Svedberg Open
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Machine Learning and Deep Learning Based Spectrum Sensing (Mldls) in Cognitive Radio Networks: A Comprehensive Review of Techniques, Applications and Challenges and Future Directions

Shraddha Nitin Magdum[1], Tanuja Satish Dhope (Shendkar)[2*]

[1]Research Scholar, Department of Electronics Engineering, Bharati Vidyapeeth (Deemed to be University) College of Engineering, Pune, Maharashtra, India, Email: shraddhagaji1993@gmail.com
[2*]Department of Electronics and Communication Engineering, Bharati Vidyapeeth (Deemed to be University) College of Engineering, Pune, Maharashtra, India. Email: tanuja_dhope@yahoo.com

Abstract
As wireless communications grow in popularity, there is growing demand for radio spectrum, but limited spectrum resources. Traditional fixed spectrum allocation may lead to underutilized bands when there are no licensed users. The Cognitive Radio (CR) technology is a solution to this issue, since by using CR technology the secondary users can detect and use the unused spectrum without interfering the primary users. Spectrum sensing is thus an important task of Cognitive Radio Networks (CRNs). The conventional Energy Detection, Matched Filter Detection and Cyclostationary Detection are limited in low Signal to Noise Ratio (SNR), noise uncertainty, fading, interference and wideband conditions. In recent times, the field of Machine Learning (ML) and Deep Learning (DL) has seen significant progress, offering intelligent solutions for enhancing sensing accuracy and adaptability. The received signal data can be used to extract useful patterns using ML methods like SVM, KNN, DT, RF and ANN. DL models, such as CNN, RNN, LSTM, CNN-LSTM, transfer learning and Transformer-based models, can automatically extract spatial and temporal signal features. Other technologies, notably cooperative spectrum sensing and reinforcement learning reinforce reliable and adaptive spectrum access. In this paper, the works on spectrum sensing using machine learning and deep learning in the last six years (2020-2025) are reviewed. It includes conventional and intelligent sensing, wideband and cooperative spectrum sensing, reinforcement learning and emerging AI sensing techniques. Some of the main difficulties such as low-SNR sensing, noise uncertainty, limited training data, computational complexity, energy consumption and real-time implementation and model generalization are discussed. New directions like lightweight DL, Transformer-based sensing, Graph Neural Networks, prediction based sensing, Explainable AI, edge intelligence and AI enabled Cognitive Radio IoT are also mentioned. The review shows that there is great potential in the synergy between CR and ML/DL, in order to enable more accurate, adaptive and efficient utilization of the spectrum in future wireless networks.

Keywords: Spectrum Sensing, Cognitive Radio Networks, Machine Learning, Deep Learning, Wide-band Spectrum Sensing, Co-operative Spectrum Sensing, Artificial Intelligence, CNN, LSTM, Reinforcement Learning, Dynamic Spectrum Access, Spectrum Management, and Cognitive Radio IoT.

Introduction

The rapid expansion of wireless communications has led to the proliferation of wireless mobile, IoT, sensor, vehicle and smart devices, driving up demand for radio spectrum. In the era of 5G, 6G and future 6G, efficient utilization of the spectrum is crucial as spectrum is a limited resource. The traditional allocation allocates licensed user to certain bands for a long period, which may lead to inefficient use of the bands when they are not used at a particular time or location [1], [2]. Cognitive Radio (CR) has been identified as one of the solutions to enhance the utilization of the spectrum. It can detect the radio environment to determine the radio channels that are available, and it can modify the transmission conditions based on the radio environment. It assigns licensed users as Primary Users (PUs) and those that are accessing spectrum opportunities that are not used are Secondary Users (SUs). The primary goal is to enable SUs to share the underutilized spectrum without causing interference to PUs [1], [3].
The four stages of the cognitive cycle are spectrum sensing, spectrum analysis, spectrum decision and spectrum access and spectrum mobility. Spectrum sensing is important among these as it can lead to interference or loss of spectrum opportunities if it makes a wrong decision [3] [4]. The traditional spectrum sensing techniques are Energy Detection (ED), Matched Filter Detection (MFD), Cyclostationary Feature Detection (CFD), eigenvalue-based and covariance-based. It is simple and does not need any prior signal information, but its performance is degraded in low Signal-to-Noise Ratio (SNR) and noise

uncertainty. Under the condition of knowing the primary signal characteristics, good detection can be achieved by MFD, and CFD can be used under the condition of high noise, but it has high calculation complexity [3] [4]. In actual Cognitive Radio Networks (CRNs), noise uncertainty, multipath fading, shadowing, interference, low SNR, the hidden terminal and rapidly changing spectrum occupancy pose further problems. An additional difficulty associated with wideband spectrum sensing is the requirement to detect many occupied and unused bands within a short time, which is hard to achieve by the traditional methods [3, 5]. In this regard, the concept of intelligent spectrum sensing has been attracting a lot of research interest and is called Machine Learning (ML). Unlike fixed mathematical models, ML can learn useful patterns from the signal data that have been collected in the past. Spectrum sensing and Dynamic Spectrum Access (DSA) have been solved using supervised, unsupervised and reinforcement learning techniques. Various techniques like Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Decision Tree, Random Forest and Artificial Neural Network (ANN) are discussed for the purpose of spectrum occupancy identification and sensing decision [6]. Typically, conventional ML techniques rely on an appropriate feature extraction and large amount of training data. As an attractive alternative, Deep Learning (DL) has shown potential to learn hierarchical features directly from signal representations in an automatic manner. CNNs are good for spatial or local patterns like spectrograms, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are used for temporal signal relationships [7, 8]. There has also been potential shown for the use of hybrid CNN-RNN architectures and transfer learning to increase the accuracy of spectrum sensing, especially for low-SNR signals and sensing environments where there is a change [7].

The need for large labelled datasets can be diminished by transferring knowledge acquired from an existing trained model to a new radio environment. Cooperative Spectrum Sensing (CSS) enables multiple SUs to cooperate in sensing and exchanging local information with a fusion centre and/or other users. It can alleviate the impact of fading, shadowing and hidden terminals, but communication overhead, energy consumption, reporting errors and security problems are still challenges. The local sensing, information fusion and decision-making in CSS can be enhanced by the use of ML and DL [6] [9]. Additionally, AI sensing is emerging as a crucial technology for Cognitive Radio IoT (CR-IoT), especially in deep fading and noise uncertainty. The goal of Wideband Spectrum Sensing (WBSS) is to sense a wide frequency range and detect multiple occupied and vacant bands. It is significant for the current CR systems, but requires more computational and hardware resources. Large volumes of spectrum data can be processed by ML and DL and useful occupancy patterns can be identified [3] and [5]. The research on hybrid DL, transfer learning, spectrum prediction and advanced neural architectures is also recent. DL is also used for spectrum prediction, spectrum sharing, resource allocation and security [11], [12]. Another key research direction is Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL). In RL, the agent discovers the reward through interaction with the environment, which includes interacting with a state, choosing an action, and getting a reward or a penalty. This can be used to assist in the selection of the spectrum, access to the spectrum, spectrum prediction and dynamic resource allocation in dynamic wireless networks [13].

Another field of interest is the use of transformer models and Graph Neural Networks (GNNs) for spectrum applications. Transformers can be used to model long-range relationships, and GNNs can be used to represent multiple sensing users and their relationships, which can be used for cooperative and distributed sensing [11, 14]. However, there are still a number of challenges for practical ML- and DL-based spectrum sensing. These include limited high-quality training data, low SNR operation, noise uncertainty, high computational complexity, memory and energy requirements, and poor generalization across environments and threats like falsified sensing data, jamming and spoofing [10]–[12]. Transfer learning, domain adaptation, online learning and continual learning could enhance the model generalization [7, 11]. Compression of models, knowledge distillation and edge intelligence can help lower computational and energy costs and reduce the need for heavy neural network models. In general, the research for 2020-2025 indicates that traditional signal processing techniques are being replaced by data-driven and adaptive spectrum sensing. First, classical ML were studied, and then CNN, RNN, LSTM and transfer-learning approaches were studied. The focus of recent research is hybrid DL, AI-based CR-IoT, prediction-based sensing, Transformer architectures and graph-based cooperative sensing [6]–[14].

Hence, a new review is needed to compare these approaches, pinpoint the shortcomings and suggest future research directions. The present paper entitled "Machine Learning and Deep Learning Based Spectrum Sensing in Cognitive Radio Networks: A Comprehensive Review of Techniques, Applications, Challenges and Future Directions" highlights the evolutionary journey of conventional spectrum sensing techniques to spectrum sensing in the era of machine learning and deep learning, cooperative learning, reinforcement learning, and emerging intelligent approaches to spectrum sensing. The main goals are to: (i) present fundamental concepts of spectrum sensing; (ii) review the classical approaches and their limitations; (iii) discuss the ML-based approaches to spectrum sensing; (iv) analyze ML-based CNN, RNN, LSTM and hybrid DL models for spectrum sensing; (v) discuss cooperative, wideband and reinforcement learning approaches to spectrum sensing; (vi) compare the recent studies from 2020 to 2025; (vii) discuss challenges of spectrum sensing such as low SNR, noise uncertainty, data availability, complexity, energy consumption and generalization; (vi viii) identify future direction of lightweight AI, transfer learning, Transformers, GNNs, prediction-based sensing, Explainable AI and edge intelligence.

This paper brings a wide-ranging discussion on Cognitive Radio Networks (CRNs) and the need for efficient spectrum sensing to achieve the objective of efficient spectrum utilization. Chapter 1 presents an overview of the CRNs, spectrum sensing and role of AI, while Chapter 2 provides details on the fundamentals of cognitive radio and traditional spectrum sensing. In Chapter 3, the authors will discuss various Machine Learning and Deep Learning techniques, including Support Vector Machines (SVM), Random Forest, CNN, LSTM, CNN-LSTM, and Transformers. Cooperative Spectrum Sensing and Reinforcement Learning for intelligent sensing decisions is discussed in chapter 4. Chapter 5 deals with Wideband Spectrum Sensing, the new developments in 2020-2025, applications, problems, gap and future prospects. The overall results are summarized in Chapter 6 and the importance of spectrum sensing using AI techniques is emphasized. Overall, the review reveals that, when integrated together, ML, DL, cooperative sensing, reinforcement learning and wideband sensing can enhance the performance of future cognitive radio systems in terms of accuracy, adaptability and efficiency.

