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Artificial Intelligence-Based Spectrum Sensing for Beyond 5G and 6G Cognitive Radio Networks: A Comprehensive Survey

Rahul Bansode¹, Vishwas Gaikwad²

¹Research Scholar, Sipna College of Engineering and Technology, Amravati, India

²Professor, Sipna College of Engineering and Technology, Amravati, India

Corresponding Author: rahulbansodespcoe@gmail.com

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ABSTRACT

The B5G and 6G wireless communication system deployments have been expanding rapidly, increasing the need for better radio spectrum use. Despite being overwhelmed with applications for licenses to use specific frequency ranges of the radio spectrum, recent studies demonstrate that many of these licensees leave unused portions of their assigned frequencies available at various times and locations. Cognitive Radio Networks (CRNs) provide an intelligent way to utilize more efficiently existing unlicensed radio spectrum while minimizing interference to licensed users. To enable this type of operation, spectrum sensing has become the essential enabling technology of CRNs. However, due to numerous factors, the conventional methods for conducting spectrum sensing, i.e., ED, MFD, CFD, and CSS are subject to reduced performance when operating under low SNRs, fading channel conditions, and other characteristics typical of dynamic wireless communications. Advances in artificial intelligence (AI) have enabled new forms of machine-based spectrum sensing technologies which allow for advanced features to be extracted automatically, adapt to changing environments, and make decisions autonomously. In addition to improvements in detection accuracy, AI-based spectrum sensing solutions can also increase the robustness and overall usage of wireless spectrum compared to traditional approaches. As a result, this paper provides an overview of AI-based spectrum sensing solutions for future CRN systems. State-of-the art ML, DL, GNN, FL, and DRL models developed between 2020-2026 were reviewed and analyzed using comparative evaluations regarding detection accuracy, computational complexity, scalability, energy efficiency, and ability for real time deployment. Additionally, several open research topics and potential future directions for the development of intelligent AI-based spectrum sensing solutions for NextGen Wireless Communications Systems including XAI, Tiny ML, DTs, EAI and AN6G Networks will be described. Therefore, this paper provides researchers a single source reference for developing intelligent, scalable and energy efficient spectrum sensing solutions for NextGen wireless communication systems.

Keywords: Cognitive Radio Networks; Spectrum Sensing; Artificial Intelligence; Machine Learning; Deep Learning; Reinforcement Learning; Beyond-5G; 6G

I. INTRODUCTION

The rapid expansion of the Internet of Things (IoT), autonomous vehicles, Industrial Automation, Extended Reality (XR) and Intelligent Edge Computing, has stimulated the research into new generation wireless communication technologies B5G and 6G. For example, next-generation wireless communications will need to support a very high number of users, be able to support the transmission of extremely large amounts of data at an extremely high rate and have latency that is virtually zero. They also require efficient use of available bandwidth in order to meet the demands of all of these devices [1], [2]. The traditional static allocation policies used with the licensing authorities have proven to result in an inefficient use of the licensed spectrum. This occurs because when the frequency band assigned to a user remains unused for long periods of time or the unlicensed band becomes congested.

To address this problem Cognitive Radios were developed by Mitola and formalized by Haykin. In addition to providing an opportunity for secondary users to utilize temporarily vacant licensed spectrum bands without interfering with primary users [1], [2]; Cognitive Radios are enabled through spectrum sensing. Therefore, the

core function of CR's is spectrum sensing; which identifies whether there is available licensed spectrum to allow SUs to dynamically access PUs' spectrum resources prior to making decision on Dynamic Access [3], [5]. Over the past twenty years there have been numerous studies using various types of traditional spectrum sensing methods including Energy Detection, Matched Filter Detection, Cyclostationary Feature Detection and Cooperative Spectrum Sensing. While these methods perform well under ideal conditions, they do not perform well in environments with Low Signal-to-Noise Ratio (SNR), Multi-path Fading, Shadowing and Highly Variable Wireless Channels [3], [5]. Additionally, most of these existing methods rely upon manual design of signal features and pre-determined threshold values; thus preventing them from adapting to varying wireless channel conditions.

Recently AI was identified as a transformational technology for intelligent spectrum sensing. Machine Learning (ML), Deep Learning (DL) and Reinforcement Learning (RL) enables CRs to learn about the spectral usage patterns from both historical data and Real Time Spectral Usage Data; thereby improving the ability of CRs to detect spectral usage, reducing false alarms and increasing adaptability [4], [6] – [15]. These AI based approaches are envisioned as playing a critical role in creating Autonomous Spectrum Management capabilities within future AI Native 6G Networks.

