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A Comparative Analysis of Different Spectrum Sensing Techniques in Cognitive Radio Networks

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Abstract

The enormous need for radio frequency (RF) spectrum brought on by the exponential rise in wireless communication technologies has caused serious spectrum shortage. Reliable and high-quality wireless communication is hampered by this lack. By allowing dynamic spectrum access for secondary users (SUs) without disturbing licensed primary users (PUs), cognitive radio networks (CRNs) have developed as a solution to this issue. This work investigates several spectrum detection methods employed in CRNs to find accessible frequency ranges. Presented here is a thorough examination of these methods, assessing their detection accuracy, complexity, and robustness performance. The paper also examines the difficulties connected with spectrum sensing and presents future research plans. In addition, it highlights the trade-offs involved in selecting appropriate sensing techniques under varying network and environmental conditions. The study compares cooperative and non-cooperative sensing approaches and discusses their practical implications in real-world CRN deployments. Emphasis is placed on the need for intelligent sensing algorithms and machine learning techniques to enhance detection reliability in dynamic spectrum environments.

Keywords: Cognitive Radio Networks (CRNs), Spectrum Sensing, Energy Detection, Matched Filter.

1. Introduction

With exponential growth of wireless devices, Internet of Things (IoT) applications, and high-bandwidth services like 5G and beyond (Muzaffar & Sharqi, 2024; Xu et al., 2025), the electromagnetic spectrum a finite and priceless resource in wireless communication is under unprecedented demand. Traditional static spectrum allocation policies, whereby regulatory agencies assign fixed frequency bands to authorized users (Primary Users, PUs), have resulted in great underutilization; studies reveal licensed spectrum remaining empty 15% to 85% of the time depending on location and frequency bands (*(4) Spectrum Sensing Techniques Applied In Cognitive Radio Networks – A Comparison*, n.d.; Muzaffar & Sharqi, 2024). This inefficientness has led to the development of Cognitive Radio Networks (CRNs), a cutting-edge paradigm allowing unlicensed secondary users (SUs) to opportunistically use vacant spectrum bands without generating detrimental interference to PUs (*(4) Spectrum Sensing Techniques Applied In Cognitive Radio Networks – A Comparison*, n.d.; Xu et al., 2025).

1.1. The Role of Spectrum Sensing in CRNs

The foundation of CRN's operation is spectrum sensing, which lets secondary users (SUs) detect and use "spectrum holes" unused licensed frequency bands and to quickly evacuate when primary users (PUs) start up activity (Associate et al., 2025; Sumithra & Suriya, 2024). Because incorrect detections either missed detections or bogus alerts can cause lost access chances or hazardous interference with PUs, the accuracy and efficiency of spectrum sensing directly affect CRN performance. Recent developments in spectrum sensing inside CRNs increasingly focus on ML-driven methods, cooperative sensing frameworks, and 5G system integration to address these challenges (Associate et al., 2025). Similar to machine learning applications in Anti-Money Laundering systems, where supervised models are used to improve detection accuracy and reduce false positives (Raffat & Ahmad, 2025), ML-based spectrum sensing in CRNs aims to enhance decision-making under uncertainty and dynamic spectrum conditions.

1.2. Spectrum Sensing Challenges

Although spectrum sensing is essential, it presents several obstacles:

1. Low Signal-to- Noise Ratio (SNR) Under real-world circumstances, PU signals are frequently masked by noise, multipath fading, and shadowing, therefore detecting at low SNR levels (*(4) Spectrum Sensing Techniques Applied In Cognitive Radio Networks – A Comparison*, n.d.) is challenging. Although straightforward, traditional energy detection methods fail under such conditions, hence more advanced techniques like cyclostationary feature detection or eigenvalue-based sensing (2018) are required.
2. Geographic barriers or deep fading can stop an SU from spotting an active PU, therefore causing interference. Cooperative sensing, in which several SUs share detection information, reduces this problem by means of spatial diversity (Xu et al., 2025).
3. Dynamic Spectrum Environments: The growing complexity of contemporary wireless systems, including 5G and IoT networks, calls for adaptive sensing methods capable of handling wideband signals and rapidly changing spectrum conditions (Xu et al., 2025).

4. Computational Complexity: Advanced sensing techniques, especially those using ML or high-order statistical analysis, call for considerable computer resources, which presents difficulties for energy-constrained equipment (Muzaffar & Sharqi, 2024).

