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Application of Machine Learning Techniques for Improved Spectrum Sensing Accuracy and Reduced False Alarm Rate in Cognitive Radio Networks: A Review

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Abstract

The increasing demand for wireless communication services has intensified concerns regarding spectrum scarcity and inefficient utilisation of available radio-frequency resources. Cognitive Radio Networks (CRNs) provide a solution through dynamic spectrum access, with spectrum sensing serving as a critical process for identifying vacant and occupied frequency bands. However, conventional sensing techniques can experience reduced detection performance and increased false alarm rates, particularly under low signal-to-noise ratio (SNR), noise uncertainty, fading, and dynamic channel conditions. This review examines the application of machine learning (ML) and deep learning (DL) techniques for improving spectrum sensing accuracy and reducing false alarm rates in cognitive radio networks. A comparative review of recent literature was conducted, focusing on studies published between 2023 and 2026. Relevant studies were analysed according to the learning technique employed, sensing environment, datasets, SNR conditions, probability of detection, probability of false alarm, accuracy, F1-score, and other reported performance measures. The reviewed evidence shows that both conventional ML and DL approaches can provide substantial improvements over traditional sensing methods, although performance varies according to experimental conditions and model architecture. In a comparative study, Random Forest achieved 97.17% accuracy, 95.7% probability of detection, and 96.93% F1-score, while demonstrating the lowest false alarm and missed-detection probabilities among the evaluated models. A U-Net-based approach reported a 99% detection probability and 5% false alarm rate at 10 dB SNR, while LSTM-based approaches demonstrated improved robustness under low-SNR conditions. Overall, the review establishes that ML-based spectrum sensing offers considerable potential for improving sensing reliability and spectrum utilisation, with adaptive, deep-learning, collaborative, and reinforcement-learning approaches emerging as promising directions for intelligent cognitive radio networks.

Keywords: *Machine Learning, Spectrum Sensing Accuracy, Reduced False Alarm Rate and Cognitive Radio Networks.*

1. Introduction

The rapid expansion of wireless communication technologies, including the Internet of Things (IoT), fifth-generation (5G) networks, and emerging sixth-generation (6G) communication systems, has resulted in an increasing demand for radio-frequency spectrum. The growth in connected devices and data-intensive applications has placed considerable pressure on the available spectrum resources, creating concerns about spectrum scarcity and inefficient utilisation. Rajasekhar and Monisha (2026) noted that the rapid growth of wireless communication has contributed to spectrum scarcity and poor utilisation, thereby increasing the importance of technologies capable of identifying and exploiting underutilised frequency bands. Cognitive Radio Networks (CRNs) have consequently emerged as an important approach to dynamic spectrum access, allowing unlicensed or secondary users to opportunistically utilise spectrum bands when they are not being occupied by licensed or primary users.

A fundamental component of a cognitive radio network is spectrum sensing, which enables a secondary user to determine whether a particular frequency band is occupied by a primary user or available for opportunistic access. Reliable spectrum sensing is therefore essential because an incorrect decision can have consequences for both spectrum efficiency and interference management. When an idle channel is incorrectly classified as occupied, a secondary user may unnecessarily avoid an available spectrum opportunity, contributing to inefficient spectrum utilisation. Conversely, when an occupied channel is incorrectly classified as vacant, transmission by a secondary user may interfere with the primary user. Pant and Srivastava (2026) identify probability of detection, probability of false alarm, and probability of missed detection as important measures of spectrum-sensing performance, with the probability of detection indicating the ability to correctly identify an occupied channel and the probability of false alarm indicating the tendency to incorrectly classify an available channel as occupied.

Conventional spectrum-sensing approaches have, however, encountered difficulties under realistic wireless conditions, particularly in the presence of noise, fading, low signal-to-noise ratios, and uncertainty about the characteristics of primary-user signals. Raji and Olwal (2026) observed that traditional sensing techniques can be sensitive to noise and may depend on prior knowledge of primary-user signals, creating challenges when spectrum conditions become dynamic or uncertain. Similarly, Rashid and Shakir (2026) reported that conventional approaches such as energy detection and feature-based techniques can experience performance challenges in low signal-to-noise ratio environments and uncertain conditions. These limitations have increased interest in data-driven approaches capable of learning patterns from signal observations rather than relying exclusively on fixed sensing thresholds or predetermined signal characteristics.

Machine learning has consequently become an important research direction for improving spectrum sensing in cognitive radio networks. Machine learning techniques can learn relationships between signal characteristics and spectrum occupancy and can subsequently use the learned patterns to classify channels as occupied or vacant. Raji and Olwal (2026), for example, comparatively investigated Random Forest (RF), K-Nearest Neighbour (KNN), and Support Vector Machine (SVM), alongside Convolutional Neural Network (CNN) and Autoencoder models. Their evaluation considered probability of detection, probability of false alarm, missed detection, accuracy, and F1-score, with Random Forest achieving a probability of detection of 95.7%, accuracy of 97.17%, and F1-score of 96.93%. The study further reported that Random Forest achieved the lowest false-alarm and missed-detection probabilities among the evaluated models, particularly under low-SNR conditions.

The application of machine learning to spectrum sensing has also expanded beyond conventional supervised classification to include deep learning, adaptive learning, reinforcement learning, and hybrid approaches. Sharma, Yadav, and Kumar (2026) examined machine-learning-based spectrum detection within an optical 5G environment using 256-QAM and highlighted the potential of combining traditional sensing methods with machine learning to improve detection accuracy, reduce latency, and support adaptive spectrum decisions. Pant and Srivastava (2026) proposed a deep-learning-enabled adaptive threshold-selection framework in which a Bi-LSTM model was used to support spectrum sensing and energy optimisation. Similarly, Kannan et al. (2026) proposed an adaptive deep reinforcement learning framework combining Deep Q-Network and Deep Recurrent Q-Network mechanisms with optimisation techniques; their model was designed to improve sensing efficiency, channel selection, collision avoidance, throughput, and adaptability under changing network conditions. These developments demonstrate that machine learning-based spectrum sensing is no longer limited to a single algorithmic approach but encompasses several learning paradigms with different performance characteristics.

