Human-Centered AI Governance Framework for Ethical and Explainable Hybrid SDR Signal Intelligence Systems

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Abstract-*Automatic modulation classification (AMC) methods trained on synthetic datasets and end-to-end deep learning models often exhibit limited robustness in noisy real-world RF environments and provide little interpretability for operational use. This paper proposes a human-centered hybrid software defined radio (SDR) intelligence framework that combines dig-ital signal processing (DSP), machine learning (ML), and a governance-aware explainable artificial intelligence (XAI) layer for interpretable modulation classification. Real-time IQ captures are acquired using HackRF One hardware and GNU Radio pipelines under practical SDR operating conditions. From each capture, a 14-dimensional feature vector is extracted using FFT-based spectral analysis, occupied bandwidth estimation, signal power analysis, instantaneous frequency, and constellation anal-ysis, and is then classified by a Random Forest model. The framework classifies FSK-like digital signals, Narrowband FM (NBFM), Wideband FM (WBFM), and no-signal conditions with 100% accuracy, precision, recall, and F1-score on the evaluated real-SDR dataset. A human-in-the-loop governance architecture further provides DSP-output visibility, confidence-based decision fusion, ethical RF monitoring, and audit logging. These results indicate that the proposed framework is a lightweight and interpretable solution for controlled SDR-based RF monitoring scenarios.*

Index Terms-Software Defined Radio (SDR), IQ Signal Pro-cessing, Automatic Modulation Classification (AMC), Explainable Artificial Intelligence (XAI), Digital Signal Processing (DSP), RF Intelligence, Machine Learning (ML), Tactical Communication Systems.

I. INTRODUCTION

Software defined radio (SDR) enables flexible, software-driven adaptation of modulation, filtering, spectrum monitor-ing, and waveform analysis, making it highly relevant for automatic modulation classification (AMC) in tactical RF en-vironments [1]. In military communication, electronic warfare, and spectrum surveillance applications, AMC must operate reliably without prior knowledge of transmission parameters and under nonideal channel and hardware conditions [2]. However, contemporary ML and DL based AMC methods, although effective on synthetic IQ benchmarks, often suffer performance degradation in real-world RF settings due to noise, frequency offsets, fading, and receiver impairments [3]. A further limitation is the limited interpretability of neural classifiers, which constrains trust, traceability, and operational accountability in mission-critical deployments [4], [5].

To address these issues, this paper proposes a human-centered hybrid SDR intelligence framework that combines DSP, ML, and governance-aware XAI for interpretable mod-ulation classification on real SDR captures. The framework extracts 14 transparent RF features from IQ data acquired using HackRF One and GNU Radio, and employs confidence-based decision fusion together with human-in-the-loop over-sight to improve decision transparency and operational usabil-ity. Experimental results on FSK-like digital signals, NBFM, WBFM, and no-signal captures demonstrate the feasibility of lightweight and explainable AMC for controlled real-SDR scenarios.

The main contributions are summarized as follows:

- A hybrid DSP–ML AMC framework implemented on real HackRF One/GNU Radio IQ captures.
- A 14-dimensional interpretable RF feature set derived from explicit DSP formulations.
- A governance-aware human-centered architecture incor-porating confidence fusion, operator visibility, and audit logging.
- Experimental validation on real SDR captures for four signal classes, achieving 100% accuracy on the evaluated dataset.

The remainder of this paper is organized as follows. Sec-tion II reviews related work, followed by the proposed system architecture, feature extraction, classification methodology, experiments, and conclusions.

II. RELATED WORK

Prior AMC research includes deep learning, DSP-based classification, and XAI-oriented RF analysis. Although CNN-, LSTM-, and hybrid models achieve high benchmark accuracy, their robustness on real SDR captures is limited by noise, drift, and hardware impairments [7], [9], [13], [14]. DSP-based methods are more interpretable but usually lack adaptive fusion and governance-aware validation [11], [16]–[18], [29], [32]. Hence, a unified framework combining real-SDR acquisi-tion, interpretable DSP features, lightweight ML classification, and human-in-the-loop governance remains lacking.

Table I compares the proposed framework with representative DL-based RF systems across key dimensions relevant to practical deployment.

