IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 12, Issue 12, December 2025

DOI: 10.17148/IARJSET.2025.121260

Intelligent Spectrum Sensing and Data Fusion Techniques in Cognitive Radio–Enabled IoT Networks: A Comprehensive Review

Rajesh Prasad[1], Nitesh Gupta[2]

M.Tech Scholar, Computer Science and Engineering, NIST, Bhopal, India[1]

Assistant Professor, Computer Science and Engineering, NIST, Bhopal, India[2]

Abstract: The rapid proliferation of Internet of Things (IoT) devices has intensified the demand for efficient spectrum utilization, making traditional static spectrum allocation insufficient. Cognitive Radio (CR) technology emerges as a promising solution by enabling dynamic spectrum access through intelligent spectrum sensing and adaptive decision-making. This review paper presents a comprehensive analysis of intelligent spectrum sensing and data fusion techniques in Cognitive Radio–enabled IoT networks. It systematically examines conventional spectrum sensing approaches, including energy detection, matched filtering, and cyclostationary detection, highlighting their limitations in noisy, heterogeneous, and large-scale IoT environments. To address these challenges, the paper explores machine learning and deep learning–based spectrum sensing methods that enhance detection accuracy, robustness, and adaptability. Furthermore, the role of data fusion is critically reviewed, focusing on data-level, feature-level, and decision-level fusion strategies that improve sensing reliability by combining observations from multiple IoT nodes. Intelligent data fusion techniques based on neural networks, fuzzy logic, and reinforcement learning are also discussed, emphasizing their capability to reduce uncertainty and communication overhead. The integration of spectrum sensing and data fusion within edge and fog computing paradigms is analyzed to support real-time and energy-efficient IoT applications. Finally, the paper identifies open research challenges related to scalability, security, latency, and standardization, and outlines future research directions toward 6G-enabled cognitive IoT systems. This review aims to serve as a valuable reference for researchers and practitioners working on intelligent spectrum management in next-generation IoT networks

Keywords: Cognitive Radio, Spectrum Sensing, Data Fusion, Internet of Things, Machine Learning, Cooperative Sensing, Dynamic Spectrum Access.

I. INTRODUCTION

The rise of the Internet of things (IoT) has changed the entire landscape of communication networks, having enabled billions of diverse objects to feel, process, and transmit information in real time. Several real-world scenarios, e.g., smart cities, industrial automation, health monitoring, intelligent transportation, and environment sensing, critically depend upon "continuous" and "reliable" wireless networking [1]. The big adopted wave of IoT technologies that have been proliferated across the globe has aggravated the need for radio spectrum and overcrowded traditionally leased areas. In this context, highlights of current spectrum measurements have shown how much of the spectrum has remained underutilized within the confines of time, space, and frequency. Such underutilization counteracts the general belief in spectrum scarcity and thus shows the downside of a rigid spectrum allocation policy, hence suggesting the way for much more creative and adaptive spectrum management approache [2].

In the Internet of Things (IoT), cognitive radio (CR) technology provides the potential promise for overcoming the constraints, allowing for dynamic spectrum access. Cognitive radio is an intelligent wireless system that can sense the radio environment around it, learn from observation, and adapt autonomously for its transmission parameters so as to utilize whatever available spectrum while curbing interference to its detriment to the licensed or primary users. Integration with IoT networks enables cognitive radio to provide efficient spectrum sharing, enhance spectral efficiency, and allow scalable connectivity to resource-constrained devices [3]. Various reasons underscore the relevance of cognitive radio in the IoT, such as scarcity in spectrum, diversity of quality of service (QoS) requirements among IoT applications, limitations in constraints for energy efficiency, and communication reliability for environments that are dynamic and heterogeneous. Cognitive-radio empowered IoT networks can effectively employ idle spectrum bands, thus

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 12, December 2025

DOI: 10.17148/IARJSET.2025.121260

simultaneously alleviating congestion, enhancing throughput, and augmenting the number of devices, such a scenario forming the linchpin for next-generation wireless systems [4].

The most basic radio operation is based on spectrum sensing. To enable secondary IoT devices to observe the presence or absence of primary users' signals and locate spectrum opportunities. The efficiency of the use of that spectrum depends on the reliability with which spectrum sensing is performed while ensuring protection is extended to licensed users [5]. The most common methods for sensing include largely energy detection, matched filtering, and cyclostationarity detection, known for their major benefits: simplicity, and theoretical underpinning. These, however, do not work well in the environment characterized by low S/N ratio, severe fading and shadowing, hardware loin(ts, and unpredictable traffic [6]. The best fit in this case is the cooperative spectrum sensing method where multiple IoT nodes are employed to sense a given band so that observations may be collated to enable betterre/liability thresholds of detection. The performance of cooperative energy detection will be well enhanced whereas there may come in a matter of challenges regarding communication overhead, scalability, and decision accuracy [7].

