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Low Complexity Deep Learning Models for LoRa RF Fingerprinting

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Outline

- Context
- Radio Frequency Fingerprinting
- Deep Learning- based LoRa Radio Frequency Fingerprinting
- Methodology
- Results & Discussion
- Conclusion

Context

- **LoRaWAN**: LPWAN standard for IoT applications
  - **LoRa: Long Range (LoRa PHY)**
    - Long range with low power consumption
    - Based on Chirp Spread Spectrum (CSS)
    - Spreading Factor: 7 – 12
    - BW: 125kHz, 250kHz and 500kHz
    - EU: 868 MHz, 434 MHz, & 2.4 GHz bands
  - **End-to-end security using AES-128 with PSK**
  - Hard on resources
  - Vulnerable to:
    - Impersonation [1] ☹
    - Eavesdropping [2] ☹
    - …..
- Requires Additional Layer of Security !!!

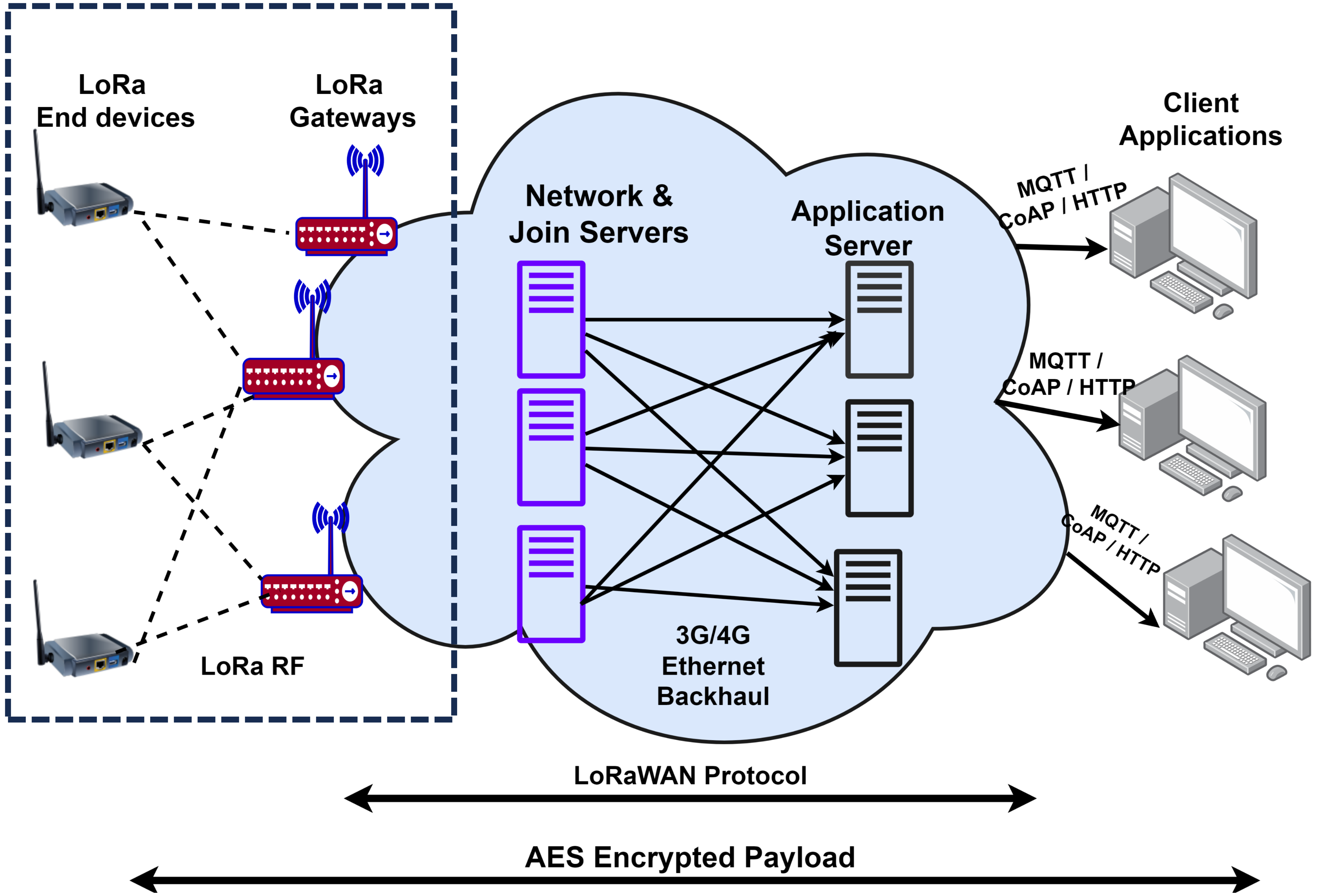


Fig 1. A Typical LoRaWAN Architecture

Radio Frequency Fingerprinting

- ✓ RF fingerprinting Identification is a physical-layer security method
- ✓ Aims to develop a unique RF fingerprint for a wireless transmitter

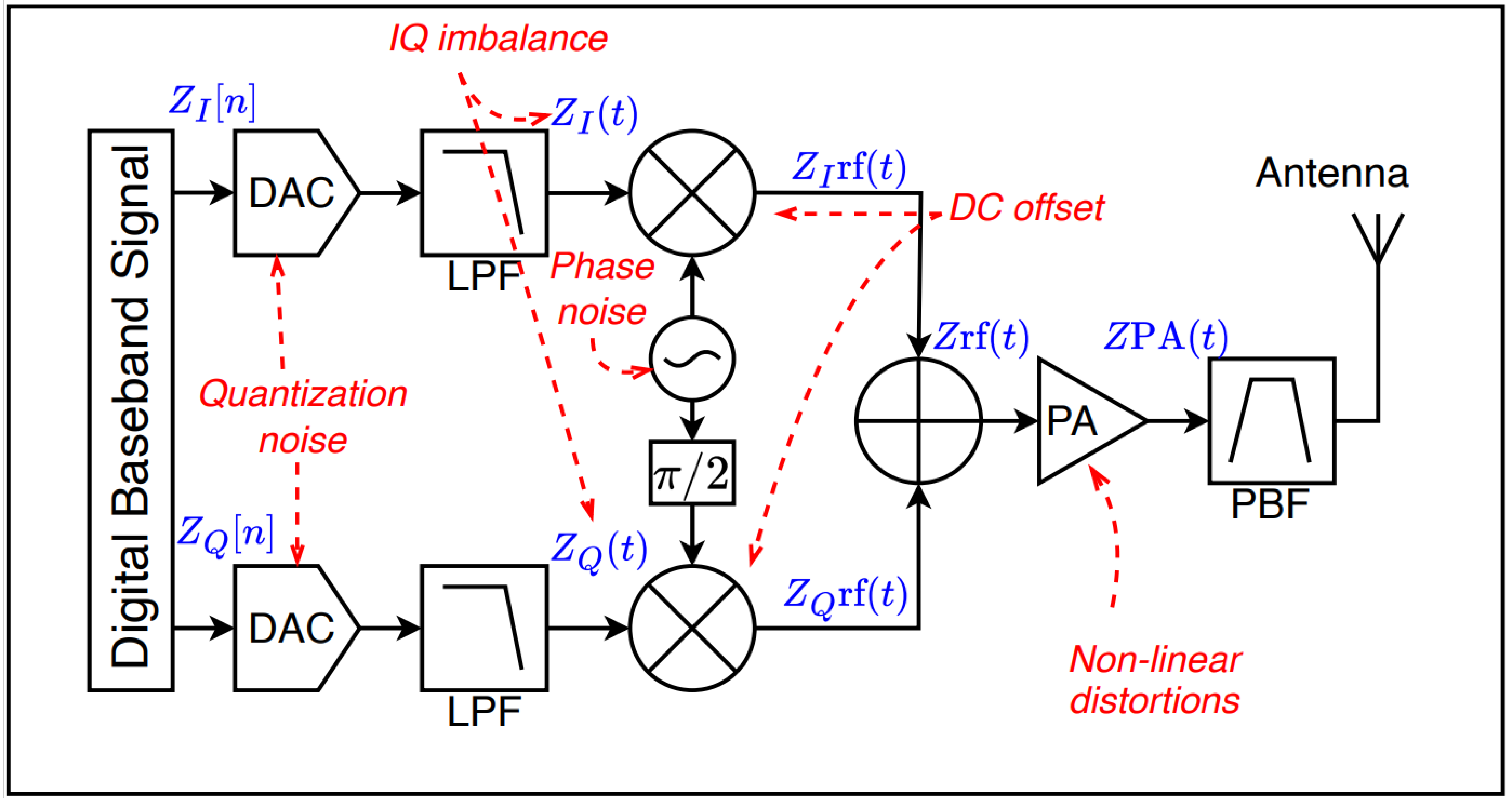


Fig 2: A typical transmitter with various RF impairments [*]