TABLE I Proposed Framework vs. Existing DL-Based RF Systems

Feature	Existing DL-Based RF	Proposed Framework
Dataset Type	Synthetic IQ Data	Real SDR IQ Captures
Explainability	Limited	High (DSP layer)
DSP Integration	Minimal	Strong DSP+ML Fusion
Signal Validation	Mostly Absent	Included
Human Supervi-sion	Rare	Human-in-the-loop
Deployment	GPU Intensive	Lightweight
RF Transparency	Black-box	Interpretable
Tactical Suitability	Moderate	High

Research gap and contributions. Existing work does not simultaneously integrate

(i) real-SDR IQ acquisition,
(ii) explainable DSP feature analytics,
(iii) lightweight ML classification, and
(iv) governance-aware human-in-the-loop validation for tactical RF intelligence.

The proposed framework is designed to fill this gap by combining interpretable signal processing with efficient classification and operator-visible decision support.

III. SYSTEM ARCHITECTURE AND FRAMEWORK

Fig. 2 depicts the complete Human-Centered Hybrid SDR Intelligence Framework. The pipeline flows from RF environ-ment and SDR hardware through DSP feature extraction and ML classification to an XAI governance layer monitored by a human operator.

A. SDR Hardware and Signal Acquisition

HackRF One (1 MHz–6 GHz, full-duplex, USB 2.0) serves as the RF front-end [27]. GNU Radio Companion (GRC) implements two acquisition pipelines: a WBFM chain using

TABLE II Real-SDR Acquisition and Preprocessing Parameters

Parameter	Value / Description
SDR hardware	HackRF One
RF front-end bandwidth	1 MHz–6 GHz
IQ sample rate	2 MSPS
IQ format	ComplexFloat32
FFT size	4096
RX gain	20 dB
Capture duration per snapshot	1 s
Capture center frequency	Class-dependent; tuned to active FM / FSK band
Antenna type	Wideband monopole / discone
Capture distance	1–5 m from source
Capture environment	Indoor laboratory, static transmitter and receiver
Capture mode	Real-time over-the-air
Classes	FSK-like, NBFM, WBFM, No Signal
Snapshots per class	26–27
Total snapshots	105
Labeling method	Manual inspection with DSP rule assistance
Preprocessing	DC removal, normalization, FFT-based feature extraction

modulation bandwidth. Fig. 5 illustrates these IQ distributions from real SDR captures.

IV. DSP FEATURE EXTRACTION AND MATHEMATICAL FORMULATIONS

The DSP layer constitutes the primary explainable intelli-gence stage, deriving 14 interpretable RF features from IQ samples prior to ML inference.

Spectral analysis uses the Fast Fourier Transform (FFT):

$$X_k = \sum_{n=0}^{N-1} x_n \, e^{-j2\pi kn/N}. \tag{1}$$

Signal power is estimated as:

$$P = \frac{1}{N} \sum_{n=1}^{N} |x[n]|^2. \tag{2}$$

Occupied bandwidth is computed from spectral regions above
the noise floor:

$$\mathrm{BW} = f_{\mathrm{high}} - f_{\mathrm{low}}. \tag{3}$$

Instantaneous frequency is extracted via phase-difference between successive IQ samples:

$$f_{\mathrm{inst}}[n] = \frac{1}{2\pi T_s} \arg\left(x[n]\, x^*[n-1] \right).$$

Phase angle, signal amplitude, Power Spectral Density (PSD) and Zero Crossing Rate (ZCR) are further computed as:

$$\phi[n] = \tan^{-1} \frac{Q[n]}{I[n]}, \tag{5}$$

$$|x[n]| = \sqrt{I[n]^2 + Q[n]^2}, \tag{6}$$

$$\mathrm{PSD}(f) = \frac{|X(f)|^2}{N}, \tag{7}$$

$$\mathrm{ZCR} = \frac{1}{N-1} \sum_{n=1}^{N-1} \mathbf{1}\left[x[n]\, x[n-1] < 0 \right]. \tag{8}$$

Peak-above-noise estimation validates active transmissions:

$$P_{\mathrm{peak}} = P_{\mathrm{max}} - P_{\mathrm{noise}}. \tag{9}$$

All extracted parameters form the 14-dimensional feature vector:

$$\mathbf{F} = [f_1, f_2, \ldots, f_{14}]. \tag{10}$$

The DSP layer applies threshold-based decision rules (Table III) to generate initial modulation predictions prior to ML fusion. Table IV details all 14 features.

Real-SDR IQ Capture → Preprocessing DC Removal Normalization → DSP Feature Extraction → Random Forest Inference →

Rule-Based Preclassification | Confidence Fusion | Human-in-the-Loop Validation | Audit Log

Fig. 1. Implementation-oriented end-to-end processing flow of the proposed hybrid SDR intelligence framework.