Despite the increasing number of machine learning and deep learning approaches, their reported performance varies according to the algorithm, signal characteristics, dataset, signal-to-noise ratio, sensing method, and evaluation conditions. Recent studies have therefore increasingly focused on comparing alternative learning techniques rather than considering a single model in isolation. Cadena Muñoz, Giral, and Hernández Suárez (2026), for instance, combined entropy-based features with SVM, KNN, and Random Forest using data collected through a Software-Defined Radio testbed and reported probability of detection above 0.9 and false-alarm rates below 0.1, demonstrating the potential of machine learning for practical spectrum sensing. At the same time, Rathod et al. (2026) identified deep learning and explainable artificial intelligence as important emerging directions in cognitive-radio spectrum sensing, while Rajasekhar and Monisha

(2026) emphasised recent advances, datasets, challenges, and future research directions in spectrum sensing. These developments establish the need for a structured comparative examination of existing machine learning-based spectrum-sensing approaches to determine how effectively different techniques improve sensing accuracy while reducing false alarm rates. Therefore, this study focuses on reviewing and comparing existing applications of machine learning techniques in cognitive radio spectrum sensing, with particular emphasis on spectrum-sensing accuracy and false alarm rate as key indicators of effective spectrum utilisation.

2. Literature Foundation

2.1 Cognitive Radio and Dynamic Spectrum Access

The increasing number of wireless devices, Internet of Things (IoT) applications, mobile services, and data-intensive communication systems has intensified the demand for radio-frequency spectrum. Although spectrum is a finite resource, conventional fixed-spectrum allocation can result in some licensed bands being heavily occupied while others remain temporarily underutilised. This mismatch between spectrum allocation and actual spectrum occupancy has motivated the development of cognitive radio (CR), in which secondary users (SUs) can opportunistically access spectrum bands when they are not being used by licensed primary users (PUs). The objective is to improve spectrum utilisation without causing harmful interference to legitimate users (Raji & Olwal, 2025; Kumar, 2025).

A cognitive radio continuously observes its radio environment and adapts its communication behaviour according to the detected spectrum conditions. Spectrum sensing therefore represents a fundamental component of the cognitive-radio decision process. Through spectrum sensing, a secondary user determines whether a channel is occupied by a primary user or represents an available spectrum opportunity. Reliable sensing is particularly important because the decision has consequences in both directions: identifying an occupied channel as vacant can result in interference with the primary user, whereas identifying a vacant channel as occupied can cause an available spectrum opportunity to be unnecessarily rejected. Consequently, effective spectrum sensing must achieve a suitable balance between reliable detection and minimisation of false alarms (Raji & Olwal, 2025; El Bandouri & Boulouird, 2026).

The importance of spectrum sensing has become more pronounced in cognitive radio-enabled IoT, 5G and beyond-5G environments. Raji and Olwal (2025) identified noise, interference, signal-strength fluctuations and dynamic network conditions as important challenges affecting spectrum sensing in cognitive radio IoT networks. Similarly, El-haryqy et al. (2024) identified noise uncertainty, low signal-to-noise ratio (SNR) and channel fading among the major conditions that make reliable spectrum sensing difficult. These conditions mean that a sensing approach that performs well under favourable signal conditions may not necessarily maintain the same performance when the signal becomes weak or the radio environment changes.

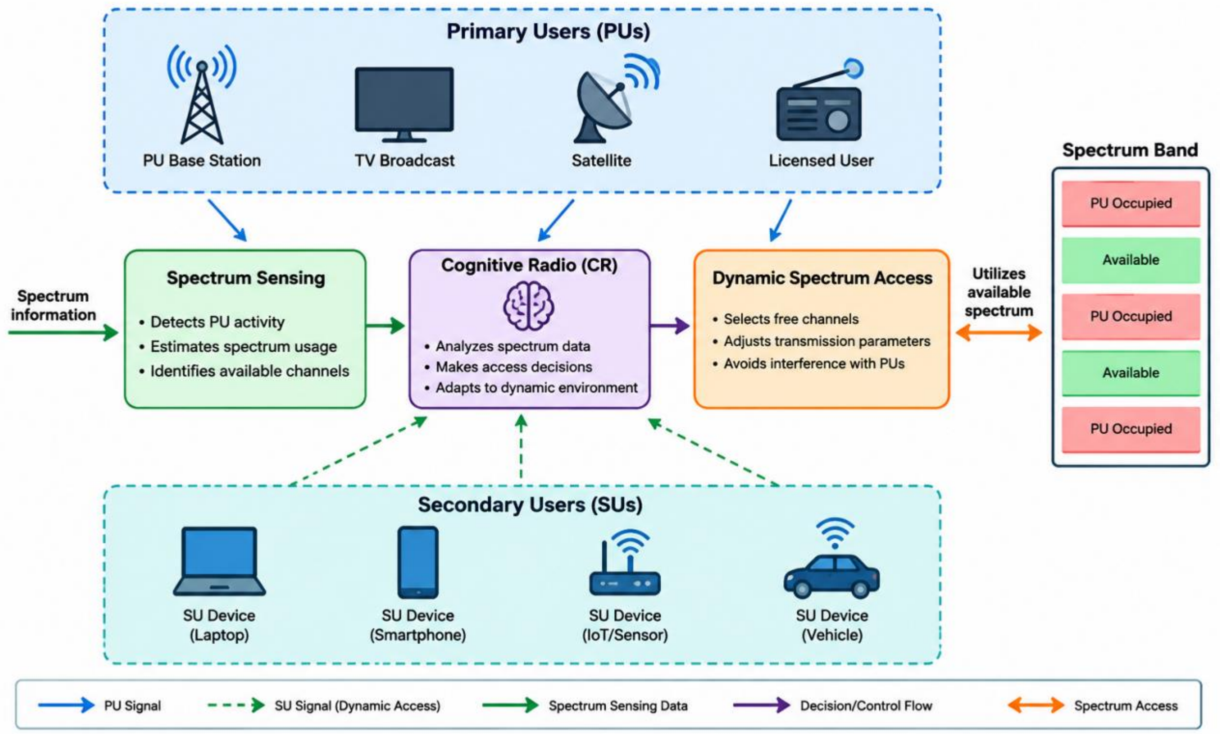


Figure 1. *General Architecture of a Cognitive Radio Network Showing Primary Users, Secondary Users, Spectrum Sensing and Dynamic Spectrum Access.*

