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Improved Waveform Classification for Integrated Radar-Communication 6G Systems via Convolutional Neural Networks

Thien Huynh-The, *Senior Member, IEEE*, Nguyen Cong Luong, Hoc Phan,

Daniel Benevides da Costa, *Senior Member, IEEE*, and Quoc-Viet Pham, *Senior Member, IEEE*

Presentation: Huan Nguyen-Duy
Student ID: 2390703
Supervisor: Dr.Tan Do-Duy

Preview

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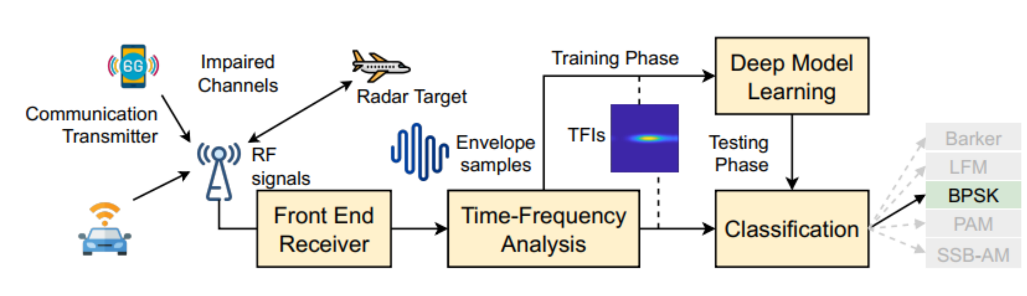
Authors	**Thien Huynh-The** Department of Computer and Communications Engineering, Ho Chi Minh City University of Technology and Education, Ho Chi Minh City, Vietnam **Nguyen Cong Luong** Faculty of Computer Science, Phenikaa University, Vietnam **Hoc Phan** Department of Computer and Communications Engineering, Ho Chi Minh City University of Technology and Education, Ho Chi Minh City, Vietnam **Daniel Benevides da Costa** Department of Electrical Engineering, King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia **Quoc-Viet Pham** School of Computer Science and Statistics, Trinity College Dublin, Ireland

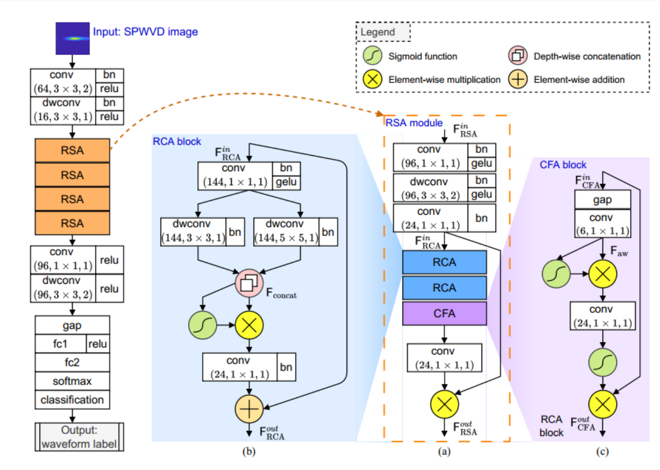
ABSTRACT

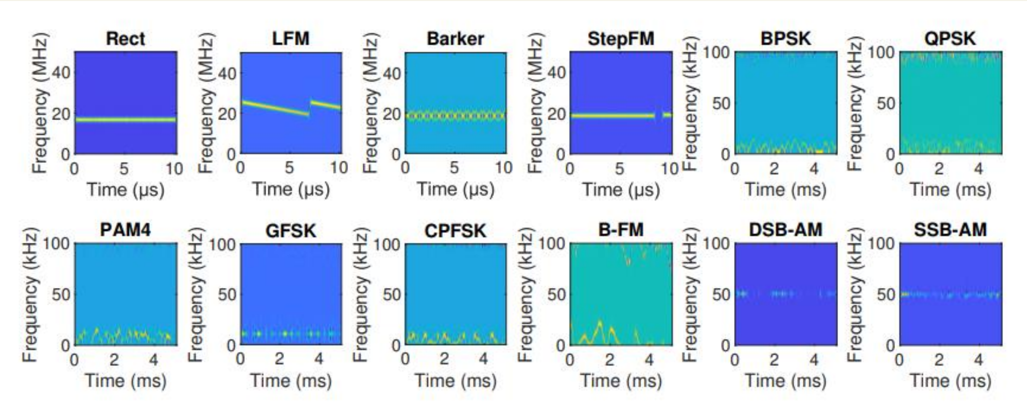
To overcome the spectrum congestion problem in next-generation wireless networks, an integrated radar-communication system with spectrum sharing becomes a promising solution, wherein radar and communication signals can be discriminated by means of modulated waveforms. This letter presents an efficient radar-communication waveform classification method by taking advantage of the combination of smooth pseudo Wigner-Ville distribution-based time-frequency analysis and deep learning to achieve a good trade-off between complexity and accuracy. To this end, a high-performance convolutional network, namely the radar-communication waveform recognition network (RadComNet), is designed with multiple cutting-edge techniques and advanced structures, including depthwise convolution for complexity reduction and residual connection and multi-level attention mechanisms for learning efficiency enhancement. Relying on the simulation results acquired on a synthetic signal dataset of 12 radar and communication waveform types with the presence of channel impairments, our proposed method shows superiority over other classification approaches and deep models in terms of accuracy and complexity.

OUTLINE

- ❑MOTIVATION
- ❑CONTRIBUTION
- ❑INTRODUCTION
- ❑SOLUTION
- ❑EVALUTION
- ❑CONCLUSION







MOTIVATION

- **Reality and Demand in next generation wireless network**
  - ☞ Demand of wide bandwidths for high performance in the next-generation wireless network.
  - ☞ Demand of accurately identified and classified types of spectrum base on waveform in limited resource.
  - ☞ Recognition radar waveform in autonomous vehicles that requires highly accurate detection in limited resource.
- **Solution for recognition and classification waveform**
  - ☞ Deep learning is exploited for radar recognition and communication modulation classification.
  - ☞ Proposing solution to reduce the size of deep learning network to reach highly accuracy and performance that have ability to deploy in limited resource devices.

CONTRIBUTION

- **The smooth pseudo WVD (SPWVD) recognition**
  - ☞ De-composing a signal into high-resolution time-frequency representation.
- **Waveform-based radar and communication signal classification**
  - ☞ Design a deep learning network that utilizes cutting edge deep learning architecture.
  - ☞ Applying modern connection structure (depth-wise convolution, residual connection, and attention mechanism)
- **Performance evaluation by Mat-Lab simulation tool**
  - ☞ Generating a synthetic signal data set that comprise 12 radar and communication types.
  - ☞ Proposing deep model that reduces complexity and increase accuracy.

