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Survey paper

AI-driven spectrum sensing: An in-depth meta-analysis of trends, challenges and opportunities

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ABSTRACT

Artificial Intelligence (AI) is playing a crucial role in transforming Spectrum Sensing (SS) and Cognitive Radio Networks (CRNs), especially for next-generation wireless communication systems. This study presents a meta-analysis of 13 survey articles, also analyzing a total of 113 primary studies, to synthesize the applications of AI, specifically Machine Learning (ML) and Deep Learning (DL), in spectrum sensing. Key models identified include Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Graph Neural Networks (GNN), among others. The analysis reveals measurable performance improvements and the main metrics to measure it. Despite these advancements, challenges persist, including computational complexity, adaptability to real-time environments, and model generalization. The study also highlights promising future directions like energy-efficient AI architectures, federated learning for decentralized CRNs, and cooperative spectrum sensing methods. Addressing these challenges and pursuing open research areas is critical to fully realize AI-powered CRNs. Such progress is expected to enable autonomous and intelligent spectrum management in beyond-5G and 6G networks, ultimately enhancing system reliability, scalability, and spectrum utilization efficiency.

1. Introduction

The rapid expansion of wireless communication technologies, driven by the proliferation of 5G and the upcoming 6G networks, has significantly increased the demand for efficient and intelligent spectrum management solutions. With the exponential growth of connected devices, the Internet of Things (IoT), and data-intensive applications, traditional spectrum allocation strategies are becoming increasingly inadequate [1–3]. Current regulatory policies, which rely on static spectrum allocation, lead to inefficiencies, as certain licensed bands remain underutilized while others face severe congestion. To overcome these limitations, Cognitive Radio Networks (CRNs) and Dynamic Spectrum Access (DSA) have emerged as promising paradigms, allowing wireless devices to autonomously sense, access, and share spectrum resources in real-time [4,5].

At the core of these adaptive communication systems lies spectrum sensing, a critical process of detecting unused spectrum bands or spectrum holes, while ensuring minimal interference with licensed Primary Users (PUs) [6]. Spectrum sensing is widely recognized as a major bottleneck in CRNs due to several challenges. First, the detection must be highly accurate and timely to prevent harmful interference, especially in low Signal-to-Noise Ratio (SNR) environments where signals are weak or masked by noise. Second, spectrum sensing algorithms must operate under stringent constraints of computational cost and energy consumption, often on resource-limited devices, which restricts the complexity of sensing techniques. Third, wireless environments are highly dynamic and non-stationary, with time-varying channel conditions, mobility, and interference, requiring sensing methods that can rapidly adapt to changing conditions. Conventional spectrum sensing techniques, such as energy detection, matched filtering, and cyclostationary feature detection, have been extensively studied and deployed. While these classical methods often offer low latency and relatively low computational complexity, they typically struggle with detection accuracy in challenging scenarios (for example, low SNR, multipath fading) and lack the ability to generalize to complex and evolving signal environments without manual reconfiguration [6].

To address these challenges, Artificial Intelligence (AI) has emerged as powerful tools for advancing spectrum sensing capabilities. AI-driven approaches can learn from historical data, adapt to changing environments, and optimize spectrum utilization without requiring predefined models or assumptions. Various AI techniques, including Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), and Federated Learning (FL), have been applied to improve detection accuracy, classify signals, predict spectrum availability, and automate

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decision-making in real-time [7,8]. Although AI-driven methods generally incur higher computational costs and latency compared to traditional techniques, advances in hardware acceleration, model optimization, and distributed processing increasingly mitigate these concerns. Importantly, AI-based sensing typically achieves significantly higher detection accuracy and robustness in low SNR and dynamic environments, enabling more reliable spectrum utilization and interference mitigation. This trade-off between increased computational demands and enhanced sensing fidelity is a defining characteristic distinguishing AI-driven spectrum sensing from conventional approaches, making AI indispensable for next-generation beyond-5G and 6G wireless networks [5].

Given the rapid advancements in AI-driven spectrum sensing, numerous studies have explored various methodologies and applications in this field. However, most existing reviews focus on specific AI techniques or narrow subdomains of spectrum sensing, lacking a comprehensive perspective that synthesizes overarching trends and challenges. While these reviews offer valuable insights, their fragmented analyses make it difficult for researchers and practitioners to identify common themes, assess existing gaps, and chart a clear direction for future advancements. Several recent surveys have examined AI applications in wireless communications and spectrum management [9–12], yet there remains a lack of a structured meta-analysis that systematically integrates and organizes these findings.

For instance, Ali and Hamouda [9] focuses specifically on cognitive radio (CR) communications, offering a taxonomy of spectrum sensing approaches for interweave CR networks. The survey categorizes sensing techniques (for example, narrowband, wideband, cooperative sensing) and reviews implementation aspects and emerging standards, but it largely addresses traditional spectrum sensing methods rather than analyzing the broader landscape of AI-driven techniques or quantitatively synthesizing research trends. Similarly, Alhammadi et al. [11] surveys the use of AI for wireless networks more broadly, emphasizing ML and DL applications for network automation, optimization, and decision-making. While it provides a comprehensive overview of AI-enabled wireless technologies and their future challenges, it does not focus specifically on spectrum sensing nor does it synthesize and organize findings across studies into a structured evidence-based framework. Likewise, Karthiga and Saravanan [12] reviews both traditional and AI-based spectrum sensing methods, comparing selected ML techniques and, in particular, DL approaches such as CNN, RNN, and DRL. While it outlines key applications, benefits, and limitations, the review remains concise, lacks a detailed methodology, and is based on the analysis of only 18 articles.

Consequently, our study performs an in-depth meta-analysis of secondary studies (surveys and reviews) focusing on AI-driven spectrum sensing. By systematically extracting and synthesizing data from these secondary studies and their included primary research articles, we address two main research questions to identify, on the one hand, the current trends, and on the other hand, the challenges, limitations, and future opportunities in AI-driven spectrum sensing for next-generation wireless networks.

To achieve this, we employ a structured methodology based on PRISMA [13] and Kitchenham's guidelines for systematic literature reviews (SLRs) [14]. Unlike traditional reviews that provide broad overviews, our study advances beyond traditional broad surveys by conducting a content-driven meta-analysis of the primary studies discussed within the selected reviews. This enables a granular categorization of AI techniques, their spectrum sensing applications, and an evaluation of their performance and limitations across different network scenarios. We comprehensively cover major AI technologies, including ML, DL, RL, and FL, and assess their contributions to core spectrum sensing tasks such as signal detection, classification, interference mitigation, and real-time decision-making.

The main contributions of this study are: (i) delivering, to the best of our knowledge, the first content-based meta-analysis of secondary studies on AI in spectrum sensing; (ii) elucidating how AI-driven approaches are revolutionizing spectrum sensing in 5G and 6G networks, enabling more efficient and intelligent spectrum management; (iii) providing a critical discussion of benefits, limitations, emerging challenges, and open research directions; and (iv) proposing a comprehensive taxonomy that maps AI techniques to spectrum sensing tasks and links these tasks to their application domains in CRNs. As a closing point, Fig. 1 provides the outline of the entire article as a way to summarize the structure and organization.

The remainder of this article is organized as follows: Section 2 reviews fundamental concepts in CRNs and spectrum sensing. Section 3 details the meta-analysis methodology. Section 4 presents the bibliometric analysis and categorization of AI technologies applied in spectrum sensing. Sections 5 and 6 explore ML and DL approaches, respectively. Sections 7 and 8 offer critical insights into benefits, challenges and opportunities. Section 9 introduces our proposed taxonomy of AI-driven spectrum sensing. Finally, Section 10 summarizes key findings and future research directions.

2. Background

The efficient management of spectrum resources is vital for the continued growth of wireless communication systems, especially as the demand for high-speed data transmission increases. Cognitive Radio (CR) technology has emerged as a solution to address this issue by enabling dynamic spectrum access. By utilizing spectrum sensing techniques, CRNs allow Secondary Users (SUs) to access underutilized spectrum bands without causing interference to Primary Users (PUs). As a result, CRNs rely on a combination of Spectrum Sensing (SS), Spectrum Decision (SD), Spectrum Sharing (SSh), and Spectrum Mobility (SM) within the Spectrum Management Framework (SMF) [15]. In this context, the focus of this article is on Spectrum Sensing, which plays a crucial role in detecting spectrum availability and ensuring interference-free operation of CRNs.

Spectrum sensing, as a key functionality in CR technology, enables SUs to identify spectrum holes and avoid interference with PUs. Several spectrum sensing schemes have been proposed, including Energy Detection (ED), Cyclostationary Feature Detection (CFD), and Matched Filter Detection (MFD), each with its advantages and limitations [16,17]. These techniques help to achieve efficient spectrum utilization, addressing the challenges posed by noise uncertainty, fading, and shadowing. However, single-user spectrum sensing may not be sufficient for accurate detection, prompting the development of Cooperative Spectrum Sensing (CoSS), which addresses the diversity of multiple sensing devices to improve detection performance [18].

Cognitive radio networks. Cognitive Radio (CR) technology is designed to efficiently utilize the spectrum by detecting available channels and dynamically adjusting the transmitter and receiver parameters in response to environmental changes [19]. CRNs enable Secondary Users (SUs) to opportunistically access unused licensed spectrum for data transmission. This is accomplished through a technique called Dynamic Spectrum Access (DSA), allowing SUs to switch between available spectrum bands without causing interference to PUs [17]. Several spectrum sensing schemes have been proposed for detecting the presence of PUs, including Energy Detection (ED), Covariance Feature Detection (CoFD), Matched Filter Detection (MFD), Cyclostationary Feature Detection (CFD), and Machine Learning (ML)-based detection [17,20–22]. However, the detection performance of single-user sensing is limited by factors such as noise uncertainty, shadowing, and multipath fading [19]. These challenges can be mitigated by enabling cooperation among CR devices. CoSS leverages spatial and multi-user diversity, improving detection accuracy and optimizing throughput in CRNs [18].

Spectrum management framework (SMF). The coexistence of PUs and SUs in CRNs presents significant challenges. To address these issues, Cognitive Radio networks implement several key features within the

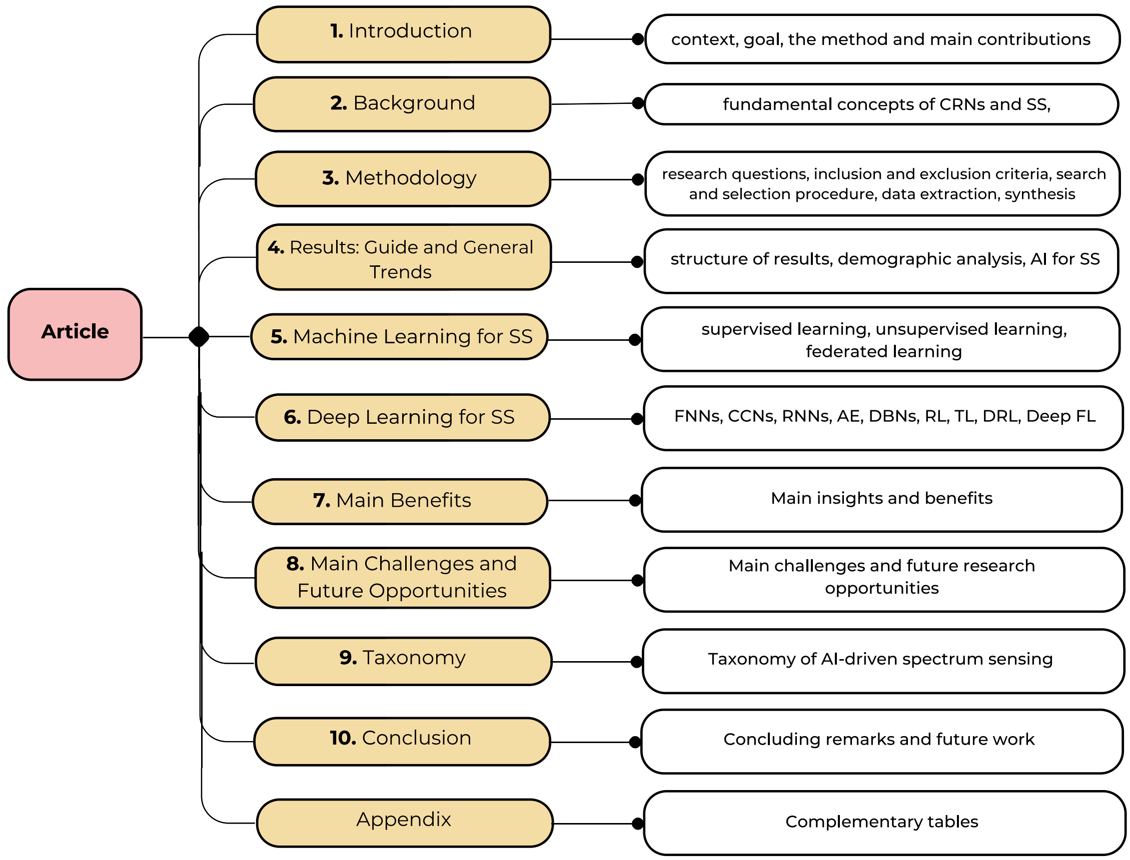

Fig. 1. Graphical outline of the article.

SMF, including interference management and Quality of Service (QoS) awareness. As mentioned earlier, SMF is composed of four main stages: Spectrum Sensing (SS), Spectrum Decision (SD), Spectrum Sharing (SSh), and Spectrum Mobility (SM) [15,23,24]. The first stage is initiated when a SU appears and gathers knowledge about the surrounding environment, including switching delay, channel capacity, path loss, interference, node location, holding time, and bit error rate (BER) [25]. These parameters are considered essential components in pre-spectrum management to ensure efficient dynamic spectrum access and interference mitigation in CRNs. Although this article focuses on Spectrum Sensing, Section 4.2 will also present the scope of each study, which may extend beyond spectrum sensing.

Spectrum sensing. Represents a key feature of CR technology that allows SUs to sense and learn the channel properties [19]. CR detects the temporarily white spaces or spectrum holes and appearance of PUs on frequency chanels without disrupting PU activities [27–29]. Once the spectrum is found available, spectrum sharing and decision functionalities enable the efficient use of vacant frequency bands [16]. The performance of spectrum sensing is critical, as all CR functionalities depend on accurate spectrum availability information. However, real-time applications face multiple challenges, including receiver uncertainty, shadowing effects, and multi-path fading [16]. A temporal spectrum hole exists only for a limited period when no PU transmission occurs.

To illustrate the spectrum sensing concept, consider a scenario where three different networks operate in separate frequency bands (see Fig. 2). If an SU detects an idle channel in Network 1 (N1), it initiates data transmission. However, once PU1 reappears, the SU must cease transmission and sense the next available channel in Network 2. If N2 is also found free, the SU resumes data transmission. Upon the reappearance of PU2, the SU repeats this process by sensing N3. This iterative sensing and channel switching process requires spectrum handover mechanisms to maintain uninterrupted transmission. Spectrum utilization in CRNs is characterized by five key dimensions: frequency, time, code, angle, and coverage space, which define the operational parameters required for efficient spectrum sensing. Each parameter must be sensed and analyzed to achieve comprehensive spectrum awareness [16,17,30].

Frequency refers to the analysis of spectrum availability across different frequency bands. Coverage space is crucial for calculating free space path loss, accounting for propagation loss in signal transmission. Angle plays a role in reducing interference when PUs and SUs transmit in diverse directions. Time determines the availability of opportunistic spectrum bands at specific moments, ensuring efficient spectrum access. Finally, code enables synchronization between PUs and SUs by incorporating knowledge of coding and timing mechanisms.

According to Gupta and Kumar [17], spectrum sensing schemes in CRNs can be broadly classified into conventional and advanced sensing schemes. In conventional schemes, two main design elements are used for mathematical modeling: the decision metric/test statistic and the threshold value. The decision metric provides the actual information related to the occupancy of the spectrum, while the threshold value differentiates between two hypotheses. In CRNs, a SU must ensure the availability of unused spectrum and the activity of PUs before data transmission. To achieve this, various sensing schemes are modeled, including: energy detection, cyclostationary feature detection, waveform-based detection, interference-aware detection, radio identification, multiband-based detection, matched filtering, receiver statistics, and energy radio detection [16,31].

On the other hand, advanced spectrum sensing schemes have emerged, such as: wideband compressive sensing, adaptive compressive sensing, spectral correlation, covariance-based sensing, maximum-to-minimum eigenvalue sensing, sequential sensing, Bayesian compressive

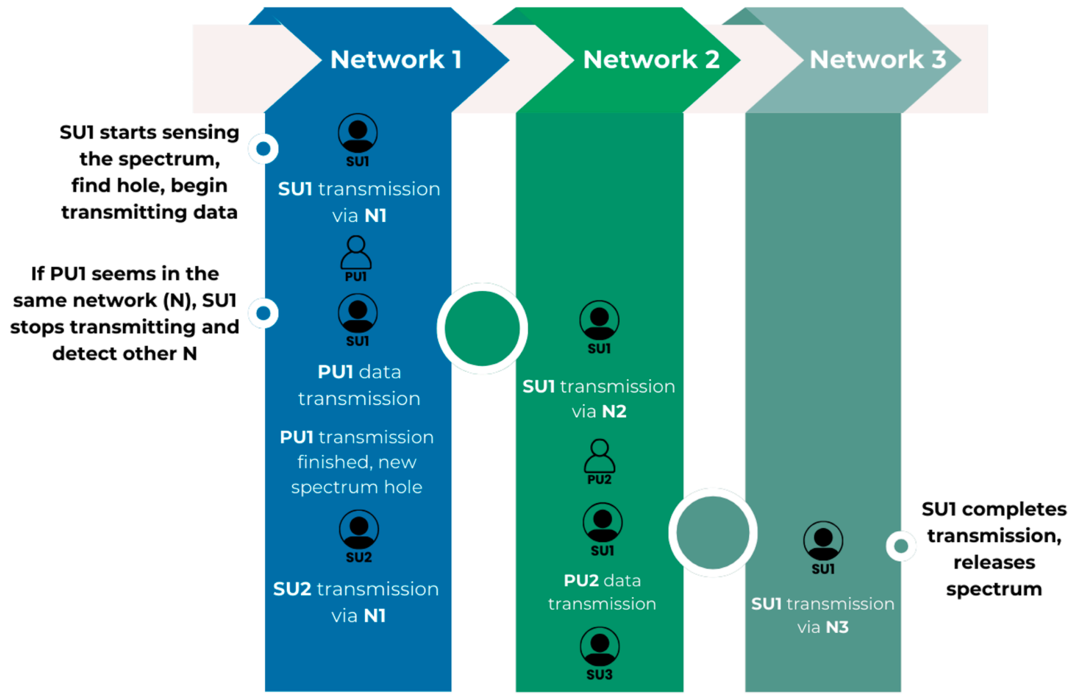

Fig. 2. Spectrum Sensing. Adaptation from Gupta and Kumar [17], Agrawal et al. [19], Gupta et al. [26]. Considering **SU1**: Secondary User 1, **PU1**: Primary User 1, and **N**: Network.

sensing, higher-order statistics, and feature template-based detection. These advanced methods aim to enhance the accuracy and efficiency of spectrum sensing [32,33].

Traditional spectrum sensing schemes mainly focus on a single frequency band, whereas recent schemes reduce the overall sensing time by cooperation among SUs to identify multiple frequency bands concurrently. Although advanced spectrum sensing improves sensing precision, there are challenges that still need to be addressed, including: signaling overhead due to sharing sensing results among SUs, the presence of malicious SUs that can degrade cooperation, and the impairments caused by differing channel parameters, such as RF imperfections and Signal-to-Interference Ratio (SIR), across different SUs. As a result, decision-making across different SUs can become random and unreliable [16,33].

Before transmitting data, the SU must verify the availability of unused spectrum and monitor the activity of PUs in CRNs. To tackle the challenges associated with this process, numerous spectrum sensing techniques have been proposed in the literature over the past decade. According to Agrawal et al. [19], these techniques can be categorized into three main types: Narrowband Spectrum Sensing (NBSS), Wideband Spectrum Sensing (WBSS), and Cooperative Spectrum Sensing (CoSS), as shown in Fig. 3. NBSS examines a single frequency channel at a time, whereas WBSS simultaneously analyzes multiple frequency channels [34]. CoSS allows SUs to perform SS in a cooperative manner to use the spectrum efficiently, focusing on the benefit of spatial and multi-user diversity [35].

3. Methodology

Originally, our objective was to survey the literature to identify the current state of AI in Spectrum Management. With this aim, we performed a unstructured screening building on our prior knowledge of the area using relevant keywords in different search engines. We found out that the publications focus on specific technologies sometimes applied to Spectrum Management, but mostly to a particular stage meaning Spectrum Sensing (SS), Spectrum Decision (SD), Spectrum Sharing (SSh), and Spectrum Mobility (SM) or CRNs in general. Based on this

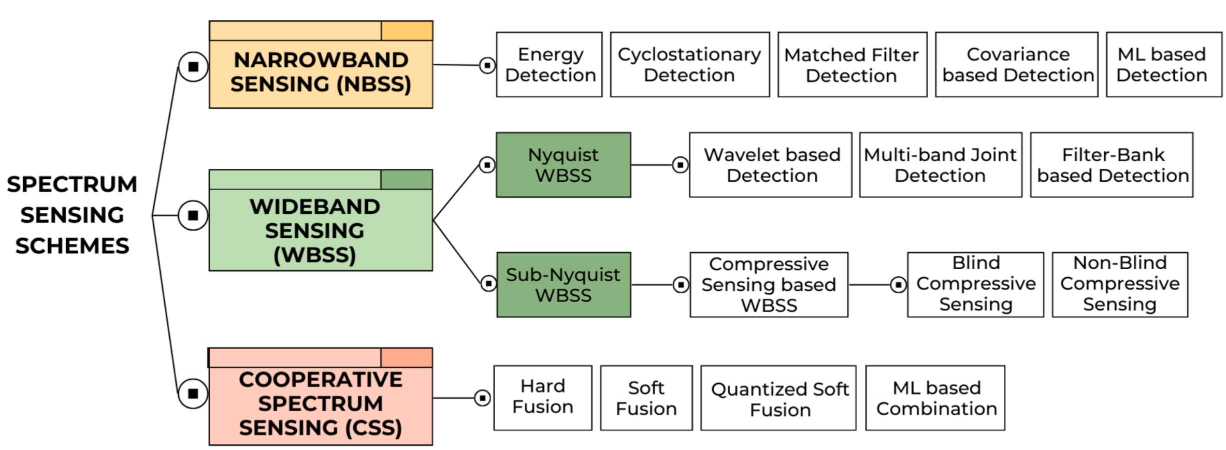

Fig. 3. Spectrum Sensing Schemes. Adaptation from Agrawal et al. [19].

insight, we decided to refine our analysis through an extensive meta-study of one of the stages in particular, *Spectrum Sensing*, to completely understand the current trends and opportunities.

Now, in order to identify relevant papers for our meta-study, we employed an adaptation of PRISMA [13] and Kitchenham's guidelines to conduct a literature review [14]. Since our focus is not on providing statistics on the publications identified but instead on a meta-study of their actual content, we carried out a literature review of the analyzed primary studies within each survey. The following subsections will describe the individual steps of our methodology, introducing the research questions (Section 3.1), the scope of this review through diverse details of the exclusion and inclusion criteria (Section 3.2), the search process (Section 3.3), the selection procedure (Section 3.5), data extraction, and the data synthesis and meta-analysis (Section 3.6).

3.1. Research questions

AI offers promising solutions to optimize spectrum management, improve signal detection, and enhance network performance, making it essential to understand not only the current trends but also the challenges and opportunities associated with integrating AI into spectrum sensing for next-generation wireless networks. To address these objectives, this study is guided by two main research questions (RQs):

- **RQ1**: *What are the current trends in AI-driven spectrum sensing for next-generation wireless networks?*
  - **RQ1.1**: *How is Machine Learning applied in spectrum sensing?*
  - **RQ1.2**: *How is Deep Learning applied in spectrum sensing?*
- **RQ2**: *What are the main benefits, challenges, and future opportunities in AI-driven spectrum sensing for next-generation wireless networks?*

To provide a comprehensive answer to RQ1, the analysis distinguishes between two core dimensions of AI techniques that have been most widely applied in spectrum sensing. The first dimension, addressed in RQ1.1, investigates how ML methods, such as supervised and unsupervised learning, are employed to improve tasks like spectrum occupancy prediction, signal classification, and interference detection. This focus enables a deeper understanding of the ways ML techniques contribute to predictive analytics, real-time decision-making, and adaptive spectrum management, while also uncovering inherent limitations, including dependency on labeled datasets, difficulties in scaling to large and heterogeneous wireless environments, and computational constraints when operating under strict latency requirements.

The second dimension, covered by RQ1.2, delves into the role of Deep Learning (DL), a subset of ML that has demonstrated exceptional performance in handling highly dynamic and complex wireless environments. DL approaches have been increasingly leveraged to perform tasks such as feature extraction from raw spectrum data, robust signal detection under low signal-to-noise ratio (SNR) conditions, interference mitigation, and end-to-end decision-making without requiring extensive domain-specific feature engineering. Through this research, the study examines both the advantages of DL, including enhanced accuracy, adaptability, and capability for handling non-stationary environments, and its challenges, such as high computational demands, significant energy consumption, and interpretability issues, which can hinder practical deployment in resource-constrained or latency-sensitive CRN systems.

Finally, addressing RQ2 allows this study to integrate the findings from both ML- and DL-focused analyses and critically assess the broader landscape of AI-driven spectrum sensing. This includes identifying key limitations that restrict widespread adoption, such as the trade-offs between computational complexity and real-time performance, the scarcity of large-scale labeled datasets for training, privacy and security concerns in distributed learning approaches, and the lack of standardized benchmarks for evaluating AI-driven solutions. At the same time, this analysis highlights future research opportunities, including the potential of emerging paradigms like federated and reinforcement learning, lightweight neural architectures for edge devices, explainable AI for decision transparency, and cross-layer optimization techniques for seamless integration of AI-driven sensing into the broader spectrum management ecosystem.

By systematically addressing RQ1, and RQ2, this study not only synthesizes the current state of AI applications in spectrum sensing but also provides a forward-looking perspective on how these technologies can evolve to meet the demands of beyond-5G (B5G) and 6G networks. This dual focus on trends and challenges ensures that the findings offer practical guidance for researchers and practitioners aiming to develop robust, scalable, and intelligent spectrum management solutions.

3.2. Inclusion and exclusion criteria

This subsection outlines the criteria used to select the studies included in this review. Publications were excluded if they met any of the following conditions: (E1) they were unrelated to the application of AI in Spectrum Sensing; (E2) they were not written in English; (E3) they were primary studies rather than secondary studies; or (E4) they were published before 2020.

The restriction to the period from 2020 to early 2025 is intentional and justified by both relevance and analytical scope. First, the field of AI-driven spectrum sensing has evolved rapidly in recent years, with major breakthroughs in machine learning architectures, distributed learning, and edge AI. Limiting the review to this four-year window ensures a focus on the most relevant, high-impact, and technologically current research. Second, because secondary studies (i.e., surveys) inherently synthesize and reflect upon earlier research, many of the primary studies published before 2020 are still captured through the lens of recent surveys. This allows the review to incorporate historical insights without diluting the focus on recent advancements. Furthermore, this review goes beyond summarizing secondary studies. It also extracts and analyzes the primary studies included within them, specifically those that present direct applications of AI to spectrum sensing. This dual-layered approach allows for a deeper, more nuanced synthesis and supports the construction of a grounded, purpose-driven taxonomy. By identifying not only the topics discussed in surveys but also the practical applications found in primary studies, we aim to create a comprehensive, structured overview of the research landscape.

Studies were included if they met at least one of the following inclusion criteria: (I1) they were secondary studies (surveys, reviews, or mappings) subjected to a rigorous peer-review process, with a specific focus on AI techniques applied to spectrum sensing; or (I2) they were relevant gray literature (for example, arXiv submissions), provided they fulfilled criterion I1. By focusing on recent, high-quality secondary literature and systematically analyzing its referenced primary applications, this review offers both topical relevance and methodological depth, providing a strong foundation for the taxonomy that follows.

3.3. Search process

The database search was first conducted in Google Scholar, with a set of 8 queries (see Table 1). Later on, these searches were complemented with known digital repositories, namely ACM Digital Libray, Springer Link, IEEE Xplore, and Elsevier, to obtain a comprehensive coverage. A set of searches were carried out from December 2024 to January 2025, to fully acknowledge articles published in the beginning of 2025 who have been submitted during 2024[1].

