

AI-Based RF Signal Classification and Direction Estimation Using SDR: A Comprehensive Survey

Harsha R [IRF23EC030], Namratha V [IRF23EC049], Jathin M [IRF23EC037],
Praneeth N [IRF23EC053], Nivedita S Desai

Department of Electronics and Communication Engineering,
RV Institute of Technology and Management, Bengaluru, India

Abstract

Recent progress in Software Defined Radio (SDR), Artificial Intelligence (AI), Machine Learning (ML), and Digital Signal Processing (DSP) has greatly enhanced intelligent RF monitoring systems. Modern wireless systems now need efficient spectrum monitoring, automatic modulation classification, interference detection, and signal direction estimation because of the growing congestion in the RF spectrum. Deep Learning models like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid CNN-LSTM architectures have shown high accuracy in tasks like RF signal classification and spectrum sensing. SDR platforms offer a flexible and cost-effective way to implement real time wireless signal analysis. This paper provides a survey of AI-based RF signal classification, spectrum sensing, direction estimation, RF interference detection, and intelligent SDR systems. It reviews various Deep Learning methods, SDR implementations, and RF monitoring techniques, along with their advantages and limitations. The survey also discusses current challenges such as low Signal-to-Noise Ratio (SNR), computational complexity, dataset dependency, and hardware constraints. It highlights future research directions for intelligent RF systems.

Keywords: Software Defined Radio (SDR), RF Signal Classification, Direction of Arrival (DoA), Deep Learning, CNN, LSTM, Spectrum Sensing, Artificial Intelligence, Modulation Recognition, Signal Processing.

I. INTRODUCTION

Wireless communication systems have rapidly expanded with the growth of modern technologies such as IoT, 5G, autonomous systems, and smart wireless networks.

This growth has led to increased RF spectrum congestion, interference, and security challenges, creating the need for intelligent RF monitoring and spectrum management systems. Traditional RF monitoring approaches primarily rely on manual feature extraction and fixed hardware architectures, which are computationally complex and less adaptable to dynamic wireless environments.

Software Defined Radio (SDR) has emerged as an effective solution for flexible and reconfigurable wireless communication systems.

SDR platforms allow real-time signal acquisition, processing, and modulation analysis using programmable software instead of fixed hardware. In recent years, Artificial Intelligence (AI) and Deep Learning techniques have been integrated with SDR systems to improve automatic modulation classification, spectrum sensing, interference detection, and signal direction estimation.

Deep Learning models such as CNNs, LSTMs, and hybrid CNN-LSTM architectures have shown better performance compared to traditional signal processing techniques, especially in noisy and low-SNR conditions [2], [4], [10].

SDR-based RF monitoring systems also provide low-cost and real-time implementation capabilities for intelligent wireless analysis [9], [12]. However, existing research mainly focuses on individual tasks such as signal classification or direction estimation rather than integrated intelligent RF monitoring systems. This paper presents a comprehensive survey of AI-based RF signal classification and direction estimation systems using SDR platforms, discussing recent developments, major challenges, and future research directions.

II. BACKGROUND AND MOTIVATION

Traditional RF communication systems heavily depend on dedicated hardware and manual signal analysis methods, making them less flexible for modern wireless applications.

The increasing number of wireless devices and communication protocols has created a demand for intelligent systems capable of automatically monitoring and analyzing RF spectrum activity.

SDR technology enables flexible wireless communication by replacing conventional hardware components with software-based processing blocks. This allows for rapid reconfiguration, real-time monitoring, and support for multiple communication standards using a single platform. At the same time, AI and Machine Learning techniques have improved automatic signal classification and intelligent spectrum sensing capabilities.

Direction of Arrival (DoA) estimation has also become important for applications such as drone detection, radar systems, electronic warfare, and wireless security.

Existing studies mainly focus on RF signal classification or DoA estimation independently, while integrated SDR-AI systems remain limited. Therefore, there is a need for low-cost, intelligent, and real-time RF monitoring systems capable of both signal classification and direction estimation.

III. OVERVIEW OF SOFTWARE DEFINED RADIO

Software Defined Radio (SDR) is a wireless communication technology in which traditional RF hardware components such as mixers, modulators, filters, and detectors are implemented using software processing techniques.

SDR systems provide high flexibility, low-cost implementation, and real-time reconfigurability for wireless communication applications.

Common SDR platforms include RTL-SDR, USRP, HackRF, and BladeRF, while software frameworks like GNU Radio are widely used for signal processing and system implementation.

SDR systems support multiple wireless standards and enable rapid prototyping for RF monitoring applications.

Several researchers have used SDR platforms for cognitive radio networks, intelligent spectrum sensing, and RF monitoring systems [9], [12].

