LoRaSONN: A Novel Self-Operational Neural Network Learning Framework for RF-Fingerprint Identification of LoRa Devices

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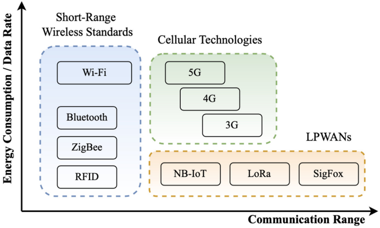
Introduction to Long Range (LoRa)

- Wireless communication technology based on Low Power Wide Area Networks(LPWANs)
- Operates in the unlicensed sub-GHz industrial, scientific, and medical (ISM) band, providing an open-source advantage
- Affordable devices capable of communicating over long distances with low power consumption
- Finds use in many Internet of Things (IoT) applications such as smart healthcare, smart agriculture and smart cities



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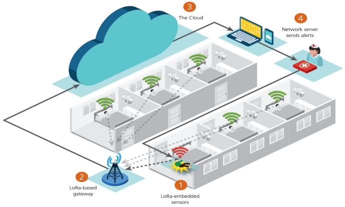

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Figure 1: (a) Comparison with legacy communication technologies [1], (b) LoRa-based smart healthcare system [2]

Radio Frequency Fingerprinting Identification (RFFI)

- RFFI is the technique used to identify IoT devices based on their RF fingerprints
- The fingerprints exist primarily due to unique hardware impairments which distort the transmitted signals
- The **traditional** methods of feature extraction based on power spectral density, Hilbert Huang Spectrum, carrier frequency offset etc., often prove ineffective due to the overlap of many hardware characteristics
- **Deep Learning** based RFFI methods mitigate the need for manual feature extraction, thereby reducing the preprocessing complexity

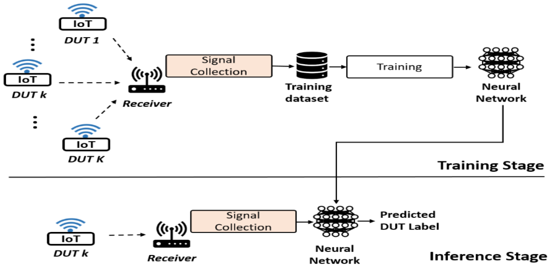

Figure 2: Deep Learning based RFFI [3]

Motivation and Database Description

- Prior works by Shen et al. [4] and [5] have classified and authenticated various LoRa devices using their open-source dataset [5]
- In both works, it was evident that classification accuracy declines as the number of test devices increases; therefore, there is a need for an all-encompassing model which can classify a variety of devices at once
- The dataset comprises IQ samples from the preamble part of 60 devices from 3 different manufacturers

Table 1: Description of the devices used

Device Index	Model	Chipset
1-45	Pycom LoPy4	SX1276
46-50	mbed SX1261 shield	SX1261
51-55	Pycom FiPy	SX1272
56-60	Dragino SX1276 shield	SX1276

➤ Through our proposed framework, we aim to classify all the 60 devices at once

Proposed Framework

Objective: To develop a Self Operational Neural Network (SONN) model for classifying 60 different LoRa devices

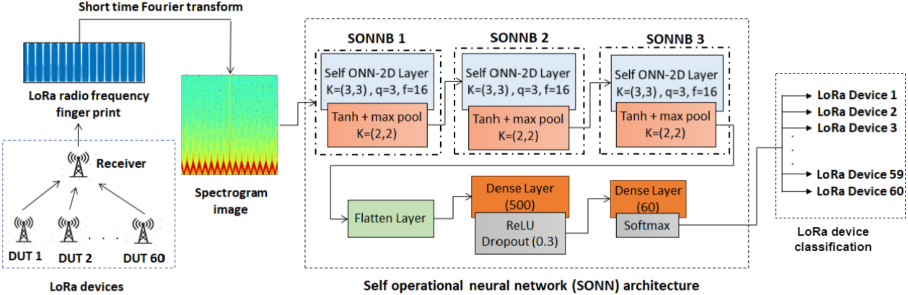

Figure 3: Block Diagram of the Proposed SONN-based LoRa RFFI

Preprocessing of Received Signals

- To represent the Time-Frequency Characteristics of LoRa signals, which are non-stationary, we have converted time domain signals into spectrogram images
- Firstly, the short-time Fourier transform (STFT) ($\mathcal{S}_{lr}(h, f)$) is calculated from the LoRa signal ($lr(t)$), which is obtained by computing the magnitude of the IQ samples of the raw input LoRa RFF
- The STFT of the ($lr(t)$) can be evaluated using the following equation [6]:

