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Electronic Warfare Framework

An Approach to Accelerate Research and Development

Abstract

The increasing dependence of modern societies and military operations on radio frequency-based and networked systems has made the electromagnetic spectrum a critical operational domain. Electronic warfare capabilities must therefore evolve toward more adaptive and rapidly deployable solutions. This article addresses the challenge of accelerating electronic warfare related research and development by introducing a compact, modular framework that enables efficient testing and validation of signal processing and machine learning-based detection algorithms in real-world conditions. To achieve this, comparison of possible technologies and architecture was made to select the optimal components. The proposed system combines a software-defined radio and an embedded processing unit to create a field-deployable platform for radio frequency signal collection, analysis and countermeasure evaluation. The framework's functionality was demonstrated through an FPV drone detection use case, where video signals transmitted by a drone were successfully identified and disrupted.

Keywords: electronic warfare, ESM, software-defined radio, machine learning, CUAV, FPV drone

Introduction

Information technology has become an integral part of modern society, fundamentally shaping daily life and global operations. The interconnection of billions of electronic devices like computers, mobile phones, and IoT (Internet of Things) systems has created a new operational domain commonly referred to as cyberspace. Instant data

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exchange within this environment enables rapid development in numerous fields, including financial services, remote monitoring of critical infrastructure and social communication. However, this heavy dependence on cyberspace also introduces vulnerabilities, for example any disruption or sabotage of these services can have serious social, economic or even military consequences.[2] In the field of defence and EW (electronic warfare), ESM (electronic support measures) plays a central role in understanding, monitoring and controlling the electromagnetic environment.[3] My research focuses on exploring the applicability of ML (machine learning) methods within this domain. Specifically, evaluating different ML models to determine which are most suitable for various signal processing tasks. The primary objective is to automate the detection and classification of specific RF (radio frequency) signals, thereby enhancing the ability to respond quickly and effectively to emerging threats.[4]

A key consideration in my work is embedded applicability. Any proposed detection method should not only be accurate, but also computationally efficient enough to operate on compact, low-power devices suitable for field use. Therefore, both algorithmic performance and hardware resource requirements are carefully evaluated. To validate detection methods, I implemented them on physical hardware, consisting of an SDR (software-defined radio) and an embedded computer unit. Although this setup has proven effective in laboratory conditions, field deployment revealed limitations in portability and usability. To overcome these issues, I designed a modular EW framework. A compact, flexible platform that supports on-field experimentation and real-time testing. Such equipment not only accelerates research but also enables rapid capability development, which is critical when facing dynamic or unpredictable threats. The Russian–Ukrainian conflict has provided several examples of rapid technological adaptation, such as the deployment of improvised drones within days of the beginning of hostilities, highlighting the importance of adaptable research platforms.[5]

This article presents the design and validation of the proposed EW framework. It begins with the fundamental considerations behind the framework's architecture and the selection of its main components, including the SDR and signal processing unit. The subsequent sections describe the system's construction, followed by a real-world test scenario focusing on FPV (first person view) drone detection. The expected outcome is a practical, adaptable EW platform that not only supports ongoing research into ML-based signal processing but also provides a foundation for accelerated R&D (research and development) and hands-on education in the field of electronic warfare.

The fundamentals of the framework

As for basic elements, the framework needs to include an SDR and a signal processing unit as shown in Figure 1. In this scenario there is a single RX (receiver) antenna for capturing RF signals. Without going into details, basically the RF tuner will amplify,

[2] Haig 2021: 91.
[3] Németh–Virágh 2023: 3.
[4] Farkas et al. 2025.
[5] Olloy 2024: 17.

down-mix and filter the received stream. Then the ADC (analogue-to-digital converter) will convert it to a digital representation that will source the signal processing unit. The signal processing unit should be capable of running ML models. This can be implemented into an MCU (micro-controller), an FPGA (field programmable gate array) or a PC (personal computer).[6] The result is then handled by the result logic. At this point we can do many things with the gathered information. It is possible to display the results or transfer them for further analysis over the user interface. Further on, the results can be used to control the SDR, therefore make it possible to achieve swiping or signal following functionality.[7]