INTRODUCTION

Signal Model

The receiver can receive pulsed radar signal and modulated communication signal in difference transmission source

The complex received signal is illustrated by:

$$y(k) = x(k) \otimes h(k) + n(k)$$

- ❑ X(k) : the transmitted radio signal
- ❑ H(k) : the transmission channel coefficient
- ❑ N(k) : the complex additive white Gaussian noise (AWGN)
- ❑ Y(k) : the radar communication received signal

INTRODUCTION

Time Frequency analysis (TFA)

The receiver can receive pulsed radar signal and modulated communication signal in difference transmission source

The energy spectrum in frequency is given by:

$$\mathrm{WVD}_s(t,\omega) = \int_{-\infty}^{\infty} s\left(t+\frac{\tau}{2}\right) s^*\left(t-\frac{\tau}{2}\right) e^{-j\omega\tau} d\tau,$$

S(t) denote for continuous signal

The total energy spectrum in frequency is given by:

$$\begin{aligned}\mathrm{WVD}_y(t,\omega) =& \mathrm{WVD}_s(t,\omega) + \mathrm{WVD}_n(t,\omega) \\ &+ 2\Re\left\{\mathrm{WVD}_{s,n}(t,\omega)\right\},\end{aligned}$$

WVDn denote for energy of noise

INTRODUCTION

The Smooth Pseudo Winger-Ville Distribution (SPWVD)

The smoothing function is given by:

$$\Xi(t,\omega) = g(t)\,H(\omega)$$

-g(t) : filter in time domain
-H(w) : filter in frequency domain

The SPWVD function is given by:

$$\mathrm{SPW}_s(t,\omega;\Xi) = \int_{-\infty}^{\infty} g(t)\,H(\omega)\,s\left(t+\frac{\tau}{2}\right) s^*\left(t-\frac{\tau}{2}\right) e^{-j\omega\tau}\,d\tau.$$

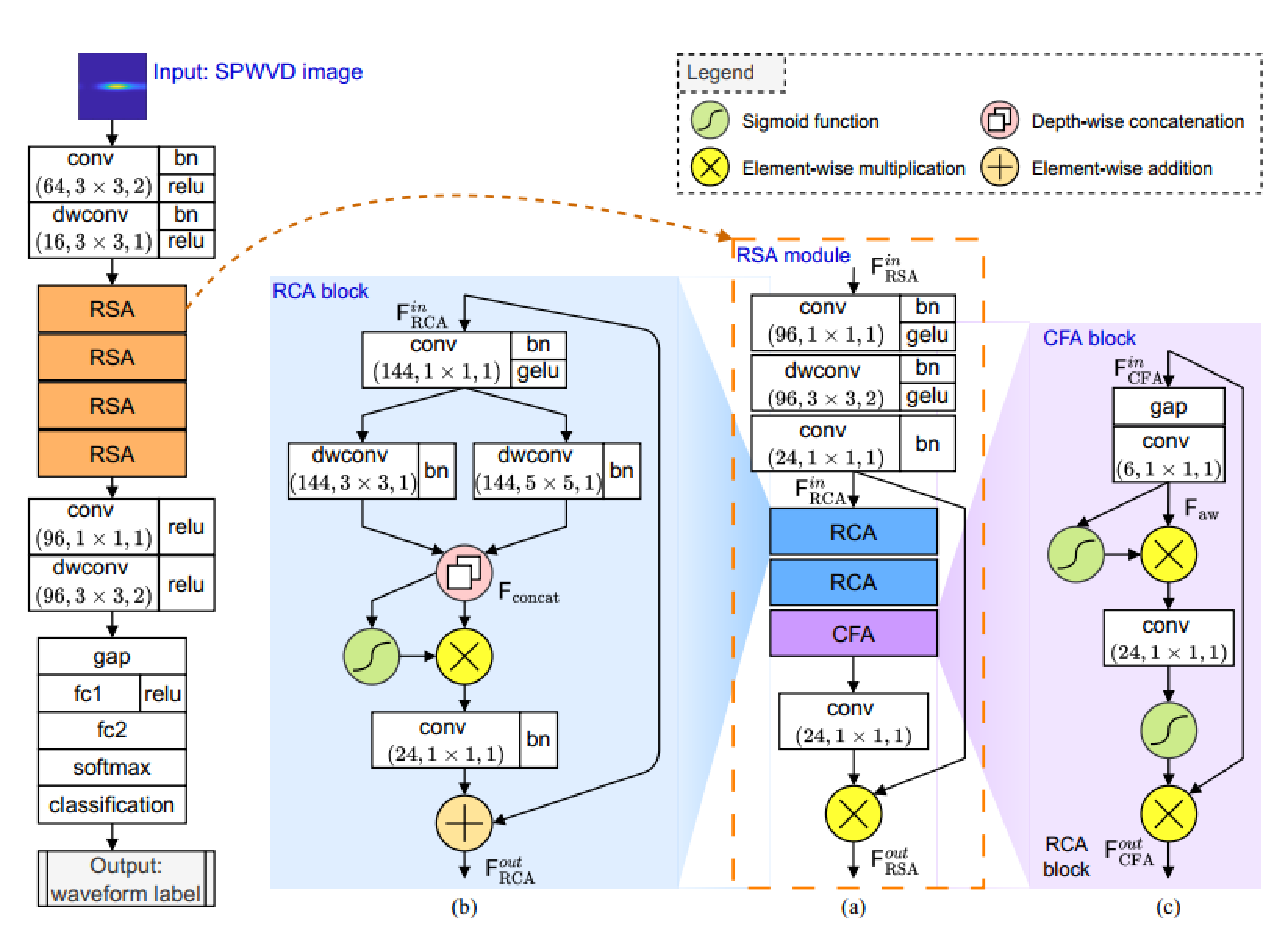
The Kaiser window function is given by:

$$c(n) = \mathcal{B}\left(\gamma\sqrt{1-\left(\frac{n-N/2}{N/2}\right)^2}\right)\mathcal{B}^{-1}(\gamma),\ \ 0 \le n \le N,$$

-B : length of N + 1
-y: shape factor

SOLUTION

RadComNet-Robust And Cost-efficient ConvNet Waveform Classification



SOLUTION

RadComNet-Robust And Cost-efficient ConvNet Waveform Classification

The input function of RCA block

$$\mathbf{F}_{\mathrm{RCA}}^{in} = \mathcal{C}_{1\times1}\left(\mathcal{G}_{3\times3}\left(\mathcal{F}_{1\times1}\left(\mathbf{F}_{\mathrm{RSA}}^{in}\right)\right)\right)$$

RCAs extract intrinsic features at multiple scales of SPWVD-based time-frequency representations

The Output function of RSA block

$$\mathbf{F}_{\mathrm{RSA}}^{out} = \mathbf{F}_{\mathrm{RCA}}^{in} \circ \mathcal{C}_{1\times1}\left(\mathrm{CFA}\left(\mathrm{RCA}\left(\mathrm{RCA}\left(\mathbf{F}_{\mathrm{RCA}}^{in}\right)\right)\right)\right)$$