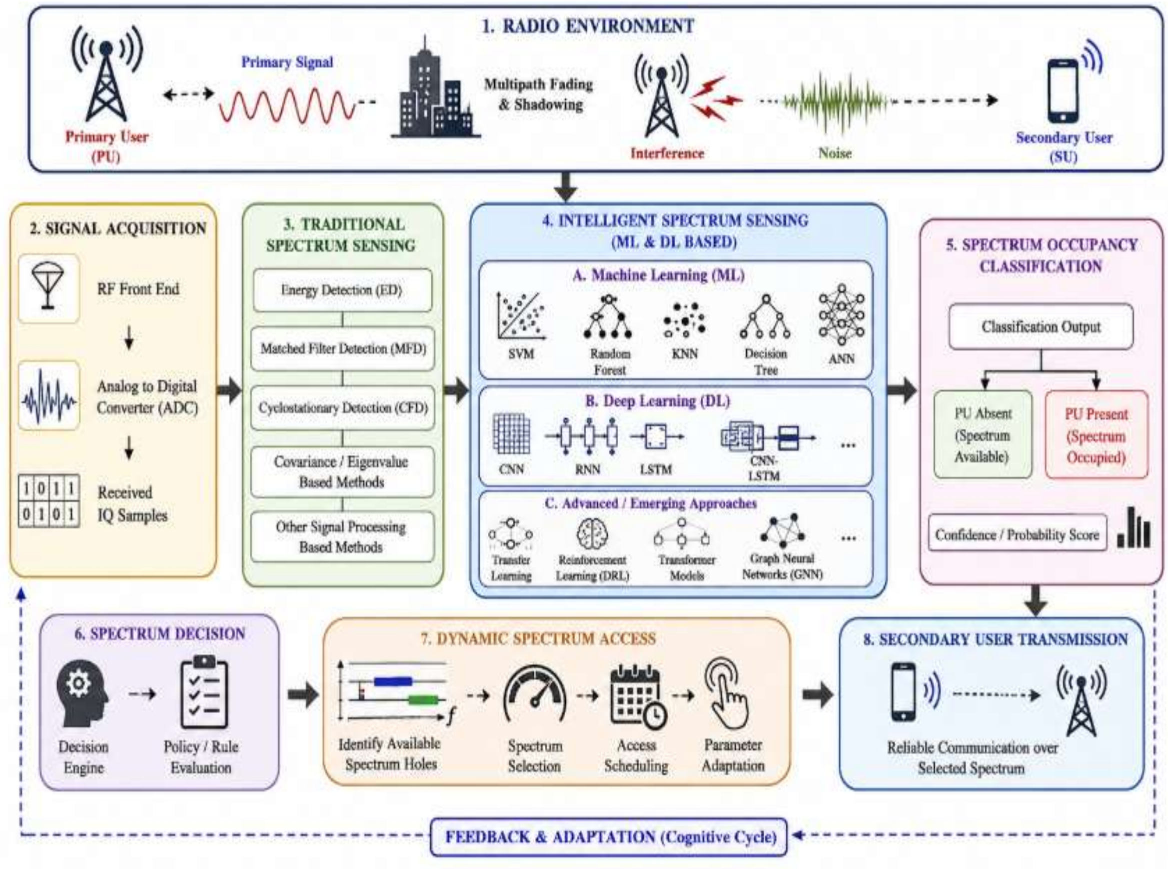

Figure 1.1. Conceptual framework of machine learning and deep learning based spectrum sensing in Cognitive Radio Networks.

2.Fundamentals Of Cognitive Radio Networks

Cognitive Radio (CR) is an intelligent radio communication technology which aims to improve the utilization of limited radio spectrum. A cognitive radio is able to listen to the immediate radio environment, and adjust its transmission properties based on the current spectrum utilization. The primary purpose is to enable temporary utilization of available unused segments of licensed spectrum by secondary users without interfering with primary users [1] [2]. A Cognitive Radio Network (CRN) is a network of smart radio devices that are able to sense, learn and decide on how to use the spectrum. The secondary user is to cease to use the former band or switch to other available bands when a primary user is active in that band. Thus the spectrum sensing is a fundamental and essential task for cognitive radio [1]. Spectrum sensing is another significant ability that should be achieved for efficient CR operation, as noted in the recent review by Muzaffar and Sharqi.

2.1 Cognitive Radio Concept

The primary users (PUs) and secondary users (SUs) are the principle users of the Cognitive Radio Network (CRN). Primary User: A licensed user who has access priority to a specific frequency band and other users are not allowed to cause harmful interference with the communications of the Primary User. On the other hand, a Secondary User is an unlicensed or cognitive user who is able to use an available spectrum band when the PU does not use it. The SU continually scans the radio spectrum to detect spectrum availability. If the PU is not present, the SU can use the empty spectrum band for communication. Once the PU is activated, however, the SU must rapidly change to a different channel or else the spectrum handoff must be performed by the SU. This type of dynamic spectrum access will help to maximize the utilization of the spectrum, while preserving the ability of licensed users to communicate.

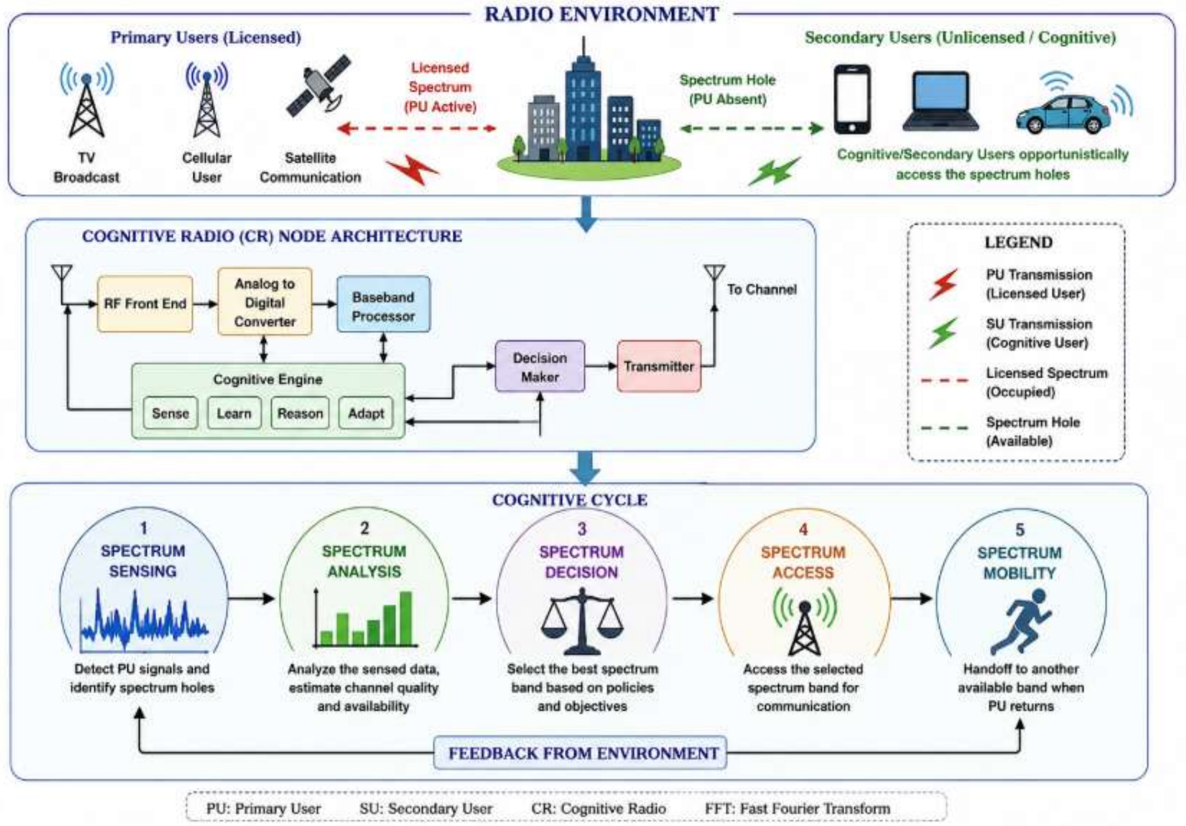

Figure 2.1 Basic architecture and cognitive cycle of a Cognitive Radio Network.

The cognitive cycle is the basic mode of operation of a cognitive radio, which continually scans and adjusts to the wireless environment. It starts with spectrum sensing, and the existence or not of primary users (PUs) is sensed. Spectrum analysis, which analyzes the characteristics, availability and quality of the detected channels, follows this. On the basis of this information, spectrum decision decides on the most appropriate channel for the communication. The cognitive radio then acquires the channel for spectrum access, leveraging the available channel and avoiding the harm to the PU. If the PU is active or the channel selected is not of good quality, the secondary user (SU) can switch to another channel that is suitable for the SU. In general, the cognitive cycle enables the cognitive radio to be able to continuously observe the radio environment, make intelligent decisions and dynamically adapt its operation. Spectrum management and spectrum sharing are also critical aspects of cognitive radio operation, aiding in efficient allocation and coordinated use of the available spectrum.

Dynamic Spectrum Access (DSA) is the ability of Secondary User (SU) to dynamically use spectrum bands temporarily unused by Primary Users (PU) instead of using them on a fixed allocation basis. The SU first senses the target frequency band to determine its occupancy status. If the channel is available, the SU can use the channel for communication with the proper transmission power and communication parameters and that a minimum interference exists. Once the PU is activated, the SU is obliged to turn off the channel or move to another channel in the same band if it is available and leave the channel to enable the PU to communicate. Therefore, DSA can more efficiently utilize existing frequency bands that are "free" for some time, and offer higher flexibility in dynamic wireless environments. It is also of great value for modern wireless networks where the availability of the spectrum and the requirement for communications constantly change.

