AI-Driven Spectrum Monitoring and Awareness for Tactical Units

Executive Summary

Modern dismounted warfighters need real-time awareness of the radio frequency (RF) spectrum to detect and identify signals, recognize usage patterns, and locate emitters. Currently, these capabilities are limited at the tactical edge – signals often must be recorded and sent to rear-echelon experts, delaying feedback for hours or days. [1] This proposal offers an **AI-driven spectrum monitoring solution** that empowers tactical units with on-the-spot RF situational awareness using an easy to understand plugin to ATAK. By leveraging advanced **machine learning** algorithms and a **multichannel SDR**, our system will automatically classify signals (identifying communication protocols like Wi-Fi, Bluetooth, GSM, etc.) and pinpoint their source location in real-time while also providing voice and data transmission capabilities.

The solution integrates with the Android Tactical Assault Kit (ATAK) on soldier-carried Android devices, providing intuitive visual alerts and maps for **Blue Force Tracking** without adding physical or cognitive burden. Our innovation lies in combining state-of-the-art deep learning for signal classification – which operates in milliseconds [8] and with superior sensitivity – with a lightweight deployment on existing military radios and handhelds. According to studies, "a CNN, trained only by synthetic data, has obtained an accuracy of up to 95 % on real-world signals"

This approach aligns with DARPA's SMART objectives by delivering **real-time RF awareness** to dismounted units, enhancing survivability and tactical decision-making through on-device intelligence. In summary, the proposed system will give non-expert operators an unprecedented capability to **monitor, analyze, and act upon the RF spectrum** in the field, all through their standard kit, meeting DARPA's goals of improved spectrum awareness for ground tactical units.

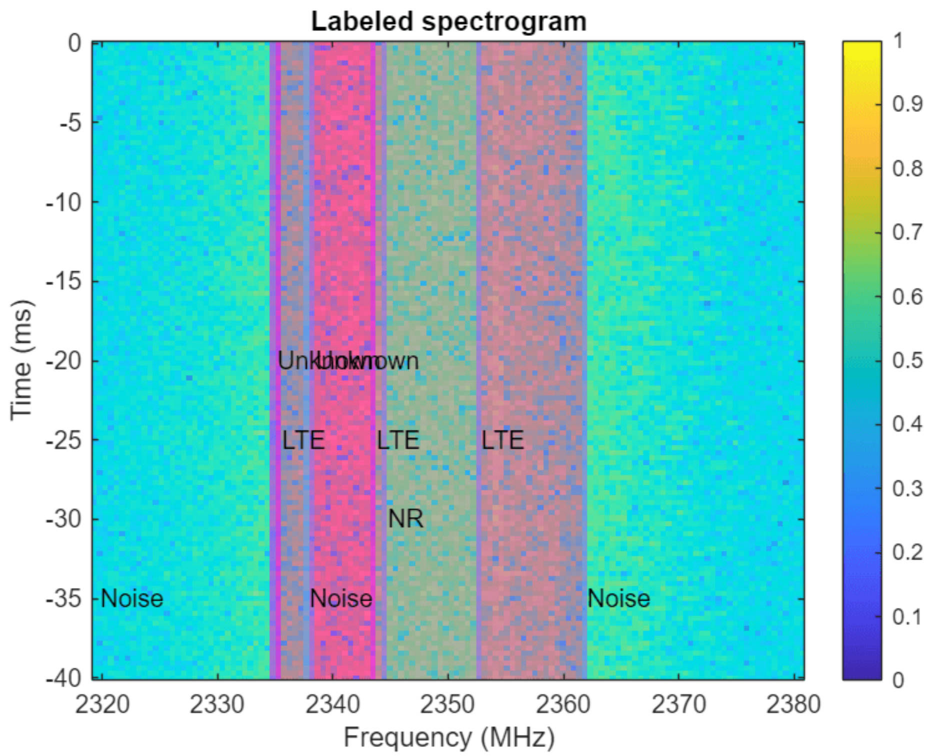
Technical Approach

Our technical approach fuses modern artificial intelligence with robust RF sensing hardware such as the Ettus X310 with the Hedgehog DSP daughterboard [9] to create a portable spectrum monitoring and awareness tool. It consists of three key elements: **(1) AI-driven Signal Classification**, **(2) Emitter Localization**, and **(3) Integration with SDR hardware and ATAK**, all within the specified SWaP criteria.