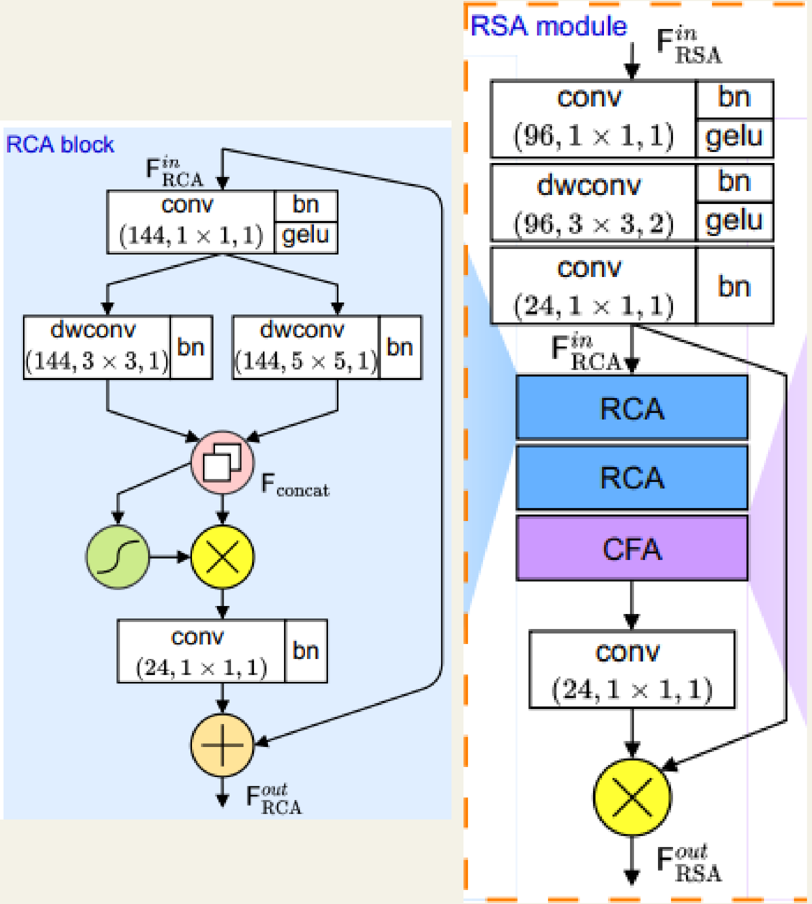
The Output function of RCA block

$$\mathbf{F}_{\mathrm{concat}} = \left\langle \mathbf{F}_{3\times3}, \mathbf{F}_{5\times5} \right\rangle,$$

$$\mathbf{F}_{3\times3} = \mathcal{G}_{3\times3}^{-}\left(\mathcal{F}_{1\times1}\left(\mathbf{F}_{\mathrm{RCA}}^{in}\right)\right)$$

$$\mathbf{F}_{5\times5} = \mathcal{G}_{5\times5}^{-}\left(\mathcal{F}_{1\times1}\left(\mathbf{F}_{\mathrm{RCA}}^{in}\right)\right)$$

$$\mathbf{F}_{\mathrm{RCA}}^{out} = \mathbf{F}_{\mathrm{RCA}}^{in} + \mathcal{F}_{1\times1}^{-}\left(\mathbf{F}_{\mathrm{concat}} \circ \left(\sigma\left(\mathbf{F}_{\mathrm{concat}}\right)\right)\right)$$



SOLUTION

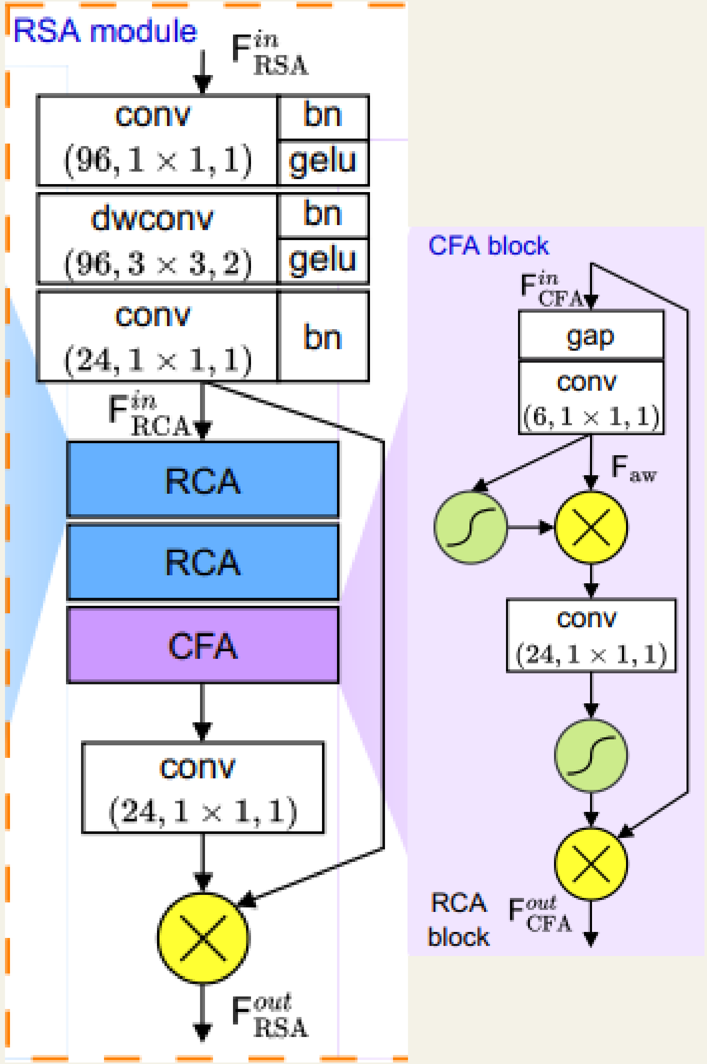
RadComNet-Robust And Cost-efficient ConvNet Waveform Classification

Attention mechainsm

$$\mathbf{F}_{\mathrm{att}} = \mathcal{C}_{1\times1}\left(\mathrm{gap}\left(\mathbf{F}_{\mathrm{CFA}}^{in}\right),\right)$$

The Output of CFA block

$$\mathbf{F}_{\mathrm{CFA}}^{out} = \mathbf{F}_{\mathrm{CFA}}^{in} \circ \sigma\left(\mathcal{F}_{1\times1}^{-}\left(\mathbf{F}_{\mathrm{att}} \circ \left(\sigma\left(\mathbf{F}_{\mathrm{att}}\right)\right)\right)\right)$$