- ✓ **Transient RFF**
- ✓ **Steady State RFF**

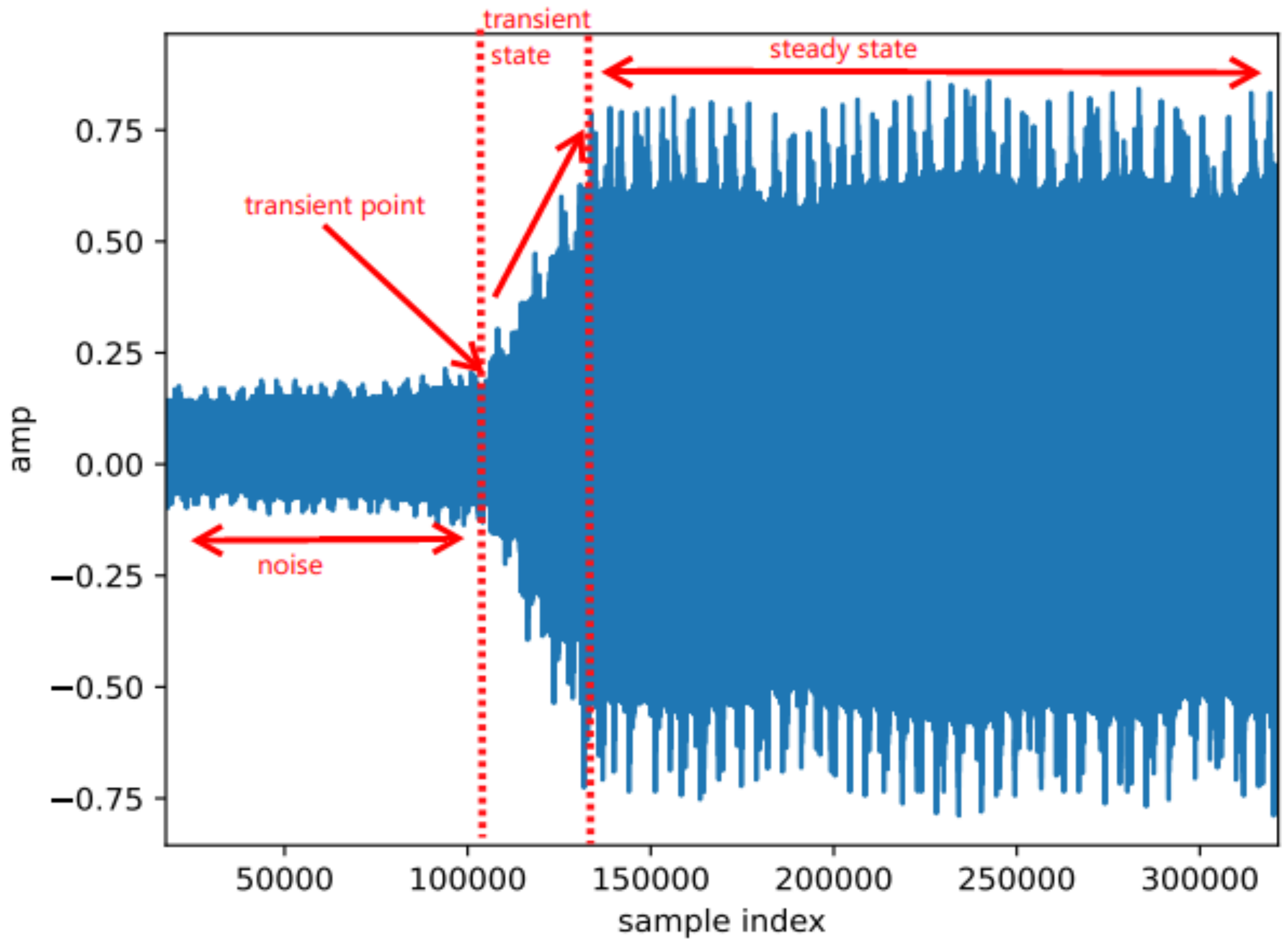


Fig 3: Types of RFF: Transient and Steady State

[*]: Ahmed, A.; Quoitin, B.; Gros, A.; Moeyaert, V. A Comprehensive Survey on Deep Learning-Based LoRa Radio Frequency Fingerprinting Identification. *Sensors* **2024**, *24*, 4411. https://doi.org/10.3390/s24134411

DL based LoRa RFF

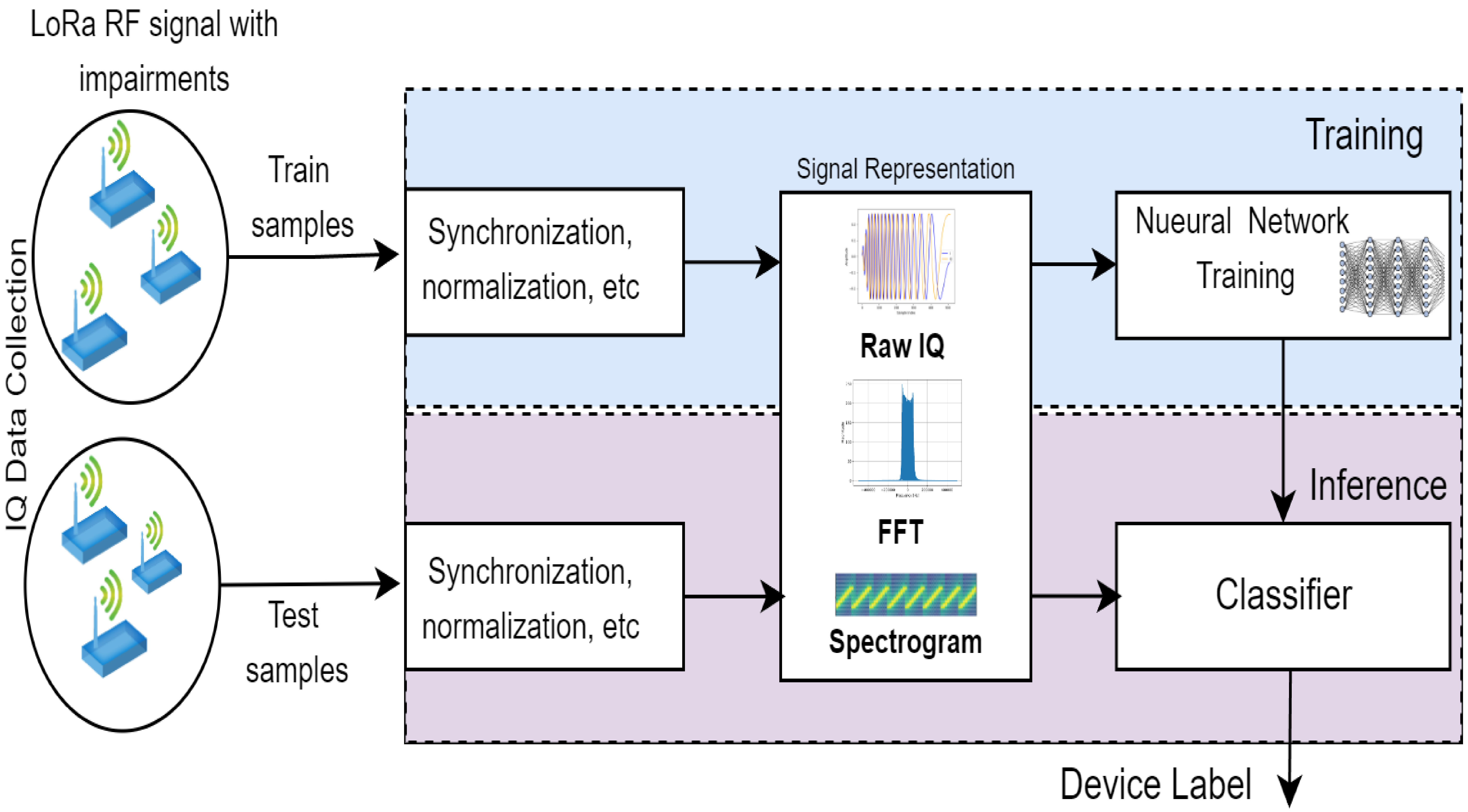


Fig. 4: A typical closed-set DL based LoRa RF identification system

Advantages:

- Radio Frequency fingerprints are unique
- RF Hardware impairments
- Hard to tamper
- No additional power requirement
- DL solves manual feature extraction

Various Challenges (Shen et al. 2024):

- **Signal Representation**
- **Model Complexity**
- Scalability
- Open set identification
- Channel Robustness
- .....
- .....
- The list goes on !