- **AI-Driven Signal Classification:** We will develop deep learning models (e.g. convolutional neural networks) [[insert reference]] trained to recognize and categorize RF signals from raw IQ data or spectral features. Deep learning has demonstrated dramatic improvements in automatic signal recognition, training on new signal types within hours and detecting/modulating signals in milliseconds. By leveraging these advances, our system can **detect and characterize signals of interest in milliseconds**, [6] even in congested or noisy environments. For example, the AI can identify a push-to-talk radio transmission versus a Wi-Fi or LTE signal, and even detect anomalous or jamming signals. The model will perform **protocol classification** – mapping complex RF measurements to user-friendly labels (e.g. "802.11 Wi-Fi" or "GSM handset") rather than just raw modulation formats, aligning with DARPA's intent to identify communications protocols in an intuitive way. We will train the AI on a diverse dataset [3] of military and commercial waveforms (including frequency-hopping or burst signals) to ensure robust performance.
- **Preparation of a Diverse Sample Database:** "A neural network can learn to make predictions only based on the available training data. Therefore it is vital for machine learning to use good training data." [5] Many open source sample databases are available, however the samples are of varying quality and some of them are considered "flawed". [3] We will create additional samples using diverse hardware to avoid biases in training data and subsequent classification errors. [5] The classifier will incorporate **anomaly detection** to flag unknown or new signal types and **intentional interference** (jamming), which are areas of interest.
- **Emitter Localization:** The localization algorithms will be informed by established electronic support (ES) methods and enhanced with machine learning for improved accuracy in multipath or low-SNR conditions. The goal is to **geolocate emitters in real-time** (or near-real-time), by exploiting the effects of multipath

propagation when available [7] and by time-based triangulation when not, [10] providing the operator with either a directional arrow or a map overlay of the likely emitter location. Unfortunately, this is only effective in some use cases and only in a short range (<1km). We will quantify localization accuracy (e.g. angular error in degrees or position error in meters) and optimize the approach to meet tactical needs.

- **Wideband Antenna:** We intend on using a R&S AU600 wideband antenna. Small and capable of receiving both horizontally and vertically polarized signals from 20MHz to 8 GHz it's a highly capable antenna that will not overly encumber ground troops.



Deep-learning algorithms enable real-time identification of multiple signal types in a congested spectrum environment. *Above:* An example spectrogram in the 2.32-2.38 GHz band shows an AI-based classifier correctly labeling LTE transmissions in a noisy signal. [] Our system will similarly detect and label diverse signals on the fly, even under noisy conditions. This AI-driven approach offers speed and sensitivity far beyond traditional signal detection methods – a trained neural network can survey and classify spectrum data orders of magnitude faster than iterative manual scanning. Moreover, once the model is trained, it can be deployed on low-SWaP hardware (such as mobile processors or SDR FPGA/GPU co-processors), enabling **edge processing** of RF data without reliance on cloud or enterprise computing. We will exploit the improved compute capabilities now available in handheld devices procured by the DoD – including multi-core CPUs and GPUs [1] – to run the AI models in real-time on an Android phone/tablet or on the SDR itself. By the end of Phase I, we expect to demonstrate that our AI models can classify priority signal types (e.g. push-to-talk radios, cell phones, Bluetooth) with high accuracy (>=90%) and low latency (under one second), laying the groundwork for more extensive signal libraries in Phase II. [8]

- **SDR Integration and ATAK Interface:** The hardware implementation will center on a **man-portable SDR** integrated with the operator's existing kit. We envision a surrogate SDR that **replicates the primary communication functions and SWaP of current tactical radios** – our approach aligns with this by potentially using a COTS multi-band SDR in Phase I that is comparable in weight and power to an AN/PRC-117G. This SDR will be configured to **simultaneously perform communications and spectrum monitoring**. A dual-channel radio like the Ettus X310 [9] can dedicate one channel to the unit's normal voice/data net and the second channel to scanning the band for signals of interest. Consideration will be given to **voice and data concurrency** so that situational awareness updates occur in the background without interrupting critical comms. The SDR's programmable architecture allows us to rapidly adjust RF parameters (tuning range, filtering, sampling rate) to cover the designated frequency bands of interest – proposals will specify the RF bandwidth our solution covers (e.g. VHF/UHF through 6 GHz) as required [1].