II. RELATED WORK AND AI-BASED SPECTRUM SENSING

A. Related Work

Spectrum sensing has been intensively studied as core functionality of CRNs. Early research mainly focused on conventional signal processing methods such as Energy Detection (ED), Matched Filter Detection (MFD), Cyclostationary Feature Detection (CFD), Eigen Detection and Cooperative Spectrum Sensing (CSS). While these methods perform reasonably well under ideal channel conditions, they suffer very badly in low Signal to Noise Ratio (SNR), multipath fading, shadowing and uncertainty of noise [3], [5]. Integration of AI has greatly improved adaptability and reliability of sensing. Machine Learning algorithms such as SVM, Decision Trees (DT), Random Forest (RF) and K Nearest Neighbors (KNN) have performed better at classifying occupancy of spectrum by learning discriminative characteristics from historical sensing data [4], [13]. More recently, Deep Learning (DL) techniques especially Convolutional Neural Networks (CNNs), Long Short Term Memory (LSTM) networks, auto encoders and Transformer architectures have enabled automatic extraction of features directly from raw RF signals and this has greatly improved sensing performance in rapidly changing wireless environments [6], [12], [18]. Recent studies have further extended spectrum sensing enabled by AI using Graph Neural Networks (GNNs), Federated Learning (FL), Explainable AI (XAI) and Deep Reinforcement Learning (DRL). These approaches support distributed learning, preserve privacy, adapt access to spectrum and manage resources intelligently and thus are promising candidates for Beyond 5G (B5G) and 6G wireless networks [6]–[15]. Despite recent surveys that focus mainly on a single AI paradigm and do not discuss lightweight AI models, edge deployment, explainability, security and native architectures for 6G, this survey reviews conventional and methods driven by AI while identifying emerging research challenges and future opportunities. Beyond focused studies on AI, foundational surveys and seminal works laid theoretical foundations for sensing spectrum and cognitive radios including taxonomy of energy detection, matched filtering and cyclostationary detection, cooperative sensing tradeoff between sensing and throughput and early dynamic access architectures [21], [22], [24], [25], [26], [27], [28], [29]. This current survey builds on this foundation focusing on emerging techniques since 2019.

B. Review Methodology

The reviewed literature was searched via a systematic search of leading scientific data bases; i.e., IEEE Xplore, Science Direct (Elsevier), MDPI, Springer Link and arXiv. This literature search was supplemented by forward and backward citations to include all relevant papers using snowballing.

To combine these keyword groups, we used "spectrum sensing", "cognitive radio", "dynamic spectrum access" and "6G" with the learning paradigm keywords "machine learning", "deep learning", "reinforcement learning", "Graph Neural Network", "Federated Learning" and "Explainable AI".

Studies were selected if they met three criteria:

- (i) Spectrum sensing or prediction in cognitive radio systems or beyond-5G/6G;
- (ii) They applied some form of artificial intelligence;
- (iii) Studies were either published in a refereed journal or as a very highly-cited pre-print, mainly during the period 2020 – 2026, but including early seminal contributions where needed for context. We kept purely non-artificial intelligence based (conventional) sensing studies only as baseline references.

All duplicate entries and all entries lacking either a methodological or experimental component were removed. The results are summarized in table I below and the comparative Tables III and IV above were derived from the same body of work.

Table I. Representative Literature Review (2020–2026).

Ref.	Year	AI Technique	Contribution	Research Gap
[18]	2020	LSTM	Temporal spectrum prediction	Limited scalability
[19]	2020	ML	Cooperative spectrum sensing	High computational cost
[17]	2022	SDR-based sensing	Practical CR implementation	Limited AI integration

[13]	2025	Machine Learning	Comprehensive ML survey	RL and FL not covered
[12]	2025	Deep Learning	CNN and LSTM review	Lack of edge deployment
[14]	2025	AI for Dynamic Spectrum Access	Intelligent spectrum management	Broad scope
[6]	2026	AI Meta-analysis	AI taxonomy and future trends	Real-time deployment
[7]	2026	Dynamic Spectrum Sensing	Two-decade comprehensive survey	Limited 6G implementation

C. AI-Based Spectrum Sensing Framework

Unlike conventional signal processing methods, AI-based spectrum sensing employs data-driven models that automatically learn spectrum occupancy characteristics from historical observations and real-time sensing data. The general framework consists of five major stages:

1. **Signal Acquisition** – Collection of RF signals from licensed spectrum bands.
2. **Pre-processing** – Noise suppression, normalization, and feature preparation.
3. **Feature Learning** – Automatic extraction of discriminative spatial and temporal features using ML or DL algorithms.
4. **Spectrum Classification** – Determination of channel occupancy using supervised, unsupervised, or reinforcement learning models.
5. **Spectrum Decision** – Dynamic spectrum access and resource allocation while protecting primary users.