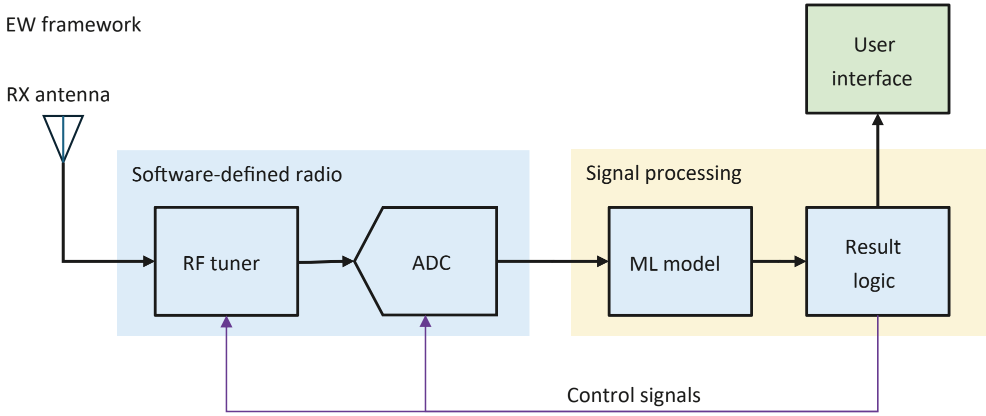

Figure 1: Basic concept of the EW framework, including an SDR and a signal processing unit
Note: The control signal feedback makes it possible to automatically control the SDR based on the results. An additional user interface is added to have control over the results.
Source: compiled by the author

The diagram of the framework gives an overview of the major components, but further investigation needs to be done to select the exact parts to be used. The overall data throughput required will outline the minimum requirements and help in selecting the right platform.[8]

Software-defined radio

The SDR device fundamentally determines the RF capability of the EW framework. Its frequency coverage, instantaneous bandwidth, dynamic range and transmit capability set the envelope of what can be observed, recorded and tested. Therefore, before selecting an SDR we must define the target signal types, the carrier bands of

6 Branco et al. 2019: 1–5.
7 Şorecău 2025.
8 Farkas 2024.

interest, required instantaneous bandwidth, and the deployment constraints, like size, weight, power and cost.

For the current study the primary detection target is the VTX (video transmitter) used on FPV drones. VTX signals are practical detection targets for several reasons. They are typically transmitted with relatively high RF power compared to low-power control links, occupy relatively wide analogue or digital video bandwidths, and their signal strength increases as the drone approaches. Observations of FPV usage in recent conflicts indicate that the majority of COTS (commercial off-the-shelf) VTX hardware operates in the 1.2 GHz and 5.8 GHz ISM (industrial, scientific and medical) band with selectable power levels from ~10 mW up to 800–2000 mW. Representative product specifications are summarised in *Table 1.*

Table 1: Working frequency range and transmitter power of VTXs commonly used in the Russian–Ukrainian war

Device	Typical frequency band	Max. TX power
TBS Unify Pro 5G8 V3[9]	5.8 GHz	800 mW
Eachine TX805S[10]	5.8 GHz	1.6 W
RushFPV Tank Solo[11]	5.8 GHz	1 W
HumbirdTec 1G3TE-V2[12]	1.2 GHz	2 W
DarwinFPV 1.2G 1.6W VTX[13]	1.2 GHz	1.6 W

Source: compiled by the author

Given the target frequency band centred around 1.2 GHz and 5.8 GHz, and the requirement to detect relatively wideband video carriers, four practical constraints follow:

- Frequency coverage: The SDR must at minimum cover the 1.2 GHz and 5.8 GHz FPV bands. Preferably other bands too to allow future expansion
- Instantaneous/baseband bandwidth: For analogue video pattern recognition a modest sample rate of 1 MSPS (mega-sample per second) is generally sufficient for initial detection. Higher sample rates will be required for raw-capture, complex demodulation or multiple-channel monitoring
- Portability and power: The framework is intended for field tests and mobile deployment, so small form factors and modest power draw are critical design drivers
- Ease of development: Research throughput is accelerated by a platform that supports high-level development and rapid prototyping (Python, GNU Radio, standard toolchains)

To make an informed selection I compared three widely available SDRs that are commonly used in research and field-deployable setups. The Ettus USRP B210, the

9 See the manual *TBS Unify Pro 5G8 (HV) Video Transmitter* 2018.
10 *Eachine TX805S Transmitter Product Instruction Manual* [s. a.].
11 *RUSHFPV Tank Solo User Manual* [s. a.].
12 *HumbirdTec VTX-1G3TE* [s. a.].
13 *DarwinFPV 1.2G 1.6W VTX* [s. a.].