Data fusion holds a prime importance for cooperative spectrum sensing, where information is fused across different nodes for more reliable global decisions. Depending on the level of abstraction, this fusion can take place in the data level, feature level, or decision level, each one plently of trade-offs between complexity, performance, and communication cost. Improved data fusion translates to improved detection performance, reduced false alarm rate, and robustness to channel distortions and malicious behaviors [8]. In cognitive radio enabled IoT networks, intelligent data fusion is equally of importance, given the fact of numerous distributed and resource-constrained devices [9]. Advanced fusion strategies, the likes of Bayesian theory, Dempster-Shafer, fuzzy logic, optimization techniques, handle uncertainty and heterogeneity of sensing reports. Recently, deliberations around machine learning and deep learning fusion methods were ongoing due to their capability to learn complex patterns, adapt to dynamic environments and enhance decision accuracy without strict statistical assumptions [7][10].

While considerable efforts have been made, a few challenges and avenues that need further research still exist in the intelligent spectrum sensing mechanisms and data fusion in the cognitive IoT network paradigm. Scalability in this respect is a serious issue since the centralised sensing and fusion methods that are standard nearly the world over seem inadequate to handle the huge numbers of IoT devices. According to another angle, energy efficiency is very pressing due to the rapid drainage of the battery resources of the IoT nodes through frequent sensing and reporting 10]. Besides this, noise uncertainty, mobility, hidden primary user, and correlated sensing data tend to degrade spectrum-sensing accuracy further. Security and privacy make spectrum access all the more reliable, with issues like false data injection and malice of sensing attacks. In sum, many of these studies rely on idealistic assumptions or rigorous simulation-based evaluations and hence their thirst for real-metal models, real data sets, and practices. Integration of edge and fog computing to decentralized intelligence, and their alignment with emerging 6G communication frameworks, all are still open research topics [11]. Fig.1 represents Block Diagram of Cognitive Radio.

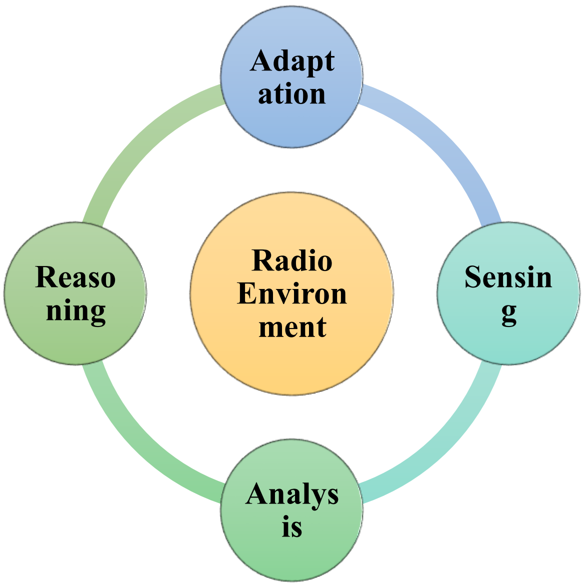

Fig. 1: Block Diagram of Cognitive Radio

DOI: 10.17148/IARJSET.2025.121260

In order to overcome these challenges, intelligent spectrum scan and data fusion mechanisms in cognitive radio-enabled IoT networks are extensively analyzed in an organized enumerative review paper is shown. The paper lays down a systematic lay review of the conventional spectrum sensing methods and machine learning-based spectrum sensing methods, discusses data fusion strategies strictly built across different layers of abstraction, and highly emphasizes, in brief, the modern intelligent and adaptive fusion methodology with its unique marksmanship [12]. Besides, the work identifies existing integration models that marry sensing and fusion with edge intelligence to improve scalability and real-time performance. Through the identification of the open challenges in the research field, the article is supposed to provide some showcasing for researchers, starting toward efficient and intelligent spectrum management in the modern IoT context [13].

I. Fundamentals of Cognitive Radio and IoT

The convergence of Cognitive Radio (CR) and the Internet of Things (IoT) represents a transformative shift for addressing spectrum inefficiency and connectivity challenges in Commonwealth wireless communication ecosystems. The IoT network consists of excessive homogeneous and low-power devices, which anticipate reliable and scalable communication.

Cognitive Radio: Principles

Cognitive Radio is the intelligent wireless communication technology that adjusts the performance by sensing and learning from the surrounding radio ecological settings. Cognitive radio was first introduced by Mitola, who had developed the concept to enhance the spectrum efficiency by allowing the unlicensed or secondary users to opportunely get access to the underutilized licensed bandwidth without causing harmful interference to the primary users [14]. The core operations of cognitive radio lie in the cognitive cycle, which summarizes spectrum sensing, spectrum analysis, spectrum decision, spectrum mobility, and spectrum sharing.

