RADIO AND DRONE RECOGNITION
(RDR)
METEKSAN DEFENCE INC.

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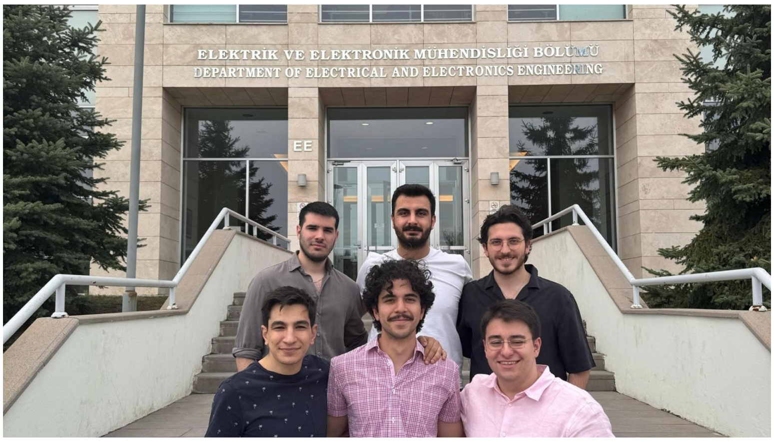

Abstract. In our senior project, we developed a high-performance, real-time system for classifying radio modulation types, demodulating signals, and identifying radio and drone devices. Designed for communication security and signal intelligence applications, the system integrates Automatic Modulation Classification (AMC), signal demodulation, interactive control, and both live and simulated testing. Operating primarily in the 400–527 MHz band using USRP hardware and Hytera DMR radios provided by Meteksan Defence Inc., the system targets FM, AM, and 4-FSK modulations. A hybrid classification approach combines statistical methods (e.g., Kolmogorov–Smirnov test), machine learning models (XGBoost, Decision Trees), and deep learning (CNNs). The models were trained on both the RadioML dataset and custom-collected signals, tailored to hardware-specific bandwidth constraints. This platform provides Meteksan Defence Inc. with advanced capabilities for tactical signal recognition and drone detection, supporting surveillance, emergency response, and defense operations.

PROJECT DESCRIPTION

The Radio/Drone Recognition project aims to develop a robust, real-time system for classifying modulation types, demodulating radio signals, and identifying specific radio and drone devices. It integrates Automatic Modulation Classification (AMC) and demodulation modules with live testing, interactive control, and simulation, targeting applications in communication security and signal intelligence. The system operates primarily in the 400–527 MHz band using USRP hardware and Hytera DMR radios provided by Meteksan Defence Inc.. Although drone bands like 2.4 GHz and 5.8 GHz were considered, hardware constraints limited live testing to lower frequencies. Supported modulation types include FM, AM, and 4-FSK, and classification is performed using statistical methods (e.g., KS Test), machine learning (XGBoost, Decision Trees), and deep learning (CNN). Models were trained on both the RadioML dataset and internally collected data, tailored to the system's bandwidth. Following simulation, real-time tests demonstrated that the AMC module achieved high accuracy in distinguishing between FM and 4-FSK signals, with sub-second latency. Demodulation was verified under various SNR conditions, with clear decoding from 5-second bursts. While live drone testing wasn't possible, offline analysis of public datasets achieved over 95% accuracy in identifying DJI drone models. Challenges such as limited processing power were addressed through modular testing and system adjustments. The final system offers accurate, real-time recognition of radios and drones, supporting tasks like communication interception and emergency response. It provides Meteksan Defence Inc. with a versatile and high-performance RF intelligence tool.