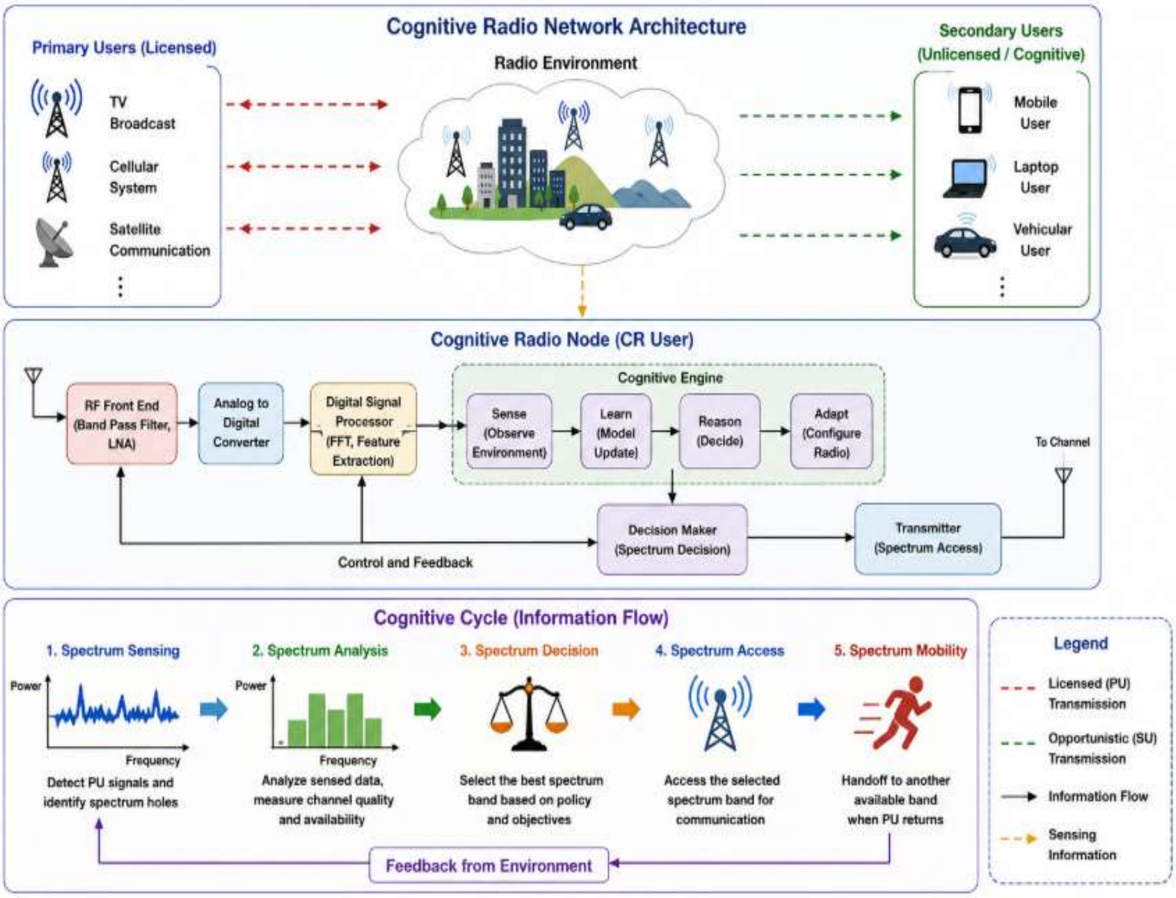

Figure 2.2 Cognitive Radio Network Architecture and Cognitive Cycle

2.3 Spectrum Sensing In Cognitive Radio

Spectrum sensing is the activity of determining whether a spectrum is being used by a primary user or is free for secondary users to access. The output of the sensor is normally expressed as in the presence (PU) or absence (PU absent) of the object. Accurate sensing is crucial as a false alarm might result in an unnecessary channel being wasted, and a missed alarm may lead to interference to the PU [1, [3]]. Some of the classical spectrum sensing techniques are Energy Detection, Matched Filter Detection, Cyclostationary Detection, eigenvalue-based and covariance-based methods. Recently, compressive sensing has also been explored for wideband spectrum sensing. One of the easiest and most popular spectrum sensing methods is Energy Detection (ED). It is a measure of the energy received from the signal over a known measurement time and is used to compare the energy it calculates to a preset threshold. When the measured energy is above the threshold, the PU is deemed to be present, and the channel is deemed to be vacant when the measured energy is below the threshold. The major benefits of ED are its ease of implementation, low computational burden and lack of any detailed prior knowledge of the PU signal. It is however highly susceptible to noise uncertainty and low SNR conditions. Matched Filter Detection (MFD) is based on a filter created by the known characteristics of the primary signal. The received signal is fed into the matched filter, and output of the filter is compared to a decision threshold. MFD can achieve high detection performance, and may need a smaller number of sensing samples if accurate information about the PU signal is available. However, it needs to be known what the parameters are, including the signal waveform, modulation and synchronization information. Thus it might not be more appropriate when the main characteristics of the signals are not known or are changing over time [3].

The attached paper also introduces matched filtering as an accurate sensing method which is based on prior information of the PUs. Cyclostationary Feature Detection (CFD) takes advantage of the cyclostationarity of communication signals. There are many signals with periodic properties, introduced by the carriers, the symbol rate or the cyclic prefix, etc. Cyclic autocorrelation function or spectral correlation function is used to analyse the received signal. If there are characteristic cyclic frequencies present, a PU signal exists. The cyclostationary detection has been shown to yield better performance than energy detection in certain low SNR and interference conditions, as it is able to distinguish the characteristics of the signal from the noise. It incurs however a higher computational complexity and longer sensing time [1], [3]. Eigenvalue based spectrum sensing is based on the eigenvalues of received signal covariance matrix for detecting the presence of a PU signal. It is not necessary to know the PU signal in advance and can take advantage of the statistical correlation of the received samples. The ratio of the maximum to the minimum eigenvalues or other statistics based on eigenvalues are common decision statistics. Under noise uncertainty, these approaches can be helpful, but the computation of the covariance-matrix and the decomposition of the eigen-values adds to the computational complexity [3].

Other approaches are based on eigenvalues, which are also well related to contemporary ML/DL methods. For instance, there has been recent work that explored the use of the covariance matrix information as input to CNN models for multiband joint spectrum sensing. Covariance based spectrum sensing is based on the correlation/covariance relationship between the received signal samples. The concept is that the basic idea of a PU signal is that the received samples will generally be correlated, while the noise will have different statistical properties. A covariance matrix can therefore be used to build-up a sensing statistic for determining the spectrum occupancy. One merit is that sometimes detailed beforehand knowledge of the PU waveform is not needed. But computing covariance matrices can lead to higher computation needs. Covariance-based sensing has been extended using deep learning in recent research. Zhang et al. introduced a CNN-based multiband joint spectrum sensing with covariance matrix aware, which fed the covariance matrix of all subbands to CNN to learn hidden correlation between subbands. One of the crucial techniques for wideband spectrum sensing is compressive Sensing (CS). A wideband CR system typically requires high sampling rates, large storage and high processing power to sense the entire frequency range with conventional Nyquist rate sampling. The idea behind compressive sensing is that the radio spectrum is often sparse, that is, few frequency bands may be used at any given time. CS takes a lesser number of samples than the conventional Nyquist sampling rate, and recovers the key information of the spectrum mathematically. CS can therefore simplify the loading of samples and hardware requirements for wide band CR systems. The need for high sampling-rate and processing requirements of wideband sensing has led to the recent investigation of compressive sensing for wideband cognitive-radio signals [4].

In summary, the traditional spectrum sensing techniques are the fundamental building blocks of the CRNs. They can however degrade in SNR, noise uncertainty, fading, interference and fast changing spectrum conditions. Such restrictions have spurred the development of Machine Learning and Deep Learning based spectrum sensing, which are to be discussed in the subsequent part of this paper. This migration from the traditional sensing to ML/sensing and DL/sensing is validated by recent reviews.

3. Machine Learning And Deep Learning Based Spectrum Sensing

A traditional spectrum sensing approach mainly relies on the signal-processing technique and a predefined threshold, e.g., Energy Detection, Matched Filter Detection, Cyclostationary Detection. Low Signal-to-Noise Ratio (SNR), noise uncertainty, fading, interference and changing spectrum conditions can cause their performance to drop. Hence the use of Artificial Intelligence (AI) such as Machine Learning (ML) and Deep Learning (DL) for spectrum sensing in Cognitive Radio Networks (CRNs) [1] and [2] has been promoted by these limitations. Machine Learning enables a cognitive radio to analyze the spectrum data and determine whether a channel is used or not. Different ML algorithms such as Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN) and XGBoost have been investigated for spectrum sensing and spectrum prediction. In 2021, a survey indicated that ML can be applied to cooperative and non-cooperative spectrum sensing and dynamic spectrum access and spectrum prediction [2].

Deep Learning is a sophisticated ML technique that can learn complex features from large sets of signals automatically. Recently, CNN, RNN, LSTM, CNN-LSTM, CNN-BiLSTM, and the Transformer models have been researched in the field of spectrum sensing. Such techniques are especially valuable in situations where the spectrum occupancy relationship to the received signal is complicated and hard to model with manually chosen features [3] and [4]. In both of the recent reviews published in 2024 and 2025, there is an evident shift from traditional ML to deep and hybrid learning techniques for intelligent spectrum sensing.

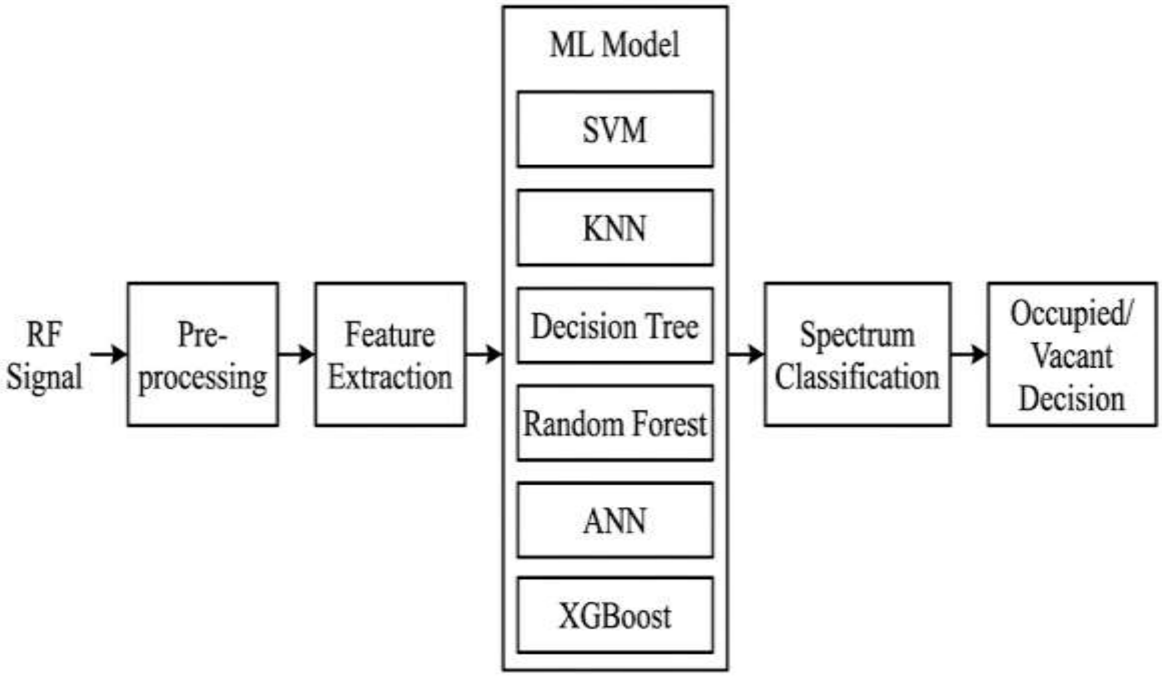

Fig. 3.1. General framework of machine learning-based spectrum sensing in cognitive radio
Fig. 3.1. General framework of machine learning-based spectrum sensing in cognitive radio networks.

Machine learning (ML) based spectrum sensing analyzes the information received to determine whether there is a primary user (PU) signal or not. The received signal is initially processed to extract the features of interest, including received energy, signal strength, statistical features, frequency-domain features and covariance features. The above features are then fed into an ML classifier for Spectrum Occupancy Detection. Some of the commonly used ML techniques are Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Decision Tree, Random Forest, Artificial Neural Network (ANN), and XGBoost. SVM gives a good classification for binary classification and is useful when training data is small or high dimensional, whereas KNN classifies the new sample by reference to the closest training sample. Decision Tree outputs rules for the decision while Random Forest is a collection of several Decision Trees to increase robustness and decrease overfitting. ANN can learn nonlinear relationship between the features of signals and the spectrum. XGBoost is excellent at classification for structured signal data. These traditional ML methods have been studied for spectrum sensing, spectrum occupancy forecasting and spectrum allocation [5]–[8].

3.3 Deep Learning Based Spectrum Sensing

Deep learning (DL)-based spectrum sensing reduces the dependence on manually designed features by learning useful representations directly from signal data. Inputs may include raw I/Q samples, frequency-domain representations, spectrograms, covariance matrices, or combinations of signal features. Convolutional Neural Networks (CNNs) are widely used to extract local signal and time-frequency characteristics, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks learn temporal dependencies in spectrum occupancy. CNN-LSTM architectures combine CNN-based feature extraction with LSTM-based temporal modelling, providing a more comprehensive representation of signal characteristics. CNN-BiLSTM further processes temporal information in both forward and backward directions, making it suitable for signals containing important temporal dependencies. Transformer models use attention mechanisms to capture long-range relationships within signal sequences and have emerged as an important approach for spectrum sensing. Hybrid architectures such as CNN-LSTM, CNN-BiLSTM, CNN-BiLSTM-Transformer, and CNN-RNN with transfer learning combine the advantages of multiple deep learning models. Recent studies have reported improved sensing performance using such hybrid approaches, particularly under low-SNR conditions, demonstrating their potential for reliable cognitive-radio spectrum sensing [3], [4], [10]–[12].

