MULT 25-607 ML for RF Spectrum Sensing

Project Proposal

Prepared for

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Executive Summary

This project aims to further the previous team's efforts in using machine learning to identify features of radio frequency (RF) signals to be able to distinguish between WiFi and Bluetooth signals. The need for a project such as this has become increasingly apparent with the rapid propagation of devices cluttering the RF spectrum. This necessitates a change in the way communication systems operate for organizations such as the Navy. Since the use of these systems is currently a human driven task, this project aims to utilize machine learning to speed up the information processing, and potentially even the decision making process.

We will be using a USRP B210 software defined radio (SDR) to capture the signals and transform them into IQ data for easier sampling. This data will then be transformed using an FFT (fast fourier transform) in order to provide the frequency information that the machine learning algorithm will use to differentiate between the RF signals. The algorithm will be a trinary classifier outputting whether the signal is WiFi, Bluetooth, or neither. The fall semester and winter break will be the first phase of the project where we are setting up and training the algorithm to recognize these signals. The spring semester will be the second phase where we will be looking at how far we can take this project. This will include things like testing with real world data as well as looking at options such as unsupervised training of the algorithm.

The project is sponsored by V2X, a military contractor who is helping to provide resources as well as background information for this project. At the end of the project we will have a combined system that utilized our RF dataset and the machine learning model, along with any documentation, to deliver to V2X.

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Section A. Problem Statement

Figure 1. USS Carl Vinson [1]

Military organizations, particularly the U.S. Navy, rely extensively on sophisticated communication systems that employ radio frequency (RF) signals for a wide array of critical operations. These RF signals are essential for the proper functioning of various systems, including radar, communication networks, and electronic warfare technologies. However, the electromagnetic spectrum's increasing congestion has presented significant challenges in the efficient identification, monitoring, and classification of RF signals. This challenge is becoming increasingly pronounced as both friendly and adversarial RF signals grow in complexity and number, especially in modern warfare scenarios where speed, precision, and reliability are paramount.

Naval vessels, which operate in dense RF environments, are particularly affected by this issue. They often encounter a cluttered electromagnetic spectrum, with signals from a wide variety of devices—both civilian and military—overlapping and competing for bandwidth. The traditional manual identification and classification of RF signals, performed by human operators, has become a bottleneck in this complex environment. This process is not only time-consuming but also highly susceptible to human error, particularly in mission-critical situations where stress and time constraints are significant factors.

An illustrative example of the risks involved is the identification of adversarial jamming or spoofing attempts designed to disrupt radar or communication systems. If an adversary successfully jams or manipulates an RF signal without immediate detection and counteraction, critical systems aboard a naval vessel could be temporarily disabled. In extreme scenarios, such disruptions could lead to catastrophic outcomes, including the potential loss of life or even the sinking of a vessel. Given the rapid and dynamic nature of electromagnetic warfare, it is clear that real-time response is essential. However, the traditional human-in-the-loop approach is increasingly inadequate to meet the speed required for effective counteraction.

The challenges posed by congested RF spectrums are not unique to the U.S. Navy. Many other military organizations, as well as civilian sectors such as aviation and emergency services, are grappling with similar issues. However, in high-stakes environments like military operations, the need for rapid and accurate RF signal classification is especially pressing. The growing sophistication of electronic warfare (EW) systems among adversaries has only exacerbated this issue. Today, many nations possess advanced EW capabilities that can effectively disrupt

RF-dependent operations, underscoring the global importance of developing robust RF signal classification and countermeasure systems. As a result, military forces around the world are investing heavily in solutions designed to enhance their RF signal processing and electronic warfare resilience.

In response to these challenges, this research project, sponsored by V2X—a Vectrus company—focuses on the intersection of electrical and computer engineering with computer science. The project's primary objective is to address the critical challenges of RF signal capture, processing, and classification by leveraging advanced machine learning techniques. V2X, a leading provider of mission-critical solutions to defense and government clients, is supporting this initiative to enhance real-time RF signal identification and classification for U.S. Navy assets. The project aims to significantly improve operational efficiency and reduce the reliance on human operators, ultimately increasing both the accuracy and speed of RF signal classification.