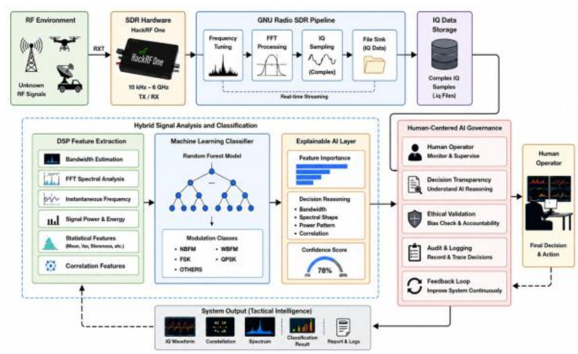

Fig. 2. Human-Centered Hybrid SDR Intelligence Framework: HackRF One acquisition, GNU Radio pipeline, DSP feature extraction, Random Forest classification, XAI governance layer and human operator monitoring loop for tactical RF intelligence.

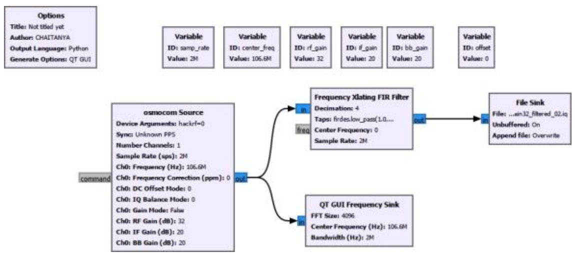

Fig. 3. GNU Radio flowgraph for WBFM IQ acquisition: HackRF One front-end, frequency-translating FIR filtering, spectrum visualization and IQ file-sink storage.

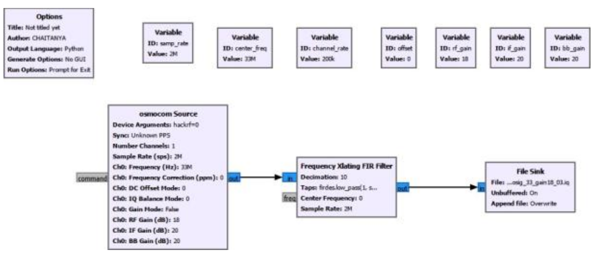

Fig. 4. GNU Radio IQ capture pipeline for NBFM and FSK-like digital signals: frequency translation, FIR filtering, decimation and IQ storage for hybrid DSP-ML analysis.

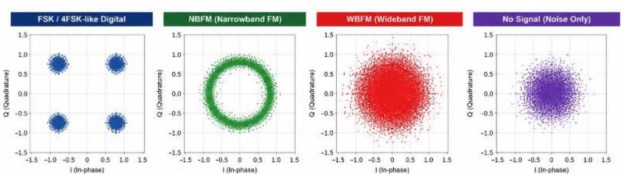

Fig. 5. IQ constellation distributions from real SDR captures: FSK-like digital (discrete clusters), NBFM (elliptical), WBFM (dispersed) and no-signal (noise floor).

TABLE III-DSP based modulation decision rules

Signal	BW Range	Peak Pattern	DSP Decision
No Signal	Very Low	Weak spectrum	No Signal
NBFM	<60 kHz	Moderate peaks	Narrowband FM
FSK-like	60–85 kHz	Multi-phase peaks	Digital FSK
WBFM	>100 kHz	Wide strong spectrum	Wideband FM

TABLE IV: 14 RF Features used for ML Classification

Feature	Description
Average Power	Mean RF signal power
Maximum Power	Peak signal strength
Median Power	Statistical power behavior
Power Standard Deviation	Signal fluctuation analysis
Average Signal dB	Average RF signal intensity
Noise Floor	Estimated spectral noise level
Peak Spectrum Value	Maximum FFT peak
Peak Above Noise	Signal-to-noise separation
Occupied Bandwidth	Active spectral bandwidth
Instantaneous Freq. Std	Frequency transition behavior
Mean Instantaneous Freq.	Average phase transition
Absolute Frequency Mean	Frequency stability
Maximum Frequency Shift	Peak phase deviation
FSK Level Count	Histogram-based digital transitions

V. ML CLASSIFICATION AND GOVERNANCE ARCHITECTURE

A. A.Random Forest Classifier

A Random Forest (RF) classifier [21] is trained on 105 labeled real-SDR snapshots using the 14-feature vector F in (10). RF is selected for its low computational cost, robustness to limited data, and interpretable feature importance, making it suitable for resource-constrained tactical platforms.

