An Analysis of the NIST Citizens Broadband Radio Service Dataset

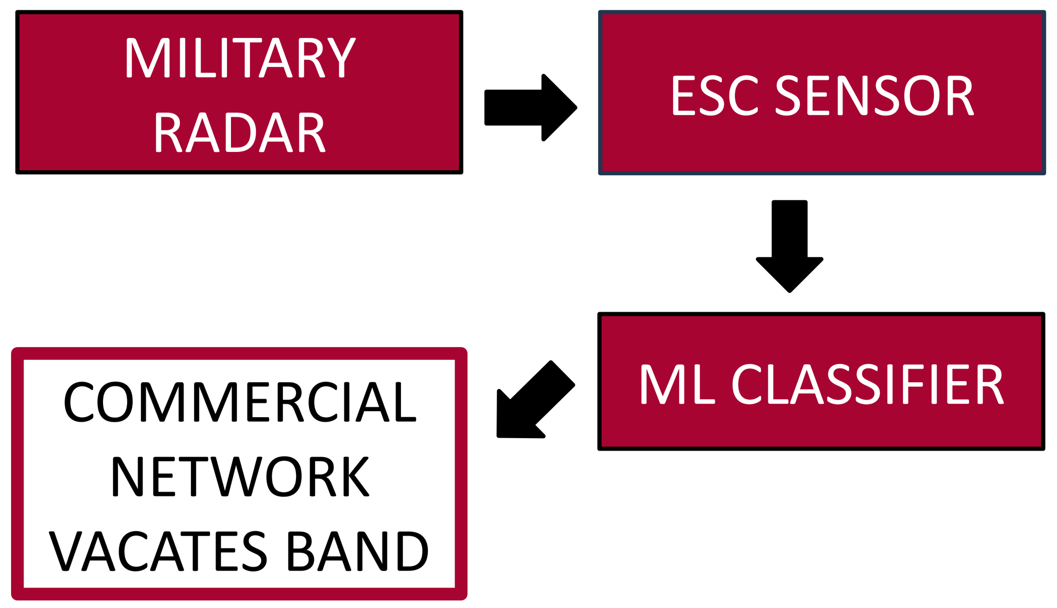
Aaron Sanchez, Elliot Small, Alan Sun, and Zachary Werle

INTRODUCTION

- The 3.5 GHz Citizens Broadband Radio Service (CBRS) band is a shared spectrum environment where commercial wireless networks must coexist with federal incumbent radar systems operated by the U.S. military. Environmental Sensing Capability (ESC) sensors are required to detect these radar signals and trigger protection mechanisms to vacate the band. Accurate and efficient radar classification is therefore critical to both protecting military operations and enabling commercial spectrum use.
- This project analyzes the NIST CBRS dataset with the goal of learning about electronic warfare and eventually developing supervised machine learning classifiers capable of identifying radar signal types directly from raw IQ data, contributing to the broader challenge of automated radar recognition in contested spectrum environments.

ELECTRONIC WARFARE

- What is Electronic Warfare? -
  - Modern EW is classified into 3 groups: Support, Attack, and Protection. It is a key component of information warfare. Protecting friendly information systems while disrupting enemy's ability to do the same.
- What is a radar?
  - Radar works by sending out radio pulses and listening for echoes to detect objects. Modern military radars deliberately disguise their signals by spreading them across wide frequency ranges or randomizing their timing so that enemies cannot easily identify them. This is called Low Probability of Intercept (LPI) radar.
- Machine Learning in EW:
  - Traditional detection systems follow fixed rules. They look for specific patterns they already know. But modern radar signals are designed to break those rules. Machine learning can learn to recognize signals from



NIST CBRS DATASET

- What is included?
  - The NIST CBRS dataset is a publicly available collection of synthetically generated radar signals, created by the National Institute of Standards and Technology specifically to support the development of machine learning-based radar detection algorithms for the 3.5 GHz band

40,000 IQ SIGNALS	800,000 samples per signal	5 RADAR CLASSES

SNR RANGE: 10-20 DB

- Data Structure:
  - Each signal is a complex-valued IQ recording, meaning it captures both the in-phase (I) and quadrature (Q) components of the radar waveform. Every signal comes with a label indicating which radar type it belongs to, making it ready for supervised classification. Signal parameters such as pulse width, pulse repetition frequency, and chirp bandwidth are randomized within realistic bounds for each waveform, making the classification task non-trivial.

MACHINE LEARNING METHODS

- Support Vector Machine:
  - A supervised learning algorithm that classifies data by finding the optimal boundary separating different classes. Because raw IQ signals are too high-dimensional to feed directly into an SVM, hand-crafted features are first extracted from each. SVMs serve as an interpretable and lightweight baseline for this project; prior work on the CBRS band has shown SVMs high detection rates. However, SVMs depend heavily on the quality of manually chosen features and cannot automatically learn new representations from data the way deep neural networks can.
- DEEP NEURAL NETWORKS:
  - Deep neural networks (DNNs), specifically complex-valued 1D Residual Networks (CResNets), represent a promising approach for radar waveform classification that operates directly on raw IQ samples without any intermediate signal transformation. Unlike hand-crafted feature approaches, DNNs learn discriminative representations automatically from data, making them well-suited to the diverse and randomized radar signal types in the CBRS band.
- Convolutional Neural Network
  - A supervised learning Deep learning approach that starts by transforming raw IQ waveforms into spectrogram images via the STFT. After transformation, a CNN is then applied to classify the images. In our case, we used a pretrained ResNet18 CNN to classify the images. Transfer learning from ImageNet was also used due to the limited size of the training data available from a

FINDINGS AND FUTURE PLANS

- FINDINGS:
  - Limited access to the dataset makes it difficult to feed models a high volume of training data.
  - When converting to Spectrogram images the short pulse widths and SNR levels that are present in the data make it difficult to generalize.
- FUTURE WORKS:
  - Download the other 3 groups of data to allow for more samples to be trained on.
  - Implement a baseline classifier using an SVM to establish a starting point for performance comparison
  - Train a complex-valued neural network (CResNet) directly on the raw IQ signals from the NIST CBRS dataset
  - Test and Analyze implementations to find best approach
  - Use findings to contribute useful insights to the broader field of automated radar recognition and electronic warfare research
  - Turn focus from supervised models towards unsupervised approaches to see if more concrete findings are possible.

ACKNOWLEGEMENTS

This work is supported by funding for the VICEROY Northwest Institute for Cybersecurity Education and Research (CySER) provided by The Office of the Undersecretary of Defense for Research and Engineering, in collaboration with the Air Force Research Laboratory and Griffiss Institute.