As part of this design, we plan to utilize an RTL-SDR V3 for signal capture, specifically targeting the 2.4 GHz band commonly used for Wi-Fi and Bluetooth communications. This RF data will be processed in real-time, starting with a Fast Fourier Transform (FFT) to break down the spectrum and extract key features. The data will then be further analyzed by focusing on the in-phase (I) and quadrature (Q) components of the signal. Similar approaches have been validated in previous research. For example, Wang, Chen, and Zhang (2021) successfully captured and processed I/Q data under real-world engineering conditions, including random noise, which demonstrated the feasibility of this approach. However, their implementation of a neural network resulted in a relatively low classification accuracy of 79%, highlighting the need for further refinement.

Recent advancements in end-to-end machine learning systems offer promising solutions. For instance, Alam et al. (2023) explored the use of deep learning techniques to detect and identify drones using RF signals. Their research successfully developed an end-to-end system that integrates RF signal processing with advanced machine learning algorithms, resulting in significant improvements in both detection speed and classification accuracy. Notably, their system achieved sub-millisecond detection times and a classification accuracy rate of 98% for unmanned aerial vehicles (UAVs), largely due to the high-quality data available from the CardRF dataset. This underscores the critical importance of access to large, high-quality datasets for training machine learning models and achieving superior performance in RF signal classification.

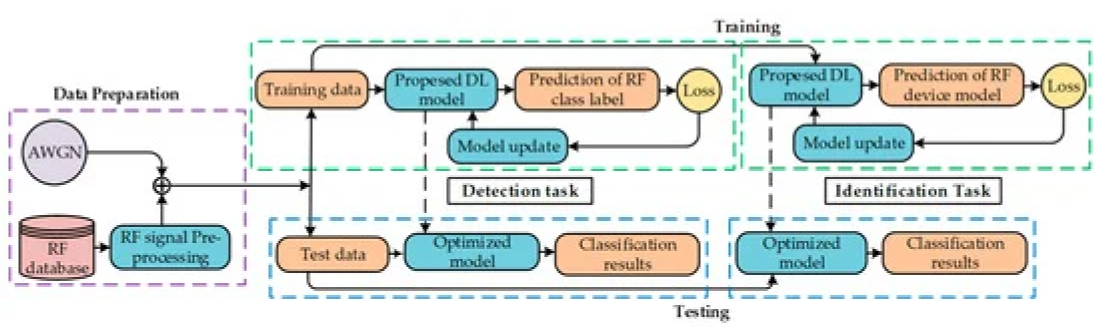


Figure 2. Architecture of signal identification in Alam et al. (2023) [3]

Building on these advancements, deep neural networks (DNNs) have emerged as powerful tools in RF signal identification, particularly in complex and crowded electromagnetic environments. Unlike traditional hand-engineered methods, which are limited by the need for domain-specific knowledge, DNNs can automatically learn features from raw RF data. This capability is crucial in environments where many transmitters share a channel or where high data rates are involved, such as naval operations. Research by Youssef et al. (2018) into DNNs with multi-stage training has shown especially promising results, achieving 100% classification accuracy for 12 different transmitters, demonstrating remarkable scalability for larger transmitter populations. By focusing on the intrinsic physical characteristics of RF signals, rather than just transmitted data, these networks offer a robust approach for rapidly identifying unknown or rogue transmitters. Incorporating DNNs into the current project can significantly enhance real-time RF signal classification, further improving both speed and accuracy while reducing reliance on human operators.

In choosing between power spectral density (PSD) and in-phase/quadrature (I/Q) neural training, research indicates that I/Q data can effectively capture intricate time and phase variations, enhancing classification in dynamic RF environments. Conversely, PSD is more suitable for frequency-based analysis, particularly for detecting jamming or interference. The decision to focus on one method will depend on the specific operational requirements of the RF environment (Elyousseph & Altamimi, 2021).