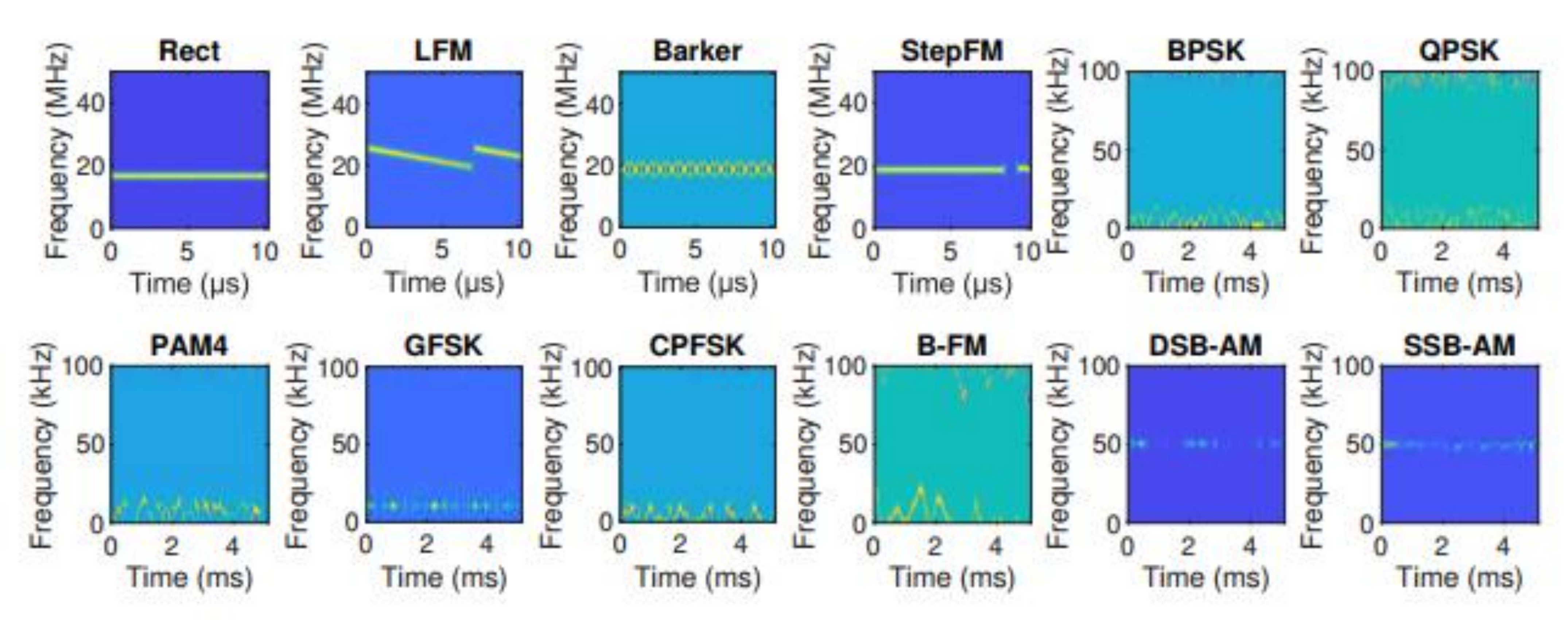
CFA refines these features by selectively amplifying the more relevant ones

- **combination of RCA and CFA improves classification accuracy**

EVALUTION

Data Set Training

SPWVD spectrum image of radar communication that were generated by MatLab tool box



EVALUTION

Data Set Training

Data Set Information of 12 waveform types

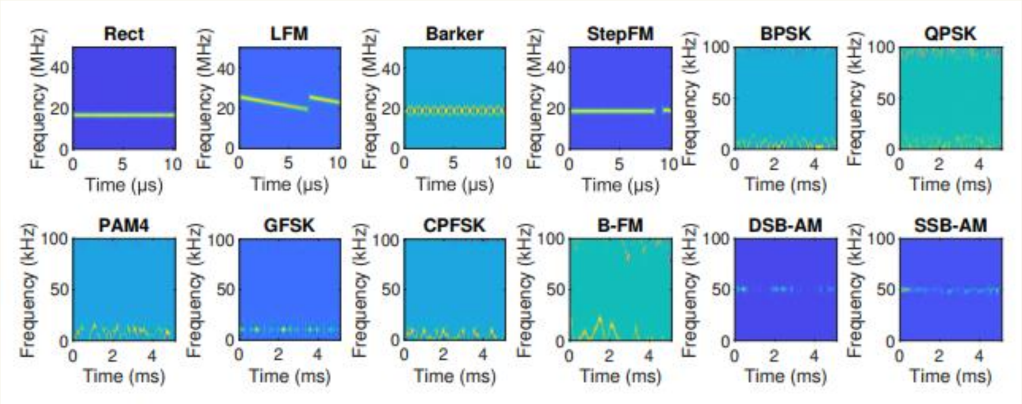
Category	Waveform type	Abbr	No. signals
Radar	Rectangular	Rect	32,768 signals per type
	Linear frequency modulation	LFM	
	Barker Code	Barker	
	Step frequency modulation	StepFM	
Communication	Binary phase-shift keying	BPSK	
	Quadrature phase-shift keying	QPSK	
	Pulse amplitude modulation 4-level	PAM4	
	Gaussian frequency shift keying	GFSK	
	Continuous phase frequency shift keying	CPFSK	
	Broadcast frequency modulation	B-FM	
	Double sideband amplitude modulation	DSB-AM	
	Single sideband amplitude modulation	SSB-AM	

EVALUTION

Data Set Training

The radar communication spectrums are generated with specific parameter:

- Path delays : [0, 9, 7] x 10^-6
- Average path gain: [0, -2, -10] dB
- Signal to noise: [-5:5:30] dB
- The Maximum Doppler shift Fd = 70 Hz
- Data image size : 224 x 224
- The number of data in each class: 393,216
- The ratio of training set: 70%
- The ratio of validation set: 15%
- The ratio of test set: 15%