The user interface will be implemented as a plugin for **Android Tactical Assault Kit (ATAK)**, capitalizing on the standard battlefield situational awareness tool carried by many warfighters [1]. ATAK's plugin architecture lets us create a custom **Spectrum Awareness plugin** that displays detected emitters and signal information on the ATAK map in an intuitive way. For instance, when the system classifies a signal, an icon can appear at the estimated location of the emitter (or simply on the user's map with a bearing line if exact geolocation is indeterminate). The icon and/or a text label will denote the type of signal along with confidence level or other relevant data. The interface will also allow the operator to review a **local RF spectrum picture**: a list of signals currently detected, a history graph of signal appearances (to build a pattern-of-life over the mission), and simple options to filter or flag signals. All information will be presented in a **user-friendly, intuitive manner**, avoiding technical jargon so that even operators without RF expertise can understand it [1]. The plugin will be designed for **touch interaction** on a chest-mounted smartphone or tablet, with minimal required input.

Under the hood, the ATAK plugin will handle all data exchange with the SDR and the AI algorithms. The SDR (connected via USB or bluetooth to the ATAK device) will feed raw samples or preprocessed spectral data to the Android device. Our signal classification engine will run either on the Android CPU/GPU/NPU or on an embedded processor in the SDR. The ATAK plugin will then receive the AI's results and display them in real-time. This tight integration means the operator uses **one device for both communication and spectrum awareness**, and the data stays local, satisfying operational security (OPSEC) by not requiring external transmission of sensitive RF data.

Concept of Employment

Our proposed AI-driven RF monitoring system integrates seamlessly into the **standard kit of a dismounted infantry unit**, using existing antennas. In practice, an operator would carry the upgraded tactical radio and an ATAK-enabled smartphone or tablet mounted on their vest. The concept of employment is designed for **non-expert users in fast-moving tactical scenarios**, emphasizing ease of use and minimal training. The system runs passively in the background, continuously scanning and analyzing the environment. **Before a mission**, the operator can pre-load a profile of expected friendly signals (to recognize and de-emphasize those) and select scanning bands of interest (for example, NATO communications bands, or frequencies known to be used by adversaries in the area). They then simply power on the radio and ATAK device; the Spectrum Awareness plugin initializes automatically.

During mission execution, the warfighter receives automated spectrum intelligence with little to no manual interaction. For example, as a patrol moves through a village, the SDR is quietly sweeping the RF spectrum. If an unknown transmission is detected (say, a burst of VHF radio traffic or a sudden spike of RF energy indicative of a jammer), the system immediately classifies it and alerts the user. The soldier might feel a haptic buzz or hear an audio tone from the ATAK device, prompting them to glance at the screen. There, they see an icon on the map labeled "Unidentified Radio Signal – Likely Push-to-Talk (FM)". In this example, the squad leader now knows a potentially hostile radio is active nearby and can make an informed decision – e.g. proceed cautiously, attempt to avoid line-of-sight to that area, or prepare to intercept. If the signal were a known friendly (say the team's own radio nets), the system would recognize it and either not alert or show it as a benign/friendly emitter, focusing the user's attention on **signals of interest** only.

Building a POL means if the unit stays in an area for hours or revisits it on multiple patrols, the system will log recurring signals and timings – for instance, noting that every morning at 0700 a certain radio comes on air for 10 minutes (which could indicate an enemy report schedule). These insights, presented as simple trend graphs or notifications ("Daily RF activity peak at 0700 – possible enemy routine"), can greatly enhance mission planning and threat anticipation.