$$\mathcal{S}_{lr}(h, f) = \int_{-\infty}^{\infty} lr(t) \cdot \mathcal{W}(t-h) \cdot e^{-j2\pi ft}, \tag{1}$$

  where $\mathcal{W}(t)$ is the Hamming window.
- Lastly, the spectrogram ($\mathcal{SP}_{lr}(h, f)$) TFR is obtained by computing the squared magnitude of each of the elements of $\mathcal{S}_{lr}(h, f)$. This process can be mathematically described as:

$$\mathcal{SP}_{lr}(h, f) = |\mathcal{S}_{lr}(h, f)|^2 . \tag{2}$$

Preprocessing (Contd.)

- The spectrograms are converted into greyscale images of shape $112 \times 112 \times 1$ and fed to the proposed SONN

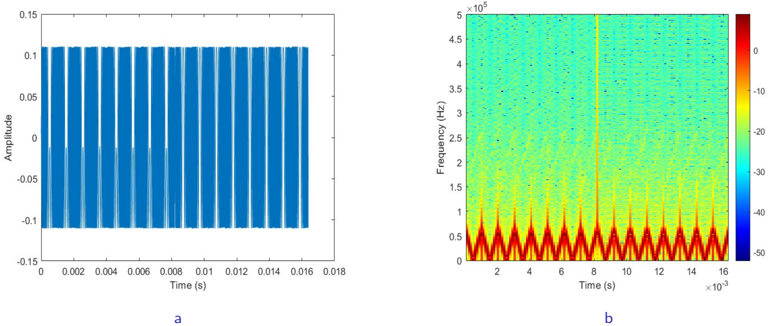

Figure 4: (a) Time domain LoRa signal, (b) Spectrogram representation of signal collected from device Pycom LoPy4

Brief SONN Description

- SONN is based on the non-linear Generative Operational Perceptron model (GOPM), which is an improvement of the vanilla operational neural networks (VONN) by addressing two limitations:
  - The requirement of a predefined library of operators
  - The need to search within that library to discover the ideal set of operators
- A novel GOPM is employed, which can create any non-linear function for each kernel element using a truncated Mac-Laurin series expansion during the training phase [7]

$$\begin{aligned}\beta(\mathcal{G}_{Fout,1}, \mathcal{G}_{Fout,2} ..., \mathcal{G}_{Fout,q}, \mathcal{I}) &= \sum_{c=1}^{C} \mathcal{G}^{T}_{Fout,c} \cdot \mathcal{I}^{c} \\ &= \mathcal{G}^{T}_{Fout,1}\mathcal{I} + \mathcal{G}^{T}_{Fout,2}\mathcal{I}^{2} + ... + \mathcal{G}^{T}_{Fout,C}\mathcal{I}^{C},\end{aligned} \tag{3}$$

where $\mathcal{I}^c$ is c^{th} power of the original tensor $\mathcal{I}$ and $\mathcal{G}_{Fout,c}$ denotes the learnable weights corresponding to each $\mathcal{I}^c$, which will be learnt by gradient descent method. Therefore, the GOPM present in the SONN transforms the input tensor by the following equation:

$$\mathcal{I}_{Fout} = \sum_{c=1}^{C} \mathcal{G}^{T}_{Fout,c} \cdot \mathcal{I}^{c} + \mathfrak{B}_{Fout}. \tag{4}$$

Classification Results and t-SNE Plot Visualisation

- The proposed LoRaSONN model can classify 60 LoRa devices and does an excellent job of generalising over all the manufacturers and types of devices by achieving an accuracy of 97%
- The model can extract meaningful features from the raw data, as can be seen from the 2D t-distributed stochastic neighbour embedding (t-SNE) plot below:

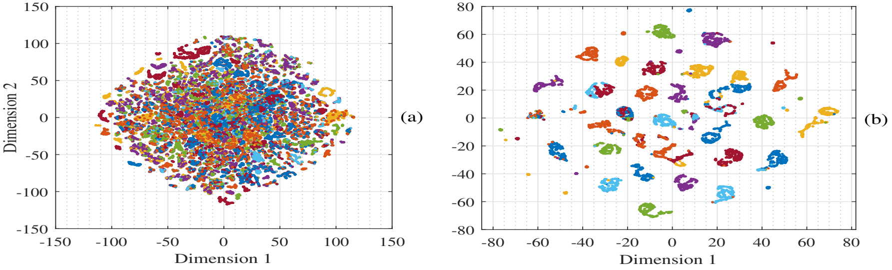

Figure 5: 2D-tSNE feature plot of (a) raw Time-Frequency Representation(TFR), and (b) the embeddings extracted from the first dense layer

Classification Results(contd.)

- Performance Metrics: We have evaluated the model using several metrics like classification accuracy (acu), specificity(spc), recall(rcl) and F1-score. These can be formulated as [6], [8]:

$$acu = \frac{TP + TN}{TP + TN + FN + FP}, sns/rcl = \frac{TP}{TP + FN}, spc = \frac{TN}{TN + FP}, \tag{5}$$

$$prc = \frac{TP}{TP + FP}, F1 - score = \frac{2 \times prc \times rec}{prc + rec}, \tag{6}$$

where TP, TN, FP, and FN denote the true positive, true negative, false positive, and false negative of classification, respectively

Table 2: Fold-Wise Classification Performance of LoRaSONN

Performance parameters (%)	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
Acu	97.01	96.91	97.13	96.97	97.01	**97.00**
Spc	96.9	96.88	96.98	96.89	97	**96.93**
Rcl	96.92	97.01	97.2	96.75	97.19	**97.01**
Prc	96.98	97.05	97.11	96.99	97.08	**97.04**

Comparison with existing models

- Comparison of the proposed LoRaSONN with
  - Transfer-learning-based models
  - Existing state-of-the-art(SOTA) models

Table 3: Performance Comparison of LoRaSONN with Different Transfer Learning Models

Model	**Model evaluation parameters(%)**					
	No. of parameters (M)	**No. of FLOPs**	**Acu**	**Prc**	**Rcl**	**F1-score**
VGG-16 [9]	138	15.59361G	96.50	96.94	96.65	96.79
ResNet 50 [9]	26.35	4.12473G	60.17	72.33	61.22	57.4
MobileNet V2 [9]	4.2	0.57279G	79.93	69.67	72.88	71.23
Proposed	**2.37**	**0.00255G**	**97.00**	**97.04**	**97.01**	**96.97**

Comparison with existing models (contd.)

Table 4: Performance Comparison of Proposed LoRaSONN with Existing SOTA Techniques on RFF-Based LoRa Device Classification

Reference	TFR	Network used	Classification method	Number of devices	Database	Performance parameters (%)
Shen et al. [4]	Spectrogram	CNN	Closed set	20	Collected own data	Acu: 97.61
Shen et al. [5]	Spectrogram	CNN KNN	Open set authentication, classification	Different subsets of data	LoRa RFFI	Acu: 98.50 (DUT 1-10); 98.40 (DUT 31-40); 88.70 (DUT 46-60)
Proposed work	**Spectrogram**	**SONN**	**Closed set**	**60**	**LoRa RFFI**	**Acu: 97.00, Prc: 97.04, Rcl: 97.01, F1-score: 96.97**

Conclusion

- Investigated the potential of SONN-based DL architecture in conjunction with the spectrogram TFR to classify the LoRa devices using the RFFs.
- The framework illustrates the superiority of SONN over vanilla pre-trained CNNs for RFF-based LoRa device identification by achieving higher classification rates with fewer parameters and computational costs.
- Using LoRaSONN, we surpassed existing state-of-the-art algorithms for RFF-based closed-set sixty class LoRa device detection by achieving the highest accuracy of 97.00%.

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Thank You