This project will enhance V2X's capabilities in navigating complex RF signal environments, laying the groundwork for future advancements in signal processing. By focusing on either power spectral density or in-phase/quadrature analysis as the training method, the project aims to address critical challenges in RF signal classification. The anticipated outcomes will significantly improve operational efficiency, demonstrating the potential impact of innovative solutions in real-world applications while providing valuable insights into the effectiveness of machine learning techniques in this domain.

Section B. Engineering Design Requirements

This section outlines the goals, objectives, specifications, and constraints that will guide the design and development of our RF spectrum sensing device. The requirements have been established through an understanding of client needs, existing technology, and thorough research. These requirements ensure the intended outcomes of client expectations and ensure the project remains aligned with previous work.

B.1 Project Goals (i.e. Client Needs)

The primary goal of this project is to improve situational awareness in radio frequency (RF) environments that are heavily contested by using machine learning to identify and categorize devices that are using a certain frequency band. This goal addresses the requirement to effectively monitor RF spectrum consumption and recognize various devices within a certain environment. The following list outlines the primary goals determined by the needs of the project to guarantee the successful implementation of this solution:

- To create a system that can identify active frequencies inside a designated RF band
- To categorize devices according to their frequency properties
- To create a machine learning model that can accurately distinguish between different kinds of devices
- To improve the efficiency of spectrum monitoring and make it more reliable and cost-efficient

B.2 Design Objectives

Design Objectives include:

- The design will detect active frequencies within the specified RF bands
- The design will be able to determine if the device is a WI-FI or Bluetooth device
- The design will process real-time data from the RF environment
- The design will use achievable software and hardware resources, including existing machine learning algorithms and RF data collection tools
- The design will be developed, tested, and validated to ensure proper effectiveness

B.3 Design Specifications and Constraints

- Design must use a USRP B210 SDR for processing signals into IQ data - (Cost constraint)
- The design will use a trinary classifier that distinguishes between Wifi, Bluetooth, or neither
- Design must have a User Interface showing which Network types are being used, ie Wifi and Bluetooth

B.4 Codes and Standards

- 802.11-2020/Cor 1-2022 - IEEE Standard for Information Technology--Telecommunications and Information Exchange between Systems
- 802.15.1-2002 - IEEE Standard for Telecommunications and Information Exchange Between Systems - LAN/MAN

Section C. Scope of Work

The primary focus of this project is to develop a system that captures live RF spectrum data and utilizes machine learning algorithms to identify specific target signals, namely Bluetooth and Wi-Fi operating in the 2.4 GHz band. The project aims to create a reliable and efficient method for RF signal detection and classification, with the following key objectives:

1. RF Spectrum Capture: We will design and implement a system utilizing Software-Defined Radio (SDR) technology for capturing RF signals in the 2.4 GHz frequency range. The SDR will provide the flexibility to tune into various frequencies and bandwidths, allowing for real-time signal capture across multiple protocols. This capability will ensure that diverse and high-quality data is gathered, which is crucial for effective machine learning model training.

2. Signal Identification via Machine Learning: The project will develop and train machine learning models capable of accurately classifying captured Bluetooth and Wi-Fi signals. This process will include creating a data pipeline that encompasses feature extraction, model training, and evaluation. We aim to ensure the models perform reliably under various conditions, accounting for factors such as signal strength and interference.

3. System Integration and Automation: A key aspect of the project is to create an autonomous system that can detect and classify signals without human intervention. This approach will enhance the efficiency and reliability of the signal identification process, streamlining operations and reducing the potential for human error.

4. Verification and Validation: The system will undergo rigorous testing to validate its performance and accuracy. We will evaluate the machine learning models to ensure they meet the required specifications and can effectively classify target signals in diverse environments.