[1] Due to the revision of the article by the reviewers, an article from mid 2025 was added to the list of primary studies. See [36]

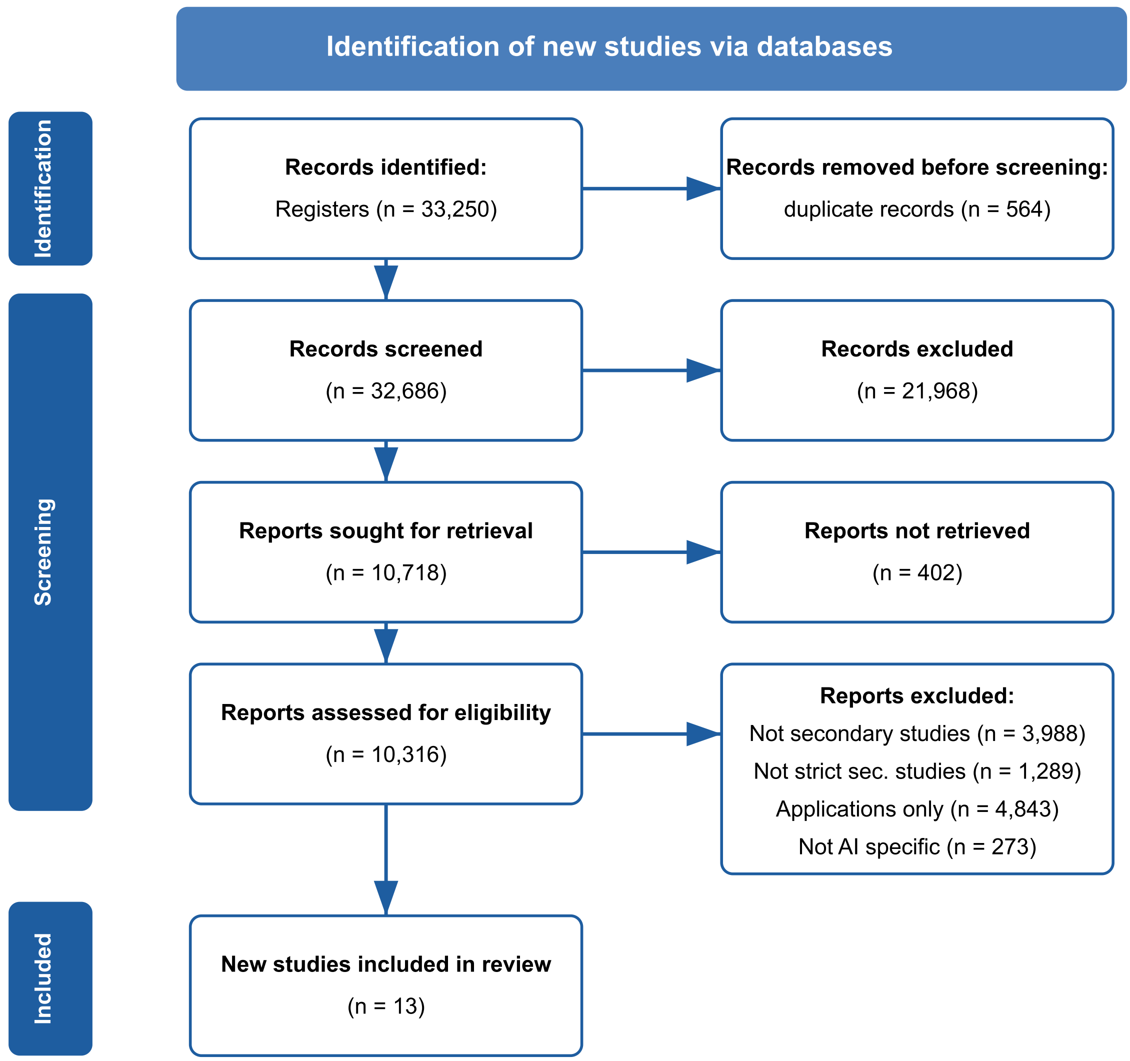

Fig. 4. PRISMA flow diagram.

Table 1
Queries and search strings.

Query number	Search query
Q1	*“artificial intelligence” AND “spectrum sensing” AND (“survey” OR “review”) AND (“5G” OR “beyond-5G”)*
Q2	*“artificial intelligence” AND “spectrum sensing” AND (“survey” OR “review”) AND (“machine learning” OR “deep learning”)*
Q3	*“artificial intelligence” AND “cognitive radio” AND “dynamic spectrum access” AND “spectrum sensing” AND (“survey” OR “review”)*
Q4	*“artificial intelligence” AND “spectrum sensing” AND “challenges” AND (“survey” OR “review”) AND (“5G” OR “beyond-5G”)*
Q5	*“AI-driven spectrum sensing” AND (“survey” OR “review”) AND “next-generation wireless networks” OR “5G” OR “beyond-5G”*
Q6	*(“AI methods” OR “machine learning” OR “deep learning”) AND “spectrum sensing” AND (“survey” OR “review”)*
Q7	*“AI applications” AND “spectrum sensing” AND “intelligent networks” AND (“survey” OR “review”) AND “5G”*
Q8	*(“meta-review” OR “systematic review”) AND “AI” AND “spectrum sensing”*

3.4. Selection procedure

The queries resulted in 33.250 possible articles, with 4.150 retrieved from Query 1 (Q1), 6.950, 3.020, 3.540, 3, 13.900, 35, and 652; from queries Q2, Q3, Q4, Q5, Q6, Q7, and Q8, respectively (see Fig. 4 for PRISMA flow diagram, following [37]). We evaluated the titles and metadata of these articles, and when a decision could not be made, we also reviewed the article’s structure, introduction, methodology, results, and conclusions. The first author conducted the initial screening, and any discrepancies were addressed through discussions among all three authors until a consensus was reached.

Following these database searches, we removed 564 duplicate articles. After applying the inclusion and exclusion criteria, a set of articles remained for further analysis. Finally, we conducted a full-text review to fully understand the context of each study, resulting in a final set of 13 secondary studies included in our analysis. From these 13 studies, we conducted backward snowballing [38] to ensure that no recent secondary studies were overlooked. However, no additional articles were included, as they were published before 2020, already part of the final set of relevant studies, or surveys not AI-specific.

3.5. Data extraction

The data items that were collected from each publication are title, publication year, authors, affiliation, affiliation type, countries, venue, venue name, publisher, type of secondary study, range of years analyzed, and amount of citations, which provided contextual information. To systematically analyze AI-driven spectrum sensing, we extracted multiple key data points from each study, to ensure a comprehensive evaluation of trends, methodologies, and contributions. The extracted data focused on the following aspects:

- *Scope of the Study*: Each survey was classified based on its primary focus, such as deep learning (DL) for spectrum sensing.
- *AI Technologies Categorization*: We identified the main AI technology used in each study, grouping them into two major categories: Machine Learning (ML) and Deep Learning (DL).
- *AI Techniques per Category*: Each AI category was further broken down into specific techniques employed for spectrum sensing. For instance: (i) Deep Learning (DL): Feedforward Neural Networks (FNNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Unsupervised Learning (USL), Reinforcement Learning (RL), and Transfer Learning (TL). (ii) Machine Learning (ML): Supervised learning methods like Support Vector Machines, and Naïve Bayes, unsupervised learning techniques such as clustering and k-Nearest Neighbors, and hybrid approaches integrating different learning paradigms.
- *Main Purposes and Contributions*: A structured description of each AI technique's objectives and contributions within the context of spectrum sensing was extracted. Whenever possible, the references associated with these contributions were also recorded. However, in some cases, survey authors provided only an internal labeling system for referenced studies, rather than explicitly citing the original works.
- *Limitations and Opportunities*: To identify research gaps and potential future directions, we documented the limitations discussed in each study, such as challenges in real-world deployment, dataset biases, computational complexity, and generalization issues. Additionally, we highlighted open research opportunities proposed by the surveyed studies, such as the need for more robust domain adaptation techniques, the integration of AI with edge computing, and energy-efficient AI models for spectrum sensing.

This structured data extraction approach allowed us to systematically analyze the evolution of AI-driven spectrum sensing techniques, providing a clear perspective on current advancements, existing challenges, and promising research directions.

3.6. Data synthesis and meta-analysis

This meta-analysis aims to systematically extract and synthesize detailed insights from recent survey studies on AI-driven spectrum sensing. Unlike traditional meta-analyses that emphasize bibliometric trends, our approach is content-focused. It analyzes both the secondary studies (surveys) and the primary studies they cite, but only when those primaries directly contribute to spectrum sensing. This dual-level analysis ensures that we capture not just the synthesized viewpoints of survey authors but also the technical depth and originality of the foundational studies informing their conclusions.

To manage this, we classified the selected surveys into two groups: (i) Surveys explicitly focused on spectrum sensing, which were fully analyzed, including their discussions, cited references, and conclusions on AI methods; and (ii) Surveys that covered spectrum sensing as part of a broader topic, such as cognitive radio networks or dynamic spectrum access. For this group, only the portions explicitly addressing spectrum sensing, along with their relevant primary references, were extracted and analyzed. This ensured the scope of the meta-analysis remained tightly aligned with our research focus.

The synthesis process involved a systematic review of both the survey texts and their cited primary studies. For each relevant primary study, we documented: (i) the AI techniques applied to spectrum sensing, (ii) the technical contribution or innovation, (iii) any performance insights or limitations mentioned, and (iv) source references to preserve traceability. This information was compiled into a structured spreadsheet to support qualitative and quantitative analysis.

In cases where survey descriptions of a primary study were too brief or ambiguous, we consulted the original study directly. We first reviewed the abstract and introduction; if further clarity was needed, we examined the methodology and results sections to accurately assess the study's relevance and contribution. By integrating this validation step, we ensured that our synthesis remained grounded in both secondary interpretations and primary evidence. This content-driven approach enables a richer and more accurate understanding of the current state of AI in spectrum sensing. It reveals technological trends, highlights unresolved challenges, and identifies emerging opportunities that can guide future research in intelligent wireless networks.

4. Results: guide and general trends

As a result of the selection process, we identified thirteen secondary studies, summarized in Table 2. The corresponding set of primary studies extracted from these surveys and included in our analysis is provided in the Appendix. Before delving into the detailed findings, we briefly outline the structure of the results to guide the reader through the forthcoming discussion. The results are organized into four main components: (i) a demographic and bibliometric overview of the selected studies (Section 4.2); (ii) a structural overview of how the findings

Table 2
Summary of selected secondary studies.

ID	Pub. year	Affiliation	Venue	Publisher	Range	Scope	Art.	Ref.
S1	2024	A/I	Journal	Elsevier	2015–2021	DL for CRNs	38	[39]
S2	2022	Acad	Journal	Elsevier	2011–2021	SS in CRNs	61	[19]
S3	2024	N/A	arXiv	arXiv	2013–2022	MA for 6G, SS	101	[40]
S4	2024	Ind	arXiv	arXiv	2013–2023	AI for SMa., 6G	110	[41]
S5	2024	Acad	Journal	Taylor & Francis	2017–2023	DL for SS	35	[42]
S6	2023	Acad	Conf.	IEEE	2010–2021	RL for CoSS	19	[43]
S7	2024	Acad	Conf.	IEEE	2019–2023	DL for SS	15	[44]
S8	2021	Acad	Conf.	IEEE	2010–2020	ML for CRNs	46	[45]
S9	2021	Acad	Journal	IEEE	2007–2020	DL in SMa	76	[46]
S10	2023	Acad	Journal	IEEE	2014–2022	IoT and CRNs	44	[47]
S11	2023	Acad	Journal	MDPI	2018–2023	DL for SS	52	[48]
S12	2023	A/I	Journal	IEEE	2011–2022	DNNs for SS	28	[49]
S13	2022	A/I	Conf.	IEEE	2012–2019	DL for SS	11	[50]

Acad: Academic affiliation, A/I: Academy/Industry affiliation, Art.: Amount of primary studies, 6G: Sixth-generation technologies for wireless communications, CRNs: Cognitive Radio Networks, Conf.: Conference, CoSS: Cooperative Spectrum Sensing, DL: Deep Learning, Ind: Industrial affiliation, IoT: Internet of Things, ML: Machine Learning, N/A: Not Applicable, Pub. Year: Publication Year, RL: Reinforcement Learning, SMa: Spectrum Management, SS: Spectrum Sensing.

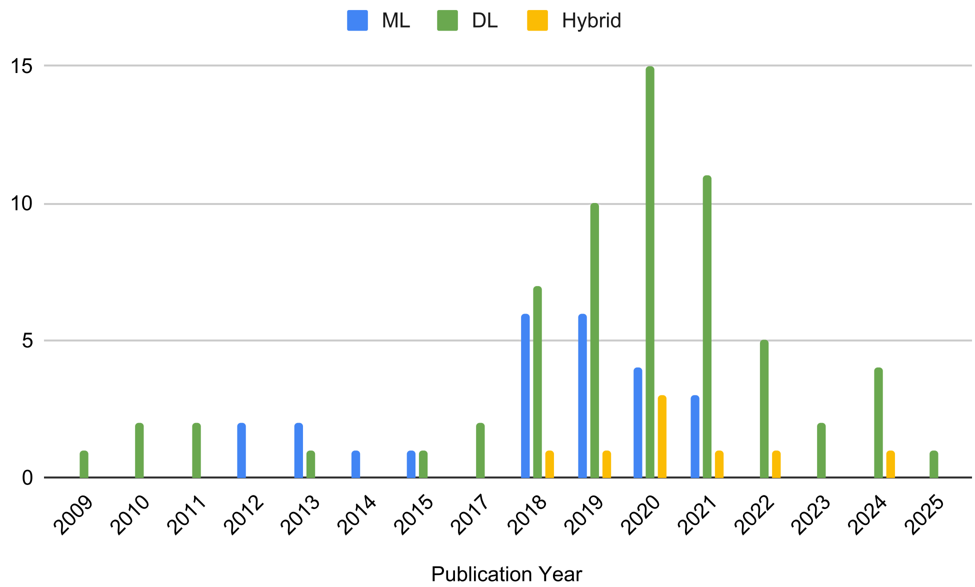

Fig. 5. AI techniques in spectrum sensing: publication year of primary studies.

are organized (Section 4.3); (iii) a detailed examination of the research questions, including analyses of AI techniques applied to spectrum sensing (Sections 5 and 6); and (iv) a discussion of key insights, open challenges, and directions for future research (Section 7).

4.1. Structuring the results

The organization of the results is structured as follows:

- **Demographic Analysis** (Section 4.2): The first step focuses on the metadata of the selected secondary studies, analyzing key bibliometric aspects such as publication years, venues, and geographical distribution. This provides insights into research trends and the evolution of AI applications in spectrum sensing. It also contains the trends among the publication years for the primary studies.
- **Content Analysis and AI classification** (Section 4.3): To systematically organize the content and findings of the studies and to serve as a base for designing and introduce our taxonomy (Section 9), this section presents a structured classification that categorizes AI technologies applied in spectrum sensing. This classification is based on the analysis done from the secondary and primary studies included in the latter.
- **Analysis of RQ1** (Sections 5 and 6): This part delves into the answers to RQ1.1 and RQ1.2, focusing on the application of ML and Deep Learning (DL) in spectrum sensing.
- **Analysis of RQ2** (Sections 7 and 8): These two sections synthesize the key findings, identify existing research gaps, and outline potential future research directions. They provide a critical evaluation of the field and highlights opportunities for advancing AI-driven spectrum sensing in 5G and beyond.
- **Taxonomy Proposal** (Section 9): Based on the content analysis in Sections 4.3, 5, 6, 7 and 8, we have designed a taxonomy of AI-driven spectrum sensing.

4.2. Demographic analysis

The demographic analysis performs the study on selected secondary studies from 2020 to 2025 with respect to geographic distribution, venue, and author affiliation, which also includes countries. Most publications (8 of 13) were published between 2023 and 2025, indicating a recent surge in research interest. This suggests that the integration of AI, and beyond-5G technologies in spectrum sensing has gained significant attention in the last few years. Later on, the increase from 2021 to 2023 is particularly notable, where the number of publications doubled.

In particular, by analyzing the publication year of the primary studies listed in Table 33, Fig. 5 presents the distribution of studies per AI technique; including ML, DL and the combination of them. The publication trend reveals a clear evolution in the application of AI techniques for spectrum sensing. In the early years (2009–2014), research was limited, with a modest presence of either ML or early DL methods, and no hybrid approaches. ML began to emerge around 2012, while DL started earlier but gained traction by 2015. A notable surge occurred from 2018 onward, with both ML and DL studies increasing substantially peaking in 2020 with 22 total publications, including a marked rise in hybrid models that combine ML and DL. From 2018 to 2021, DL consistently outpaced ML in frequency, reflecting a shift toward more complex, data-driven architectures. Hybrid models began appearing around 2018 and have steadily grown, suggesting an interest in leveraging complementary strengths of ML and DL. Post-2021, the overall volume of publications declined slightly, but hybrid approaches maintained a steady presence, indicating ongoing refinement rather than decline in AI-driven spectrum sensing research.

4.2.1. Distribution per venue

Journals are the dominant publication venue (38.5 %), indicating that peer-reviewed, in-depth research articles constitute a major portion of the literature. Furthermore, conference proceedings account for 23 % of the selected articles, showing that some of the latest advancements in the field are being discussed in conference settings. This is common for rapidly evolving fields like spectrum sensing and AI, where early-stage findings and novel approaches are frequently presented at conferences before journal publication.

Finally, preprints on arXiv represent 15.3 % of the dataset, signifying that many researchers prefer open-access platforms to disseminate their findings quickly. This also highlights the dynamic nature of the field, where rapid-sharing mechanisms are utilized before formal peer-reviewed publication. IEEE dominates with 5 articles published across journals and conferences, with *IEEE Access* as its major representative. Elsevier, MDPI, and Springer journals also contribute significantly, highlighting a preference for high-impact, peer-reviewed venues.

4.2.2. Distribution by countries of affiliation

We have identified 13 distinct countries, with India as the leading country (38.5 %) which highlights the significant research contributions

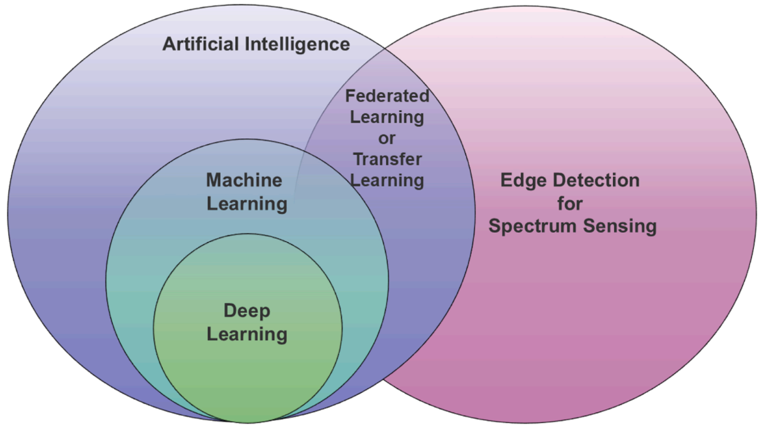

Fig. 6. AI techniques for Spectrum Sensing.

of Indian institutions to spectrum sensing, AI, and cognitive radio networks. There is considerable geographical diversity, with institutions from Asia, Europe, North America, and Africa contributing to the field. Another important remark is that some studies are products of multinational collaboration, such as S1 (India, Finland, Sweden), S10 (UAE, Australia), and S12 (UK, Bulgaria, Greece), which reflects an increasing trend of interdisciplinary and international cooperation in this domain. European representation is indeed significant with contributions from Finland, Sweden, the UK, Greece, and Bulgaria.

4.2.3. Distribution by type of affiliation

Academia dominates the field (53.8 %), with universities and research institutions contributing the majority of the selected articles. This reflects the strong theoretical and methodological focus of the field, as academic institutions typically lead in developing new AI models, federated learning approaches, and spectrum-sharing frameworks. Collaborations between academia and industry (15 %) are emerging, particularly between European and Asian institutions, suggesting a shift towards more applied research. In particular, it is important to point out CSIRO’s Data61 which is the data and digital specialist arm of Australia’s national science agency, the affiliation from S4.

Shared affiliations (23 %) suggest a growing trend in academia-industry collaboration, with studies such as: S1 (Mepco Schlenk Engineering College, India; VTT Finland and Linköping University, Sweden), and S12 (University of Huddersfield, UK; Technical University of Sofia, Bulgaria; Aristotle University of Thessaloniki, Greece). These collaborations suggest that both theoretical and applied research are increasingly merging, particularly in fields requiring real-world spectrum deployment.

4.3. AI for spectrum sensing (RQ1)

To systematically analyze the role of AI in spectrum sensing and effectively address and comprehend the main trends in the field, AI-based approaches have been categorized into two major groups: Deep Learning (DL) and Machine Learning (ML). This categorization is based on three key aspects: (i) the theoretical foundations of AI methodologies, (ii) insights from the existing literature, derived from both secondary and primary studies on AI-driven spectrum sensing that apply these techniques across various applications, and (iii) the recognition that Federated Learning (FL), while typically classified as an ML technique, can also be associated with DL depending on the combination of models and techniques used [40,42,51,52]. This distinction is crucial to understanding how different AI methodologies contribute to optimizing spectrum efficiency.

Although DL is a subset of ML (see Fig. 6), this study considers them as separate categories to provide a more structured and insightful analysis of AI-driven spectrum sensing. Traditional ML techniques, such as Support Vector Machines (SVM), and k-nearest neighbors (KNN), rely on manually selected features and are often more interpretable and computationally efficient. In contrast, DL models, including Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), automatically extract hierarchical features from raw spectral data, enabling more complex pattern recognition and achieving higher accuracy. Given these fundamental differences in methodology, computational requirements, and application scope, distinguishing ML from DL allows a clearer understanding of their respective roles in spectrum sensing. This separation also facilitates a more precise identification of each category’s advantages, limitations, and research gaps, ultimately providing a comprehensive overview of AI techniques in the field. Table 3 presents all AI techniques identified in the analyzed studies, categorized according to their learning paradigms, complemented by Fig. 7.

Machine Learning: ML offers a more interpretable and computationally efficient alternative to DL for certain spectrum sensing tasks. Many ML algorithms are well-suited for scenarios where feature selection and domain knowledge play a crucial role in model performance. Moreover, ML applications, particularly those discussed in Section 5, will be organized according to the techniques presented in Table 3. ML techniques remain essential for efficient spectrum sensing in resource-constrained environments, where DL may be computationally prohibitive.

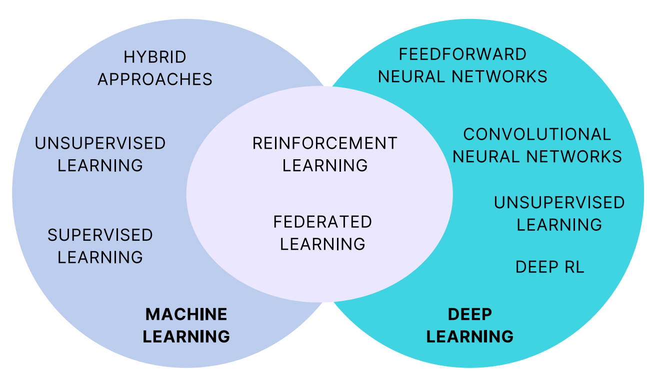

Fig. 7. General Classification of AI techniques.

- *Supervised Learning*: Techniques such as Support Vector Machines, Naïve Bayes, and Bayesian Learning, which rely on labeled data to train models for prediction and classification tasks.
- *Unsupervised Learning*: Methods like clustering-based approaches such as k-means and GMM, and K-Nearest Neighbors, which discover patterns and structures in data without the need for labeled examples.
- *Reinforcement Learning (RL)*: A type of learning where an agent interacts with its environment and learns to make decisions by receiving feedback in the form of rewards or penalties.
- *Hybrid ML Approaches*: Techniques that combine multiple learning methods like supervised and unsupervised to address the strengths of each for more robust and efficient solutions.
- *Federated Learning (FL)*: A decentralized approach within ML that enables multiple devices or nodes to collaboratively train a model without sharing raw data, ensuring privacy and data security.

Deep Learning: DL has gained prominence in spectrum sensing due to its ability to automatically extract hierarchical features from raw spectral data. Unlike traditional ML techniques that require manual feature selection, DL models can identify complex patterns and enhance classification accuracy without human intervention [40,53]. DL-based spectrum sensing techniques have demonstrated significant improvements in accuracy, adaptability, and robustness against noise and interference, making them essential for AI-driven spectrum management. The following techniques, summarized in Table 3, will be discussed in Section 6.

- *Feedforward Neural Networks*: Multi-Layer Perceptrons (MLPs) and Deep Neural Networks (DNNs), which are foundational models for supervised learning tasks, often used for classification and regression.
- *Convolutional Neural Networks*: Standard CNNs and hybrid CNN-LSTM approaches, commonly used for image and signal processing tasks due to their ability to extract spatial hierarchies of features.
- *Recurrent Neural Networks*: RNNs and Long Short-Term Memory (LSTM) networks, designed to handle sequential data and capture temporal dependencies, ideal for time-series prediction and dynamic signal processing.
- *Unsupervised Learning*: Autoencoders and Deep Belief Networks (DBNs), which are utilized for learning representations of data without labeled input, useful for feature extraction and anomaly detection.

Table 3
Classification of AI techniques in spectrum sensing.

Category	Description		
	Learning Type	AI Technique	Combination
	Supervised Learning	Support Vector Machines (SVM)	–
	Supervised Learning	Naïve Bayes	–
	Supervised Learning	Bayesian Learning	–
	Unsupervised Learning	k-means Clustering	–
Machine Learning	Unsupervised Learning	K-Nearest Neighbors (KNN)	KNN in CNNs
	Unsupervised Learning	Learning with Q-Learning	USL + QL
	Hybrid	Hybrid Model	k-means + SVM
	Hybrid	Hybrid Model	SVM + k-means + GMM
	Hybrid	Ensemble Learning Framework	CNNs, RNNs
	FL - RL	Federated Resource Allocation	–
	FL - SL	FL	–
	FL - RL	Federated RL (FRL)	RL with A3C algorithm
	ML/DL	FL-based SS (FLSS)	
-Deep Learning	Supervised Learning	MLP	–
	Supervised Learning	DNNs	–
	Supervised Learning	Standard CNNs	–
	Supervised Learning	Hybrid CNNs	–
	Supervised Learning	RNNs	–
	Supervised Learning	LSTM	–
	Unsupervised Learning	AEs	–
	Unsupervised Learning	DBNs	–
	Supervised Learning	DRL	–
	Supervised Learning	MARL	–
	Supervised Learning	CNN-LSTM	Fusion of CNN and LSTM
	Supervised Learning	Hybrid CNN-LSTM	Combination of CNN and LSTM
	Supervised Learning	DLSenseNet	Modified CNN blocks + LSTM
	Supervised Learning	CNN-BiLSTM-SA-CONCAT	CNN + BiLSTM + Self-attention layers
	Supervised Learning	Parallel CNN-LSTM	Parallel CNN + LSTM
	Supervised Learning	BiLSTM-SA	BiLSTM + Self-attention
	Supervised Learning	CNN-LSTM	CNN + LSTM for CoSS
	FL - SL	Deep FL	FL with DNNs
	FL - SL	Federated Edge Learning (FEEL)	CNNs
	FL - SL	FL	RNN, CNN, LSTM, MLP, GRU
	FL - SL	Federated AMC	Distributed model training

A3C: Asynchronous Advantage Actor-Critic, AMC: Automatic Modulation Classification, AEs: Autoencoders, BiLSTM: Bidirectional Long Short-Term Memory, CNN: Convolutional Neural Network, DBNs: Deep Belief Networks, DL: Deep Learning, DNNs: Deep Neural Networks, DRL: Deep Reinforcement Learning, FEEL: Federated Edge Learning, FL: Federated Learning, FRL: Federated Reinforcement Learning, GMM: Gaussian Mixture Model, GRU: Gated Recurrent Unit, KNN: K-Nearest Neighbors, k-means: k-means Clustering, LSTM: Long Short-Term Memory, MARL: Multi-Agent Reinforcement Learning, ML: Machine Learning, MLP: Multi-Layer Perceptron, QL: Q-Learning, RL: Reinforcement Learning, RNN: Recurrent Neural Networks, SL: Supervised Learning, SVM: Support Vector Machines, USL: Unsupervised Learning.

Table 4
Applications of machine learning - supervised learning in spectrum sensing.

AI technique	Purpose	Details	Ref.
SVM, Weighted KNN	SS, CoSS	Combines SVM with weighted KNN to enhance detection of PU activity, achieving improved detection probability and computational efficiency. Radial Basis Function kernel outperforms conventional methods.	[56]
SVM	SS, User Grouping	Proposes a supervised learning-based CoSS model using SVM to reduce cooperation overhead and optimize CR user grouping. Introduces algorithms for detecting normal and abnormal users, improving sensing efficiency and security.	[57]
SVM	SS	Adapts SVM for multi-antenna CRNs, using beamformer-aided features to improve classification capabilities. Incorporates error-correcting output codes for better classification performance in varying operating conditions.	[58]
SVM, Linear Kernel	SS, Real-Time Spectrum Detection	Uses SVM with a linear kernel to classify channels based on energy level estimations, achieving the highest detection probability and low classification delay, making it effective for real-time spectrum detection.	[59]
SVM, k-means	SS	Applies a two-step model with k-means clustering followed by SVM for final classification. Achieves high accuracy (97.6 %) for spectrum sensing.	[60]
Naïve Bayes	SS, Spectrum Detection	Uses Naïve Bayes classifiers based on received signal power and cyclic prefix correlation for probabilistic spectrum detection in CRNs.	[45,61]
Bayesian Learning	SS, CoSS	Proposes a Bayesian learning-based clustering framework to optimize sensing thresholds and improve detection probability in CRNs, outperforming traditional methods in terms of detection and false alarm rates.	[62]

CoSS: Cooperative Spectrum Sensing, CR: Cognitive Radio, CRNs: Cognitive Radio Networks, KNN: K-Nearest Neighbors, PU: Primary User, SS: Spectrum Sensing, SVM: Support Vector Machines.