Internet of Things (IoT) Overvie

The Internet of Things (IoT) is a concept in which there exists a network of interconnected physical entities that are empowered with sensors, actuators, processing units, and communication interfaces, to collect and exchange data over the Internet. IoT devices, thus, scope into smart homes, healthcare, industrial automation, agriculture, transportation, environmental monitoring, and other domains.[15] The computing capability, memory, and energy resources of these devices are mostly limited while setting forth computational requirements to manage voluminous data with communication reliability [16].

IoT Communication Challenges

Challenges that immediately limit the performance and scalability of the network for IoT communication are the very issues ensuing through the mass connectivity of devices. Thousands of devices may attempt connectivity with the network simultaneously, causing congestion and a greater probability of collision [17]. Energy efficiency is a matter of much concern-other than these-devices being small and self-sustained by their own batteries. Given battery strength and expected operational durations in the long run without maintenance, any operation requiring recurring communication and sensing will-day by day and even more-obviously affect device lifetime [18]. Fig. 2 represents Cognitive radio (CR)-Internet of Things (IoT) spectrum-heterogeneous environment

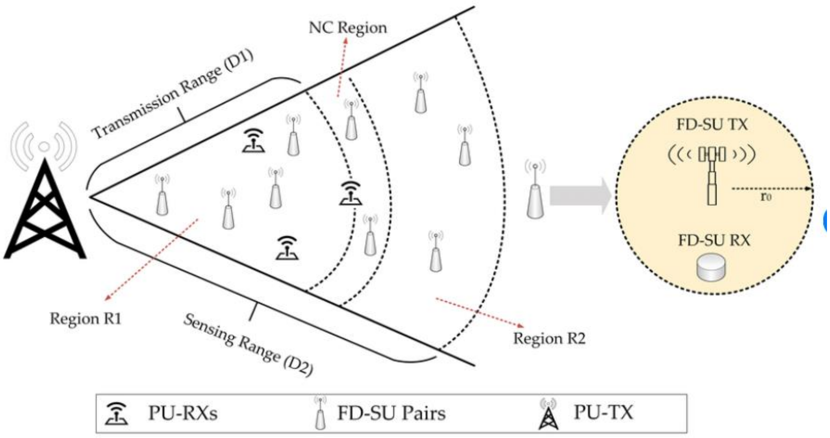

Fig. 2: Cognitive radio (CR)-Internet of Things (IoT) spectrum-heterogeneous environment

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁝ Peer-reviewed & Refereed journal ⁝ Vol. 12, Issue 12, December 2025

DOI: 10.17148/IARJSET.2025.121260

Spectrum Scarcity and Underutilization

With wireless services and IoT deployments marching on without stopping, spectrum scarcity has arisen as a serious problem. About any frequency band instead appears to be statically assigned to developed license holders, leading to congestion in popular bands (e.g., ISM). However, any periodic and geographical dimension will attest empirical studies that display underutilization, with multiple licensed spectrum bands. Rigidity in the regulatory structure prevents frequent spectrum assignment ultimately leading to ineffectiveness [19].

Cognitive Radio–Enabled IoT Architecture

Over the conventional IoT communication paradigms, the implementation of Cognitive Radio-based technologies, in general, represents the idea of introducing spectrum-use awareness intelligence. These cognitive-radio-equipped IoT devices come endowed with spectrum-sensing modules and adaptive transceivers. They basically keep an eye on the radio environment to detect vacant spectrums and immediately adjust their transmission-related parameters [17]-[18]. Moreover their many IoT nodes are engaged in a cooperative and collaborative spectrum-sensing operation whereby the multiple sensor nodes share the crucial information needed for enhancing accuracy with regard to detection.

Smart data fusion may involve central or distributed decision-making entities, such as fusion centers, edge servers, or fog nodes, aggregating sensor data. Edge computing is very crucial by significantly minimizing latency and communications overhead through local processing and real-time decision-making. The architecture employs learning mechanisms, such as machine learning models, to increase the response mechanism and allow for long-term optimization [19]. It is expected that the integrated framework may provide energy efficiency, scalability, and the reliability of communications, tailored well for future IoT systems and networks beyond 5G/6G. Fig. 3 represents Cognitive Radio Network Architecture.

