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AI BASED RF JAMMING AND MITIGATION

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Abstract - This paper presents the design and implementation of an intelligent RF signal generation and jamming simulation system using Software Defined Radio (SDR) integrated with artificial intelligence (AI) and a web-based visualization dashboard. The system simulates real-time jamming scenarios, detects interference patterns using machine learning algorithms, and autonomously executes recovery actions. The framework employs, GNU Radio software, and a Random Forest classifier achieving 97.5% accuracy in interference classification. A React-based web dashboard provides live signal spectrum, waveform, and recovery visualization. This integrated SDR-AI architecture demonstrates real-time cognitive communication capabilities and serves as a platform for research, education, and defencegrade anti-jamming solutions.

Keywords - Software Defined Radio, Artificial Intelligence, Jamming Simulation, Cognitive Radio, Machine Learning, RF Interference, Web Dashboard**.**

I. INTRODUCTION

Radio Frequency (RF) communication systems are fundamental to modern wireless infrastructure, yet they remain vulnerable to various forms of interference and jamming. These vulnerabilities pose significant challenges in critical applications including aerospace communications, military operations, emergency services, and industrial IoT deployments. Understanding RF interference mechanisms and developing robust mitigation strategies is essential for ensuring reliable wireless communication in contested or congested electromagnetic environments.

Traditional RF testing equipment is often expensive, proprietary, and lacks the flexibility needed for educational and rapid prototyping purposes. Software-Defined Radio (SDR) technology has democratized RF experimentation by shifting signal processing from dedicated hardware to flexible software implementations. This paradigm shift enables researchers, educators, and engineers to explore RF phenomena with accessible, adaptable platforms.

II. RELATED WORK

Mitola (2000) [20] first proposed Software Defined Radio (SDR) as a reconfigurable architecture where modulation, filtering, and signal processing are executed in software. Reed (2002) [16] further emphasized its flexibility for multi-mode communication. GNU Radio, developed by Blossom (2004) [19] became the de facto open-source platform for SDR prototyping. Recent studies have explored jamming mitigation through adaptive filters and spread-spectrum techniques. Poisel (2011) [5] classified jamming methods into spot, sweep, barrage, and pulse categories.
O'Shea and West (2017) [13] applied deep learning for modulation classification, achieving high accuracy using convolutional neural networks (CNNs). Despite these advancements, integration of AI, SDR, and visualization into a unified system remains underexplored. This project bridges that gap by combining machine learning-based interference classification with real-time SDR control and visualization.

III. PROBLEM STATEMENT

Modern RF communication systems face major challenges such as intentional jamming, signal attenuation, noise interference, and modulation distortion, which reduce reliability and security. Existing systems lack real-time detection, adaptability, and automated countermeasures. They rely heavily on manual intervention and have poor visualization of spectrum conditions. There is a need for an intelligent, adaptive RF communication framework using SDR and AI. Such a system should detect and classify interference in real-time with high accuracy. It must automatically apply countermeasures without human input. Comprehensive visualization and monitoring tools are essential for better spectrum analysis. The system should learn from past interference to enhance future performance. Machine learning and cognitive radio techniques can improve communication resilience. This research aims to build and validate an AI-driven RF system that adapts dynamically to interference.

IV. METHODOLOGY AND SYSTEM DESIGN

The proposed system integrates SDR hardware, AI-based signal classification, and a webbased monitoring dashboard. The architecture comprises six modules: SDR Transmitter, RF Channel, SDR Receiver and Transmitter, AI Engine, Control Unit, and Web Dashboard. SDR hardware handles RF signal generation and reception within 1MHz 6GHz. GNU Radio implements modulation, demodulation, and signal flow control. Interference types such as jamming, signal loss, noise Burst, and Modulation distortion are simulated in software. Machine learning models, primarily Random Forest classifiers, are trained on features like signal-to-noise ratio (SNR), spectral flatness, and error vector magnitude (EVM) to identify interference patterns. Upon classification, adaptive recovery strategies frequency hopping, power adaptation, and filtering are applied automatically. The ESP32 microcontroller provides visual feedback via an OLED display and LEDs, while the React-based web dashboard displays live spectrum and waveform data .