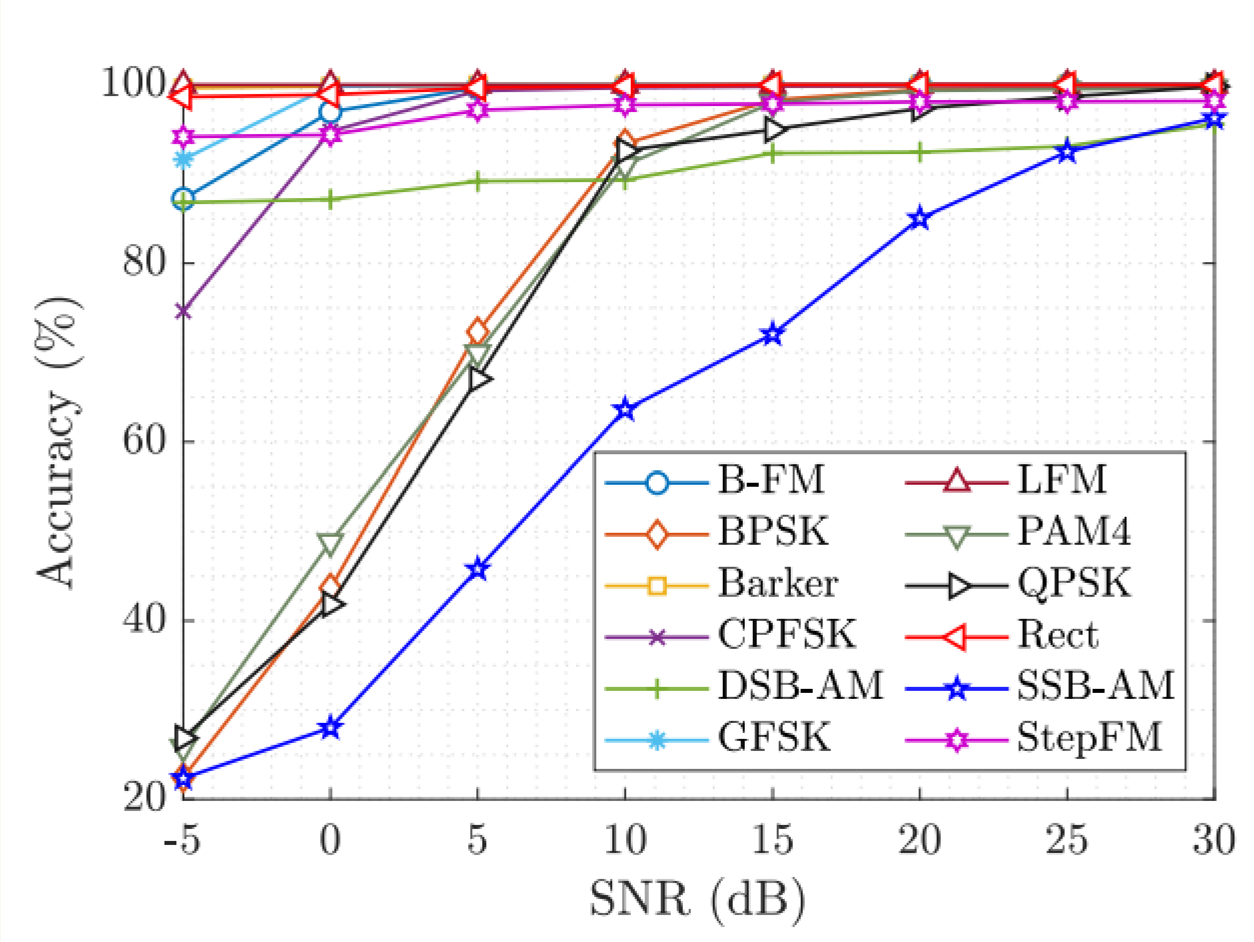


Hardware for training deep learning network

- CPU: 3.8 GHz
- RAM: 64 GB
- GPU: Nvidia GTX 3060Ti

EVALUTION

RadComNet classification performance



The classification accuracy for each radar waveform signal class increase when the Signal to Noise (SNR) is high.

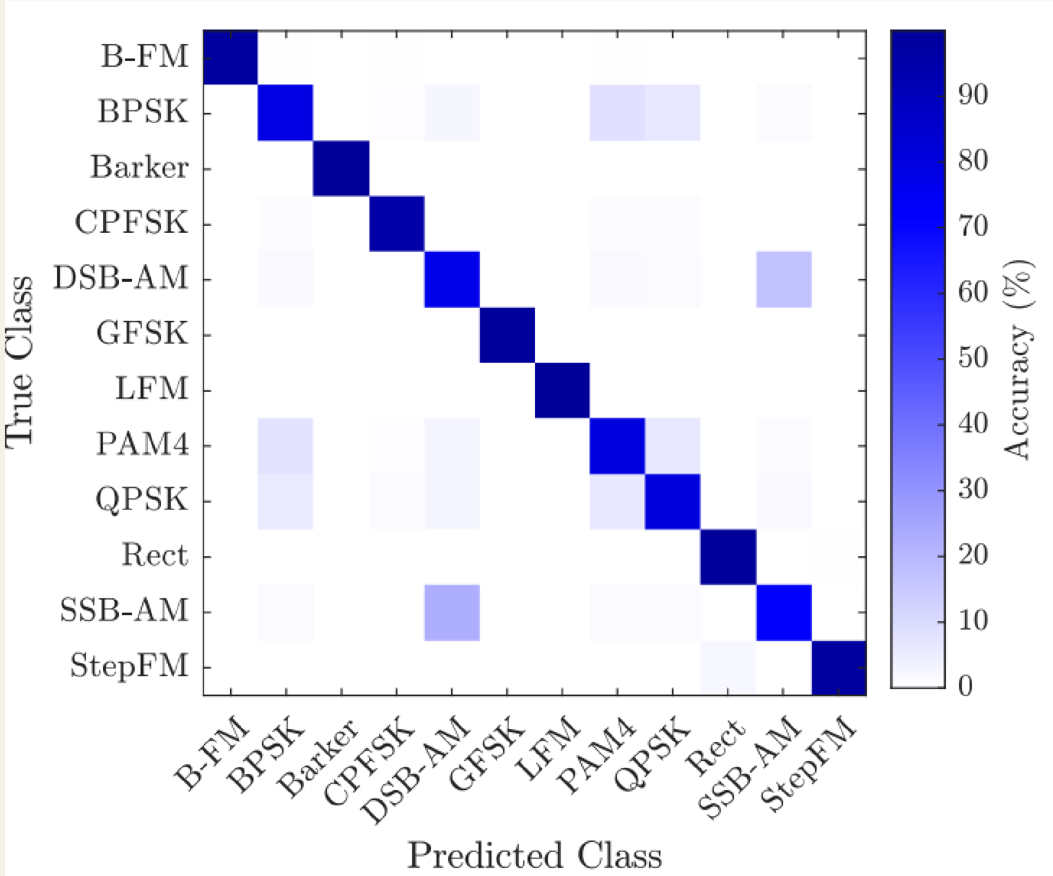
All waveform reached than 90% at SNR = 25dB

Rect, Barker, LFM, StepAM, BFM, GFSK, and CPFSK are outstanding with over 95% at 5dB.

EVALUTION

RadComNet Confusion matrix

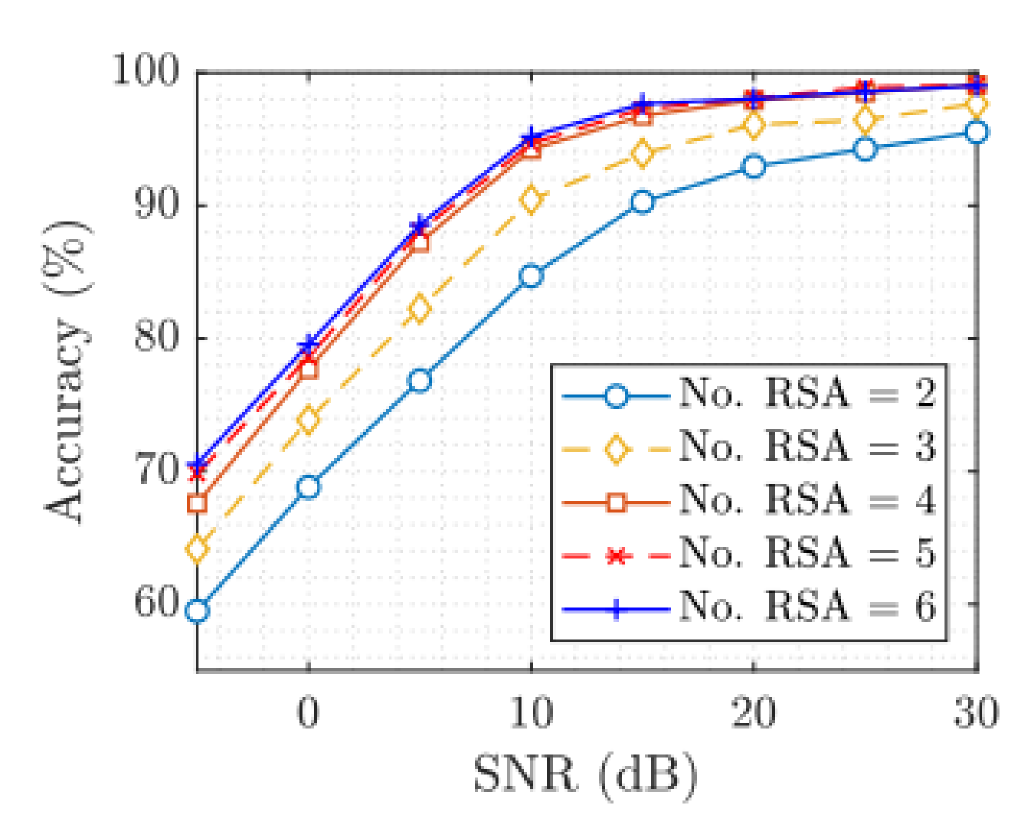
RadComNet reached impressive result at all classification classes