C.1 Deliverables

Project Deliverables

The project deliverables include:

1. RF Dataset: A comprehensive collection of captured RF spectrum data, specifically targeting Bluetooth and Wi-Fi signals in the 2.4 GHz range. This dataset will be gathered

through live data collection, which can take place in a lab setting or remotely, utilizing Software-Defined Radio (SDR) technology for flexible and efficient data capture.

2. Machine Learning Model: A trained model capable of accurately identifying and classifying Bluetooth and Wi-Fi signals from the collected RF data. The coding and training processes for this model will be performed on local machines with a github repo, allowing team members to work effectively from various locations. This flexibility in development enables continuous iteration and improvement of the model.

3. Combined System: An integrated solution that merges the RF dataset and the machine learning model, facilitating real-time signal detection and classification. This system will leverage both the collected data and the trained model to provide accurate and timely results with a user interface.

4. Documentation: This includes user manuals, system architecture descriptions, and guidelines for future enhancements or modifications. Comprehensive documentation will ensure that all aspects of the project are clearly communicated and easily accessible for future reference.

5. Academic Deliverables: Additional outputs will include essential academic documents, such as:
    a. Team contract
    b. Project proposal
    c. Preliminary design report
    d. Fall poster and presentation
    e. Final design report
    f. Capstone EXPO poster and presentation

C.2 Milestones

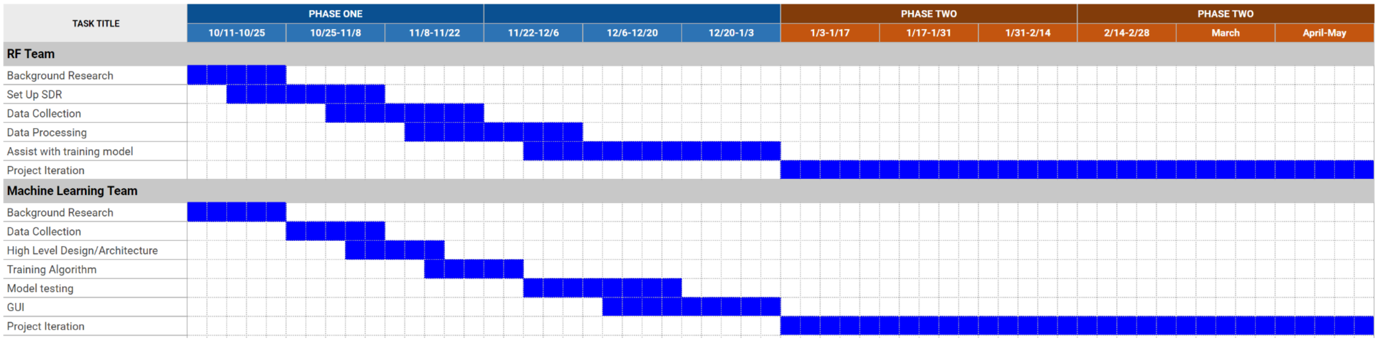
This project has two teams that are working on their own respective aspects through the project, these being the RF/SDR team and the other being the machine learning and GUI team. At the beginning this results in the two parts of the project having separate milestones. The RF team's first major milestone will be getting to the point of capturing testing data, this means our

SDR is programmed to capture signals and transform it to IQ data. The next major milestone is when we have created the process to capture and prep this data so it is ready for training the machine learning algorithm. This means we have developed a process to get clean, usable data that has been converted to the frequency domain and formatted properly.

For the machine learning team, the first major milestone will be mapping out the layers of the machine learning algorithm as well as what functions those layers will use. The next major milestone will be after the initial training of the algorithm. After this the major milestone will be when the algorithm is able to distinguish between the signals at a minimum of 90% accuracy.

These milestones up to this point are planned for the fall semester and winter break. For the spring semester we will be mapping out where we'd like to based on the progress up to that point. We would like to explore possibilities such as testing on real-world data as well as unsupervised learning.