- *Reinforcement Learning*: Standard RL, Transfer Learning, and Deep Reinforcement Learning (DRL), where agents learn optimal actions through feedback from the environment, applicable in adaptive and decision-making tasks.
- *Federated Learning*: When FL integrates DL models, it becomes Deep Learning-based Federated Learning (Deep FL), which remains part of the ML umbrella but with a specific focus on deep learning techniques.

Federated Learning: FL has emerged as a privacy-preserving AI paradigm in spectrum sensing, enabling distributed devices to collaboratively train models without sharing raw data. This decentralized approach is particularly beneficial for CRNs, IoT-enabled spectrum monitoring, and edge-based AI applications [53,54]. FL addresses key challenges related to data privacy and scalability in AI-driven spectrum sensing, making it a promising approach for future wireless networks. The integration of AI into spectrum sensing has introduced more intelligent, adaptive, and efficient methods for managing wireless spectrum resources.

Although FL is fundamentally built upon ML principles, it represents an independent paradigm due to its decentralized learning framework, emphasis on privacy preservation, and adaptability in distributed networks. Unlike conventional ML, which requires centralized data aggregation for training, FL enables local model training on edge devices, for example: SUs in CRNs, and shares only model updates instead of raw data. This characteristic is particularly valuable for spectrum sensing in large-scale, privacy-sensitive, and resource-constrained wireless networks [53,55]. Given these architectural and functional distinctions, FL represents a paradigm shift in AI-driven spectrum management. However, depending on how it is integrated with AI techniques and models, it can also be categorized under DL (see Table 3). For this reason, applications involving ML will be discussed in Section 5, while those related to DL will be covered in Section 6.

The following sections provide an in-depth analysis of AI techniques applied to spectrum sensing, based on findings from recent literature. The analysis is structured around specific research questions (RQs), and in particular, Section 5 focuses on ML for spectrum sensing, Section 6 explores DL applications in the field; and Section 7 focus on the challenges, limitations and future opportunities.

5. Machine learning for spectrum sensing (RQ1.1)

Machine Learning, as a discipline of Artificial Intelligence (AI), can be understood as the ability of a system to portray intelligent decisions based on experience [19]. ML techniques play a crucial role in improving CoSS in CRNs. By modeling spectrum sensing as a classification, clustering, or decision-making problem, ML-based approaches significantly enhance detection probability, reduce sensing time, and optimize spectrum utilization. These methods can be broadly categorized into Supervised Learning (Section 5.1), and Unsupervised Learning (Section 5.2).

5.1. Supervised learning

Supervised Learning (SL) models are extensively used in spectrum sensing, as they rely on labeled training data to classify spectrum availability. These methods include Support Vector Machines (SVMs), K-Nearest Neighbors (KNN), and Decision Trees (DT), each contributing to improved detection accuracy and computational efficiency. Table 4 presents the identified contributions of SL-based approaches to spectrum sensing.

5.1.1. Support vector machines

These approaches have demonstrated significant improvements in detection probability and computational efficiency. A study by Thilina et al. [56] explores the application of SVM and weighted K-Nearest Neighbors (KNN) for Cooperative Spectrum Sensing (CoSS) to enhance the detection of PU activity. By modeling the PU network as a random geometric network, the study examines how different SVM kernels impact detection probability. The weighted KNN classifier further improves performance by adjusting feature weights based on Receiver Operating Characteristic (ROC) curves. Performance evaluations indicate that SVM, particularly with the Radial Basis Function (RBF) kernel, and weighted KNN outperform conventional CoSS methods in terms of detection accuracy and computational speed.

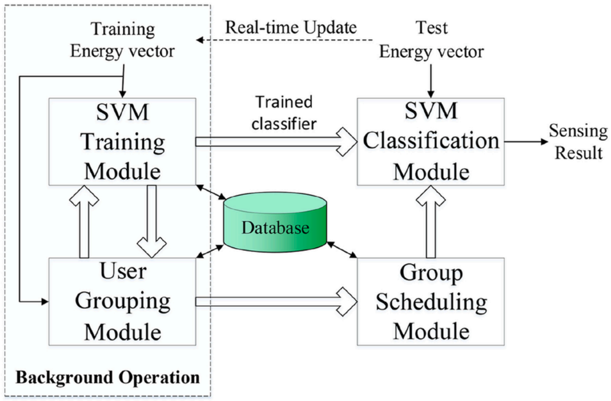

Fig. 8. Illustration of the CoSS framework with a user grouping SVM model proposed in Li et al. [57].

Building on these findings, Li et al. [57] propose a supervised learning-based CoSS model using SVM to reduce cooperation overhead and optimize CR user grouping, as shown in Fig. 8. Their approach introduces three user-grouping algorithms: identifying and separating normal and abnormal users, detecting redundant users to enhance sensing efficiency, and minimizing average correlation for optimal grouping. Simulation results demonstrate that these algorithms increase classification speed and reduce training time while improving sensing efficiency and security. For instance, the proposed Algorithm 3 increased classification speed by 24.65 % while maintaining high sensing accuracy.

SVM has also been adapted for multi-antenna CRNs, as explored by Awe et al. [58]. Their work introduces a spatiotemporal spectrum sensing strategy, where beamformer-aided features enhance SVM's classification capabilities under different operating conditions. The inclusion of error-correcting output codes further refines multi-class SVM models, significantly improving false alarm rates, detection accuracy, and overall classification performance. Thilina et al. [59] investigate SVM and weighted KNN for CoSS, using energy level estimations as feature vectors to classify channels as available or unavailable. Among the classifiers tested, SVM with a linear kernel achieves the highest detection probability and a classification delay of 5.67×10^{-5} s for 1000 samples, making it the most precise method for real-time spectrum detection.

Similarly, Mikaeil et al. [60] employ SVM in a two-step ML model, where k-means first determines PU status, followed by SVM classification of new input data. Performance evaluations indicate that SVM achieves an accuracy of 97.6 %, proving to be an effective tool for spectrum sensing. Awe et al. [58] apply multi-class SVM for spectrum sensing in multi-antenna CRNs, integrating beamformer-aided features to enhance classification under varying user conditions. Their spatiotemporal spectrum sensing strategy improves false alarm rates, detection accuracy, and classification performance.

With respect to the performance analysis, SVM-based spectrum sensing approaches demonstrate high detection accuracy, particularly when combined with techniques like CNN feature extraction. They perform robustly in high-noise environments and achieve good classification performance across various modulation types. However, the sensitivity to hyperparameters and kernel selection can affect false alarm rates and model reliability. Later on, SVM implementations are generally lightweight in terms of hardware requirements and are feasible for deployment in SDR-based spectrum sensing systems, especially when preprocessing (for example, using feature reduction) is applied. However, training complexity may increase with large datasets and multi-class classification scenarios. Finally, and while not explicitly quantified in FLOPs, SVMs are considered moderately efficient, particularly when used with feature selection techniques. They are suitable for real-time detection tasks due to their fast inference time once trained. However, training may be computationally expensive in high-dimensional spaces.

5.1.2. *Naïve Bayes and Bayesian learning*

In addition to SVM, Naïve Bayes classifiers have been employed in spectrum sensing applications. These models classify spectrum availability based on received signal power and cyclic prefix correlation, providing a probabilistic framework for spectrum detection [45]. Later on, Liu et al. [62] propose a Bayesian learning-based clustering framework for CoSS in CRNs, optimizing sensing thresholds by minimizing the total Bayesian cost. Their approach integrates Bayesian fusion for false alarm and detection probability estimation, achieving higher detection probability and lower error rates at $SSNR \geq -6$ dB, outperforming traditional non-clustered CoSS.

Regarding the performance (see Table 5), Naive Bayes-based techniques offer rapid detection but generally lower classification accuracy compared to more complex models. Their false alarm rate can be higher due to the assumption of feature independence. Bayesian learning methods provide probabilistic decision-making and are effective in environments with uncertainty or limited data. Furthermore, these models are lightweight and highly feasible for low-resource environments. Their simple mathematical structure enables easy deployment on embedded or mobile devices for spectrum sensing applications. Finally, Naive Bayes and Bayesian models are highly energy-efficient due to their low computational complexity. Their inference processes are well-suited for real-time applications, especially in scenarios where energy conservation is critical.

5.2. *Unsupervised learning*

Unlike SL, unsupervised learning (USL) techniques do not rely on labeled training data. Instead, they analyze patterns and structures within the data to detect spectrum availability. These models are particularly useful in dynamic wireless environments where prior knowledge about the system is limited. Table 6 presents the identified contributions of USL-based approaches to spectrum sensing.

5.2.1. *Clustering*

One widely used approach is k-means clustering, which partitions data into different clusters based on similarities in signal features. In unsupervised CoSS, the extracted feature vectors are processed through a clustering algorithm, and each cluster centroid is compared with a predefined threshold to classify spectrum availability [19]. This method allows CRNs to autonomously identify available spectrum without the need for labeled datasets. Thilina et al. [59] employ k-means clustering and Gaussian Mixture Models (GMM) for unsupervised CoSS. Performance evaluations show that k-means is the fastest (classification delay of 1.9×10^{-5} s), while GMM requires a longer training time (1.12796 s for 1000 samples). These findings highlight k-means' computational efficiency in real-time spectrum sensing. Furthermore, Cao et al. [40] apply k-means and GMM in CoSS, enhancing sensing efficiency by effectively grouping users when prior spectrum information is incomplete.

As for performance comparison (see Table 7), clustering-based methods, such as k-means or hierarchical clustering, are effective in identifying spectrum occupancy patterns without labeled data. However, their accuracy can vary depending on signal-to-noise ratios and the homogeneity of signal types. These methods often require post-processing to reduce false alarms. Later on, clustering algorithms have moderate hardware demands and can be implemented on systems with limited computational capacity, especially when the number of clusters is fixed and known a priori. Finally, clustering approaches are generally less energy-intensive but may require iterative updates, impacting efficiency in dynamic environments. Their real-time adaptability is moderate, depending on the algorithm's convergence rate.

Table 5
SVM, NB, and Bayesian learning approaches for spectrum sensing.

Technique	Input to algorithm	Prep. data	Key features of architecture	Metrics	Performance	Ref.
SVM	Received signal power data at multiple SUs (grid layout); features from signal statistics	Signal data under varying PU locations, noise, path-loss; training sets 10–1000 samples	SVM with Linear, Poly-2, RBF kernels; KNN with Euclidean, Cityblock distances	Training time (s), classification time (s), detection prob., false alarm rate (ROC)	SVM-RBF: 1.16s training (500 samples), best detection accuracy; KNN-Euclidean fastest (0.059s classification); SVM classification $< 10^{-4}$s; outperform Fisher, AND, OR rules	[56]
SVM	Simulation with 64-bit PC, i5 processor	$N = 100$, $K = 10,000$; linear kernels	Centralized CSS with FC and 10/20 CR users	Training time, classification speed, speed improvement ratio	Improvement over existing model	[57]
SVM	Beamformed energy vectors from multi-antenna SUs; BPSK signals; SNR -15 to -24 dB	2000 vectors; 400 for training; features via sector angular filtering	Binary SVM (CSVM), Multiclass SVM (MSVM), MIMSVM; ECOC, DAG, OVO structures	Pd, Pfa, AUC, Classification Accuracy, Runtime	BFSVM $Pd \approx 0.99$ @$Pfa = 0.1$ vs. NBFSVM $Pd \approx 0.74$ @ -15 dB; BFSVM AUC = 0.9933 vs. NBFSVM = 0.9149; Accuracy $52\,\% - 60\,\%$ (ECOC MSVM)	[58]
SVM	Energy vectors from 25 SUs in 5×5 grid over 4000×4000 m^2; 100 µs sampling window, 5 MHz bandwidth	1000 energy vectors, 500 training; shadowing	Supervised: SVM (Linear, Poly), KNN; Unsupervised: K-means, GMM; Baseline: Fisher, AND/OR	Pd, Pfa, Classification delay, Training time	SVM-Linear: Highest Pd, low delay, moderate training (1.658 s); K-means comparable Pd, low delay; KNN fastest training (50 µs), high delay	[59]
SVM	Energy detection data from 7 cooperative nodes (SNR -20 to -24 dB), 1000 samples/node	Framed energy detection outputs as features; single-user threshold labeling	SVM, KNN, Decision Tree, Naïve Bayes for cooperative fusion; 1000 labeled frames training	Accuracy, Precision, Recall, ROC	SVM: Accuracy 97.6 %, Precision 83.9 %, Recall 100 %; DT and KNN 100 % Accuracy/Precision/Recall; NB 98.9 % Accuracy	[60]
Naïve Bayes	128D features from OFDM signals (30 OFDM symbols, 1024 subcarriers, TU6 model)	5000 runs per SNR/hypothesis; train $N = 1000$; statistical moments features	Naïve Bayes with class reduction; compared to BPNN, ED, CP-based, ASHT-based	Pd, SSER, ROC (SNR = -18 dB), Prediction time (CPU)	NBC outperforms BPNN & threshold methods at low SNR; fast predictions; ROC near optimal LRT; fast convergence with > 500 samples	[61]
Bayesian Learning	Local energy detection from 100 nodes; PU presence prob = 0.5; SSNR = $-5, 0, 5, 10$ dB	Bayesian cost to optimize threshold λ; nodes clustered by proximity to FC	Intra-cluster CSS with Bayesian threshold learning; optimized λ to minimize cost; clustering fusion	Total Bayesian Cost, Total Detection Probability, Sensing Time	Cost minimized; reaches zero for SSNR > -5 dB; Bayesian clustering better detection than traditional CSS	[62]

DNN: Deep Neural Network, MLPs: Multilayer Perceptrons (MLPs).

5.2.2. *K-nearest neighbors*

Shah et al. [63] apply K-Nearest Neighbors (KNN)-based models for spectrum sensing in Convolutional Neural Networks (CNNs), demonstrating improved spectral efficiency through adaptive clustering techniques. As for performance discussion (see Table 7), k-NN is simple yet effective for signal classification. While it achieves reasonable accuracy, its performance is highly sensitive to the choice of k and the distance metric. Detection time is slower for large datasets, and false alarm rates may rise due to the model's sensitivity to noise. Later on, due to its need to store and compare all training samples during inference, k-NN is more demanding in memory and computation, making it less ideal for deployment on hardware-constrained platforms unless optimized. Finally, k-NN is computationally expensive during inference, especially as dataset size grows. It is not inherently energy-efficient and has limited real-time adaptability unless paired with dimensionality reduction or approximate nearest neighbor techniques.

5.2.3. *Reinforcement learning*

Unsupervised models are often combined with RL techniques, where the system learns optimal spectrum sensing strategies through interaction with the environment. Q-Learning and Transfer Learning are examples of RL-driven approaches that help cognitive radios adapt to changing spectral conditions while maximizing spectrum utilization efficiency [19,64]. Within ML, we can mention that RL-based spectrum sensing methods exhibit adaptability in dynamic environments and can optimize detection strategies over time. They typically offer improved detection accuracy and low false alarm rates as the learning progresses. However,

Table 6
Applications of machine learning - unsupervised learning in spectrum sensing.

AI technique	Purpose	Details	Ref.
k-means and GMM	SS, Unsupervised CoSS	Applies k-means and GMM for unsupervised CoSS. k-means provides faster classification, while GMM requires longer training time.	[59]
k-means and GMM	CoSS, SS	Advocates for k-means and GMM to improve cooperative spectrum sensing efficiency by effectively grouping users when prior spectrum information is incomplete.	[40,57]
KNN in CNNs	SS	Uses KNN-based models integrated with CNNs to improve spectral efficiency through adaptive clustering techniques.	[63]
USL with Q-Learning	SS	Combines unsupervised learning with RL techniques, such as Q-learning, for adapting to changing spectral conditions while maximizing spectrum utilization efficiency.	[19,64]
Hybrid Model (k-means + SVM)	SS	Proposes a hybrid model where k-means clustering first detects PU activity, followed by SVM classification for final decision-making, achieving high classification accuracy (97.6 % for SVM).	[60]
Ensemble Learning Framework	SS	Uses ensemble learning with multiple deep learning models (CNNs, RNNs) and stacking fusion centers to improve detection performance in dynamic spectrum environments.	[42,65]

CoSS: Cooperative Spectrum Sensing, CR: Cognitive Radio, CNNs: Convolutional Neural Networks, CRNs: Cognitive Radio Networks, GMMs: Gaussian Mixture Models, KNN: K-Nearest Neighbors, PU: Primary User, RL: Reinforcement Learning, SS: Spectrum Sensing, SVM: Support Vector Machines.

initial performance may be suboptimal during early exploration phases. Further, RL approaches require more computational resources for training due to the iterative learning process. Nonetheless, once trained, deployment is feasible even on modest hardware depending on the complexity of the learned policy. Finally, RL introduces higher complexity and energy usage during training but allows efficient real-time decision-making after convergence. Its adaptability makes it highly suited for non-stationary environments where energy consumption can be traded off with intelligent spectrum use.

5.2.4. *Hybrid approaches*

To further enhance spectrum sensing performance, researchers have explored hybrid ML models that integrate supervised and unsupervised techniques. Mikaeil et al. [60] propose a two-step hybrid approach, where k-means clustering first determines PU activity, followed by an SVM classifier for final decision-making. This reduces training overhead while maintaining high classification accuracy (97.6 % for SVM, 100 % for KNN and DT). Similarly, Thilina et al. [59] integrate SVM (supervised) with k-means and GMM (unsupervised) for spectrum sensing, demonstrating that SVM achieves the best detection accuracy, while k-means is the fastest in classification speed.

Later on, Ensemble Learning (EL) techniques use multiple ML models to increase detection robustness, improve accuracy, and enhance adaptability in dynamic spectrum environments [42]. Liu et al. [65] introduce an ensemble learning framework using multiple DL models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). By employing stacking fusion centers, their approach integrates predicted probabilities from different models, improving overall detection performance in uncertain and fluctuating environments.

As for performance comparison (see Table 7), hybrid models combining SL and USL, for example, SVMs with clustering or CNN feature extraction with SVM, show improved detection accuracy and robustness across varied spectrum conditions. These approaches can significantly reduce false alarm rates by leveraging complementary strengths of different algorithms. Later on, hardware requirements increase with hybridization, especially when deep feature extractors are involved. However, with proper model optimization and modular design, these systems can be deployed in edge or cloud-assisted environments. Finally, hybrid methods are inherently more complex and consume more energy, particularly during training and inference phases. Yet, they provide a good trade-off between accuracy and adaptability, making them suitable for environments where detection precision outweighs energy constraints.

5.3. *ML-based federated learning (ML-FL)*

Federated Learning has been extensively applied in wireless communications, particularly in optimizing resource allocation and spectrum management. ML-based FL approaches incorporate supervised and reinforcement learning techniques to enhance network efficiency and security while minimizing communication overhead. Samarakoon et al. [66] introduced an FL-based framework for ultra-reliable low-latency communication (URLLC) in vehicular networks, incorporating reinforcement learning to optimize power control and resource allocation. Similarly, Chen et al. [67] proposed an FL-based joint user selection and resource allocation model that employs SL techniques to account for packet errors and wireless resource availability, improving decision-making in dynamic environments.

Spectrum sensing, a critical aspect of CRNs, also benefits from ML-based FL approaches. Chen et al. [68] developed a Federated Learning-based Spectrum Sensing (FLSS) framework that enables distributed training across secondary users (SUs), reducing communication overhead and improving processing efficiency. Furthermore, RL-based Federated Learning (FRL) integrates RL principles into FL, enhancing decision-making for Dynamic Spectrum Access. The application of FRL in Space-Air-Ground Integrated Networks (SAGIN) through the Asynchronous Advantage Actor-Critic (A3C) algorithm optimizes resource management and transmission strategies [41].

As for performance evaluation (see Table 8), Federated learning (FL) in spectrum sensing maintains high detection performance while preserving data privacy. Although it may slightly lag behind centralized models in terms of accuracy, it is effective in distributed environments and scales well with multiple devices. Detection accuracy remains competitive with modest trade-offs in false alarms and latency. Later on, FL frameworks are designed to run on edge devices with limited resources. However, their feasibility depends on the local model size and communication overhead for updates. Lightweight models such as shallow MLPs or SVMs are commonly used to enhance feasibility. Finally, FL reduces energy use related to data transmission but introduces periodic computation for local model training and update aggregation. While less efficient than local-only methods, its real-time adaptability and

Table 7
Unsupervised learning approaches for spectrum sensing.

Technique	Input to algorithm	Prep. data	Key features of architecture	Metrics	Performance	Ref.
SVM	Received signal power data at multiple SUs (grid layout); features from signal statistics	Signal data under varying PU locations, noise, path-loss; training sets 10–1000 samples	SVM with Linear, Poly-2, RBF kernels; KNN with Euclidean, Cityblock distances	Training time (s), classification time (s), detection prob., false alarm rate (ROC)	SVM-RBF: 1.16 s training (500 samples), best detection accuracy; KNN-Euclidean fastest (0.059s classification); SVM classification $< 10^{-4}$ s	[56]
KNN in CNNs	SINR estimates from FBSs via USRP; interference and transmission feedback states; actions: power levels 0–30 dB	Real-time USRP testbed; 2 FBSs + 1 MBS; 2 subchannels/FBS; GMSK 0.5 Mbps	Two Q-learning variants (PDPA-Q, CDPA-Q); custom MAC protocol PAQ; compared with Equal Power (EP)	Aggregate FBS capacity; MBS capacity vs. target; convergence rate; iterations vs. exhaustive search	Q-learning variants outperform EP; MBS capacity meets target; CDPA-Q best; faster convergence; robust to incremental deployment	[63]
USL with Q-Learning	Same as above (SINR from FBSs via USRP; interference states; power levels 0–30 dB)	Same real-time USRP setup	Same two Q-Learning variants; custom MAC PAQ; compared with EP scheme	FBS capacity; MBS capacity vs. target; convergence rate; iterations	PDPA-Q & CDPA-Q outperform EP; MBS at/above target; CDPA-Q best FBS; faster convergence; stable performance in worst cases	[64]
Ensemble Learning	64×64 SCD-plane inputs from SUs sensing OFDM (802.11g, 16QAM); one PU; AWGN; local reports to FC each OFDM symbol	Two balanced datasets (100k/class) for SU	FC training; bagging SU subsets (10k/class) & SU CNNs (3 variants)	Pd, Pf, complexity per architecture, performance vs. SU count and SNR	Proposed outperforms energy/feature detection; Pf = 0.00005 with FC stacking; higher complexity boosts Pd, reduces Pf; Pd saturates after 64 SUs	[65]
FL with RL	Queue length samples from VUEs, local gradients, GPD params, traffic arrivals (Poisson, mean 500 kbps)	Manhattan model (250×250 m), 60 RBs shared; max power 10W; vTx follows vRx at 50 m, 60 km/h	Async-FL, SVRGD optimizer, GPD estimation; compared to CEN, sync-FL, QSR, QSO, FP	max queue length, transmit power, data exchange, reliability, tail queue distribution	Async-FL impact: -79 % data, -35 % power, -29 % latency, +60.9 % reliability, -28.6–41.9 % tail queue	[66]
FL with SL	Local user data (linear regression, MNIST classification), wireless link quality info	Circular network (500 m radius), 15 users; synthetic	MNIST data; joint FL loss, user selection, RB allocation, power; Hungarian algorithm for RBs; CNN/FNN per user	FL loss (MSE, cross-entropy), ID accuracy, convergence gap, Hungarian iterations	Up to 4.1 % accuracy gain; < 9 % convergence gap; better with more data/users; efficient RB allocation	[67]
FL-based SS	Local signal samples at each SU (QPSK, length 128), 16 antennas/SU, SNR −20 to 0 dB	10–30 SUs; noise uncertainty ±1 dB; covariance matrix features	Federated Learning with ShuffleNetV2; gradients to FC, no raw data sharing; lightweight model	Detection probability, false alarm, ROC, Pd vs. SNR	At Pf = 1 %, Pd improves from 94.7 % (10 SUs) to 98.8 % (25 SUs); outperforms GLRT; close to centralized	[68]

DNN: Deep Neural Network, MLPs: Multilayer Perceptrons (MLPs).

Table 8
ML approaches in federated learning (FL) for spectrum sensing.

AI technique	Purpose	Details	Ref.
FL with RL	Resource allocation and power control	Applied in ultra-reliable low-latency communication (URLLC) for vehicular networks	[66]
FL with SL	User selection and resource allocation	Accounts for packet errors and wireless resource availability	[67]
FL-based SS (FLSS)	Distributed Spectrum Sensing	Enables training across secondary users (SUs), reducing communication overhead	[68]
FL-based RL (FRL)	Dynamic Spectrum Access	Utilizes the A3C algorithm in Space-Air-Ground Integrated Networks (SAGIN)	[S51] in Sabir et al. [41]

A3C: Asynchronous Advantage Actor-Critic, CRNs: Cognitive Radio Networks, CoSS: Cooperative Spectrum Sensing, GMM: Gaussian Mixture Models, KNN: K-Nearest Neighbors, SVM: Support Vector Machines, RL: Reinforcement Learning, SL: Supervised Learning, SS: Spectrum Sensing, URLLC: Ultra-reliable Low Latency Communication.

Table 9
Summary of RQ1.1: ML for spectrum sensing and their applications, strengths and limitations.

Purpose	AI technology	Real-world application example	Key strengths	Challenges/limitations
Spectrum Sensing	SVM (Standard, Multi-Class, Hybrid)	CoSS in CRNs	High classification accuracy, adaptable to varying conditions	High computational cost, sensitive to parameter tuning
	Bayesian Learning	Adaptive clustering for spectrum detection	Strong probabilistic modeling, improves detection probability	Requires prior knowledge for accurate modeling
	KNN (Standalone, Hybrid)	Enhanced spectrum classification	Fast, simple, and effective for small datasets	Performance degrades with high-dimensional data
Cooperative Spectrum Sensing (CoSS)	k-means Clustering	Autonomous spectrum detection	Effective in unlabeled data scenarios, fast clustering	Struggles with complex, overlapping classes
	GMM	Probabilistic spectrum classification	Handles uncertainty well, flexible in real-world conditions	Requires significant training time, sensitive to initialization
Interference Management	Hybrid Models (SVM + k-means + GMM)	Adaptive interference classification	Combines supervised and unsupervised learning for robustness	Computationally intensive, requires large datasets
	Ensemble Learning	Dynamic interference mitigation in CRNs	Boosts accuracy by integrating multiple models	Increased complexity, requires extensive training
Spectrum Adaptation	Q-Learning (Hybrid with Unsupervised Learning)	Adaptive spectrum access optimization	Learns optimal strategies over time	Training convergence can be slow, sensitive to reward function
	Beamformer-Aided SVM	Spectrum allocation in multi-antenna systems	Enhances spatial filtering for interference rejection	Requires high computational resources

CRNs: Cognitive Radio Networks, CoSS: Cooperative Spectrum Sensing, GMM: Gaussian Mixture Models, KNN: K-Nearest Neighbors, SVM: Support Vector Machines.

privacy-preserving properties make it viable for long-term deployment in heterogeneous sensing environments.

5.4. Summary of RQ1.1

ML techniques play a crucial role in spectrum sensing by enabling intelligent decision-making in dynamic wireless environments. Unlike DL, ML models often require structured feature engineering and are more interpretable, making them well-suited for real-time spectrum monitoring and optimization tasks. Table 9 presents an overview of key ML-based approaches applied to spectrum sensing, interference management, and spectrum adaptation. These techniques span supervised learning such as SVM and Bayesian Learning, unsupervised learning such as k-means, GMM, and hybrid models that integrate multiple paradigms to enhance detection accuracy and adaptability. Each method is evaluated based on its real-world applications, key strengths, and associated challenges, providing insights into their effectiveness in cognitive radio networks and beyond-5G wireless systems.

6. Deep learning for spectrum sensing (RQ1.2)

Deep learning (DL) has emerged as a powerful tool for addressing the challenges of spectrum sensing in CRNs. By applying data-driven learning paradigms, DL models can autonomously detect, classify, and predict spectrum availability, mitigating the limitations of traditional sensing techniques. The flexibility and adaptability of DL architectures allow them to operate effectively under dynamic channel conditions, noise uncertainty, and non-stationary spectrum environments while optimizing spectrum utilization [39,49,69].

The application of DL in spectrum sensing spans multiple architectural designs, each tailored to specific tasks within the spectrum management pipeline. Multilayer perceptrons (MLPs) (Section 6.1.1) and deep neural networks (DNNs) (Section 6.1.2) serve as foundational architectures, enabling spectrum sensing by learning from raw or processed signal data. Convolutional neural networks (CNNs) (Section 6.2) and their hybrid forms integrate spatial feature extraction to improve cooperative sensing and enhance spectral efficiency. Recurrent neural networks (RNNs) (Section 6.3) and long short-term memory (LSTM) (Section 6.3.2) networks are employed to model temporal dependencies in signal variations, making them well-suited for predicting primary user activity and handling time-series spectral data. Furthermore, hybrid CNN-LSTM architectures (Section 6.2.3) combine spatial and temporal feature extraction for more robust spectrum analysis.