2.2 Conventional Spectrum Sensing Techniques

Several conventional techniques have been developed for spectrum sensing, including energy detection, matched-filter detection and cyclostationary feature detection. Among these, energy detection is attractive because of its relatively simple implementation and because it does not require detailed prior knowledge of the primary-user signal. However, its performance is strongly influenced by noise uncertainty and the choice of an appropriate detection threshold. Ahmed et al. (2025), for example, developed a machine-learning approach around energy detection specifically to address the conventional requirement of calculating a sensing threshold. Their study demonstrates how machine learning can be incorporated into an established sensing mechanism rather than necessarily replacing the entire conventional sensing process.

Matched-filter detection can provide efficient detection when information about the transmitted signal is available, but its requirement for prior knowledge can limit its applicability in heterogeneous and dynamic wireless environments. Cyclostationary feature detection, on the other hand, exploits statistical characteristics of modulated signals and can distinguish signals from noise more effectively under certain conditions, although it generally involves greater computational complexity. The continuing limitations of conventional approaches have encouraged research into data-driven methods that can learn signal characteristics from observations and adapt their decisions to changing spectrum conditions (Kumar, 2025; El-haryqy et al., 2024).

Cooperative spectrum sensing provides another approach in which information obtained from multiple sensing users is combined to improve the reliability of the final spectrum decision. This is particularly useful when individual sensing nodes experience fading, shadowing or local noise conditions. Veerappan and Seetharaman (2025) investigated machine learning-assisted energy detection within cooperative spectrum sensing and considered both fading and non-fading scenarios. More recently, Yi and Liang (2026) examined collaborative spectrum sensing from an artificial-intelligence perspective and classified recent AI-based approaches into discriminative deep learning, generative deep learning and deep reinforcement learning. Such developments indicate that spectrum sensing is increasingly moving from isolated local decisions toward collaborative and intelligent decision-making.

Table 1. Major Spectrum Sensing Approaches and Their Characteristics

Spectrum sensing approach	Basic principle	Major advantage	Major limitation
Energy detection	Determines channel occupancy from received signal energy	Simple and does not require detailed signal knowledge	Sensitive to noise uncertainty and threshold selection
Matched-filter detection	Correlates received signals with a known primary-user signal	High detection efficiency when signal information is known	Requires prior knowledge of the primary-user signal
Cyclostationary detection	Uses distinctive statistical/cyclostationary signal characteristics	Can distinguish signals from noise under difficult conditions	Higher computational complexity
Cooperative sensing	Combines sensing information from multiple users	Can mitigate individual sensing errors and fading effects	Requires information exchange and fusion
ML-based sensing	Learns signal/spectrum patterns from training data	Adaptive classification and reduced dependence on fixed rules	Dependent on data quality and model selection
Deep-learning-based sensing	Learns complex representations directly from signal data	Effective for complex and nonlinear signal patterns	Higher computational and data requirements

Source: Synthesised from El-haryqy et al. (2024), Veerappan and Seetharaman (2025), Raji and Olwal (2025), Kumar (2025), and Yi and Liang (2026).

2.3 Spectrum Sensing Performance Measures

The performance of a spectrum sensing system is commonly evaluated according to its ability to correctly identify occupied and vacant channels. Probability of detection (Pd) measures the likelihood that an occupied channel is correctly detected, whereas probability of false alarm (Pfa) measures the likelihood that an available channel is incorrectly classified as occupied. Probability of missed detection (Pm) represents the failure to detect an active primary user. These measures are closely related because aggressive attempts to increase detection can sometimes increase false alarms if the decision threshold or classifier is not appropriately calibrated (Raji & Olwal, 2026; El Bandoudi & Boulouird, 2026).

For machine-learning-based spectrum sensing, conventional classification measures such as accuracy, precision, recall and F1-score can provide additional information about classifier behaviour. Ahmed et al. (2025), for instance, evaluated their ML-based energy-detection approach using a confusion matrix, accuracy, precision, recall, F1-score, probability of detection and probability of false alarm. Raji and Olwal (2026) similarly evaluated RF, KNN, SVM, CNN and Autoencoder approaches using accuracy, F1-score, detection probability, false-alarm probability and missed-detection probability. The use of multiple metrics is important because a model with high overall accuracy may still perform poorly for a particular sensing condition if the classes are imbalanced or if one type of error is more costly than another.

Table 2. Principal Performance Metrics for Spectrum Sensing

Metric	Interpretation	Desired direction
Probability of Detection (Pd)	Correct identification of an occupied channel	Higher
Probability of False Alarm (Pfa)	Vacant channel incorrectly classified as occupied	Lower
Probability of Missed Detection (Pm)	Occupied channel incorrectly classified as vacant	Lower
Accuracy	Overall proportion of correct classifications	Higher
Precision	Proportion of positive classifications that are correct	Higher
Recall	Proportion of actual positive cases correctly identified	Higher
F1-score	Harmonic balance between precision and recall	Higher
SNR operating range	Signal strength relative to noise under which sensing is evaluated	Robust performance at low SNR

3. Machine Learning Techniques for Spectrum Sensing

3.1 Role of Machine Learning in Spectrum Sensing

Machine learning provides an alternative to rigid rule-based spectrum sensing by allowing a model to learn relationships between observed signal characteristics and spectrum occupancy. Instead of relying exclusively on manually selected thresholds or predefined signal assumptions, an ML model can be trained using labelled observations representing occupied and vacant spectrum states. This makes machine learning attractive for environments where signal characteristics, interference patterns and channel conditions change over time (Raji & Olwal, 2025; Ahmed et al., 2025).