HackRF One R9, and the RTL-SDR Blog V4 dongle. Their summarised characteristics are presented in Table 2.

Table 2: Comparing features of selected SDRs

SDR type	Frequency coverage	Max. sample rate	Notes
Ettus USRP B210[14]	70 MHz – 6 GHz Dual Rx/Tx channels	56 MSPS	High dynamic range, excellent front end and sensitivity FPGA is available for custom processing
HackRF One R9[15]	1 MHz – 6 GHz Half-duplex single channel	20 MSPS	Moderate sensitivity for general use Transceiver (TX/RX) capable 8-bit I/Q Good community support
RTL-SDR Blog V4[16]	500 kHz – 1.766 GHz Only RX, single channel	3.2 MSPS	Low cost; receive-only Limited bandwidth and dynamic range compared to HackRF and USRP

Source: compiled by the author

For a field-deployable EW framework to detect FPV drone VTXs, support embedded testing, be compact and battery-operable and accelerate iterative R&D, HackRF One represents a reasonable compromise:

- Frequency coverage from 1 MHz to 6 GHz comfortably includes the 1.2 GHz and 5.8 GHz bands and allows future expansion into other bands without hardware change
- RX and TX (transmit) capability enables not only passive detection but also controlled active tests in lab conditions
- Baseband throughput up to 20 MSPS is more than sufficient for the 1 MSPS pattern recognition requirement I described, while still permitting higher-rate captures for analysis when necessary
- SWaP (size, weight and power) and cost favour HackRF over a USRP B210. HackRF is smaller, cheaper and easier to integrate in a mobile enclosure. It also gives rapid software prototyping via GNU Radio and Python

A practical caveat is that HackRF's ADC resolution and front-end filtering make its absolute sensitivity and dynamic range lower than Ettus USRP devices. Later on, if required to maximise detection range or operate in extremely congested RF environments, a higher-performance transceiver should be considered. For an R&D and field-trial platform where rapid iteration and portability matter, HackRF One is an optimal choice.

[14] *Ettus USRP B210* [s. a.].
[15] HackRF documentation: https://hackrf.readthedocs.io/en/latest/index.html
[16] See: www.rtl-sdr.com/about-rtl-sdr

Signal processing unit

After the radio front-end and data acquisition functions are realised by the Software Defined Radio (SDR), the next essential stage in the framework is the signal processing unit. While the SDR is responsible for digitising the received radio frequency (RF) spectrum and forwarding the sampled data, the processing unit interprets this information to identify relevant patterns or potential threats. The efficiency and accuracy of this step depend largely on the computing architecture used, as it must balance high computational demand with low power consumption and real-time responsiveness. Therefore, the selection of an appropriate processing platform is a critical design decision in building a deployable EW framework.

For signal processing tasks, a wide range of computing platforms can be utilised. The goal of my work is to identify the most suitable technological direction that provides an optimal balance between computational performance, energy consumption and development complexity. In this study, four hardware architectures were examined: FPGA, CPU (Central Processing Unit), GPU (Graphics Processing Unit), and ASIC (Application-Specific Integrated Circuit). Their relative computational capacity and power demand are illustrated in Figure 2.[17]