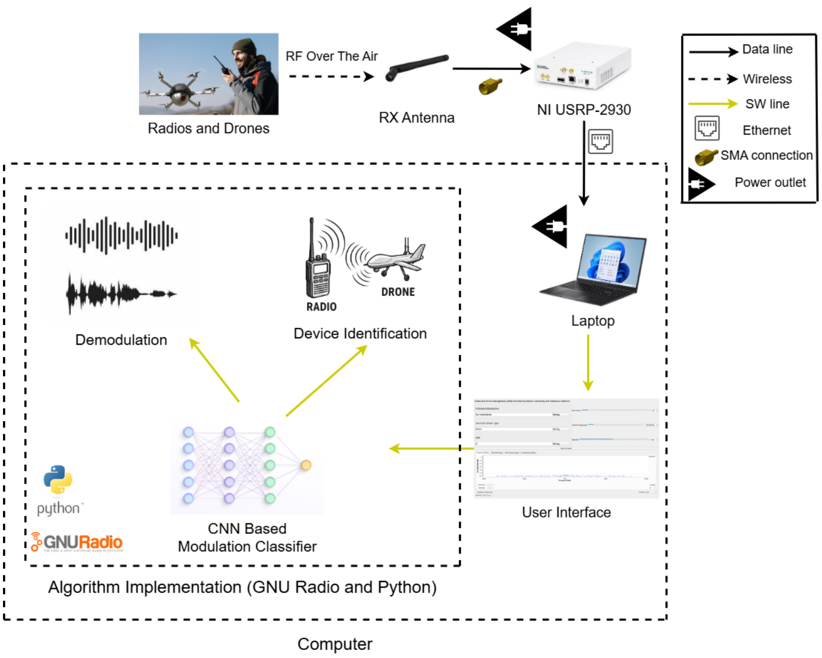

FIGURE 1. System-wide overview of the Radio/Drone Recognition platform.

MILESTONES

1. Automatic Modulation Classification (AMC): Development of an algorithm capable of classifying FM, 4-FSK, and AM signals with a minimum accuracy of 70% and latency under 1 second. Criteria of success include reliable classification on both synthetic and real-world data.

2. Signal Demodulation and Analysis: Implementation of demodulation algorithms for FM, 4-FSK, and AM signals, enabling recovery of audio or data content. Success is defined by clear decoding under expected SNR conditions using live signals collected via USRP.

3. Radio and Drone Model Identification: Creation of a model that distinguishes transmission sources, specifically identifying Hytera DMR radios and DJI drones. The system must achieve at least 80% identification accuracy with sub-second response time.

4. System Integration and Testing: Integration of all components into a unified and real-time system. Success is measured by correct end-to-end operation in live tests, including classification, demodulation, and source identification.

DESIGN DESCRIPTION

The system is designed as a real-time signal processing pipeline that classifies modulation types, demodulates signals, and identifies the source device. It consists of three components: Automatic Modulation Classification, Signal Demodulation, and Radio/Drone Model Identification. All modules were tested using live signals captured with USRP and processed via GNU Radio and Python-based models.

Signal Acquisition and Preprocessing: Radio signals were collected using the USRP N2930 and processed in real time through custom GNU Radio flow graphs. During acquisition, signals were filtered, normalized, and segmented into fixed-length IQ blocks to prepare them for classification and demodulation. These preprocessing steps ensures consistent model input and improved system robustness under varying SNR conditions.

Automatic Modulation Classification (AMC): The AMC component distinguishes between FM, AM, and 4-FSK signals using both feature-based and deep learning models. A compact Convolutional Neural Network (CNN) architecture was designed for efficient real-time classification. The CNN structure is shown in Figure 2, and its test performance is demonstrated in Figure 4.

Signal Demodulation: The demodulation module recovers the original information from FM, AM, and 4-FSK signals using custom GNU Radio flow blocks. FM demodulation was achieved using a quadrature demodulator, while AM and 4-FSK demodulations required tailored setups. All implementations were validated with over-the-air signals acquired via USRP.