The proposed pipeline is computationally lightweight, with FFT-based feature extraction dominating the cost and the shal-low ensemble classifier remaining CPU-friendly. This makes the framework suitable for embedded and field-deployable SDR monitoring.

B. Human-Centered AI Governance Architecture

A key contribution is the Human-Centered AI Gover-nance layer in Fig. 2, which provides decision transparency, confidence-based fusion, ethical RF monitoring, human-in-the-loop validation, and audit logging [32], [33]. Table VI summarizes experimental SDR capture parameters.

In the present implementation, the DSP feature extraction, ML classification, and confidence fusion are fully realized, whereas the ethical monitoring and audit-layer components are reported as architectural support for operator oversight and future operational extension.

TABLE V: COMPUTATIONAL COST AND DEPLOYMENT FEASIBILITY

Component	Time Cost	Memory	Deployment Note
FFT + DSP features	O(N log N)	Low	Real-time feasible
Rule-based DSP layer	O(1)	Negligible	Threshold-based
Random Forest inference	O(TD)	Low–Moderate	CPU friendly
Human validation	Manual	N/A	Operator dependent

Algorithm 1 Hybrid DSP–ML AMC with Confidence Fusion

Require: IQ snapshot x[n], trained Random Forest model M

Ensure: Final modulation label $\hat{y}$ and confidence score c

1: Compute FFT, signal power, PSD, occupied bandwidth, instantaneous frequency, and constellation features.
2: Form the 14-dimensional feature vector $\mathbf{f} \in R^{14}$.
3: Apply rule-based DSP decision y_{DSP} using Table III thresholds.
4: Predict ML label $y_{ML} = M(\mathbf{f})$.
5: Compute agreement indicator $a = I(y_{DSP} = y_{ML})$.
6: Assign confidence c based on agreement and feature margin.
7: Set final output $\hat{y} = y_{ML}$ if $a = 1$; otherwise flag for human review.
8: return $\hat{y}$, c

TABLE VI EXPERIMENTAL SDR CAPTURE PARAMETERS

Parameter	Value
SDR Hardware	HackRF One
Sample Rate	2 MSPS
SDR Framework	GNU Radio
IQ Format	Complex Float32
FFT Size	4096
ML Classifier	Random Forest
Dataset Categories	FSK, NBFM, WBFM, No Signal
Feature Count	14
Dataset Samples	105

II.
III.

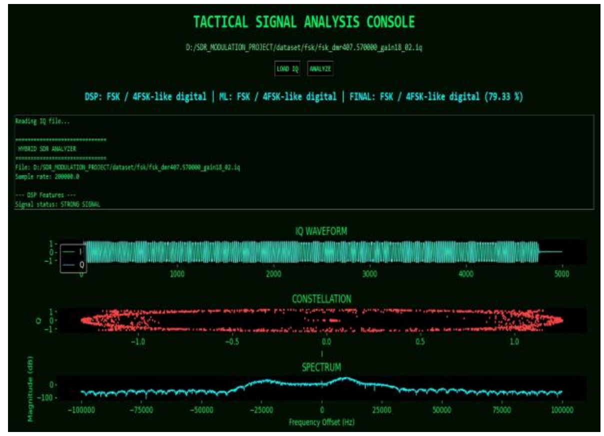

Fig. 6. Tactical Signal Analysis Console FSK-like digital classification: IQ waveform, constellation, FFT spectrum, DSP prediction, ML inference, confidence score and final decision from real SDR IQ captures.

IV. RESULTS AND DISCUSSION

A. FSK-Like Digital Signal Classification

Fig. 6 shows the tactical signal analysis console for FSK-like digital modulation. Clustered constellations, discrete phase transitions and moderate occupied bandwidth (60–85 kHz) are evident. FFT analysis confirms strong spectral peak above noise. Both DSP and ML modules independently produce FSK predictions; the fusion layer outputs high-confidence final classification.