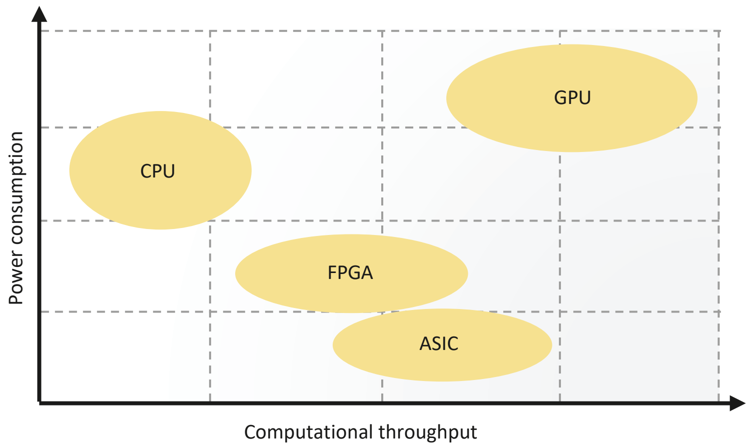

Figure 2: Comparison of power consumption and throughput of different technologies
Source: compiled by the author

Each architecture offers distinct advantages and limitations:

- FPGA: These devices provide highly parallel and deterministic processing, making them ideal for low-latency signal processing applications such as real-time demodulation or protocol decoding. However, FPGA development requires specialised knowledge of hardware description languages (HDL) and toolchains, which significantly increases development time. Although their energy efficiency is excellent, their flexibility is limited once the logic has been synthesised.

[17] Zhang 2019: 49.

- CPU: Traditional processors offer great flexibility and ease of programming, with extensive software support and mature development environments. While CPUs generally provide lower raw processing throughput compared to GPUs or FPGAs, they remain sufficient for a wide range of signal processing tasks when paired with efficient algorithms and optimised libraries. Their low power consumption and compact form factor make them particularly suitable for mobile and embedded EW applications.
- GPU: Designed for massive parallel computation, GPUs deliver extremely high performance for data-intensive operations such as deep learning or spectral analysis. However, their high energy demand and typically bulky thermal management requirements limit their use in field-deployable systems. In addition, GPU programming, while more accessible today through CUDA or OpenCL, still requires specific expertise and careful optimisation to achieve full performance.
- ASIC: These are custom-designed chips optimised for a specific task, providing unmatched energy efficiency and performance once manufactured. Nevertheless, the extremely high development cost and lack of reconfigurability make ASICs impractical for research and prototyping, especially in fast-changing electronic warfare environments where adaptability is critical.

The comparison clearly shows that no single architecture is universally superior. The optimal choice depends on the operational context and design priorities. In my research, the CPU-based approach has been selected, specifically implemented using the Raspberry Pi platform. This decision was guided by the following considerations:

- Low power consumption: Suitable for mobile and battery-powered field applications
- Compact design: Easily integrates with SDR hardware
- Ease of programming: Supports high-level languages such as Python, enabling rapid prototyping and flexible model deployment
- Adequate performance: Sufficient computational capacity to execute machine learning-based signal detection in real time

By utilising the Raspberry Pi as the signal processing unit, the framework achieves an effective balance between performance, energy efficiency and portability, while maintaining the flexibility necessary for rapid research and development cycles.

Construction

After selecting the two core components, the Raspberry Pi as the signal processing unit and the HackRF One as the SDR transceiver, the next objective was to design a compact and field-deployable EW platform that constitutes the hardware foundation of the proposed framework. The assembled system aims to serve as both a research platform and a functional prototype, capable of real-time signal collection, analysis and active testing in realistic environments.

