COE491 Senior Design Presentation

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

Presented By:

Hamza Ahmed Abushahla, 90279
Ghanim Abdulla Alarai Al-Ali, 89804
Sultan Khalid Abdalla, 89987
Muhammad Ismail Sadaqat, 90340

Advised By:

Dr. Mohamed AlHajri

Dr. Taha Landolsi

Table of Contents

Problem Statement

- Exponential growth of mobile and IoT devices
- Unprecedented demand for radio frequency (RF) spectrum [1]
- Pushing 4G and 5G bands to their limits [1]
- Licensed spectrum bands often underutilized [5]
- Congestion, interference, and performance issues
- Spectrum scarcity threatens communication system efficiency [7]

Motivation

Cognitive radio (CR) is a significant and active research topic (Approx. 30K Publications)

Deep learning (DL) improves spectrum sensing (SS)

Adapts to various spectral patterns and interference

Intersects with embedded Machine Learning (ML), energy-efficient computing, and sustainability

Literature Review

CR Fundamentals [7, 10]

- RF spectrum users: Primary Users (PUs) & Secondary Users (SUs)
- Spectrum holes concept
- CR Networks: Centralized & Distributed

uper

ral N

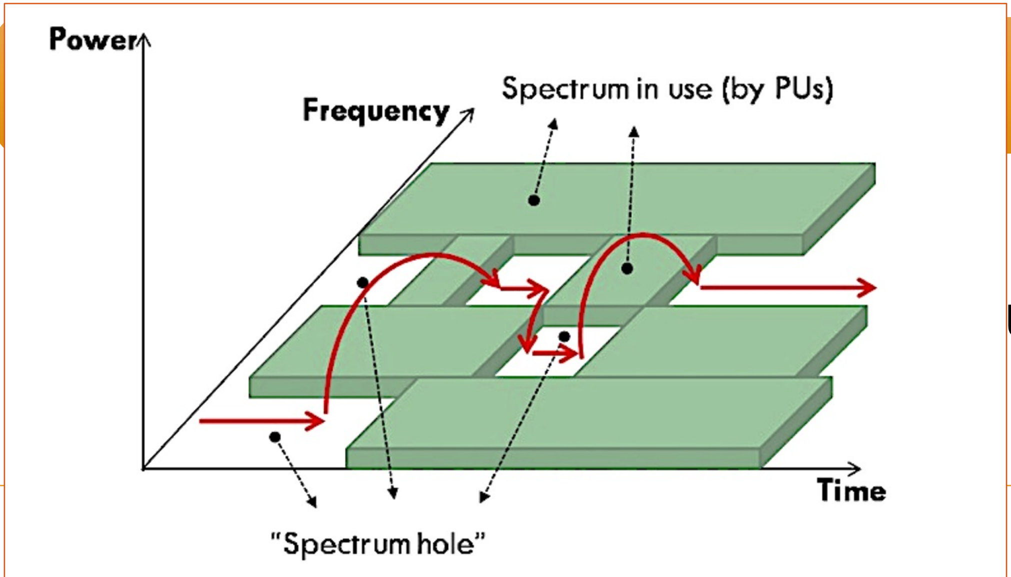

Fig. 1. Spectrum hole concept [7]

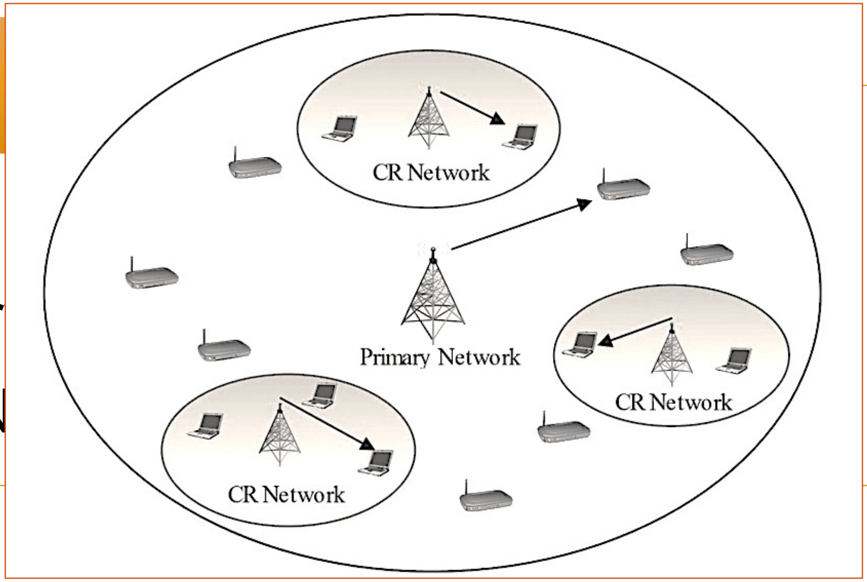

Fig. 2. CR networks within a primary network [10]

