

An Empirical Analysis of Various Techniques for Spectrum Sensing in Cognitive Radio Networks

Rajesh Kulkarni

Department of CSE,
Mvsr engineering College nadargul Hyderabad
kulkarni_cse@mvsrec.edu.in

Abstract: In Cognitive Radio Networks (CRNs), effective spectrum sensing is crucial for detecting and utilizing idle frequency bands without interfering with primary users. To address the growing demands of modern wireless systems, spectrum sensing must evolve to support higher reliability, adaptability, and minimal latency in diverse environments. However, existing spectrum sensing methods are highly susceptible to noise uncertainty, perform poorly under low Signal-to-Noise Ratio (SNR) conditions, and often rely on prior knowledge of the primary user's signal characteristics. These challenges limit the reliable detection of available spectrum and reduce the overall efficiency and robustness of dynamic spectrum access in CRNs. Consequently, developing an efficient spectrum sensing model is vital to improve spectrum utilization and overcome the shortcomings of current CRN approaches. Furthermore, recent advancements in AI-driven sensing and collaborative frameworks highlight the need for updated evaluations of existing techniques. This survey offers a comprehensive review of the spectrum sensing techniques employed in CRNs. It examines different categories of methods, their underlying motivations, and the research gaps in the field. In this survey, a total of 25 research papers are analyzed in terms of publication year, employed techniques, performance metrics, datasets, and methodologies. Moreover, conventional models are classified into Deep Learning (DL)-based models, Machine Learning (ML)-based models, Energy Harvesting-based models, and Blockchain-based models. This expanded classification helps clarify how emerging technologies contribute to improving sensing precision, scalability, and system-level security. By outlining the advantages and limitations of each approach, this analysis supports the development of spectrum sensing systems that are more accurate, reliable, and energy-efficient in dynamic wireless environments.

Keywords: Spectrum Sensing, Cognitive Radio Networks, Deep Learning, Machine Learning, Blockchain.

Nomenclature

Abbreviation	Description
CRN	Cognitive Radio Network
PU	Primary User
SU	Secondary User
SNR	Signal-to-Noise Ratio
DL	Deep Learning
ML	Machine Learning
DNN	Deep Neural Network
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory Network
Bi-LSTM	Bidirectional Long Short-Term Memory
ELM	Extreme Learning Machine
DBN	Deep Belief Network
HSS	Hybrid Spectrum Sensing
ASA-NN	Advanced Squirrel Algorithm-trained Neural Network
SP-CA	Spectrum Prediction-Channel Allocation
BO-RF	Bayesian-Optimized Random Forest
KNN	K-Nearest Neighbor
WSS	Wideband Spectrum Sensing
EH-CRN	Energy-Harvesting Cognitive Radio Network
EEISS	Energy Efficient & Interference-Aware Spectrum Sensing
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
MSE	Mean Square Error
AIR	Average Inference Ratio
BL	Belief Level
QAM	Quadrature Amplitude Modulation
IRS	Intelligent Reflecting Surface
HOD-CODO	Human Opinion Dynamics-Continuous Opinion Dynamics Optimizer
ANFIGA-CS	Adaptive Neuro-Fuzzy with Improved Genetic Algorithm Channel Selection

1. Introduction

In the early 1990s, spectrum scarcity was not a significant issue, and a large portion of the spectrum was readily available. However, as early wireless systems began to evolve, researchers gradually recognized inefficiencies in static allocation despite the abundance of spectrum. As a result, wireless networks primarily relied on a fixed spectrum assignment policy. However, with the rapid growth of bandwidth-intensive wireless applications, the spectrum became increasingly scarce. This showed that a substantial portion of the spectrum licensed to primary radio users was underutilized and exhibited high temporal variability. To address this inefficiency, the Federal Communications Commission (FCC) permitted unlicensed devices to use licensed spectrum as long as they do not cause interference to primary users. This regulatory shift served as a foundational step toward enabling more intelligent and autonomous communication systems. This regulatory decision paved the way for the development of CRNs, which offer a flexible approach compared to fixed spectrum allocation. CRNs enable opportunistic use of temporarily idle spectrum, known as spectrum holes. Within CRNs, there are two types of users: primary radio users and cognitive radio users. Primary radio users operate on licensed spectrum, while cognitive radio users do not have licensed spectrum and can operate either on unlicensed bands or on the temporarily unused spectrum of primary radio users. If a primary radio user returns to a spectrum band currently in use by a cognitive radio user, the cognitive radio user must immediately vacate the band to avoid interference and switch to another available idle spectrum from the spectrum pool [1].