Beyond supervised learning, autoencoders (AEs) (Section 6.4.1) are used for feature extraction and dimensionality reduction, often aiding in unsupervised and semi-supervised spectrum sensing tasks. Deep belief networks (DBNs) (Section 6.4.2) facilitate primary user behavior classification and predictive spectrum sensing, improving spectrum allocation strategies. Reinforcement learning techniques have also gained traction, with deep reinforcement learning (DRL) (Section 6.7) and multi-agent reinforcement learning (MARL) optimizing dynamic spectrum access policies and cooperative spectrum sensing strategies.

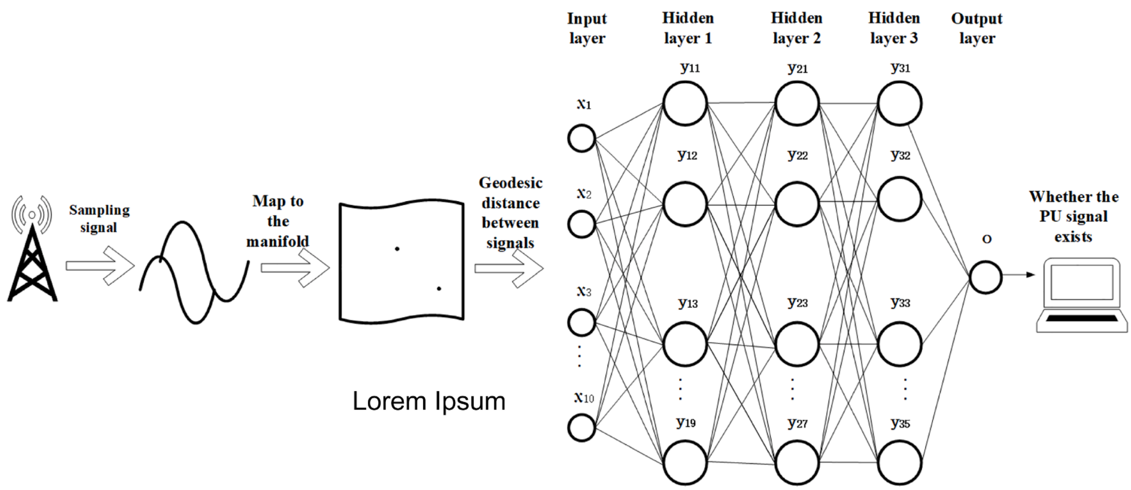

Fig. 9. CoSS based on MLP and information geometry proposed in Du et al. [70].

6.1. Feedforward neural networks

6.1.1. Multilayer perceptron

MLP is a type of feedforward Artificial Neural Network (ANN) composed of one or more hidden layers [49]. When an MLP consists of multiple hidden layers, it is classified as a Deep Neural Network (DNN). The number of neurons in the input layer corresponds to the dimensions of the input dataset, while the number of neurons in the output layer matches the number of output labels or classes. The configuration of hidden layers, including their number and neuron count, is typically optimized to enhance accuracy. Table 10 presents contributions to spectrum sensing using MLP-based approaches, while Table 11 contains the main architectural details, performance and metrics.

Several studies have explored the application of MLPs in spectrum sensing [49]. Du et al. [70] proposed an MLP with three hidden layers for centralized CoSS, integrating information geometry with DL, as shown in Fig. 9. Their method, termed IG-DNN, utilizes geodesic distances derived from covariance matrices of sensed signals and noise as input features. The model aggregates spectrum sensing data from multiple SUs operating at various SNRs, improving detection accuracy. Experimental results indicate that increasing the number of SUs and SNR levels enhances spectrum sensing performance. Notably, IG-DNN outperformed IG-FCM [71] and Maximum Mean Envelope (MME)-k-means [72] across various simulation scenarios.

Patel et al. [73] designed an MLP with two hidden layers, optimizing key hyperparameters such as the number of neurons per layer, activation function, learning rate, and optimization algorithm to improve spectrum sensing. The model's input features included energy values from current and previous sensing events and Zhang statistics, while the output indicated the primary user's channel status. Their approach assigned distinct ANN architectures to different radio technologies, resulting in a 63 % performance improvement over Cumulative Energy Detection (CED) and Improved Energy Detection (IED) techniques.

Additionally, Nasser et al. [74] introduced a hybrid spectrum sensing scheme, training an MLP with two hidden layers using test statistics from six different spectrum sensing detectors. The input dataset incorporated statistical outputs from techniques such as energy detection (ED), autocorrelation detection, maximum eigenvalue detection, and goodness-of-fit detection, along with SNR values. Results demonstrated that incorporating more than three detectors increased the probability of detection (PoD) to 0.93 while simultaneously minimizing the false alarm rate (FAR).

As shown in Table 11 adapted from Syed et al. [49], the analyzed studies demonstrate that simple ANNs and MLP-based DNNs are effective for spectrum sensing across a variety of input types, from energy and cyclostationary features to geodesic distances, detector outputs, and raw radio signal statistics. Most approaches use one to three hidden layers, with minimal preprocessing (often limited to filtering or transient peak removal). Reported performance varies significantly by scenario: while PoD values approach 1 at higher SNRs (≥–10 dB) or when leveraging multiple detectors, some studies still achieve PoD > 0.6 even at challenging SNRs (−20 dB) with limited training samples or multiple secondary users. Overall, these results indicate that lightweight ANN and MLP-based architectures can achieve high detection probabilities (often > 0.8) with low false alarm rates when appropriately tuned for the sensing environment and feature set.

Finally, MLP-based models demonstrate strong potential in spectrum sensing under low SNR conditions. Early implementations show a probability of detection (PoD) reaching 1 at SNR ≥ -10 dB using ANN architectures [75]. At lower SNRs, such as −20 dB, PoD remains around 0.4 with a probability of false alarm (PFA) of 0.022 [76], while more advanced MLP structures achieve $PoD > 0.8$ under similar noise levels [73]. Ensemble approaches using multiple detectors yield an average PoD of 0.93 with near-zero false alarm rates [74]. Additionally, ROC curve evaluations confirm $PoD > 0.6$ in the challenging SNR range of -20 to -14 dB [70]. From a hardware perspective, MLPs with 1–3 hidden layers are lightweight and compatible with embedded systems such as Arduino or SDR-based platforms, enabling practical deployment. Their shallow architecture ensures low computational complexity (FLOPs), making them energy-efficient and suitable for real-time applications, especially in resource-constrained environments.

6.1.2. Deep neural networks

In a neural network, the first layer is the input layer, which receives features from the data and learns from them. The intermediate layers, known as hidden layers, process and combine the input data. The final layer is the output layer, where the model's predictions are made based on its performance. When the model undergoes extensive training on a large dataset, the accuracy of classification and categorization improves. The key distinction between a Neural Network (NN) and DL lies in the number of hidden layers. Increasing the number of hidden layers, or the depth of the network, transforms a neural network into a Deep Neural Network (DNN) [39].

DNNs extend traditional MLPs by incorporating multiple hidden layers, significantly enhancing their ability to model complex, non-linear patterns in spectrum data. These models eliminate the need for

Table 10
Applications of multilayer perceptrons (MLPs) in spectrum sensing.

AI technique	Purpose	Details	Ref.
MLP (IG-DNN)	Centralized CoSS	Aggregates data from multiple SUs at various SNR levels to improve detection accuracy.	[70]
MLP	Signal Classification	Optimizes hyperparameters for PU channel status classification, improving spectrum sensing performance by 63 %.	[73]
MLP	Hybrid Spectrum Sensing	Combines test statistics from multiple spectrum sensing detectors to enhance detection probability and reduce false alarms.	[74]

CoSS: Cooperative Spectrum Sensing, DNN: Deep Neural Networks, PU: Primary User, SNR: Signal-to-Noise Ratio, SU: Secondary User.

Table 11
ANN and MLP-based approaches for spectrum sensing.

Technique	Input to algorithm	Prep. data	Features of architecture	Metrics	Performance	Ref.
ANN	1 energy, 3 cyclostationary feature values of amplitude-modulated signal in AWGN	N/A	Single hidden layer	PoD, PFA	PoD can reach 1 when testing SNR ≥ -10 dB and training SNR is between -30 dB and 10 dB.	[75]
ANN	4 features obtained from the energy and Zhang statistics of current and previous samples from 4 radio technologies	Filtering of signals, removal of transient peaks	Single hidden layer	PoD, PFA	PoD close to 0.4 at SNR = -20 dB for FM broadcasting signals with PFA = 0.022 and sample size of 500.	[76]
DNN	Geodesic distance between signals	Simulated with MATLAB	MLP with 3 hidden layers	PoD, PFA, ROC curves	PoD > 0.6 for PFA = 0.2, SNR = -20 dB to -14 dB, and 2 SUs.	[70]
DNN	Four radio technologies using USRP	Filtering of captured signals, removal of transient peaks	MLP with 2 hidden layers	PoD vs. SNR curves	PoD > 0.8 for SNR = -20 dB, number of training samples per class = 100.	[73]
DNN	Test statistics from six detectors and SNRs	N/A	MLP with 2 hidden layers	PoD, FAR	Average PoD of 0.93, almost zero FAR with more than three detectors.	[74]

ANNs: Artificial Neural Networks, AWGN: Additive White Gaussian Noise, DNN: Deep Neural Networks, MLP: Multilayer Perceptrons, PoD: Probability of Detection, PFA: Probability of False Alarm, FAR: False Alarm Rate, ROC: Receiver Operating Characteristic.

manual feature engineering, allowing them to autonomously learn relevant signal characteristics from raw data. By leveraging their high representational capacity, DNNs have been widely adopted for spectrum sensing tasks, including signal detection, noise estimation, and classification in CRNs. Table 12 presents identified contributions to spectrum sensing using DNN-based approaches.

One of the primary applications of DNNs in spectrum sensing is signal detection, where these models can accurately identify signals without requiring prior knowledge of the transmission environment. This capability enables more efficient and adaptable spectrum management in dynamic wireless conditions, improving detection accuracy even in highly unpredictable environments [40]. Similarly, DNNs play a crucial role in noise estimation, extracting key features from received signals to enhance sensing performance, particularly in low-SNR scenarios. By effectively distinguishing useful signal components from background noise, DNN-based approaches improve spectrum sensing reliability under adverse conditions [42].

Beyond fully connected deep networks, deep CNNs have been employed for spectrum sensing due to their ability to process high-dimensional spectral data efficiently. CNNs extract spatial features from received power spectra, enabling them to recognize signal patterns more effectively than traditional machine learning approaches. Additionally, transfer learning techniques have been integrated into CNN-based models, allowing them to quickly adapt to new wireless environments with minimal retraining [45]. These properties make CNNs particularly valuable for applications requiring rapid response to changing spectral conditions, such as cooperative spectrum sensing and interference mitigation. Furthermore, the Deep Sensing CNN architecture proposed in Peng et al. [77], which consists of two convolutional layers and two dense layers, demonstrated strong performance in detecting Frequency-Limited Gaussian-distributed signals under Additive White Gaussian Noise (AWGN) conditions. It achieved results close to those of an optimal sensing algorithm and exhibited robustness when transferred across different domains using transfer learning.

DNNs have also played a role in SL-based spectrum sensing. As described by Cao et al. [40], supervised learning models, particularly DNNs, can exploit radio frequency spectrum characteristics to assist in intelligent spectrum decision-making. These models have been particularly effective in Reconfigurable Intelligent Surface (RIS)-assisted 6G networks, where they optimize spectrum allocation and enhance Non-Orthogonal Multiple Access (NOMA) performance by allowing multiple users to share time-frequency resources [78–80].

Deep learning models have demonstrated significant potential in spectrum sensing, particularly in RIS-assisted 6G networks. Cao et al. [40] explored DNN-based spectrum sensing, where the model exploits radio frequency spectrum characteristics to assist RIS controllers in making intelligent spectrum decisions, improving spectral efficiency with reduced computational complexity.

Finally, DNNs offer enhanced detection accuracy across dynamic and low-SNR environments by effectively extracting and representing complex features [40,81,82]. Integration with Convolutional

Table 12
Applications of deep neural networks (DNNs) in spectrum sensing.

AI technique	Purpose	Details	Ref.
DNN	Signal Detection	DNNs accurately detect signals without prior knowledge of transmission environments, enhancing detection accuracy in dynamic conditions.	[40,81]
DNN	Noise Estimation	Extracts key features from received signals to improve spectrum sensing performance, especially in low SNR conditions.	[42,82]
DNN (CNN Integration)	Spectrum Sensing	CNNs process high-dimensional spectral data, enabling effective recognition of signal patterns and improving detection performance.	[77]
DNN (RIS-based SS)	Spectrum Management	Assists Reconfigurable Intelligent Surface (RIS) controllers in optimizing spectrum allocation and enhancing NOMA performance in 6G networks.	[40,78,79]

CNNs: Convolutional Neural Networks, DNN: Deep Neural Networks, NOMA: Non-Orthogonal Multiple Access, RIS: Reconfigurable Intelligent Surface, SNR: Signal-to-Noise Ratio.

layers improves recognition and sensing capabilities [77], while hybrid schemes involving Reconfigurable Intelligent Surfaces (RIS) further enhance spectrum utilization and management performance in future 6G systems [79]. Hardware feasibility remains moderate, as DNNs typically require more resources than MLPs but are still deployable in real-world systems with careful optimization. In terms of complexity, DNNs involve deeper architectures with nonlinear activations such as ReLU and softmax, balancing accuracy with runtime performance. Their adaptability to non-stationary signal conditions and robustness at low SNR make them suitable for semi real-time implementations, particularly in settings where moderate hardware support is available.

6.2. Convolutional neural networks (CNNs)

6.2.1. Standard CNNs

CNNs are a powerful tool in SS due to their ability to automatically extract spatial and spectral features from input data, reducing reliance on manual feature engineering. CNNs process spectrum data by treating spectral matrices similarly to images, making them particularly effective for signal classification, noise robustness, and cooperative spectrum sensing tasks. Table 13 presents identified contributions to spectrum sensing using CNN-based approaches.

AI-enabled spectrum management applications can be categorized into Resource Management, Beam Management, and Channel Management, with the latter further divided into Spectrum Sensing and Channel Estimation [41]. Within this framework, CNNs have demonstrated enhanced detection accuracy, robustness in noisy environments, and improved adaptability across diverse conditions. Key contributions include the application of deep CNNs with transfer learning for efficient TV signal detection across diverse environments and the use of CNNs for noise estimation, demonstrating the advantage of DL in refining Radio Frequency (RF) signal detection over conventional methods.

CNN-based spectrum sensing techniques. Several studies have further validated CNN-based spectrum sensing techniques. Cao et al. [40] highlighted that CNN models improve cooperative spectrum sensing and spectrum monitoring by eliminating the dependence on predefined threshold values, leading to enhanced signal detection accuracy across various SNR conditions [7,59]. Additionally, CNNs trained on power spectrum data have been shown to outperform conventional detection methods in colored noise environments, improving robustness in non-Gaussian noise scenarios [42,87].

CNN-based models have also been applied to spatially aware spectrum sensing, where CNNs analyze correlation matrices of sensed signals to facilitate adaptive cooperative sensing [45,88]. This enables SUs to dynamically adjust sensing parameters based on spatial correlations, improving spectrum utilization efficiency. Another approach addresses covariance matrix graph representations in CNN models to enhance OFDM signal detection accuracy, demonstrating CNNs' ability to process structured spectral information for more reliable signal classification [42,89].

Beyond structured datasets, CNNs have proven effective in real-world scenarios. The authors in Saber et al. [90] employed a CNN with two convolutional layers to classify signals generated from an Arduino board and received by an RTL-SDR. By transforming signals into time-frequency representations, the model achieved superior classification performance compared to traditional methods, particularly when varying the distance between the transmitter and receiver. Similarly, Zheng et al. [87] designed a CNN model with two convolutional layers and six residual blocks to address noise power uncertainty in spectrum sensing. Their model was trained on signals with various modulation techniques, including QAM and PSK, achieving a 90.55 % accuracy rate. It also demonstrated strong performance in detecting unseen modulations and real-world Aircraft Communications Addressing and Reporting System (ACARS) signals, outperforming traditional spectrum sensing methods in Probability of Detection (PoD) [39].

Furthermore, CNNs have also been applied in challenging spectrum sensing conditions. For example, CNNs have shown remarkable effectiveness in handling noise uncertainty [42]. Techniques such as the Matching Network-Based Environment-Robust Spectrum Sensing (MN-ERSS) [91] and the DetectNet Neural Network [81] combine CNN and LSTM layers (Fig. 10) to utilize modulated signal structures, enhancing detection in noisy environments.

CNNs have also demonstrated substantial performance gains in low-SNR environments [42]. The LeNet-5 architecture [92] improved SS using OFDM cyclic spectrum properties, while other studies [93] incorporated cyclostationary and energy features, achieving significant detection improvements at −20 dB SNR.

The authors in Kim et al. [94] proposed a CNN-based DL framework for classifying the modulation schemes used in Wi-Fi 6 and 5G downlink OFDM transmissions, aimed at spectrum sensing. It introduces a cyclic autocorrelation function (CAF)-based estimator to determine the OFDM symbol duration and cyclic prefix length without requiring access to protocol control information. The signal is then processed to extract modulation-insensitive features, particularly addressing synchronization errors. These features are transformed into 2D histograms of phase and amplitude, which serve as the input to a CNN classifier. The system operates with IQ samples and does not need preambles or resource allocation knowledge. It performs robustly in both synthetic (AWGN) and over-the-air (OTA) environments, achieving ≥ 97 % classification accuracy at SNRs above the transmission threshold.

Later on, Chew and Cooper [95] reformulates the spectrum sensing problem as an image classification task and applies a repurposed CNN (AlexNet) to distinguish between noise and the presence of a signal. It uses only a small training dataset (a few hundred samples) and

Table 13
Applications of convolutional neural networks (CNNs) in spectrum sensing.

AI technique	Purpose	Details	Ref.
CNN	Signal Detection	CNNs enhance detection accuracy and adaptability in dynamic spectrum environments, improving signal classification and reducing dependency on predefined thresholds.	[40,41]
CNN	Noise Estimation	CNNs are utilized for noise estimation, enhancing the detection of RF signals in noisy environments and improving robustness in non-Gaussian noise conditions.	[41,42]
CNN	Spectrum Sensing	CNNs analyze correlation matrices of sensed signals, enabling dynamic adjustment of sensing parameters for cooperative spectrum sensing.	[45]
CNN	Signal Identification	CNNs process wideband spectrum data for automatic signal identification, improving precision in separating signals of interest from noise and interference.	[42,83]
CNN	CoSS, Spectrum Sensing	CNNs are applied in cooperative spectrum sensing scenarios, improving detection accuracy by aggregating sensing outcomes from multiple secondary users.	[84,85]
CNN	Spectrum Monitoring, PU act. recog.	CNNs are used for detecting PUs activity patterns and recognizing PUs presence through modulation format identification.	[42,86]

CoSS: Cooperative Spectrum Sensing, CNNs: Convolutional Neural Networks, PU: Primary User, PU act. recog.: PU Activity Recognition.

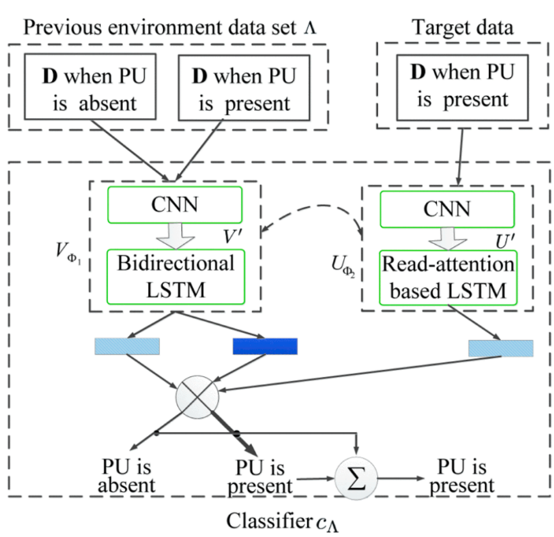

Fig. 10. Architecture of the Matching Network-Based SS, composed of CNN and LSTM, as proposed by [91].

evaluates performance in the presence of interference and under varying signal conditions. The CNN-based detector outperforms both traditional energy detection (ED) and other ML techniques reported in earlier work. A key advantage is that the CNN does not require noise floor estimation, unlike ED, which relies on constant false alarm rate (CFAR) thresholds tightly linked to accurate noise measurements. The CNN detector maintains high detection probability (98.75%) at 0 dB, having been trained on signals at −9 dB SNR, and achieves better performance with less sensitivity to interferers. Additionally, the fine-tuning approach demonstrates that complex CNNs like AlexNet can be effectively adapted for new tasks using limited samples and standard hardware. While AlexNet's performance is strong, the authors suggest future directions in reducing computational complexity, broadening interference handling, and extending the model to more complex signal environments.

Moreover, CNNs have also been applied for wideband spectrum characterization and automatic signal identification. The benefits of employing DL for wideband spectrum characterization and automatic signal identification are substantial. As stood by [42], prior research thoroughly reviewed methods for automatic signal identification using DL, discussing approaches like object detection for signal classification and segmentation tasks to separate signals of interest (SOI) from noise and interference. These techniques transform wideband analysis into an image segmentation problem, improving precision and efficiency.

CNNs in cooperative spectrum sensing (CoSS). CNNs have also been successfully applied in CoSS scenarios. A study by [84] explored a CNN-based data fusion method for five SUs and a mobile PU, using raw I/Q samples transmitted over Rayleigh and Nakagami-m fading channels. The CNN model outperformed traditional ED-based AND and majority fusion rules across different fading conditions, with better performance observed under Rayleigh fading. Likewise, Chen et al. [85] introduced a CoSS algorithm that uses distributed SUs to gather sensing samples and mitigate fading and shadowing effects. This approach, featuring a DL-based detection framework, employed a CNN and utilized the sample covariance matrix as the test statistic, referred to as the CoSS-CNN algorithm. It demonstrated notable improvements in detection efficiency under complex conditions.

Lee et al. [96] proposed the Deep Cooperative Sensing (DCS) CNN for CoSS, which combined the sensing outcomes of multiple SUs. DCS demonstrated superior performance when aggregating soft decisions compared to traditional methods such as the K-out-of-N rule and SVM. It was particularly effective in high-noise scenarios and low-sample conditions, though at the cost of higher computational time. Similarly, Lee et al. [97] explored environment-specific CoSS using CNNs, incorporating spatial and spectral correlations in individual sensing. Their approach ensured improved CoSS performance with moderate training samples and lower computational complexity.

Furthermore, the authors in Giri and Majumder [98] proposed an Extreme Learning Machine (ELM)-based approach for CoSS. ELMs are a type of feedforward neural network where only the output weights are optimized, while the hidden layer parameters remain fixed. The authors conducted simulations in both fading and non-fading environments. The results indicate that the ELM-based method may outperform conventional techniques under these conditions.

CNNs in spectrum monitoring and PU activity recognition. CNN models have also been used for PU activity recognition, for example, extracting energy correlation features for identifying PU activity patterns or applying CNNs for PU presence detection by recognizing modulation formats [42,99]. Further, Perumal and Nagarajan [100] have proposed a compressive spectrum sensing framework for 5G networks using CRNs. It addresses a CNN classifier to detect PU activity based on a cyclostationary feature detection method integrated with compressive sensing techniques. The framework employs CNNs to learn from the spectrum data, processed through compressive sensing, and aims to optimize detection probability and minimize Mean Squared Error (MSE). The CNN-based model is trained and tested on datasets generated across various SNR levels. Performance is benchmarked against two existing models: the Adaptive Wideband Spectrum Sensing (WSS) algorithm and Modulation Classification and Sensing using Functional Adaptive Modulation (MCS-FAM). The proposed method consistently achieves higher detection probability, especially under low SNR, and lower MSE than the competing techniques. An accuracy of 98.5 % is reported.

CNN-based methods have demonstrated improved spectrum occupancy detection without relying on specific PU transmission knowledge. These studies collectively highlight the versatility of CNNs in spectrum sensing, reinforcing their ability to improve detection accuracy, noise robustness, and cooperative sensing performance in various spectrum environments. Table 14, partially adapted from Syed et al. [49], shows that the reviewed CNN-based spectrum sensing approaches demonstrate substantial diversity in input representations, architectural complexity, and performance outcomes. Inputs span cyclostationary and energy features, covariance matrices, spectrograms, modulation-specific signals, synthetically generated waveforms, and real-world spectrum measurements, with preprocessing generally limited to normalization, standardization, or time–frequency transformation. Architectures vary from shallow networks with a single convolutional layer to highly complex designs, such as the 85-layer Deep-CRNet with residual-inception blocks, reflecting differing trade-offs between computational cost and detection accuracy.

Performance results indicate that even lightweight CNNs can outperform classical detectors, achieving notable gains at low SNRs, for example, a PoD approximately 0.5 higher than conventional cyclostationary feature detection at −20 dB SNR, while deeper networks consistently deliver high accuracy, with several studies reporting classification rates exceeding 90 % and PoD values above 0.8 under adverse noise and fading conditions. These findings underscore the adaptability of CNN-based models for diverse spectrum sensing contexts, particularly when designed to balance complexity with the target deployment environment.

CNN-based spectrum sensing models consistently outperform classical and shallow learning baselines in both classification and detection tasks. For instance, CNN-3 achieves a $FROC - AUC$ of 0.994 [101], while other models report nearly perfect detection (PoD = 0.994) and extremely low false alarms (PFA = 0.0023) [90]. High detection rates, such as 96.7 % PoD at PFA = 1.9 % under SNR = −18 dB, further underscore their effectiveness [102]. Classification tasks also benefit from CNNs, with accuracies up to 90.55 % [87], and reliable performance is maintained across SNR ranges including −6 dB and even at −20 dB [88,95,103].

Regarding hardware feasibility, simpler CNNs like LeNet-5 are deployable on edge devices, while deeper networks incorporating residual or inception blocks require GPU or FPGA acceleration. The architectural depth contributes to increased FLOPs, particularly in complex variants like Deep-CRNet (85 layers). Nevertheless, energy-efficient alternatives and model compression techniques allow for trade-offs that preserve real-time adaptability in constrained settings.

Furthermore, the authors in Kumar et al. [104] evaluated spectrum sensing performance using metrics such as probability of detection (P_d), false alarm rate (FAR), probability of false alarm (PFA), bit error rate (BER), peak-to-average power ratio (PAPR), and power spectral density (PSD). The experimental setup included 3000 training samples, a 512-point FFT, 5 MHz channel bandwidth, and a roll-off factor of 0.32. Deep learning models (CNNs and RNNs) outperformed traditional methods like matched filtering (MF) and energy detection (ED). CNNs and RNNs achieved reliable detection at lower SNRs (1.2 dB and 1.6 dB) compared to MF (4 dB) and ED (4.8 dB), and showed better PFA-to-P_d trade-offs in noisy conditions. PSD analysis showed reduced spectrum leakage with deep models, with out-of-band radiation decreasing from 1800 (ED) to 3000 (CNNs). For BER at 10^{-3}, CNNs and RNNs required lower SNRs (3.8 dB, 4.7 dB) than MF and ED. PAPR results also favored DL models, which yielded significantly lower values (6.4 dB for CNNs vs. 12.1 dB for ED). Overall, DL-based sensing offers clear advantages in detection accuracy, spectral efficiency, and power performance.

6.2.2. Hybrid CNN approaches

Hybrid CNN models have been increasingly adopted in SS due to their ability to integrate feature extraction capabilities with advanced optimization techniques, enhancing detection accuracy, energy efficiency, and security in dynamic environments. Table 15 presents identified contributions to spectrum sensing using hybrid CNN-based approaches. A notable hybrid approach involves CoSS using transfer learning, as demonstrated by Do and Koo [106]. Their model employs SUs to harvest energy while transmitting spectrum sensing decisions to a fusion center. This CNN-based CoSS framework enhances security and energy efficiency by incorporating private-key encryption for secure data transmission. The fusion center utilizes CNN-based processing to aggregate sensing data and determine the active status of PUs, thereby maximizing network security levels. However, further numerical evaluations are required to optimize the model for more dynamic CRNs settings. The model's performance was assessed using the following evaluation metrics: Probability of Detection (P_d), Probability of False Alarm (P_f) and Sensing Error (P_e).

To address noise uncertainty in spectrum sensing, hybrid CNN models have been developed with optimized feature extraction techniques [42]. For instance, the Short-Time Fourier Transform CNN (STFT-CNN) [107] integrates temporal and spectral features without requiring prior domain knowledge, while the Stacked Autoencoder Spectrum Sensing (SAE-SS) [108] utilizes a stacked autoencoder to mitigate timing delays, noise uncertainty, and carrier frequency offset (CFO).

Optimization techniques have further enhanced CNN-based spectrum sensing in fading channel conditions. One such method employs Glow Worm Swarm Optimization (GWSO) to refine CNN-based fading channel classification [109]. Compared to traditional classifiers such as SVMs, this approach achieves superior classification accuracy under both fading and non-fading conditions [42]. Additionally, several hybrid optimization-based approaches have been explored to enhance spectrum sensing and management [40]. These include: (i) KNN-Enhanced CNN Learning, where the integration of K-nearest neighbor with CNNs improves spectral efficiency and classification reliability by refining feature extraction and decision-making [110]; (ii) I/Q Sample-Based Deep Learning Models, which leverage in-phase/quadrature (I/Q) samples for deep learning-driven signal detection and spectrum management. This approach is particularly effective under sub-Nyquist sampling conditions, reducing computational overhead while maintaining high detection accuracy [111]; and (iii) Q-Learning for Channel Selection, where reinforcement learning techniques, such as Q-learning, optimize spectrum sensing sequences to enhance idle channel discovery and overall spectrum utilization efficiency [45].