This intelligent framework significantly improves sensing accuracy, adaptability, and robustness in heterogeneous wireless environments, enabling autonomous spectrum management for future AI-native 6G networks.

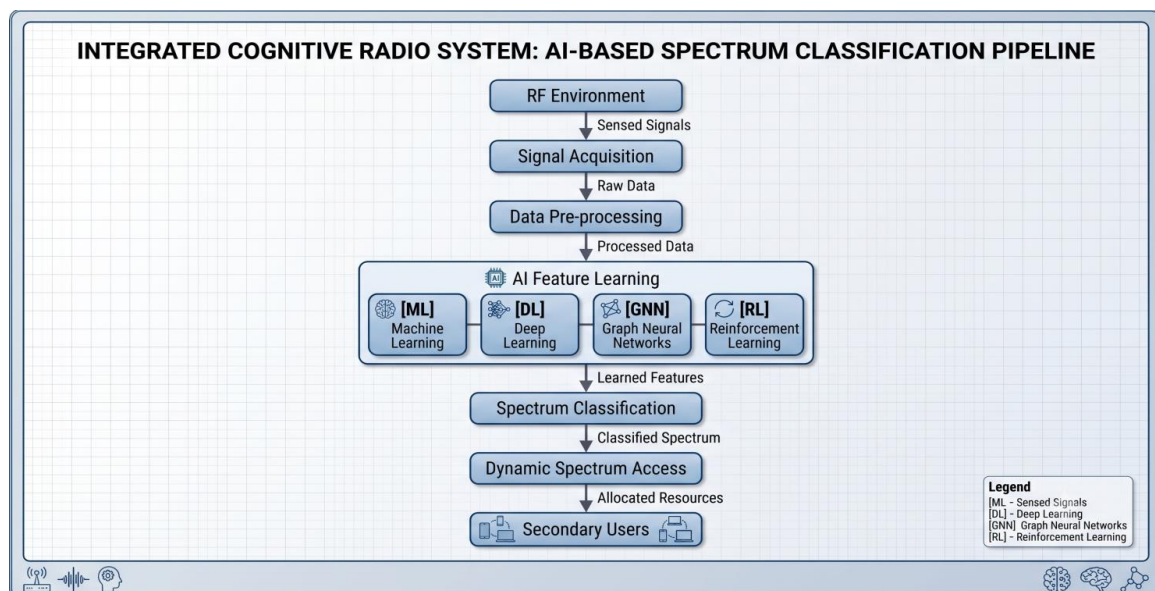


Figure 1. AI-Based Spectrum Sensing Framework.

The figure 1 shown illustrates how the data driven-spectrum sensing approach (pipeline) goes through several steps including data acquisition/preprocessing; automatic feature extraction/classification; and finally a data driven decision regarding which bands may be accessed for spectrum sharing. This is different from using a fixed detection threshold to determine whether there is interference in an available band, since the feature-extraction/decision-stages can evolve with time as channel characteristics change. Therefore, this system also provides a method to protect the rights of the original user of each band (primary user), and allows secondary users to obtain permission to use each band when it is unoccupied.

D. Key Contributions of This Survey

The authors of this paper decided to develop a cross-disciplinary survey, unlike many of the most recently published surveys that were based on a specific learning paradigm, or a specific application. While Falco et al. conducted a meta-analysis of their own data and used it in combination with a decade-long analysis of their own bibliography [6], while also conducting a 20-year survey of their bibliography as well [7]; Falco et al. are concerned with identifying patterns in the use of bibliometrics; Arianti et al., [13] and Raji & Olwal [9], conducted a systematic review of machine- and deep-learning classification methods. Therefore, the current study compares and contrasts traditional anomaly detection techniques, using conventional machine learning, deep learning, graph neural networks, and deep reinforcement learning all within the same comparative framework; while at the same time linking each identified research gap to an emerging enabling technology (federated learning, explainable AI, TinyML/Edge AI, and Digital Twins) for AI-Native 6G. In addition to its emphasis on comparing and contrasting

these different paradigms, the primary differentiator between this work and the work referenced herein is the explicit connection made between gaps in existing research, and the enabling technologies that have emerged in support of AI-Native 6G. Compared with previous survey articles, this paper provides the following contributions:

- Comprehensive review of conventional and AI-based spectrum sensing techniques.
- Comparative evaluation of ML, DL, GNN, and DRL models.
- Identification of research gaps in scalability, explainability, privacy, and edge deployment.
- Discussion of emerging technologies including Federated Learning, TinyML, Digital Twins, and AI-native 6G.
- Future research roadmap for intelligent and autonomous spectrum sensing.

III. AI-BASED SPECTRUM SENSING TECHNIQUES

AI has completely changed how Spectrum Sensing is done. The old way of doing this used threshold based systems to detect RF signal presence. In contrast, today's new AI technology uses data driven models that can learn complex RF pattern representations. Instead of using manual hand-crafted feature extraction (like in traditional systems) an AI model will automatically discover the most discriminative space-time characteristics within an RF signal. As a result, AI models for Spectrum Sensing are able to provide much better performance than traditional models under conditions of very low Signal-to-Noise Ratios (SNRs), fading channels, and rapidly changing wireless channel characteristics [4] [6].

A. Machine Learning-Based Spectrum Sensing

Classification of Spectrum Occupancy in Cognitive Radio Systems is typically performed by machine learning algorithms that utilize either labeled datasets or previously sensed datasets. The use of these algorithms enhances the accuracy of detecting available spectrum, while at the same time preserving a relatively low level of computational complexity which is beneficial to resource constrained cognitive radios systems.

Support Vector Machines (SVM): SVM construct a single hyperplane that optimally separates occupied and unoccupied spectrum. SVM can be very effective when datasets are small; however, it may require great care in selecting the appropriate kernel and designing features for the dataset [4] [13].

Random Forest (RF): RF uses a collection of decision trees to create a highly robust and accurate classifier while minimizing over-fitting. Due to the ability of RF to classify wireless environments, including those composed of many different types of wireless communications as stable and capable of tolerating significant amounts of interference, it has been extensively used for heterogeneous wireless communication environments [13].

Decision Trees (DT) and K-Nearest Neighbor (KNN): DT provides a method for performing inference quickly, as well as is easy to implement. KNN will determine how to classify unknown samples from their nearest neighbors. While DT and KNN have the benefit of being computationally inexpensive; they both have limitations in terms of scalability when dealing with larger scale spectrum sensing [4] [13].

B. Deep Learning-Based Spectrum Sensing

Deep learning automates feature engineering directly from IQ samples and spectrograms and RF measurements. CNNs excel at capturing spatial features from spectrum images and spectrograms and perform very well under low SNR conditions. They are widely used for modulation recognition, interference detection and occupancy classification [12], [18], [6]. LSTM networks model dependencies in time series spectrum observations and are useful for occupancy prediction and forecasting traffic. Their recurrent structure improves long term prediction but also increases computational cost [18], [12]. Recent research shows that Transformers perform better than recurrent models for large scale spectrum prediction for 6G communication systems [6], [7]. Graph Neural Networks (GNNs) model cooperative cognitive radios as graphs and this allows modeling efficiently the spatial relationships among distributed sensing nodes. This greatly improves spectrum sensing accuracy and scalability [7], [9].

C. Reinforcement Learning-Based Spectrum Sensing

Reinforcement Learning enables Cognitive Radios to continuously learn Optimal Spectrum Access Strategies from the wireless environment via real time interaction. In contrast to using pre-labeled training data, RL Agents will dynamically select unused radio frequency bands that produce a positive reward or minimize interference to Primary Users [10]. Deep Reinforcement Learning (DRL) Algorithms including; Deep Q Network (DQN); Double DQN; Deep Deterministic Policy Gradient (DDPG); and Multi Agent Reinforcement Learning (MARL) have shown very good results in Dynamic Spectrum Allocation, Spectrum Handoffs, Channel Selection, and Interference Management [10][14]; these methods are likely to be central to developing Autonomous AI-Native 6G Wireless Networks.