SDR-based IoT communication architectures have also been proposed to improve interoperability among wireless communication protocols [13]. In addition, AI-enabled SDR systems have shown promising performance in spectrum monitoring, cybersecurity, and anti-jamming applications [14].

Despite these advantages, SDR systems still face limitations related to bandwidth, processing speed,

synchronization, and hardware constraints during real-time implementation.

IV. RF SIGNAL CLASSIFICATION

RF signal classification is the process of identifying modulation types and communication signals from received wireless transmissions.

It is an important component of intelligent RF monitoring systems, spectrum management, and cognitive radio networks.

Traditional RF classification methods rely on manually extracted features and statistical signal analysis, while modern approaches utilize Deep Learning techniques for automatic feature extraction and improved classification accuracy.

A. Traditional Signal Classification Methods

Traditional RF signal classification techniques include energy detection, cyclostationary feature extraction, kurtosis-based methods, and likelihood-based approaches.

These methods analyze statistical and spectral characteristics of RF signals to identify modulation schemes.

Prasetyo et al. [11] proposed an SDR-based monitoring system combining energy detection and kurtosis methods for blind spectrum monitoring.

Huu Nghia Tran et al. [30] introduced a dual intermediate frequency classification algorithm capable of operating under low-SNR conditions.

Although traditional methods provide acceptable performance, they suffer from high computational complexity, sensitivity to noise, and dependency on manual feature extraction.

B. Deep Learning-Based RF Signal Classification

Deep Learning techniques have significantly improved RF signal classification performance by automatically learning complex signal features from raw I/Q data.

CNNs are effective for spatial feature extraction, while LSTMs capture temporal dependencies in RF signals.

Mario Blassiny [2] proposed an LSTM-based signal classification system using raw RF data.

Tim O'Shea et al. [4] demonstrated that Deep Learning models outperform traditional expert-feature methods under realistic wireless channel conditions. Peng Wu et al. [5] proposed an Inception-ResNet-based architecture for automatic modulation classification with improved convergence and accuracy.

Zhra Zuheir Yahya and others [6] used pre-trained CNN models like ResNet and MobileNet for SDR-based modulation classification. Hila Elyousseph and others [7] made a hybrid image-based RF classification system that uses both time and frequency information. Raluca Nelega and others [8], and Dinanath Padhya and others [31] suggested hybrid CNN-LSTM models that can get high classification accuracy with real-world SDR data.

Although Deep Learning methods give good classification results, they need big training data and lots of computing power for real-time use.

V. SPECTRUM SENSING AND RF MONITORING

Spectrum sensing is a key part of cognitive radio and smart RF monitoring systems.

It helps detect wireless spectrum usage, signal presence, and interference in real time.

Julio Manco and others [9] looked into SDR-based spectrum sensing methods for cognitive radio and talked about the challenges in real SDR hardware.

Zeghdood Sabrina and others [10] made a CNN-LSTM system for SDR-based spectrum sensing when signal strength is low.

Anastasia Khodakova and others [12] developed a GNU Radio system for signal detection and recognition that can do real-time modulation classification and RF monitoring.

Shadman Rahman Doha and others [14] reviewed AI-based SDR systems for use in cognitive radio, anti-jamming, and smart spectrum awareness.

AI-based spectrum sensing systems improve detection and adaptability, but hardware limits and the need for lots of computing power are still big problems for real-time use.

VI. DIRECTION OF ARRIVAL (DoA) ESTIMATION

Direction of Arrival (DoA) estimation finds out where an RF signal is coming from.

DoA systems are used in radar, drone detection, wireless security, and military communication.

A. RSS-Based Direction Estimation

Ricardo K. Miranda and others [15] studied DoA estimation using RSS and directional antenna arrays for drone tracking.

The system helped reduce noise and lower power use.

B. SDR-Based DoA Systems

Mahmoud A. Khalil and others [16] made a low-cost, high-precision DoA system using dual-channel SDR receivers and Vivaldi antennas.

Evgeniya Egorova and others [17] looked at sensitivity and SNR limits in SDR-based direction finding.

C. AI-Based Direction Finding

S. Shashank and others [18] created an optimized direction finding method using vector projection and K-means clustering to find jamming signal directions while cutting down on computing needs.

Overall, SDR-based DoA systems are affordable and have good accuracy, but low signal strength and hardware syncing issues are still major problems.

VII. RF INTERFERENCE, JAMMING, AND SECURITY

RF interference and jamming are serious threats to wireless systems, especially in military, drone, and secure communication.

Kruthika and others [19] built an AI system for detecting and stopping RF jamming using SDR and Random Forest classifiers to spot interference and fix it.