Hybrid CNN architectures, including STFT-CNN and GWSO-optimized CNNs, exhibit enhanced performance under noise and fading scenarios, capitalizing on auxiliary transformations and optimization strategies [107,109]. Further improvements are observed when

Table 14
CNN-based approaches for spectrum sensing.

Input to algorithm	Prep. data	Key features of architecture	Eval metrics	Performance	Ref.
Cyclostationary and energy features	Standardization of cyclostationary and energy feature sets	CNN with 1 convolution layer	PoD vs. SNR curves	PoD about 0.5 higher than CFD at SNR: −20 dB	[103]
Oversampled raw signal data converted into image-like representations	Signals oversampled (OSR = 4)	fine-tuned AlexNet CNN architecture	Detection probability, constant false alarm rate (CFAR), accuracy in presence of narrowband interference	98.75 % detection probability at SNR = −6 dB; no noise floor required	[95]
Sensing data generated from multiple SUs (sim)	Individual sensing results contain spatial and spectral correlations modeled explicitly; data generated through detailed simulation of mobile SUs and PU transmissions with fading, shadowing, and noise effects.	CNN with 3 convolution layers (DCS)	Average of Probability of False Alarm (PFA) and Probability of Miss Detection (PMD), Receiver Operating Characteristic (ROC) curve: PFA vs. Probability of Detection; Area Under Curve (AUC) values for ROC.	AUC for DCS with SD: 0.952 and DCS with HD: 0.95	[96]
CM of current frame and matrix formed by stacking CMs from past frames	Appropriate stacking of CMs from past frames	CNN with 2 convolution layers Inspired from LeNet architecture	PoD vs. SNR curves	PoD > 0.725 with deterministic PU activity and uncorrelated model, SNR: −20 dB, antennae: 8	[88]
IQ samples from SISO Wi-Fi 6 and 5G DL signals (resampled to 20 MHz); transformed into 2D histograms of phase and amplitude	OFDM parameter estimation using CAF to determine subcarrier spacing (SCS) and CP length; OTA and AWGN datasets	CNN classifier trained on histograms	Classification Accuracy, Robustness to high-order modulations, Channel diversity (AWGN, OTA)	≥ 97% with OTA data above transmission SNR threshold	[94]
Sample covariance matrix of received signals from multi-antenna array (M = 28 antennas, N = 100 samples)	Compute sample covariance matrix from received signal; signals modeled as Gaussian vectors	CNN with 2 convolutional layers from LeNet-5 architecture	ROC curves, Probability of Detection (PD), Probability of False Alarm (PFA), PD vs. SNR curves	PoD = 96.7 % at PFA: 1.9 % and SNR: −18 dB	[102]
3.5 GHz band spectrograms	Spectrogram data normalized and structured for single and multichannel detection	CNN with 1 convolution layer called CNN-3	ROC curves and Area Under ROC Curve (ROC-AUC), free-response ROC curves (FROC) and normalized area under FROC curve (FROC-AUC)	CNN-3 has FROC-AUC of [0.994, 0.398] for Set A and 95 % confidence interval	[101]
BPSK modulated random bits incorporating Rayleigh and Nakagami-m fading, AWGN	Data normalization	CNN with 1 convolutional layer	Classification accuracy	Classification accuracy of 77.99 % for Rayleigh fading and 77.33 % for Nakagami fading	[84]
Signals of 8 modulation types and noise generated by simulation	Power normalization	NN with 2 convolution layers, 6 residual blocks in cascade	PoD vs. SNR curves	Classification accuracy: 90.55 %, PoD > 0.6 for SNR = 10 dB and pink noise	[87]
Filtered and sampled radio signals generated in MATLAB	Raw signal samples	CNN with 2 convolution layers (Deep Sensing)	Probability of Detection, Probability of False Alarm, Area Under the Curve (AUC) for Pd vs. number of training examples (in range [0, 1000])	PoD > 0.8 for PFA = 0.05, SNR = −4 dB	[77]
Synthetically generated complex waveforms of PU signal and noise	Complex waveform frames, binary classification labels (Signal = 1, Noise = 0), no synthetic impairments for OTA signals subset	Deep-CRNet implemented in MATLAB R2020a; uses 64-dimensional latent vector from GAP layer; trained via SGDM optimizer with momentum = 0.9	Accuracy, Precision, Recall, Specificity, False Positive Rate (FPR), False Negative Rate (FNR), ROC-AUC, Average Precision (AP), binary cross-entropy loss	Classification accuracy = 94.47 % at SNR = 0 dB	[105]
Compressed spectrum measurements derived via cyclostationary feature detection, processed from signals at various SNR levels	Signals sampled under multiple SNR conditions, and processed via compressive sensing	CNN classifier trained to detect PU activity from compressed input	Detection Probability (Pb), False Alarm Probability (PFa), Miss Detection Probability (MDP), Mean Squared Error (MSE), Receiver Operating Characteristic (ROC) across SNR ranges	Accuracy up to 98.5 % in low SNR scenarios, Pb 0.65 vs. 0.55 (Adaptive WSS) and 0.6 (MCS-FAM); Lower MSE than baseline models.	[100]
Artificially generated ASK and FSK modulated signals with an Arduino Uno card and a 433 MHz wireless transmitter	Transformation into time-frequency representations	CNN with 2 convolution layers	PoD, PFA, classifier accuracy	PoD = 0.994, PFA = 0.0023 and classifier accuracy: 100 %	[90]

Table 14
continued

Input to algorithm	Prep. data	Key features of architecture	Eval metrics	Performance	Ref.
A matrix of individual sensing results from multiple SUs over multiple bands	Collected real world spectrum data	CNN	Accuracy	Accuracy of 89 % in spatial/spectrum correlation	[97]
Local Sensing decisions from SUs	Sensing data is normalized based on SNR, ranging from −16 dB to −6 dB for training the CNN	CNN, RL, TL	Probability of Detection (P_d), Probability of False Alarm (P_f), Sensing Error (P_e)	–	[106]

Table 15
Applications of hybrid CNN approaches in spectrum sensing.

AI technique	Purpose	Details	Ref.
Hybrid CNN	CoSS, Spectrum Sensing	CNN-based cooperative sensing with transfer learning improves security, energy efficiency, and detection accuracy by incorporating private-key encryption for secure data transmission.	[106]
STFT-CNN	Noise Estimation, Noise Uncertainty	Hybrid model combining Short-Time Fourier Transform (STFT) and CNN for feature extraction, addressing noise uncertainty in spectrum sensing.	[42,107]
SAE-SS	Spectrum Sensing, Noise and Timing Delay Mitigation	Stacked Autoencoder (SAE) combined with CNN mitigates timing delays, noise uncertainty, and CFO in spectrum sensing.	[42,108]
CNN, GWSO	Spectrum Sensing, Fading Channel Optimization	Hybrid CNN model optimized by Glow Worm Swarm Optimization (GWSO) for superior classification in fading and non-fading channels.	[42,109]
KNN-Enhanced CNN	Signal Detection	Hybrid model integrating KNN with CNN to improve spectral efficiency and classification reliability.	[40,110]
I/Q Sample-Based DL	Spectrum Management, Signal Detection	DL model using I/Q samples for signal detection and spectrum management in sub-Nyquist sampling conditions.	[40,111]
Q-Learning, CNN	Spectrum Sensing, Channel Selection	Q-learning integrated with CNN for optimizing spectrum band sensing sequences and improving idle channel discovery.	[45]

CFO: Carrier Frequency Offset, CoSS: Cooperative Spectrum Sensing, CNNs: Convolutional Neural Networks, DL: Deep Learning, GWSO: Glow Worm Swarm Optimization, I/Q: In-phase and Quadrature, KNN: K-Nearest Neighbors, PU: Primary User, SAE: Stacked Autoencoder, SU: Secondary User, STFT: Short-Time Fourier Transform.

integrating KNN modules, which raise classification precision [110], or when incorporating encryption mechanisms that ensure secure and reliable CoSS [106]. However, these hybrid models increase processing demands, rendering them more suitable for cooperative edge-cloud systems rather than fully on-device execution. The added layers and algorithmic components translate to moderate-to-high FLOPs, limiting energy efficiency for ultra-low-power applications. Still, improved robustness and adaptability, especially through transfer learning, justify the overhead in many practical deployments, where real-time operation is secondary to detection reliability.

6.2.3. Hybrid CNN-LSTM networks

Hybrid CNN-LSTM architectures integrate CNNs for feature extraction with long short-term memory (LSTM) networks for temporal pattern recognition, significantly improving SS performance, especially in low-SNR conditions. Table 16 presents identified contributions to spectrum sensing using hybrid CNN-LSTM-based approaches. CNNs excel at capturing spatial features, while LSTMs retain temporal dependencies, making them particularly effective in scenarios involving noise uncertainty, such as overcoming the SNR-wall problem, where SS detectors fail when SNR falls below a certain threshold [42].

One such approach, DetectNet [81], integrates convolutional, LSTM, and fully connected layers to extract hidden structures from PU signals. It utilizes the RadioML2016.10a dataset, which includes eight modulation types: 8PSK, BPSK, QPSK, GFSK, CPFSK, QAM64, QAM16, and PAM4. The noise samples follow a zero-mean Circularly Symmetric Complex Gaussian (CSCG) distribution, with energy normalization applied to mitigate sensitivity to signal energy variations. A two-stage training strategy, incorporating early stopping and monitoring performance trade-offs across epochs, enhances its performance. DetectNet outperforms conventional models in probability of detection, and probability of false alarm across various modulation schemes. Its extended application, SoftCombinationNet, uses DetectNet at each sensing node to aggregate soft information for centralized PU status decisions.

The article [113] presents a DL-based spectrum sensing model designed to enhance detection under low SNR conditions, called SenseNet. The method combines multiple features, including energy statistics, power spectrum, cyclostationary characteristics, and I/Q components, into a unified input matrix. The architecture is based on a modified CLDNN, like structure with LSTM layers to improve time-series feature extraction. The network is trained using synthetic datasets generated in MATLAB, including QPSK, 8PSK, and noise signals, over a Rayleigh fading channel across an SNR range of −20 dB to 5 dB. At −20 dB, SenseNet achieves 58.8 % detection accuracy, outperforming traditional CNNs by 3.3 %, validating the benefit of multi-feature fusion and time-series modeling via LSTM. The study confirms that increasing the number of features yields diminishing returns, and highlights the trade-off between detection improvement and feature-set complexity. It also notes the need for large labeled datasets and suggests exploring unsupervised learning in future work for real-world deployment.

Another study [99] employs a CNN-LSTM model that extracts energy correlation features from covariance matrices using CNN layers

Table 16
Applications of hybrid CNN-LSTM approaches in spectrum sensing.

AI Technique	Purpose	Details	Ref.
DetectNet (CNN-LSTM)	Signal Detection	CNN-LSTM model that extracts hidden structures from PU signals, achieving superior detection performance across various modulation schemes. Utilizes RadioML2016.10a dataset for training.	[81]
CNN-LSTM	PU Activity Detection	Model extracts energy correlation features from covariance matrices and feeds them into an LSTM for PU activity modeling, outperforming traditional SS methods under Gaussian/Laplace noise conditions.	[99]
DLSenseNet (CNN-LSTM)	Spectrum Sensing	Hybrid model incorporating CNN, LSTM, and modified inception blocks, demonstrating robustness in diverse noise environments and outperforming other deep learning-based models.	[3]
CNN-BiLSTM-SA-CONCAT	Spectrum Sensing	BiLSTM-based CNN architecture with self-attention and concatenation layers, showing the best sensing performance at low SNR levels and superior robustness across various modulation schemes.	[112]
CNN-LSTM Fusion	Low-SNR Spectrum Sensing	Combines CNN and LSTM networks to improve SS accuracy under low-SNR conditions by extracting both spatial and temporal features.	[46]
Parallel CNN-LSTM	Low-SNR Spectrum Sensing	Parallel CNN-LSTM model for SS without prior channel knowledge, improving recognition of signal types in severe noise conditions.	[42,99]
CNN-RNN Hybrid	Signal Detection	Hybrid CNN-RNN model enhancing SS accuracy by distinguishing PU signals from noise, showing promise in challenging wireless environments.	[42,76]

BiLSTM: Bidirectional Long Short-Term Memory, CNN: Convolutional Neural Networks, CR: Cognitive Radio, DNN: Deep Neural Networks, LSTM: Long Short-Term Memory, PU: Primary User, RNN: Recurrent Neural Networks, SNR: Signal-to-Noise Ratio.

before feeding them into an LSTM network to model PU activity patterns. The architecture comprises two convolutional layers, an LSTM layer, and a dense layer. It processes QPSK-modulated PU signals under Gaussian/Laplace noise conditions and employs a lognormal state sojourn time model with semi-Markov state transitions for PU activity representation. This model surpasses traditional SS techniques such as MED, SSE, and AGM, as well as the DL-based APASS detector, demonstrating superior robustness in noisy and noise-uncertain environments.

DLSenseNet [3] follows a similar hybrid CNN-LSTM approach but incorporates modified inception blocks, LSTM layers, and FC layers. The model utilizes eight modulation types from the RadioML2016.10b dataset and employs CSCG noise vectors to simulate PU activity absence. Due to its energy normalization process, DLSenseNet generalizes well across diverse noise environments. Comparative evaluations show that it outperforms models such as CNN, ResNet, LeNet, LSTM, CLDNN, and DetectNet in detection performance across various modulation schemes while maintaining minimal sensitivity to modulation order.

A BiLSTM-based deep neural network (DNN) proposed by Xing et al. [112] combines convolutional, BiLSTM, concatenation, self-attention, and fully connected layers. By utilizing bidirectional scanning of input data, this architecture captures both long- and short-term dependencies. Ablation studies reveal that the CNN-BiLSTM-SA-CONCAT model achieves the best sensing performance at SNR levels below −5 dB, outperforming CNN, CNN-LSTM, and other BiLSTM-based variants. Despite longer training and detection times, it consistently reports the lowest sensing error across various SNR conditions. Its robustness is further confirmed by consistent performance across different modulation schemes and sample lengths, where longer signal samples provide improved temporal information and reduced sensing errors.

The fusion of CNN, LSTM, and fully connected networks further enhances SS accuracy in low-SNR conditions without prior PU information [46,114]. These hybrid CNN-LSTM models have been particularly effective in PU activity detection, as they efficiently extract both spatial and temporal features [42]. By handling feature extraction with CNNs and using LSTMs for long-term memory retention, these architectures demonstrate improved detection probabilities, reducing false alarms and enhancing spectrum occupancy detection. CNN-LSTM combinations have also been explored for CoSS, where traditional decision threshold-based methods are replaced with deep learning-based models

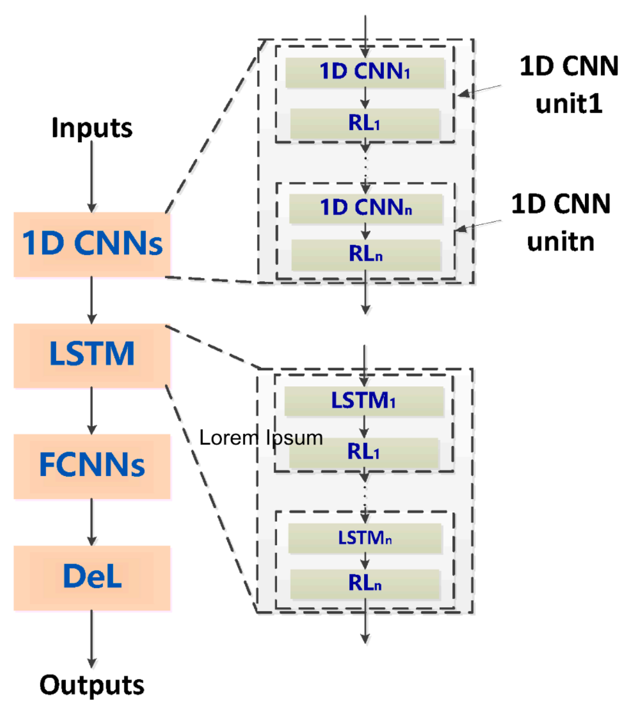

Fig. 11. Architecture of a hybrid CNN-LSTM network for SS, proposed by [114].

[42]. These hybrid architectures achieve high detection probabilities even at low SNR levels, significantly improving SS performance in cooperative CR environments. LSTM-based CoSS models are particularly useful for handling fading scenarios and noise variations, demonstrating increased adaptability to dynamic CRNs [84].

In low-SNR environments [42], hybrid CNN-LSTM models have been tailored to function effectively in these conditions. Xu et al. [115] proposed a parallel CNN-LSTM model to enable SS without prior channel knowledge, allowing the recognition of signal types even under severe noise conditions. Additionally, BiLSTM architectures combined with self-attention mechanisms have been employed to extract regional features and correlations, significantly improving performance under low-SNR conditions [112].

Hybrid models integrating CNNs and RNNs have shown promise in improving SS accuracy for low-SNR signals. A CNN-RNN hybrid model presented in Solanki et al. [3] enhances SS accuracy by distinguishing PU signals from noise, making it a viable alternative for challenging wireless environments. Furthermore, hybrid CNN-LSTM models have been proposed to improve CoSS flexibility and detection accuracy [116]. These models excel in extracting spatiotemporal features, making them resilient to low SNR conditions and dynamic user topologies. LSTM-based CoSS models have been applied to fading scenarios and noise variations, providing robust SS solutions in cooperative CR environments [42,84].

Table 16 describes the analyzed CNN-LSTM-based spectrum sensing techniques leverage hybrid architectures that combine convolutional layers for spatial feature extraction with LSTM blocks to capture temporal dependencies, often enhanced by specialized modules such as inception, bidirectional LSTM (BiLSTM), or self-attention layers. These models typically utilize inputs from benchmark datasets (for example, RadioML2016), synthetic modulation signals, or covariance matrices, with preprocessing largely limited to energy normalization or covariance computation to mitigate noise and complexity. Despite the architectural sophistication, performance remains modest at extremely low SNRs (for example, -20 dB), with reported probabilities of detection generally around $0.4 - 0.47$ and sensing errors below 0.35 in most cases, often at controlled false alarm rates (for example, $PFA \leq 0.1$). Nonetheless, these hybrid models demonstrate improved temporal learning capabilities over purely convolutional networks, particularly in scenarios involving non-stationary or sequential signal characteristics, positioning them as promising solutions for robust spectrum sensing in challenging noise environments.

Finally, hybrid CNN-LSTM models combine spatial and temporal learning capabilities, leading to notable gains in detection accuracy and reliability. DetectNet achieves superior performance across various modulation schemes, with improved PoD and PFA compared to baseline methods [81]. More advanced structures, such as CNN-BiLSTM-SA-CONCAT, deliver optimal results at SNRs below -5 dB, attaining the lowest sensing error among compared models [112]. CNN-LSTM configurations show robust operation at -20 dB SNR, with PoD ranging from 0.4 to 0.47, sensing error below 0.35, and PFA remaining at or below 0.1 [3,99]. These models demonstrate resilience under fading and dynamic spectrum conditions. On the hardware side, the inclusion of sequence modeling via LSTM and deep convolutional modules increases computational demand, often necessitating high-end GPUs or FPGAs for real-time capability. Dual-pipeline architectures introduce significant FLOPs and detection latency, making deployment on constrained devices difficult. Nonetheless, their high accuracy and robustness make them viable candidates for centralized, cloud-supported cognitive radio systems where energy cost is secondary to performance.

6.3. Recurrent neural networks and variants

6.3.1. Recurrent neural networks

Recurrent Neural Networks (RNNs), a subset of artificial neural networks, are designed for time-series data by incorporating feedback loops that allow past outputs to influence future predictions. This capability makes them particularly well-suited for spectrum sensing tasks, where temporal dependencies play a critical role in detecting PU activity and managing spectrum availability. RNN-based models have demonstrated significant improvements in spectrum sensing accuracy by capturing long-term dependencies in signal patterns [42]. One notable approach integrates an ensemble of CNN and RNN architectures to classify PU and SU statistics, thereby estimating spectrum availability in 5G base stations. This hybrid CNN-RNN model effectively mitigates the impact of noise uncertainty, leading to enhanced detection performance even in challenging wireless environments [42].

The study in Jung and Jeong [117] proposes a RNN-based spectrum sensing technique for CR systems that determines the spectrum occupancy status (busy or idle) of PUs using only received signal energy, without requiring prior knowledge of PU signal characteristics. The methodology involves applying a Fast Fourier Transform (FFT) to sequentially received signals to obtain their spectral representations. These spectra are then stacked to form a 2D spectrogram, which is segmented based on sensing channel bandwidth. These spectrogram segments are fed into a binary classification deep learning model to decide channel occupancy. To prepare the data, FFT is applied to each segment of incoming signal data, and the resulting spectra are stacked to form a 2D spectrogram. This spectrogram is then divided into segments according to channel bandwidth, creating input samples for the deep learning model. Each sample is labeled as either "busy" or "idle," forming a binary classification dataset.

The architecture features a deep learning model based on RNNs, trained specifically for spectrum sensing without relying on intentionally idle channels. Compared to previous CNN-based approaches, the RNN model has approximately two-thirds the number of learnable parameters, offering a more lightweight alternative. Evaluation metrics include False Detection Rate (FDR) and Miss Detection Rate (MDR), alongside comparative performance analyses against CNN-based detectors and traditional threshold-based methods. The model's sensitivity to SNR conditions is also considered in the evaluation. In terms of performance, the RNN-based detector achieves results comparable to CNN-based models without the need for dedicated empty channels. It outperforms threshold-based detectors by approximately 2 dB and offers significantly improved spectral efficiency due to the elimination of

By capturing both spatial features via CNNs, and temporal correlations through RNNs, these architectures offer a robust solution for dynamic spectrum access, ensuring more reliable PU activity detection and improved spectrum efficiency.

6.3.2. Long short-term memory networks

Long Short-Term Memory (LSTM) networks are an advanced form of RNNs that address the vanishing gradient problem, making them particularly effective for capturing long-range dependencies in spectrum data. These networks excel at extracting temporal correlations from time-series spectrum data, a key aspect of SS in CRNs. A notable LSTM-based spectrum sensing model was introduced by Lees et al. [101], which addressed the power of CNNs alongside LSTMs. Table 18 presents identified contributions to spectrum sensing using LSTM-based approaches.

Soni et al. [118] investigated the temporal relationships inherent in spectrum data using empirical setups with LSTM networks. To ensure the training process was unbiased, they incorporated data with low-SNR. Their study demonstrated that a single hidden layer LSTM achieved the highest validation accuracy. In their work, two models were proposed: the LSTM-based SS (LSTM-SS) and PU Activity Statistics-based SS (PAS-SS). These models aim to capture temporal correlations and spectrum occupancy trends, which are crucial for predicting spectrum availability, planning spectrum sensing, and ultimately improving spectral efficiency and overall system performance. PAS-SS, in particular, utilizes an LSTM network with three hidden layers for prediction and an ANN with one hidden layer for classification.

The experiments conducted by Soni et al. [118] utilized data from two empirical setups: one employing a USRP device and the other

Table 17
CNN-LSTM-based approaches for spectrum sensing.

Input to algorithm	Prep. data	Key features of architecture	Eval metrics	Performance	Ref.
Positive samples: data generated in 8 modulation techniques based on RadioML2016.10a dataset, negative samples: additive noises based on zero mean circularly symmetric complex Gaussian distribution	Energy normalization	CNN-LSTM with 2 convolution and 2 LSTM layers (DetectNet); SoftCombinationNet for CoSS: 3 dense layers	ROC curves, PoD vs. SNR curves	PoD close to 0.4 at SNR = −20 dB, PFA = 0.1, for real state sojourn time model without noise uncertainty	[81]
RadioML2016.10b, CSCG noise vector with zero mean	Energy normalization	CNN-LSTM having an inception block followed by an LSTM block (DLSenseNet)	PoD, PFA, sensing error	For QAM-16 signals with sample length of 512, PFA = 0.04 %, sensing error = 12.78 %, and PoD = 46.98 % at SNR = −20 dB	[3]
Data generated using GNU Radio	Data normalization	CNN-LSTM having convolution, BiLSTM, and SA layers	Sensing error vs. SNR curves, ROC curves, detection, training time	Sensing error < 0.35 at SNR = −20 dB	[112]
Sample covariance matrix from the self-generated samples	Use of sample covariance matrix to reduce computational complexity	CNN-LSTM with 2 convolution layers and 1 LSTM layer	ROC curves, PoD vs. SNR curves	PoD close to 0.4 at SNR = −20 dB, PFA = 0.1, for real state sojourn time model without noise uncertainty	[99]

Table 18
Applications of LSTM approaches in spectrum sensing.

AI technique	Purpose	Details	Ref.
LSTM-SS	Spectrum Sensing	LSTM-based model for SS, capturing temporal correlations in spectrum data. Outperforms CNNs and ANNs in detection performance, particularly under low-SNR conditions.	[118]
PAS-SS (LSTM-ANN)	PU Activity Detection	Combines LSTM for prediction and ANN for classification, capturing spectrum occupancy trends. Achieved higher classification accuracy and detection performance compared to traditional methods.	[118]
LSTM	Energy Correlation Detection	LSTM network used to detect temporal energy correlations, enhancing detection performance in non-stationary environments. Boosts robustness in dynamic spectrum sensing.	[40,99]
CNN-LSTM Hybrid	Spectrum Sensing	Combines CNN and LSTM networks to improve SS, using CNN's spatial feature extraction and LSTM's temporal dependencies.	[101]

ANN: Artificial Neural Network, CNN: Convolutional Neural Network, LSTM: Long Short-Term Memory, PU: Primary User, SS: Spectrum Sensing, SNR: Signal-to-Noise Ratio.

using a digital spectrum analyzer. Comparisons between LSTM-SS and other machine learning techniques, such as CNNs and ANNs, revealed that LSTM-SS outperformed them in terms of detection performance, as evidenced by the PoD versus SNR curves. Furthermore, LSTM-SS also demonstrated higher classification accuracy compared to models such as Gaussian Naïve Bayes and Random Forest. However, despite the improved accuracy, LSTM-SS required longer training and execution times compared to other models. Additionally, LSTM-based models have been shown to be effective in detecting temporal energy correlations, which further enhances detection performance under non-stationary conditions [40,99]. This ability to model and predict energy trends over time significantly boosts the robustness and adaptability of spectrum sensing in dynamic environments.

We have also found a study [119] that proposes a hybrid DL-based spectrum sensing method combining LSTM and Extreme Learning Machine (ELM) to improve detection in cognitive radio networks, particularly under variable SNR conditions. Traditional methods (energy detection, cyclostationary features, matched filtering) are limited by complexity, sensitivity to thresholds, and dependence on prior signal knowledge. To overcome these limitations, the authors design a practical testbed using Raspberry Pi 3 Model B++ with an RTL-SDR dongle and GNU Radio, enabling real-time data acquisition across various SNR levels and frequency bands. The proposed LSTM-ELM model extracts temporal spectral features while integrating contextual parameters like energy, distance, and duty cycle for improved sensing accuracy. The model demonstrates superior performance over other learning-based techniques, particularly in low-SNR scenarios, achieving high Pd, low Pf, and improved accuracy, precision, and recall. However, this performance comes at the cost of long training times and higher computational demands, highlighting a trade-off between accuracy and efficiency. The study also points to future research needs such as handling multiple PUs and SUs, and broader applications in IoT/WSN and 5G/B5G contexts.

In summary, LSTM-based models are highly effective for detecting temporal patterns and optimizing spectrum sensing in CRNs. While they offer superior detection accuracy, their increased computational demands, particularly in terms of training and execution times, should be considered when choosing a model for real-time applications. As such, Table 19 shows that the approaches primarily exploit the recurrent architecture's capability to capture temporal dependencies in spectral data, leveraging either raw spectrograms from the 3.5 GHz

Table 19
LSTM-based approaches for spectrum sensing.

Input to algorithm	Features of architecture	Eval metrics	Performance	Ref.
3.5 GHz band spectrograms	LSTM cells with 50 % dropout between them followed by a fully connected layer and output layer	ROC curves	ROC-AUC of [0.994, 0.398] for Set B and 95 % confidence interval	[101]
Data acquired using USRP added with AWGN, and WGN, digital spectrum analyzer	LSTM cells followed by sigmoid activation (LSTM-SS), LSTM with 2 hidden layers + ANN with one hidden layer (PAS-SS)	PoD vs. SNR curves, ROC curves, classification accuracy vs. SNR curves	Classification accuracy > 90 % for SNR >= −10 dB	[118]

band or hardware-acquired signals augmented with noise. These models are relatively simple, incorporating stacked LSTM layers, often with dropout regularization or paired with additional fully connected or ANN layers, to enhance generalization and classification accuracy. Despite the absence of extensive preprocessing, the architectures demonstrate robust performance, achieving ROC-AUC values near 0.994 for spectrogram-based inputs and classification accuracies exceeding 90 % at SNRs as low as –10 dB. These results indicate that LSTM-based methods can effectively handle temporal dynamics and noise resilience, although their reliance on sequential modeling alone may limit their adaptability in more complex or highly non-stationary spectrum environments compared to hybrid CNN-LSTM counterparts.