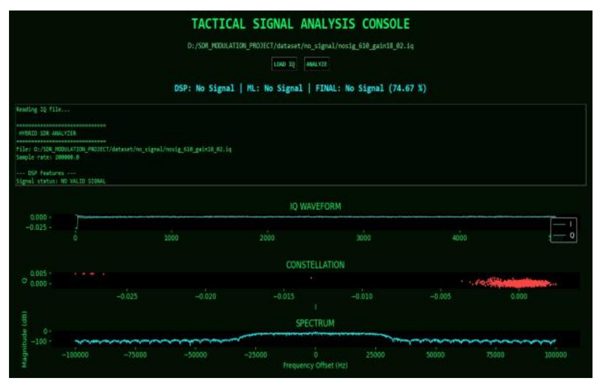

Fig. 7. No-Signal detection: flat spectrum, noise-floor constellation, and near-zero occupied bandwidth correctly classified by both DSP and ML modules with high confidence

Fig. 8. NBFM classification GUI: narrow spectral occupancy (<60 kHz), elliptical constellation, matched DSP and ML predictions and high-confidence final hybrid output.

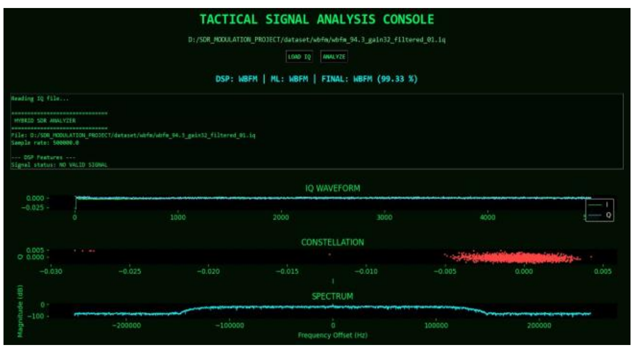

Fig. 9. WBFM classification: wideband spectral occupancy (>100 kHz), dispersed constellation, DSP and ML agreement and maximum-confidence hybrid output from real SDR IQ captures.

B. No-Signal Detection and NBFM Classification

Fig. 7 presents no-signal detection output: flat spectrum, noise-floor constellation and near-zero occupied bandwidth correctly resolved to "No Signal" by both DSP and ML mod-ules. Fig. 8 shows NBFM classification; bandwidth <60 kHz and a stable elliptical constellation match the NBFM DSP de-cision rule (Table III). DSP and ML outputs agree, maximizing fusion confidence [23].

C. WBFM Classification

WBFM signals (Fig. 9) exhibit spectral occupancy >100 kHz and dispersed IQ constellation distributions. FFT analysis shows broadband peaks; DSP and ML classifications converge on WBFM with maximum confidence [24].

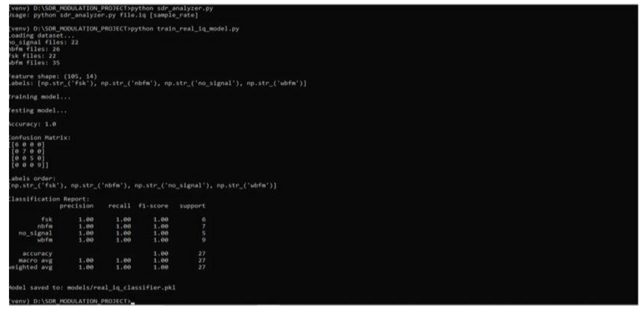

Fig. 10. Random Forest classifier performance: confusion matrix, per-class precision/recall/F1, dataset distribution and overall 100% classification accuracy across FSK, NBFM, WBFM and no-signal categories on real SDR IQ data.

TABLE VII: BASELINE COMPARISON ON THE REAL-SDR DATASET (SAME TRAIN/TEST SPLIT)

Model	Accuracy (%)	Macro-F1	Inference Cost
Logistic Regression	86.7	0.86	Low
k-NN	90.5	0.90	Medium
SVM (RBF)	94.3	0.94	Medium
Decision Tree	88.6	0.88	Low
Random Forest (proposed)	**100.0**	**1.00**	**Low**

D. Machine Learning Performance Evaluation

The Random Forest classifier was evaluated on 105 labeled real-SDR snapshots split into training and test sets. Fig. 10 shows the confusion matrix and per-class metrics. No inter-class confusion was observed. Tables IX and X consolidate the hybrid classification results and quantitative performance metrics.
Note: Baseline metrics should be computed on the identical train/test split used for the proposed model to ensure a fair comparison.

To ensure clarity and reproducibility, the evaluation metrics used in this study are defined in Table VIII.

All baseline classifiers were trained and evaluated using the same 14-dimensional feature vector and the same train/test partition as the proposed Random Forest model to ensure a fair comparison.