2. Literature Review

A comparative study of spectrum sensing methods in cognitive radio networks (CRNs) exposes a wide range of approaches, each with unique benefits and drawbacks. Factors like signal-to-noise ratio (SNR), ambient circumstances, and computational complexity affect the effectiveness of these methods. Key spectrum sensing methods are discussed in the next parts together with their relative performance.

Conventional Spectrum Sensing Methods Simple and commonly used, energy detection (ED) nonetheless experiences great false positive rates in low SNR conditions (Chaudhary & Mahajan, 2022). High detection accuracy comes with matched filter detection (MFD); nevertheless, it demands previous knowledge of the primary user's signal, hence reducing its adaptability (Bagwari & Singh, 2012). Though complicated and requiring longer observation durations, Cyclostationary Feature Detection (CFD) works well in low SNR conditions and is noise resistant (Bagwari & Singh, 2012). Advanced Spectrum Sensing Methodologies is a fresh technique known as Variable Time Segment Monitoring (VTSM) dynamically modifies time segments for better detection accuracy and lower false alarms, especially in challenging situations (Soproniuk & Komar, 2024). By combining data from several users, Cooperative Spectrum Sensing improves detection accuracy and resolves problems including shadowing and multipath fading (Khan & Nakagawa, 2013). Notably, recent advancements in intelligent detection systems such as the integration of Grey Wolf Optimization with Deep Belief Neural Networks in malware detection demonstrate the potential of hybrid AI models to optimize feature selection and enhance classification accuracy, offering valuable insights for further refining adaptive spectrum sensing strategies (Ahmad et al., 2024). Performance Metrics Low SNR cyclostationary detection outperforms other methods, Bagwari and Singh, 2012. Energy detection generates more false alarms than more advanced techniques like CFD (Chaudhary & Mahajan, 2022), therefore increasing False Alarm Rate (Pf). To reduce pointless handoffs and increase spectrum use in CRNs, Khalid and Farooq (2025) suggested an Adaptive Hybrid Handoff (AHH) algorithm that dynamically switches between proactive and reactive techniques depending on primary user arrival patterns (Muhammad Farooq, 2019). Although conventional approaches give basic spectrum sensing techniques, sophisticated methods like VTSM and cooperative sensing provide improved performance in dynamic settings. But, the complexity and resource requirements of these advanced methods might restrict their use in certain situations.

3. Methodology

Four main spectrum sensing methods used in Cognitive Radio Networks (CRNs) are assessed using a qualitative comparative analysis approach based on a systematic review of available literature. The goal is to evaluate these methods over main performance aspects, therefore emphasizing their respective trade-offs and usefulness under different network scenarios.

1. Selection of Methods: Four well-known spectrum sensing methods were chosen for comparison according on their frequency in the literature and their applicability to present CRN uses:
    - Energy Detection
    - Matched Filter Detection
    - Cyclostationary Feature Detection
    - Wavelet-Based Detection

Offering a representative cross-section of modern CRN sensing methods, these techniques span a wide spectrum of complexity, signal awareness, and noise handling capacity (Arjoune & Kaabouch, 2019; H.R & C, 2015).

2. Data Sources and Review Approach: Peer-reviewed journal papers, experimental assessments, and technical reports with empirical measurements or theoretical study of the chosen methodologies are used to generate the comparison. Data was gathered on important performance indicators including sensing time, resilience to noise, computing demands, and appropriateness across several SNR levels.
   To ensure consistency, only studies that met the following criteria were included:
    - Peer-reviewed or technically verified.
    - Provided explicit values or categorical descriptions for at least three of the five selected metrics.
    - Covered either simulated or real-world performance under standard conditions.
3. Evaluation Framework: Each technique was evaluated against five core performance metrics (table-1):

Table No 1: Metric description

Metric	Description
Prior Knowledge	Whether the sensing method requires known characteristics of the PU signal.
Computational Complexity	Relative hardware/software resource demands.
Robustness to Noise	Effectiveness in low SNR or noisy environments.
Sensing Time	Duration needed for accurate PU detection.
Suitable SNR Range	Optimal SNR range in which the technique performs reliably.

4. Data Synthesis: Visualizing and compiling the results across all approaches calls for a comparative matrix. Qualitative descriptors (e. g. , High, Medium, Low) were standardized based on reported trends and cross-validated across several sources where numerical values were unavailable or inconsistent. This synthesis lets one direct future implementations via a direct technique-to-technique comparison.