6.4. Unsupervised learning approaches

6.4.1. Autoencoders

Autoencoders (AEs) are unsupervised learning models commonly used in SS for feature learning and anomaly detection. These networks are designed to reduce the dimensionality of input data while reconstructing it as accurately as possible. The architecture of an AE typically consists of three layers: an input layer, a hidden layer, and an output (reconstruction) layer. During training, the model performs an encoding-decoding process, where the encoding stage maps the input to a compressed hidden representation, and the decoding stage reconstructs the input from that representation. Variants of AEs, with multiple hidden layers in both the encoder and decoder, have been employed in SS tasks to further enhance performance. Table 20 presents identified contributions to spectrum sensing using AEs-based approaches.

Cheng et al. [120] developed two frameworks using Stacked Autoencoder (SAE) models to improve spectrum sensing for Orthogonal Frequency Division Multiplexing (OFDM) signals. Their first model, SAE-SS, utilizes an unsupervised feature extraction phase followed by fine-tuning with a Logistic Regression classifier. A second model, SAE-TF, was introduced to enhance performance under low-SNR conditions by incorporating both time and frequency domain signals as input, applying Fast Fourier Transform (FFT) to extract additional hidden features. While SAE-TF demonstrates superior sensing performance compared to SAE-SS, it requires more input units, leading to increased training complexity. Comparative evaluations revealed that SAE-TF achieved lower Probability of Miss Detection (PM) than traditional and neural network-based techniques under varying SNR conditions.

In another approach, a Variational Autoencoder (VAE) was applied in an unsupervised detector known as Unsupervised Deep Spectrum Sensing (UDSS) to reduce the reliance on labeled data. The VAE model differs from conventional AEs by incorporating a probabilistic parameter layer after the hidden layer. The VAE-GMM-based approach in UDSS uses three hidden layers in both the encoder and decoder to cluster the data, with minimal labeled noise data used to differentiate between clusters representing PU signals and noise. Performance evaluations showed that UDSS achieved near-CNN-level sensing performance with limited labeled data, consistently outperforming other detectors such as MED and Kernel k-means across various scenarios [121].

Subray et al. [122] explored different types of AEs like Deep, Variational, and LSTM AEs, for classifying LTE and Wi-Fi signals. The deep AE and VAE models had two hidden layers in both their encoder and decoder, while the LSTM AE used three hidden layers. For signal capture and simulation, USRP B210 with GNU Radio was employed for LTE signals, while Wi-Fi signals were generated using MATLAB. Precision and recall metrics indicated that the Deep AE, using exponential linear unit (ELU) activation, was the most effective model for the classification task.

Further advancements in spectrum sensing were achieved with SAE for OFDM feature extraction. SAE models have been found to extract hidden features from OFDM signals, significantly improving classification performance in low-SNR conditions [46]. SAE-SS, a specific SAE-based model, was introduced to address timing delay, noise uncertainty, and carrier frequency offset, thereby enhancing spectrum sensing in complex environments [42,120]. Another DL-based framework, end-to-end automatic wideband spectrum characterization (ASCW), integrates modulation classification, spectrum reconstruction, and sensing at sub-Nyquist rates, achieving improved performance across a range of conditions [123].

In the context of unsupervised learning [42], an Unsupervised Learning-based Detector (UDSS) for spectrum sensing has proven to be effective in handling non-Gaussian noise while requiring fewer labeled training samples [121]. Stacked Autoencoder based Spectrum Sensing Method (SAE-SS) and SAE-SS5 with time-frequency domain signals (SAE-TF), in particular, have been shown to provide enhanced accuracy in low-SNR scenarios, making them valuable tools for spectrum sensing in challenging environments.

Autoencoders, particularly SAE and VAE models, offer robust solutions for spectrum sensing, enhancing feature extraction, anomaly detection, and classification even in the absence of labeled data. These models have demonstrated significant advantages in a range of scenarios, including low-SNR environments, by improving detection performance and reducing the need for extensive labeled datasets. Their continued development and integration with other techniques, such as DBNs for PU activity prediction, are further optimizing spectrum utilization and cognitive radio systems [42].

As such, from Table 21, it is possible to mention that AE-based spectrum sensing approaches a both traditional and variational architectures to extract compact, noise-resilient representations from diverse input types, including OFDM-generated BPSK signals, real and simulated LTE and Wi-Fi samples, and covariance matrices of QPSK signals under Gaussian or Laplacian noise. These methods frequently employ minimal preprocessing, such as FFT transformation, signal augmentation, or covariance vectorization, and utilize multi-layer encoder-decoder networks, often combined with logistic regression classifiers or LSTM extensions, to enhance detection accuracy and generalization. The evaluated models demonstrate strong performance under varied conditions, with deep AEs achieving precision rates close to 99 98 % and variational AEs maintaining probability of detection (PoD) above 0.3 even at low SNRs (−14 dB) and stringent false alarm thresholds. These findings underscore the efficacy of AE-based designs in learning robust latent features for spectrum sensing, particularly in scenarios with non-Gaussian noise and complex signal structures, though their reliance on extensive training data and sensitivity to noise uncertainty remain potential limitations.

Table 20
Applications of autoencoder approaches in spectrum sensing.

AI technique	Purpose	Details	Ref.
SAE-SS	Spectrum Sensing	Stacked Autoencoder (SAE) model for feature extraction from OFDM signals, with fine-tuning using Logistic Regression. Achieved improved detection performance in varying SNR conditions.	[120]
SAE-TF	Spectrum Sensing	Enhanced version of SAE-SS incorporating time and frequency domain signals using FFT for feature extraction. Demonstrated better performance under low-SNR but with increased training complexity.	[120]
UDSS (VAE)	Unsupervised Spectrum Sensing	Variational Autoencoder (VAE) model for unsupervised spectrum sensing, reducing reliance on labeled data. Achieved near-CNN-level performance and outperformed traditional detectors.	[121]
Deep AE	Signal Classification	Autoencoder-based model for LTE and Wi-Fi signal classification using deep AEs. Outperformed other models in precision and recall metrics, particularly with ELU activation.	[122]
SAE-SS (OFDM)	Spectrum Sensing	SAE model used for feature extraction from OFDM signals, improving classification accuracy in low-SNR environments and mitigating issues like timing delay and CFO.	[42,120]
End-to-End ASCW	Spectrum Sensing	Deep learning-based framework combining modulation classification, spectrum reconstruction, and sensing at sub-Nyquist rates. Demonstrated improved performance across various conditions.	[42,123]

AE: Autoencoder, ASCW: Automatic Spectrum Classification and Wavelength, CFO: Carrier Frequency Offset, ELU: Exponential Linear Unit, FFT: Fast Fourier Transform, OFDM: Orthogonal Frequency Division Multiplexing, SAE: Stacked Autoencoder, SNR: Signal-to-Noise Ratio, SS: Spectrum Sensing, VAE: Variational Autoencoder.

Table 21
AE-based approaches for spectrum sensing.

Input to Algorithm	Key Features of Architecture	Eval Metrics	Performance	Ref.
OFDM system generated with BPSK modulation	SAE-SS and SAE-TF both have 2 hidden layers followed by Logistic regression classifier	PM vs. SNR, PFA vs. PM, PM vs. ratio of incorrect labels curves, training time	PM of SAE-TF increases from 0.0098 to 0.0114 with an increase in noise uncertainty from 0.5 dB to 1 dB at SNR = −10 dB	[120]
I/Q samples, phase and amplitude values derived from the I/Q samples of LTE signals acquired using a USRP and Wi-Fi signals generated in MATLAB	Deep AE: 2 hidden layers, VAE: 2 hidden layers, LSTM AE: 3 hidden layers	Precision and recall	Precision = 99.98 %, recall = 87.76 % for Deep AE using IEEE 802-11ax samples with 64-QAM modulation	[122]
Flattened CMs of unit energy QPSK modulated signals and Gaussian or Laplacian noise	VAE with 3 hidden layers in both encoder and decoder	ROC curves, PoD vs. SNR curves	PoD > 0.3 with Laplacian noise and uncorrelated model, SNR = −14 dB, PFA = 0.001, antennae = 16	[121]

6.4.2. *Deep belief networks*

Deep Belief Networks (DBNs) are probabilistic generative models that play a crucial role in PU activity prediction and spectrum occupancy classification within CR systems. These networks are particularly effective in classifying PU behavior, which increases detection probability and optimizes spectrum utilization in CR systems [42,124]. By learning complex hierarchical representations of input data, DBNs enable more accurate predictions of PU activity, thus improving the efficiency of spectrum allocation.

The ability of DBNs to classify PU behavior allows them to proactively predict PU activity, a critical aspect of minimizing interference and maximizing spectrum usage. By anticipating when and where PUs are likely to be active, DBNs can guide the allocation of spectrum resources, ensuring that SUs can operate without causing harmful interference to licensed users. This proactive approach to spectrum sensing enhances the overall efficiency and performance of CR systems, making them more adaptable to dynamic and unpredictable wireless environments.

The study in Almuqren et al. [125] introduces the Optimal DL Empowered Malicious User Detection for Spectrum Sensing (ODL-MUDSS) framework for identifying and classifying malicious users (MUs) in CRNs. The system is composed of three core components: preprocessing, DBN-based MU detection, and Sand Cat Swarm Optimization (SCSO) for hyperparameter tuning. The DBN model captures hierarchical features of sensing reports to distinguish between normal and malicious users, using Restricted Boltzmann Machines (RBMs) in a layer-wise unsupervised pretraining setup, followed by supervised fine-tuning for classification. SCSO further improves detection performance by optimizing model parameters. Evaluated under varying malicious user proportions and channel conditions (fading and non-fading), ODL-MUDSS achieves superior performance compared to baseline classifiers (SVM, Logistic Regression, Naive Bayes, stacking), reaching 97.75 % in accuracy, precision, recall, and F1-score, and higher Isolation Rate across MU ratios.

In summary, DBNs significantly impact spectrum sensing by improving PU activity prediction, which in turn helps reduce interference and optimize spectrum allocation strategies. Their use in spectrum occupancy classification further enhances CR systems' ability to adapt and operate efficiently, contributing to the advancement of intelligent spectrum management.

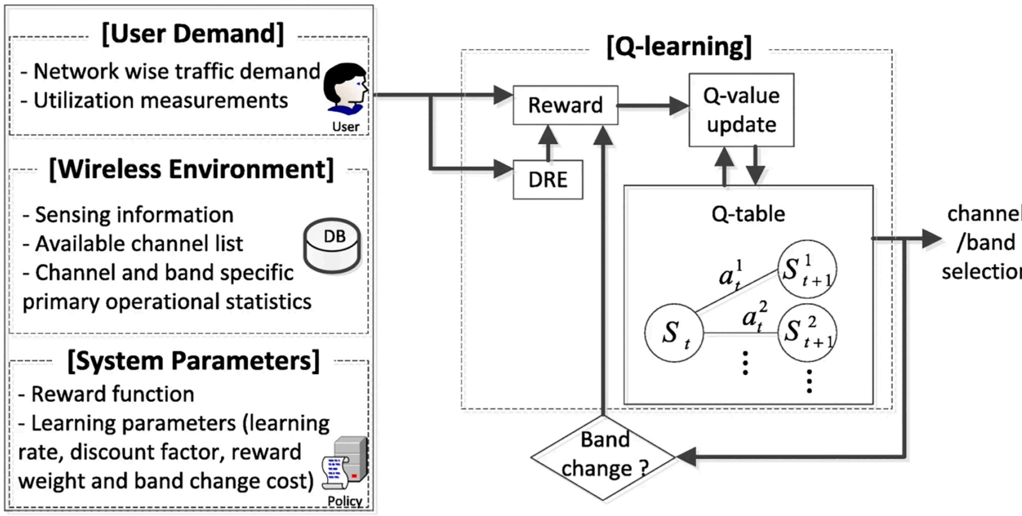

Fig. 12. System architecture for SS based on reinforcement learning, proposed by [127].

6.5. Reinforcement learning approaches

Reinforcement Learning (RL) has gained significant attention for optimizing various aspects of CRNs, such as spectrum sensing, energy efficiency, and resource allocation. By enabling autonomous learning and decision-making, RL enhances the adaptability of SUs in dynamic and distributed environments, where spectrum availability and network conditions constantly change. Table 22 presents identified contributions to spectrum sensing using RL-based approaches.

CoSS is a key area where RL has shown considerable potential, where multiple SUs collaborate to detect and report spectrum occupancy, with the goal of improving detection accuracy and reducing interference to PUs. RL-based approaches for CoSS can be categorized into centralized and distributed models, each offering distinct advantages.

Centralized CoSS typically relies on a head node or fusion center to manage tasks such as sensing allocation and optimizing parameters. One study proposed a system where the FC selects cooperating neighbors and their report sequence using a finite-horizon Markov decision process, collecting binary occupancy data from SUs and fusing it using majority rules [126]. Another study explored a clustered model where the cluster head uses Q-learning to select an optimal set of channels [127], as shown in Fig. 12. Specifically, Q-learning was used to dynamically select the optimal band group and channel. As a reward function, the system considered user demand, wireless environment and system parameters. The user demand module determined the desired data rate (DDR) of the network and measured the average channel utilization used.

The wireless environment module stores spectrum sensing results. The system parameter module is used to establish the reward function and Q-learning parameters. If the band of the newly selected channel is different from the previous one, the overhead for band group change is adopted in the reward function. In addition, Deep Reinforcement Learning (DRL) has been utilized to select cooperative partners and initiate cooperation requests [128]. In contrast, offline RL models have been employed to predict channel states for multiple future time steps, enhancing decision-making for long-term planning [129].

Distributed CoSS has gained attention due to its resilience against single points of failure and its ability to reduce latency. In a distributed environment, each SU learns the optimal channels to sense and shares its information with others for joint decision-making [130]. Distributed models have also been applied to multi-band, multi-user networks [142], where Q-learning and Deep Q-network (DQN) methods are used to balance exploration and exploitation, enhancing spectrum sensing performance across the network [131]. Other studies have explored approaches that integrate Q-learning with evolutionary game theory and multi-agent environments for improved cooperation and resource allocation [43,143].

In addition to improving spectrum sensing, RL has also been integrated with graph neural networks (GNNs) to optimize energy efficiency in CRNs. The combination of RL and GNNs has demonstrated significant improvements in system energy efficiency, particularly for distributed cooperative sensing across various network scales [51]. These methods not only enhance energy consumption management but also improve the overall performance of large-scale CRNs.

Moreover, RL has been used in real-time spectrum handoff decisions. For instance, Koushik et al. [52] implemented RL and Transfer Learning (TL) to manage spectrum handoff in a CRN testbed using universal software radio peripheral (USRP) and GNU Radio. This approach allows new nodes to adapt quickly by using TL, significantly reducing the number of packet transmissions required compared to traditional RL methods . This ability to adapt quickly to dynamic spectrum changes improves the long-term performance and real-time adaptability of the network. The authors in Oksanen et al. [141] have introduced a sensing policy for selected frequency bands in order to provide more opportunities to SUs; improving sensing performance, energy efficiency and throughput.

RL techniques such as Q-learning and DQNs have been employed to manage dynamic spectrum access without the need for accurate channel state information. These techniques enable SUs to make effective spectrum access decisions even in the absence of precise channel data, thereby increasing data rates and protecting PUs [132]. Multi-agent DRL has also been applied to device-to-device (D2D) communication, where sharing historical states, actions, and policies helps improve spectral efficiency and resource allocation without direct signal interaction [133].

Various RL-based CoSS schemes aim to achieve different cooperation gains. For example, one approach incorporates collision penalties into the reward function to prevent SUs collisions [43]. Other studies have focused on improving reliability by using actor-critic networks to select reliable cooperation partners, reflecting partner reliability in the reward function [134]. Energy efficiency has also been a focus, where Q-learning is used to train SUs to select the next hop for data transmission based on energy usage and remaining energy [135]. Throughput maximization has been explored through the multi-armed bandit (MAB) problem, optimizing the channel sensing order to maximize throughput [136].

Table 22
Applications of reinforcement learning in spectrum sensing.

AI technique	Purpose	Details	Ref.
Centralized CoSS	CoSS	Uses finite-horizon Markov decision process for SS and cooperation, with majority rule fusion.	[126]
Q-learning	CoSS, Channel selection	A clustered model with Q-learning for optimal channel selection in cooperative sensing scenarios.	[127]
Deep RL	CoSS, Cooperative Partner Selection	Uses DRL to select cooperative partners and optimize cooperation requests in spectrum sensing.	[128]
Offline RL	CoSS, Channel State Prediction	Predicts future channel states to optimize decision-making and improve long-term planning in CoSS.	[129]
Q-learning	CoSS	Distributed model where each SU learns optimal channels to sense, enabling joint decision-making and reducing latency.	[130]
Q-learning and DQN	CoSS	Combines Q-learning and DQN methods to enhance SS performance in multi-user, multi-band networks.	[131]
RL with GNNs	Energy Efficiency	Integrates RL with GNNs for energy-efficient distributed cooperative sensing across large-scale CRNs.	[51]
RL with Transfer Learning	Energy Efficiency, Spectrum Handoff	Uses RL and transfer learning for adaptive spectrum handoff decisions, improving performance in real-time CRN scenarios.	[52]
Q-learning	DSA	Employs Q-learning for spectrum access management without relying on accurate channel state information, enhancing data rates and protecting PUs.	[132]
Multi-agent DRL	DSA, D2D Communication	Applies multi-agent DRL to improve spectrum efficiency and resource allocation in D2D communication, sharing historical states, actions, and policies.	[133]
Q-learning with Collision Penalties	CoSS	Introduces collision penalties in reward function to prevent SU collisions and improve cooperation in CoSS.	[43]
Actor-Critic Networks	CoSS, Reliable Partner Selection	Uses actor-critic networks to select reliable cooperation partners based on reward functions reflecting partner reliability.	[134]
Q-learning	Energy-efficient Data Transmission	Q-learning applied to select the next hop for data transmission based on energy usage and remaining energy, optimizing energy efficiency.	[135]
Q-learning and MAB	Spectrum Sensing, Throughput Maximization	MAB and Q-learning used to optimize channel sensing order for maximum throughput in spectrum sensing.	[136]
DQN with Coordination Graphs	CoSS, Partner Selection	Enhances DQN-based partner selection with coordination graphs to reduce time and energy consumption in CoSS.	[137]
Q-learning with MAB and Upper Confidence Bound	Spectrum Sensing	Dual spectrum and partner selection approach that balances detection performance, scanning overhead, and access latency using Q-learning and MAB.	[138]
MADDPG	CoSS, Spectrum and Partner Selection	Uses MADDPG for spectrum and partner selection, demonstrating high success probabilities.	[139]
RL, RFE, ML-based sensor fusion	Collaborative spectrum sensing	A cloud-based heterogeneous collaborative spectrum sensing system.	[140]
Sensing policy	CoSS	On selected frequency bands, to provide opportunities to SUs	[141]

CoSS: Cooperative Spectrum Sensing, DSA: Dynamic Spectrum Access, D2D: Device-to-Device communication, DQN: Deep Q-Network, DRL: Deep Reinforcement Learning, GNN: Graph Neural Networks, MAB: Multi-Armed Bandit, MADDPG: Multi-Agent Deep Deterministic Policy Gradient, MDP: Markov Decision Process, PU: Primary User, RFE: Recursive Feature Elimination, RL: Reinforcement Learning, SS: Spectrum Sensing, SU: Secondary User, UCB: Upper Confidence Bound.

Table 23
RL-based approaches for spectrum sensing.

Technique	DL framework & CRN App	Datasets	Accuracy/metrics	Ref.
RL with GNN	energy efficiency optimization	custom network simulation data	energy efficiency improvement: 15 % compared to baseline	[51]
Channel occupancy patterns, SU detection probabilities	Q-learning for dynamic scanning preference list, D-UCB for cooperation partner selection	RL, Q-learning, Discounted Upper Confidence Bound (D-UCB)	Average number of attempts: Lower than reference algorithms, Average call block rate: Reduced compared to QLNC and QLKN, Average detection probability: Higher than both QLNC and QLKN algorithms, with better sensitivity to channel status changes	[138]
Channel status (idle or occupied), packet error rate (PER)	Channel sensing based on energy detection, reward feedback based on PER	RL (q-learning), transfer learning (knowledge sharing from expert nodes)	Number of packet transmissions to achieve optimal condition, performance drop during interruptions, and recovery time after spectrum handoff (RL: 20 packet transmissions (30 s), total time 30 s, TL: 3 packet transmissions (4 s), total time 16 s)	[52]

Later on, the article [140] presented CLOUD-DRF, a cloud-based heterogeneous collaborative spectrum sensing system. The framework simulates a real-world environment with edge devices (sensors) that possess varying capabilities, for example: SNR tolerance, observation length, and bandwidth. Each edge device runs a custom CNN model to perform modulation classification locally and extracts intermediate features (from the penultimate fully connected layer). These features are then transmitted to the cloud, where ML-based sensor fusion occurs. Three AI-based fusion strategies are evaluated: XGBoost-based fusion, recursive feature elimination (RFE) for feature selection; and RL for adaptive fusion. The goal is to optimize bandwidth usage by minimizing the number of features transmitted without sacrificing classification performance. The system proves robust under simulated heterogeneous conditions and offers a model-agnostic fusion framework suitable for next-generation network applications.

Further advancements have been made to improve the RL models themselves. Coordination graphs have been employed to enhance DQN-based partner selection, reducing both time and energy consumption [137]. A dual spectrum and partner selection approach has been introduced to balance detection performance, scanning overhead, and access latency using Q-learning and MAB with an upper confidence bound policy [138]. In addition, multi-agent deep deterministic policy gradient (MADDPG) has been used for spectrum and partner selection, demonstrating high success probabilities compared to other RL methods [43,139].

Reinforcement learning plays a pivotal role in enhancing the performance and efficiency of cognitive radio networks. It optimizes various aspects, including spectrum sensing, energy efficiency, resource allocation, and real-time adaptability. By enabling autonomous learning, RL techniques contribute to the advancement of more intelligent, adaptive, and efficient CR systems, offering significant improvements in spectrum management, cooperation, and network performance.

6.6. *Transfer learning*

Transfer learning has emerged as a powerful technique in CNNs to enhance SS across diverse environments. By using pre-trained models and adapting them to new spectrum conditions, transfer learning reduces training complexity while maintaining high detection performance. Table 24 presents identified contributions to spectrum sensing using RL-based approaches. One notable application of transfer learning in spectrum sensing involves TV signal detection. In this context, transfer learning applied to CNN-based models has demonstrated improved spectrum sensing accuracy across different environments, effectively adapting to variations in signal characteristics and noise levels [40].

A study further highlights the role of transfer learning in mitigating noise uncertainty, a critical challenge in spectrum sensing. By transferring knowledge from previously trained models, CNNs can better generalize across varying noise conditions, leading to more robust detection capabilities. Additionally, research has also proposed a deep CNN-based transfer learning architecture specifically designed for spectrum sensing in TV bands [144]. This approach not only ensures reliable performance but also significantly reduces the computational burden associated with training deep learning models from scratch. By reusing feature representations learned from prior datasets, the model achieves efficient signal classification with minimal retraining efforts.

A novel study [36] proposed an advanced spectrum sensing framework for 5G and LTE signals using DL models, with a strong emphasis on hyperparameter tuning and semantic segmentation. Two main strategies were explored. On the one hand, a custom semantic segmentation network trained from scratch on 128×128 RGB spectrograms derived from raw wireless signals (5G NR and LTE); and on the other hand, transfer learning using DeepLabv3 + with a ResNet-50 backbone trained on 256×256 spectrograms, which improved accuracy and reduced training cost. Training data included both synthetic (via MATLAB 5G/LTE toolboxes) and real-world captured signals, processed using standard-compliant channel models and converted to spectrograms using STFT. Signals were randomized in frequency to simulate dynamic spectrum conditions.

A pixel-wise semantic segmentation approach was used, labeling each pixel as LTE, 5G NR, or Noise. Performance peaked at 98.2 % accuracy (InceptionV3) and 97.3 % (DenseNet121) after systematic tuning, especially in conditions where low-SNR frames (often uninformative) were excluded. The models tested included: DenseNet121, InceptionV3, ResNet-18, ResNet-50, MobileNetv2, EfficientNet, and DeepLabv3 + (transfer learning). It also highlights challenges such as computational cost and the difficulty of sensing under low-SNR, dynamic conditions, suggesting that transfer learning and lighter models may be suitable for edge deployment. In summary, transfer learning in CNN-based spectrum sensing offers a practical solution for improving detection accuracy while reducing training complexity. Its ability to adapt to diverse spectrum environments makes it a valuable approach for real-world cognitive radio applications.

6.7. *Deep reinforcement learning*

In a Deep Reinforcement Learning (DRL) framework, deep neural networks such as CNNs, ANNs, and DNNs are used to approximate Q-values, mapping state-action pairs to expected rewards. Table 25 presents identified contributions to spectrum sensing using DRL-based approaches. The learning process involves iteratively adjusting weight coefficients using gradient-based optimization techniques. The choice of neural network architecture is crucial, as different models perform differently in DRL applications. CNNs, for instance, excel in spatial feature extraction, while fully connected DNNs offer flexibility for sequential decision-making [46].

Table 24
Applications of transfer learning in spectrum sensing.

AI technique	Purpose	Details	Ref.
Transfer Learning	SS, TV Signal Detection	Applies transfer learning to CNN-based models for improved spectrum sensing accuracy across different environments, adapting to variations in signal characteristics and noise levels.	[S29] in Cao et al. [40]
Transfer Learning	SS, Noise Uncertainty Mitigation	Uses pre-trained CNN models to generalize better across varying noise conditions, improving robustness and detection capabilities in challenging environments.	[42,144]
CNN-based Transfer Learning	SS, TV Bands	Proposes a deep CNN-based transfer learning architecture for spectrum sensing in TV bands, reducing computational burden and enhancing signal classification with minimal retraining.	[144]
Transfer Learning	SS	Utilizes knowledge from pre-trained models to adapt to diverse spectrum environments, improving detection performance and reducing training time.	[42,145]
Transfer Learning	SS for 5G and LTE signals	(1) Custom semantic segmentation model from scratch; (2) DeepLabv3 + with ResNet-50 via transfer learning	[36]

CNN: Convolutional Neural Network, SS: Spectrum Sensing, SU: Secondary User.

Table 25
Applications of deep reinforcement learning (DRL) in spectrum sensing.

AI technique	Purpose	Details	Ref.
DRL	SS, Power Control	Introduces a DRL-based joint algorithm for spectrum sensing and power control in cognitive small cells, optimizing spectrum usage and detecting PU presence while transmitting data. Achieves performance close to genie-aided methods in high-SNR regimes.	[146]
DRL	SS, Power Control	Applies DRL to power-domain NOMA systems, dynamically adjusting power levels and transmission strategies to enhance spectral efficiency and minimize interference.	[147]
Q-learning and DQN	CoSS	Combines Q-learning and DQN methods to enhance SS performance in multi-user, multi-band networks.	[131]

CNRs: Cognitive Radio Networks, NOMA: non-orthogonal multiple access, PU: Primary User, SS: Spectrum Sensing, SNR: Signal-to-Noise Ratio.

One important application of DRL in spectrum sensing is optimizing the sensing-throughput trade-off. Literature has also shown DRL-based joint spectrum sensing and power control algorithm for downlink communications in a cognitive small cell [46,146]. This approach allows SUs to detect the presence of PUs while simultaneously transmitting data, thereby maximizing spectrum utilization. The proposed scheme demonstrated performance close to that of a genie-aided method, particularly in high-SNR regimes, highlighting the potential of DRL to enhance spectrum efficiency in unknown environments.

Beyond spectrum sensing, DRL has also been applied to power-domain non-orthogonal multiple access (NOMA) systems. AI-driven techniques have been developed to improve spectrum utilization efficiency by enabling multiple PUs to share frequency bands through power-domain NOMA [45,147]. By dynamically adjusting power levels and optimizing transmission strategies, these methods enhance spectral efficiency while minimizing interference, making them particularly suitable for next-generation wireless networks. Overall, DRL represents a significant advancement in cognitive radio networks, providing autonomous decision-making capabilities for spectrum sensing, power control, and resource allocation. By integrating deep learning techniques, DRL enhances the adaptability and efficiency of CR systems, paving the way for intelligent and highly optimized wireless communication networks.

6.7.1. DL-based federated learning (deep FL)

DL-based FL techniques have gained significant traction in wireless communications, particularly in automatic modulation classification (AMC), traffic prediction, and spectrum management (see Table 26). Deep FL employs DNNs for decentralized training, allowing for improved learning performance while preserving data privacy. Wang et al. [53] introduced an FL-based distributed AMC system that utilizes deep learning models trained directly on client devices instead of a centralized server. This approach reduces data leakage risks while maintaining classification accuracy. In spectrum sensing, deep FL enhances CoSS by integrating CNNs, improving detection probability while minimizing communication costs [148].