The fundamental concept of cognitive radio is spectrum reuse, which enables secondary users to access and transmit on the spectrum allocated to primary users whenever it is underutilized. This dynamic reuse not only improves spectrum efficiency but also supports emerging network paradigms like 5G, 6G, and massive IoT communication. To achieve this, secondary users must perform spectrum sensing regularly, which involves detecting the presence of primary users [2]. Spectrum sensing is a crucial function in cognitive radios, as devices need to accurately identify weak primary signals of potentially unknown types. Achieving such accuracy becomes particularly challenging in environments with high mobility, fluctuating noise levels, and unpredictable interference patterns. Generally, spectrum sensing techniques are categorized into three types, including energy detection, matched filter coherent detection, and cyclostationary feature detection [3]. In cognitive wireless radio networks, ML algorithms are well-suited for identifying the occurrence of primary user signals. ML techniques can detect patterns in data, enabling the classification of datasets, such as determining whether a primary user signal is present or absent [4]. However, traditional ML approaches require manual feature extraction, which is time-consuming and demands expert knowledge. Hence, DL, a data-driven subset of ML, overcomes this limitation by automatically extracting intricate patterns and characteristics from input data. Deep Neural Network (DNN) methods are highly flexible and resilient in uncertain radio environments. Traditional spectrum sensing methods often struggle with issues, such as low detection accuracy, high false alarm rates, and poor adaptability to changing signal conditions. As CRNs increasingly integrate into heterogeneous wireless systems, addressing these challenges becomes essential for ensuring seamless coexistence with licensed networks. Thus, the development of advanced model for spectrum sensing in CRNs is significant as it enhances detection accuracy, efficiency, and adaptability in dynamic wireless environments [5].

This review paper presents a comprehensive assessment of conventional models developed for spectrum sensing in CRNs, aiming to enhance spectrum utilization. By comparing diverse methodologies, the review provides deeper insights into the strengths and weaknesses of existing approaches. The methods are systematically classified into four main approaches, such as DL-based, ML-based, Energy harvesting-based, and Blockchain-based models. Each paper is assessed using the employed methodology, toolset, datasets used, published year, and evaluation metrics. Furthermore, this review underscores the drawbacks of existing research and finds significant gaps in the literature. These gaps reveal the need for hybrid frameworks that combine learning models, security features, and energy-aware mechanisms. These insights highlight the importance for continued research and the development of more precise and efficient methods for effective spectrum sensing in CRN.

This survey is organized as follows: Section 2 classifies prior models for spectrum sensing in CRN. Section 3 provides a literature survey of existing research on spectrum sensing in CRN. Section 4 highlights the complexities and limitations associated with traditional models. Section 5 presents the assessment of techniques, tools used, performance metrics, datasets, and publication years. Finally, Section 6 describes the conclusion of the review.

1.1 Problem Definition

Spectrum sensing in CRN aims to automatically detect primary users and determine available frequency bands, facilitating efficient and dynamic spectrum utilization. Spectrum sensing involves monitoring the radio environment, identifying idle channels, and classifying spectrum occupancy, while ensuring minimal

interference with licensed users. Given the diversity of propagation conditions and user mobility, accurate detection becomes even more challenging in real-world scenarios. However, classical models posed limitations, like lower detection accuracy in fading environments, restricted flexibility to heterogeneous network conditions, and high computational overhead. Consequently, there is a growing need for more intelligent and robust spectrum sensing models that enhance detection reliability, optimize spectrum usage, and provide scalable solutions for dynamic and complex CRN scenarios.

2. Categorization of traditional methods for spectrum sensing in CRN

This part presents an outline of distinct approaches employed for spectrum sensing in CRN. Traditional methods for these tasks are broadly classified into four main categories, such as DL-based, ML-based, Energy harvesting-based, and Blockchain-based methods. As the complexity of wireless communication environments continues to increase, organizing these methods into clear categories is essential for understanding their operational differences and practical applicability. Figure 1 presents the categorization of conventional models used for spectrum sensing in CRN.