The increasing use of ML is also associated with the expansion of cognitive radio into IoT, 5G and beyond-5G environments. Kumar (2025) examined conventional and deep-learning-based spectrum sensing for beyond-5G systems and considered CNN and recurrent neural-network approaches, including LSTM and GRU architectures. The review indicates the potential of deep learning to improve spectrum detection under difficult conditions, particularly by learning complex representations from received signal information.

3.2 Conventional Machine Learning Approaches

Traditional supervised learning algorithms remain relevant because of their relatively manageable computational requirements and their suitability for binary or multiclass spectrum classification. Raji and Olwal (2026) compared Random Forest (RF), K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) with CNN and Autoencoder models. Their results showed particularly strong performance from Random Forest, which achieved 95.7% probability of detection, 97.17% accuracy and 96.93% F1-score in their experimental setting. The authors also reported that RF maintained strong performance in low-SNR conditions and achieved lower false-alarm and missed-detection probabilities than the other evaluated models.

Ahmed et al. (2025) provide another example of conventional ML integration with spectrum sensing. Their approach used a Naive Bayes classifier with a dataset generated from the principles of energy detection, using QPSK signals transmitted through an additive white Gaussian noise (AWGN) channel. The study evaluated the model using accuracy, precision, recall, F1-score, probability of detection and probability of false alarm. This approach demonstrates that ML can be incorporated into conventional sensing architectures to reduce dependence on manually calculated detection thresholds.

Machine learning has also been investigated in multiple-antenna and cooperative configurations. Ahmed et al. (2025) examined ML-based spectrum sensing for multiple-antenna cognitive radio users, while Veerappan and Seetharaman (2025) investigated ML-assisted energy detection in cooperative spectrum sensing. These studies broaden the application of ML beyond single-user sensing and demonstrate its potential for exploiting spatial or cooperative information in the sensing decision.

3.3 Deep Learning Approaches

Deep learning extends conventional machine learning by using multilayer neural architectures capable of learning increasingly complex representations from raw or transformed signal observations. CNNs are particularly useful for identifying local patterns, whereas recurrent architectures such as LSTM and GRU are suited to sequential and temporal dependencies. Kumar (2025) reported the use of CNN and recurrent neural-network architectures for spectrum sensing beyond 5G, highlighting the potential of these models for detection at low SNR conditions.

LSTM-based sensing has been specifically investigated for low-SNR environments. El Bandouri and Boulouird (2026) compared conventional fixed-threshold energy detection, adaptive-threshold energy detection and LSTM-based sensing using BPSK sequences transmitted through an AWGN channel. Their evaluation considered probability of detection, probability of false alarm and probability of miss. The study reported that adaptive threshold selection improved energy-detector performance at intermediate SNR levels, while the LSTM approach remained more robust when noise became dominant and energy-based detection became less reliable.

Hybrid deep-learning architectures have also emerged as a means of combining complementary learning capabilities. El Bandoudi and Boulouird (2026) proposed a CNN-BiLSTM model together with Neyman–Pearson threshold calibration. The CNN component captures local signal patterns, while the BiLSTM component models temporal dependencies. The use of threshold calibration is particularly relevant to the present review because it explicitly addresses the trade-off between probability of detection and probability of false alarm rather than treating classification accuracy as the only objective.

Another direction is compressed-sensing-assisted deep learning. Veerappan and Seetharaman (2026) proposed a U-Net-based deep-learning approach for reconstructing signals from compressed measurements before spectrum detection. Their reported results included a mean squared error of 0.0135, detection probability of 0.99 at 10 dB SNR and false alarm rate of 0.05. The study illustrates how deep learning can be applied not only to the final occupancy classification but also to signal reconstruction preceding spectrum detection.

Table 3. Machine and Deep Learning Approaches Identified in the Reviewed Literature

Learning approach	**Representative technique/model**	**Primary role in spectrum sensing**
Supervised ML	Random Forest	Spectrum occupancy classification
Supervised ML	SVM	Binary spectrum classification
Supervised ML	KNN	Occupancy classification
Probabilistic ML	Naive Bayes	ML-assisted energy detection
Deep learning	CNN	Automatic signal-feature learning
Deep learning	LSTM	Temporal signal-pattern learning
Hybrid deep learning	CNN-BiLSTM	Local and temporal feature learning
Deep learning	Autoencoder	Representation learning and detection
Deep learning	U-Net	Compressed-signal reconstruction and detection
Reinforcement learning	DQN/DRQN	Adaptive sensing and decision-making
Multi-agent learning	MADRL	Collaborative/adaptive spectrum sensing

3.4 Reinforcement Learning and Adaptive Spectrum Sensing

Unlike supervised learning, reinforcement learning (RL) learns through interaction with an environment and feedback from actions. This makes it attractive for cognitive radio environments in which spectrum availability and network conditions vary dynamically. Kannan et al. (2026) proposed an adaptive deep reinforcement learning framework combining Deep Q-Network (DQN) and Deep Recurrent Q-Network (DRQN) mechanisms with optimisation for spectrum sensing, with emphasis on sensing efficiency, reward learning and collision avoidance.