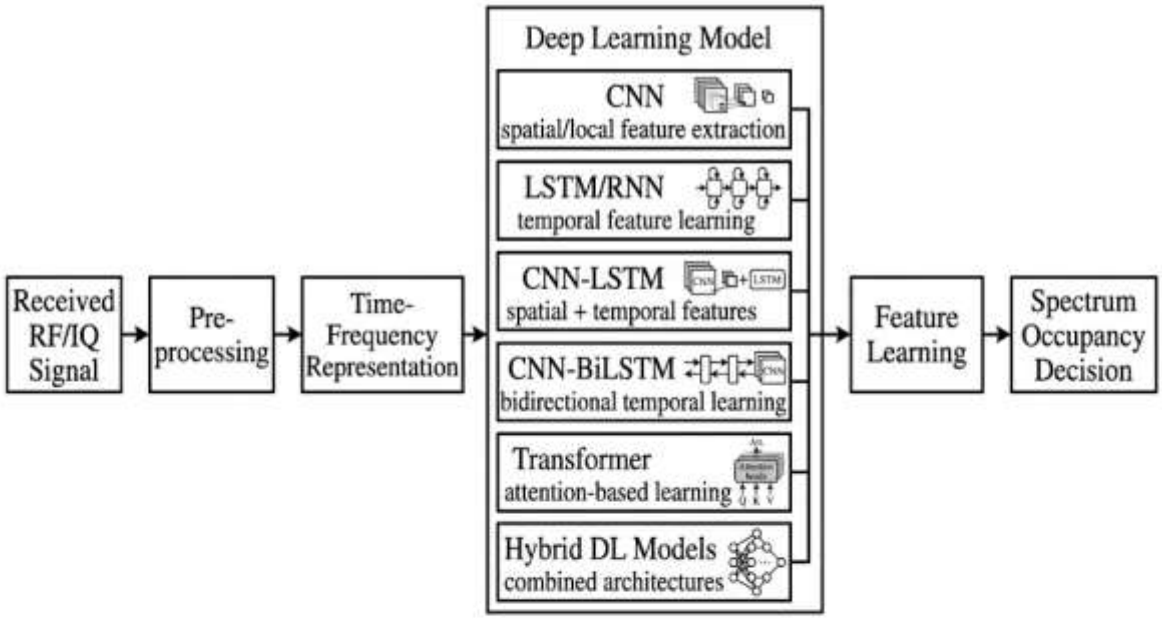

Fig. 3.2. Deep learning-based spectrum sensing architecture using CNN, RNN/LSTM, hybrid networks and Transformer models.

3.4 Comparison of ML and DL Based Spectrum Sensing

The main difference between ML and DL approaches is the way features are obtained and learned. Traditional ML models normally require selected features before classification, while DL models can learn complex features automatically from suitable signal representations.

Method	Learning type	Main strength	Main limitation	Typical use
SVM	Supervised ML	Good classification with limited data	Parameter/kernel selection	Binary spectrum classification
KNN	Supervised ML	Simple and easy to implement	High testing cost for large datasets	Spectrum classification
Decision Tree	Supervised ML	Easy interpretation	Can overfit	Occupancy classification
Random Forest	Ensemble ML	Robust and stable classification	Larger model size	Spectrum sensing/allocation
ANN	Neural ML	Handles nonlinear relationships	Training depends on architecture/data	Signal classification
XGBoost	Ensemble ML	Strong performance on structured features	Less suitable for raw high-dimensional signals	Spectrum prediction/classification
CNN	Deep Learning	Automatic local feature extraction	Requires training data and computation	Signal/spectrogram sensing
RNN/LSTM	Deep Learning	Learns temporal relationships	Sequential training can be costly	Time-varying spectrum
CNN-LSTM	Hybrid DL	Spatial + temporal learning	Higher complexity	Dynamic spectrum sensing
CNN-BiLSTM	Hybrid DL	Bidirectional temporal learning	More computational demand	Sequential spectrum sensing
Transformer	Deep Learning	Long-range dependency learning	High computational requirement	Complex signal sequences

Hybrid DL	Hybrid DL	Combines multiple strengths	High complexity and training cost	Low-SNR/complex environments

Recent studies have demonstrated that ML and DL can be used in conjunction, but not as a one-size-fits-all solution. For instance, in the 2022 TV-spectrum study, SVM, KNN, and Decision Tree were compared to each other, and newer studies have shifted towards CNN, recurrent networks, hybrid networks, and Transformers.

4. Cooperative And Reinforcement Learning Based Spectrum Sensing

Cognitive Radio Network (CRN): Accurate spectrum sensing is crucial for the CRN to sense and utilise the unused spectrum and to maintain protection for PU. There are some sensing errors which a single Secondary User (SU) can suffer from noise, fading, shadowing, interference and hidden node problem. Cooperative Spectrum Sensing (CSS) is a technique that addresses these problems by allowing multiple SUs to observe the same spectrum and combining their observations to make a more accurate global decision [1]. The overall CSS process involves local sensing, information sharing, data fusion, and global spectrum decision. Centralized or distributed is possible for implementing CSS. With centralized CSS, multiple SUs are supposed to send their sensed data to a Fusion Center (FC) that fuses data and decides whether PU is present or not. This is a simple way of deciding, but can cause the introduction of communication overhead and dependency on the FC. Distributed CSS is an approach that removes the FC and allows SUs to communicate within each other to agree on which spectrum they will use, thus introducing more communication complexity but at the same time scaling up and making the system more robust. The CSS fusion techniques are primarily hard fusion and soft fusion techniques. In hard fusion, each SU sends a binary decision (1 or 0) about the presence or absence of a PU, and the FC provides rules like OR, AND or majority voting. Hard fusion results in the loss of some of the sensing information and decreases reporting overhead. Soft fusion: The SUs send sensing statistics or measurements, and the FC maintains more information, which could yield improved detection performance but results in higher communications and processing demands. Therefore, CSS has a bit of compromise in terms of its sensing accuracy and communication overhead. Machine Learning (ML) can be used to enhance CSS by learning the reliability of the SUs under the different channel conditions. In the case of multiple SUs, rather than a fixed fusion, the ML models can process the multiple measurements, and then output an adaptive spectrum decision. Cooperative spectrum sensing techniques have been studied, including SVM, KNN, Decision Tree, Random Forest, K-Means, Gaussian Mixture Models, ANN and XGBoost [2]–[7]. The work of deep learning and distributed learning methods has been further investigated in recent studies. Some CNN-LSTM models that incorporate multi-head self-attention and attention-based Graph Neural Networks have been explored to learn complex spatial and temporal relationships between collaborating SUs. The above developments suggest that ML and DL based CSS can offer adaptive and reliable spectrum sensing under dynamic and low SNR wireless scenarios.

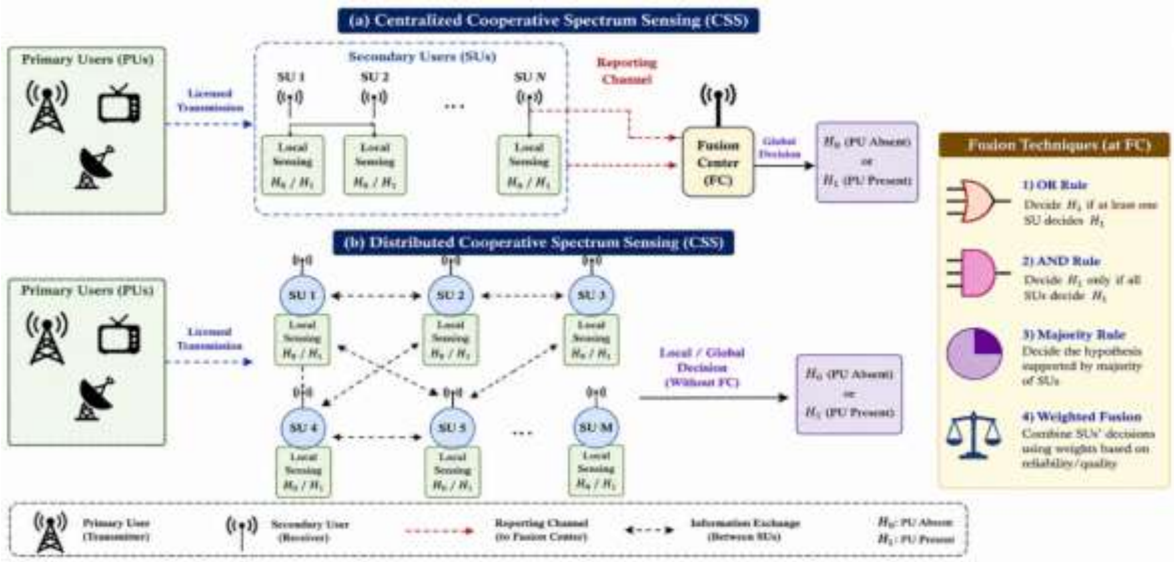

Fig. 4.1. Centralized and distributed cooperative spectrum sensing architecture in cognitive radio networks.

Reinforcement Learning (RL) is a technique that allows a cognitive radio to learn optimal decisions on how to sense and access the spectrum by interacting with the wireless environment. In contrast, supervised learning assumes that the agent has access to labeled training data, whereas RL doesn't. For cognitive radio networks, the agent can be a Secondary User (SU) and the state can be the channel conditions, the results of channel sensing, the interference, and the spectrum availability.

The possible actions are sensing or selection, access to the spectrum, changing channels, and the rewards will be set based on throughput, spectrum utilization, successful transmission and interference reduction. The Q-learning is a model-free RL algorithm that can learn the state-action values without the need of a full mathematical model of the wireless environment. However its Q-table grows in size when there are more channels, users and environmental states. Deep Reinforcement Learning (DRL) is a fusion of RL and deep neural networks that can be used for large state spaces and changing state spaces. Dynamic spectrum access and sensing have been explored using approaches like Deep Q-Network (DQN), Double DQN, Policy Gradient, Actor-Critic, Soft Actor-Critic (SAC) and Multi-Agent Deep Reinforcement Learning (MADRL). DRL can learn to optimize the use of the spectrum and how much throughput it can provide while minimizing interference as channel conditions change. RL can be used for selecting SUs to participate, finding sensing channels, finding sensing intervals and optimizing information fusion in Cooperative Spectrum Sensing (CSS), identifying reliable users and reducing unnecessary sensing operations.

Previous works demonstrate the potential of DRL to forecast the PU activity and allow for avoidance of sensing in a suitable time window in the future which, in turn, alleviates sensing energy consumption. Multi-Agent Reinforcement Learning (MARL) is well suited for distributed CRNs since the SUs are independent learning agents that can cooperate or compete to jointly attain common goals in spectrum management. It has been studied for cooperative spectrum sensing and channel access in distributed and UAV based cognitive radio networks. Another method to enhance the security of CSS is the use of RL-based approaches for detecting unreliable and malicious users that are participating in Spectrum Sensing Data Falsification (SSDF) attacks. During the last few years (2024-2025), more research efforts have been recently devoted to integrating RL and advanced deep-learning approaches into CSS, such as CNN-LSTM with attention, graph neural networks, federated learning with Swin-Transformer, and Q-learning-based adaptive sensing thresholds. The developments are moving towards adaptive, intelligent, distributed, secure and dynamic spectrum sensing from fixed sensing/fusion strategies for dynamic wireless environments.