Methodology

Research Questions:

- **What is impact of using different signal representation (IQ, FFT, Amp/Phase) on the accuracy of model?**
- **Can we reduce the parameters (complexity) of a model without compromising the accuracy?**

Dataset: (Shen et al, 2022)

Hardware:

- 30 LoRa devices (Pycom LoPy4)
- USRP N210 SDR as Receiver
- Whip antennas

RF Parameters:

- Indoor environment
- Carrier Frequency: 868.1 MHz
- Sampling rate 1MS/s
- BW: 125KHz
- Spreading Factor 7
- Code rate 4/5

LoRa Tx: Pycom LoPy4

LoRa Rx: USRP N210 SDR

```
In [61]: print(data_train)
[[-0.00290618-0.05313189j -0.02153722-0.05378306j -0.0425642 -0.04476689j
  ... -0.39165947-0.45650479j -0.20011072-0.5670293j
  -0.02078168-0.60889018j]
 [ 0.00600547+0.05899644j  0.02393316+0.07105944j  0.04772553+0.07782059j
  ... -0.18533437-0.22635107j -0.16966186-0.23300758j
```

LoRa data in raw IQ format captured with USRP N210

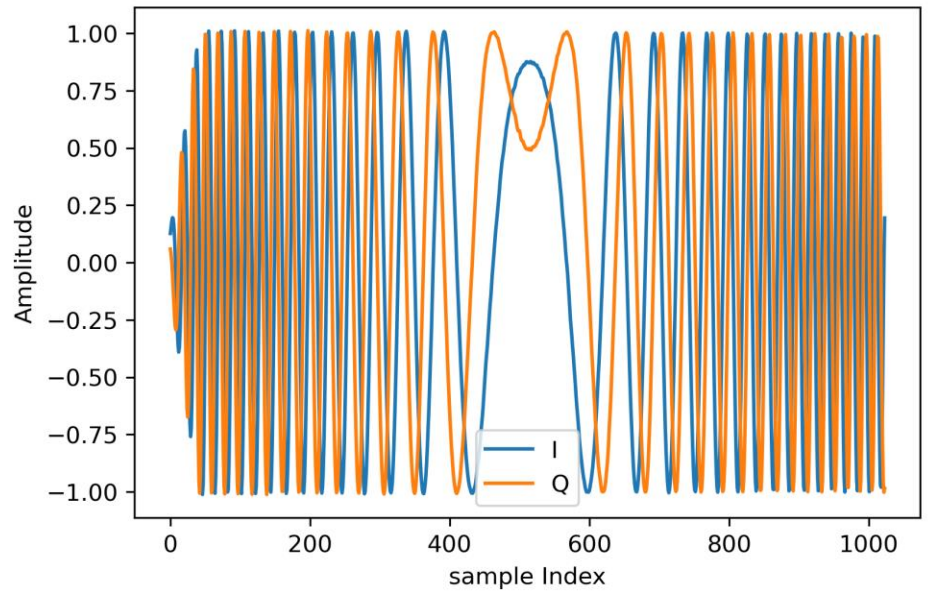
Dataset publicly accessible@: https://ieee-dataport.org/open-access/lorarffidataset

Methodology (Cont…)

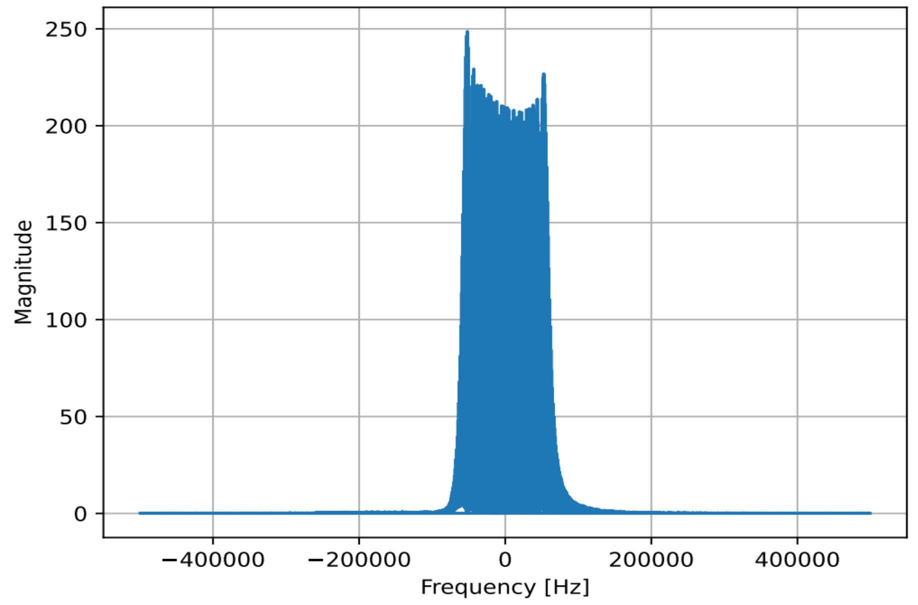
Signal Representation

- ✓ Time Domain IQ
- ✓ Frequency Domain (FFT)
- ✓ Amplitude/Phase
- ✓ Time Frequency Domain (Spectrogram)

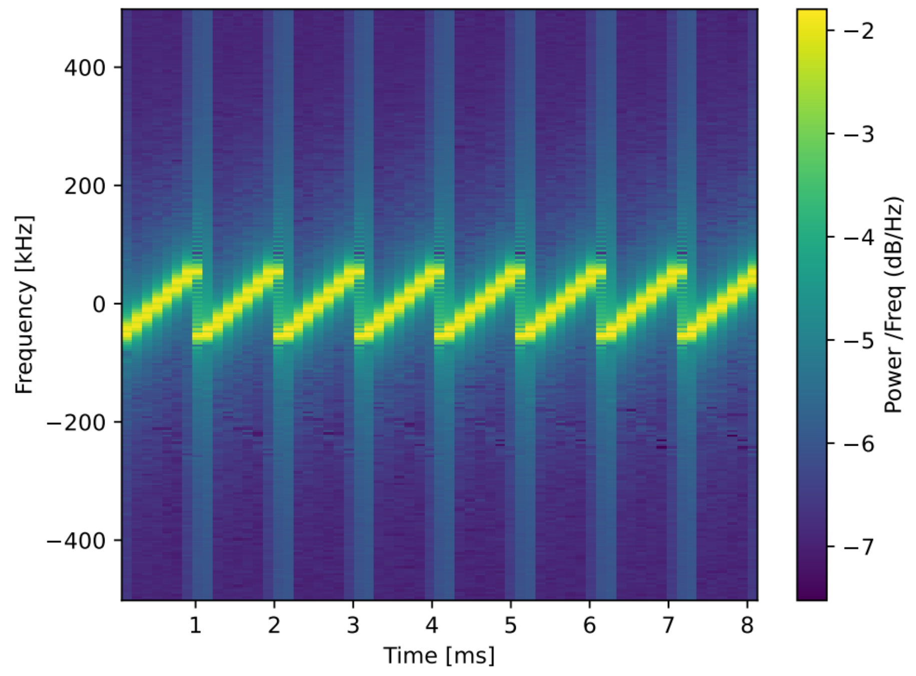
- IQ sequence of 8192 samples (8 preamble upchirps)
- Spectrogram:
  - Short Time Fourier transform (STFT)
  - Win_length=256
  - Overlap=50%
  - Cropping → final shape (102, 62)