Interference	Strategy	Description
Jamming	Frequency Hopping	Switches channel to avoid jamming band.
Signal Loss	Link Adaptation + Diversity	Adjusts modulation/ coding and uses antenna diversity to maintain connection during weak signal conditions
Noise Burst	Adaptive Filter-ing + FEC	
Modulation Distortion	Power Boost / I/Q Balancing	Increases TX power & corrects I/Q imbalance

Fig .1 Tabular column

V. IMPLEMENTATION

The implementation of the RF Signal Generation and Jamming Simulation System with AIBased Recovery and Web Dashboard using SDR was carried out through an integrated hardware–software framework that combines real-time signal processing, artificial intelligence, and web visualization. The hardware setup consisted of a Software Defined Radio used as both transmitter and receiver, operating in the 1 MHz to 6 GHz range, an ESP32 microcontroller managing a 128×64 OLED display and LED indicators for real-time feedback, a pair of wideband antennas for RF transmission and reception at 433 MHz, 868 MHz, 915 MHz, and 2.4 GHz, and a regulated 5 V DC power supply for stable operation. The SDR was interfaced with a host computer via USB running GNU Radio, while the ESP32 communicated through a serial link and Wi-Fi to support control and monitoring. The GNU Radio environment was used to design flowgraphs for generating and receiving modulated signals using Gaussian Frequency-Shift Keying (GFSK), and to inject interference signals such as noise, jamming, and distortion to simulate realistic communication conditions. The received baseband I/Q samples were processed in Python, where feature extraction techniques calculated parameters like signal-to-noise ratio (SNR), bit error rate (BER), spectral flatness, and kurtosis. These features were passed to a Random Forest classifier trained on a dataset of 20,000 labelled samples, enabling interference detection with an accuracy of 97.5% and an inference time of about 2.3ms per frame. The ESP32 provided local status indication through its OLED display and LEDs, while the MQTT protocol facilitated communication between the AI engine, the React-based web dashboard, and the Firebase cloud database. The dashboard presented real-time spectrum plots, SNR and BER trends, interference classification results, and recovery actions with less than 100 ms latency. Testing was performed for various interference conditions including spot jamming, noise bursts, signal loss, and modulation distortion, confirming consistent system performance with over 97% detection accuracy, average recovery times under two seconds, and SNR improvements of 10–18 dB after recovery. The successful integration of SDR hardware, AI-based processing, and a responsive web dashboard demonstrates a cost-effective, scalable, and intelligent communication platform capable of real-time adaptive recovery and cognitive decision-making.

