Cognitive Radio Spectrum Sensing and Allocation: A Low-Complexity Deep Learning Approach

Hamza Ahmed Abushahla (90279) | Ghanim Abdulla Al-Ali (89804) | Sultan Khalid Abdalla (89987) | Muhammad Ismail Sadaqat (90340)

Advised by: Dr. Mohamed AlHajri & Dr. Taha Landolsi

Problem Statement

- Exponential growth in mobile and IoT devices strains 4G, 5G, and future 6G networks [1].
- Licensed spectrum bands are often underutilized, causing congestion and interference [2].
- Resultant spectrum scarcity threatens communication system efficiency [3].

Motivation

- **Cognitive radio (CR)** is a significant and active research topic.
- **Deep Learning (DL)** adapts to various spectral patterns and interference.
- Intersection with research in **Embedded Machine Learning (TinyML)**.
- Addressing challenges in **energy-efficient computing** and **sustainable** spectrum management.

Objectives

- Develop a low-complexity **convolutional neural network (CNN)**-based algorithm for real-time **spectrum sensing (SS)** and allocation.
- Enhance spectral efficiency by optimizing the utilization of available frequency bands.
- Design a hardware setup to simulate a centralized CR network, showcasing the SS algorithm in a practical scenario.

Methodology

- Established hardware setup with a central node, two primary users (PUs), and two secondary users (SUs). PUs are assigned frequency bands using frequency division multiple access (FDMA): 433 MHz and 500 MHz respectively.
- CNN model trained on both an acquired dataset [4] and a generated one to accurately determine the presence or absence of PUs in the spectrum.
- Model quantized using TensorFlow Lite and deployed on a Raspberry Pi (central node).
- Central node runs the CNN-based SS algorithm to detect spectrum holes and allocate them to SUs on a first-come-first-served basis.

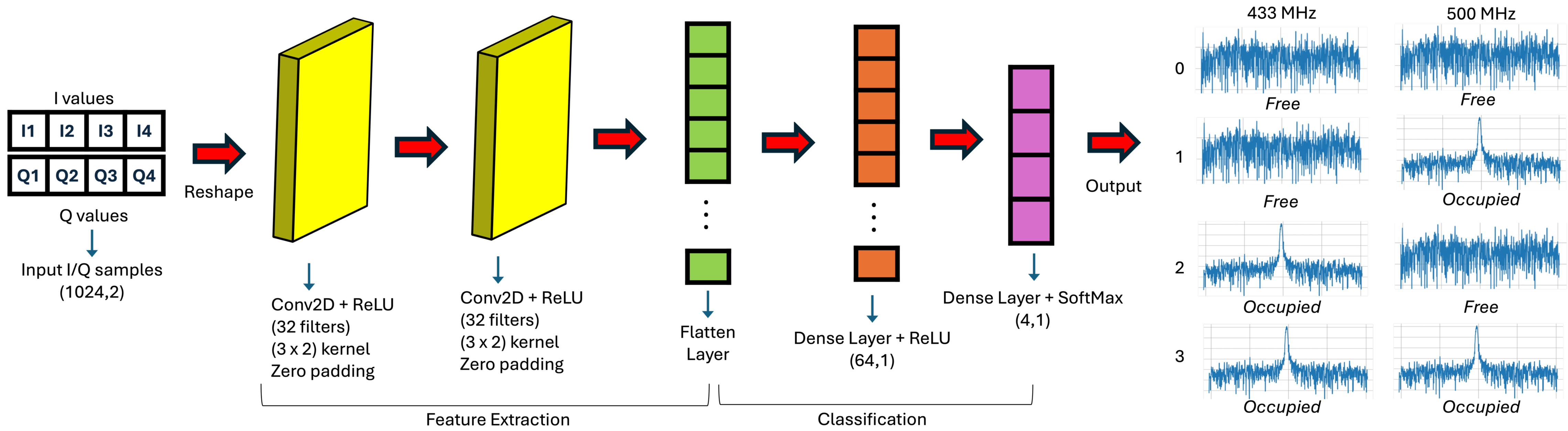

Fig. 1: Network architecture of the CNN model

System Diagram

- Central node monitors 433 MHz and 500 MHz; receives SU requests via 440 MHz.
- SU-1 requests transmission, placed first in FIFO queue.
- RTL-software defined radio (SDR) captures I/Q samples; CNN-SS model outputs [1,0] indicating 433 MHz occupied, 500 MHz free.
- Central node allocates free 500 MHz to SU-1.