(a) Time Domain IQ (First Symbol) of Preamble 1024 samples



(b) FFT of LoRa Preamble



(d) : Spectrogram of LoRa IQ (8 preamble upchirps: 8192 samples)

Fig 5: LoRa Signal Representation

Methodology: Deep Learning Models

ResNet Models for Spectrogram data

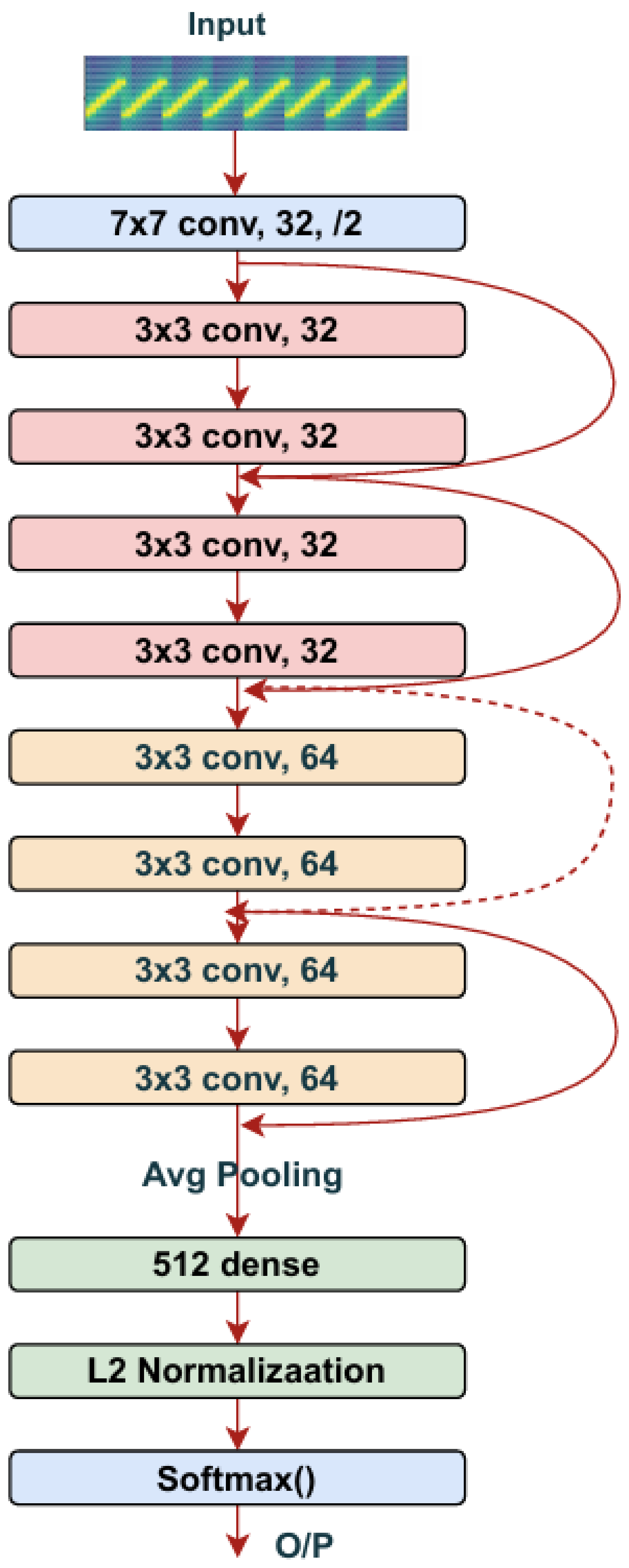


Fig: 6 Original ResNet Proposed by Shen et al (2022).