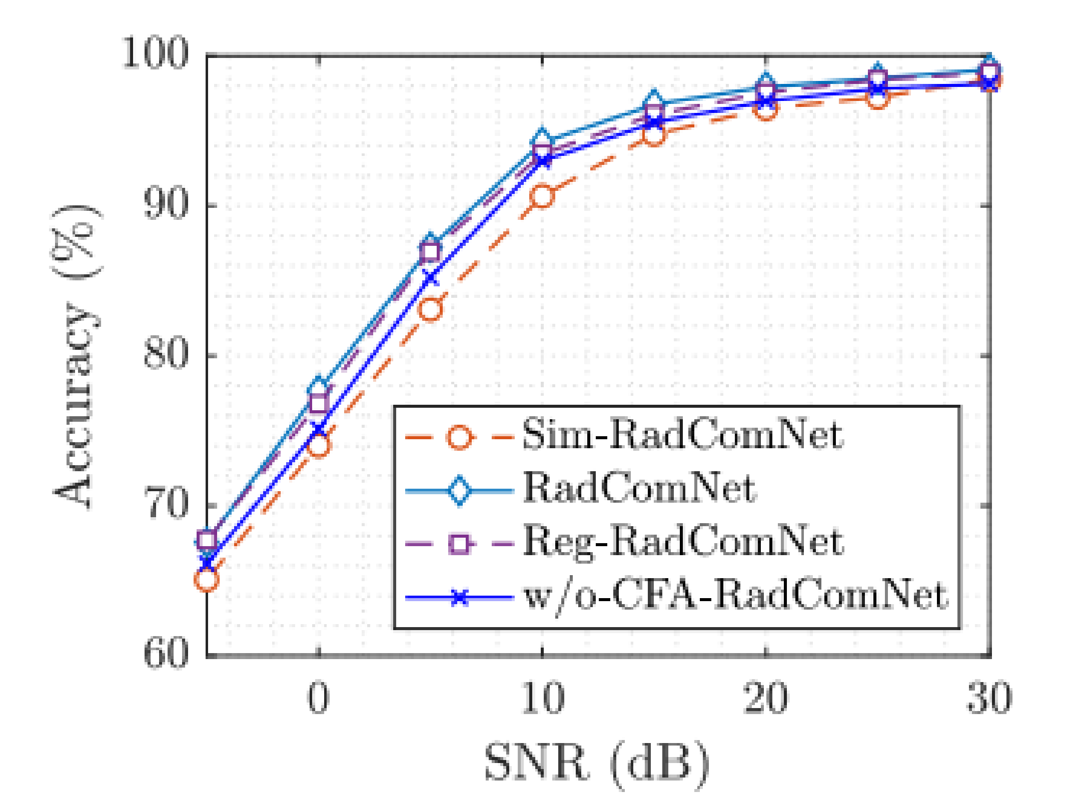
EVALUTION

RadComNet Performance in different deep network design

Classification performance with different the number of RSA blocks



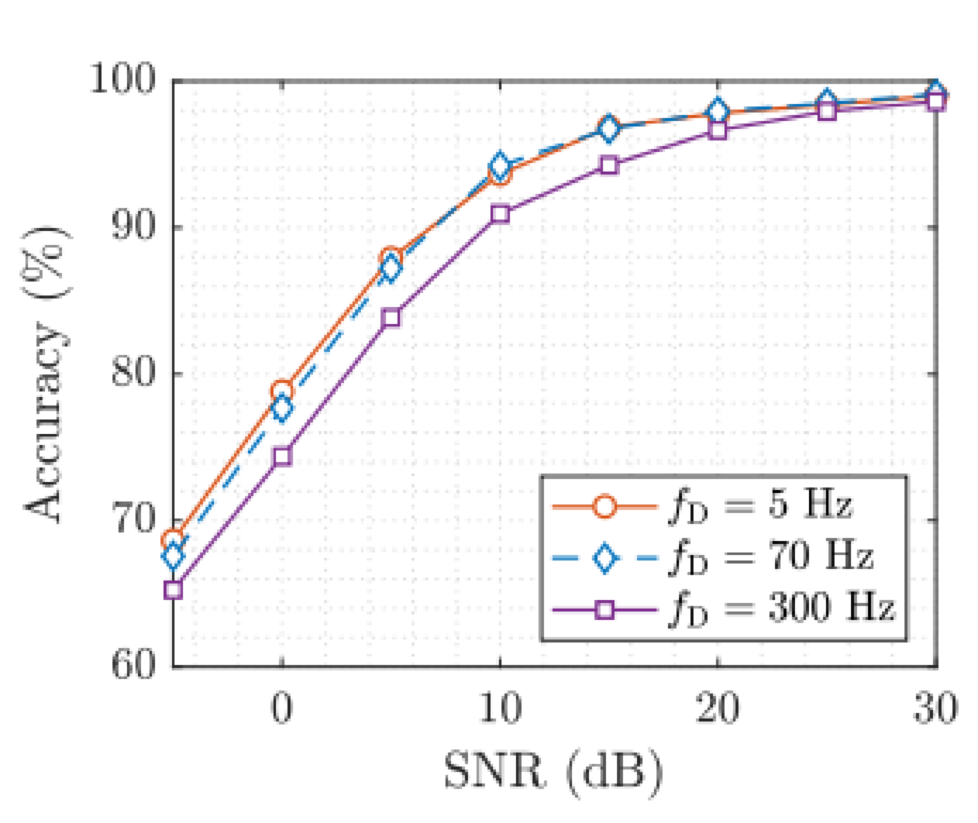
Classification performance with different network designs