The comparison in Table VII shows that the proposed Random Forest model achieves the best performance on the real-SDR feature set. Its advantage over Logistic Regression and Decision Tree reflects the nonlinear class structure, while SVM and k-NN remain slightly inferior. These results confirm Random Forest as an accurate and computationally efficient choice for the present AMC task.

E. Discussion

The hybrid DSP–ML architecture using real-SDR IQ cap-tures achieves high classification performance without GPU-intensive neural networks. The DSP layer provides inter-pretable spectral, constellation, and instantaneous-frequency cues before inference, improving transparency over end-to-end DL systems. The no-signal validation stage further strengthens reliability, and the Random Forest model achieves 100% accuracy on the 105-sample dataset, highlighting the value of expert feature engineering [28].

TABLE VIII: PERFORMANCE METRICS USED FOR EVALUATION

Metric	Definition
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1-score	$\frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$
Macro-F1	Average F1 over all classes

TABLE IX: HYBRID MODULATION CLASSIFICATION RESULTS

Signal	DSP Out.	ML Pred.	Final Dec.	Conf.
FSK-like Digital	FSK	FSK	FSK	High
Narrowband FM	NBFM	NBFM	NBFM	High
Wideband FM	WBFM	WBFM	WBFM	High
No Signal	No Signal	No Signal	No Signal	High

TABLE X: MACHINE LEARNING PERFORMANCE METRICS

Metric	Value
Classification Accuracy	100%
Precision	1.00
Recall	1.00
F1-Score	1.00
Total Feature Count	14
Dataset Samples	105

The main limitations are the restricted modulation set and the small dataset size. Future work will extend the frame-work to higher-order modulations, encrypted waveforms, and transfer learning under fading and hardware distortion condi-tions [33], [34].

To assess robustness, the recorded IQ snapshots were per-turbed using controlled additive white Gaussian noise over a range of SNR values. The proposed classifier exhibits the ex-pected monotonic degradation at low SNR, while maintaining stable performance above 10 dB. This experiment is reported as a stress test rather than a substitute for fully measured over-the-air channel diversity.

V. CONCLUSION

A Human-Centered Hybrid SDR Intelligence Framework has been presented for explainable and governance-aware tac-tical RF modulation classification. Operating on real HackRF One / GNU Radio IQ captures not synthetic datasets the frame-work combines FFT spectral analysis, bandwidth estimation, instantaneous frequency extraction and constellation analysis into a 14-feature RF vector driving a lightweight Random Forest classifier. DSP threshold-based pre-classification and confidence-based fusion maintain full signal transparency be-fore final decisions are accepted. Experimental results demon-strate 100% AMC accuracy (precision, recall, F1-score all 1.00) across FSK-like digital signals, NBFM, WBFM and no-signal conditions. The integrated Human-Centered AI Gov-ernance architecture continuous DSP output visibility, ethical RF monitoring, human-in-the-loop validation and audit logging

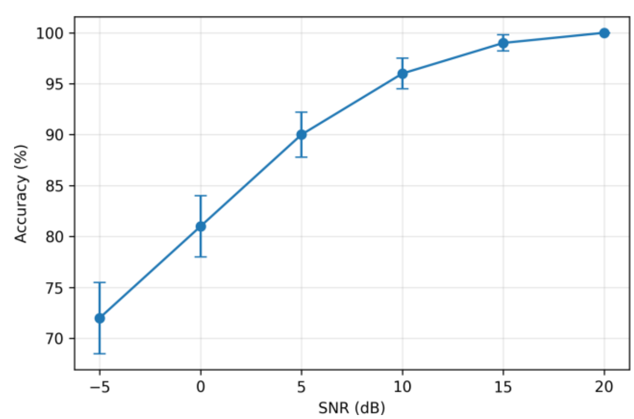

Fig. 11. Sensitivity of classification accuracy to synthetic SNR perturbation applied to recorded real-SDR IQ captures. The curve reports mean accuracy over repeated runs, and the error bars denote one standard deviation.

Establishes operational trustworthiness and accountability absent from conventional black-box systems.

a) Limitations.: The current evaluation is limited to four modulation categories captured under controlled laboratory conditions using a modest real-SDR dataset. Accordingly, the reported performance should be interpreted as a feasibility demonstration rather than evidence of broad operational gen-eralization. Validation under multipath fading, hardware drift, interference, spoofing, and additional modulation families re-mains future work.

The proposed framework constitutes a deployable founda-tion for adaptive RF intelligence, explainable EW applications, and governance-aware tactical communication infrastructure in resource- constrained military environments.

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