Advanced applications of deep FL extend to wireless traffic management. Sabir et al. [41] demonstrated the effectiveness of deep FL in 5G traffic prediction, using RNNs, CNNs, LSTM, MLP, and gated recurrent units (GRU) to enhance forecasting accuracy while reducing computational costs. Additionally, Federated Edge Learning (FEEL) applies CNNs with Non-Orthogonal Multiple Access (NOMA) in 5G networks, significantly reducing energy consumption.

Deep FL's contributions to AI-driven spectrum management (AISM) are evident in its applications for Joint Radio Optimization (JRO), DSA, and traffic prediction [41]. By enabling decentralized data security and optimizing spectrum utilization, deep FL plays a crucial role in the evolution of wireless communication networks, particularly as FL extends to 6G architectures.

6.8. Summary of RQ1.2

The rapid evolution of wireless communication networks, particularly in B5G and future 6G systems, has intensified the demand for

Table 26
Deep learning approaches in federated learning (FL).

AI technique	Purpose	Details	Ref.
FL-based deep neural networks (DNNs)	AMC	Trains models on client devices instead of a centralized server to reduce data leakage.	[53]
CNN-based FL for CoSS	Spectrum sensing optimization	Improves detection probability while minimizing communication costs.	[148]
Deep FL for Wireless Traffic Prediction	5G traffic forecasting	Uses RNN, CNN, LSTM, MLP, and GRU for accurate low-cost predictions.	[S57, S58] in Sabir et al. [41]
Federated Edge Learning (FEEL) with CNNs	Energy-efficient network management	Applies NOMA in 5G networks to reduce energy consumption.	[S26] in Sabir et al. [41]
Deep FL	Spectrum Management, JRO, DSA	Enhances decentralized data security and spectrum utilization for 6G networks	[S51] in Sabir et al. [41]
Deep FL with RL (Deep FRL)	Intelligent spectrum management	Integrates RL with DL architectures to optimize resource allocation.	[S7] in Sabir et al. [41]
FL	Network efficiency, 5G Traffic Prediction	Utilizes both ML and DL for accurate forecasting.	[S58] in Sabir et al. [41]

AMC: Automatic Modulation Classification, CNRs: Cognitive Radio Networks, CoSS: Cooperative Spectrum Sensing, DNNs: Deep Neural Networks, DSA: Dynamic Spectrum Access, FEEL: Federated Edge Learning, FL: Federated Learning, GRU: Gated Recurrent Units, JRO: Joint Radio Optimization, LSTM: Long Short-Term Memory, MLP: Multi-Layer Perceptron, NOMA: Non-Orthogonal Multiple Access, RL: Reinforcement Learning, RNN: Recurrent Neural Network.

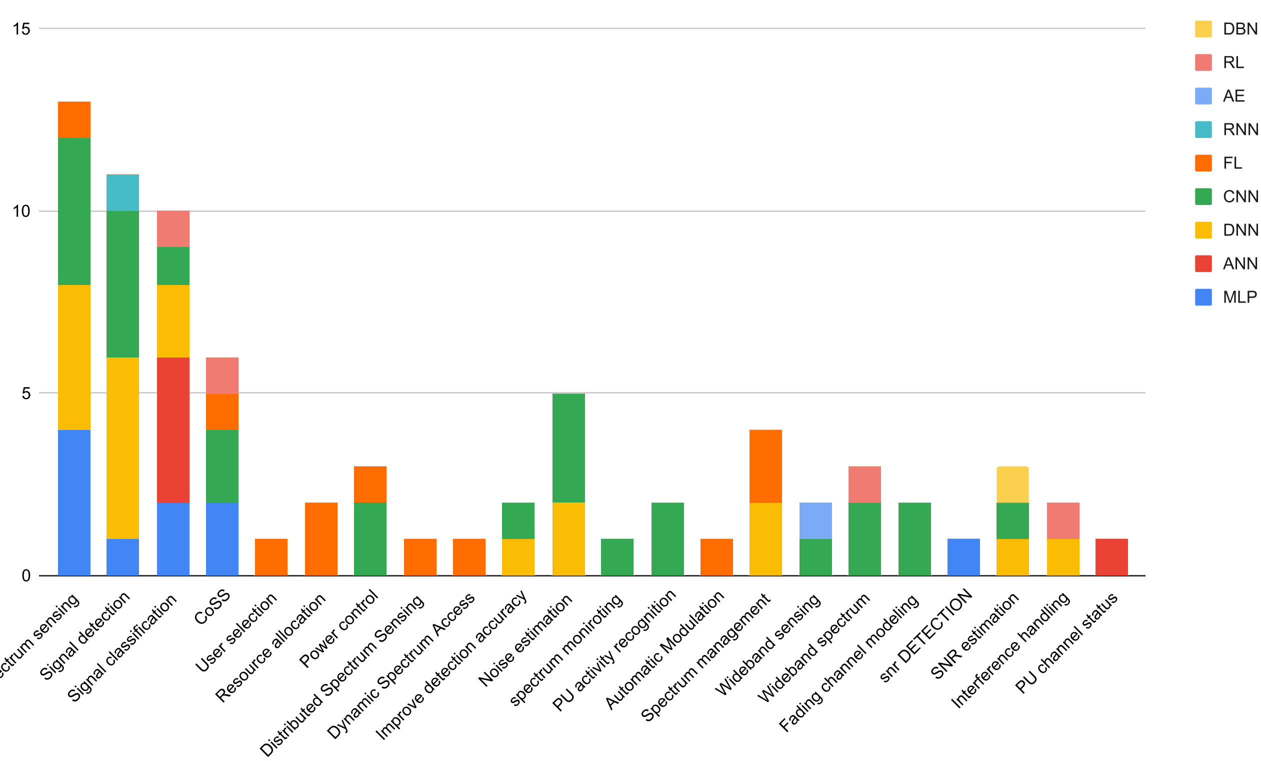

Fig. 13. Main Spectrum Tasks with DL techniques.

intelligent spectrum sensing solutions. Traditional spectrum sensing techniques often struggle in complex, dynamic environments characterized by interference, low-SNR conditions, and rapidly fluctuating spectral availability. DL has emerged as a transformative approach, offering powerful feature extraction, adaptive learning, and real-time decision-making capabilities. Table 27 categorizes key DL-based AI technologies applied to spectrum sensing, mapping each technique to its real-world application, strengths, and associated challenges; complemented by Fig. 13. The structure follows a functional perspective, linking each AI technique to a specific spectrum sensing task, such as signal detection, classification, interference mitigation, and channel modeling. This structured approach highlights how different deep learning models,

Table 27
Summary of RQ1.2: DL for spectrum sensing and their applications, strengths and limitations.

Purpose	AI technology	Real-world application example	Key strengths	Challenges/limitations
Signal Detection	FNNs (MLP, DNNs)	Cognitive Radio Networks (CRNs)	Flexible structure for non-linear mappings	Requires large amounts of labeled data
	CNNs (Standard, Hybrid)	Automated signal identification in IoT systems	Excellent for spatial and frequency domain analysis	Sensitive to input data quality
	RNNs (LSTM)	Real-time signal detection in dynamic environments	Captures temporal dependencies well	High computational cost for long sequences
Signal Classification	FNNs (MLP, DNNs)	Classifying interference types in dynamic channels	Good at multi-class classification	Prone to overfitting with complex data
	CNNs (Hybrid CNN-LSTM)	Wireless communication systems interference classification	Combines spatial and temporal feature extraction	Requires extensive training data
	RL (Deep RL)	Dynamic interference management in CRNs	Learns optimal strategies through experience	Training instability, long training times
Wideband Spectrum Characterization	k-means Clustering	Autonomous spectrum detection	Effective in unlabeled data scenarios, fast clustering	Struggles with complex, overlapping classes
	GMM	Probabilistic spectrum classification	Handles uncertainty well, flexible in real-world conditions	Requires significant training time, sensitive to initialization
Wideband Sensing	Unsupervised (Autoencoders)	Cognitive spectrum sensing in wideband systems	Efficient at detecting anomalies in wideband data	Struggles with highly complex, noisy data
	CNNs (Standard)	Spectrum mapping for wideband analysis in IoT	High accuracy in frequency analysis	Requires high resolution and large datasets
Interference Handling	RL (Standard RL)	Managing interference in 5G/6G networks	Adapts in real-time to interference patterns	Sensitive to the reward function design
	FNNs (DNNs)	Mitigating interference in satellite communications	Strong predictive power in interference scenarios	Needs extensive labeled training data
SNR Estimation	FNNs (MLP, DNNs)	Estimating SNR for signal processing in wireless systems	Good for high-dimensional signal data	May struggle with very noisy environments
	RNNs (LSTM)	Real-time SNR estimation for dynamic channels	Captures long-term dependencies in signal strength	Requires significant computational power
	Unsupervised (Deep Belief Networks)	Low-SNR estimation in dense environments	Effective in unsupervised scenarios with minimal prior data	Prone to poor convergence without proper tuning
Fading Channel Modeling	RNNs (LSTM)	Modeling fading in urban wireless networks	Learns complex temporal patterns in fading channels	Needs careful tuning for long sequences
	CNNs (Hybrid CNN-LSTM)	Wireless fading channel modeling for IoT systems	Combines temporal and spatial feature learning	High computation cost and complexity

including Feedforward Neural Networks (FNNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Reinforcement Learning (RL), contribute to enhanced spectrum efficiency and intelligent wireless resource management.

6.9. ML and DL: main performance metrics

Based on the analysis, Table 29 summarizes the common performance metrics employed across various AI techniques applied to spectrum sensing and related domains. It highlights which metrics are most frequently used with each method and provides notes on their typical interpretation or usage context. This overview facilitates understanding the evaluation focus depending on the AI approach. Further, Table 28 provides detailed descriptions of the key performance metrics referenced in the preceding table. Understanding these metrics is essential for interpreting and comparing results across studies utilizing diverse AI techniques.

Across the spectrum of AI techniques for sensing and classification tasks, certain performance metrics emerge as standard benchmarks, reflecting both the nature of the problems addressed and the characteristics of the algorithms.

The Probability of Detection (Pd) and False Alarm Rate (Pfa or Pf) are the most universally reported metrics, especially prevalent in classical methods like Support Vector Machines (SVM), Naïve Bayes, and ensemble learning techniques. These metrics directly capture the effectiveness and reliability of signal detection, which is paramount in spectrum sensing contexts. The Receiver Operating Characteristic (ROC) curve and its Area Under the Curve (AUC) counterpart complement these by illustrating the tradeoff between detection and false alarms, thus providing a holistic performance measure.

In reinforcement learning and capacity-optimization frameworks (such as KNN, Q-Learning, and RL-based models), additional metrics like network capacity (for example, FBS/MBS capacity) and convergence rate reflect the dynamic nature of learning and system throughput objectives. These metrics focus not only on detection performance but also on the operational efficiency and learning stability over time.

Neural network-based techniques, spanning from traditional Artificial Neural Networks (ANN) to more complex Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and hybrid architectures (for example, CNN-LSTM), commonly report Probability of Detection and False Alarm Probability (PoD/PFA) alongside accuracy measures. They often include specialized metrics such as sensing error and Probability of Miss Detection (Pm) to assess robustness and reliability in real-time or noisy environments. Additionally, training time and computational complexity become more relevant as models grow in depth and sophistication, particularly in hybrid and federated learning scenarios.

Table 28
Performance metrics description.

Metric	Description / Notes
Pd (Probability of Detection)	Probability of correctly detecting a signal
Pfa / Pf (False Alarm Rate)	Probability of falsely detecting a signal
ROC / AUC (Receiver Operating Characteristic / Area Under Curve)	Standard metric to show tradeoff of Pd vs. Pfa
Accuracy / Classification Accuracy	Correct classification rate
Training Time / Classification Time	Efficiency / computational cost
Precision / Recall	Used occasionally for classification quality
Sensing Error / Miss Detection Probability (Pm)	Errors related to detection
Capacity Metrics (FBS/MBS capacity)	For network throughput in RL/Q-learning models
Loss Metrics (MSE, Cross-Entropy)	Used in federated learning and training quality
Convergence Rate	How fast training converges

Table 29
Common performance metrics by AI technique.

AI technique	Common performance metrics used	Notes / Typical metrics description
SVM (Support Vector Machine)	Detection Probability (Pd), False Alarm Rate (Pfa), ROC (AUC), Training Time, Classification Accuracy, Precision, Recall	Pd and Pfa especially common; also run-time/training speed
Naïve Bayes / Bayesian Learning	Pd, False Alarm Rate, ROC, Total Bayesian Cost, Sensing Time	Pd and ROC common; Bayesian cost used in some studies
KNN / Q-Learning / RL-based	Capacity (FBS/MBS), Convergence Rate, Detection Probability, False Alarm Rate	Mostly in reinforcement or capacity optimization contexts
Ensemble Learning	Pd, Pf, Complexity, Performance vs. SU count and SNR	Pd and Pf (False alarm probability) standard
Federated Learning (FL)	Detection Probability, False Alarm Rate, ROC, Loss (MSE, cross-entropy), Accuracy, Convergence	Pd, Pf, ROC are most frequent
Artificial Neural Networks (ANN)	Probability of Detection (PoD), Probability of False Alarm (PFA)	PoD/PFA very common
Deep Neural Networks (DNN)	Pd, Pf, PoD, PFA, ROC curves, Accuracy, False Alarm Rate (FAR), SNR-wall	Pd, Pf, ROC, PoD/PFA dominate
Convolutional Neural Networks (CNN)	Pd, Pf, ROC, PoD vs. SNR curves, Classification Accuracy, Precision-Recall, Sensing Error, CFAR	ROC, Pd, Pf, PoD common; also accuracy and robustness
Hybrid CNN (CNN + other nets, for example, LSTM)	ROC, Pd, Pf, PoD, Probability of Miss Detection (Pm), Sensing Error, Training Time	ROC, Pd, Pf remain dominant; added sensing error, training time
Hybrid CNN-LSTM / CNN-RNN	Pd, Pf, ROC, PoD, Sensing Error, Classification Accuracy	Similar to hybrid CNN, emphasis on time-series modeling

Federated Learning (FL) introduces loss metrics such as Mean Squared Error (MSE) and cross-entropy, which focus on model convergence and training quality, emphasizing the distributed nature of training across multiple nodes while preserving privacy.

Overall, these trends demonstrate a clear distinction between metrics emphasizing detection accuracy and reliability, computational efficiency, and learning dynamics depending on the AI technique and application context. The choice of metrics thus reflects both the evaluation priorities and the technical characteristics inherent to each AI approach.

7. Main benefits in AI-driven spectrum sensing (RQ2)

The use of AI, particularly DL and ML techniques, has fostered various changes in SS and CRNs. These advances have significantly enhanced spectrum efficiency, interference management, and resource allocation, moving beyond traditional spectrum management techniques to smarter, adaptive solutions. This section integrates the key insights from the reviewed surveys and the primary studies included, highlighting the effectiveness of AI models, the challenges they face, and potential directions for future research (see summary in Table 30, and Fig. 14). The latter summarizes the distribution of ML and DL techniques applied in spectrum sensing and related cognitive radio tasks. It categorizes studies based on learning paradigms-supervised, unsupervised, hybrid, federated learning, and highlights the prevalence of popular models such as SVM, k-means, CNNs, RNNs, LSTMs, autoencoders, and reinforcement learning approaches. The visualization illustrates not only the diversity of AI techniques, but also the growing integration of hybrid and federated frameworks, reflecting the evolution of spectrum sensing research toward more adaptive and collaborative methods.

7.1. Machine learning and statistical approaches in spectrum sensing

Literature has shown that spectrum sensing methods based on ML and statistical analysis have been widely investigated. Khasawneh et al. [47] have explored various spectrum sensing approaches using machine learning models, including kernel functions and higher-order

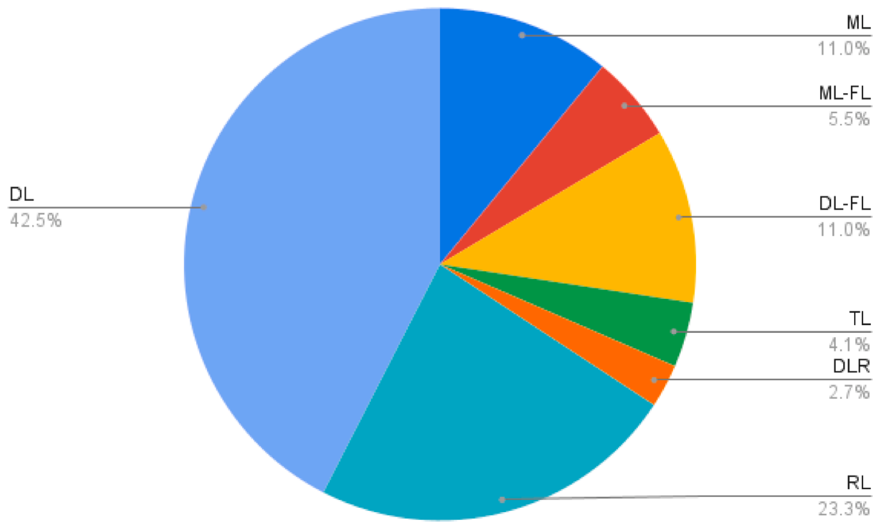

Fig. 14. AI Techniques in Spectrum Sensing: Percentage-Based Prevalence Across Studies.

Table 30
Synthesis of secondary studies with benefits, challenges, limitations, and future directions.

ID	Scope (years)	Focus	Key benefits	Challenges / limitations	Future research
S1	2015–2021	DL for CRNs	Improved detection accuracy and robustness to noise in wideband sensing [39,56,57]; Lower false alarms in low-SNR regimes.	High complexity and energy cost for real-time DL models [81,85]; Scarcity of large annotated datasets.	Lightweight DL architectures (CNN–LSTM hybrids) [77]; Dataset generation (synthetic + real) for CRNs.
S2	2011–2021	Spectrum Sensing in CRNs	Comprehensive comparison of ML (SL/USL) for cooperative and distributed sensing [59,63]; Insights on clustering for energy efficiency.	ML models struggle in non-stationary, fast-fading channels [64]; Limited scalability in large CRNs.	Adaptive and transfer learning methods for dynamic CRNs; Integration with FL for privacy [68].
S3	2013–2022	Multiple Access for 6G (includes SS)	Highlighted DL-enabled joint optimization of access and sensing; Potential for ultra-low latency 6G spectrum decisions.	DL models face generalization issues in unseen bands; 6G standardization gaps.	Cross-domain generalization (meta-learning) [84]; Joint access-sensing with RIS and THz bands.
S4	2013–2023	AI for Spectrum Management (6G)	Showed FL and DRL synergy for 5G/6G dynamic spectrum access [41]; Reduces central coordination needs.	Communication overhead in FL; Heterogeneity of devices degrades convergence.	Hierarchical FL (HFL) [68]; Edge-native DRL with low-bandwidth updates.
S5	2017–2023	DL for Spectrum Sensing	DL-CNN/DNNs achieve superior PU detection under noise [83,86]; DRL offers adaptive sensing strategies.	Requires GPU-level hardware; Vulnerable to adversarial attacks.	Robustness-oriented DL (adversarial training); Energy-aware DRL for mobile CRNs.
S6	2010–2021	RL for Cooperative SS	DRL optimizes sensing time/band selection [43,84]; Improved network throughput.	Training instability and exploration cost; Delayed convergence in large networks.	Model-based DRL (MBRL) to reduce training data; Safe RL for regulatory compliance.
S7–S13	Mixed (2010–2023)	Hybrid (ML/DL/FL for SS and CRNs)	Summarized benefits across cooperative SS, FL-enabled privacy, and hybrid CNN–MLP architectures [47–49].	Data heterogeneity (non-IID data in FL); Energy and bandwidth bottlenecks in distributed SS.	Semi-supervised and federated semi-supervised learning; Hardware-friendly pruning and quantization.

statistics. For example, a spectrum sensing method using a Gaussian kernel function maps observation signals to a high-dimensional feature space, which enables the construction of a kernelized test statistic for improved detection in Gaussian mixture noise environments. These models can help overcome the challenges posed by noise uncertainty in spectrum sensing, especially in complex environments.

Another notable technique is the Eigenvalue-Moment-Ratio (EMR)-based spectrum sensing, which has shown promise for IoT devices. This method achieves a high detection probability while maintaining low false alarm rates, making it well-suited for resource-constrained IoT applications [149]. Additionally, a statistical approach that employs multiple high-order cumulants has been proposed for full-duplex-enabled cognitive IoT networks, enhancing signal detection by analyzing the detailed properties of signals [47,53]. Within cognitive IoT networks, advanced statistical methods have been integrated with cognitive mechanisms for dynamic adaptation to changing network conditions. A study by Hong et al. [150] introduces a RF spectrum sensing receiver that improves frequency channel selectivity, enabling more efficient utilization of available spectrum resources in real-time.

7.2. Deep learning as a paradigm shift in spectrum sensing

Traditional spectrum sensing techniques, such as energy detection, matched filtering, and cyclostationary feature detection, are based on conventional signal processing methods. While these methods have been widely used, they often face limitations, especially in complex environments with low-SNR conditions or noise uncertainty. The integration of DL models has provided significant improvements in these areas by enabling the automatic extraction of complex patterns and features from raw data. This capability allows for better detection performance under challenging conditions, with the ultimate goal of efficiently utilizing spectrum resources [39,44,46,48–50]. Furthermore, the authors in Kumar [5] have concluded, based on experiments, that DL methods such as CNNs and RNNs can outperform conventional spectrum sensing techniques. RNNs handle dynamic signal changes over time, while CNNs enhance spatial resolution and noise reduction.

Performance gains with CNNs and hybrid models. Studies such as Zheng et al. [87] have demonstrated that Convolutional Neural Networks (CNNs) can significantly enhance spectrum sensing accuracy, surpassing conventional methods like maximum-minimum eigenvalue ratio-based and frequency domain entropy-based methods. By applying transfer learning, CNN models were shown to efficiently detect new, untrained signals, proving their adaptability to dynamic environments. The hybrid CNN-LSTM model proposed by Xie et al. [99] and DetectNet [81] enables superior feature extraction and signal classification, resulting in improved sensing accuracy even in noisy or fading channels.

7.3. AI-driven link quality estimation for reliable CRN communication

Accurate link quality estimation is vital for ensuring Quality of Service (QoS) in CRNs. AI-based models are increasingly being used to predict link reliability, allowing cognitive radios to dynamically adjust transmission parameters such as power and modulation schemes based on the estimated quality of the link. Traditional statistical models and predefined thresholds are being replaced by data-driven AI models that learn directly from past signal conditions, resulting in better adaptability and improved transmission efficiency. The authors in Zhang and Luo [48] have also pointed out the need for studying dynamic threshold settings.

Deep learning for proactive link adaptation. We have observed the use of CNNs and RNNs to process raw signal samples, SNR, and CSI, demonstrating that these AI models could effectively predict link stability [46]. This proactive link adaptation minimizes the occurrence of dropped connections and improves spectrum utilization. By processing large amounts of real-time data, these models can predict link quality ahead of time, enabling adaptive decisions that optimize communication between secondary users. Furthermore, predictive link estimation allows for reduced latency and increased throughput, which is especially critical in high-mobility scenarios.

7.4. Intelligent mobility management in cognitive radio networks

In CRNs, mobility management is essential for maintaining reliable communication, especially when users move between different spectrum bands or access points. The AI-driven approach to mobility management, including the use of RL and hybrid CNN-LSTM models, offers new ways to address the challenges of handover decision-making. These models are particularly effective in managing dynamic spectrum availability and user mobility patterns, ensuring smooth connectivity without significant delays or service interruptions.

Deep reinforcement learning for handover optimization. We have also identified the use of DRL for optimizing handover decisions in CRNs [42]. By considering factors such as channel quality, spectrum availability, and mobility patterns, the DRL agent dynamically selects the optimal handover strategy to ensure seamless communication. Simulation results indicated that DRL outperformed traditional methods, resulting in lower handover delays and improved network stability.

Predicting optimal access points with CNN-LSTM. The CNN-LSTM hybrid model proposed by Zheng et al. [87] showed great promise in predicting the optimal access points for mobile nodes. By incorporating features such as channel quality and user mobility, the model accurately forecasts which access point will provide the best connection for the mobile device. This approach minimizes unnecessary handovers and improves spectrum efficiency, thereby ensuring that secondary users remain connected to the most reliable access points at all times.

8. Main challenges and future opportunities in AI-driven spectrum sensing (RQ2)

Recent advances in DL, particularly CNNs and hybrid architectures, have significantly improved spectrum sensing performance in CRNs. However, these advancements face several challenges. Most models are trained on controlled, simulated datasets, such as RadioML2016.10b, which often fail to capture the full variability of real-world spectrum conditions [49]. Consequently, domain adaptation and data augmentation techniques are critical to enhance model robustness and applicability in dynamic environments. Additionally, efficient utilization of hardware resources is essential, since CR devices often have stringent limitations in memory, energy, and processing capabilities [44].

Overall, the surveyed technologies can be viewed along two complementary dimensions: (i) algorithmic techniques such as AI/ML, optimization, and mathematical modeling that drive decision-making and spectrum sensing accuracy, and (ii) infrastructural technologies such as IoT/CIoT, 5G/6G, and software-defined radios that enable real-world deployment. This dual perspective clarifies how advances in algorithms must be supported by scalable, resource-efficient infrastructures to achieve practical DSS systems.

DL-based algorithms typically achieve high accuracy under favorable high-SNR conditions, but their performance can degrade significantly under low-SNR environments [48]. Although some models show promise in maintaining effectiveness across varying SNR levels [3], robustness against adversarial attacks remains an open issue [44,48]. In particular, CRNs are vulnerable to spoofed signals, poisoning attacks during training, and carefully crafted perturbations that can mislead sensing models. Approaches such as adversarial training, robust feature extraction, and hybrid detection pipelines must be explored to safeguard AI-based spectrum sensing in hostile environments.

Another critical challenge lies in the generalization capabilities of AI models. Models trained on narrow or simulated environments often overfit, failing to generalize to diverse spectrum conditions characterized by mobility, interference, and weather variations. Overfitting not only reduces sensing reliability but also makes systems more susceptible to adversarial manipulation. To mitigate these limitations, future research should emphasize transfer learning, online learning, and active learning to improve adaptability in dynamic CRNs.

Computational complexity and latency further complicate practical deployment. Real-time inference is essential, yet many DL models are too resource-intensive for edge devices. Techniques such as model compression, pruning, and quantization can drastically reduce computational costs, though care must be taken to avoid significant accuracy loss. Combining these methods with edge AI, hardware-aware neural architectures, and knowledge distillation could enable efficient real-time sensing without sacrificing robustness.

Integrating AI-driven link quality estimation and spectrum sensing in distributed CRNs introduces additional hurdles, including computationally expensive model training and inference. Devices with limited resources struggle to perform real-time processing, and coordination among distributed AI systems introduces further complexity. To address these trade-offs, research should focus on distributed computing frameworks, model pruning, and efficient communication protocols to achieve low-latency and energy-efficient solutions suitable for CRNs.

AI-powered mobility management in CRNs encounters difficulties related to real-time decision-making, scarcity of training data, overfitting, model complexity, and model interpretability [104]. Federated learning (FL) offers a promising avenue, enabling collaborative model training across devices while preserving privacy and scalability. Combining federated approaches with multi-agent systems and edge computing could enhance adaptability and performance in large-scale, dynamic CRNs.

While FL and CoSS offer significant benefits, such as preserving user data privacy, enabling distributed model training, and improving spectrum sensing accuracy in heterogeneous environments, they also introduce important trade-offs. One of the primary challenges lies in balancing communication overhead with performance gains. FL requires periodic transmission of model updates between edge devices (secondary users) and the central aggregator, which can lead to increased bandwidth usage and energy consumption, particularly in large-scale networks with many participating devices. However, this overhead is often offset by the reduction in raw data transmission, since only model parameters or gradients are shared instead of full datasets, thus lowering the overall communication burden compared to centralized approaches.

Moreover, the size and complexity of the local models directly impact the communication cost. Larger models or more frequent updates increase overhead but may yield higher detection accuracy and faster convergence. Lightweight models, such as shallow neural networks or simpler classifiers, help mitigate this cost at some expense of potential accuracy. Additionally, cooperative sensing techniques can improve detection reliability by leveraging spatial diversity among SUs, but they require coordination and exchange of sensing information, further contributing to communication demands. In summary, system designers must carefully evaluate these trade-offs based on application requirements, network topology, and device capabilities to optimize both sensing performance and resource efficiency.

Furthermore, Table 31 illustrates the evolutionary progression of AI techniques in spectrum sensing, where each newer approach addresses limitations found in earlier methods. Classical techniques like SVM and Naïve Bayes faced challenges such as manual feature engineering, poor scalability, and unrealistic assumptions of feature independence. These were progressively addressed through hybrid models and neural networks capable of handling high-dimensional, non-linear relationships. Unsupervised methods like k-means, while useful for clustering, lacked classification capabilities and adaptability, challenges overcome by deep learning models that extract robust features from raw input. Similarly, feedforward neural networks were improved upon by recurrent models like LSTMs, which better capture temporal dynamics crucial in non-stationary spectrum environments. Further, issues of privacy and computational load in centralized ML/DL methods have led to the adoption of Federated Learning, enabling decentralized model training. Finally, reliance on labeled data in supervised learning is being mitigated by reinforcement, unsupervised, and emerging self-supervised techniques, allowing for more scalable and autonomous spectrum sensing solutions.