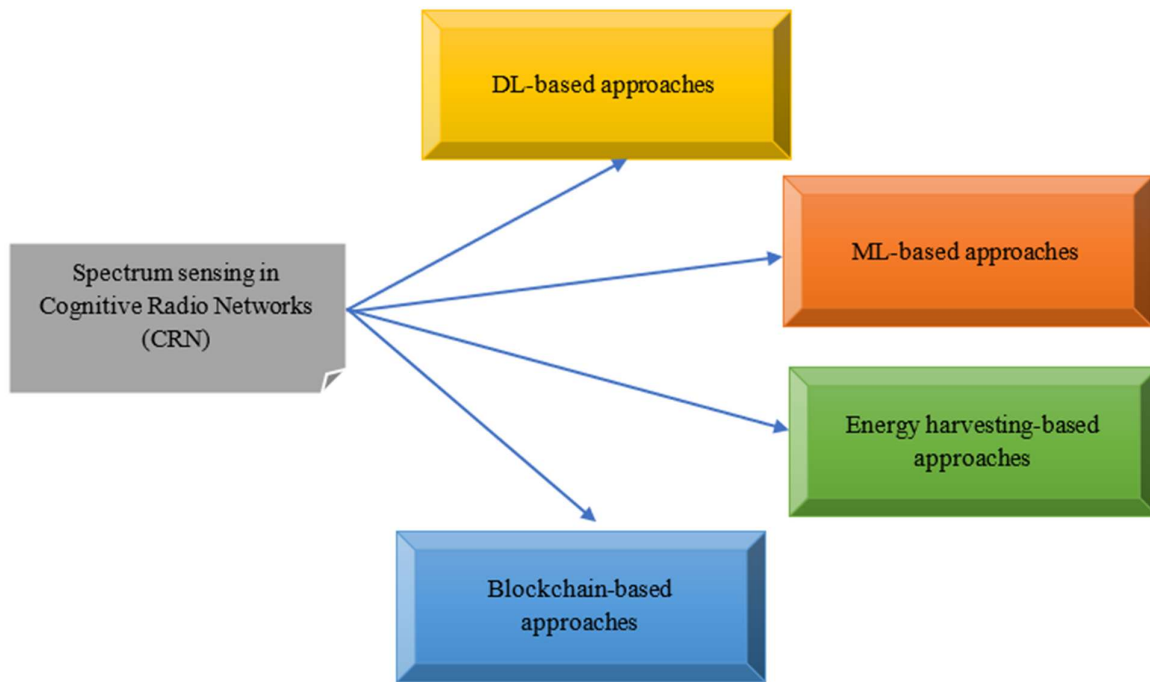


Fig. 1. Categorization of conventional models for spectrum sensing in CRN

3. Literature survey

This section presents an in-depth review of conventional methods for spectrum sensing in CRN, providing insights that contribute to the development and enhancement of advanced and efficient sensing systems. The analysis also helps identify recurring limitations across models, offering direction for designing more resilient and intelligent sensing architectures.

3.1 DL-based Model

DL-based models have emerged as powerful tools for spectrum sensing in CRN, utilizing their capability to automatically extract complex patterns from large-scale wireless data. This capability is especially valuable in environments where traditional feature-engineered models fail to capture nonlinear spectrum behavior. By employing advanced architectures, these models effectively capture both spectral and temporal features relevant to dynamic spectrum environments. This approach enables accurate detection of available channels and contributes to improved network performance and decision-making. The main challenges encountered by traditional DL-based approaches in spectrum sensing are outlined below.

Saraswathi M and Logashanmugam E [6] designed a Spectral Sensing Technique for Cognitive Radio Networks (SST-CRN). This method effectively enhanced spectrum utilization and resolved the issue of spectrum scarcity by combining bio-inspired optimization with DL-based spectrum sensing. This

integration improved the coordination of cognitive radios, optimized the allocation of spectrum resources, and enabled adaptive responses to changing environmental and user conditions. Additionally, the hybrid framework demonstrated promise for supporting multi-objective optimization in fluctuating radio environments. However, the method involved higher computational complexity and substantial resource demands during training and deployment, which created difficulties in resource-constrained scenarios. Additionally, the optimization algorithm encountered issues with convergence speed and susceptibility to local optima in highly dynamic environments.

D. K. Patel, *et al.* [7] developed an ANN-based hybrid spectrum sensing technique. This model demonstrated a strong ability to learn complex patterns in the data, leading to high classification accuracy and improved spectrum sensing performance. It effectively utilized information from current and previous sensing events and optimized key operational parameters to achieve consistent and superior results across various radio technologies. The approach was flexible, allowing adjustments in sample size to suit different application requirements. Furthermore, the model showed potential for integration with cooperative sensing mechanisms to enhance reliability in decentralized networks. However, the method was limited to scenarios with a single primary and a single secondary user, and it failed to improve its performance and applicability in networks with multiple users.

K. Wang, *et al.* [8] devised a Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) networks for spectrum sensing in CRN. The approach combined spatial feature extraction with temporal data analysis, allowing it to perform effectively in dynamic environments with multiple users and frequent signal variations. It improved the system's ability to handle interference and identify spectrum states more precisely, contributing to better resource allocation and communication reliability. The model also demonstrated strong potential for supporting intelligent spectrum management and dynamic adaptation in evolving wireless networks. Its hybrid design proved valuable for applications requiring fine-grained recognition of rapid spectrum transitions. However, it faced difficulties in very low signal conditions, where maintaining consistent performance was challenging. Additionally, the approach required substantial computational resources and complex model training, which restricted its applicability in resource-constrained networks.

M. Saraswathi and E. Logashanmugam [9] implemented a Bidirectional Long Short-Term Memory (Bi-LSTM) for spectrum sensing in CRN. The method enhanced detection accuracy, reduced sensing errors, and maintained stable performance even under difficult conditions with low signal strength. It demonstrated strong adaptability, enabled faster decision-making, and effectively learned dynamic spectrum patterns, making it suitable for modern connected systems and next-generation communication networks. It also promoted efficient resource management and supported the increasing demands of connected devices in spectrum-limited environments. Moreover, the bidirectional design allowed the model to consider both past and future signal contexts, improving predictive capability. However, the approach involved greater energy consumption and longer training times due to its advanced structure. Moreover, ensuring the security and privacy of the sensing process remained important, as malicious interference or data breaches reduced reliability and trustworthiness in real-world applications.