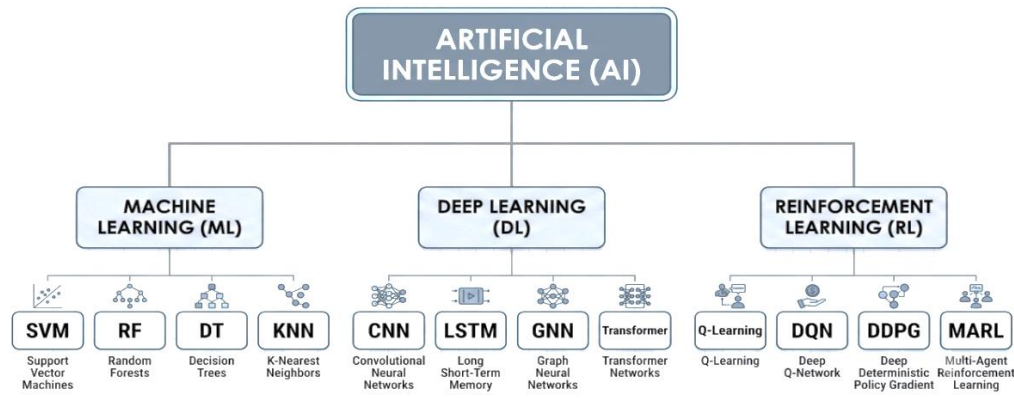


Figure 2. Taxonomy of AI-Based Spectrum Sensing.

Figure 2 organizes surveyed techniques into a taxonomy with three branches: machine learning (e.g., SVM, decision trees, random forests and K nearest neighbors), deep learning (e.g., CNNs, LSTMs, Transformers and graph neural networks) and reinforcement learning (e.g., DQN, Double DQN, DDPG and multi agent reinforcement learning). This taxonomy traces progression from classifiers that rely on hand crafted features to automatic feature extraction and ultimately autonomous decision making, which is important for comparison carried out in Section IV.

Table II. Comparison of AI-Based Spectrum Sensing Techniques.

Technique	Learning Type	Feature Extraction	Detection Accuracy	Complexity	Major Limitation
SVM	Supervised	Manual	High	Medium	Kernel selection
Random Forest	Supervised	Manual	High	Medium	Large ensemble size
Decision Tree	Supervised	Manual	Medium	Low	Overfitting
CNN	Deep Learning	Automatic	Very High	High	Large training dataset
LSTM	Deep Learning	Automatic	Very High	High	Slow training
Transformer	Deep Learning	Automatic	Excellent	Very High	Computational cost
GNN	Deep Learning	Automatic	Excellent	High	Graph construction
DQN	Reinforcement Learning	Learned	Excellent	High	Training instability
MARL	Reinforcement Learning	Learned	Excellent	Very High	Multi-agent coordination

Discussion

The development of artificial intelligence (AI) based on spectrum sensing represents an evident move toward using traditional supervised learning versus deeper learning with more autonomous reinforcement learning. Although many classic Machine Learning (ML) applications continue to be appealing because of their low computational overhead, the ability to extract features automatically through CNNs and LSTMs makes them preferable for accurate spectrum sensing. Additionally, recent advances in Graph Neural Networks (GNN), Federated Learning, and Multi-Agent Reinforcement Learning (MARL) represent the direction toward which future Beyond-5G and 6G wireless systems will manage their distributed, private, and intelligent use of radio frequency (RF) resources [6]-[15].

IV. COMPARATIVE ANALYSIS, RESEARCH GAPS AND FUTURE RESEARCH DIRECTIONS

AI is also increasing spectrum sensing within Cognitive Radio Networks (CRNs) for better detection accuracy, adaptation and decision making. Conventional methods of signal processing for detecting spectrum use can be outperformed using AI based learning methodologies that can develop complex models on RF observation data over time. However, the actual implementation of such technologies are still challenged by high computational complexity, high power consumption, lack of standards regarding security as well as limited availability of benchmarking data sets [6],[17].

A. Comparative Analysis

Table III and Figure3 compares conventional and AI-based spectrum sensing techniques using important performance metrics including detection accuracy, adaptability, computational complexity, and suitability for real-time deployment.

Table III. Comparative Analysis of Spectrum Sensing Techniques.