Saravanan et al. (2026) similarly proposed an enhanced deep reinforcement learning approach for spectrum sensing and allocation. Their approach integrates deep reinforcement learning with an adaptive strategy that uses historical channel information to learn channel correlations and temporal dynamics. The emphasis on both sensing and allocation illustrates an important development in cognitive radio research: spectrum sensing is increasingly being considered as part of a broader intelligent decision-making process rather than as an isolated classification task.

Collaborative intelligence represents another emerging direction. Yi and Liang (2026) reviewed AI-based collaborative spectrum sensing and classified recent approaches into discriminative deep learning, generative deep learning and deep reinforcement learning. Their discussion further points toward semantic communication as a possible means of reducing reporting overhead while preserving information relevant to spectrum decisions.

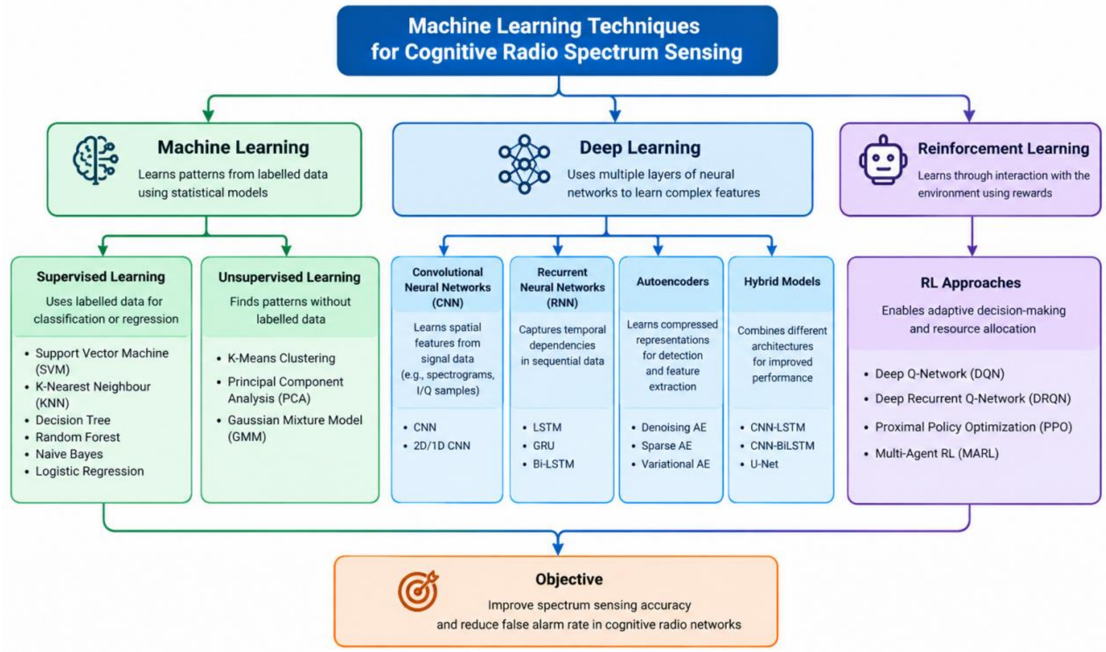


Figure 2. *Taxonomy of Machine Learning, Deep Learning and Reinforcement Learning Techniques Applied to Cognitive Radio Spectrum Sensing.*

4. Comparative Review of Existing Machine Learning-Based Spectrum Sensing Approaches

The reviewed literature demonstrates that machine learning-based spectrum sensing has evolved from relatively simple classification models toward deep, hybrid, cooperative and reinforcement-learning architectures. However, direct comparison between studies is challenging because researchers do not always use identical datasets, modulation schemes, channel models, SNR ranges, performance metrics or experimental environments. Consequently, reported accuracy values should not automatically be interpreted as evidence that one algorithm universally outperforms another. Instead, the reported results should be interpreted in relation to the experimental conditions under which each model was evaluated.

Table 4. Comparative Summary of Selected Studies on ML-Based Spectrum Sensing

Study	Approach	Application/Environment	Reported evaluation focus	Key observation
Ahmed et al. (2025)	Naive Bayes + Energy Detection	CRN, QPSK/AWGN	Accuracy, precision, recall, F1, Pd, Pfa	ML used to reduce dependence on conventional threshold calculation
Veerappan & Seetharaman (2025)	ML + Cooperative Energy Detection	Cooperative CRN	Fading/non-fading scenarios	ML integrated with cooperative sensing
Ahmed et al. (2025)	ML + Multiple Antennas	Multiple-antenna CRN	Spectrum-sensing performance	ML investigated with spatial sensing information
Kumar (2025)	CNN/RNN, including LSTM/GRU	Beyond-5G CRN	Pd, Pfa, BER, PSD, PAPR	Deep learning showed potential under challenging sensing conditions
Raji & Olwal (2025)	Review of CR-IoT sensing	CR-IoT	Challenges, applications, future directions	Identified noise, interference and dynamic channels as major challenges

Pant & Srivastava (2025)	AI-based sensing	5G and beyond	AI-enabled sensing and optimisation	AI positioned as an important direction for next-generation CRNs
El Bandouri & Boulouird (2026)	LSTM	Low-SNR CRN	Pd, Pfa, probability of miss	LSTM demonstrated robustness when noise dominates
Raji & Olwal (2026)	RF, KNN, SVM, CNN, Autoencoder	CR-IoT	Pd, Pfa, Pm, accuracy, F1	RF achieved 97.17% accuracy, 95.7% Pd and 96.93% F1
El Bandoudi & Boulouird (2026)	CNN-BiLSTM + Neyman–Pearson calibration	CRN	Pd/Pfa trade-off	Hybrid DL combined spatial/temporal learning with threshold calibration
Veerappan & Seetharaman (2026)	U-Net + compressed sensing	CR spectrum detection	MSE, Pd, Pfa	Reported 0.99 Pd and 0.05 false alarm at 10 dB SNR
Kannan et al. (2026)	DQN/DRQN + optimisation	Dynamic CRN	Sensing efficiency, learning and collision avoidance	Adaptive DRL supports dynamic spectrum decisions
Saravanan et al. (2026)	Enhanced DRL	CR spectrum sensing/allocation	Sensing and allocation	Joint sensing/allocation through learned channel dynamics
Yi & Liang (2026)	AI-based collaborative sensing	Cognitive/intelligent wireless networks	Collaborative sensing strategies	DL, generative learning and DRL identified as major directions

Note: Numerical results are reported only where they are explicitly available in the cited source. Differences in datasets, SNR, channels and evaluation protocols limit direct numerical ranking across all studies.