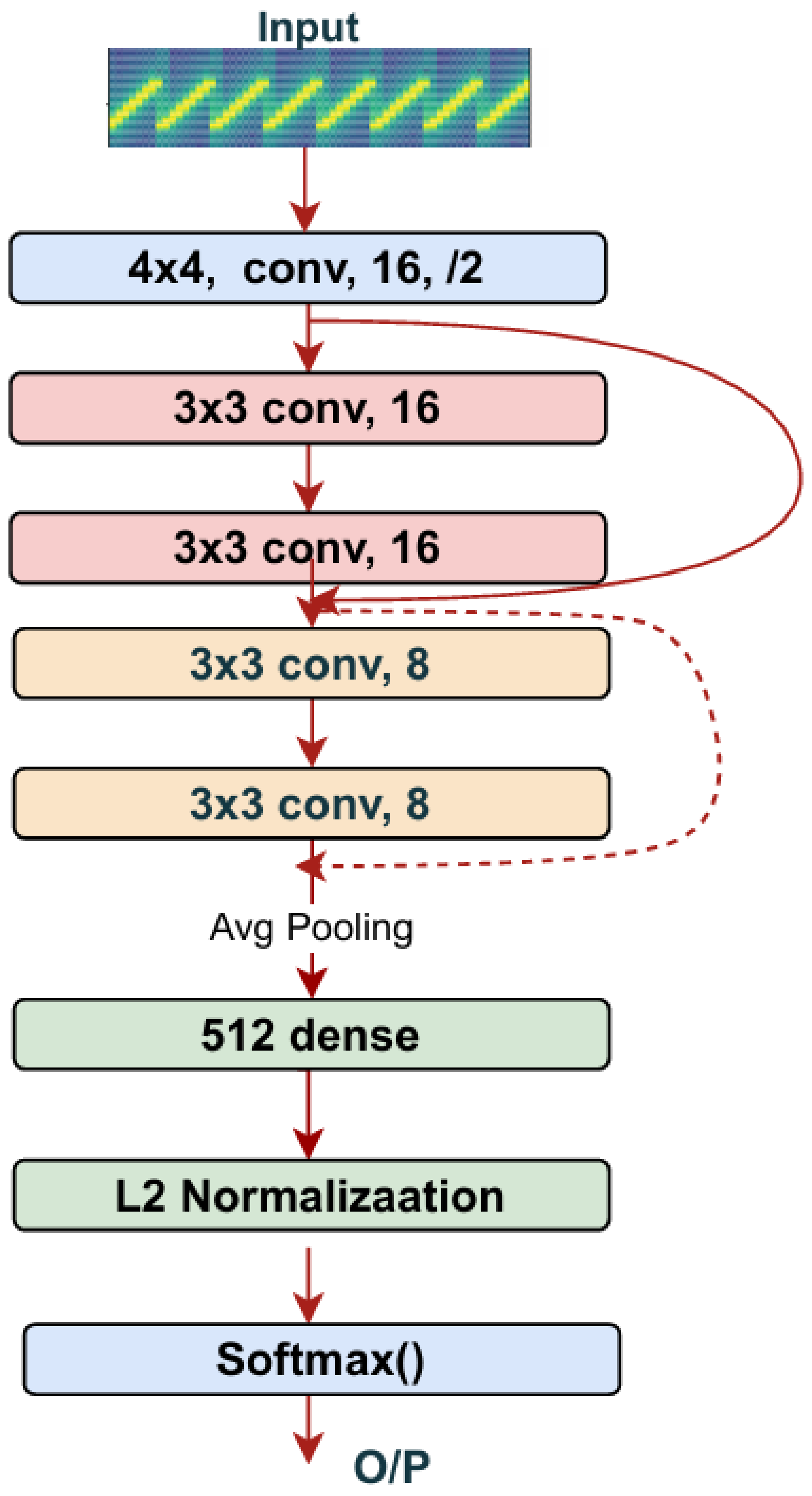


Fig: 7 Final Optimized (Opt. 4) ResNet Model

• 1D-CNN Model for IQ, FFT, A/phase data

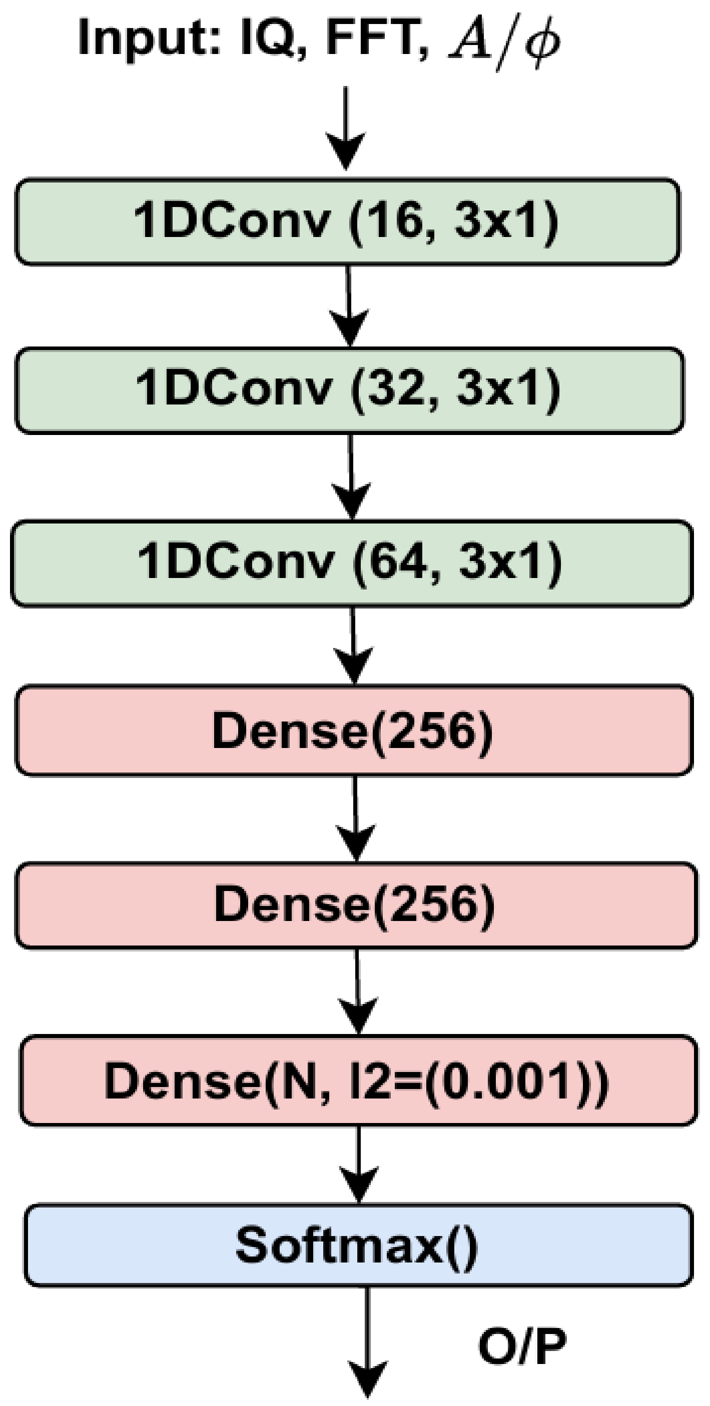


Fig 8: 1D-CNN Model for (IQ, Am/phase and FFT) Sequence data

• Model Training:

- Training set: 30K frames (1K per device)
- Test Set: 12K frames (400 per device)
- Optimizer: RMSprop (**initial LR:0.001**)
- Learning Rate Scheduler (every **20 epoch**)
- Loss function: categorical cross entropy
- L2 normalization: **0.01**
- Callback function
- Epoch: **400**

Results

1D-CNN (IQ, FFT, Amp/phase)

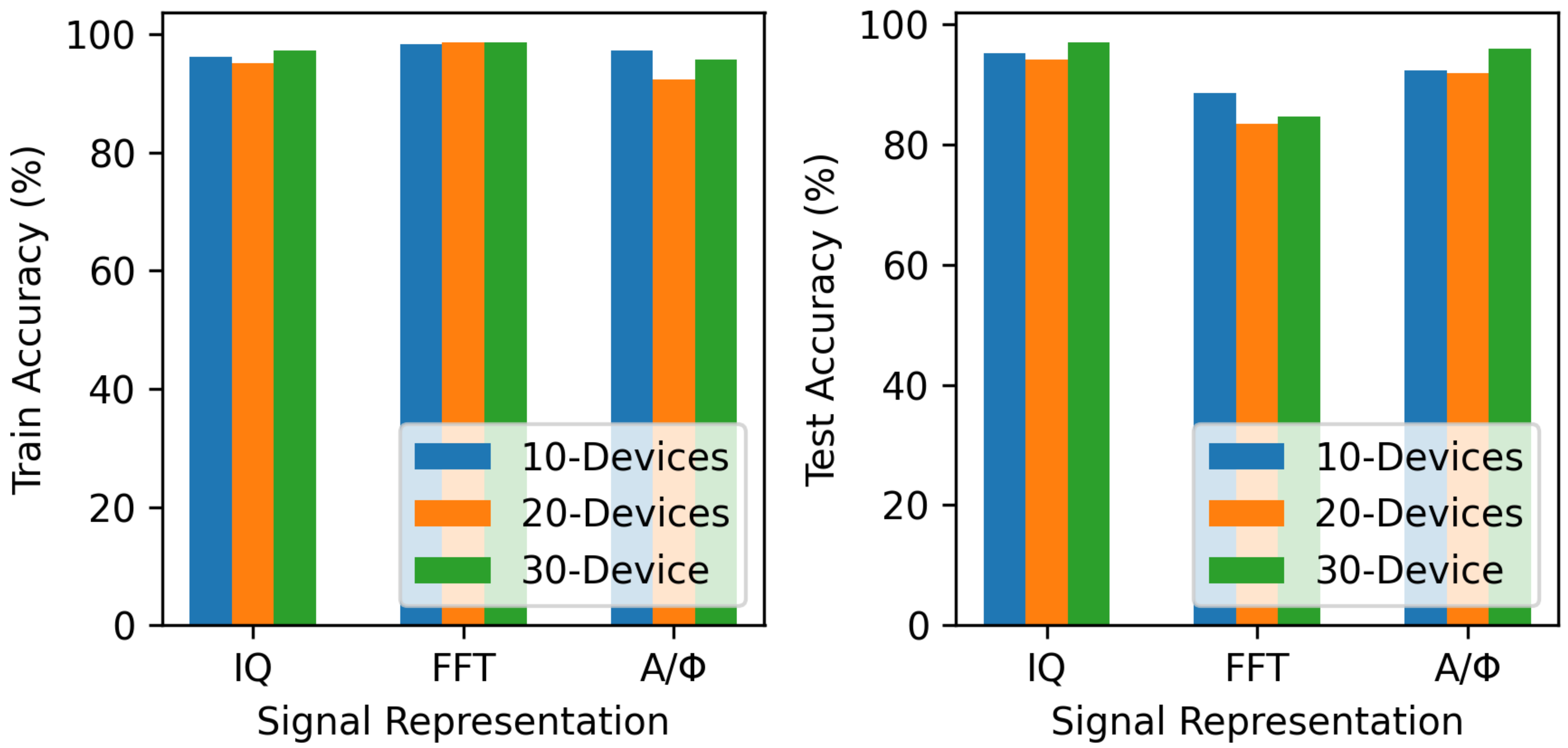


Fig 9: Train and Test accuracy of 1D-CNN Model Vs number of range of devices Using IQ, FFT,

Table I: 1D-CNN Model Accuracy Vs # of devices over different signal representations

	Train Accuracy (%)			Test Accuracy (%)		
# devices	**10**	**20**	**30**	**10**	**20**	**30**
1D-CNN						
IQ	96.24	95.21	97.26	95.20	94.21	97.06
A/ϕ	97.25	92.42	95.82	92.33	91.86	95.91
FFT	98.38	98.72	98.62	88.62	83.53	84.74

Table II: 1D-CNN Model Complexity

Type	# Epochs	Train Time (s)	Parameters	Size
IQ	123	563	98,478	834 KB
A/ϕ	154	855	98,478	834 KB
FFT	109	619	98,478	834 KB

Results (Cont...)