3.1. Spectrum Sensing Techniques

CR performance depends on spectrum sensing. It helps identify spectrum holes (unused bands) and helps to avoid interference with PUs. The most often used strategies are listed below:

3.1.1. Energy Detection

Measures signal energy in a band and contrasts it to a threshold define the principle here. The secondary user (SU) collects samples of the received signal $r(t)$, which under two hypotheses (figure-1) are either:

H0*: noise only, *r(t)=n(t)r(t)

H1*: signal plus noise, *r(t)=s(t)+n(t) (Kockaya & Develi, 2020)

These samples pass through a band-pass filter → A/D converter → squared and accumulated over a time T. The test statistic is (Kockaya & Develi, 2020):

$$\mathrm{T} = \sum_{n-1}^{n} [|r[n]|^2]$$

Finally, TTT is compared to a threshold λ:

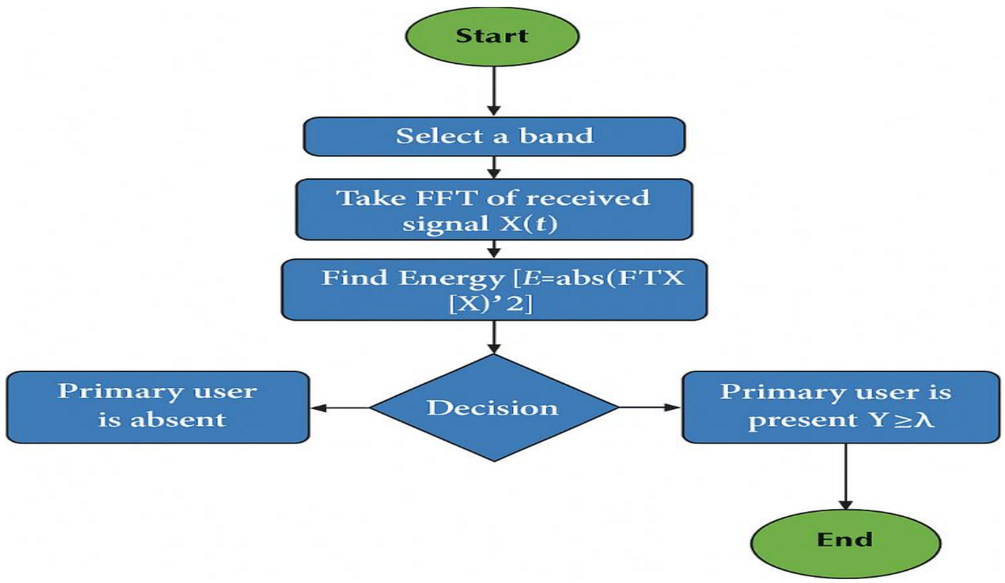
- If T>λ, the SU decides **PU present** (H_1)
- Otherwise, **PU absent** (H_0)

Advantages: The advantages of these techniques are explained in table-2 given below.

Table No 2: Advantages of Energy Detection Sensing Technique

Feature	Explanation
Simplicity	No prior knowledge of the PU signal waveform is required—just measure energy (Ejaz et al., 2012)
Low Complexity	Requires minimal hardware/software—band-pass filter, ADC, square-law, and integrator
Signal-Agnostic	Compatible with any signal type (e.g., OFDM, QPSK) as it only looks at power

Figure No1: Flowchart of Energy Detection-Based Spectrum Sensing



Block diagrams above illustrate (Figure-01) the filter–square–integrate structure and flowchart of the energy detection process.