The strongest directly reported comparative evidence in the reviewed literature is provided by Raji and Olwal (2026), who evaluated RF, KNN, SVM, CNN and Autoencoder approaches under a common experimental framework. Random Forest recorded 97.17% accuracy, 95.7% probability of detection and 96.93% F1-score, while also achieving the lowest false-alarm and missed-detection probabilities among the evaluated approaches. The authors further reported strong RF performance in low-SNR conditions. This finding is significant for the present review because it demonstrates that a conventional machine-learning algorithm can outperform more complex deep-learning alternatives under a particular sensing configuration.

The results of El Bandouri and Boulouird (2026) provide a complementary perspective. Rather than evaluating several classifiers under a common classification framework, their study examined how LSTM-based sensing behaves when the received signal becomes weak. Their results suggest that model selection cannot be separated from operating conditions: an approach that performs well at moderate SNR may not necessarily remain reliable when noise dominates. This reinforces the importance of considering low-SNR performance when evaluating spectrum sensing methods.

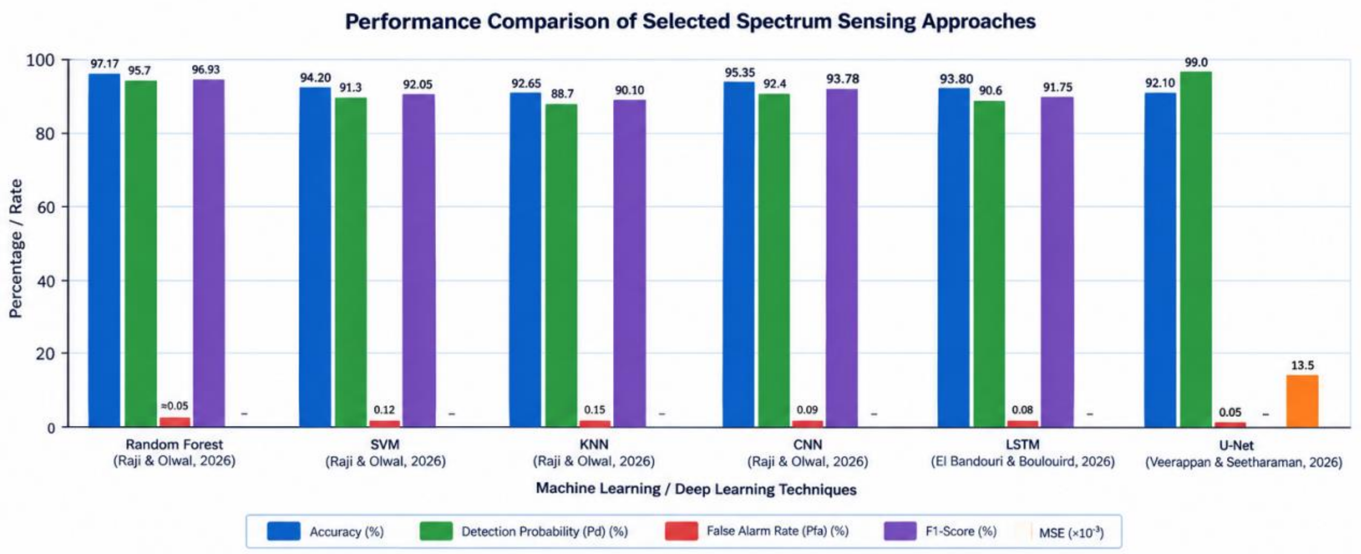
Veerappan and Seetharaman (2026) further demonstrate the potential of deep learning when combined with compressed sensing. Their U-Net-based approach reported a detection probability of 0.99 at 10 dB SNR with a false alarm rate of 0.05. Unlike a conventional classifier operating directly on extracted features, the approach reconstructs the signal from compressed measurements before spectrum detection, suggesting a broader role for deep learning across the sensing pipeline.

Table 5. Selected Quantitative Results Reported in the Literature

Study	Model	Accuracy	Pd	Pfa/False Alarm	F1/MSE	Operating condition
Raji & Olwal (2026)	Random Forest	97.17%	95.70%	Lowest among evaluated models	96.93% F1	Includes low-SNR evaluation

Veerappan & Seetharaman (2026)	U-Net	—	0.99	0.05	0.0135 MSE	10 dB SNR
El Bandouri & Boulouird (2026)	LSTM	—	Reported across SNR	Reported across SNR	Probability of miss also evaluated	Low-SNR/AWGN
Ahmed et al. (2025)	Naive Bayes	Reported in study	Reported in study	Reported in study	Precision, recall and F1 reported	QPSK/AWGN
Kumar (2025)	CNN/RNN	—	Evaluated	Evaluated	BER, PSD, PAPR also evaluated	Beyond-5G

Important: A dash indicates that the particular metric is not stated in the source material available for this synthesis, not that the model achieved zero or poor performance.