Literature Review

Spectrum Allocation [35, 40]

- Dynamic spectrum allocation (DSA) in centralized CR networks
- Processes SU requests on a first-come-first-serve (FCFS) basis
- Allocates spectrum holes to SUs based on real-time availability

Hardware Platforms [42, 43]

- Low-cost and efficient hardware platforms for SS
- Microcontrollers, RF transmitters, and USB-software defined radio (SDR)
- Embedded ML and DL-based SS algorithms

Design Objectives

A low-complexity CNN-based algorithm for SS

Queueing model for DSA

Centralized CR network architecture

Hardware implementation to showcase algorithm in a practical scenario

Implementation: Hardware

- Central node
- PU node
- SU node
- RTL-SDR
- RF Transceivers
- Sensors
- System Interface

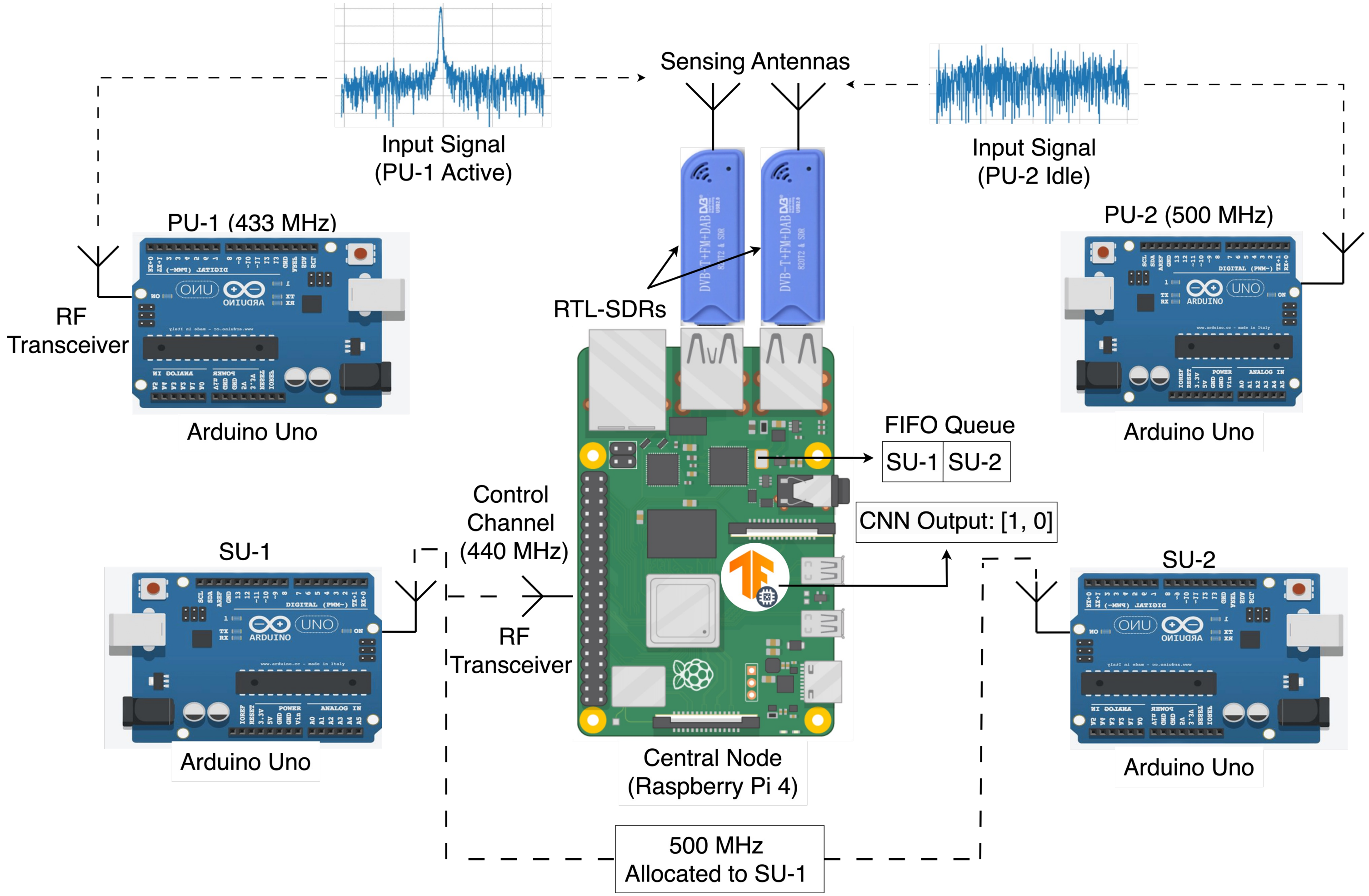

Fig. 3. System block diagram

Implementation: Software

- Frequency Division Multiple Access (FDMA)
- Control Channel: 440MHz
- In-phase & quadrature (I/Q) samples
- Compressed CNN-based SS algorithm
- DSA queue for SU spectrum utilization