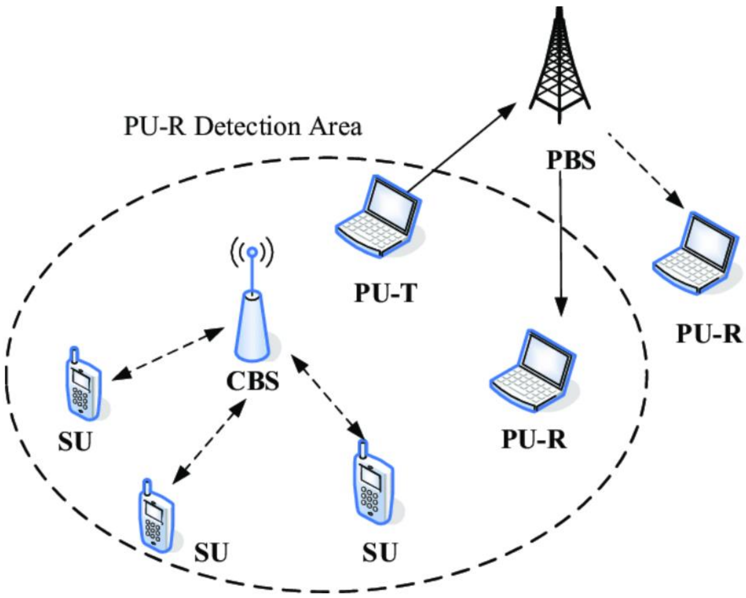

Fig. 3: Cognitive Radio Network Architecture

II. SPECTRUM SENSING TECHNIQUES

Spectrum sensing is a fundamental function of cognitive radio systems, enabling secondary users to identify unused spectrum bands while ensuring non-interference with licensed primary users. The primary objective of spectrum sensing is to accurately detect the presence or absence of primary user signals in a given frequency band and to identify spectrum holes that can be opportunistically accessed by IoT devices [20]. Reliable spectrum sensing is essential for efficient spectrum utilization, regulatory compliance, and quality-of-service assurance in cognitive radio–enabled IoT networks.

Spectrum sensing techniques can be broadly classified based on the detection principle employed. **Energy detection** is the most widely used method due to its low computational complexity and lack of prior knowledge requirements about the primary user signal. It determines spectrum occupancy by comparing the received signal energy against a predefined threshold. However, its performance degrades significantly under low signal-to-noise ratio (SNR) conditions and noise uncertainty [21]. **Matched filter detection** offers optimal detection performance when the primary user signal characteristics are known, as it maximizes the SNR. Despite its accuracy, this method is impractical for heterogeneous IoT environments due to high complexity and the need for prior signal information. **Cyclostationary feature detection** exploits periodic statistical properties of modulated signals, enabling robust detection even in noisy environments, though

DOI: 10.17148/IARJSET.2025.121260

at the cost of increased computational overhead. **Waveform-based detection** utilizes known signal patterns such as preambles or pilots to improve detection accuracy, while **compressive sensing** leverages signal sparsity to reduce sampling rates and sensing overhead, making it suitable for wideband spectrum sensing in resource-constrained IoT devices [22]. Fig. 4 represents spectrum sensing scenario [8].

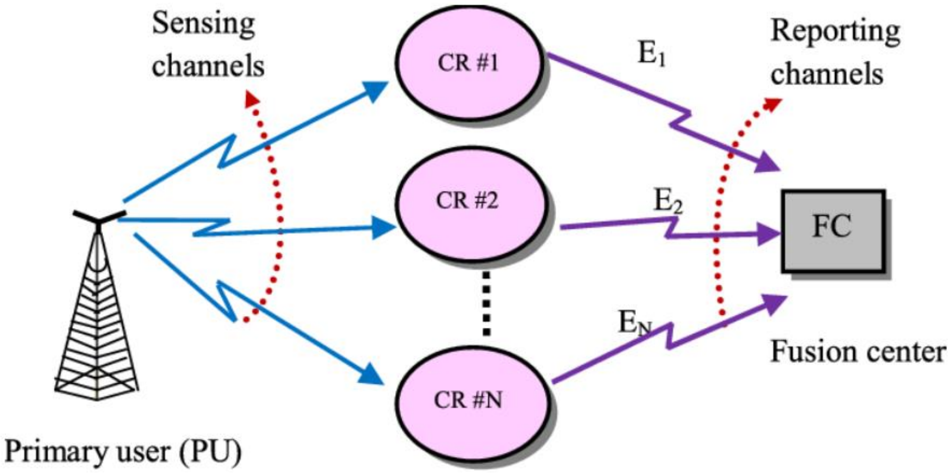

Fig.4: Spectrum Sensing Scenario [8]

To overcome the limitations of individual sensing, **cooperative spectrum sensing** is employed, where multiple IoT nodes collaborate to sense the spectrum. In **centralized approaches**, sensing data is collected at a fusion center for global decision-making, offering high accuracy but increased communication overhead. **Distributed approaches** eliminate the need for a central entity, improving scalability and robustness [23]. **Relay-assisted sensing** further enhances detection reliability by forwarding sensing information through intermediate nodes.

Despite these advancements, spectrum sensing faces several challenges, including fading and shadowing effects that distort received signals, noise uncertainty that impacts threshold-based detection, and the hidden primary user problem caused by obstacles or deep fading [24]. Performance evaluation of spectrum sensing techniques typically relies on metrics such as probability of detection and false alarm, sensing time, and energy efficiency. Balancing accuracy, latency, and energy consumption remains a critical design consideration in cognitive IoT networks [25].