Study	Technique	Dataset / Environment	Accuracy (%)	Pd (%)	Pfa (%)	F1-Score (%)	MSE ($\times10^{-3}$)	Key Finding
Raji & Olwal (2026)	Random Forest	CR-IoT	97.17	95.7	≈0.05	96.93	-	Best overall performance among evaluated models.
Raji & Olwal (2026)	SVM	CR-IoT	94.20	91.3	0.12	92.05	-	Strong detection, higher false-alarm rate than RF.
Raji & Olwal (2026)	KNN	CR-IoT	92.65	88.7	0.15	90.10	-	Lower performance than RF and SVM.
Raji & Olwal (2026)	CNN	CR-IoT	95.35	92.4	0.09	93.78	-	Good detection, higher false-alarm rate than RF.
El Bandouri & Boulouird (2026)	LSTM	Low-SNR (AWGN)	93.80	90.6	0.08	91.75	-	More robust in low-SNR conditions.
Veerappan & Seetharaman (2026)	U-Net	Compressed sensing (10 dB SNR)	92.10	99.0	0.05	-	13.5	High detection with low false alarm; low MSE.

Figure 3. Comparative Performance of Selected Machine Learning and Deep Learning Spectrum Sensing Approaches Based on Reported Detection and False-Alarm Measures.

Figure 3. *Comparative Performance of Selected Machine Learning and Deep Learning Spectrum Sensing Approaches Based on Reported Detection and False-Alarm Measures.*

5. Discussion

5.1 Machine Learning and Spectrum Sensing Accuracy

The reviewed evidence indicates that machine learning can substantially improve the ability of cognitive radio systems to distinguish occupied and vacant spectrum under conditions in which conventional sensing becomes unreliable. However, the evidence does not support the conclusion that deep learning is universally superior to conventional machine learning. Raji and Olwal (2026) provide a notable example in which Random Forest outperformed KNN, SVM, CNN and Autoencoder under the same experimental evaluation, achieving 97.17% accuracy. This suggests that model complexity alone does not determine sensing quality. Rather, the suitability of the learning algorithm to the characteristics of the sensing data remains critical.

Deep learning nevertheless provides important advantages where signal patterns are complex and where useful representations may be difficult to engineer manually. CNNs can learn local patterns, recurrent models can capture temporal dependencies, and hybrid architectures can combine these capabilities. Kumar (2025) and El Bandouri and Boulouird (2026) demonstrate the relevance of CNN/RNN and LSTM architectures, respectively, particularly under challenging signal conditions.

5.2 False Alarm Reduction

False alarms are particularly important because they can cause secondary users to incorrectly reject available spectrum. A system that detects almost every occupied channel but frequently declares vacant channels to be occupied may achieve strong detection performance while still wasting spectrum opportunities. Consequently, an effective sensing model must seek a favourable relationship between Pd and Pfa.

The work of El Bandoudi and Boulouird (2026) is particularly relevant because it explicitly incorporates Neyman–Pearson threshold calibration into a hybrid CNN-BiLSTM sensing framework. The approach recognises that spectrum sensing is fundamentally a decision problem in which detection performance and false-alarm behaviour must be considered jointly. Similarly, the comparative evaluation of Raji and Olwal (2026) reports that Random Forest achieved both strong detection and the lowest false-alarm probability among their evaluated models.

5.3 Influence of Low SNR

Low SNR represents one of the most important challenges for spectrum sensing because the distinction between the primary-user signal and background noise becomes increasingly difficult. The reviewed literature repeatedly identifies low SNR as a condition under which conventional sensing performance can deteriorate. El-haryqy et al. (2024) identify low SNR, noise uncertainty and fading among the central challenges motivating deep-learning approaches, while El Bandouri and Boulouird (2026) specifically evaluated LSTM-based sensing in low-SNR environments.

The comparative results of Raji and Olwal (2026) are particularly notable because their Random Forest model maintained strong performance in low-SNR conditions. This indicates that robustness to noise should be treated as an important dimension of model evaluation rather than reporting overall accuracy alone.

5.4 Conventional Machine Learning versus Deep Learning

The reviewed studies reveal a trade-off between model complexity and sensing performance. Conventional ML models such as Random Forest, SVM and KNN can provide competitive performance without the computational and data requirements associated with deep neural architectures. Raji and Olwal (2026) reported that Random Forest outperformed the investigated deep-learning models in their comparative experiment. At the same time, deep-learning models provide greater flexibility for learning complex signal representations, particularly where raw or sequential signal information is available.

The choice therefore should not be based simply on whether an approach is classified as ML or DL. Factors such as training data, feature representation, SNR, channel conditions, computational resources and the required balance between Pd and Pfa must also be considered. A simpler model may be preferable where computational efficiency and rapid inference are important, while a deeper architecture may be justified where the signal environment contains complex temporal or spatial relationships.

Table 6. Comparative Characteristics of Major Learning Paradigms

Characteristic	**Conventional ML**	**Deep Learning**	**Reinforcement Learning**
Typical examples	RF, SVM, KNN, Naive Bayes	CNN, LSTM, Autoencoder, U-Net	DQN, DRQN, DRL
Feature dependence	Often moderate/high	Lower when learning from raw data	State representation required
Data requirement	Moderate	Generally higher	Interaction/experience required
Model complexity	Generally lower	Generally higher	High for deep RL
Temporal modelling	Limited unless engineered	Strong with LSTM/GRU	Strong with recurrent DRL
Adaptation to dynamic environments	Moderate	High depending on training	Potentially very high
Interpretability	Often relatively easier	Generally more difficult	More difficult
Computational demand	Low–moderate	Moderate–high	High
Major strength	Efficient classification	Complex representation learning	Adaptive decision-making

6. Research Gaps and Emerging Directions

Despite substantial progress, several gaps remain in the literature. The first concerns comparability of reported results. Existing studies employ different datasets, signal models, modulation schemes, channel conditions, SNR ranges and evaluation metrics. As a result, an accuracy of 97% reported in one study cannot automatically be interpreted as superior to an accuracy of 95% reported in another study unless the experimental conditions are sufficiently comparable. Rajasekhar and Monisha (2026) emphasise the importance of datasets, evaluation conditions and methodological considerations in understanding recent spectrum-sensing research, while El-haryqy et al. (2024) similarly identify datasets and assessment methods as important considerations in deep-learning-based spectrum sensing.