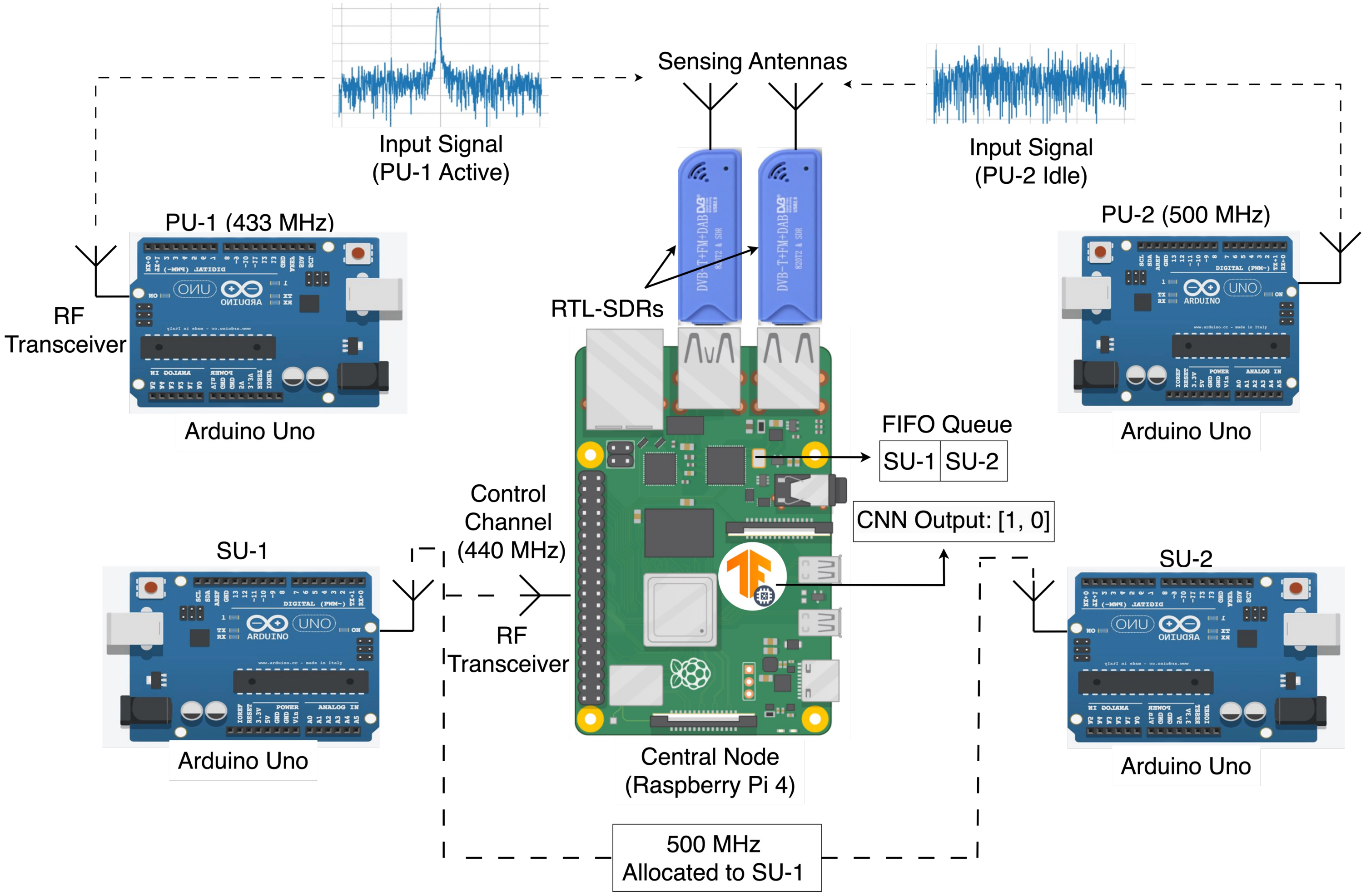

Fig. 3. System block diagram

Implementation: CNN-Based DL Model

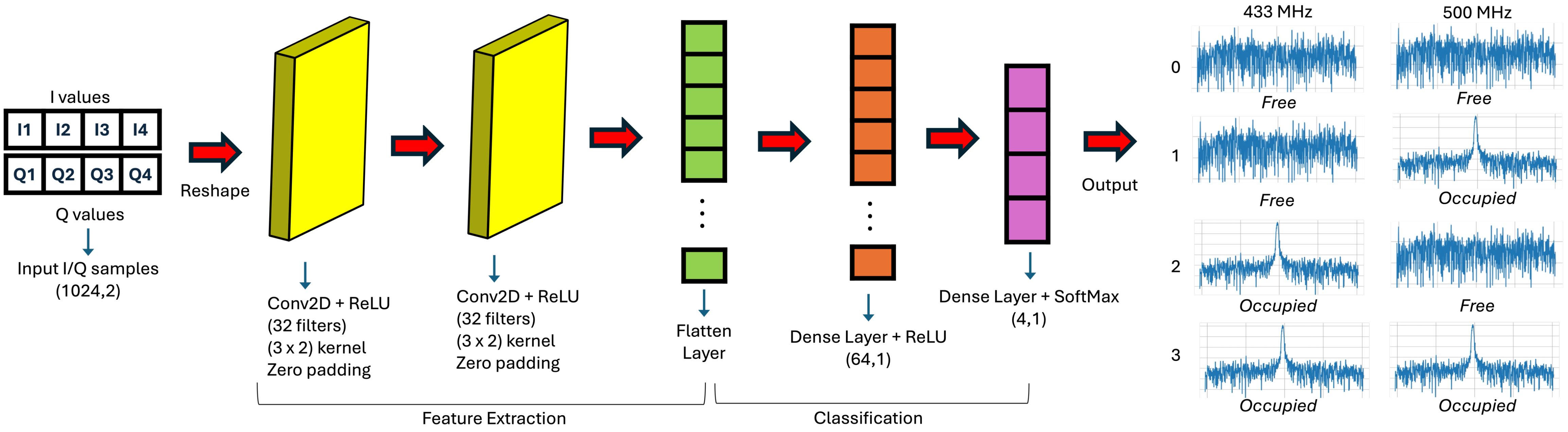

Fig. 4. Network architecture of the CNN model

Implementation: Model Training

Acquired “SDR Dataset” [43]

- Non-synthetic dataset emulating real Wi-Fi communications
- I/Q samples from four 5-MHz-wide channels (20 MHz total)
- Captured using USRP N210 SDRs via GNU Radio
- Dataset divided: 80% for training, 10% for validation, 10% for testing

Our Collected Dataset

- 300,000 I/Q samples from 433 MHz and 500 MHz
- Captured through GNU Radio using two RTL-SDR antennas
- Arduino devices acted as PU transmitters for four scenarios
- Energy detection used to determine frequency occupancy
- Dataset divided: 80% for training, 10% for validation, 10% for testing

Implementation: Training, Validation, and Testing Results

- **Acquired “SDR Dataset”:**
  - Trained on 287,971 data samples over 15 epochs
    - Achieved high accuracy of 98.54% with low loss of 0.0473
  - Tested on separate set of 31,997 data samples
    - Attained high accuracy of **93.73%** with loss of 0.2255

