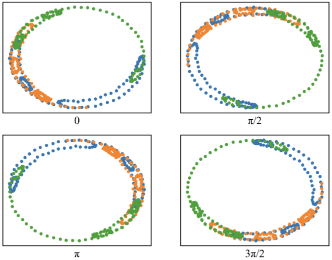
Figure: Visual Representation of RadioML 2016.10A

Data Augmentation Technique Using Phase Shifting

Data augmentation through phase shifting effectively enhances the diversity of radio signal datasets. The augmented signals are computed by rotating the phase of in-phase (XI) and quadrature (XQ) components as follows:

$$\begin{bmatrix} X_I' \\ X_Q' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} XI \\ XQ \end{bmatrix}$$

where θ is the angle of rotation. Common rotations include 0, $\frac{\pi}{2}$, π, and $\frac{3\pi}{2}$, each producing unique data variations. We expan … aset



Model Architecture and Optimization Details

Table: MCLDNN Model Architecture

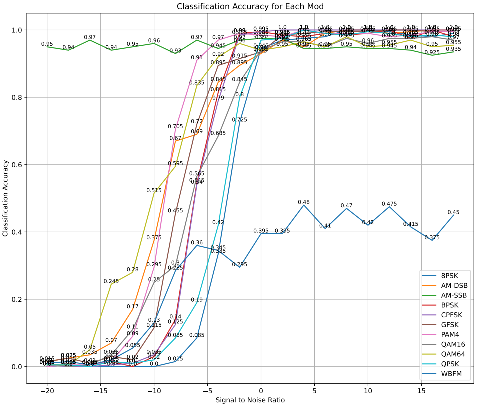
Layer	Configuration
Conv2D	Filters: 16, Kernel: (2, 3), Activation: relu, Padding: SAME
Threshold	GAP, Dense: 32 (relu), Dense: 1 (sigmoid)
Conv2D	Filters: 32, Kernel: (2, 3), Activation: relu, Padding: SAME
Conv2D	Filters: 64, Kernel: (2, 3), Activation: relu, Padding: VALID
GRU	Units: 64
Dense	Units: 11, Activation: softmax

Table: Optimization and Training

Param.	Value
Optimizer	Adam
Batch Size	400
Epochs	10,000
Early-Stop.	Patience: 50
Reduce LR	Factor: 0.5, Patience: 5
Data Split	Training: 70%, Testing: 30%
Loss:	Categorical Crossentropy
Trainable Parameters:	29517

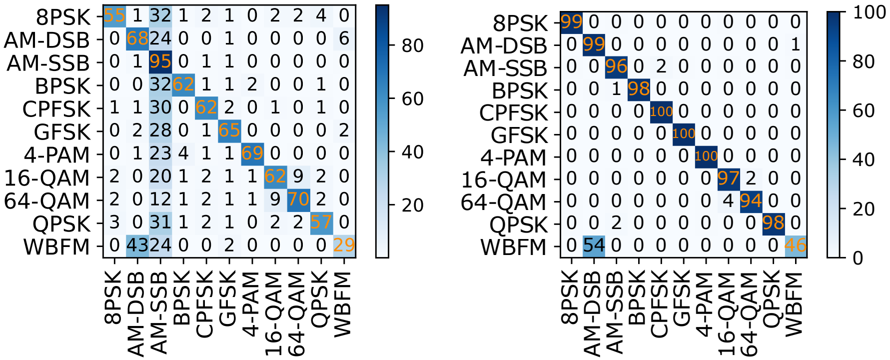
We used Classification Accuracy and Model Complexity as Evaluation Criteria