III. RELATED WORK

Janu et al. [1] (2021) presented a comprehensive survey on machine learning–based cooperative spectrum sensing (CSS) and dynamic spectrum sharing (DSS). The study analyzed feature extraction methods, learning paradigms, and performance metrics, highlighting supervised, unsupervised, and reinforcement learning approaches.
Hilina et al. [2] (2019) proposed ML-driven CSS algorithms using K-means, GMM, SVM, and weighted KNN. Energy estimates were treated as feature vectors, and results showed superior detection accuracy and reduced delay compared to conventional CSS methods.
Zheng et al. [3] (2020) introduced a robust spectrum sensing approach outperforming eigenvalue- and entropy-based techniques. The method demonstrated adaptability to unseen signals and colored noise, with further performance gains via transfer learning.
Gao et al. [4] (2019) developed a deep learning–based signal detector exploiting inherent signal structures without prior channel or noise information. A cooperative DL framework further improved sensing performance over traditional approaches.
Nasser et al. [5] (2018) examined the integration of cognitive radio in 5G and beyond networks, focusing on spectrum sensing for dynamic frequency allocation. The study outlined key challenges and future research directions.
Arjoune et al. [6] (2018) provided a detailed survey of spectrum sensing techniques, including narrowband, wideband, compressive sensing, and ML-based methods. The paper highlighted implementation challenges and future research opportunities.
Lees et al. [7] (2020) evaluated classical and ML-based radar detection techniques using over 14,000 real-world spectrograms. CNN-based models consistently outperformed classical methods, achieving a strong balance between accuracy and complexity.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.311 ⁝ Peer-reviewed & Refereed journal ⁝ Vol. 12, Issue 12, December 2025
DOI: 10.17148/IARJSET.2025.121260

Liu et al. [8] (2021) proposed a covariance matrix–aware CNN (CM-CNN) for spectrum sensing with strong theoretical analysis. The method achieved near-optimal detection performance at very low SNR levels.
Lee et al. [9] (2019) introduced Deep Cooperative Sensing (DCS), a CNN-based CSS framework that learns optimal fusion strategies without explicit mathematical modeling. The method significantly improved sensing accuracy by exploiting spatial and spectral correlations.
Jaishanthi et al. [10] (2017) proposed a multi-agent–based adaptive spectrum allocation framework. Environmental data were used to support intelligent decision-making and improve communication service quality.
Ramchandran et al. [11] (2018) introduced an energy-efficient and interference-aware spectrum sensing scheme using game theory. The approach improved throughput, detection probability, and residual energy of secondary users.
Zhou et al. [12] (2019) presented a comprehensive survey of deep learning architectures and training methodologies. The study highlighted the superiority of DL over traditional ML methods in complex data analysis tasks.
Song et al. [13] (2020) explored AI-enabled IoT networks with emphasis on spectrum access and sensing. Deep reinforcement learning techniques were shown to effectively address dynamic spectrum sharing challenges.
Delvecchio et al. [14] (2020) investigated adversarial evasion attacks against deep learning–based signal classifiers. The work revealed vulnerabilities in ML-enabled communication systems and proposed secure communication strategies.
Sagduyu et al. [15] (2018) analyzed adversarial attacks targeting learning-based spectrum access. Defense mechanisms were proposed to improve robustness and throughput in IoT networks.
Lin et al. [16] (2021) proposed a hybrid DRL–LSTM framework for UAV spectrum sharing. The approach achieved faster convergence and higher throughput compared to conventional RL techniques.
Shi et al. [17] (2021) presented a deep learning–based signal classification framework addressing unknown signals, spoofing, and interference. Integrated scheduling significantly enhanced spectrum sharing performance.
Zhang et al. [18] (2020) applied asynchronous actor–critic learning for power control in spectrum sharing systems. The proposed approach achieved rapid convergence while satisfying QoS requirements.
Natarajan et al. [21] (2019) proposed a reconfigurable CR-IoT framework optimizing energy efficiency, network capacity, and interference. Experimental results demonstrated improved robustness and scalability.
Zhang et al. [22] (2019) introduced an adaptive modulation and coding selection algorithm. The method significantly outperformed UCB and SNR-based schemes with minimal overhead.
Gupta et al. [28] (2017) provided a comprehensive taxonomy and mathematical modeling of spectrum sensing schemes. The survey outlined applications, open issues, and future research directions in cognitive radio networks.
Venketeswaran et al. [29] presented a comprehensive review of research integrating Machine Learning (ML) and Artificial Intelligence (AI) with Fiber Optic Sensing (FOS) technologies. The study highlighted emerging trends in FOS development and emphasized their growing importance in industrial applications, particularly energy system monitoring. Additionally, the authors identified key challenges and outlined future research directions to enhance intelligent FOS deployment.
Vimal et al. [30] proposed an intelligent caching and cache management framework to reduce execution delays in Mobile Edge Computing (MEC) environments. Their approach utilized a cognitive agent model combined with Reinforcement Learning, specifically Multi-Objective Ant Colony Optimization (MOACO), to optimize resource allocation. Performance evaluation demonstrated improved quality of service and efficient utilization of MEC resources among neighboring user equipment.