For additional detail, the user can drill down on the ATAK device (e.g. tap an icon to see signal technical details if they desire, like frequency and modulation), but this is optional. Thus, a **typical usage workflow** would be: (1)

Operator turns on the system as part of pre-mission comms check, (2) System runs continuously without input, (3) Operator reacts only when the system notifies a detection or when they proactively check the spectrum picture, (4) Post-mission, the collected RF log can be reviewed for intelligence or fed up the chain for analysis (if appropriate). The system is also designed to **fail safe** – if for some reason the AI cannot classify a signal or the sensor malfunctions, it will notify the user with a general alert (rather than remaining silent) so they are aware of potential gaps.

Interoperability & Feasibility

Our solution is engineered to interoperate seamlessly with existing Department of Defense communication systems and to be feasible within the constraints of dismounted operations:

- **Transparent Integration with Tactical Radios:** We will ensure that the primary function of the soldier's radio – voice and data communication – is **not degraded or interrupted** by the spectrum monitoring tasks. The SDR hardware and firmware will be configured so that monitoring processes run in parallel with communications, utilizing a separate channel. Our design goal is **zero impact on existing comms**, so that the warfighter does not have to trade communication capability for awareness. Additionally, our software will conform to standard radio interfaces and waveforms, preserving compatibility with **JNIPR-compliant waveforms and encryption** used in current nets.
- **No Additional Physical Burden:** The proposed system will **not require the warfighter to carry extra unique equipment** beyond their standard kit. In practice, this means our Phase II prototype will be a **drop-in replacement radio** that fits the same pouch and uses the same battery as a PRC-117. Future integration may even allow the system to be reduced to the size of a PRC-163. All processing will utilize the radio's internal computing resources and the soldier's ATAK device, avoiding the need for dedicated displays or processors. Feasibility analysis will include power consumption estimates to show that an Android device and radio can support the AI processing for the duration of a mission without exhausting batteries.
- **Interoperability with DoD Networks and Software:** On the software side, the ATAK plugin will follow the **Developer guidelines** to remain compatible with the broader TAK ecosystem. This means it can run on the standard ATAK app used across DoD and even by other agencies, and it can coexist with other plugins (e.g. mapping, Blue Force Tracking) without conflict.
- **Feasibility and Risk Mitigation:** A major feasibility consideration is whether the AI and signal processing can run in real-time on portable hardware. Our proposal addresses this by leveraging the latest mobile computing improvements and by optimizing algorithms for efficiency. As noted, deep learning inference can be very fast and power-efficient with proper optimization. We will perform a detailed feasibility study in Phase I to demonstrate (through calculation, simulation, or prototype) that a representative processor (e.g. Qualcomm Snapdragon SoC or an FPGA+DSP in a radio) can handle the necessary throughput (scanning, digitizing, and classifying potentially millions of samples per second). By the end of Phase I, through both analysis and limited benchtop testing, we will have shown that our approach is technically feasible within the SWaP and operational constraints.

Scalability & Dual-Use Applications

The envisioned system is inherently scalable and possesses significant dual-use potential beyond military applications:

- **Scalability (Military):** The solution can scale from an individual operator up to larger units and broader frequency coverage. The system is scalable in the sense of **covering a wider spectrum** or new signal types: since it is fundamentally a software-defined solution, expanding to new frequency bands or integrating new AI models for different signal classes is mostly a matter of software updates or plugging in additional training data. This makes it adaptable to evolving threats and theater needs. The democratization of spectrum awareness across the force could fundamentally change tactics, techniques, and procedures; part of our Phase I/II concept of employment refinement will consider any new TTPs or training needed to effectively use the system at scale.