Technique	Detection Accuracy	Low SNR Performance	Adaptability	Computational Cost	Real-Time Deployment
Energy Detection	Medium	Poor	Low	Low	Excellent
Matched Filter	High	Good	Low	Medium	Excellent
Cyclostationary Detection	Very High	Excellent	Low	High	Moderate
SVM	High	Good	Medium	Medium	Good
Random Forest	High	Good	Medium	Medium	Good
CNN	Very High	Excellent	High	High	Good
LSTM	Very High	Excellent	Very High	High	Moderate
Transformer	Excellent	Excellent	Very High	Very High	Moderate
Graph Neural Network	Excellent	Excellent	Very High	High	Good
Deep Reinforcement Learning	Excellent	Excellent	Excellent	High	Excellent

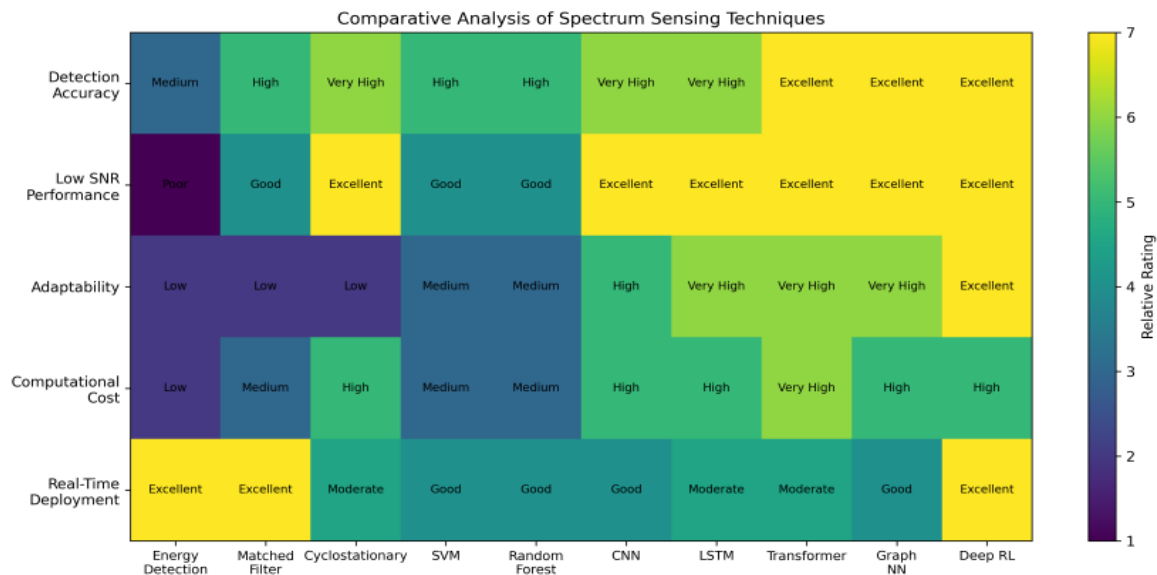


Figure 3. Comparative Analysis Heat Map.

Table III clearly shows that approaches driven by AI consistently outperform conventional spectrum sensing methods in environments that change quickly. Deep Learning and Reinforcement Learning models show high detection accuracy and robustness but they need much higher computational resources. Therefore, lightweight architectures for AI remain an active research topic for cognitive radios enabled at edges [18], [6], [7]. To supplement qualitative ratings in Tables II and III it is useful to note quantitative behavior reported directly in primary studies. Deep learning detectors consistently raise detection probability very high at low SNR: systematic review by Arianti et al. [13] finds that deep learning methods dominate recent results. Machine learning classifiers implemented on software defined radio testbeds have achieved detection probabilities above 0.9 and false alarm rates below 0.1 in actual measurements [13]. Scheme by Soni et al. [18] based on LSTM, which exploits statistics of primary users, reports roughly a 10% improvement in classification accuracy compared to baselines under comparable low SNR conditions. Numbers remain dependent on datasets and SNR levels and there is no common benchmark (discussed in Section IV B) that limits direct comparison between studies; standardized metrics such as ROC curves cataloged by Guimarães [11] are therefore recommended for future evaluations.

B. Research Gap Analysis

Despite significant progress in AI-enabled spectrum sensing, several research challenges remain unresolved. Table IV summarizes the major research gaps and corresponding future research opportunities.

Table IV. Research Gap Analysis.