S. E. Rajavel, *et al.* [10] introduced an ANN for optimizing spectrum sensing in CRN. This model ensured the protection of licensed users from interference and enabled secure communication through a location-based management system, which reduced packet loss and improved network reliability. It provided efficient utilization of the available spectrum, leading to better communication quality and improved overall performance. The model also offered predictable sensing behavior, making it suitable for controlled or semi-static deployments. However, the approach involved complex implementation due to the dynamic nature of spectrum allocation. It also demanded higher processing power and faced scalability limitations in large or highly mobile networks. Moreover, it failed to optimize sensing efficiency and reduce system overhead.

V. Mohanakurup, *et al.* [11] presented an LSTM and Extreme Learning Machines (ELM) for spectrum sensing in CRN. This model effectively captured and learned the statistical patterns of spectrum data, enabling highly accurate detection even under low-signal conditions. The implementation on a custom testbed allowed for data collection across varying frequencies, demonstrating robust performance and reliable detection capabilities. The combination of LSTM and ELM enhanced generalization ability, making the hybrid model adaptable to diverse spectrum scenarios. However, the approach required long processing times, which limited practical deployment. Additionally, it faced difficulties in managing multiple primary and secondary users simultaneously and failed to handle dynamic network conditions efficiently.

A. Nasser, *et al.* [12] employed an Artificial Neural Networks based Hybrid Spectrum Sensing (ANN-based HSS). This method combined multiple detection inputs to enhance reliability of spectrum sensing. By integrating information from several sources, the system was able to distinguish more effectively between idle and active spectrum conditions, resulting in more consistent and dependable detection outcomes. The approach demonstrated improved performance as the number of inputs increased,

highlighting its scalability and robustness. This multi-input strategy positioned the model well for cooperative and multi-agent sensing environments. However, the method required greater computational resources due to the integration of multiple inputs. It also involved longer training times and higher processing demands, which limited its efficiency and practical deployment in resource-constrained environments.

G. Eappen., *et al.* [13] implemented an Advanced Squirrel Algorithm-trained Neural Network (ASA-NN) for spectrum sensing in CRN. The approach reliably identified available spectrum opportunities, resulting in higher communication throughput and improved overall data transmission quality. It demonstrated strong performance in practical scenarios and effectively adapted to dynamic spectrum conditions, making it suitable for critical applications. Its bio-inspired optimization nature provided a competitive advantage in complex and nonlinear spectrum environments. However, the method required substantial processing resources during training and implementation. It also depended on accurate system calibration and coordination, which limited its efficiency in highly dynamic or resource-constrained environments.

3.2 ML-based Model

ML-based models offer data-driven approaches to identify patterns and anomalies in wireless signals for spectrum sensing in CRN. These models utilize features extracted from radio frequency data to classify occupied and unoccupied channels. By providing reliable and automated sensing, ML-based methods contribute to efficient spectrum utilization and interference avoidance. Despite their simplicity and lower computational cost compared to DL models, many ML techniques struggle when dealing with highly nonlinear or rapidly fluctuating spectrum conditions. The major issues faced by classical ML-based models in spectrum sensing are detailed below.

D. Arivudainambi., *et al.* [14] devised a SP-CA algorithm for spectrum sensing in CRN. This model effectively improved spectrum utilization and alleviated the problem of spectrum scarcity through a centralized cooperative framework. By employing an eigenvalue-based detection approach, it reduced sensing time and enhanced detection accuracy. The use of a probabilistic inference mechanism enabled accurate prediction of channel quality using estimated idle duration and sensing precision, allowing efficient channel selection and allocation to secondary users. The probabilistic nature of the model also made it suitable for environments where channel conditions exhibit moderate stability. However, the approach did not consider the mobility of secondary users or the activity patterns of primary users, which influenced performance and adaptability in dynamic communication environments.

Raghavendra L R and Manjunatha R C [15] introduced a Bayesian-Optimized Random Forest (BO-RF) for optimizing spectrum sensing in CRN. The method effectively improved the ability to identify available channels for secondary users without interfering with primary users, which enhanced accuracy and reliability. This made the model particularly advantageous for semi-static CRN deployments where periodic updates are sufficient. The approach allowed for adaptive learning, enabling the system to adjust to changing environments and maintain efficient performance without requiring complete retraining. However, it depended on precise and careful training to make accurate decisions, which increased complexity and required additional effort for implementation and maintenance. Additionally, the used incremental learning process increased the overall computational and operational demands.

O. P. Awe., *et al.* [16] presented a K-means clustering algorithm for spectrum sensing in CRN. This model effectively improved performance by overcoming difficulties in fading channel conditions. The method enhanced the estimation of channel conditions and dynamically updated the spectrum sensing process, which increased the reliability of detecting primary user activity. This adaptive approach allowed the system to respond efficiently to changing channel environments and maintain consistent performance. Moreover, the clustering-based technique helped reduce dependency on prior knowledge of signal characteristics, contributing to its versatility. However, the approach involved complex processing and continuous monitoring of channel conditions, which increased operational demands and made it difficult to operate in highly dynamic or resource-constrained environments.