Original and Optimized ResNet Model

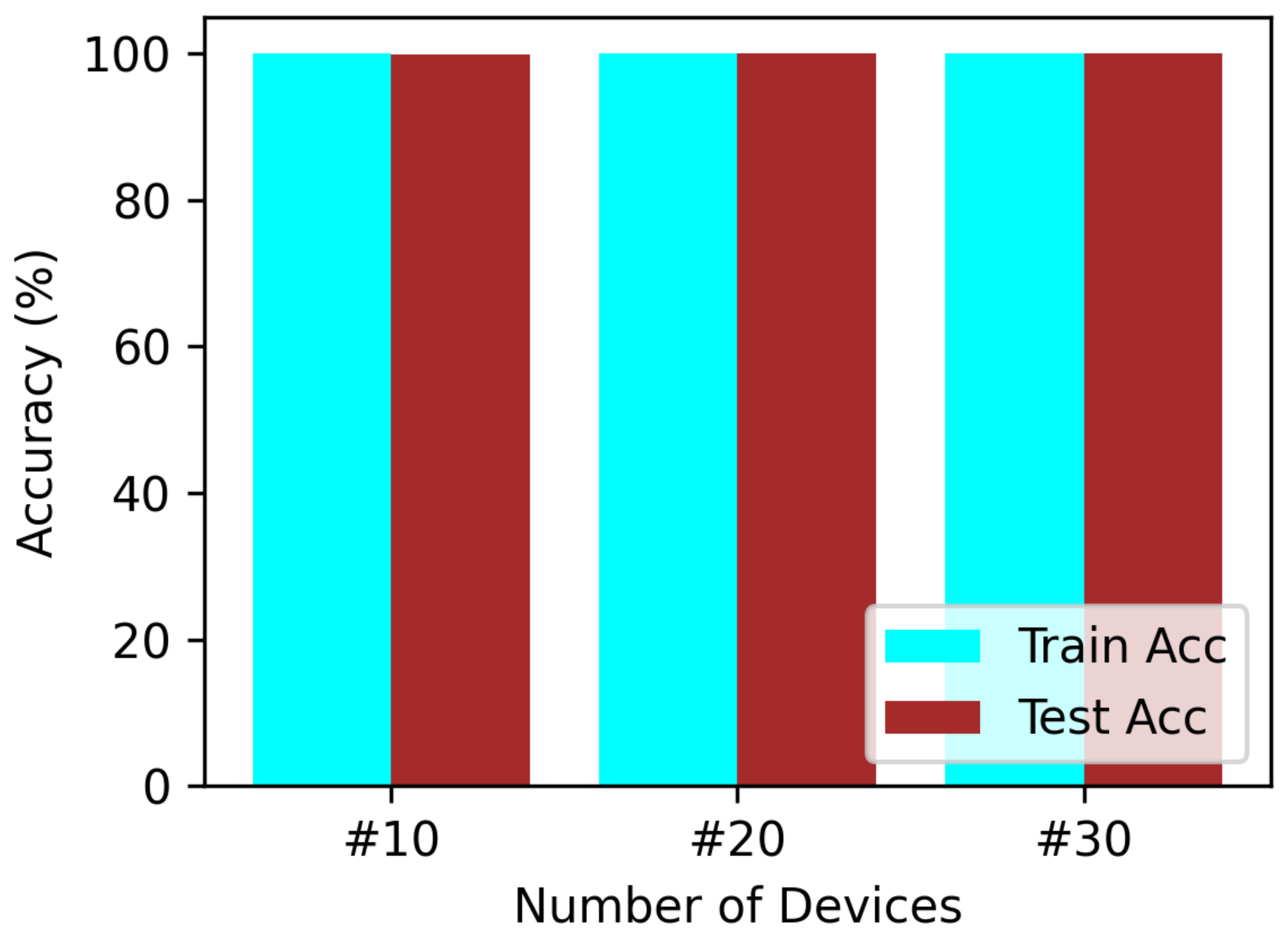


Fig 10: Train and Test accuracy **of** Original ResNet Model on different range of devices

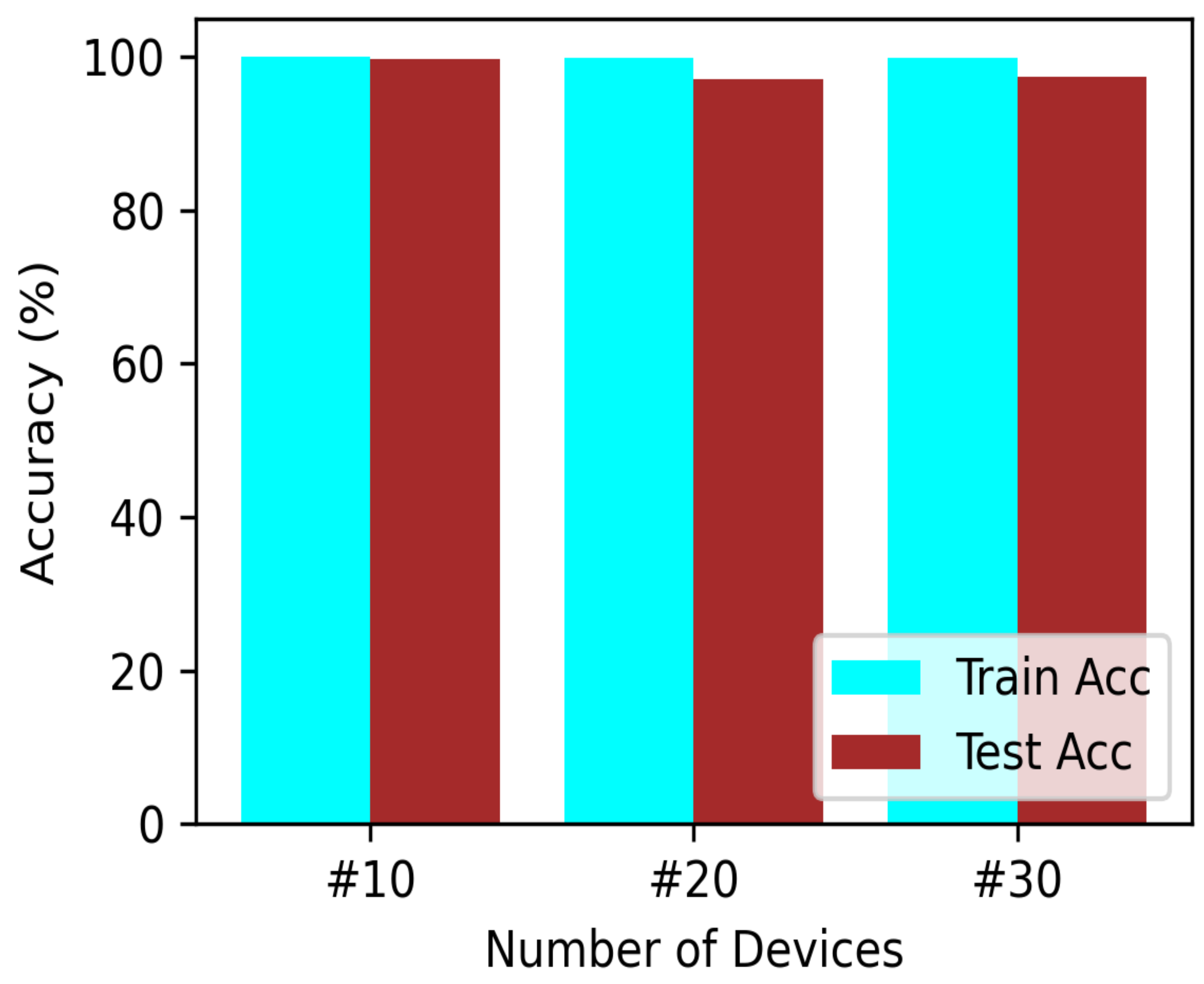


Fig 11: Train and Test accuracy of Final **Optimized (Opt. 4) ResNet Model** on different range of devices

Tabel III: Original Vs Optimized ResNet Models Performance (30 Devices)

Model	Parameters	Reduc. (%)	Train time (s)	Accuracy		Size (MB)
				Train	Test	
Original	12,475,422	0.00	1048	99.97	99.39	95.3
Opt. 1	6,203,150	50.28	668	99.97	98.93	47.5
Opt. 2	3,099,030	75.13	773	99.92	98.58	23.8
Opt. 3	1,554,842	87.55	540	99.23	78.63	12.0
Opt. 4	1,558,886	87.55	575	99.89	97.42	12.0

Results (Cont ...)