Existing Research	Current Limitation	Future Research Opportunity
CNN-based sensing	Large model size	Lightweight CNN using pruning and quantization
LSTM prediction	High inference latency	Transformer-based spectrum prediction
Centralized AI models	Privacy concerns	Federated Learning
Deep Learning	Lack of interpretability	Explainable AI (XAI)
Cooperative sensing	Communication overhead	Graph Neural Networks
Reinforcement Learning	Slow convergence	Multi-Agent Reinforcement Learning
Edge deployment	High energy consumption	TinyML and Edge AI
Simulation studies	Limited real-world datasets	Open RF benchmark datasets

The literature indicates that future spectrum sensing systems should not only maximize detection accuracy but also support privacy preservation, explainability, scalability, and real-time operation on resource-constrained edge devices [6]–[15].

C. Future Research Directions

The following future trends are predicted by authors from literature from 2020 through 2026 based upon recent research related to utilizing artificial intelligence with beyond fifth generation (beyond 5G) and sixth generation (6G) wireless communication systems:

- **Federated Learning (FL):** It allows multiple entities to train a single AI model together but provides each entity with only the output results from that trained model and therefore does not require the entities to share their individual collected raw data. This is particularly beneficial when dealing with private information or when collecting large amounts of data which may result in high communication costs; [6],[7]
- **Graph Neural Networks (GNNs):** It provides a means to effectively learn and represent complex relationships among distributed cognitive radios. These learned representations allow cognitive radios to cooperate to achieve better-than-individual performance in terms of both cooperative spectrum sensing as well as interference management; [7], [9]
- **Tiny Machine Learning (TinyML) and Edge Artificial Intelligence (Edge AI):** It involves deploying very light-weight versions of machine learning algorithms into extremely small embedded Internet-of-Things (IoT) devices such as software defined radios. The deployment of these types of algorithms enables low-latency spectrum sensing at an extremely low cost;
- **Explainable Artificial Intelligence (XAI):** It enables users of AI systems to understand how AI-based decisions were made. Therefore, XAI enables wireless system managers to have confidence in AI-decisions regarding trustworthiness of spectrum allocations in mission critical wireless systems.
- **Digital Twin Assisted Cognitive Radio Systems:** It provides virtual replicas of physical wireless environments. The use of digital twins enables real-time spectrum predictions, optimal network configurations, and adaptive resource allocation;
- **Multi-Agent Reinforcement Learning (MARL):** MARL enables autonomous cognitive radios to make autonomous decisions about how best to allocate available spectral resources so as to minimize interference among radios and maximize overall spectral efficiency; [10],[14];
- **AI-Native 6G Wireless Networks:** Future 6G wireless networks are envisioned to be comprised of two primary components. First, they will utilize edge intelligence and/or semantic communications. Second, they will be able to autonomously make decisions with regards to optimizing spectrum utilization, predicting changes in the physical environment, dynamically allocating available spectral resources, and managing mobile nodes within the wireless network.

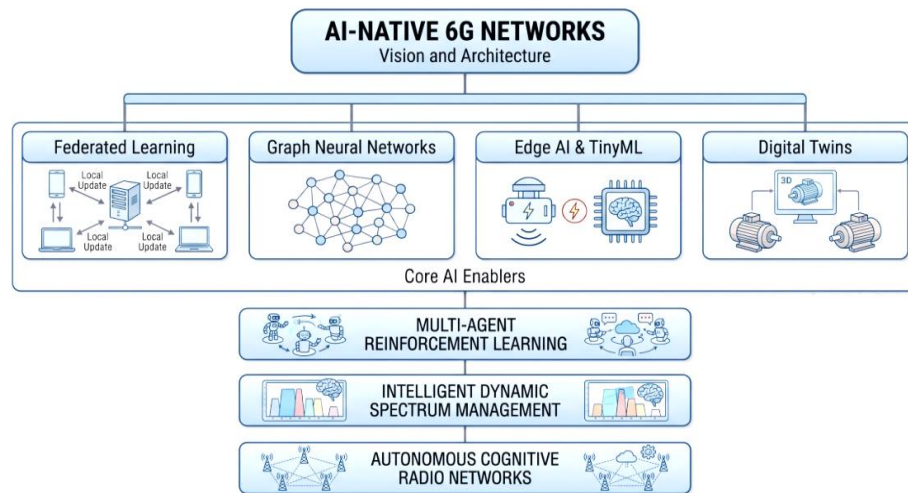


Figure 3. Future AI-Driven Spectrum Sensing Roadmap.