H. A. Shah and I. Koo [17] employed a KNN for spectrum sensing in CRN. The method effectively enhanced the reliability of spectrum sensing by enabling the model to learn from environmental conditions and account for the true status of the primary user. It improved the accuracy of detection through the classification of sensing reports and the use of reliability-based decision-making at both the cognitive radio and fusion center levels. The approach ensured more consistent and dependable identification of spectrum availability, even under fading conditions, and improved spectrum utilization. Additionally, its simplicity and ease of implementation made it an attractive option for small- to medium-scale CRN deployments. However, the method required extensive data collection and training to achieve accurate learning, which increased computational and storage demands. Additionally, its performance was affected in highly dynamic environments where the signal characteristics and user reliability changed frequently.

3.3 Energy Harvesting-based Model

Energy harvesting-based models have shown great potential for spectrum sensing in CRN, enabling sustainable and self-powered operation of wireless devices. By capturing energy from ambient sources, these models enable cognitive radios to perform sensing and communication tasks without relying solely on conventional battery power. This contributes to a prolonged network lifetime, reduced operational costs, and more reliable spectrum utilization in dynamic wireless environments. In recent studies, researchers have increasingly focused on integrating adaptive energy management strategies to further enhance sensing reliability under fluctuating energy conditions. The primary challenges encountered by prior energy harvesting-based methods in spectrum sensing are outlined below.

Q. Zhao., *et al.* [18] implemented a WSS for spectrum sensing in wideband CRN. This approach efficiently utilized the frequency-domain sparsity of the wideband spectrum to conserve energy by lowering the sampling rate and sensing duration. It achieved significant improvements in energy efficiency and reduced overall energy consumption. Additionally, the method demonstrated promising scalability for wideband environments where rapid sensing decisions are required. The approach effectively optimized sensing operations while maintaining better performance under various constraints. However, its efficiency relied heavily on the sparsity characteristics of the spectrum, making it less effective in dense or dynamically changing spectral environments where sparsity conditions were not prominent.

X. Liu., *et al.* [19] devised an EH-CRN for cooperative spectrum sensing in CRN. This approach effectively optimized the cooperative spectrum sensing process by considering the energy availability of secondary users, ensuring that only those with sufficient energy participated in sensing. It accurately characterized the decision-making process and energy constraints, enabling adaptive adjustment of participation based on energy levels. The approach allowed the network to operate efficiently under varying energy conditions and maximize achievable throughput while protecting primary transmissions. Furthermore, the algorithm supported balanced energy consumption among nodes, reducing the risk of premature node failures. However, the method involved complex analysis and decision-making processes, which increased operational demands. Additionally, its reliance on all active users participating limited energy efficiency, making it difficult to perform in highly energy-constrained scenarios.

A. A. Olawole., *et al.* [20] designed a Cooperative Spectrum Sensing with Energy Harvesting model. The approach determined the total sensing time for each secondary user and distributed it efficiently across multiple channels. It improved the active participation of secondary users, enhanced overall network throughput, and allowed better utilization of available spectrum resources. The approach also provided a structured framework for handling complex optimization problems, making the sensing process more systematic and reliable. This structured optimization contributed to improved fairness among participating users and better energy distribution across sensing intervals. However, it required careful management of energy harvesting sources, as only an optimal number could maximize performance, which limited flexibility in highly dynamic or resource-constrained conditions. Additionally, the method involved complex calculations and coordination among users, which increased computational demands and affected scalability in larger networks.

M Ramchandran and E N Ganesh [21] introduced an EEISS for improving the throughput in CRN. This model enhanced energy efficiency and throughput in CRNs by dynamically adjusting the sensing time based on the residual battery of secondary users and setting the transmit power according to signal strength and energy availability. The approach provided a dynamic framework for decision-making, allowing the system to operate efficiently under varying energy and signal conditions. This adaptability made the model particularly suitable for scenarios involving intermittent energy harvesting. However, it required accurate estimation of energy levels and signal strength, which increased computational effort and system complexity. Additionally, the adaptive nature of the method led to instability or suboptimal performance in rapidly changing network environments.

M. B. Usman., *et al.* [22] presented an Energy detection with entropy method for spectrum sensing in CRN. The method efficiently improved spectrum sensing performance by enhancing detection accuracy and reducing false alarms in low signal conditions under the considered channel model. The approach contributed to more efficient utilization of frequency resources and improved sensing precision through the integration of entropy-based analysis. Its combination of statistical and entropy-driven features offered a more robust alternative to conventional energy detection techniques. However, it was evaluated only under a single channel model, which limited its general applicability in more complex environments. The use of a fixed threshold restricted adaptability to changing signal conditions. Additionally, the method assumed randomly generated input signals, which did not fully represent practical communication scenarios.

L. C. Kawala., *et al.* [23] designed a unified system model for spectrum sensing in CRN. This model efficiently addressed the dual challenges of spectrum efficiency and energy sustainability in CRN. It improved spectrum utilization, enhanced sensing reliability under low-signal conditions, and allowed dynamic adjustment between energy harvesting and data transmission based on network activity. The

method demonstrated fast convergence, strong scalability, and overall efficient performance, making it suitable for deployment in complex network environments. Its unified architecture also enabled flexible reconfiguration for different CRN applications, enhancing versatility. However, the model involved considerable computational complexity and relied on precise network information, which limited its robustness in highly dynamic or uncertain wireless conditions. Additionally, implementing the system in large-scale networks posed difficulties related to resource management and adaptability.