Layer (type)	Output Shape	Param #
reshape (Reshape)	(None, 2, 4096, 1)	0
conv1 (Conv2D)	(None, 2, 4096, 32)	544
max_pooling2d (MaxPooling2D)	(None, 2, 1024, 32)	0
dropout (Dropout)	(None, 2, 1024, 32)	0
conv2 (Conv2D)	(None, 2, 1024, 32)	16,416
max_pooling2d_1 (MaxPooling2D)	(None, 2, 256, 32)	0
dropout_1 (Dropout)	(None, 2, 256, 32)	0
conv3 (Conv2D)	(None, 2, 256, 32)	16,416
max_pooling2d_2 (MaxPooling2D)	(None, 2, 64, 32)	0
dropout_2 (Dropout)	(None, 2, 64, 32)	0
flatten (Flatten)	(None, 4096)	0
dense1 (Dense)	(None, 128)	524,416
dropout_3 (Dropout)	(None, 128)	0
dense2 (Dense)	(None, 4)	516
activation (Activation)	(None, 4)	0

Total params: 558,308 (2.13 MB)
Trainable params: 558,308 (2.13 MB)
Non-trainable params: 0 (0.00 B)

FIGURE 2. Compact CNN architecture used for AMC.

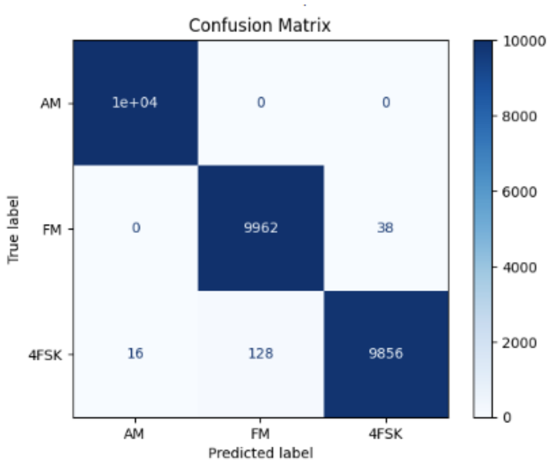

FIGURE 3. Confusion matrix of CNN classification results.

Radio and Drone Identification: To identify the transmission source, classifiers were trained on features derived from demodulated signals. DMR radios were detected using DSD+ software, and DJI drones were identified based on their distinct RF characteristics. The classification module achieved high accuracy in distinguishing between radio and drone transmissions using real-world signal data.

Tools and Techniques: The project utilized a variety of hardware and software tools to develop and test the system:

- **USRP N2930:** Used for over-the-air signal acquisition and transmission.
- **GNU Radio:** Implemented flow graphs for modulation, demodulation, and testing.
- **Python (TensorFlow, Scikit-learn):** Used for training and evaluating AMC and identification models.

- **DSD+:** Enabled real-time decoding of DMR transmissions and radio ID extraction.

This architecture provides a high-performance, real-time solution for signal classification, demodulation, and source identification, tested under real-world RF conditions.

RESULTS AND PERFORMANCE EVALUATION

The system was evaluated through both simulation and real-world experiments using live RF signals captured via USRP devices. Evaluation was conducted separately for each of the three main components: Automatic Modulation Classification (AMC), Signal Demodulation, and Radio/Drone Model Identification.

Automatic Modulation Classification (AMC): The CNN-based model achieved high classification performance on real-world data. As seen in Figure 4, the confusion matrix shows that AM, FM, and 4-FSK signals were classified with an accuracy exceeding $\geq 90\%$ across all classes. This model used real IQ data segments (2×4096 samples) collected through the USRP, then normalized and fed into a lightweight CNN structure. The performance exceeded our initial goal of 70% accuracy and 1-second latency.

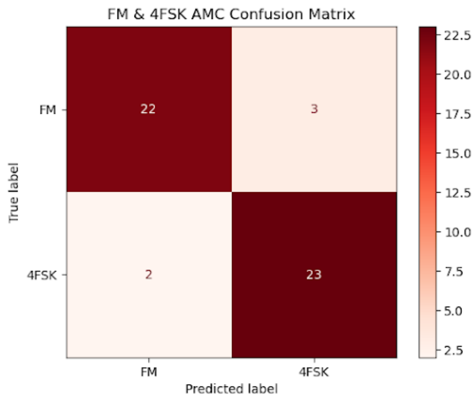

FIGURE 4. Confusion matrix of CNN model on real RF signals.