Performance Evaluation of CRFFTD-Net



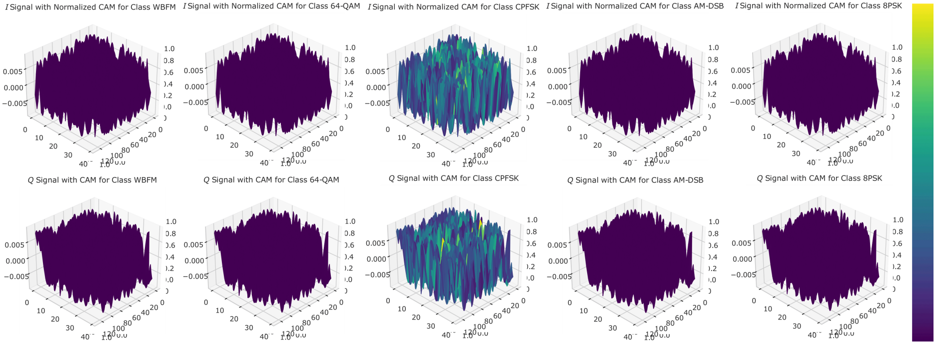
The CRFFTD-Net achieves **high classification accuracy at SNRs above** -6dB, with peak accuracies reaching 100% for several modulation types. Despite this high performance at moderate to high SNR levels, **the model faces challenges** at lower SNRs, particularly with confusion between modulation types like WBFM and AM-DSB

Classification Challenges at Low SNRs



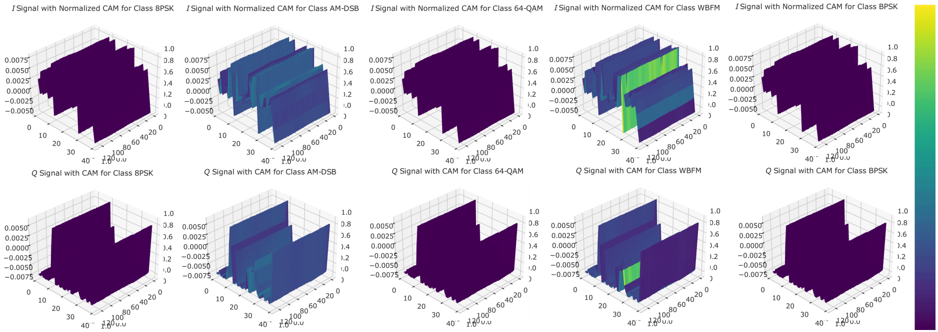
At low SNR levels, CRFFTD-Net struggles with **misclassifications** between **WBFM** and **AM-DSB**, largely due to their similar silent periods and time-domain characteristics. The confusion matrix shows a **46%** correct classification rate for WBFM, with **54%** misclassified as AM-DSB.

GradCam++ Analysis of Modulation Classification



GradCam++ was used to analyze activation patterns for CPFSK, showing significant localized activations compared to other classes. This standardized approach helps clarify which signal features most influence model decisions.

GradCam++ Analysis for AM-DSB Modulation



GradCam++ reveals high **CAM values** for both **AM-DSB** and **WBFM** at 18 **dB SNR**, demonstrating shared discriminative features that lead to **frequent misclassifications**.

Comparison with State-of-the-Art Approaches

Table: Comparisons among various state-of-the-art models

Model Name	# Parameters	Average Accuracy %
MCLDNN [?]	406199	60.48
PET-CGDNN [?]	71871	59.65
SCNN [?]	104495	47.82
Complex CNN [?]	2749275	57.21
TDRNN [?]	41821	**63.5**
ULNN [?]	8825	62.83
CRFFTD-Net (Ours)	**29517**	**63.4**

CRFFTD-Net ranks second in accuracy with significantly fewer parameters, illustrating its efficiency compared to other advanced models like TDRNN and SCNN.

Conclusions

- This study introduces **CRFFDT-Net**, a novel deep learning model for **Automatic Modulation Classification** (AMC) that utilizes **Convolutional Random Fourier Features** in SinCos form along with dynamic thresholding and recurrent neural processing.
- The **2D convolutional RFFSinCos layer** significantly enhances the representation of IQ signal components, improving **accuracy** and **adaptability** across different signal-to-noise ratios (SNRs).
- **Experimental findings** confirm CRFFDT-Net's superiority over conventional methods, especially in environments with **high SNR**, and its capability to efficiently classify diverse modulation types.

Conclusions

- The **dynamic threshold denoising stage** refines signal clarity for better classification by reducing noise interference, while the use of **Grad-CAM++** for interpretability provides essential insights into the network's decision-making processes.
- CRFFTD-Net offers **high classification accuracy with fewer parameters** compared to other leading models, making it suitable for **real-time AMC** in various communication settings.
- Future work will focus on **extensive testing** across different datasets and a comparative analysis to further validate the effectiveness of the SinCos Fourier Features, aiming to enhance the model's **robustness** and **performance** in dynamic environments.