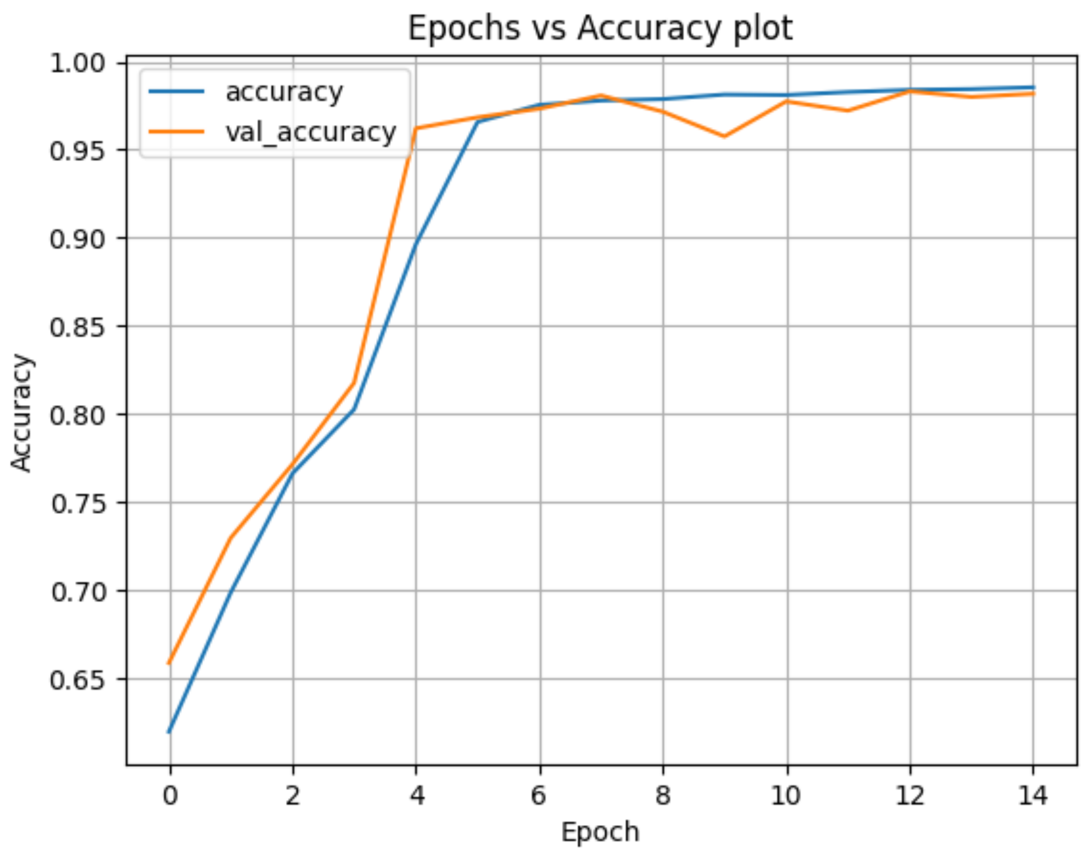

Fig. 5. Accuracy plot on the acquired SDR dataset

Implementation: Training, Validation, and Testing Results

- **Our Collected Dataset:**
  - Trained on 240,000 data samples over 15 epochs
    - Achieved exceptional accuracy of 98.98% with loss of 0.0190
  - Tested on distinct set of 60,000 data samples
    - Achieved impressive accuracy of **96.43%** with loss of 0.3057