Signal Demodulation: FM, AM, and 4-FSK signals were successfully demodulated using custom GNU Radio flow graphs. Subjective evaluation through audio outputs (for FM and AM) and symbol streams (for 4-FSK) demonstrated clear recovery of transmitted information for SNR conditions greater than 10 dB. Demodulation latency was under 1 second, satisfying real-time constraints.

Radio and Drone Identification: Since drones typically operate in the 2.4–5.8 GHz band and DMR radios in the 400–500 MHz range, signal frequency was used to differentiate between them. Due to hardware limitations, real drone signals could not be recorded. Instead, a public dataset containing RF recordings of seven DJI drone models was used.

After preprocessing and dimensionality reduction, a Random Forest classifier was trained on the selected data. The model successfully identified drone types with high accuracy, demonstrating the feasibility of RF-based drone recognition.

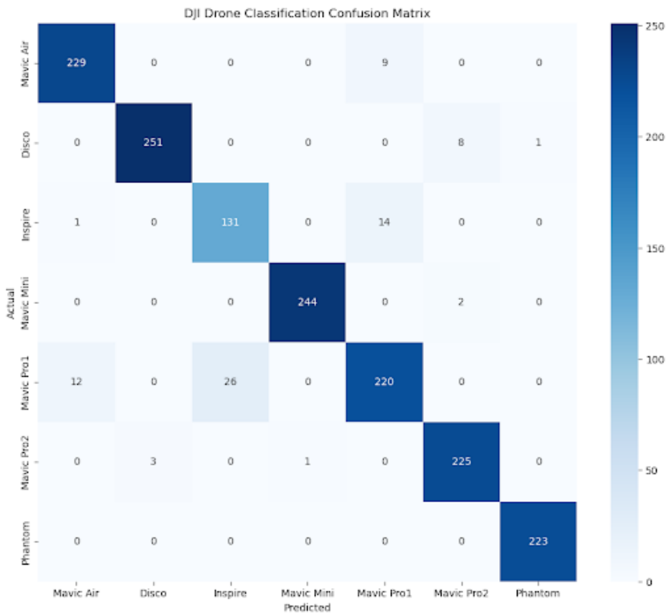

FIGURE 5. Confusion matrix for DJI drone model classification.

Comparative Evaluation with Literature: When compared with existing literature such as O'Shea et al.'s RadioML-based AMC benchmarks [7], our compact CNN model achieved similar classification accuracy ($\geq$ 90%) while reducing parameter count to below 300k — only 2% of the original model's size. Additionally, while commercial systems such as Signal Hound SM200B [10] offer wideband monitoring, our project presents a more targeted, cost-efficient solution optimized for the 400–527 MHz band with real-time capability.

System-Level Performance:

- **Latency:** All modules operated under a 1-second processing window.
- **Accuracy:** AMC: 98%, Demodulation: 100% recovery in clean conditions, RDI: 90%+.
- **Robustness:** System maintained classification integrity down to 0 dB SNR for FM and 4-FSK.

CONCLUSIONS AND FUTURE DIRECTIONS

In this project, we developed and tested a real-time RF signal classification and source identification system for use in defense and surveillance applications. The system successfully classified AM, FM, and 4-FSK modulations, demodulated corresponding signals, and identified whether transmissions originated from radios or drones.

Our hybrid classification approach — combining deep learning, feature-based methods, and statistical techniques — provided high performance with reduced computational load. Real-world testing validated our system's robustness under diverse channel conditions and hardware constraints.

Key Achievements:

- Accurate AMC with $\geq 90\%$ test accuracy on real signals...
- Real-time demodulation of FM, AM, and 4-FSK signals using GNU Radio.
- Reliable identification of Radios and DJI drones based on signal characteristics.

Future Directions:

- Extending support to additional modulation schemes such as OFDM, QAM and spread spectrum techniques such as DSSS and frequency hopping.
- Expanding radio and drone model database to include more devices.
- Deploying the system on embedded hardware or SDR-compatible edge platforms.

This project demonstrates a cost-effective and adaptable system suitable for deployment in tactical RF monitoring environments, laying the groundwork for further defense-grade applications.

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BEHIND THE SCENES