Appendix 1: Project Timeline



Appendix 2: Team Contract (i.e. Team Organization)

Step 1: Get to Know One Another. Gather Basic Information.

Task: This initial time together is important to form a strong team dynamic and get to know each other more as people outside of class time. Consider ways to develop positive working relationships with others, while remaining open and personal. Learn each other's strengths and discuss good/bad team experiences. This is also a good opportunity to start to better understand each other's communication and working styles.

Team Member Name	***Strengths each member bring to the group***	***Other Info***	***Contact Info***
Shane Simes	Adaptability, Strong organization skills	Strong skills in many different coding languages, good at document/report drafting	simess@vcu.edu
Daniel Hartman	Flexibility, communication skills	Knowledgeable in HFFS, proficient at soldering, knowledgeable in multiple programming languages	hartmand2@vcu.edu
Kush Patel	Adaptable, quick to learn.	Technical knowledge in embedded systems, strong skills in various languages and tools.	Patelku2@vcu.edu
Baaba Jeffrey	Organization, adaptability, collaborative skills	Skillful in multiple programming languages	Jeffreybt@vcu.edu

Other Stakeholders	***Notes***	***Contact Info***
Yanxiao Zhao Tamer Nadeem	 Was on similar project last year	yzhao7@vcu.edu tnadeem@vcu.edu
Riley Stuart		Riley.Stuart@gov2x.com

John Robie		John.Robie@gov2x.com

Step 2: Team Culture. Clarify the Group's Purpose and Culture Goals.

Task: Discuss how each team member wants to be treated to encourage them to make valuable contributions to the group and how each team member would like to feel recognized for their efforts. Discuss how the team will foster an environment where each team member feels they are accountable for their actions and the way they contribute to the project. These are your Culture Goals (left column). How do the students demonstrate these culture goals? These are your Actions (middle column). Finally, how do students deviate from the team's culture goals? What are ways that other team members can notice when that culture goal is no longer being honored in team dynamics? These are your Warning Signs (right column).

Resources: More information and an example Team Culture can be found in the Biodesign Student Guide "Intentional Teamwork" page (webpage | PDF)

Culture Goals	***Actions***	***Warning Signs***
Respect and Support	- Encourage open communication and active listening during meetings. - Provide constructive feedback and recognize each other's strengths.	- Team members interrupt each other frequently. - Criticism is not constructive or lacks respect.
Accountability	- Clearly define each member's responsibilities and deadlines. - Regularly review progress and address any issues promptly.	- Missed deadlines are frequent without explanation. - Lack of follow-through on assigned tasks.

Acknowledging Contributions	- Recognize and praise individual achievements during team meetings. - Provide positive feedback and encourage peers.	- Team member's efforts are consistently overlooked. - No acknowledgment of significant contributions during team discussions.
Constructive Feedback	- Offer feedback that is specific, actionable, and supportive. - Encourage a culture where feedback is welcomed and acted upon.	- Feedback is vague, overly critical, or not delivered in a constructive manner. - Team members become defensive or disengaged during feedback sessions.
Collaborative Problem-Solving	- Engage in open discussions to address issues collaboratively. - Foster an environment where all opinions are considered and valued.	- Problems are ignored or handled in isolation. - Team members shut down or dismiss others' suggestions without discussion.

Step 3: Time Commitments, Meeting Structure, and Communication

Task: Discuss the anticipated time commitments for the group project. Consider the following questions (don't answer these questions in the box below):

- What are reasonable time commitments for everyone to invest in this project?
- What other activities and commitments do group members have in their lives?
- How will we communicate with each other?
- When will we meet as a team? Where will we meet? How Often?
- Who will run the meetings? Will there be an assigned team leader or scribe? Does that position rotate or will the same person take on that role for the duration of the project?

Required: How often you will meet with your faculty advisor advisor, where you will meet, and how the meetings will be conducted. Who arranges these meetings?
See examples below.