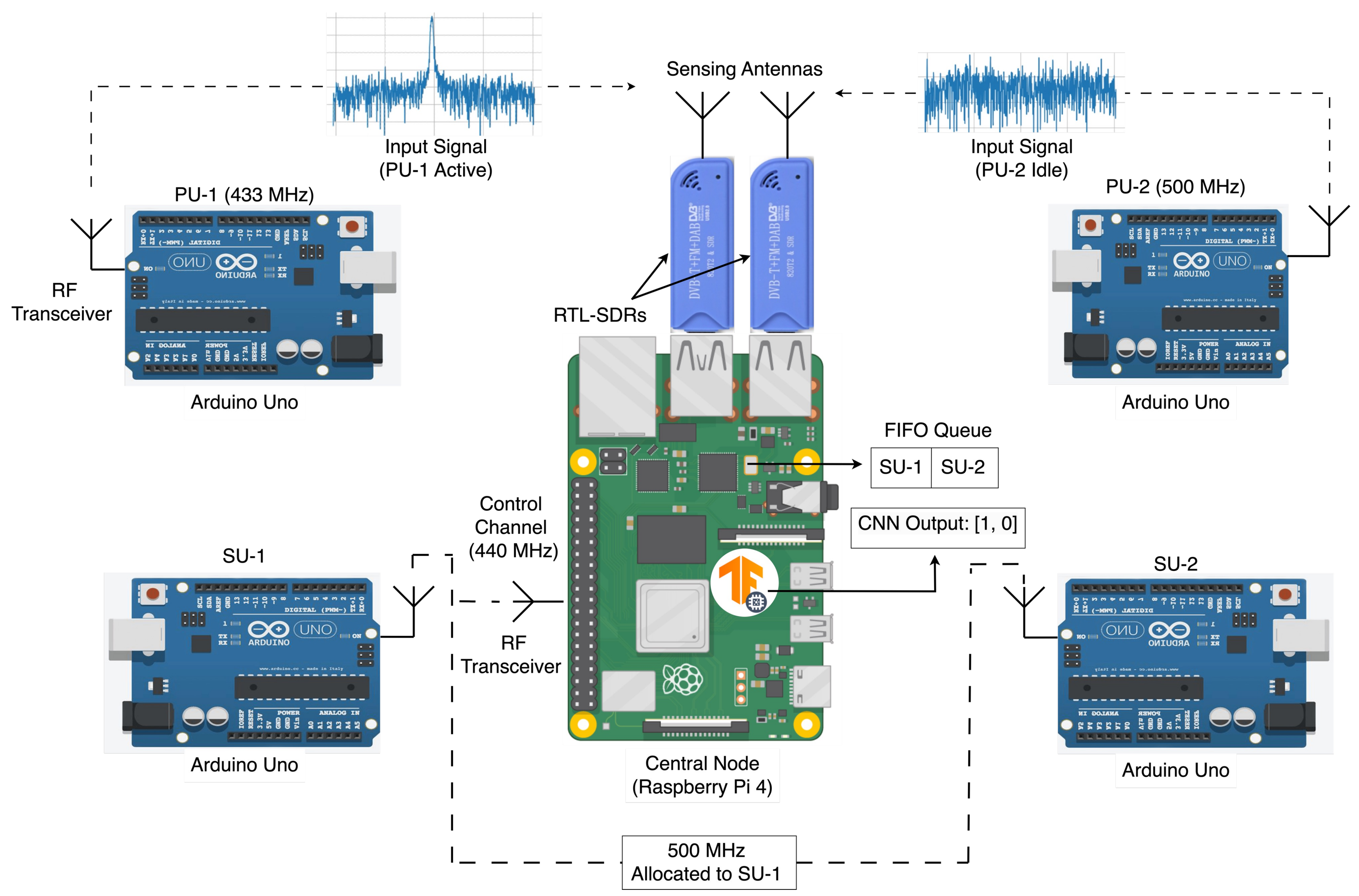

Fig. 2: System architecture and modeled scenario

Results

- Below are the results comparing model performance before and after applying different levels of quantization, presented for both the acquired SDR dataset and our experimentally generated dataset:

Table 1: Performance on acquired SDR dataset

Model	Accuracy (%)	Size (MB)
Baseline (Float 32)	93.73	12.14
Float 16	93.74	4.058
TF Lite Float 16	93.77	2.021

Table 2: Performance on generated dataset

Model	Accuracy (%)	Size (MB)
Baseline (Float 32)	96.43	48.12
Float 16	96.43	16.05
TF Lite Float 16	96.18	8.02

- Quantization achieved an **83%** reduction in the model size with no loss in accuracy.
- This ensures **low complexity**, enabling optimal performance for sustainable operation on low-powered devices in real-time applications.

References

[1] A. Upadhye, P. Saravanan, S. S. Chandra, and S. Gurugopinath, “A Survey on Machine Learning Algorithms for Applications in Cognitive Radio Networks,” in 2021 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Jul. 2021, pp. 01–06. doi: 10.1109/CONECCT52877.2021.9622610.

[2] J. Xie, J. Fang, C. Liu, and X. Li, “Deep Learning-Based Spectrum Sensing in Cognitive Radio: A CNN-LSTM Approach,” IEEE Commun. Lett., vol. 24, no. 10, pp. 2196–2200, Oct. 2020, doi: 10.1109/LCOMM.2020.3002073.

[3] M. D. Shehabeldin, “Learning-based spectrum sensing and access for cognitive radio systems,” M.S. thesis, American University of Sharjah, Sharjah, UAE, 2015.

[4] D. Uvaydov, S. D’Oro, F. Restuccia, and T. Melodia, “DeepSense: Fast Wideband Spectrum Sensing Through Real-Time In-the-Loop Deep Learning,” in IEEE INFOCOM 2021 - IEEE Conference on Computer Communications, Vancouver, BC, Canada: IEEE, May 2021, pp. 1–10. doi: 10.1109/INFOCOM42981.2021.9488764.