Sebastián Ratto and others [20] studied SDR systems for disrupting UAV signals.

Shengjian Mao and others [21] developed a method for identifying drones using RF signal classification from SDR data.

AI improves jamming detection but SDR bandwidth and processing limits affect real-time performance.

VIII. RF SIGNAL GENERATION SYSTEMS

RF signal generation systems are used in radar, phased arrays, testing, and simulation. Kenji Kawakami and others [22] created a phased array system with RF generators inside each module. Isamu Chiba and others [23] built a reconfigurable APAA with self-correcting features. Bowen Xia and others [24] made a low-cost GNSS signal generator using FPGA. Jiafen Zhang and others [25] developed a multi-channel wideband generator with DDS. These systems offer better performance and flexibility but need more complex setups and hardware.

IX. MACHINE LEARNING TECHNIQUES FOR RF SYSTEMS

ML techniques help in intelligent RF systems by doing automatic feature extraction, signal sorting, and spectrum analysis.

TABLE I
COMPARISON OF RF SIGNAL CLASSIFICATION TECHNIQUES

ALGORITHM	STRENGTH	LIMITATION
CNN	Good at spatial features	Needs big data
LSTM	Captures time patterns	High training cost
CNN-LSTM	Good classification	Uses a lot of computing power
Random forest	Simple to use	Not scalable
Transfer learning	Less training needed	Relies on pre-trained models

CNNs are used a lot for modulation classification. LSTMs are good for time-based RF signals. Hybrid CNN-LSTM systems use both and work well with low signal strength.

X. CHALLENGES AND LIMITATIONS

Despite progress, intelligent RF systems still have problems.

TABLE II
COMPARISON OF MACHINE LEARNING ALGORITHMS FOR RF SYSTEMS

CHALLENGE	IMPACT
Low SNR	Worse classification
Big datasets	Hard training
Heavy computing	Needs powerful hardware
SNR bandwidth	Limits monitoring range
Hardware syncing	DoA errors
Frequency shifts	Lower accuracy
Environmental noise	Signal distortion

Most DL models need big labeled data and strong hardware.

SDR systems also face issues with bandwidth, processing speed, and real-time processing. Environmental noise and low signal strength make systems less reliable.

XI. RECENT ADVANCEMENTS

Recent AI-enabled SDR systems use self-supervised learning, hybrid CNN-LSTM models, FPGA acceleration, edge AI, and smart spectrum monitoring.

Researchers have also made real-world over-the-air RF data and multi-modal sensing systems for better signal analysis.

AI-integrated SDR systems now support adaptive sensing, anti-jamming, and automated monitoring. These improvements help with better accuracy, faster response, and more intelligent wireless analysis.

XII. FUTURE SCOPE AND RESEARCH DIRECTIONS

Future work should focus on creating lightweight AI models for embedded SDR systems.

TinyML and Edge AI can bring real-time RF intelligence to low-power devices.

Systems that combine RF classification, spectrum sensing, and DoA estimation should be developed for autonomous monitoring.

Future wireless tech like 6G will need smart and adaptive RF systems for complex environments.

Standard datasets, better SDR hardware, and efficient sensing methods will also help shape future intelligent RF systems.

XIII. CONCLUSION

This survey looks at the latest developments in using AI to classify and estimate the direction of RF signals with SDR platforms.

Techniques like CNNs, LSTMs, and mixed CNN-LSTM models greatly improve the ability to recognize different signal types and sense the spectrum, compared to older methods.

SDR technology offers a flexible, affordable, and real-time way to build smart RF monitoring systems.

Also, AI-based systems for estimating signal direction and detecting interference help make wireless networks more secure and aware of the spectrum they're using.

But there are still challenges, such as high computational needs, poor performance in low signal conditions, the need for large data sets, problems with synchronization, and hardware limits.

Future work should focus on creating lighter AI models, better integrated SDR systems, and real-time solutions for monitoring RF signals in next-gen wireless networks.

REFERENCES

- [1] K. Davaslioglu, S. Boztas, Y. E. Sagduyu, M. C. Erten, and E. Ayanoglu, "Self-Supervised RF Signal Representation Learning for Next Generation Signal Classification with Deep Learning," 2023.
- [2] M. Blassiny, "A Deep Learning-Based Signal Classification Approach for Spectrum Sensing using LSTM Networks," 2022.
- [3] T. Wang, G. Yang, P. Chen, Z. Xu, M. Jiang, and Q. Ye, "A Survey of Applications of Deep Learning in Radio Signal Modulation Recognition," 2022.
- [4] T. O'Shea, T. Roy, and T. C. Clancy, "Over the Air Deep Learning Based Radio Signal Classification," 2017.
- [5] P. Wu, B. Sun, S. Su, et al., "Automatic Modulation Classification Based on Deep Learning for Software-Defined Radio," 2020.
- [6] Z. Z. Yahya and D. M. Ali, "Software Defined Radio (SDR) Signals Classification via Convolutional Neural Networks," 2023.