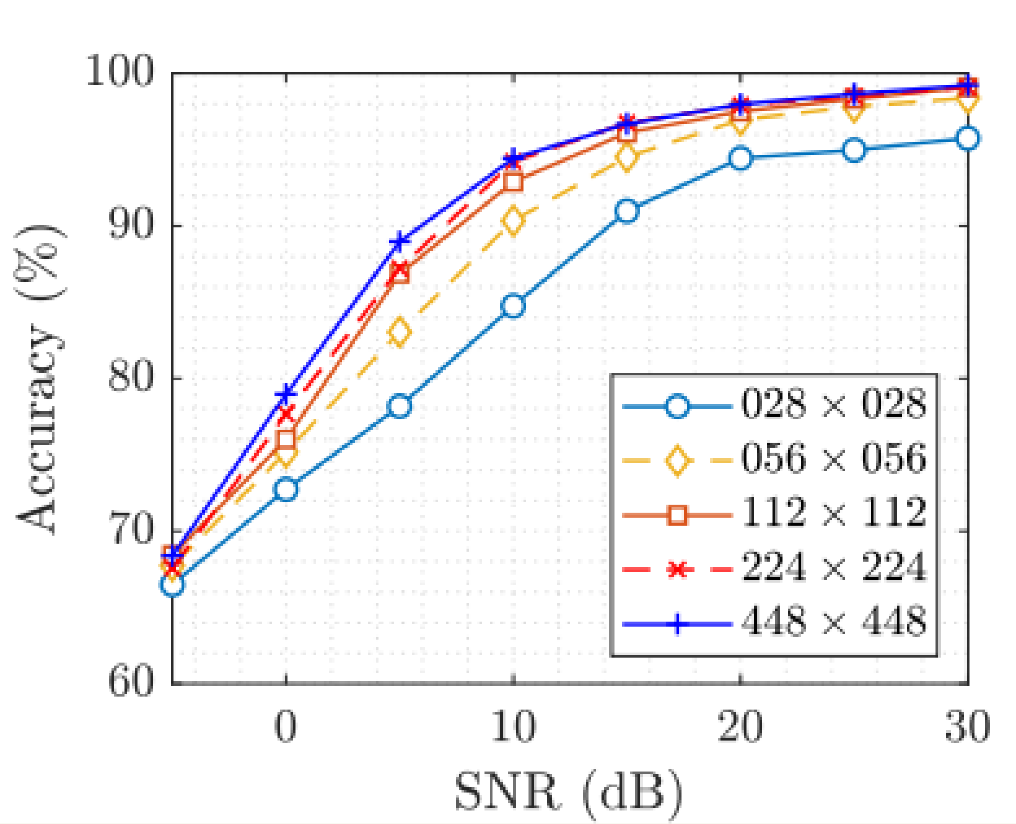
EVALUTION

RadComNet Performance in different Parameters

Classification performance in different doppler shifts Fd



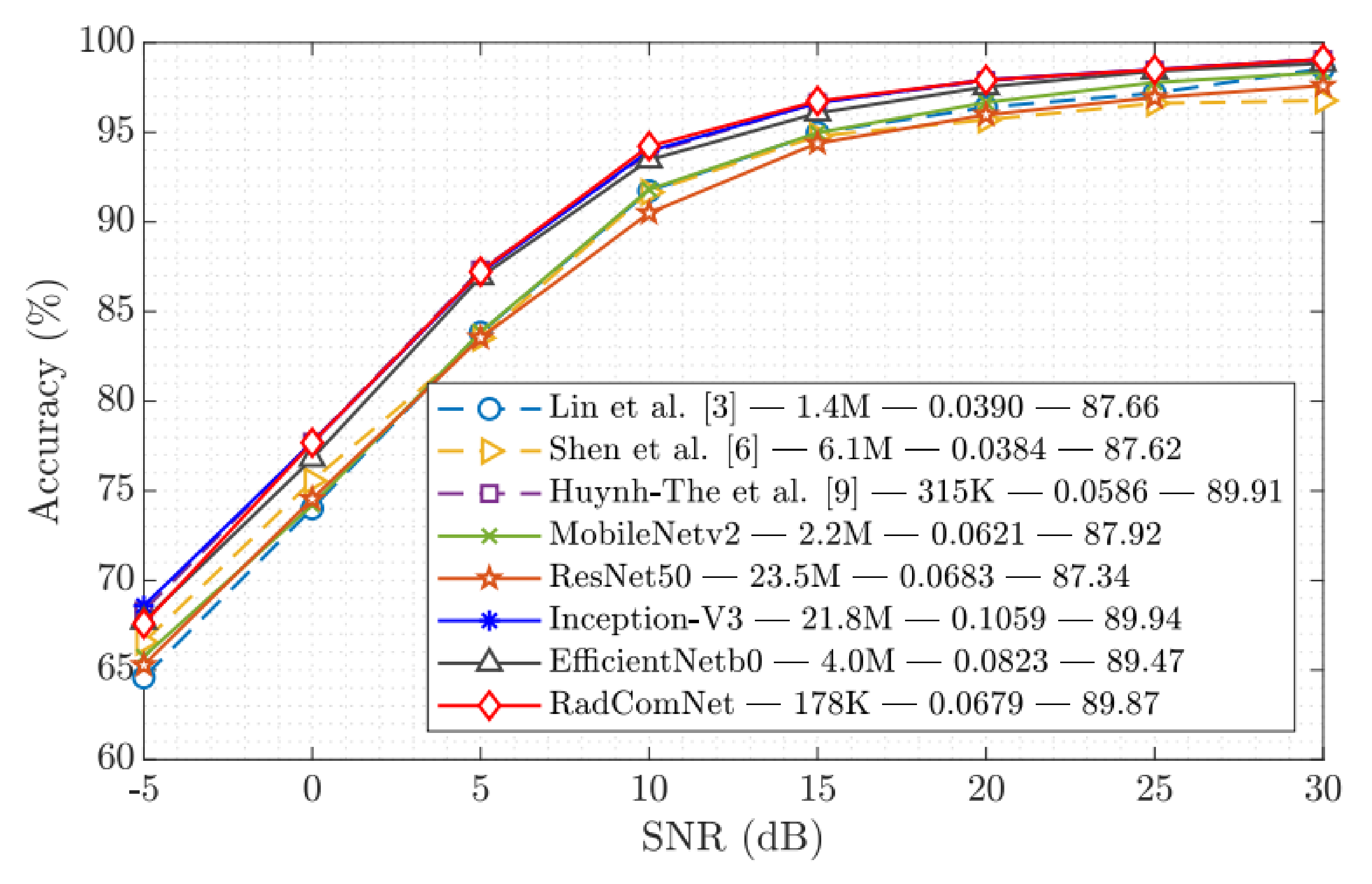
Classification performance in difference image sizes