Meeting Participants	***Frequency Dates and Times / Locations***	***Meeting Goals Responsible Party***
Students Only	Every Tuesday at 7 pm at the library in person	Actively work on projects. Bring up questions about the project.
Students + Faculty advisor	May join weekly 7 pm meetings through Zoom	Update faculty advisor and get answers to our questions (Any of the team members will scribe; Baaba will create meeting agenda and lead meeting)
Project Sponsor	Meeting Monday 9/9 in person then meeting online after that through zoom	Update project sponsor and make sure we are on the right track (Shane will create meeting agenda and lead meeting; Kush/Daniel will present prototype so far)

Step 4: Determine Individual Roles and Responsibilities

Task: As part of the Capstone Team experience, each member will take on a leadership role, ***in addition to*** contributing to the overall weekly action items for the project. Some common leadership roles for Capstone projects are listed below. Other roles may be assigned with approval of your faculty advisor as deemed fit for the project. For the entirety of the project, you should communicate progress to your advisor specifically with regard to your role.

- **Before meeting with your team**, take some time to ask yourself: what is my "natural" role in this group (strengths)? How can I use this experience to help me grow and develop more?
- **As a group,** discuss the various tasks needed for the project and role preferences. Then assign roles in the table on the next page. Try to create a team dynamic that is fair and equitable, while promoting the strengths of each member.

Communication Leaders

Suggested: Assign a team member to be the primary contact for the client/sponsor. This person will schedule meetings, send updates, and ensure deliverables are met.

Suggested: Assign a team member to be the primary contact for faculty advisor. This person will schedule meetings, send updates, and ensure deliverables are met.

Common Leadership Roles for Capstone

1. **Project Manager:** Manages all tasks; develops overall schedule for project; writes agendas and runs meetings; reviews and monitors individual action items; creates an environment where team members are respected, take risks and feel safe expressing their ideas.
   Required: On Edusourced, under the Team tab, make sure that this student is assigned the Project Manager role. This is required so that Capstone program staff can easily identify a single contact person, especially for items like Purchasing and Receiving project supplies.
2. **Logistics Manager:** coordinates all internal and external interactions; leads in establishing contact within and outside of organization, following up on communication of commitments, obtaining information for the team; documents meeting minutes; manages facility and resource usage.
3. **Financial Manager:** researches/benchmarks technical purchases and acquisitions; conducts pricing analysis and budget justifications on proposed purchases; carries out team purchase requests; monitors team budget.
4. **Systems Engineer:** analyzes Client initial design specification and leads establishment of product specifications; monitors, coordinates and manages integration of subsystems in the prototype; develops and recommends system architecture and manages product interfaces.
5. **Test Engineer:** oversees experimental design, test plan, procedures and data analysis; acquires data acquisition equipment and any necessary software; establishes test protocols and schedules; oversees statistical analysis of results; leads presentation of experimental finding and resulting recommendations.
6. **Manufacturing Engineer:** coordinates all fabrication required to meet final prototype requirements; oversees that all engineering drawings meet the requirements of machine shop or vendor; reviews designs to ensure design for manufacturing; determines realistic timing for fabrication and quality; develops schedule for all manufacturing.

Team Member	***Role(s)***	***Responsibilities***
Shane Simes	Project Manager	- Primary contact for sponsor - Manage scheduling - Schedule monthly meeting with sponsor - Help with any task that's needed -
Kush Patel	Systems Engineering	- Overview of product design
Daniel Hartman	Test Engineering Finances	- Data acquisition - Design testing plan - Research for purchasing decisions - Track budget

Baaba Jeffrey	Logistics Manager	- Primary contact for advisor - Ensure all deadlines are met - Ensure everyone is on the same page and up to date with the project

Step 5: Agree to the above team contract

Team Member: Shane Simes *Signature: Shane Simes*

Team Member: Kush Patel *Signature: Kush Patel*

Team Member: Baaba Jeffrey *Signature: Baaba Jeffrey*

Team Member: Daniel Hartman *Signature: Daniel Hartman*

References

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