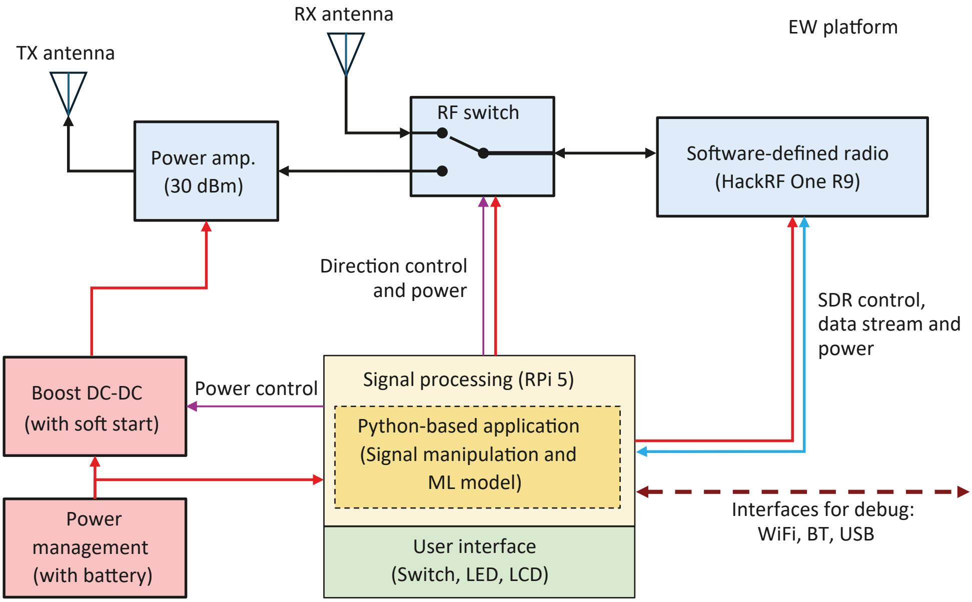

Figure 3: Block diagram of the EW platform, including SDR, signal processing CPU, power management and additional RF components
Source: compiled by the author

A high-level block diagram of the platform is presented in Figure 3. The system consists of several interconnected modules, each fulfilling a distinct role in the overall architecture.

- Software-Defined Radio (HackRF One R9): Operates as the RF front end, responsible for capturing and transmitting signals within the 1 MHz to 6 GHz frequency range. Because HackRF operates in half-duplex mode, an RF switch is included to alternate between transmit and receive paths.
- Signal Processing Unit (Raspberry Pi 5): Acts as the central control and signal processing node. It runs the machine learning algorithms responsible for detection and classification, provides the user interface, and manages communication between subsystems. The Raspberry Pi is equipped with a small touch LCD display, which allows real-time debugging, visual feedback and configuration during field tests.
- RF Power Amplifier (PA): The transmit chain includes a broadband power amplifier with an output power of approximately 30 dBm. While it can support general tasks such as signal emulation, system calibration and active testing, its primary purpose within the EW framework is to enable controlled jamming experiments.
- Power Management System: The entire setup is powered by an integrated battery pack with onboard power regulation. Between the main power system and the RF amplifier, a Boost DC-DC converter with a soft-start function is implemented to provide the required 12 V rail for the amplifier while avoiding current surges at startup. The remaining modules are powered from the regulated low-voltage outputs of the power pack.

- User Interface and Indicators: To support standalone operation and quick situational awareness, three status LEDs are installed: green for system power, yellow for warnings or system activity, and red to indicate transmitter operation. A small buzzer provides audible feedback for system events or alerts. The transmit function can be manually enabled or disabled using a dedicated hardware switch, ensuring safe and controlled RF emission during testing.

The mechanical layout emphasises compactness and ease of integration. All modules are mounted within a lightweight enclosure that provides sufficient shielding between the RF and digital sections. The resulting unit can operate autonomously in the field or be connected to a development workstation for debugging and data analysis.

Functionally, the Raspberry Pi serves as the core development platform, allowing to deploy, test and refine signal processing algorithms or trained neural networks directly on hardware. Because the setup combines SDR flexibility, embedded processing and local user interaction, it effectively bridges the gap between simulation environments and real-world EW testing. As my research primarily focuses on AI-assisted RF signal processing, the constructed equipment enables both RF data collection and on-site validation of developed detection and classification models. This dual-use capability accelerates the research cycle and supports iterative model improvement based on real signal conditions.

In summary, the constructed EW equipment represents a compact, modular, and energy-efficient platform suitable for both laboratory research and field deployment. Its architecture allows rapid reconfiguration of the SDR and processing algorithms, supporting a wide range of experiments from passive signal monitoring to active transmission tests. The integration of an embedded processing unit, power management and intuitive user interface ensures autonomous operation without external peripherals. These characteristics make the system an ideal testbed for validating machine learning-based signal processing approaches under realistic conditions.