3.4 Blockchain-based Model

Blockchain-based models are gaining attention due to their capability to ensure secure, decentralized, and tamper-proof data management. By integrating blockchain technology, spectrum sensing decisions and data exchanges among cognitive radio users are recorded transparently and immutably, ensuring trust and accountability. These models facilitate collaborative sensing while preventing malicious activities, data falsification, and unauthorized access. In addition, blockchain introduces a distributed ledger structure that reduces dependency on central authorities, thereby improving resilience against single points of failure. The main complexities related to traditional blockchain-based approaches in spectrum sensing for CRN are described as follows.

A. Khanna, *et al.* [24] implemented a blockchain based security enhancement and spectrum sensing method for managing spectrum in CRN. The method effectively enhanced spectrum management and security by detecting and reducing the impact of malicious users in the network. It improved the reliability and performance of spectrum sensing, ensuring that false information from harmful actors did not degrade system operations. The approach strengthened overall network integrity and maintained efficient data transmission. Moreover, the integration of blockchain improved traceability of sensing decisions, making malicious attempts easier to identify and investigate. However, the method relied on continuous monitoring and analysis to detect malicious behavior, which increased system complexity and operational demands. Additionally, the focus on security and detection mechanisms introduced additional processing overhead, potentially affecting efficiency in highly dynamic or resource-constrained environments.

D. Balakumar and S. Nandakumar [25] developed a M-ary Quadrature Amplitude Modulation (QAM) technique for spectrum sensing in CRN using blockchain. This model improved detection performance by reducing the effects of fading, shadowing, and noise in radio environment, which led to better reliability and stability in communication. The cooperative framework facilitated efficient information exchange and supported adaptive thresholding, improving sensing efficiency under varying signal conditions. Furthermore, the blockchain layer ensured secure sharing of sensing data, preventing malicious nodes from injecting false results into the cooperative process. However, the approach required careful coordination among nodes, which increased communication overhead and system complexity. Additionally, its effectiveness depended on maintaining favorable signal conditions, and its performance declined under severe fading or low signal scenarios.

3.5 Others

Various conventional methods for spectrum sensing in CRN are explained below.

S. Velmurugan, *et al.* [26] developed an ANFIGA-CS for collaborative spectrum sensing in CRN. The approach enabled efficient identification of available spectrum slots within the radio band through a multi-stage process. Its layered operational design minimized sensing inaccuracies leading to improved overall network performance. The integration of clustering and adaptive rule optimization strengthened decision-making efficiency. This hybrid neuro-fuzzy and evolutionary design also allowed more flexible adaptation to dynamic spectrum conditions. However, the method involved higher computational complexity due to multiple processing stages and failed to incorporate more advanced learning mechanisms to optimize channel selection.

R. Garg and N. Saluja [27] employed a HOD-CODO for in-band spectrum sensing in CRN. The devised model reduced false alarms and increased throughput while ensuring high protection for primary users. It demonstrated the capability to balance sensing time and data transmission, resulting in more efficient utilization of the frame period and higher overall throughput. The approach was adapted well to varying signal-to-noise conditions, showing improved decision-making through a socially inspired mechanism that mimicked intelligent human interactions. The use of opinion dynamics enabled more natural convergence of decisions among secondary users participating in cooperative sensing. However, the method's reliance on careful parameter optimization and the trade-offs added complexity to its operation. Additionally, its performance required enhancement for lower signal conditions, and it failed to balance efficiency and reliability.

M. Khasawneh and A. Agarwal [28] designed a collaborative approach for monitoring nodes behavior during spectrum sensing. The model enhanced network security and spectrum sensing reliability by

monitoring node behavior during sensing process, which allowed adversary nodes to be identified and eliminated. It increased overall network performance and supported proactive responses to passive attacks and reactive responses to active attacks. This continuous behavior analysis strengthened trust management among cooperating nodes, further enhancing sensing accuracy. However, the model required continuous monitoring and evaluation of node behavior, which increased energy demands. Additionally, balancing the level of security with energy consumption posed difficulties, and the method's reliance on reputation-based monitoring limited responsiveness in highly dynamic or large-scale network environments.

A. Mustafa., *et al.* [29] developed a decentralized cooperative algorithm for efficient sensing of spectrum in CRN. This model enabled secondary users to coordinate and exchange information effectively, allowing for quick and efficient decision-making even as primary users dynamically entered or left the network. The method demonstrated high reliability and improved performance under challenging conditions, requiring fewer iterations, less processing time, and faster convergence. It supported cooperative behavior among network nodes, enhancing overall spectrum utilization and system efficiency. Its distributed nature reduced dependency on centralized controllers, making it more suitable for large-scale CRN deployments. However, the approach faced difficulties in environments with noise, interference, or network instability. The system's performance was affected by unequal delays or jitters, which increased instability.