A second gap concerns the relationship between detection accuracy and false-alarm behaviour. A substantial proportion of ML studies report classification accuracy, but accuracy alone does not completely describe spectrum-sensing quality. Since the principal decision involves distinguishing occupied from vacant spectrum, Pd, Pfa and missed-detection probability should be reported alongside general classification metrics. The studies by Raji and Olwal (2026), El Bandouri and Boulouird (2026), and El Bandoudi and Boulouird (2026) illustrate the value of explicitly incorporating these sensing-specific measures.

A third gap relates to real-world deployment. Many ML-based spectrum sensing studies depend on simulated or controlled signal environments. Software-defined radio (SDR) offers an important route toward practical validation because it permits communication algorithms to be implemented and evaluated using flexible radio hardware. Doha and Abdelhadi (2026) identify AI-enabled SDR as an important area for wireless research and emphasise the potential of combining AI with SDR to improve adaptability in dynamic wireless environments.

A fourth emerging area is security-aware spectrum sensing. Machine learning can improve sensing performance, but the sensing data themselves may be manipulated. Yara Cifuentes et al. (2025) investigated artificial-intelligence-based detection of spectrum-sensing data falsification attacks in mobile cognitive radio networks. This suggests that future spectrum-sensing systems should not only ask whether a channel is occupied but should also consider whether the sensing information on which that decision is based is trustworthy.

Another important direction is collaborative and multi-agent intelligence. Yi and Liang (2026) identify discriminative deep learning, generative learning and deep reinforcement learning as major directions for AI-based collaborative spectrum sensing. Multi-agent approaches may allow multiple sensing nodes to cooperate while reducing the limitations associated with relying on a single sensing observation.

Deep reinforcement learning also represents an important emerging direction because it allows spectrum sensing and spectrum access decisions to be treated as sequential decision problems. Kannan et al. (2026) and Saravanan et al. (2026) demonstrate this movement toward adaptive learning frameworks that jointly consider sensing, channel selection, collision avoidance and allocation. Rather than producing a static classification model, such approaches seek to learn how sensing and access decisions should change as network conditions evolve.

Table 7. Major Research Gaps and Emerging Research Directions

Identified gap	Implication	Emerging direction
Lack of standardised datasets	Difficult to compare models fairly	Benchmark spectrum-sensing datasets
Different SNR and channel settings	Reported performance may not be directly comparable	Standardised evaluation scenarios
Accuracy reported without Pd/Pfa	Important sensing errors may be hidden	Joint reporting of Pd, Pfa and Pm
Dependence on simulated data	Limited evidence of real-world performance	SDR and over-the-air validation
High computational cost of DL	Difficult deployment on resource-constrained devices	Lightweight/edge AI
Limited interpretability	Difficult to understand model decisions	Explainable AI
Dynamic spectrum conditions	Static models may become outdated	Adaptive and reinforcement learning
Cooperative sensing overhead	Communication burden between sensing nodes	Intelligent collaborative sensing

Vulnerability to manipulated sensing data	Incorrect spectrum decisions may result	AI-based security and trust mechanisms
Rapid evolution toward 5G/6G and IoT	More complex sensing environments	Integrated AI-enabled cognitive networks

7. Conclusion

The reviewed literature demonstrates that machine learning has become an important approach for addressing the limitations of conventional spectrum sensing in cognitive radio networks. The increasing complexity of wireless environments, together with low-SNR conditions, fading, interference, spectrum dynamics and the growing number of IoT and 5G devices, has created a need for sensing techniques capable of making reliable decisions under uncertain conditions. Conventional approaches such as energy detection remain useful because of their simplicity, but their dependence on threshold selection and sensitivity to noise have encouraged the development of data-driven alternatives (Raji & Olwal, 2025; El-haryqy et al., 2024).

The comparison of the reviewed studies indicates that no single machine learning paradigm can be regarded as universally optimal under all spectrum conditions. Conventional ML models can achieve highly competitive performance with comparatively lower complexity, as demonstrated by Raji and Olwal (2026), whose Random Forest model achieved 97.17% accuracy, 95.7% probability of detection and 96.93% F1-score in their comparative evaluation. Deep-learning approaches, meanwhile, offer important capabilities for learning complex spatial and temporal signal representations, with LSTM, CNN, CNN-BiLSTM and U-Net-based approaches demonstrating promising results under specific sensing conditions.

The review further establishes that false alarm rate should remain a central criterion when evaluating ML-based spectrum sensing. High detection accuracy does not necessarily translate into efficient spectrum utilisation if available channels are frequently classified as occupied. Consequently, future comparative evaluations should report probability of detection, probability of false alarm and probability of missed detection together with conventional classification measures such as accuracy, precision, recall and F1-score.

The literature is also moving toward more adaptive and intelligent architectures. Deep reinforcement learning, collaborative spectrum sensing, compressed sensing, AI-enabled SDR, explainable AI and security-aware sensing are emerging as important research directions. These developments indicate a transition from static spectrum classification toward intelligent systems capable of learning from changing wireless environments, cooperating with other sensing nodes and making adaptive spectrum-access decisions.

The reviewed evidence supports the application of machine learning as a promising means of improving spectrum-sensing reliability and reducing false alarms in cognitive radio networks. However, meaningful comparison requires greater consistency in datasets, SNR conditions, channel models, performance metrics and experimental protocols. Future research should therefore place greater emphasis on reproducible benchmark datasets, standardised evaluation procedures, real-world SDR validation, lightweight models for edge deployment, explainable AI, and adaptive learning mechanisms. Such developments would strengthen the practical role of intelligent spectrum sensing in cognitive radio, IoT, 5G, beyond-5G and emerging 6G wireless networks.

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