- [7] H. Elyousseph and M. L. Altamimi, "Deep Learning Radio Frequency Signal Classification with Hybrid Images," 2021.
- [8] R. Nelega, M. Gorlan, Z. A. Polgar, et al., "Generation and Deep Learning-Based Classification of RF Signals Represented as I/Q Time Series," 2025.
- [9] J. Manco, I. Dayoub, A. Nafkha, et al., "Spectrum Sensing in Software Defined Radio for Cognitive Radio Networks: A Survey," 2022.
- [10] Z. Sabrina, T. Djamel, T. Camel, M. Ammar, S. Said, and N. Okba, "SDR Implementation of Spectrum Sensing using Deep Learning," 2023.
- [11] Prasetyo, R. V. W. Putra, et al., "Kurtosis and Energy Based Spectrum Detection for SDR Based RF Monitoring System," 2016.
- [12] A. O. Khodakova, Y. D. Naumova, S. A. Chechenya, et al., "Development of Signal Detection and Recognition Algorithm Using Software-Defined Radio," 2025.
- [13] S. Jaloudi, "Communications of Smart Systems Based on Software-Defined Radio and Internet of Things," 2025.
- [14] S. R. Doha and A. Abdelhadi, "Artificial Intelligence in Software Defined Radio: A Survey," 2025.
- [15] R. K. Miranda, et al., "Enhanced Direction of Arrival Estimation via Received Signal Strength of Directional Antennas," 2018.
- [16] M. A. Khalil, M. A. Abouelatta, et al., "Low-Cost High-Precision Direction of Arrival (DOA) Estimation Using Dual-Channel Receivers SDR," 2024.
- [17] E. D. Egorova, E. A. Ischenko, and S. M. Fedorov, "Study of SDR-Based Direction Finding Under Threshold Sensitivity Depending on Signal-To-Noise Ratio," 2024.
- [18] S. Shashank, V. B. Narayane, P. Saxena, and A. Baheti, "Direction Estimation of a Jamming Signal Using an Optimized Direction-Finding Algorithm," 2025.
- [19] K. V. H., G. M. Aradhyatham, B. K., et al., "AI Based RF Jamming and Mitigation," 2025.
- [20] S. L. Ratto Valderrama and N. A. Montes Aracena, "Advancements in Signal Interference Systems for Targeted Disruption of Unmanned Aerial Systems," 2023.
- [21] S. Mao, N. Yu, M. Li, et al., "RF Signal Classification-based Drone Identification with Multimodal Database," 2023.
- [22] K. Kawakami, H. Nakamizo, K. Tajima, et al., "A Ku-Band RF Module Transmitter Including an RF Signal Generator for a Flexible Phased-Array System," 2013.
- [23] I. Chiba, H. Nakamizo, K. Tajima, et al., "A Flexible and Precise APAA System with RF Modules Including a Signal Generator," 2013.
- [24] B. Xia and W. Chen, "A Fully Digital RF Signal Generation Scheme for Low-Cost GNSS Signal Generator," 2024.
- [25] J. Zhang, et al., "Design and Implementation of Multi-Channel Wideband and RF Signal Generator," 2014.
- [26] X. Wang and M. Song, "High-Precision Temperature Control for RF Detection in Signal Generators Based on Adaptive Kalman Filtering and Fuzzy PID," 2025.
- [27] S. Lee, S. Chen, T. Cho, W. Liu, and T. Chen, "D.O.E. Method Application to Optimize System Level RF Signal Path with Antenna Design," 2022.
- [28] Z. Li, Z. Wang, H. Luo, et al., "Weak RF Signal Detection Based on Single-Mode Optoelectronic Oscillator," 2023.
- [29] A. Vijayam S., J. Zacharias, and A. Chandrasenan, "Generation of Real-Time RF Switching Signal by Polarization-Dependent Four Wave Mixing Technique," 2022.

- [30] H. N. Tran, T. A. Podstigaev, and N. N. Trong, "A Signal Classification Algorithm with Detection at Two Intermediate Frequencies for RF Spectrum Monitoring," 2022.
- [31] D. Padhya, K. Acharya, B. K. Dahal, and D. B. Khatri, "CNN-LSTM Hybrid Architecture for Over-the-Air Automatic Modulation Classification Using SDR," 2025.