4.1 Comparison of CSS and RL-Based Spectrum Sensing

Approach	Main idea	Advantages	Limitations
Centralized CSS	SUs send information to FC	Simple global decision	FC dependency and overhead
Distributed CSS	SUs cooperate without FC	Scalable and robust	Coordination is difficult
Hard Fusion	Binary local decisions	Low communication cost	Loss of sensing information
Soft Fusion	Complete sensing statistics	Better information utilization	Higher bandwidth requirement
ML-Based CSS	ML learns sensing/fusion decision	Adaptive classification	Requires training data
Q-Learning	Learns action-value relationship	Simple and model-free	Large Q-table
DRL	Neural network + RL	Handles large state spaces	High computational cost
Multi-Agent RL	Multiple SUs learn jointly	Suitable for distributed CRNs	Training and coordination complexity
Federated/Distributed AI	Local learning without sharing raw data	Better privacy	Communication and aggregation complexity

Cooperative and RL-based spectrum sensing provide better adaptability and sensing reliability, but there are still several challenges. The more Secondary Users (SUs) are communicating with one another or with a Fusion Center (FC) the more communication overhead is involved. It is also challenging to synchronize distributed and mobile SUs in rapidly changing wireless environments. Reliable and secure learning mechanisms are needed to ensure good performance of CSS, especially when malicious users are able to provide false sensing information. In addition, RL and DRL models need repeated interaction with the environment, and can be quite complex both in terms of computational and training load. Another challenge is the design of the suitable reward function, since maximizing throughput or spectrum usage without taking interference into consideration could negatively impact Primary Users (PUs). Multi-agent systems can generate a non-stationary environment and the complexity of coordination can be increased in the presence of simultaneous learning and interaction among agents. However, practical deployment is still challenging as many ML/RL approaches have been tested only in simulation, and using them at real-time deployment on Software Defined Radios (SDRs), IoT devices and low-power cognitive radios necessitates computationally efficient models. An extra consideration in a centralized CSS is privacy—sensing information is sent to the FC. While dependent on sharing raw sensing information, federated and distributed learning can mitigate the need to share raw information by imposing extra communication and model-aggregation demands.

The future studies are thus being directed towards distributed, adaptive, secure, less complex intelligent spectrum sensing. Federated learning can be used to allow the SUs to train their local models without sharing raw sensing data. Multi-Agent DRL can be used for cooperative sensing and channel-access decisions, and Graph Neural Networks can be used to model the relationships between cooperating SUs. Adaptive choice of sensing users, channels, and thresholds can be achieved by using RL, and long-range dependencies of sensing data can be captured by transformer-based models. Secure AI-based CSS should also be able to identify malicious users and to protect sensing information. Lightweight AI models are crucial in the context of IoT and edge devices where computational power is constrained. Combining the optimum of spectrum sensing and access with RL can further enhance overall network efficiency. The latter methods are likely to enable 6G and intelligent radio networks with highly dynamic spectrum environments, where the recent activity in multi-agent SAC, federated learning, graph neural networks, and adaptive Q-learning suggests a shift towards intelligent and distributed spectrum management.

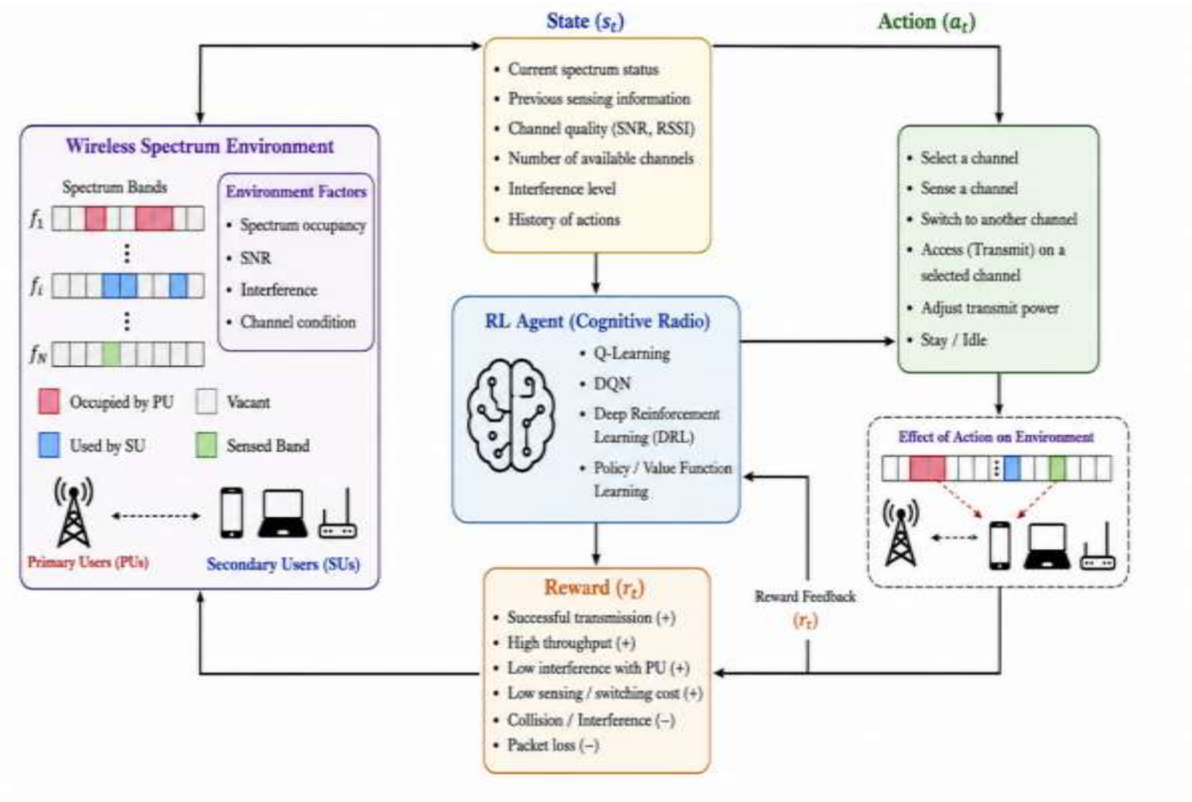

Fig. 4.2. Reinforcement learning framework for adaptive spectrum sensing and channel selection in cognitive radio networks.

5. Wideband Spectrum Sensing, Recent Trends, Applications, Challenges And Future Directions

An important part of Cognitive Radio Networks (CRNs) is Wideband Spectrum Sensing (WBSS) that a cognitive radio should perform to determine the use of available subbands and available subbands. While narrowband sensing only returns information about one frequency band, WBSS returns information about several frequency bands and therefore can be used to effectively identify spectrum holes in a congested and dynamically changing wireless environment. However, high frequency sensing produces a lot of data, which in turn traditionally needs high sample rates, leading to greater complexity, computational load and energy usage of the hardware. In this context, compressive sensing, sub-Nyquist sampling and intelligent ML/DL are important strategies for enhancing the efficiency of WBSS. The wideband RF signal is sampled, and the spectrum is reconstructed or analysed, subbands are detected and their occupancy is determined. Some of the prominent difficulties are the high sampling rate of the Nyquist based systems, complexity of computation, high energy consumption, low-SNR detection, identification of multiple subbands, and hardware limitations. Spectrum Sparsity is the key property used in Compressive Sensing (CS) for solving the sampling problem; in this approach, only a few frequency bands are used at a given time. The CS takes less samples than the normal Nyquist rate and reconstructs the desired spectrum data. Recently, CS techniques have been combined with subband energy detection, modulated wideband converters and deep learning to reduce sampling requirements, ADC power consumption and reconstruction complexity. Machine Learning (ML) further enhances WBSS by learning the patterns from the spectrum measurements and classify the subbands based on their signal properties. The subband classification or spectrum occupancy detection can be performed using SVM, KNN, Decision Tree, Random Forest, ANN and XGBoost. The practical feasibility of ML-based WBSS has been recently shown with SVM implementation based on SDR features (energy and goodness-of-fit), which has demonstrated a better detection performance at low SNR. The I/Q samples, spectrograms and power-spectrum information can be automatically learned as complex representations by Deep Learning (DL) techniques like CNN, LSTM, CNN-LSTM, CNN-BiLSTM, and Transformer. Recent efforts have investigated CNN-based sensing using spectral correlation features, real over-the-air signals, multi-representation inputs and subband-shuffling augmentation for sensing and classification in low-SNR scenarios. Therefore, implementing a wideband spectrum-sensing system with compressive sensing and ML/DL is a desirable approach for achieving accurate and energy-efficient practical wideband spectrum-sensing systems.

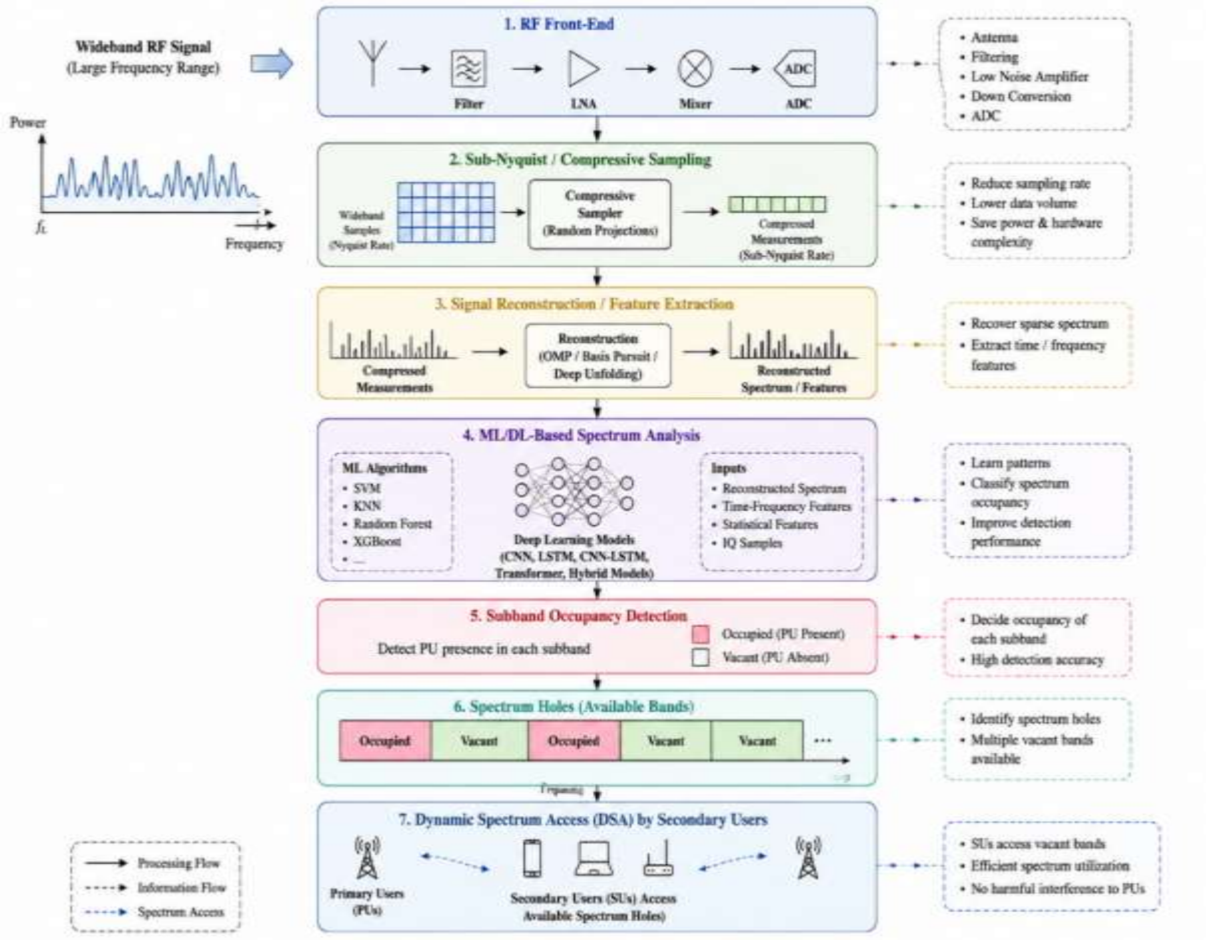

Fig. 5.1. Wideband spectrum sensing architecture using compressive sampling and intelligent spectrum analysis.