P. J. Smith., *et al.* [30] devised a multisample sphericity test and meta-analysis for spectrum sensing in CRN. This approach focused on efficient spectrum sensing for both centralized and decentralized scenarios. The approach minimized the data exchanged between secondary users and the central processor, making it more suitable for large-scale networks while maintaining reliable detection performance. It provided analytical expressions and the used simple data fusion techniques to enhance decision-making efficiency. The statistical basis of the method made it computationally lightweight, enabling efficient execution even on low-power CRN devices. However, the approach involved additional design complexity for distributed coordination and required careful calibration to maintain accuracy. Moreover, the system still depended on consistent communication among network nodes, which was affected by network delays or errors in practical deployments.

4. Research Gap and Complexities

The research gaps observed in conventional spectrum sensing in CRN methods are,

The primary complexities tackled by traditional DL-based methods for spectrum sensing in CRN are summarized below. The developed model in [7] considered single primary user and a single secondary user, which limited its applicability in more complex network scenarios with multiple users. This constraint prevents the model from capturing heterogeneous user behaviors that commonly exist in real-world CRNs. The method also relied on carefully selected input features and optimized parameters, making it less flexible and potentially sensitive to changes in the environment or dataset. The method designed in [11] focused on scenarios with limited numbers of primary and secondary users, and made it less suitable for more complex network environments. Additionally, its reliance on specific data collection setups and statistical features reduced flexibility and generalizability to different network conditions or technologies.

The main shortcomings of conventional ML-based approaches for spectrum sensing in CRN are outlined below. The method devised in [16] heavily relied on accurate estimation of channel conditions, which was difficult in highly dynamic changing environments. As a result, ML models often fail to maintain consistent performance when faced with sudden signal fluctuations or mobility-induced variations. Moreover, its performance degraded in scenarios with severe fading or extensive scattering, limiting reliability.

Key issues related to existing energy harvesting-based methods are detailed below. The approach developed in [19] relied heavily on the participation of multiple nodes, which increased system complexity and coordination requirements. Such dependency weakens performance when nodes experience uneven energy harvesting rates or intermittent availability. Its performance was constrained by the energy availability of nodes, this potentially reduced the reliability and efficiency of the network. The designed model in [22] assumed a specific type of input signal, which did not reflect more diverse or practical signal scenarios, limiting the generalizability. In addition, this method relied on predetermined thresholds, which reduced adaptability in dynamic environments. This fixed-threshold limitation restricts responsiveness to fluctuating signal conditions, making real-time adaptation challenging.

The complexities encountered in prior blockchain-based techniques are as follows. The model developed in [25] required cooperation among multiple nodes, which increased system complexity and dependency on network coordination. Furthermore, blockchain operations introduce latency and computational overhead, which can slow down time-sensitive spectrum sensing decisions. Its performance degraded significantly under low-quality signal scenarios, making it less robust in dynamic or harsh environments.

5. Evaluation and Discussion

This part provides an assessment of prior methods developed for spectrum sensing in CRN. The conventional approaches are categorized using year of publication, techniques used, datasets utilized, and performance metrics. This evaluation helps identify research trends, methodological preferences, and potential gaps in experimental validation across existing studies.

5.1 Evaluation using Techniques

Figure 2 illustrates the analysis of prior schemes utilized for spectrum sensing in CRN. The assessment shows that 32% of research papers used DL approaches, 16% of articles used ML models, 24% of papers used energy harvesting approaches, 8% of research articles integrated blockchain technology, and 20% of research papers used other strategies. This distribution indicates a strong shift toward intelligent sensing solutions, with DL gaining prominence due to its superior feature extraction capability. Here, the assessment reveal that DL-based approaches are most widely utilized for spectrum sensing in CRN.

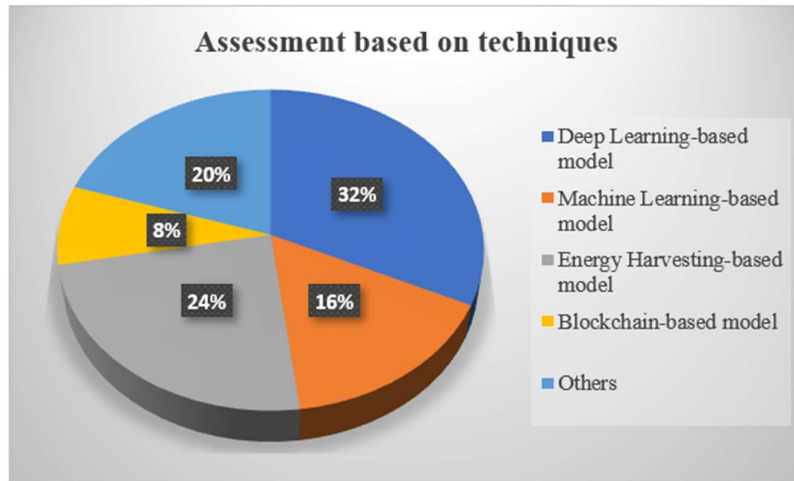


Fig. 2. Assessment using techniques

5.2 Analysis using Toolset

Figure 3 shows the evaluation based on toolset utilized to evaluate the performance of spectrum sensing models in CRN. Here, the tools include Python, MATLAB, Keras, TensorFlow, and NS2 simulator. Among these, MATLAB is the most frequently utilized tool, appearing in 12 of the research articles. This trend highlights MATLAB's popularity for simulating wireless environments and signal-processing tasks, particularly in early-stage algorithm development.