- **Dual-Use Applications:** Beyond the military, the core capability – **portable, AI-powered RF monitoring** – has strong applications in the public safety and commercial domains. First responders, law enforcement, and disaster relief teams increasingly rely on clear communications and could benefit from a tool to **detect interference or unauthorized signals**. For example, firefighters at a disaster site could use a similar device to identify if any rogue transmitters or devices are jamming their radios. The Department of Homeland Security has identified needs to "detect, identify, and locate RF interference sources that may be disrupting first responder communications", [12] which our technology directly addresses. In a dual-use scenario, the system might be used at large public events by security teams to scan for suspicious transmissions (e.g. an illicit drone control signal or an unauthorized radio on emergency channels). Commercially, telecommunications providers and regulators could deploy the solution for **spectrum management** – for instance, identifying illegal broadcasters or sources of interference in urban environments. The device could become a smart spectrum analyzer for industry technicians, far more automated than current equipment

For each dual-use vertical, we'll ensure that any required modifications (frequency ranges, user interface tweaks, compliance with civilian spectrum rules) are documented. The underlying AI engine can be retrained on civilian signal datasets (commercial LTE, public safety bands, etc.) to tailor performance to those scenarios. In Phase I we will engage with at least preliminary discussions of these expansions, but the primary focus remains the **military utility**. A key point is that the success of our system in the military realm naturally paves the way for spin-offs: the **technology readiness** achieved through DARPA funding can be directly applied to pressing needs like first responder comms reliability. This aligns with SBIR Phase III goals of commercialization and wider usage.

Phase I Work Plan

Phase I will be a 6-month effort (with a budget of approximately $150K) focused on demonstrating **feasibility** of the AI-driven spectrum monitoring concept. We have structured the work into four quarters, each with clear milestones and performance metrics, in accordance with DARPA's recommendation for quarterly technical milestones:

1. **Q1 – System Design & Requirement Analysis:** We will kick off with an in-depth design phase. Tasks: Define the system architecture (radio hardware, processing module, ATAK plugin structure) and identify key technical requirements for detection accuracy, latency, bandwidth, and integration. We will perform a **trade study** of candidate SDR platforms and data sources. Additionally, we'll gather and generate initial training data for the AI – e.g. simulate or record sample RF signals (friendly and threat) using lab equipment. The team will develop a preliminary signal processing pipeline on a PC to validate the concept (for example, show that a simple neural network can classify a few example waveforms from an SDR). **Milestone (end of Q1):** Complete architecture design review and demonstration of a rudimentary signal classification on recorded data. **Metrics:** documented system block diagram and interface specs; initial classifier accuracy >80% on a small test set of 3-5 signal types in offline tests.
2. **Q2 – Algorithm Development (AI & DF):** In Q2, we focus on building the core algorithms for signal classification and emitter localization. Tasks: Develop or adapt a **deep learning model** for RF signal classification – likely starting with known architectures from literature (e.g. CNNs for modulation recognition) and customizing them for our problem. We'll train and validate this model on datasets that include noise and interference to approximate field conditions. In parallel, develop the preliminary **direction-finding/localization module**: set up simulations to estimate how accurately we can get bearing from one or two antennas; if using a multi-antenna SDR, simulate phase differences, otherwise simulate movement-based DF. We will also start creating the ATAK plugin (basic skeleton that can run on an Android device and display dummy data) and ensuring we can communicate between a laptop/SDR and the Android app. **Milestone:** Laboratory demonstration of the AI classification algorithm processing live or streamed SDR data for a limited case (e.g. identify at least 3 distinct signal classes in real-time in a controlled environment). Also, a report on expected localization precision based on simulation. **Metrics:** classification accuracy goal ~90% on a broadened test set; classification decision latency <1 second in lab tests; localization error for a test emitter <±10° in simulation.
3. **Q3 – Integration & Prototype Demonstration:** Q3 will integrate the pieces into a prototype and test the system in a representative environment. Tasks: Port the trained AI model to run on an **Android device or embedded processor** – this may involve using TensorFlow Lite or ONNX on the Android ATAK device

for on-device inference. Integrate the SDR with the Android: use an SDK or library to stream samples from the SDR to the app. Complete the ATAK plugin UI to display real classification/localization outputs. We will then conduct a **live demo in a controlled setting**: for example, set up one or two transmitters (signal generators or handheld radios) at known locations, and have our prototype (SDR + Android) detect and display them. We'll involve a non-expert user to operate the system to gauge usability. Throughout Q3, we also refine the algorithms based on test results (improving robustness, reducing false alarms, etc.). **Milestone:** Integrated prototype system running in real-time, demonstrated indoors or in a field test, showing the ability to detect and classify signals and roughly locate an emitter. We will likely host a live or video demonstration for DARPA at this stage to showcase progress. **Metrics:** detection sensitivity – able to detect signals at least 10 dB above the noise floor; successful classification of >80% of test transmissions in real-time; correct bearing indication within 15° for a test emitter at 100 m distance (if applicable); ATAK UI feedback from test users indicates intuitive understanding (subjective, but we will gather user comments).