8.1. Challenges for 6G and multiple access systems

The evolution toward 6G networks brings novel challenges for AI-powered multiple access (MA) systems, particularly in spectrum sensing, sharing, and management [40].

Spectral efficiency in 6G networks. The massive proliferation of connected devices and data traffic in 6G, especially with higher frequency bands like mmWave and THz, leads to issues such as channel access collisions, empty slots, and increased control overhead. AI must improve resource allocation strategies, particularly for non-orthogonal multiple access (NOMA) and orthogonal multiple access (OMA), to enhance spectral efficiency while minimizing interference.

Energy efficiency. Achieving tenfold improvements in energy efficiency compared to 5G is crucial for 6G. AI-driven MA systems should incorporate low-power communication mechanisms such as on-demand transmissions, sleep/wake scheduling, and adaptive power control. Additionally, AI can optimize energy harvesting and battery management to support sustainable network operation.

A recurring technical insight across the literature is the trade-off between detection accuracy and energy efficiency, especially in low-SNR and dense IoT environments. Similarly, real-time adaptability often conflicts with computational complexity, highlighting the need for lightweight models deployable at the edge. Studies also reveal that while ML-based models deliver impressive accuracy (for example, P22 reporting 99.1 %), their scalability in hardware-constrained environments remains an open challenge

Ultra-low latency and reliability. Mission-critical applications demand ultra-low latency and high reliability, posing challenges for conventional resource allocation. AI models need to develop sophisticated scheduling and resource management schemes that ensure minimal delay and high availability, surpassing limitations of traditional contention-based and contention-free mechanisms.

Massive connectivity and scalability. 6G will connect billions of devices across ground, air, and space in complex 3D networks. AI must handle massive device density and provide scalable, flexible spectrum sharing solutions that maintain compatibility across heterogeneous network environments. Later on, from a systems perspective, 6G-enabled CIoT, satellite-terrestrial integration, vehicular networks, and rural connectivity represent fertile grounds for DSS. These contexts demand ultra-low latency, high reliability, and adaptive spectrum sensing under heterogeneous conditions. The convergence of DSS with blockchain, reconfigurable intelligent surfaces (RIS), and quantum-inspired optimization is another frontier with significant potential.

Security, privacy, and heterogeneity. Centralized AI approaches raise security and privacy concerns, especially with sensitive user data. Decentralized and distributed learning methods, including federated learning, offer enhanced security and privacy guarantees. Addressing heterogeneity in device capabilities and network conditions is also essential for robust AI-powered MA in 6G. Furthermore, emerging scopes point toward the integration of deep learning architectures (CNN, LSTM, Autoencoders) and hybrid AI models with federated and edge learning, enabling distributed and privacy-preserving sensing. Large Language Models (LLMs) and foundation models, though in their infancy for wireless communications, represent a potential paradigm shift for knowledge-driven spectrum management. Additionally, adversarial robustness in AI models, particularly against jamming and Byzantine attacks, is expected to become a core research direction.

8.2. AI and RIS-aided 6G communication

AI will play a strategic role in the evolution of 6G technologies, with a focus on three key areas: holographic beam spectroscopy, sensing in the THz band, and reconfigurable intelligent surfaces (RIS) [151]. The most advanced research directions are moving toward the adoption of next-generation AI frameworks, such as non-autoregressive multi-resolution generative networks and adversarial transformers, which enable the imputation of missing sensing sequences and highly accurate prediction of future environmental dynamics.

Using holographic spectroscopy, AI models will be able to be trained by exploiting the optical (or quasi-optical) characteristics of the THz band, optimizing the extraction of sensing parameters such

Table 31
Progression of AI techniques in spectrum sensing: addressing limitations of previous methods.

Step	Technique	Limitations	Addressed by / improvements 1
1	**Support Vector Machine (SVM)**	Requires manual feature engineering; poor scalability with large datasets; low adaptability to non-stationary environments	**k-means + SVM / Hybrid Models**: Unsupervised clustering reduces manual feature work; hybrid models improve accuracy and adaptability
2	**Naïve Bayes / Bayesian Learning**	Assumes feature independence; struggles with high-dimensional data	**Ensemble Learning / Neural Networks**: Ensembles improve generalization and robustness; neural networks model non-linear relationships
3	**k-means, GMM (Unsupervised ML)**	Limited to clustering without classification; sensitive to initialization; lacks adaptability	**Deep Learning (CNN, DNN)**: Learns hierarchical features from raw input; robust to noise and dynamic changes
4	**Feedforward Neural Networks (MLP, DNN)**	Lack memory for temporal signals; fixed input-output mapping unsuitable for dynamic conditions	**Recurrent Neural Networks (RNNs, LSTM)**: Capture temporal dependencies; effective in tracking PU activity and SNR variations
5	**Standard ML/DL Techniques**	Require centralized data sharing (privacy issues); high computational load at the edge	**Federated Learning (FL)**: Enables decentralized training without raw data exchange; reduces central processing load
6	**Supervised Learning Techniques**	Depend heavily on large labeled datasets	**Reinforcement / Unsupervised / Self-Supervised Learning**: RL learns via interaction; unsupervised models detect patterns without labels; self-supervised learning leverages pseudo-labels

Table 32
Taxonomy of AI-driven spectrum sensing.

AI category	Learning paradigm	Analysis domain	CRN architecture	Purpose/performance goal
ML	Supervised (SVM, Naïve Bayes, Bayesian)	Spectrum-domain	Centralized	PU detection, classification, threshold optimization
	Unsupervised (k-means, GMM, KNN)	Spectrum-domain	Centralized/Distributed	Clustering, anomaly detection
	RL (Q-Learning)	Signal/Spectrum-domain	Centralized or Single-Agent	Dynamic sensing, learning-based access
	Hybrid ML (SVM + k-means, Ensembles)	Spectrum-domain	Centralized	Combined detection and classification
	ML + FL (SVM, RL)	Spectrum-domain	Decentralized	Resource allocation, cooperative sensing
DL	Supervised (CNN, RNN, LSTM, MLP)	Signal-domain	Centralized/Distributed	Modulation recognition, signal classification
	Hybrid (CNN-LSTM, BiLSTM-SA)	Signal-domain	Centralized/Edge-assisted	Feature fusion, hierarchical learning
	Unsupervised (AEs, DBNs)	Signal-domain	Centralized	Feature extraction, occupancy estimation
	DRL, MARL	Signal-domain	Decentralized	Adaptive spectrum sensing, coordination
	DL + FL (CNN, RNN, GRU)	Signal-domain	Decentralized (Edge/SU-level)	Real-time inference, privacy-preserving
FL	FL with ML (SVM, RL)	Spectrum-domain	Decentralized	Distributed spectrum access, privacy
	FL with DL (CNN, RNN, LSTM)	Signal-domain	Edge-assisted/SU-level	End-to-end sensing, real-time coordination

as frequency, phase, and pulse width [152]. This will significantly improve the spatial and temporal resolution of environmental maps, even in complex scenarios, through the use of tensor decomposition techniques based on probabilistic and nonlinear models. A concrete example is illustrated in work [152], in which the proposed framework showed significantly shorter recovery times than traditional schemes based on CSI note and beam tracking, with a latency reduction of up to 270 ms. In addition, the system proved to be more robust to fluctuations in user behavior and speed, achieving a 61 % improvement in instantaneous reliability compared to CSI note-based approaches.

8.3. Final future insights

While AI techniques have made significant progress in enhancing spectrum sensing within CRNs, several critical challenges remain before large-scale deployment in beyond-5G and 6G networks can be realized. The main barriers include reliance on simulated datasets that fail to capture real-world variability, the vulnerability of deep models to adversarial manipulation, and the high computational demands that clash with the constraints of edge and IoT devices. These limitations underscore the persistent tension between accuracy, robustness, and feasibility in real-world scenarios.

At the same time, new opportunities are emerging through the integration of distributed and federated learning, model compression, and energy-aware optimization-approaches that can reduce overhead while maintaining strong detection performance. Moreover, disruptive paradigms such as reconfigurable intelligent surfaces (RIS), edge intelligence, and cross-layer co-design offer promising avenues to scale DSS solutions for 6G and beyond.

Addressing these challenges requires moving beyond isolated algorithmic innovation toward holistic frameworks that jointly consider hardware constraints, energy efficiency, adversarial robustness, and adaptive spectrum management. This perspective provides the foundation for identifying concrete future research directions and accelerating the transition of DSS from experimental prototypes to robust, large-scale deployments.

1. **Dataset Realism Gap**
   Most AI-driven DSS models are still trained and benchmarked using simulated datasets such as RadioML, which, although valuable, fail to capture the variability of real-world propagation, interference, and hardware effects. This overreliance often inflates reported performance, creating a significant gap between laboratory results and field deployment.
   Emerging scope: domain adaptation, transfer learning, and the creation of standardized, open-source datasets with realistic conditions are essential to ensure reproducibility and applicability in real deployments. For example, hybrid datasets combining synthetic and over-the-air samples can mitigate this gap.
2. **Robustness Under Uncertainty**
   While many architectures perform well in high-SNR regimes, low-SNR conditions remain the primary bottleneck across studies. Interference, fading, and adversarial perturbations further degrade reliability, especially in dense IoT or mobile environments.
   Key insight: hybrid approaches (for example, CNNs coupled with traditional energy detection or feature-based sensing) often generalize better across varying SNRs, indicating that robustness cannot rely solely on end-to-end DL.

Table 33
Summary of primary studies.

Ref	Pub year	AI cat	Purpose
1 [3]	2021	DL	Spectrum sensing using CNN-LSTM
2 [56]	2012	ML - SL	Spectrum Sensing, CoSS
3 [57]	2018	ML - SL/USL	SS, User Grouping, CoSS
4 [58]	2018	ML - SL	Spectrum Sensing, multi-antenna CRNs
5 [59]	2013	ML - SL/USL	Spectrum Sensing, Real-Time Spectrum Detection, Unsupervised CoSS
6 [60]	2014	ML - SL/USL	Spectrum Sensing
7 [61]	2019	ML - SL	Spectrum Sensing, Spectrum Detection
8 [62]	2019	ML - SL	Spectrum Sensing, CoSS
9 [63]	2018	ML - USL	Spectrum Sensing
10 [65]	2018	ML - USL	Spectrum Sensing
11 [66]	2019	ML - FL	Resource allocation and power control
12 [67]	2020	ML - FL	User selection and resource allocation
13 [68]	2021	ML - FL	Distributed Spectrum Sensing
14 [100]	2022	DL	Compressive spectrum sensing framework for 5G networks
15 [70]	2020	DL - MLP	Centralized CoSS
16 [73]	2020	DL - MLP	Signal Classification
17 [74]	2021	DL - MLP	Hybrid Spectrum Sensing
18 [81]	2019	DL - DNN	Signal Detection
19 [82]	2023	DL - DNN	Noise Estimation
20 [77]	2020	DL - DNN	Spectrum Sensing
21 [78]	2019	DL - DNN	Spectrum Management
22 [79]	2021	DL - DNN	Spectrum Management
23 [83]	2021	DL - CNN	Signal Identification
24 [84]	2020	DL - CNN	CoSS, Spectrum Sensing
25 [85]	2020	DL - CNN	CoSS, Spectrum Sensing
26 [86]	2018	DL - CNN	Spectrum Monitoring, PU Activity Recognition
27 [56]	2012	ML	Spectrum sensing and cooperative sensing using SVM and weighted KNN
28 [57]	2018	ML	Spectrum sensing and user grouping with SVM and k-means/GMM
29 [58]	2018	ML	Spectrum sensing for multi-antenna CRNs using multi-class SVM
30 [59]	2013	ML	Real-time spectrum detection via SVM (linear) and unsupervised k-means/GMM for cooperative sensing
31 [60]	2014	ML	Spectrum sensing via SVM and hybrid k-means clustering
32 [61]	2019	ML	Spectrum detection using Naive Bayes
33 [62]	2019	ML	Cooperative spectrum sensing using Bayesian learning
34 [63]	2018	ML	Spectrum sensing with unsupervised CNNs and KNN integration
35 [64]	2015	ML	Distributed spectrum sensing with unsupervised Q-learning
36 [65]	2018	ML	Spectrum sensing via ensemble learning
37 [66]	2019	ML	Resource allocation and power control via federated learning with RL
38 [67]	2020	ML	User selection and resource allocation via federated learning with supervised models
39 [68]	2021	ML	Distributed spectrum sensing using federated learning (FLSS)
40 [70]	2020	DL	Centralized cooperative spectrum sensing with IG-DNN (MLP)
41 [73]	2020	DL	Signal classification using MLP
42 [74]	2021	DL	Hybrid spectrum sensing with MLP
43 [81]	2019	DL	Signal detection using DNN
44 [82]	2023	DL	Noise estimation using DNN
45 [77]	2020	DL	Spectrum sensing via DNN integrated with CNN
46 [78]	2019	DL	Spectrum management using RIS-based DNN
47 [79]	2021	DL	Spectrum management using RIS-based DNN
48 [83]	2021	DL	Signal identification with CNN
49 [84]	2020	DL	Cooperative spectrum sensing using CNN
50 [85]	2020	DL	Cooperative spectrum sensing using CNN

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Table 33
Continue

Ref	Pub year	AI category	Purpose
51 [86]	2018	DL	Spectrum monitoring and primary user activity recognition via CNN
52 [88]	2019	DL	Spectrum sensing using CNN
53 [89]	2018	DL	Spectrum sensing using CNN
54 [91]	2021	DL	Spectrum sensing using CNN
55 [92]	2020	DL	Spectrum sensing using CNN
56 [145]	2019	DL	Transfer learning for spectrum sensing with CNN
57 [80]	2021	DL	Spectrum sensing and allocation with DNN (SL)
58 [93]	2009	DL	Spectrum sensing using CNN
59 [96]	2019	DL	Deep cooperative spectrum sensing using CNN
60 [97]	2017	DL	Cooperative spectrum sensing with CNN
61 [99]	2020	DL	Spectrum sensing and signal detection with CNN-LSTM
62 [106]	2018	DL	Cooperative spectrum sensing using hybrid CNN and transfer learning
63 [107]	2020	DL	Noise estimation and uncertainty mitigation with STFT-CNN
64 [109]	2021	DL	Fading channel optimization and spectrum sensing with CNN-GWSO
65 [110]	2018	DL	Signal detection via KNN-enhanced CNN
66 [111]	2021	DL	Signal detection and spectrum management with I/Q sample-based DL
67 [112]	2022	DL	Spectrum sensing via hybrid CNN-BiLSTM-SA-CONCAT
68 [76]	2017	DL	CNN-RNN hybrid for spectrum-related tasks
69 [114]	2019	DL	Spectrum sensing accuracy at low SNR with CNN-LSTM
70 [115]	2020	DL	Signal detection under noise using CNN-LSTM
71 [116]	2023	DL	Cooperative spectrum sensing with CNN-LSTM
72 [101]	2019	DL	Spectrum sensing using CNN-LSTM
73 [118]	2020	DL	Primary user activity detection via LSTM
74 [120]	2019	DL	Spectrum sensing using stacked autoencoder (SAE-SS)
75 [121]	2020	DL	Unsupervised spectrum sensing using variational autoencoder
76 [122]	2021	DL	Signal classification using deep autoencoder
77 [123]	2021	DL	End-to-end spectrum sensing using ASWC autoencoder
78 [124]	2015	DL	Spectrum utilization optimization with deep belief networks
79 [126]	2010	DL	Centralized cooperative spectrum sensing via reinforcement learning
80 [127]	2019	DL	Channel selection for cooperative sensing using Q-learning
81 [128]	2020	DL	Cooperative partner selection with deep RL
82 [129]	2021	DL	Channel state prediction using offline RL
83 [130]	2011	DL	Cooperative spectrum sensing with Q-learning
84 [131]	2019	DL	Cooperative spectrum sensing using Q-learning and DQN
85 [132]	2021	DL	Dynamic spectrum access with Q-learning
86 [133]	2019	DL	DSA and D2D communications via multi-agent deep RL
87 [134]	2010	DL	Reliable partner selection with actor-critic networks
88 [135]	2011	DL	Energy-efficient transmission using Q-learning
89 [136]	2013	DL	Spectrum sensing and throughput maximization with Q-learning and MAB
90 [95]	2020	DL	Spectrum sensing as an image classification
91 [119]	2022	DL	Improve detection in CRNs, under variable SNR conditions
92 [117]	2022	DL	Determines the spectrum occupancy status of PUs
93 [98]	2022	DL	Technique for CoSS with Extreme Learning Machine
94 [137]	2020	DL	Partner selection via DQN with coordination graphs
95 [138]	2020	DL	Spectrum sensing with Q-learning + MAB + UCB
96 [139]	2021	DL	Cooperative spectrum and partner selection using MADDPG
97 [142]	2013	DL	Distributed cooperative spectrum sensing using Q-learning and DQN
98 [143]	2018	DL	Distributed cooperative sensing using Q-learning and game theory
99 [144]	2020	DL	TV band spectrum sensing using CNN-based transfer learning
100 [146]	2018	DL - deepRL	Spectrum sensing and power control via deep RL
101 [147]	2020	DL - deepRL	Spectrum sensing and power allocation via deep RL
102 [125]	2024	DL	A framework for identifying and classifying malicious users in CRNs
103 [36]	2025	DL - TL	Spectrum sensing framework for 5G and LTE signals
104 [113]	2024	DL	DL-based spectrum sensing model designed to enhance detection under low SNR conditions
105 [94]	2024	DL	Classifying the modulation schemes used in Wi-Fi 6 and 5G downlink OFDM transmissions.
106 [140]	2024	DL - RL	A cloud-based heterogeneous collaborative spectrum sensing system
107 [148]	2020	DL - FL	Spectrum sensing optimization
108 S29 in Cao et al. [40]	–	TL	SS, TV Signal Detection
109 S57, S58 in Sabir et al. [41]	–	DL - FL (Deep FL)	5G traffic forecasting
110 S26 in Sabir et al. [41]	–	DL - FL (FEEL with CNNs)	Energy-efficient network management
111 S51 in Sabir et al. [41]	–	FL-based RL (FRL)	Dynamic Spectrum Access
112 S7 in Sabir et al. [41]	–	DL - FL (Deep FL)	Intelligent spectrum management
113 S58 in Sabir et al. [41]	–	DL - FL	Network efficiency, 5G Traffic Prediction
114 S26 in Sabir et al. [41]	–	DL - FL (Deep FL)	Spectrum Management, JRO, DSA

3. **Generalization Challenge**
AI models often overfit to narrow training environments, limiting their adaptability when deployed in new spectral regions or under unseen channel dynamics. This problem is particularly acute in CRNs where PU activity and spectrum availability are highly non-stationary.
Emerging scope: online learning, active learning, and federated learning paradigms are needed to enable continuous adaptation while preserving privacy across distributed nodes.

4. **Computation vs. Deployment**
Many DL models achieve high detection accuracy but require large FLOPs, significant memory, and specialized hardware. Such requirements conflict with the energy and computational constraints of IoT devices and edge nodes.
Technical takeaway: lightweight architectures, pruning, quantization, and hardware-aware co-design are not optional optimizations but prerequisites for practical deployment. Case studies show that com-

pressed CNNs can achieve comparable accuracy with 60–80 % reduced complexity.

5. **Energy–Accuracy Trade-off**
Achieving high sensing accuracy often demands greater energy consumption, which conflicts with the needs of battery-powered or ultra-dense IoT networks. Energy efficiency is therefore tightly coupled with spectrum sensing feasibility.
Emerging scope: energy-aware training, distributed cooperation among nodes, and joint optimization of sensing + communication processes are promising pathways to balance accuracy and power usage.
6. **Security and Privacy Concerns**
AI-based DSS models are vulnerable to spoofing, poisoning, and perturbation-based attacks, which can mislead spectrum decisions and compromise CRN reliability. Privacy leakage in centralized training pipelines also raises concerns in sensitive applications.
Key insight: adversarial training, redundancy mechanisms, and decentralized frameworks (for example, federated learning with differential privacy) are needed to enhance trustworthiness in hostile environments.
7. **Scalability for 6G and Beyond**
DSS must evolve to cope with massive connectivity, ultra-low latency demands, and heterogeneity across 5G/6G and future networks (for example, space-air-ground integrated systems). Current models rarely scale effectively under these conditions.
Emerging lesson: DSS frameworks need to be co-designed with edge intelligence, RIS, and distributed AI to ensure scalability across 3D integrated networks.
8. **Emerging Opportunities**
Beyond incremental improvements, disruptive opportunities lie in the integration of DSS with Reconfigurable Intelligent Surfaces (RIS), blockchain for trust and auditability, and Large Language Models (LLMs) for adaptive decision-making and cross-layer reasoning.
Future scope: these synergies are largely unexplored but hold the potential to redefine spectrum intelligence and provide scalable solutions for complex 6G ecosystems.

While AI techniques have made significant progress in enhancing spectrum sensing within CRNs, several critical challenges remain before large-scale deployment in beyond-5G and 6G networks can be realized. The main barriers include reliance on simulated datasets that fail to capture real-world variability, the vulnerability of deep models to adversarial manipulation, and the high computational demands that clash with the constraints of edge and IoT devices. These limitations underscore the persistent tension between accuracy, robustness, and feasibility in real-world scenarios.

At the same time, new opportunities are emerging through the integration of distributed and federated learning, model compression, and energy-aware optimization-approaches that can reduce overhead while maintaining strong detection performance. Moreover, disruptive paradigms such as reconfigurable intelligent surfaces (RIS), edge intelligence, and cross-layer co-design offer promising avenues to scale DSS solutions for 6G and beyond. Addressing these challenges requires moving beyond isolated algorithmic innovation toward holistic frameworks that jointly consider hardware constraints, energy efficiency, adversarial robustness, and adaptive spectrum management. This perspective provides the foundation for identifying concrete future research directions and accelerating the transition of DSS from experimental prototypes to robust, large-scale deployments.

As CR technology continues to play a vital role in the future of wireless communication networks, especially in the context of 5G and 6G, several critical challenges remain. Agrawal et al. [19] identified specific issues related to narrowband and wideband sensing, as well as cooperative spectrum sensing techniques. Addressing these challenges will require further advancements in AI and ML-based models, focusing on handling more diverse datasets, adapting to changing network conditions, and ensuring real-time processing with low-latency and energy-efficient solutions. Key future directions include:

- developing models that can simultaneously handle narrowband and wideband spectrum sensing tasks,
- improving the robustness of spectrum sensing techniques in the face of dynamic, real-time channel conditions,
- integrating cooperative spectrum sensing with AI-driven algorithms to improve performance and reliability,
- enhancing federated learning approaches to support decentralized CRN systems, ensuring both privacy and scalability,
- designing AI pipelines resilient to adversarial threats, including spoofed signals and poisoning attacks, to secure CRNs.

Looking forward, AI, particularly DL, ML, and RL, is transforming spectrum sensing, link quality estimation, and mobility management in cognitive radio networks. CNNs, LSTMs, and hybrid models have demonstrated superior performance in detecting spectrum availability, predicting link stability, and optimizing handovers. However, challenges such as computational complexity, generalization issues, adversarial threats, and real-time deployment constraints remain key barriers to widespread adoption. Future research should therefore prioritize energy-efficient AI, robust learning frameworks, and seamless integration with next-generation wireless infrastructures to fully harness the potential of AI-driven CRNs in beyond-5G and 6G ecosystems.

9. Taxonomy of AI-driven spectrum sensing

To provide a structured understanding of the role of AI in spectrum sensing, we introduce a taxonomy that organizes existing approaches along four key dimensions: (i) learning paradigm, (ii) analysis domain, (iii) network architecture, and (iv) functional purpose or performance goal. This taxonomy offers a comprehensive perspective on how Machine Learning (ML), Deep Learning, and Federated Learning techniques are integrated into CRNs and other wireless systems for spectrum sensing.

9.1. Dimension 1: learning paradigm

AI techniques for spectrum sensing can be categorized into the following learning paradigms:

- **Supervised Learning:** Algorithms trained on labeled datasets. Techniques include ML methods like Support Vector Machines (SVMs), Naïve Bayes, and Bayesian Learning, as well as DL models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These are widely used for classification, signal detection, and modulation recognition.
- **Unsupervised Learning:** Algorithms that identify patterns in unlabeled data, such as k-means Clustering, Gaussian Mixture Models (GMMs), Autoencoders (AEs), and Deep Belief Networks (DBNs). These are often employed for anomaly detection, spectrum occupancy clustering, and feature extraction.
- **Reinforcement Learning (RL):** Algorithms that learn optimal sensing strategies through interactions with the environment. Techniques include Q-Learning, Deep Q-Networks (DQNs), and Multi-Agent Reinforcement Learning (MARL), useful for dynamic spectrum access and adaptive sensing.
- **Hybrid and Federated Learning:** Hybrid models combine multiple paradigms (for example, CNN-LSTM, SVM + k-means, RL + DNN) to improve performance and adaptability. Federated Learning supports decentralized model training across edge nodes, enhancing privacy and scalability in distributed CRNs.

9.2. Dimension 2: analysis domain

AI models for spectrum sensing can operate in different data domains:

- **Signal-Domain Analysis:** Direct processing of raw IQ (Inphase/Quadrature) samples or time-series signals, typically using DL models (for example, CNNs, RNNs, LSTMs) for tasks such as modulation classification, channel estimation, and real-time signal detection.
- **Spectrum-Domain Analysis:** Analysis based on processed features such as power spectral density (PSD), energy histograms, or signal statistics. ML techniques (for example, SVMs, Naïve Bayes, k-means) are favored here due to their lower computational complexity.

9.3. Dimension 3: CRN architecture

Deployment and training architectures shape the design of AI-based sensing systems:

- **Centralized Architecture:** A fusion center aggregates data from multiple secondary users (SUs) and applies AI models for decision-making. Common in supervised ML and DL applications.
- **Decentralized Architecture:** Includes edge-level inference or Federated Learning where individual nodes train and/or apply models locally. Suitable for preserving privacy, reducing latency, and enabling scalability in dynamic or large-scale networks.

9.4. Dimension 4: purpose and performance objectives

Each AI technique is often tailored for specific goals in spectrum sensing:

- **Detection of Primary Users (PU):** Techniques like SVM, k-means, and CNNs are used to enhance detection sensitivity and minimize interference.
- **Classification and Modulation Recognition:** Supervised methods (SVM, CNN, RNN) and hybrid DL architectures are used to classify signals, channels, or modulation schemes.
- **Efficiency Improvement:** Hybrid models and FL are adopted to enhance spectrum utilization, reduce cooperation overhead, or increase energy/time efficiency.
- **Dynamic and Adaptive Sensing:** RL and DRL models are employed to enable intelligent decision-making in dynamic environments.
- **Privacy-Preserving and Distributed Sensing:** FL-based models support secure, decentralized sensing without sharing raw data.

9.5. Innovation and potential of the taxonomy

This four-dimensional taxonomy unifies previously fragmented efforts by integrating algorithmic paradigms, data processing modes, deployment architectures, and intended functional purposes into a cohesive framework. It highlights several emerging trends, including a notable shift from classical machine learning toward end-to-end deep learning and decentralized federated learning solutions. There is an increasing reliance on signal-domain data for real-time sensing, typically leveraging CNN and RNN architectures. Additionally, the integration of hybrid models, such as CNN-LSTM and deep reinforcement learning, has gained traction for enabling adaptive sensing in volatile environments. Despite these advances, certain promising synergies remain underexplored, particularly the combination of unsupervised deep learning with federated learning for anomaly detection. Beyond serving as a classification scheme, this taxonomy functions as a strategic tool by revealing research gaps, such as the limited deployment of federated learning in real-time wideband sensing, aligning novel approaches with standardized categories to facilitate benchmarking, and guiding practitioners in selecting AI methods tailored to specific system requirements.

10. Conclusions

The integration of AI, in particular ML and DL, has revolutionized spectrum sensing and CRNs, significantly improving spectrum efficiency, interference management, and resource allocation. These methods have demonstrated superior performance in detecting weak signals and adapting to diverse and dynamic spectrum conditions, establishing their indispensability for beyond-5G (B5G) and 6G networks.

Our analysis has highlighted the transformative potential of techniques such as statistical methods, CNNs, and hybrid models that have achieved significant advances in signal detection and classification. At the same time, challenges related to model generalization, computational complexity, and real-time processing have been evidenced, which remain critical hurdles. Promising approaches, such as domain adaptation, online learning, and federated learning, offer viable paths to improve robustness and adaptability in complex and resource-limited environments.

Looking forward, AI-driven spectrum sensing will play a central role in addressing the needs of next-generation networks, such as ultra-low latency, massive connectivity, and energy efficiency. To fully exploit the potential of AI in 5G and 6G ecosystems, future research needs to focus on developing robust, scalable, and privacy-compliant AI models that can meet the increasing complexity and requirements of these systems.

CRediT authorship contribution statement

Mariana Falco: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization; **Antonino Pagano:** Writing – review & editing, Visualization, Investigation, Conceptualization; **Daniele Croce:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Data availability

Data is included within the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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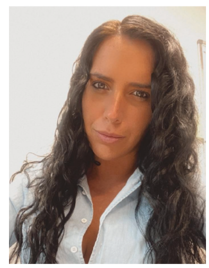

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