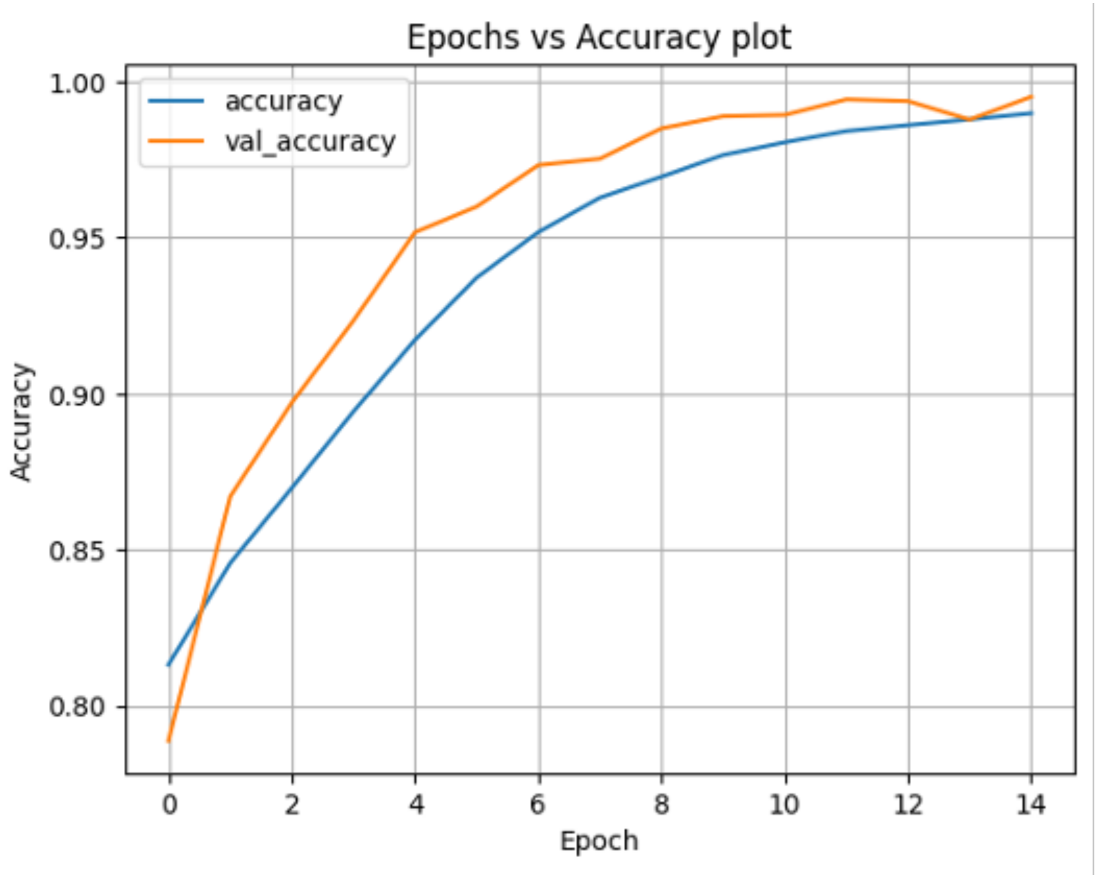

Fig. 6. Accuracy plot on the collected dataset

Implementation: Model Compression Results

- Compression using post-training quantization
- Reduces the number of bits required to represent model weights
- Lowers memory complexity of DL model
- Crucial for deployment on resource-constrained devices

- Quantization achieved an **75%** reduction in model size with no loss in accuracy

Table 1. Performance on the acquired SDR dataset

Model	Accuracy (%)	Size (MB)
Baseline (Float 32)	93.73	4.23
Float 16	93.74	2.11
Float 8	91.74	1.06
TF Lite Float 16	93.77	2.02

Table 2. Performance on the collected dataset

Model	Accuracy (%)	Size (MB)
Baseline (Float 32)	96.43	16.80
Float 16	96.43	8.40
Float 8	96.40	4.2
TF Lite Float 16	96.18	8.02