IV. DATA FUSION IN COGNITIVE RADIO IOT NETWORKS

TABLE I SUMMARY OF DATA FUSION IN COGNITIVE RADIO IOT NETWORKS

Ref	Focus Area	Fusion Level / Rule / Architecture	Results / Limitations
Hamda et al., [31] 2023	Multisensor data fusion under uncertainty in IoT	Decision-level fusion using **Dempster–Shafer theory** with belief entropy weighting	Improved decision accuracy under conflicting sensor data; however, computational complexity increases with number of sources
Al-Hassani et al., [32] 2022	Cooperative spectrum sensing in CR-IoT	**AND/OR/L-out-of-N rules**, centralized fusion	Achieved higher detection probability compared to single-node sensing; performance degrades with correlated sensing reports
Li et al., [33] 2021	Bayesian data fusion for IoT sensing	**Bayesian fusion**, centralized architecture	Provides probabilistic optimal decisions; requires accurate prior probabilities, limiting practicality in dynamic CR-IoT

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 12, December 2025

DOI: 10.17148/IARJSET.2025.121260

Kumar & Bera, [34] 2020	Hard and soft decision fusion in cognitive radio networks	Decision-level fusion, centralized	Soft fusion improves sensing reliability; incurs higher communication overhead
Zhang et al., [35] 2024	Distributed fusion for large-scale IoT	**Distributed fusion architecture**, feature-level fusion	Enhances scalability and reduces latency; limited robustness against malicious or faulty nodes
Rahman et al., [36] 2023	Trust-aware data fusion in CR-IoT	Hybrid fusion with trust weighting	Reduces false spectrum decisions caused by malicious users; trust computation adds processing overhead
Singh et al., [37] 2022	Feature-level fusion for IoT data analytics	Feature-level fusion with ML classifiers	Improves classification accuracy; feature extraction increases energy consumption in IoT nodes
Ahmed et al., [38] 2021	Data-level fusion in sensor-based IoT	Data-level fusion, centralized	Preserves raw information richness; sensitive to noise and synchronization errors
Chen et al., [39] 2025	Hybrid fusion architecture for CR-enabled IoT	Hybrid (centralized + distributed) fusion	Balances scalability and accuracy; architecture complexity limits real-time deployment
Patel & Roy,[40] 2024	Communication-efficient fusion strategies	Decision-level fusion with compression	Reduces communication overhead; slight degradation in detection accuracy

V. APPLICATIONS AND USE CASES

TABLE III APPLICATIONS AND USE CASES OF COGNITIVE RADIO–ENABLED IOT NETWORKS

Application Domain	Use Case	Role of Cognitive Radio	Spectrum Sensing & Data Fusion Benefits	Key Challenges
Smart Cities	Smart traffic management, surveillance, smart lighting	Dynamic spectrum access to support dense IoT deployments	Cooperative sensing improves spectrum availability; data fusion enhances situational awareness and decision accuracy	High node density, interference, scalability
Industrial IoT	Factory automation, predictive maintenance, process monitoring	Reliable and low-latency communication in congested industrial spectrum	Feature- and decision-level fusion improve fault detection and spectrum reliability	Harsh environments, strict latency constraints
Vehicular Networks (VANETs)	Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication	Opportunistic spectrum access for high-mobility nodes	Fast cooperative sensing and fusion enable robust connectivity and collision avoidance	High mobility, rapid topology changes
Remote Healthcare	Wearable health monitoring, emergency alerts	Adaptive spectrum usage ensures continuous connectivity	Data fusion integrates multi-sensor health data for accurate diagnosis and alerts	Privacy, energy constraints, reliability
Agriculture & Environmental Monitoring	Precision farming, soil and climate monitoring, disaster detection	Efficient spectrum use in remote and rural areas	Data-level and feature-level fusion improve sensing accuracy and coverage	Sparse infrastructure, energy efficiency

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 12, December 2025
DOI: 10.17148/IARJSET.2025.121260

VI. OPEN CHALLENGES AND FUTURE DIRECTIONS

Scalability in Large-Scale IoT Deployments
Designing scalable sensing and fusion frameworks that efficiently manage massive IoT nodes without excessive overhead remains a critical challenge [27].
Real-Time Processing and Latency
Achieving low-latency, real-time spectrum sensing and data fusion under dynamic spectrum conditions is essential for time-critical IoT applications.
Security and Privacy in Sensing and Fusion
Ensuring secure, privacy-preserving sensing and fusion mechanisms against malicious users and data manipulation is an open research issue [28].
Standardization Efforts
Lack of unified standards for cognitive IoT sensing and fusion hinders interoperability, large-scale deployment, and cross-vendor compatibility.
Beyond 5G and 6G Integration
Integrating cognitive IoT with beyond-5G and 6G networks requires intelligent, AI-driven spectrum management and ultra-reliable low-latency communication [29].