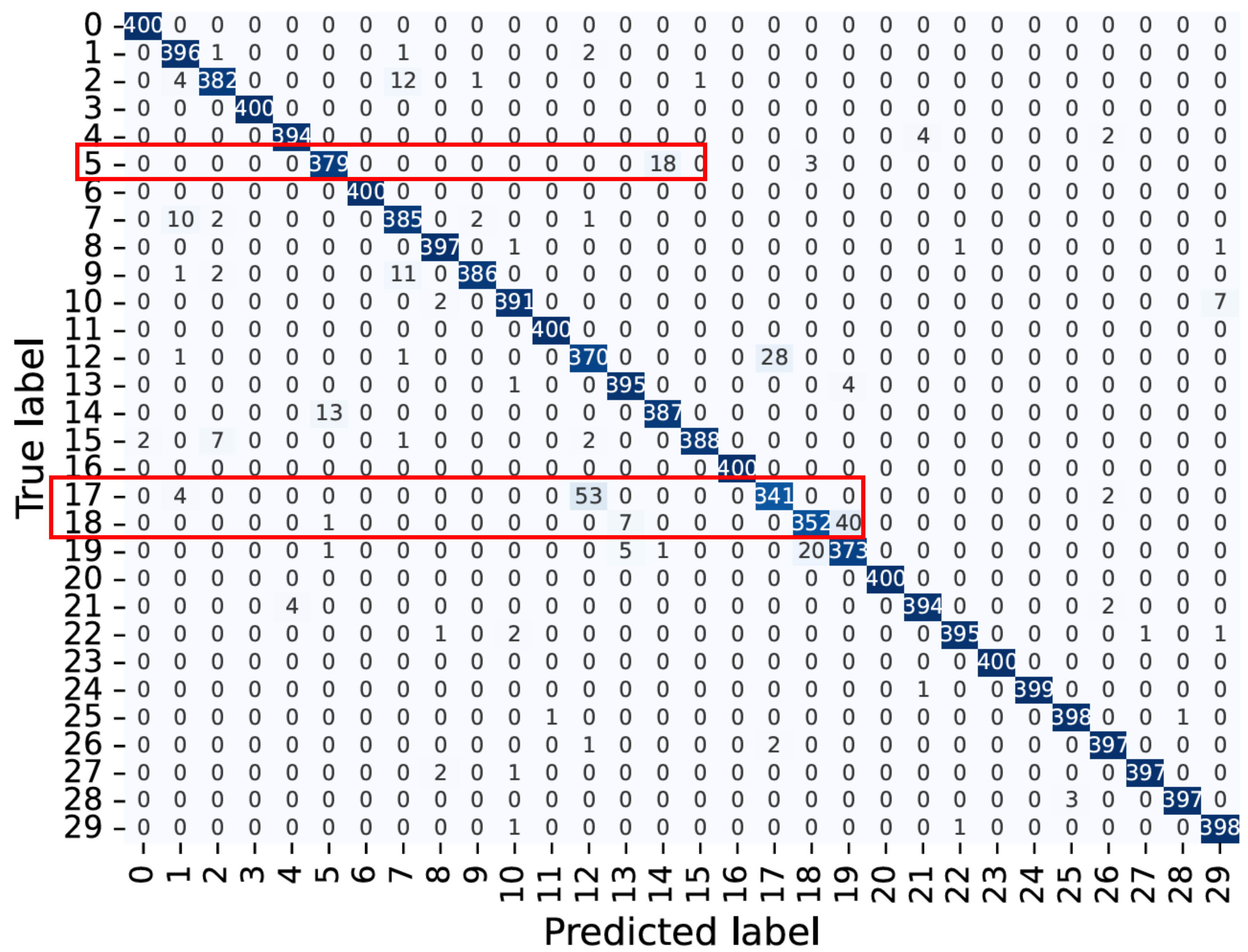


Fig 12: Confusion Matrix **(1D-CNN using IQ)**

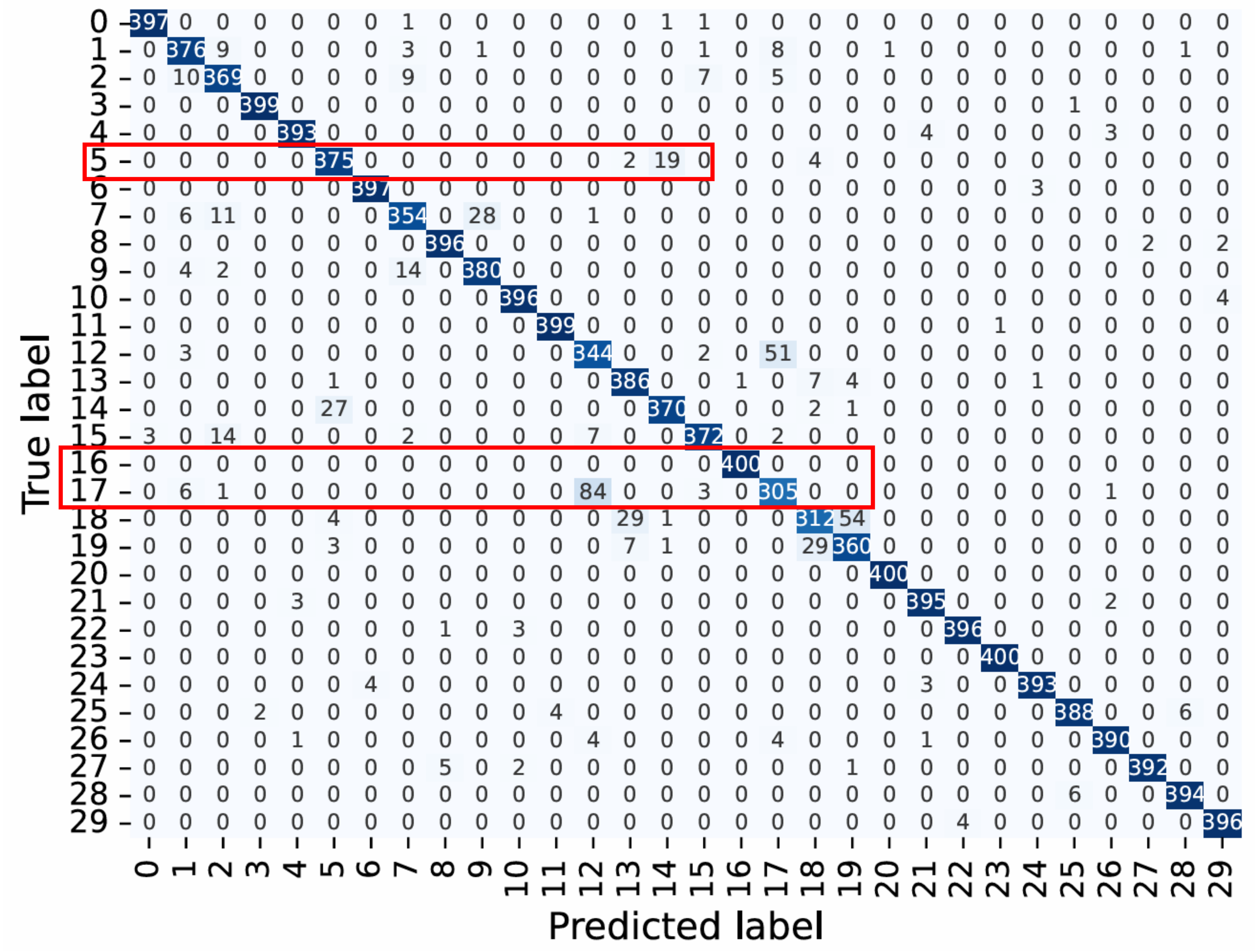


Fig 13: Confusion Matrix **(1D-CNN using Amp/Phase)**

Results (Cont…)