Implementation: Experimental Setup

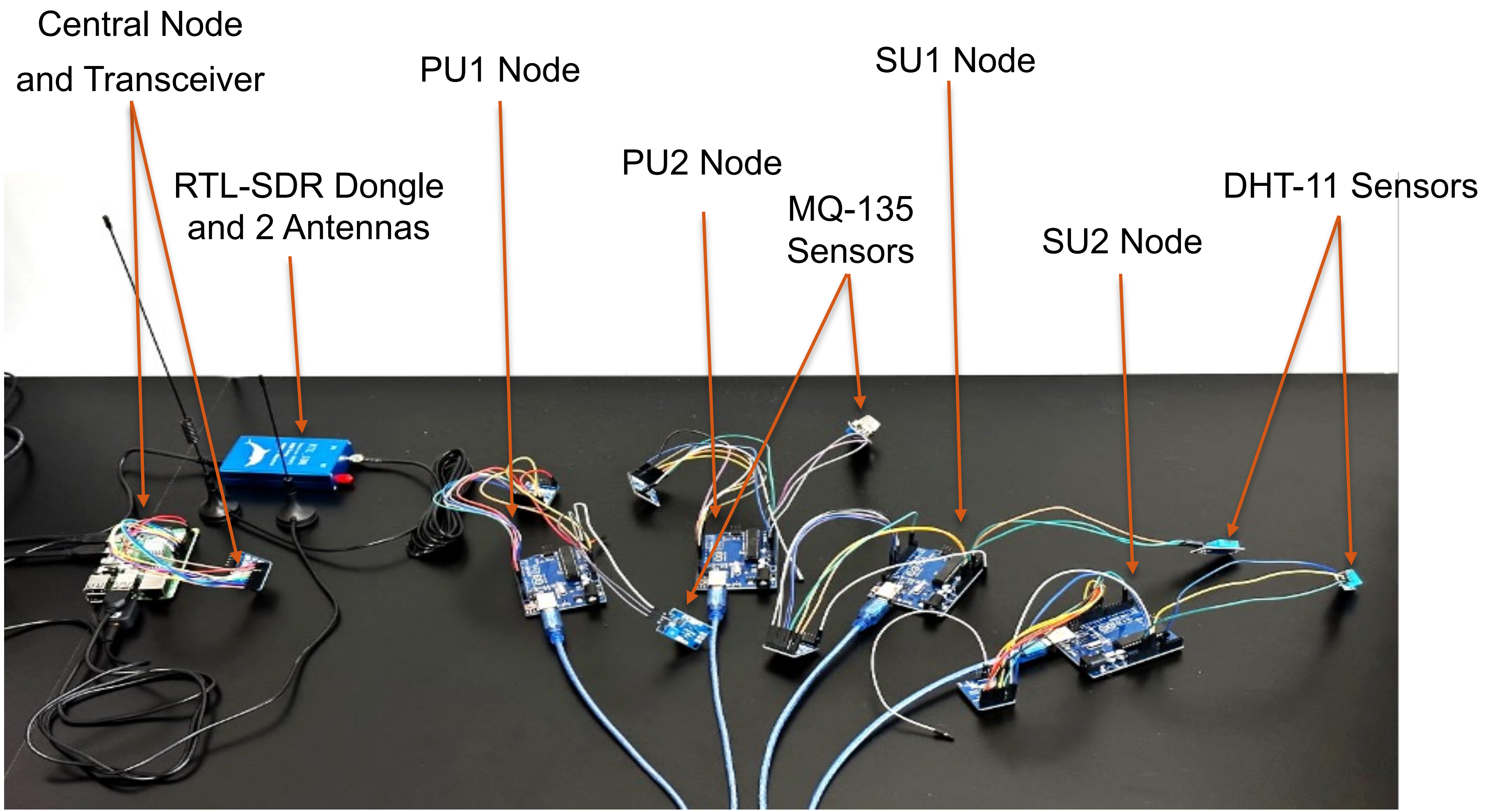

Fig. 7. Hardware experimental setup

Implementation: System Interface

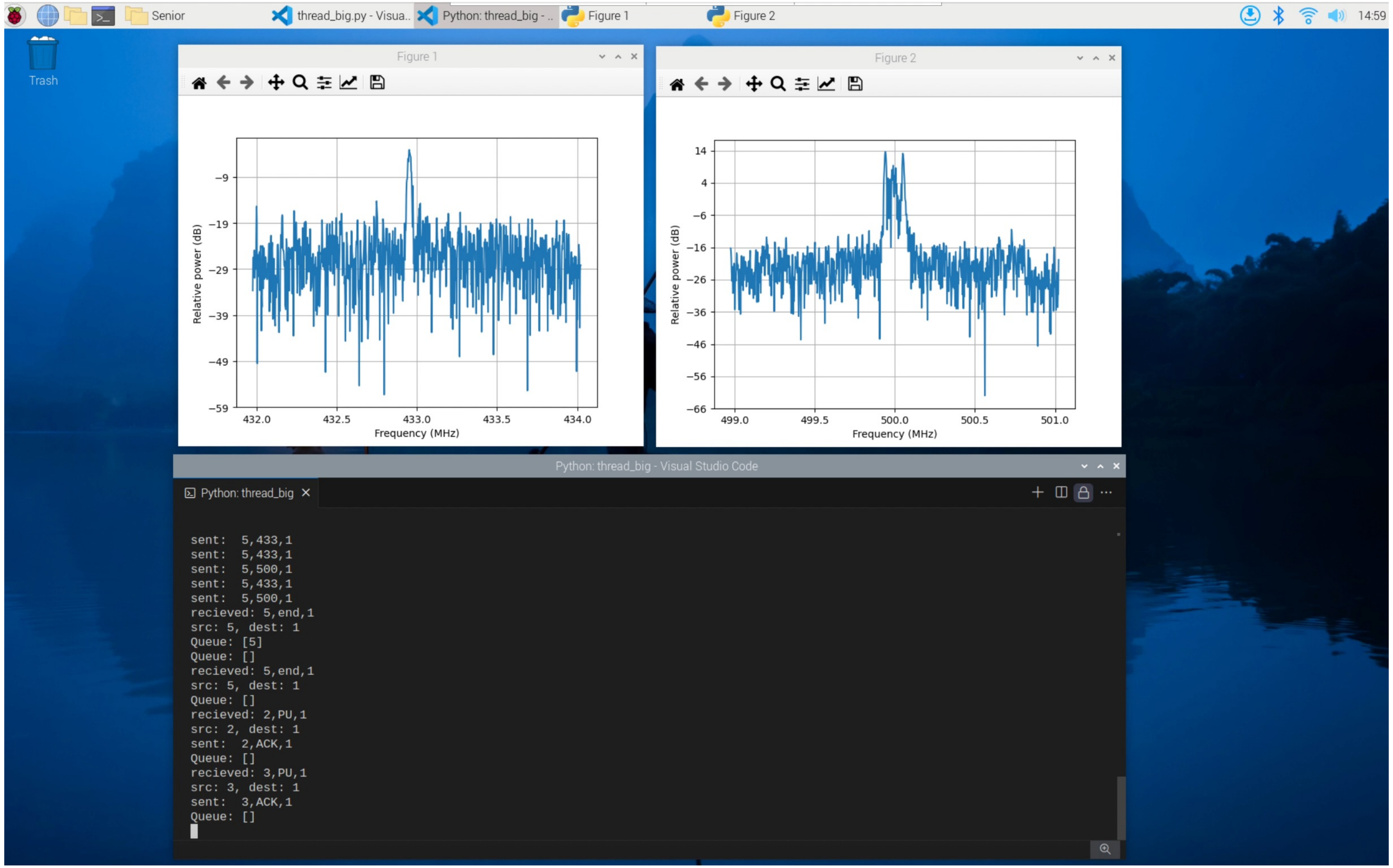

Fig. 8. System interface showing PU and SU activity

Implementation: System Interface

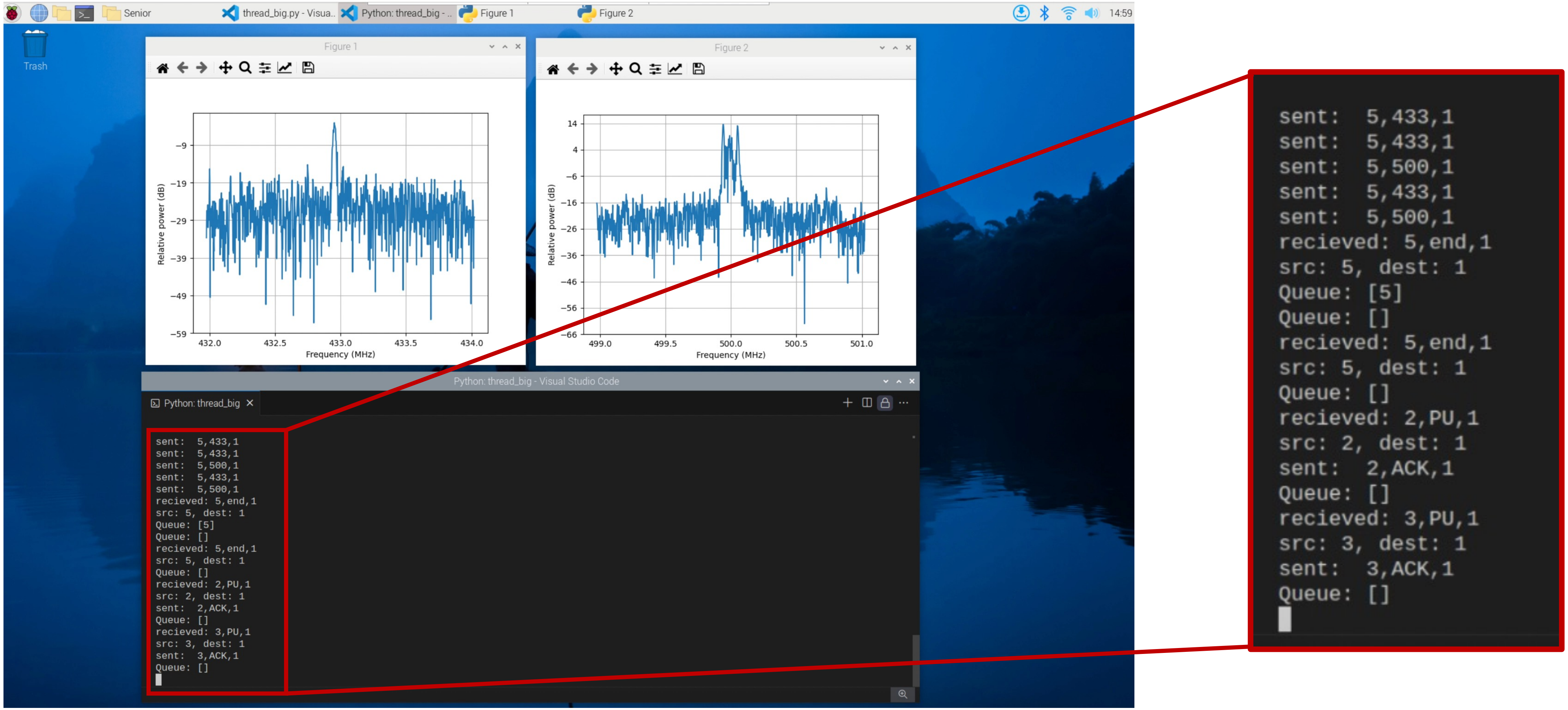

Fig. 8. System interface showing PU and SU activity

System Testing and Validation

Occupied Spectrum Scenarios:

- Tested system response to single and simultaneous PU transmissions.
- Verified DL model’s accuracy in identifying occupied channels.

Unoccupied Spectrum Scenarios:

- Examined system’s handling of no PU activity and multiple SU requests.
- Confirmed correct channel allocation by the central node.

Dynamic Changes in Spectrum Occupation:

- Assessed system’s adaptability to sudden PU arrivals during SU transmissions.
- Verified reallocation of channels based on DL model updates.

Conclusion

- Spectrum scarcity is a growing challenge
- Develop an intelligent spectrum sensing and allocation system
- Utilize advanced DL algorithms and CR techniques
- Optimize utilization of available frequency bands
- Translate research into a practical implementation

Future Work

- Further refine and improve the DL-based SS and allocation system
- Deploy it in real-world scenarios to validate and improve its performance
- Explore other DL-based architectures and optimization techniques
- Adapt the DL-SS system to meet the demands of future 6G networks

Thank you for listening!