The research conducted in 2020-2025 was clearly a shift from traditional signal-processing methods to intelligent, adaptive, and data-driven methods for spectrum sensing. A lot of research was conducted on Machine Learning (ML) techniques like SVM, ANN, KNN, and Decision tree for spectrum classification and cooperative sensing. These techniques are still applicable as they can achieve effective sensing performance with lower computational demands than large deep-learning models. With its capability to automatically learn complex signal features, Deep Learning (DL) has come into more use. CNNs have been used for spectrum sensing and spectrum classification, and RNNs and LSTMs have been employed to model temporal features of spectrum data. Hybrid CNN-RNN architectures have been shown to benefit sensing performance by incorporating CNN to extract features and LSTM/RNN to model temporal information, especially under low-SNR and transfer learning situations. In order to adaptively sense and access the spectrum, reinforcement learning (RL) and deep reinforcement learning (DRL) have been proposed, allowing cognitive radios to learn from their interactions with the wireless environment.
The cooperative sensing and mitigating of Spectrum Sensing Data Falsification (SSDF) attacks have also been studied in DRL. Another area that is becoming a popular direction is Federated Learning (FL), which solves the privacy and communication issues by training local models and sending out updates to the model instead of the raw data that has been gathered by the cognitive radio. Recently, privacy-aware cooperative spectrum sensing has been achieved by integrating FL with enhanced architectures (e.g., Swin-Transformer). Transformer based models are becoming popular as they can model long-range relationships between signals and between cooperating users through their attention mechanisms. Their collaboration with federated learning is a step towards advanced and privacy-preserving spectrum sensing. At the same time, research is progressing from simulation-based evaluation towards practical Software Defined Radio (SDR) implementations. Recent wideband spectrum-sensing (WSS) research based on SDR has illustrated the need of verifying the validity of ML-based approaches under realistic noise, interference, hardware, and channel conditions. In general, the research trend of the last five years (2020-2025) shows that the spectrum sensing systems are becoming more intelligent, adaptive, distributed, privacy-preserving, and real-time.
The major spectrum sensing approaches can be compared as follows.

Technique	Main Principle	Advantages	Limitations	Suitable Environment
Energy Detection	Measures signal energy	Simple and low cost	Sensitive to noise uncertainty	Basic CR systems
Matched Filter	Uses known PU signal information	High detection performance	Requires prior PU information	Known signal systems
Cyclostationary Detection	Uses signal periodicity	Good noise resistance	High computational complexity	Weak-signal environments
Eigenvalue Detection	Uses covariance/eigenvalue characteristics	Less dependence on noise power	Computationally complex	Unknown signal conditions
Covariance Detection	Uses signal correlation	Does not require detailed PU information	Matrix processing required	Multi-signal environments
Compressive Sensing	Uses spectrum sparsity	Lower sampling requirement	Reconstruction complexity	Wideband sensing
SVM	Supervised classification	Good classification with limited data	Requires training	ML-based sensing
Random Forest	Ensemble decision trees	Robust classification	Larger model	Structured spectrum data
ANN	Nonlinear learning	Learns complex patterns	Training required	Signal classification
CNN	Automatic feature extraction	Good for signal/spectrogram data	High computation	DL-based sensing
LSTM/RNN	Temporal learning	Learns spectrum	Training	Dynamic

		time dependence	complexity	spectrum
CNN-LSTM	Spatial + temporal learning	Combines CNN and LSTM advantages	Higher complexity	Dynamic WBSS
Transformer	Attention-based learning	Long-range dependency learning	High computational cost	Advanced 5G/6G systems
Federated Learning	Distributed model learning	Better data privacy	Communication overhead	Distributed CRNs
Reinforcement Learning	Learns through rewards	Adaptive decisions	Reward design required	Dynamic spectrum access

5.1 Applications of Spectrum Sensing and Cognitive Radio

Spectrum sensing and the technology of Cognitive Radio (CR) are widely applicable to several modern wireless systems. Spectrum sensing is used in 5G and beyond-5G/6G networks for Dynamic Spectrum Access (DSA) to detect the unused frequency bands in a time period which consequently can enhance the spectrum utilization efficiency. CR can be dynamically used to select and identify channels in the large number of IoT devices operating on limited spectrum, such as smart homes, smart cities, industrial IoT, smart agriculture and environmental monitoring. Likewise, in smart-grid, cognitive radio can be used to enable reliable communication between the smart meters, the control system and the sensors by dynamically utilising the available spectrum and alleviating congestion. Cognitive radio could also be beneficial in vehicular networks or ad-hoc networks, which involve vehicles needing to communicate reliably for safety or traffic-management purposes. By implementing the concept of spectrum sensing, dynamic channel selection is possible while minimizing interference to users already using the system. As for emergency and public safety communications, CR can serve as temporary communication links if the infrastructure is damaged or overloaded in disaster situations, aiding fire and rescue services, the police, disaster management teams, and emergency medical services. Another application where the use of ML for cooperative spectrum sensing can help is in healthcare and Internet of Medical Things (IoMT) systems, where channel availability and interference management issues are crucial. Another important application is the UAV and drone networks since UAVs are deployed in highly dynamic environments and wireless connectivity is essential. Multiple UAVs can be accommodated by dynamic channel selection via cognitive radio, cooperative sensing and multi-agent learning.

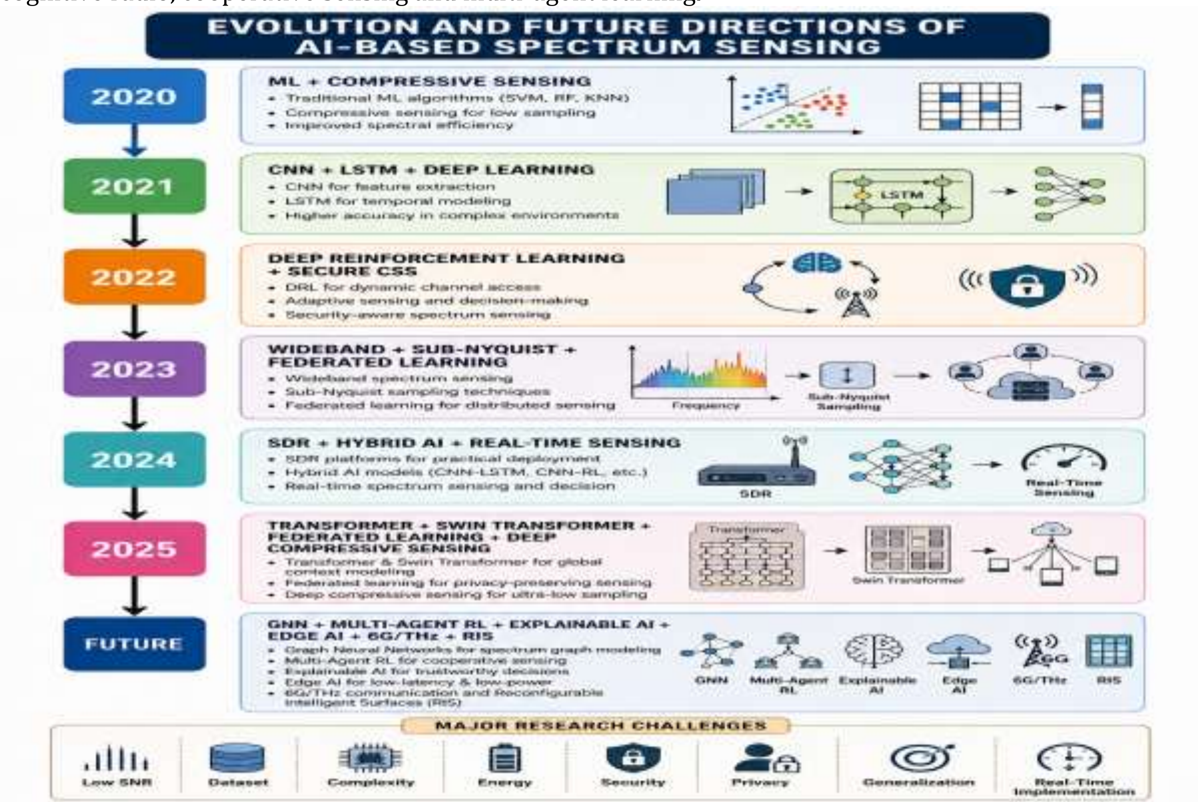

Fig. 5.2. Evolution of intelligent spectrum sensing from conventional machine learning to deep learning, federated learning, Transformer models and future 6G technologies.

The wideband spectrum sensing is also applicable to military and security applications of spectrum monitoring, communication and interference detection over a wide frequency range. Last, with the development of the 6G and Terahertz (THz) communication, novel spectrum-sensing needs have been emerged at the higher frequencies. The literature reviewed confirms that the 325 GHz band offers great potential for high data rate telecommunication, backhaul, imaging and sensing applications, as well as challenges related to propagation loss, hardware restrictions, and regulations. Therefore, spectrum sensing is emerging as a major enabler to achieve efficient, reliable, and adaptive spectrum utilization in 5G/6G, IoT, smart-grid, vehicular, emergency, healthcare, UAV, military, and emerging THz spectrum communication systems.