VII. CONCLUSION

This review analyzed intelligent spectrum sensing and fusion methods in cognitive radio-assisted IoT networks, technologies that play a crucial role in spectrum scarcity alleviation and support for massive IoT connectivity. The survey studied the fundamentals of cognitive radio, such as advanced spectrum sensing methods and multi-level data fusion methods, and the fact cooperative sensing and fusion enhance detection accuracy, reliability, and spectrum utilization effectively. The paper identified that one can also provide reliable enhancements of fading, noise uncertainty, and hidden primary user problems by combining decision-, feature-, and data-level fusion types together with appropriate fusion rules and architectures. The same review has seen that intelligent fusion frameworks play a key role in functioning in a variety of IoT applications such as intelligent cities, smart industry, vehicular networks, healthcare, and environment monitoring. Specifically, this paper put together a collection of recent survey material published from 2020–2025, systematically classifying the spectrum sensing and fusion techniques and discussing some practical limitations. This attempt also highlighted that future cognitive IoT systems must have AI-enabled and secure, low-latency sensing and fusion mechanisms to evolve to the next generation networks such as beyond-5G or 6G. The intelligent spectrum sensing and data fusion will always remain key technologies for a robustly intelligent, green, and scalable cognitive radio–enabled IoT ecosystem

REFERENCES

[1]. Janu, Dimpal, Kuldeep Singh, and Sandeep Kumar. "Machine learning for cooperative spectrum sensing and sharing: A survey." *Transactions on Emerging Telecommunications Technologies* 33.1 (2022): e4352.
[2]. Thilina, Karaputugala Madushan, et al. "Machine learning techniques for cooperative spectrum sensing in cognitive radio networks." *IEEE Journal on selected areas in communications* 31.11 (2013): 2209-2221.
[3]. Zheng, Shilian, et al. "Spectrum sensing based on deep learning classification for cognitive radios." *China Communications* 17.2 (2020): 138-148.
[4]. Gao, Jiabao, et al. "Deep learning for spectrum sensing." *IEEE Wireless Communications Letters* 8.6 (2019): 1727-1730.
[5]. Nasser, Abbass, et al. "Spectrum sensing for cognitive radio: Recent advances and future challenge." *Sensors* 21.7 (2021): 2408.
[6]. Arjoune, Youness, and Naima Kaabouch. "A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions." *Sensors* 19.1 (2019): 126.
[7]. Lees, W. Max, et al. "Deep learning classification of 3.5-GHz band spectrograms with applications to spectrum sensing." *IEEE transactions on cognitive communications and networking* 5.2 (2019): 224-236.
[8]. Liu, Chang, et al. "Deep CM-CNN for spectrum sensing in cognitive radio." *IEEE Journal on Selected Areas in Communications* 37.10 (2019): 2306-2321.
[9]. Lee, Woongsup, Minhoe Kim, and Dong-Ho Cho. "Deep cooperative sensing: Cooperative spectrum sensing based on convolutional neural networks." *IEEE Transactions on Vehicular Technology* 68.3 (2019): 3005-3009.
[10]. Jaishanthi, B., E. N. Ganesh, and D. Sheela. "Priority-based reserved spectrum allocation by multi-agent through reinforcement learning in cognitive radio network." *Automatika* 60.5 (2019): 564-569.