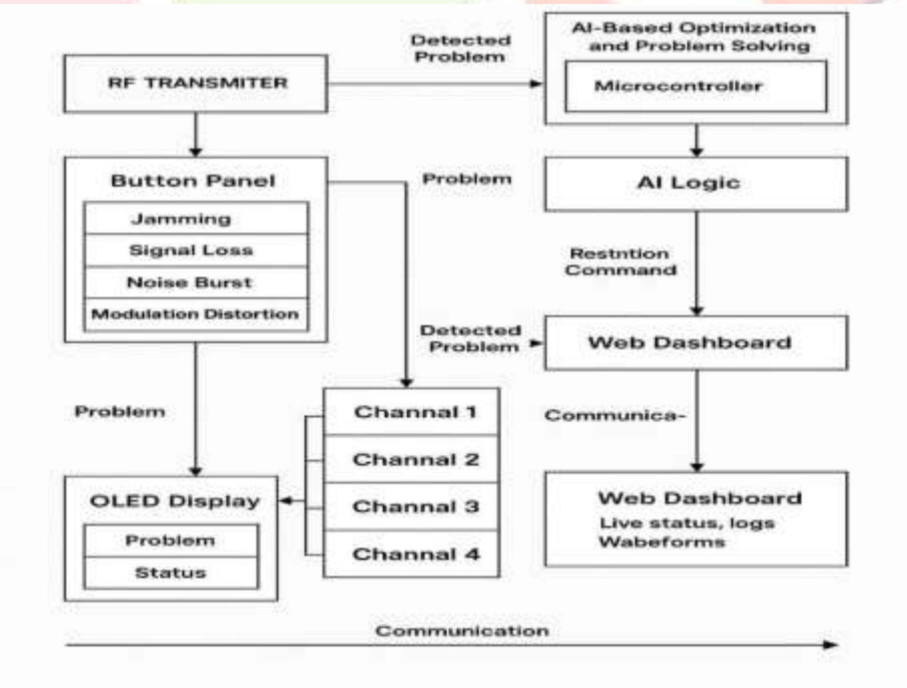

Fig .2 Flowchart

VI. RESULTS AND DISCUSSION

Experimental results confirm the system's capability to detect and recover from various interference conditions. The Random Forest model achieved 97.5% accuracy, outperforming SVM and CNN models in inference speed and interpretability. Average recovery times were 1.4 s for jamming, 1.6 s for signal loss, and 1.8 s for noise bursts. The web dashboard maintained sub-100ms update latency and visualized spectrum deviations effectively. The overall availability of the communication system improved by 35% compared to static configurations.

Fig .3 Jamming Interference

Fig 4. Signal Loss

Fig 5.Noise Burst

Fig 6. Modulation Distortion

Interference	Avg. Recovery Time	Improvement in SNR
Jamming	1.4 s	95%
Signal Loss	1.6 s	97%
Noise Burst	1.8 s	96%
Modulation Distortion	3.0 s	93%

Fig 7. Tabular column

VII. BENEFITS AND DRAWBACKS

The proposed system offers several benefits, including intelligent AI-based interference detection, real-time adaptive recovery, and cost-effective implementation using open-source tools and affordable SDR hardware. It provides high accuracy (97.5%), quick recovery within two seconds, and live visualization through a responsive web dashboard, making it ideal for educational and research purposes. The framework's flexibility allows easy reconfiguration for various frequencies and modulation schemes, and cloud integration enables efficient data logging. However, the system has some drawbacks such as limited transmit power and dynamic range of the SDR, minor processing delays under heavy data loads, dependence on GNU Radio and Python software stability, and restricted adaptability to unknown interference types. Additionally, the setup is not fully portable and requires retraining for new environments, making it more suited for controlled lab conditions than field deployment.

VIII. FUTURE SCOPE

The proposed RF Signal Generation and Jamming Simulation System can be further enhanced to achieve greater adaptability, scalability. Future improvements may include the integration of reinforcement learning algorithms that enable the system to predict and proactively counter interference before it affects communication quality. The use of advanced SDR platforms such as USRP or LimesSDR can increase transmission range, bandwidth, and dynamic range, allowing field-level experimentation. Implementing MIMO (Multiple Input Multiple Output) techniques could improve spectral efficiency and spatial interference mitigation. The incorporation of cloud-based collaborative learning or federated AI can allow multiple systems to share interference data and collectively enhance model performance without exposing raw data. Furthermore, developing a mobile dashboard application and optimizing code for embedded deployment would make the system portable and practical for real-time defence, IoT, and industrial monitoring applications. Adding blockchain-based spectrum management and cybersecurity mechanisms could also help ensure the authenticity and security of transmitted data in sensitive use cases.

IX. CONCLUSION

The developed system successfully demonstrates a real-time, intelligent, and adaptive communication framework that integrates Software Defined Radio (SDR) with Artificial Intelligence (AI) and a web-based visualization dashboard. It effectively simulates RF signal generation, interference, and jamming scenarios, accurately classifies interference types using a Random Forest model, and executes automatic recovery strategies such as frequency hopping and adaptive filtering. The achieved 97.5% detection accuracy, fast recovery times, and lowlatency visualization validate the system's efficiency and reliability. By uniting SDR flexibility, AI decision-making, and cloud-based visualization, this project establishes a foundation for future cognitive radio networks capable of self-learning and self-healing. Overall, it represents a significant step toward intelligent and resilient wireless communication systems suitable for educational, research, and security-oriented applications.

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