EVALUTION

RadComNet Performance in different Parameters

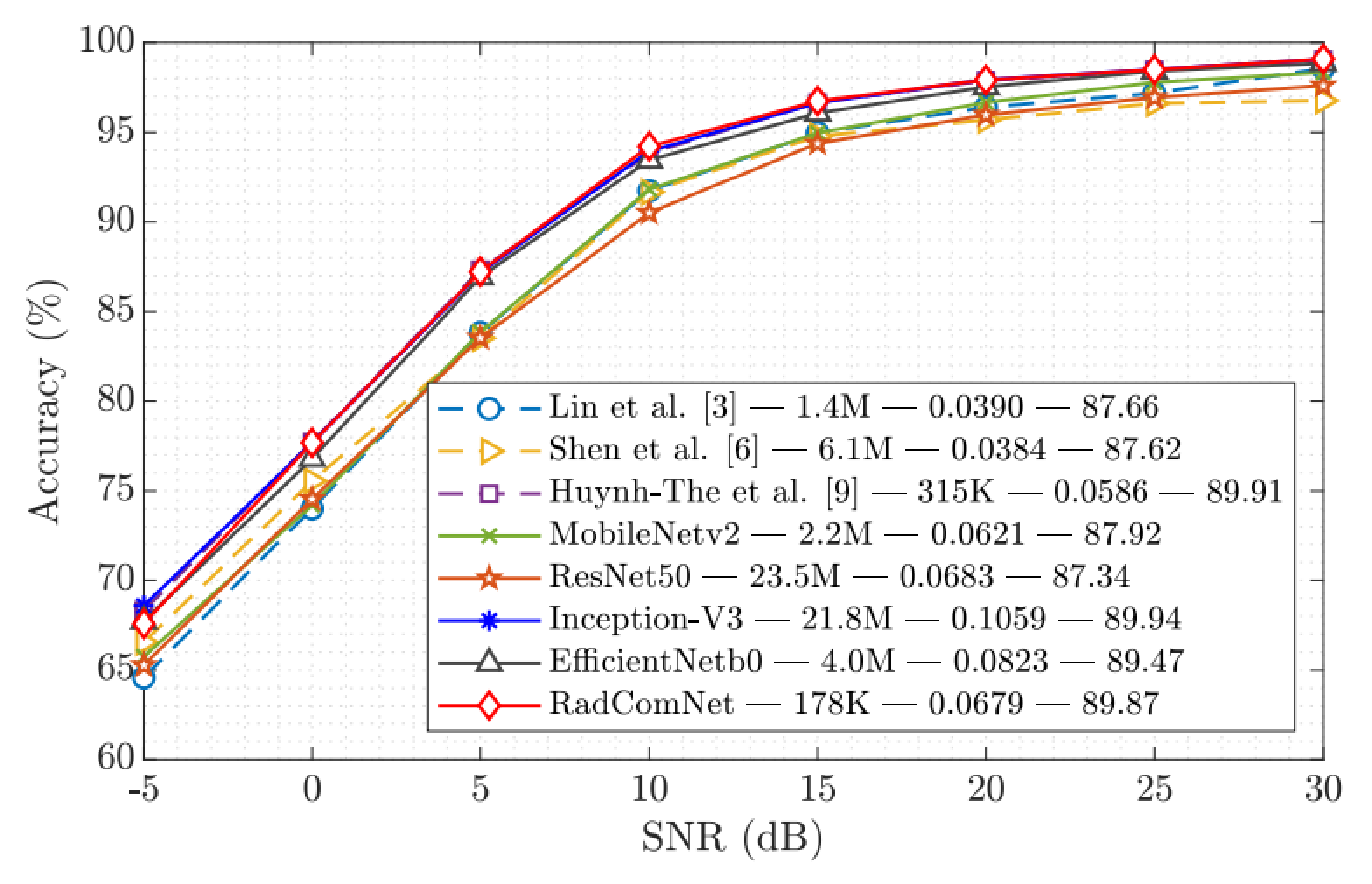
Performance comparison between RadComNet with other existing methods and various backbone networks



EVALUTION

RadComNet Performance in different Parameters

Performance comparison between RadComNet with other existing methods and various backbone networks



EVALUTION

RadComNet Performance in different Parameters

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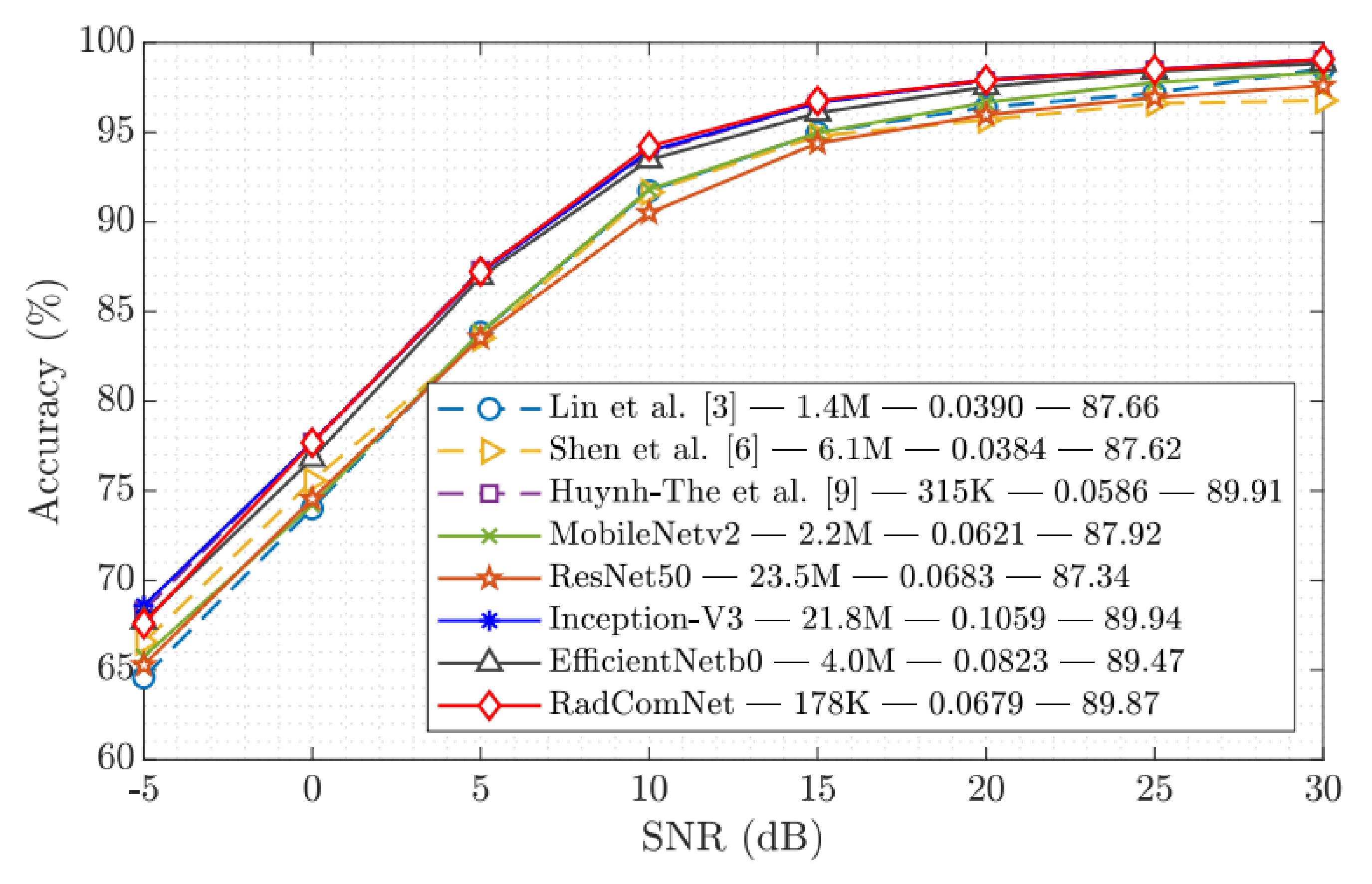

CONCLUSION

1. Introduction of RadComNet: Efficient radar-communication waveform classification method.
2. Aim: Alleviation of spectrum congestion through deep ConvNet with SPWVD representation.
3. Features: Cutting-edge architecture, multiple techniques, and advanced topologies.
4. Goal: Reduction of complexity without compromising accuracy.
5. Performance: Robust classification on a dataset of 12 radar and communication waveforms.
6. Comparison: RadComNet achieves comparable accuracy to other deep models but with significantly lower complexity and faster processing, suitable for resource-constrained devices.

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