4. **Q4 – Performance Evaluation & Reporting:** In the final quarter, we will rigorously evaluate the system's performance and address any remaining gaps. Tasks: Conduct systematic tests across different signal scenarios (multiple overlapping signals, varying distances, presence of friendly signals, etc.) to measure performance metrics such as false alarm rate, missed detection rate, and classification accuracy under stress. Optimize the system for SWaP: profile CPU and memory usage on the Android device and ensure it can run for extended periods (e.g. at least 3 hours continuous) without issues. If any aspect still runs on a laptop (due to ease in Phase I), plan the migration to embedded hardware for Phase II. We will also refine the **concept of operations** based on what we learned – e.g. adjust how often the system scans or how it presents alerts for best tactical use. Finally, we will compile the Phase I final deliverables: a comprehensive technical report, which will include all calculations, test data, analysis of results, and an updated system design for Phase II. This report will explicitly compare our approach's expected Phase II performance to existing specialized solutions (such as current SIGINT/EW units), showing the trade-offs and advantages. We will also outline a **commercialization and transition roadmap**. **Milestone:** Delivery of the Phase I Final Report and a Phase II proposal draft. We will define clear Phase II objectives (e.g. expand to X band, integrate onto Y radio platform, achieve Z accuracy) informed by Phase I outcomes. **Metrics:** All required Phase I documentation completed; performance goals met or rationale provided for any shortfalls with a mitigation plan; preliminary Phase II plan endorsed by stakeholders (including identification of a potential military transition partner or test unit).

Throughout Phase I, we will maintain **monthly status reports** and engage with DARPA for feedback at each milestone. Each quarter's progress will be measured against the above targets, ensuring that by the end of Phase I we have a validated feasibility study and a strong case to proceed to prototype development. Importantly, the Phase I work will also delve into interoperability (confirming our system can work with or as a replacement for e.g. PRC-117G) and scalability (projecting how the solution could be used in larger contexts), as required by the solicitation. The entire Phase I will cost approximately $150K, allocated across labor for AI/software development, procurement of a COTS SDR and test equipment, and field testing expenses.

Expected Outcomes & Transition Plan

By the end of Phase I, we expect to have demonstrated the core feasibility of AI-driven spectrum monitoring for tactical units, setting the stage for Phase II prototype development. **Expected outcomes** include:

- **Validated Feasibility:** A proof-of-concept system (at TRL 4-5) showing that a portable device can autonomously detect, classify, and localize RF signals in real-time without hindering communications. This will be documented through test data and a comparative analysis of performance. For example, we anticipate achieving at least ~90% correct classification of targeted signal types and localization within manageable error bounds (e.g. <15°). We will also quantify the system's RF coverage (bandwidth monitored) and pattern-of-life capability (e.g. able to log hours of spectrum activity ande derive basic trends).
- **ATAK Plugin Prototype:** Even if at a basic level, we will have an operational ATAK plugin from Phase I that demonstrates the user interface and can ingest real (or simulated) data. This serves as a starting point for Phase II where we'll fully integrate and polish the interface. Having this early prototype also facilitates

user feedback – we can involve a few end-users (military communications sergeants, etc.) to try the interface and provide input on usability, which we will roll into Phase II improvements. It also proves the **interoperability** of our approach: by seeing it run on ATAK, we confirm it works within existing DoD software frameworks.

During Phase II, we plan to **produce full prototypes** and deliver them to select DoD units for evaluation. The transition plan in Phase I will identify which units and in what contexts (e.g. a test with an Army infantry platoon at a combat training center, or experimentation with Special Operations Forces who frequently use ATAK). We will also prepare for the certifications and approvals needed (spectrum certification, safety, etc.) to use the device in real operations by Phase III.