Real-life scenario

As an initial validation of the developed EW framework, a practical FPV drone detection and countermeasure scenario was implemented. The objective was to identify approaching FPV drones based on their VTX signals and to test the operational effectiveness of the hardware setup in real conditions. The applied detection method is based on our previously published study.[18] In this implementation, the SDR continuously samples short segments of the RF spectrum over selected frequency bands where FPV VTX signals are typically found. The sampling rate is intentionally kept low to minimise computational load, while still preserving enough temporal and spectral resolution to reconstruct a coarse representation of the transmitted video waveform. Rather than performing full colour or frame decoding, only the signal structure is analysed to determine whether it corresponds to a composite video signal or not.

[18] Farkas et al. 2025: 2–7.

An autocorrelation-based detection algorithm is currently applied. This method identifies the repetitive frame patterns characteristic of analogue FPV video transmissions. When a potential FPV video signal is detected, the system provides audio and visual feedback:

- The LCD display and LEDs indicate a detection event
- An acoustic warning is generated through the buzzer
- The SDR locks onto the detected frequency for further observation

Once a detection is confirmed, the operator can manually activate the jammer. In this mode, a narrowband interference signal, approximately with 100 kHz bandwidth that is significantly narrower than the video channel, is transmitted through the RF power amplifier. The intention is to disrupt the drone operator's video link by injecting localised interference, effectively blinding the drone operator, and potentially causing to lose control over the drone or abort the mission. The final platform with a rugged enclosure is demonstrated in Figure 4.

Figure 4: Realised EW platform in a rugged enclosure for field testing
Source: compiled by the author

Field tests demonstrated that the detection and jamming functionality works effectively in the 1.2 GHz band, achieving reliable detection within 100–300 meters, depending on environmental conditions and the transmitter's output power. However, due to the reduced sensitivity of HackRF One in the 5.8 GHz range, the detection range at that band is limited to approximately 10 meters. For extended-range detection in the 5.8 GHz band, employing a USRP B210 or a comparable high-sensitivity SDR would be a suitable improvement.

Future work will focus on replacing the current autocorrelation-based approach with a neural network-based detection algorithm, leveraging CNNs (convolutional neural networks) trained on real RF samples. The constructed EW platform and framework will be used to collect, label and process these training datasets, enabling the development of more robust and adaptive detection models. This way the framework will not only serve as an operational tool but also as a scalable R&D platform for AI-driven EW applications.

Conclusion

The original objective of my research was to accelerate EW research and development by designing a modular and field-deployable framework that enables rapid testing of signal processing algorithms and embedded implementations. The motivation arose from the increasing complexity of the electromagnetic environment, the proliferation of unmanned aerial systems and the growing reliance on real-time situational awareness in modern conflicts. Detecting, classifying and responding to different RF emissions requires a flexible, scalable, and hardware-validated approach. To address these challenges, an EW framework concept was developed that combines SDR technology with embedded signal processing on a compact computing platform. The article presented the logical build-up of this framework, including the selection and comparison of hardware components, system integration and functional validation.

In the first stage, various SDR platforms were evaluated based on frequency coverage, bandwidth, sensitivity, power consumption and cost. HackRF R9 was selected as the most balanced solution for field research, offering sufficient performance and flexibility at a moderate cost and size. For signal processing, four processing were analysed, and the Raspberry Pi was chosen as the processing unit due to its low power demand, small form factor and ease of software development in Python. A compact EW prototype was then constructed. The resulting equipment supports both passive monitoring and active transmission, and it is suitable for mobile field tests.

To validate the framework, a real-life FPV drone detection scenario was implemented. The system successfully detected analogue and digital FPV video signals using an autocorrelation-based algorithm, providing visual and acoustic alerts and enabling manual activation of a narrowband jammer. The experiment demonstrated the feasibility and operational readiness of the concept for short-range detection and countermeasure testing.

Beyond the immediate results, the developed EW framework has broader implications. It provides a research and educational platform that can be easily adapted for various signal analysis tasks, machine learning experiments, or system demonstrations. Future work will focus on implementing neural network-based signal classification, expanding detection range with higher-sensitivity SDRs, and refining power management for extended autonomous operation. In summary, the presented work delivers a functional and adaptable electronic warfare research platform that bridges the gap between laboratory simulations and field-ready experimentation. By combining flexible SDR technology, embedded computing and AI-based signal processing, the framework contributes to faster prototyping, better adaptability and improved response capability in future EW system development.

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