Figure 3 shows the research roadmap looking into the future of how sensing will move away from centralized deep learning based detectors and go towards ultra-low latency distributed sensors that are also trusted. Federated Learning and Graph Neural Networks provide the means to enable cooperative sensing in an efficient way that preserves privacy. Tiny ML and Edge AI can be used as a first step to achieve ultra-low latency on device sensing. Explainable AI and Digital Twins can serve as long term foundational technologies for developing AI Native Trustworthy Cognitive Radio Network of the Future (i.e. 6G).

D. Emerging Enabling Technologies

Because some of the technology references are very brief in the "future directions" section, this section elaborates on the four anticipated to have the most significant influence on AI-Native Cognitive Radio in the near term:

Federated learning: FL makes it possible for spatially dispersed secondary users to cooperatively train a common sensing model, utilizing model updates instead of raw I/Q data samples. FL has multiple benefits including preserving user's private data; reducing the communication overhead of cooperative sensing; and decreasing the single point of failure inherent in centralized fusion. Challenges for FL include, but are not limited to; developing robustness against non-identical independent distribution of spectrum data among nodes; developing robustness against poisoning and stragglers amongst client nodes; and developing communications efficient ways to aggregate client node updates [6][9].

Explainable AI (XAI): The opaque nature of deep detector-based systems is an impediment to their widespread adoption in mission critical and highly regulated spectrum use scenarios. Techniques that are aimed toward providing explainability to these black box systems, which may be referred to as attention visualization and feature attribution methods, provide insight into why a frequency band was declared either occupied or vacant, increase confidence in system decision-making processes, facilitate easier regulatory approvals, and enable engineers to identify failure mechanisms when operating under low signal-to-noise ratio conditions [6].

Digital Twins: A digital twin maintains a continuously updated virtual replica of a radio environment. Utilizing digital twins enables predictive modeling of the radio environment, "what if" type simulations, and offline training of reinforcement-learning agents prior to deployment. When combined with edge intelligence, digital twins can also enable real time optimization of network performance and dynamic resource allocation within cognitive radio networks [7] [14].

TinyML and Edge-AI: By deploying compressed models (utilizing techniques such as pruning, quantization, and knowledge distillation) directly onto software defined radios and embedded IoT devices provides ultra-low latency, ultra-low power consumption based on device sensing capabilities without requiring access to the cloud. As many secondary users utilize battery powered devices, this capability will greatly enhance scalability and availability of always-on-spectrum-awareness in high-density 6G deployments [12][13].

Key Findings

This survey shows AI has become the foundation for sensing intelligent spectrum use for future wireless networks. Conventional signal processing remains attractive for straightforward and inexpensive implementations. Deep Learning and Reinforcement Learning greatly improve accuracy, adaptability and autonomous management of spectrum. Emerging technologies such as Federated Learning, Graph Neural Networks, Explainable AI, TinyML and Digital Twins are expected to be very important in realizing scalable networks that preserve privacy and use energy efficiently for 6G cognitive radios.

V. CONCLUSION

Recent rapid evolution of B5G and 6G wireless communication systems has increased demand for intelligent and efficient use of spectrum. CRNs have emerged as promising solutions for improving spectral efficiency through opportunistic access while protecting licensed users. Conventional sensing techniques such as Energy Detection, Matched Filter Detection, Cyclostationary Feature Detection and Cooperative Sensing perform poorly at low SNR, under channels that experience fading and in highly dynamic wireless environments. This survey conducted a comprehensive review of AI approaches for spectrum sensing in future cognitive radio networks. ML, DL and RL approaches were systematically studied with respect to detection accuracy, computational complexity, adaptability scalability and real time implementation. Comparative study showed that approaches driven by AI consistently outperform conventional sensing techniques by directly learning complex occupancy patterns from data and adapting to changing wireless environments. Despite these advances however, still unresolved practical challenges remain. Limited benchmark RF datasets, high computational cost, preservation of privacy, energy consumption, interpretability of models and deployment on constrained edge devices continue to impede practical realization of systems enabled by AI. Emerging technologies such as Federated Learning, XAI, TinyML, Digital Twins, Edge AI and Multi Agent Reinforcement Learning offer promising solutions to address these challenges and enable autonomous spectrum management in native AI 6G networks. In summary, sensing spectrum using AI represents a key enabling technology for intelligent future wireless communication systems. Continued research into lightweight architectures of AI, trustworthy learning frameworks, distributed intelligence and deployment in the real world will be very important for realizing scalable networks that are secure and energy efficient and supporting stringent performance of Beyond 5G and 6G applications.

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