DOI: 10.17148/IARJSET.2025.121260

[11]. Ramchandran, M., and E. N. Ganesh. "Energy Efficient and Interference-aware Spectrum Sensing Technique for Improving the Throughput in Cognitive Radio Networks." IOP Conference Series: Materials Science and Engineering. Vol. 993. No. 1. IOP Publishing, 2020.
[12]. Zhou, Lei, et al. "Application of deep learning in food: a review." Comprehensive reviews in food science and food safety 18.6 (2019): 1793-1811.
[13]. Song, Hao, et al. "Artificial intelligence enabled Internet of Things: Network architecture and spectrum access." IEEE Computational Intelligence Magazine 15.1 (2020): 44-51.
[14]. Delvecchio, Matthew David. Enhancing Communications Aware Evasion Attacks on RFML Spectrum Sensing Systems. Diss. Virginia Tech, 2020.
[15]. Sagduyu, Yalin E., Yi Shi, and Tugba Erpek. "IoT network security from the perspective of adversarial deep learning." 2019 16th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON). IEEE, 2019.
[16]. Lin, Yun, et al. "Dynamic spectrum interaction of UAV flight formation communication with priority: A deep reinforcement learning approach." IEEE Transactions on Cognitive Communications and Networking 6.3 (2020): 892-903.
[17]. Shi, Yi, et al. "Deep learning for RF signal classification in unknown and dynamic spectrum environments." 2019 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN). IEEE, 2019.
[18]. Zhang, Haijun, et al. "Power control based on deep reinforcement learning for spectrum sharing." IEEE Transactions on Wireless Communications 19.6 (2020): 4209-4219.
[19]. Raj, Suman, and Sarfaraz Masood. "Analysis and detection of autism spectrum disorder using machine learning techniques." Procedia Computer Science 167 (2020): 994-1004.
[20]. Dai, Ling, et al. "A deep learning system for detecting diabetic retinopathy across the disease spectrum." Nature communications 12.1 (2021): 3242.
[21]. Natarajan, Yuvaraj, et al. "An IoT and machine learning-based routing protocol for reconfigurable engineering application." IET Communications 16.5 (2022): 464-475.
[22]. Zhang, Lin, et al. "Deep reinforcement learning-based modulation and coding scheme selection in cognitive heterogeneous networks." IEEE Transactions on Wireless Communications 18.6 (2019): 3281-3294.
[23]. Mohan, Amrita, et al. "Review on remote sensing methods for landslide detection using machine and deep learning." Transactions on Emerging Telecommunications Technologies 32.7 (2021): e3998.
[24]. Zheng, Qinghe, et al. "Spectrum interference-based two-level data augmentation method in deep learning for automatic modulation classification." Neural Computing and Applications 33.13 (2021): 7723-7745.
[25]. Cui, Feiyun, et al. "Advancing biosensors with machine learning." ACS sensors 5.11 (2020): 3346-3364.
[26]. Khodatars, Marjane, et al. "Deep learning for neuroimaging-based diagnosis and rehabilitation of autism spectrum disorder: a review." Computers in Biology and Medicine 139 (2021): 104949.
[27]. Chuma, Euclides Lourenco, and Yuzo Iano. "Novelty sensor using integrated fluorescence and dielectric spectroscopy to improve food quality identification." 2022 IEEE Sensors. IEEE, 2022.
[28]. Gupta, Mani Shekhar, and Krishan Kumar. "Progression on spectrum sensing for cognitive radio networks: A survey, classification, challenges and future research issues." Journal of Network and Computer Applications 143 (2019): 47-76.
[29]. Venketeswaran, Abhishek, et al. "Recent advances in machine learning for fiber optic sensor applications." Advanced Intelligent Systems 4.1 (2022): 2100067.
[30]. Vimal, S., et al. "Enhanced resource allocation in mobile edge computing using reinforcement learning based MOACO algorithm for IIOT." Computer Communications 151 (2020): 355-364.
[31]. A. Kumar and S. Bera, "Hard and soft decision fusion techniques for cooperative spectrum sensing in cognitive radio networks," *IEEE Systems Journal*, vol. 14, no. 2, pp. 2385–2396, Jun. 2020.
[32]. M. Ahmed, R. Hussain, and J. Kim, "Data-level fusion approaches for IoT-based cognitive radio networks," *IEEE Internet of Things Journal*, vol. 8, no. 9, pp. 7234–7246, May 2021.
[33]. Y. Li, H. Zhang, and X. Chen, "Bayesian data fusion for cooperative spectrum sensing in cognitive IoT networks," *IEEE Transactions on Wireless Communications*, vol. 20, no. 11, pp. 7421–7434, Nov. 2021.
[34]. R. Singh, P. K. Sharma, and D. N. K. Jayakody, "Feature-level data fusion using machine learning for intelligent IoT systems," *IEEE Access*, vol. 10, pp. 45678–45690, 2022.
[35]. F. Al-Hassani, S. Al-Rubaye, and A. Anpalagan, "Fusion rule-based cooperative spectrum sensing for cognitive radio IoT," *IEEE Communications Letters*, vol. 26, no. 8, pp. 1865–1869, Aug. 2022.
[36]. S. Rahman, M. A. Hossain, and K. S. Kwak, "Trust-aware data fusion framework for secure cognitive radio–enabled IoT networks," *IEEE Internet of Things Journal*, vol. 10, no. 5, pp. 4120–4133, Mar. 2023.
[37]. A. Hamda, L. Chaari, and M. Kamoun, "Decision-level data fusion using Dempster–Shafer theory for cognitive IoT applications," *IEEE Sensors Journal*, vol. 23, no. 14, pp. 15620–15632, Jul. 2023.

DOI: 10.17148/IARJSET.2025.121260

[38]. J. Zhang, Y. Wang, and L. Hanzo, "Distributed data fusion architectures for large-scale cognitive IoT networks," *IEEE Transactions on Network Science and Engineering*, vol. 11, no. 1, pp. 210–223, Jan. 2024.

[39]. P. Patel and S. Roy, "Communication-efficient decision fusion strategies for spectrum sensing in CR-IoT," *IEEE Access*, vol. 12, pp. 33450–33463, 2024.

[40]. X. Chen, Z. Liu, and H. V. Poor, "Hybrid data fusion architectures for next-generation cognitive radio–enabled IoT networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 11, no. 1, pp. 45–58, Feb. 2025.