In summary, Phase I will conclude with a successful feasibility demonstration and a comprehensive plan to rapidly advance the technology. Success will be measured by meeting the technical milestones and achieving stakeholder buy-in for Phase II. By delivering a strong final report and transition strategy, we will secure the support needed to move into Phase II where we build and field-test prototypes, working towards eventual deployment. Our ultimate transition goal is to turn this SBIR project into a fielded capability – giving U.S. forces a decisive edge in spectrum awareness – and to transition the tech to broader use such as first responders, fulfilling the dual-use mission envisioned in Phase III. The unique advantage of our AI-enhanced RF monitoring system is its **fusion of cutting-edge AI with soldier-proof design**: this will be emphasized to transition partners, as it promises a high-impact payoff (real-time situational awareness of the invisible spectrum) with a low barrier to adoption (no new hardware burden, simple integration). We believe this value proposition will drive successful transition into both military acquisition and commercial uptake, following a successful Phase II demonstration of the prototype in an operational setting.

1. “SBIR: Spectrum Monitoring and Awareness in Real-Time (SMART) - Open Topic | DARPA.” Accessed March 20, 2025. https://www.darpa.mil/research/programs/smart.
2. “Tactical Assault Kit (TAK) – Air Force Research Laboratory.” Accessed March 20, 2025. https://afresearchlab.com/technology/information-technology/tactical-assault-kit-tak/.
3. Scholl, Stefan. “Overview of Open Datasets for RF Signal Classification.” *Panoradio SDR* (blog), November 3, 2024. https://panoradio-sdr.de/overview-of-open-datasets-for-rf-signal-classification/.
4. Scholl, Stefan. “Https://Arxiv.Org/Pdf/2206.12967.” Accessed March 20, 2025. https://arxiv.org/pdf/2206.12967.
5. Scholl, Stefan. “RF Training Data Generation for Machine Learning.” *Panoradio SDR* (blog), December 20, 2022. https://panoradio-sdr.de/rf-training-data-generation-for-machine-learning/.
6. Maliniak, David. “AI/ML Software Enhances Real-Time RF Situational Awareness.” Microwaves & RF, October 2, 2024. https://www.mwrf.com/technologies/embedded/software/article/55143628/microwaves-rf-ai-ml-software-enhances-real-time-rf-situational-awareness.
7. O’Connor, Alan C, Pawan Setlur, and Natasha Devroye. “Single-Sensor RF Emitter Localization Based on Multipath Exploitation,” n.d.
8. spectric-labs. “Using Deep Learning for Signal Detection and Classification.” Spectric Labs, March 9, 2023. https://www.spectric.com/post/using-deep-learning-for-signal-detection-and-classification.
9. Ettus Research, Ettus Research, a National Instruments. “USRP X310 High Performance Software Defined Radio.” Ettus Research. Accessed March 20, 2025. https://www.ettus.com/all-products/x310-kit/.
10. Feng, Xuefeng, Zhen Huang, Jiazhi He, Ying Xiao, and Dingli Xue. “Direct Position Determination for Single Sensor Emitter Localization with Unknown Period.” In *2022 IEEE 2nd International Conference on Information Communication and Software Engineering (ICICSE)*, 205–9, 2022. https://doi.org/10.1109/ICICSE55337.2022.9828900.
11. “R&S®AU600 Active Omnidirectional Receiving Antenna System | Rohde & Schwarz.” Accessed March 21, 2025. https://www.rohde-schwarz.com/us/products/aerospace-defense-security/omnidirectional-stationary/rs-au600-active-omnidirectional-receiving-antenna-system_63493-74950.html.

12. Shahid, Hasan. "Radio Frequency Detection, Spectrum Analysis, and Direction Finding Equipment," n.d. Accessed March 21, 2025 https://www.dhs.gov/sites/default/files/saver-msr-rf-detection_cod-508_10july2019.pdf
13. "Spectrum Sensing with Deep Learning to Identify 5G and LTE Signals." Accessed March 21, 2025. https://www.mathworks.com/help/comm/ug/spectrum-sensing-with-deep-learning-to-identify-5g-and-lte-signals.html.