5.2 Major Challenges

While the field of spectrum sensing research has made considerable strides, there are still many challenges that hinder the practical application of spectrum sensing. Weak Primary User (PU) signals can be masked by noise, causing low-SNR detection to be a major problem. While Machine Learning (ML) and Deep Learning (DL) can enhance detection, their effectiveness relies on the quality and variety of training data. Another significant uncertainty is noise, as noise levels may fluctuate from one day to another, leading to a greater number of false alarms and non-detections in practice. Moreover, the availability of proper data sets is also a challenge for the DL-based spectrum sensing. It is hard to get large and representative RF data sets for various locations, types of signals, values of SNR, fading conditions, different interference and hardware configurations. As a result, training models in one environment may not be able to transfer well to another environment. There are various factors that can cause a difference between the simulated and real world, including hardware noise, multipath fading, interference, modulation schemes and sampling hardware. Transfer learning and cross domain learning are thus gaining importance as methods for the enhancement of the model generalization. Other considerations include energy usage and computational complexity, especially for CNN, LSTM, Transformer and hybrid models on battery-powered devices, IoT nodes, mobile cognitive radios, and edge platforms. However, future systems will need to focus not only on detection accuracy, but also on energy efficiency because they will need to use energy to sample the RF in a continuous wideband way, to process the signals and to make inferences using AI. Security is another important issue in which the Cognitive Radio Networks can be vulnerable to the attacks of Spectrum Sensing Data Falsification (SSDF), jamming, spoofing, eavesdropping and adversarial attacks. These AI-driven sensing models can also be susceptible to biased training data and adversarial inputs.AI models of sensing can be susceptible to bias in the training data and adversarial inputs. As the number of cooperating users increases, the amount of communication overhead and synchronization requirements increases as well. Moreover, many DL models are embodied in black boxes, thus requiring Explainable AI (XAI) to bring some transparency to the spectrum decision-making process. Finally, there is a problem with the practical hardware implementation as ADC limitations, imperfection of RF-front-end, sampling-clock error, quantization noise, hardware noise, processing delay etc. can lead to performance differences between simulation and hardware implementation. Hence, the validation of the intelligent spectrum-sensing systems is imperative using SDR and hardware approach to ensure the reliability, efficiency, security, and eventually practical deployment of the intelligent systems.

6. Conclusion

Cognitive Radio (CR) is a potential solution that can be used to increase the utilization of limited and congested radio-frequency (RF) spectrum. This review gave a thorough discussion of conventional spectrum sensing techniques, Machine Learning (ML), Deep Learning (DL), Cooperative Spectrum Sensing (CSS), Reinforcement Learning (RL), Wideband Spectrum Sensing (WBSS) techniques in Cognitive Radio Networks (CRNs). The traditional spectrum sensing techniques include Energy Detection, Matched Filter Detection, Cyclostationary Detection, Eigenvalue-Based Detection, Covariance-Based Detection and Compressive Sensing, which can be adversely influenced by noise uncertainty, low SNR, computational complexity and the dynamic wireless environments. The use of ML techniques to learn patterns from sensing data can enhance the classification and prediction of spectra, such as SVM, KNN, Decision Tree, Random Forest, ANN, and XGBoost. DL models like CNN, LSTM, CNN-LSTM, CNN-BiLSTM and Transformer models also provide feature extraction and learning of temporal and long-range features automatically. CSS enhances sensing reliability through data fusion of multiple secondary users, and RL and DRL offer adaptive sensing, channel selection and spectrum-access decisions. The advantages of WBSS and compressive sensing also contribute to efficient monitoring of multiple frequency bands, while requiring less sampling. The latest research conducted in 2020-2025 has shown that the traditional signal processing techniques are shifting to intelligent, adaptive, and distributed spectrum sensing techniques. Hybrid deep-learning models, Federated Learning, Graph Neural Networks, Transformer architectures, multi-agent reinforcement learning, compressive sensing, and SDR-based implementations are emerging approaches that are being considered. The techniques can be applied to 5G/6G, IoT, smart grids, vehicular wireless, UAVs, healthcare, emergency communication, and other next generation wireless systems. Despite all of these progresses, there are still many challenges associated with low SNR detection, noise uncertainty, limited real world data, model generalization, computation and energy consumption, security, communication overhead, and hardware implementation. The future research scope should be lightweight, robust, explainable, secure and energy efficient AI models with real-world datasets and experimental validation using SDR. Alternative approaches that combine traditional signal processing, ML, DL, CSS, and RL with compressive sensing are expected to yield more adaptive and reliable spectrum-sensing solutions. In conclusion, intelligent spectrum sensing holds significant promise for enabling efficient spectrum use, minimizing interference, ensuring reliable communication, and autonomous spectrum management in the future 5G-Advanced, 6G, and beyond wireless networks.

References

1. M. U. Muzaffar and R. Sharqi, "A review of spectrum sensing in modern cognitive radio networks," Telecommunication Systems, vol. 85, pp. 347–363, 2024.
2. A. Upadhye, P. Saravanan, S. S. Chandra, and S. Gurugopinath, "A Survey on Machine Learning Algorithms for Applications in Cognitive Radio Networks," 2021.
3. M. U. Muzaffar and R. Sharqi, "A review of spectrum sensing in modern cognitive radio networks," Telecommunication Systems, 2024.
4. A. Utepova, N. Smailov, and P. Komada, "A Review of Recent Deep Learning Methods in Spectrum Sensing," Journal of Emerging Technologies and Computing, vol. 1, no. 1, 2025.
5. Y. Zouine et al., "A review of deep learning techniques for enhancing spectrum sensing and prediction in cognitive radio systems: approaches, datasets, and challenges," International Journal of Computers and Applications, vol. 46, no. 12, pp. 1104–1128, 2024.
6. S. Solanki, V. Dehalwar, J. Choudhary, M. L. Kolhe, and K. Ogura, "Spectrum Sensing in Cognitive Radio Using CNN-RNN and Transfer Learning," IEEE Access, vol. 10, pp. 113482–113492, 2022, doi: 10.1109/ACCESS.2022.3216877.
7. S. Solanki et al., "Spectrum Sensing in Cognitive Radio Using CNN-RNN and Transfer Learning," IEEE Access, 2022.
8. H. Mahmoud et al., "Cooperative Spectrum Sensing with ML Approaches in CR Networks for IoMT Applications," 2024. The attached paper identifies cooperative ML-based sensing as an important recent direction.
9. M. S. Miah, M. Schukat, E. Barrett, M. Morales Cespedes, and A. Garcia Armada, "Enhanced spectrum sensing for AI-enabled cognitive radio IoT with noise uncertainty," ITU Journal on Future and Evolving Technologies, vol. 6, no. 1, pp. 76–91, 2025.
10. S. K. Jagatheesaperumal, I. Ahmad, M. Höyhtyä, S. Khan, and A. Gurtov, "Deep Learning Frameworks for Cognitive Radio Networks: Review and Open Research Challenges," Journal of Network and Computer Applications, vol. 233, 104051, 2025.
11. Y. Zouine et al., "A review of deep learning techniques for enhancing spectrum sensing and prediction in cognitive radio systems: approaches, datasets, and challenges," International Journal of Computers and Applications, 2024.
12. S. Q. Jalil, S. Chalup, and M. H. Rehmani, "Cognitive Radio Spectrum Sensing and Prediction Using Deep Reinforcement Learning," 2021.
13. P. Nandhini and S. Vimalnath, "Optimized Multi Scale Graph Neural Network with Attention Mechanism for Cooperative Spectrum Sensing in Cognitive Radio Networks," Scientific Reports, 2025.
14. M. U. Muzaffar and R. Sharqi, "A review of spectrum sensing in modern cognitive radio networks," Telecommunication Systems, vol. 85, no. 2, pp. 347–363, 2024, doi: 10.1007/s11235-023-01079-1.
15. A. Upadhye, P. Saravanan, S. S. Chandra, and S. Gurugopinath, "A Survey on Machine Learning Algorithms for Applications in Cognitive Radio Networks," 2021. The attached paper also identifies this work as a recent review of ML techniques in CR networks.
16. Dhope, T., Simunic, D., Dhokariya, N., Pawar, V., & Gupta, B. (2013). Performance Analysis of Angle of Arrival Estimation Algorithms for Dynamic Spectrum Access in Cognitive Radio Networks. In 2nd International Conference on ICACCI (pp. 121-126).

17. Dhope, T., & Simunic, D. (2013). On the Performance of DoA Estimation Algorithms in Cognitive Radio Networks: A New Approach in Spectrum Sensing. In 36th International Convention MIPRO (pp. 507- 512).
18. Dhope, T., & Simunic, D. (2012). On the Performance of AoA Estimation Algorithms in Cognitive Radio Networks. In International Conference on Communication, Information and Computing Technology (pp. 1-5).
19. Dhope, T., & Simunic, D. (2012). Cluster Based Cooperative Spectrum Sensing in Cognitive Radio Net- works: A Survey. In International Conference on Communication, Information and Computing Technol- ogy (pp. 1-6).
20. Y. Arjoune and N. Kaabouch, "A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions," Sensors, vol. 19, no. 1, 2019. This is a foundational reference for conventional sensing methods; the newer 2024 review updates the field through modern CR and 5G applications.
21. S. Mostafa, M. Nagah, M. Megahed, and M. Salama, "Application of Compressive Sensing (CS) to Wide-Band Cognitive Radio Signals," IUSRJ International Uni-Scientific Research Journal, vol. 4, no. 3, pp. 15–22, 2023, doi: 10.59271/s44685-023-2206-3.
22. J. Zhang, Z. He, H. Rui, and X. Xu, "Multiband Joint Spectrum Sensing via Covariance Matrix-Aware Convolutional Neural Network," IEEE Communications Letters, 2022. This work is also listed in the attached paper's recent-literature table.
23. L. Cai, K. Cao, Y. Wu, and Y. Zhou, "Spectrum Sensing Based on Spectrogram-Aware CNN for Cognitive Radio Network," IEEE Wireless Communications Letters, 2022.
24. S. Solanki, V. Dehalwar, J. Choudhary, M. L. Kolhe, and K. Ogura, "Spectrum Sensing in Cognitive Radio Using CNN-RNN and Transfer Learning," IEEE Access, 2022. The attached paper reports this work as a recent DL-based spectrum sensing approach using CNN-RNN and transfer learning.
25. M. U. Muzaffar and R. Sharqi, "A review of spectrum sensing in modern cognitive radio networks," Telecommunication Systems, vol. 85, pp. 347–363, 2024, doi: 10.1007/s11235-023-01079-1.
26. A. Upadhye, P. Saravanan, S. S. Chandra, and S. Gurugopinath, "A Survey on Machine Learning Algorithms for Applications in Cognitive Radio Networks," 2021.
27. N. El-haryqy, Z. Madini, and Y. Zouine, "A review of deep learning techniques for enhancing spectrum sensing and prediction in cognitive radio systems: approaches, datasets, and challenges," International Journal of Computers and Applications, vol. 46, no. 12, pp. 1104–1128, 2024, doi: 10.1080/1206212X.2024.2414042.
28. A. Utepova, N. Smailov, and P. Komada, "A Review of Recent Deep Learning Methods in Spectrum Sensing," Journal of Emerging Technologies and Computing, vol. 1, no. 1, 2025, doi: 10.47344/2trfzg43.
29. Dhope, T., Simunic, D., & Zentner, R. (2013). Comparison of DoA Estimation Algorithms in SDMA System. Automatika Journal, 54, 199-209.
30. Dhope, T., Simunic, D., Dhokariya, N., Pawar, V., & Gupta, B. (2014). What about Spectrum Opportunities in Angle Dimension for Dynamic Spectrum Access in Cognitive Radio Context? Wireless Personal Communications, 75(3), 1-21.
31. "Case study of TV spectrum sensing model based on machine learning techniques," Ain Shams Engineering Journal, vol. 13, no. 2, 101540, 2022, doi: 10.1016/j.asej.2021.06.026.
32. N. Suganthi, S. Kumar K., and K. Govindharaju, "Spectrum Allocation in Cognitive Radio based Traffic Monitoring System Using Machine Learning," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 4, pp. 951–959, 2024.
33. T. A. Oyewo, U. S. Dauda, and A. S. Mohammed, "Spectrum Occupancy Prediction Using a Modified XGBoost Machine Learning Algorithm," International Conference on Scientific and Academic Research, vol. 1, pp. 232–237, 2023.
34. A. M. Joykutty and B. Baranidharan, "Optimized Cooperative Spectrum Sensing in Cognitive Radio Sensor Networks Using Extended XGBoost Model," International Journal of Computer Networks and Applications, vol. 12, no. 4, pp. 554–571, 2025, doi: 10.22247/ijcna/2025/34.
35. S. E. Abdelbaset, H. M. Kasem, A. A. Khalaf, A. H. Hussein, and A. A. Kabeel, "Deep Learning-Based Spectrum Sensing for Cognitive Radio Applications," Sensors, vol. 24, no. 24, 7907, 2024, doi: 10.3390/s24247907.
36. S. Solanki, V. Dehalwar, J. Choudhary, M. L. Kolhe, and K. Ogura, "Spectrum Sensing in Cognitive Radio Using CNN-RNN and Transfer Learning," IEEE Access, vol. 10, pp. 113482–113492, 2022, doi: 10.1109/ACCESS.2022.3216877.
37. "Spectrum sensing using deep learning for proficient data transmission in wireless sensor networks for wireless communication," Ain Shams Engineering Journal, vol. 15, no. 7, 102784, 2024, doi:

10.1016/j.asej.2024.102784.
38. Y. Zhang and Z. Luo, "A Deep-Learning-Based Method for Spectrum Sensing with Multiple Feature Combination," Electronics, vol. 13, no. 14, 2705, 2024, doi: 10.3390/electronics13142705. ### References ch4
39. K. M. Thilina, K. W. Choi, N. Saquib, and E. Hossain, "Machine Learning Techniques for Cooperative Spectrum Sensing in Cognitive Radio Networks," IEEE Journal on Selected Areas in Communications, vol. 31, no. 11, pp. 2209–2221, 2013.
40. P. Nandhini and S. Vimalnath, "Optimized multi scale graph neural network with attention mechanism for cooperative spectrum sensing in cognitive radio networks," Scientific Reports, vol. 15, Art. no. 41130, 2025, doi: 10.1038/s41598-025-24947-z.
41. P. Venkatapathi, H. Khan, S. Srinivasa Rao, and G. Immadi, "Cooperative Spectrum Sensing Performance Assessment using Machine Learning in Cognitive Radio Sensor Networks," Engineering, Technology & Applied Science Research, vol. 14, no. 1, pp. 12875–12879, 2024, doi: 10.48084/etasr.6639.
42. S. Q. Jalil, S. Chalup, and M. H. Rehmani, "Cognitive Radio Spectrum Sensing and Prediction Using Deep Reinforcement Learning," 2021.
43. W. Jiang, W. Yu, W. Wang, and T. Huang, "Multi-Agent Reinforcement Learning for Joint Cooperative Spectrum Sensing and Channel Access in Cognitive UAV Networks," Sensors, vol. 22, no. 4, 1651, 2022, doi: 10.3390/s22041651.
44. Z. Li, X. Liu, and Z. Ning, "Dynamic spectrum access based on deep reinforcement learning for multiple access in cognitive radio," Physical Communication, vol. 54, Art. no. 101845, 2022, doi: 10.1016/j.phycom.2022.101845.
45. X. Wang, Y. Teraki, M. Umehira, H. Zhou, and Y. Ji, "A Usage Aware Dynamic Spectrum Access Scheme for Interweave Cognitive Radio Network by Exploiting Deep Reinforcement Learning," Sensors, vol. 22, no. 18, 6949, 2022, doi: 10.3390/s22186949.
46. "Deep Reinforcement Learning based reliable spectrum sensing under SSDF attacks in Cognitive Radio networks," Journal of Network and Computer Applications, vol. 205, Art. no. 103454, 2022, doi: 10.1016/j.jnca.2022.103454.
47. H. A. Benzater, D. Teguig, and N. Lassami, "Enhanced Cooperative Compressive Spectrum Sensing in Cognitive Radio Networks," Transactions on Emerging Telecommunications Technologies, vol. 35, Art. no. e70000, 2024, doi: 10.1002/ett.70000.
48. K. Wang, Y. Chen, D. Bo, and S. Wang, "A novel multi-user collaborative cognitive radio spectrum sensing model: Based on a CNN-LSTM model," PLOS ONE, vol. 20, no. 1, e0316291, 2025, doi: 10.1371/journal.pone.0316291.
49. S. Vedachalam and D. Raj, "Development of a Privacy-Preserved and Secure Cooperative Spectrum Sensing System in Cognitive Radio Networks Using ATSNRNN-Enabled FPPDES with Machine Learning," IEEE Access, 2024, doi: 10.1109/ACCESS.2024.3484508.
50. N. K. Boddukuri, "Adaptive Sampling Point and Q-Learning-Based Sensing Threshold for Spectrum Energy Detection in Cognitive Radio Networks," International Journal of Communication Systems, 2025, doi: 10.1002/dac.6090.
51. D. R. Nickel, A. B. Das, D. J. Love, and C. G. Brinton, "Multi-Agent Hybrid SAC for Joint SS-DSA in CRNs," 2024.
52. The following references are suitable for your 2020–2025 review-paper reference list. I have prioritised recent papers and included the strongest sources used in this chapter.
53. S. Khamayseh and A. Halawani, "Cooperative Spectrum Sensing in Cognitive Radio Networks: A Survey on Machine Learning-based Methods," Journal of Telecommunications and Information Technology, no. 3, pp. 36–46, 2020, doi: 10.26636/jtit.2020.137219.
54. A. Moawad, K. C. Yao, A. Mansour, and R. Gautier, "A Wideband Spectrum Sensing Approach for Cognitive Radios Based on Cepstral Analysis," IEEE Open Journal of the Communications Society, 2020, doi: 10.1109/OJCOMS.2020.3007171.
55. E. Astaiza Hoyos, O. J. Salcedo Parra, and W. Y. Campo Muñoz, "Centralized sub-Nyquist wideband spectrum sensing for cognitive radio networks over fading channels," Computer Communications, vol. 153, pp. 561–568, 2020, doi: 10.1016/j.comcom.2020.02.039.
56. K. Kockaya and I. Develi, "Spectrum sensing in cognitive radio networks: threshold optimization and analysis," EURASIP Journal on Wireless Communications and Networking, vol. 2020, Art. no. 255, 2020.
57. S. Khamayseh and A. Halawani, "Cooperative Spectrum Sensing in Cognitive Radio Networks: A Survey on Machine Learning-based Methods," Journal of Telecommunications and Information Technology, 2020.

58. Dhope, T., & Simunic, D. (2012). Performance Analysis of Covariance Based Detection in Cognitive Radio. In 35th International Convention MIPRO (pp. 737-742).
59. Dhope, T., & Simunic, D. (2012). Hybrid Detection Method for Spectrum Sensing in Cognitive Radio. In 35th International Convention MIPRO (pp. 765-770).
60. Dhope, T., Simunic, D., & Prasad, R. (2011). Hybrid Detection Method for CR. In 13th International Conference on Soft COM (pp. 1-5).
61. H. Xing, H. Qin, S. Luo, P. Dai, L. Xu, and X. Cheng, "Spectrum sensing in cognitive radio: a deep learning based model," Transactions on Emerging Telecommunications Technologies, vol. 33, no. 1, 2021, doi: 10.1002/ett.4388.
62. O. P. Awe, D. A. Babatunde, S. Lambotharan, et al., "Second order Kalman filtering channel estimation and machine learning methods for spectrum sensing in cognitive radio networks," Wireless Networks, vol. 27, pp. 3273–3286, 2021, doi: 10.1007/s11276-021-02627-w.
63. A. Upadhye, P. Saravanan, S. S. Chandra, and S. Gurugopinath, "A Survey on Machine Learning Algorithms for Applications in Cognitive Radio Networks," 2021.
64. S. Syed, P. Lazaridis, F. Khan, Q. Ahmed, et al., "Deep Neural Networks for Spectrum Sensing: A Review," IEEE Access, 2023, doi: 10.1109/ACCESS.2023.3305388.
65. M. U. Muzaffar and R. Sharqi, "A review of spectrum sensing in modern cognitive radio networks," Telecommunication Systems, vol. 85, pp. 347–363, 2024, doi: 10.1007/s11235-023-01079-1.
66. G. Burel, E. Radoi, R. Gautier, and D. Le Jeune, "Wideband Spectrum Sensing Using Modulated Wideband Converter and Data Reduction Invariant Algorithms," Sensors, vol. 23, no. 4, 2263, 2023, doi: 10.3390/s23042263.
67. A. K. Varma, A. K. Vishwakarma, A. K. Tiwari, and D. Mitra, "Discriminating Statistical Feature for Wideband Spectrum Sensing," Revue Roumaine des Sciences Techniques – Série Électrotechnique et Énergétique, 2023, doi: 10.59277/RRST-EE.2023.68.1.14.
68. S. Zeghdoud, T. Tanougast, D. Teguig, M. Mesloub, S. Sadoudi, and B. Belqassim, "SDR implementation of wideband spectrum sensing using machine learning," International Journal of Communication Systems, vol. 37, no. 16, e5907, 2024, doi: 10.1002/dac.5907.
69. S. E. Abdelbaset et al., "Deep Learning-Based Spectrum Sensing for Cognitive Radio Applications," Sensors, vol. 24, no. 24, 7907, 2024.
70. S. Q. Jalil, S. Chalup, and M. H. Rehmani, "Cognitive Radio Spectrum Sensing and Prediction Using Deep Reinforcement Learning," 2021.
71. "Deep Reinforcement Learning based reliable spectrum sensing under SSDF attacks in Cognitive Radio networks," Journal of Network and Computer Applications, vol. 205, 103454, 2022, doi: 10.1016/j.jnca.2022.103454.
72. M. Wasilewska, H. Bogucka, and H. V. Poor, "Secure Federated Learning for Cognitive Radio Sensing," 2023.
73. Z. Du and L. Chen, "A Collaborative Spectrum Sensing Algorithm Based on Reputation Update against Malicious User Attacks," Security and Communication Networks, 2023, Art. no. 7844054, doi: 10.1155/2023/7844054.
74. H. A. Ansari, "Deep Learning With Harmonic Elk Herd Optimization for Spectrum Sensing With Cyclostationary in Cognitive Radio Network," Transactions on Emerging Telecommunications Technologies, 2025, doi: 10.1002/ett.70215.
75. H. Zeng, Y. Yu, G. Liu, and Y. Wu, "A Robust Method Based on Deep Learning for Compressive Spectrum Sensing," Sensors, vol. 25, no. 7, 2187, 2025, doi: 10.3390/s25072187.
76. S. Zheng, Z. Ye, L. Zhang, K. Yue, and Z. Zhao, "Deep Learning-Based Wideband Spectrum Sensing with Dual-Representation Inputs and Subband Shuffling Augmentation," 2025.
77. "Cross-domain intelligent cooperative spectrum sensing algorithm based on Federated Learning and Swin-Transformer neural network," Engineering Applications of Artificial Intelligence, vol. 157, 111370, 2025, doi: 10.1016/j.engappai.2025.111370.
78. "Spectrum sensing-focused cognitive radio network for 5G revolution," Frontiers in Environmental Science, vol. 11, 1113832, 2023, doi: 10.3389/fenvs.2023.1113832.
79. Y. Xu, Y. Li, and T. Q. S. Quek, "RIS-Enhanced Cognitive Integrated Sensing and Communication: Joint Beamforming and Spectrum Sensing," 2024.