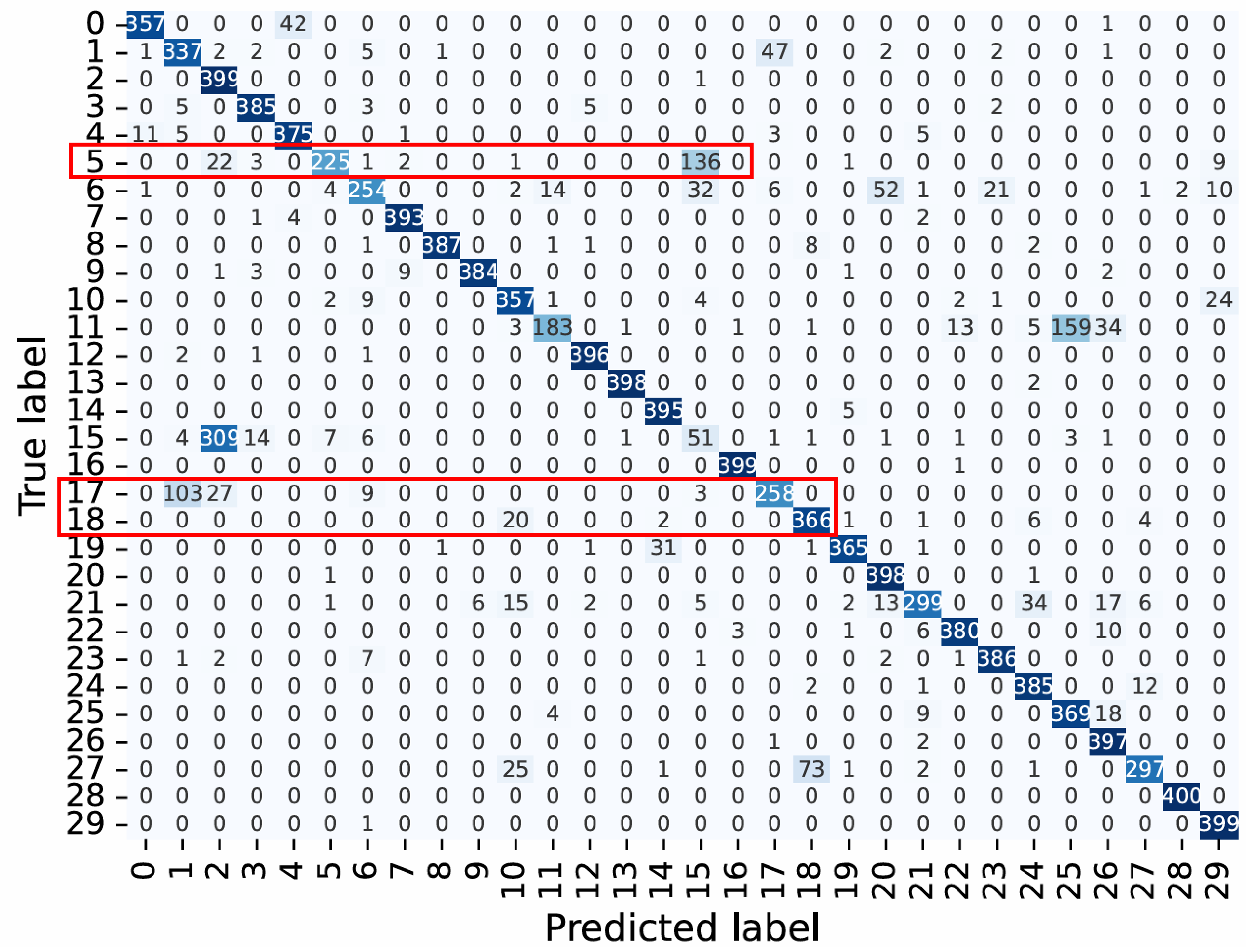


Fig 14: Confusion Matrix **(1D-CNN using FFT)**

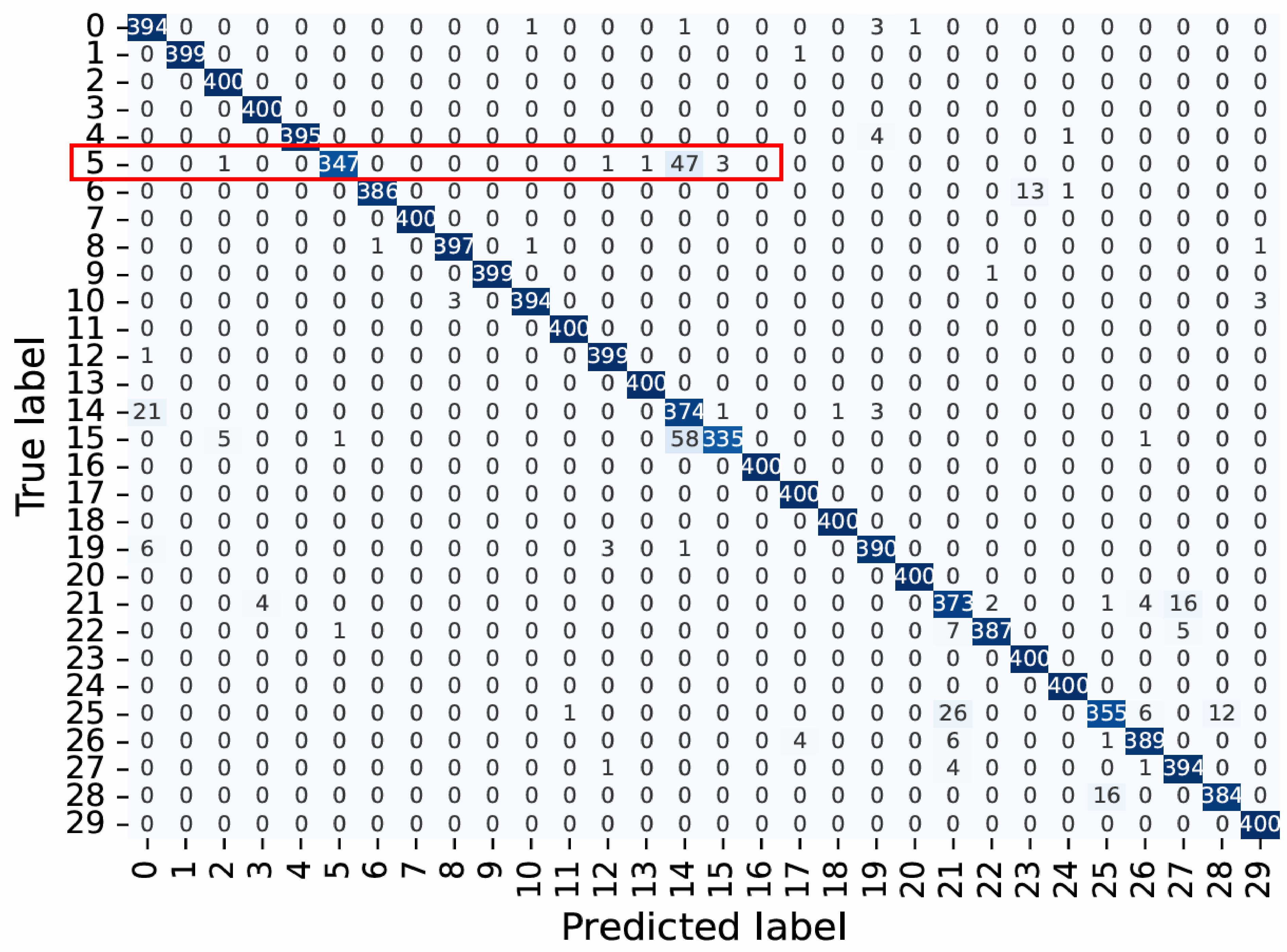


Fig 15: Confusion Matrix **(Final Optimized ResNet Opt.4)**

Conclusion and Future Work

- ✓ Choosing the right signal representation is crucial for DL based LoRa RFFI
- ✓ In our case, for 1D-CNN, time domain IQ signal provides the best performance
- ✓ The complex models can be optimized into lightweight model without compromising the performance

- **Future Research:**

- ✓ Combining IQ and FFT
- ✓ Channel robustness of DL based LoRa RFFI systems
- ✓ scalability
- ✓ Open-set identification

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THANK YOU!

Aqeel Ahmed (PhD Researcher, University of Mons, Belgium)

Until Next Year!

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