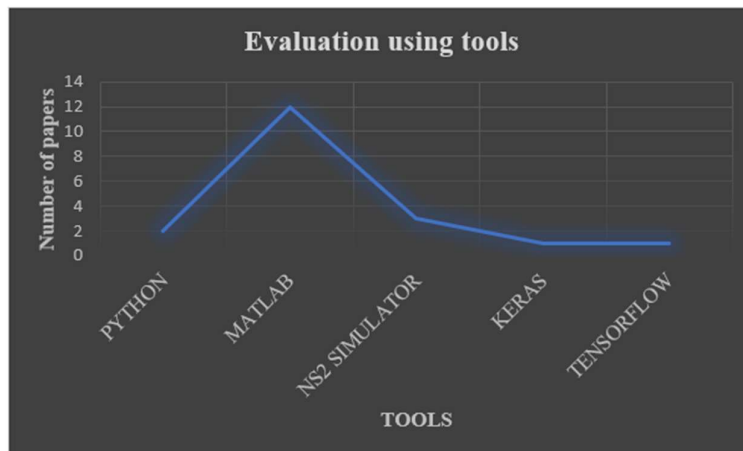


Fig. 3. Analysis based on tools

5.3 Evaluation based on Published Year

This part assesses 25 research articles according to their year of publication. The assessment shows that most articles were published in 2022. This suggests heightened research interest in spectrum sensing during that period, likely driven by advancements in AI and the growing need for efficient spectrum management in 5G and beyond. Table 1 summarizes the distribution of publications over the years.

Table 1. Evaluation using published year

Published Year	Number of papers
2016	[18]
2017	[28]
2018	[17] [30]
2019	[20]
2020	[7] [19] [21] [27]
2021	[12] [13] [16] [29]
2022	[10] [11] [14] [22] [24] [26]
2023	[15] [25]
2024	[6] [9]
2025	[8] [23]

5.4 Assessment based on Metrics

Figure 4 presents the evaluation of parameters used for assessing spectrum sensing in CRN. The most widely used metrics include AIR, average throughput, SNR, probability of detection, probability of non-fading channels, probability of miss alarm, probability of error, ROC curve, probability of false alarm, sparsity order, compression rate, normalized throughput, MSE, active probability, AUC, F-Score, sensing performance gain, total error probability, missed detection probability, number of selected sensing nodes, energy efficiency, average delivery rate, average residual energy, probability of successful delivery, total probability of error, perception error, training time, testing time, spectrum utilization, BL, K-rule, sensing error, packet drop, packet delivery ratio, prediction accuracy, recall, precision, probability of missing ratio, number of iterations, asymptotic convergence factor, CPU processing time. The assessment of the existing literature showed that probability of detection is the most widely utilized metrics for spectrum sensing in CRN, appearing in 17 of reviewed articles. This indicates that most researchers prioritize accurate differentiation between occupied and idle spectrum bands, as it directly impacts interference avoidance and system reliability.

6. Conclusion

In CRNs, spectrum sensing is essential for detecting primary users and identifying vacant frequency bands for dynamic spectrum allocation. Furthermore, the increasing density of wireless devices demands sensing mechanisms that can operate reliably even under extreme interference and spectrum congestion. However, conventional spectrum sensing models exhibit poor performance in highly dynamic or crowded environments, which struggle to distinguish between multiple signal types, and rely heavily on prior knowledge of primary user signals. Moreover, these approaches often involve high computational complexity and face significant challenges in implementing cooperative or collaborative sensing across large-scale networks. Such limitations hinder scalability, making it difficult for CRN systems to maintain consistent performance as network size and traffic demands grow. As a result, existing methods lack adaptability to dynamic spectrum conditions and resilience against malicious or faulty nodes, ultimately reducing the reliability and efficiency of spectrum utilization in CRNs. This survey examines 25 research papers focused on spectrum sensing in CRN, classifying them according to methodological approaches, including DL, ML, energy harvesting, and blockchain-based techniques. The methods are analyzed based on toolset utilized, evaluation parameters, year of publication, and datasets employed. The analysis indicates that DL-based models are the most widely used approach. The MATLAB is identified as the widely used toolset. Additionally, the probability of detection metrics is commonly used across the articles. This comprehensive review underscores the potential for researchers to develop advanced DL techniques capable of automatically analyzing spectrum data, thereby improving detection accuracy of primary users, minimizing the reliance for manual spectrum monitoring, and enhancing the effectiveness of spectrum sensing in CRN. Future spectrum sensing frameworks may further benefit from hybrid models that combine DL with reinforcement learning or federated learning to enable decentralized and privacy-preserving decision-making. Such approaches enable more intelligent and dynamic allocation of frequency bands, optimize spectrum utilization, and ensure reliable communication in complex and heterogeneous network environments.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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