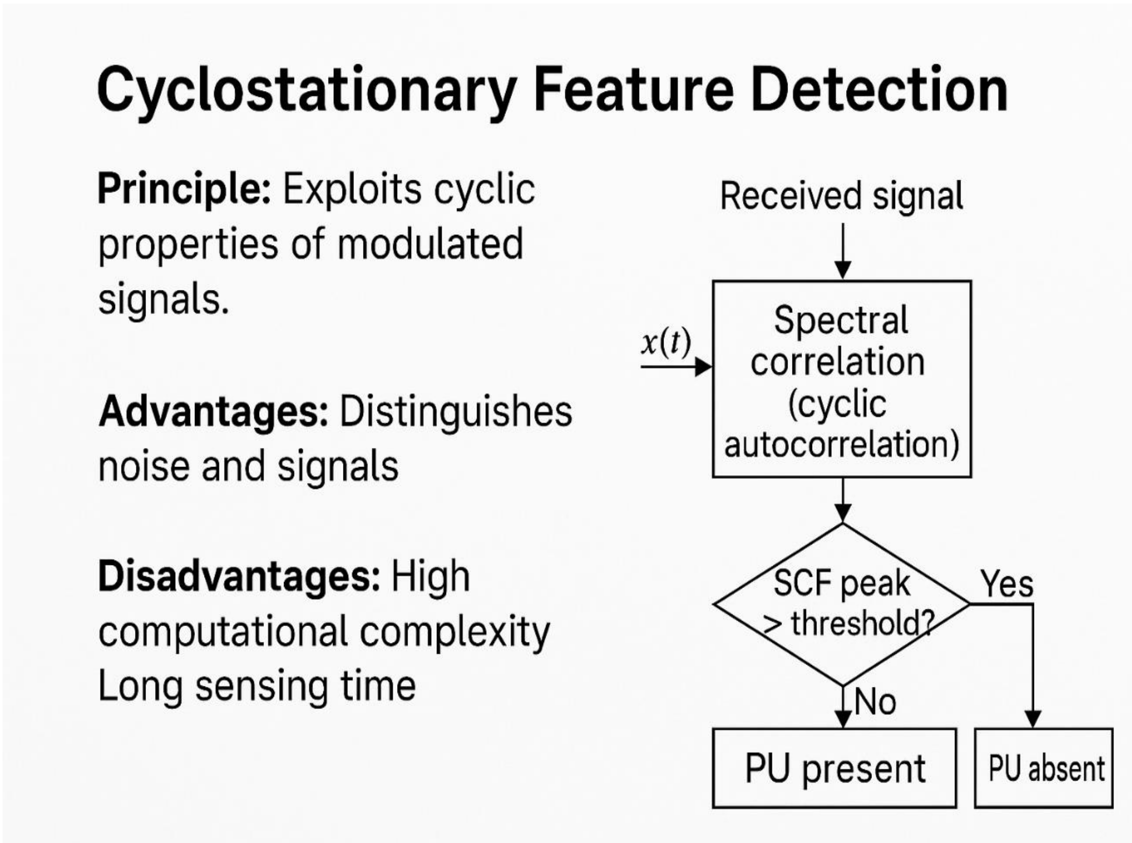
Disadvantages:

1- Underperformance at low signal-to-noise ratioThe SU fights to differentiate bits when PU signal strength approaches noise level, which results in false alerts or missed detections (Martínez & Andrade, 2016).
2- Inability to distinguish noise from signalEnergy detection treats all energy alike, leading to an inability to discriminate between noise and structured signals—increasing false detections (Ejaz et al., 2012).
3- Noise volatility and the SNR barrierSmall mistakes in noise power prediction can produce a detection threshold either too high or too low. Below a certain SNR (the "SNR wall"), detection becomes unreliable irrespective of sensing time (Martínez & Andrade, 2016).

3.1.2. Cyclostationary Detection Technique

Unlike stationary noise, CFDs takes use of the periodic statistical features of modulated signals due to characteristics like carrier frequency, symbol rate, cyclic prefixes, etc. Which mark nonzero values in their spectral correlation function (SCF) (Zeng et al., 2010). Seeking peaks at particular cyclic frequencies (α) where primary user (PU) signals show periodicity, the SU calculates the cyclic autocorrelation or SCF of the incoming signal. Detection is noted when these peaks cross a threshold (Harit Mehta, 2014) as shown in figure 2.

Figure No 2: Cyclostationary feature detection technique



Advantages

1- Signal–Noise Discrimination

- By using SCF peaks absent in noise, CFD distinguishes noise from modulated signals.

2- Strength at poor SNR

- Unlike energy detection, CFD has high detection probability even with faint PU signals; measurements reveal it can detect at SNRs as low as –8 dB with almost zero false alarms (Chatterjee et al., 2015).
- CFD is shown to outperform energy detection in low-SNR scenarios by a broad study.

3- Capacity for modulation classification and signal identification

- Because cyclic frequencies are modulation-specific, CFD may distinguish PUs from interferers or jammers by means of signal kinds (Nawaz et al., 2017).

Disadvantages

1- High Computational Complexity

- Estimating SCF usually entails 2D FFTs or cyclic autocorrelation—computer intensive, particularly for wideband signals (Nawaz & Alzahrani, 2023).

- Though complexity persists, improvements like FRESH filters and compressed sensing can cut labor (Saggar & Mehra, 2013).

2- Long Sensing Time Required

- Accurate cyclic feature extraction across several cycles necessitates large sample sizes, therefore increasing sensing lengths and decreasing responsiveness (Hassan et al., 2012).

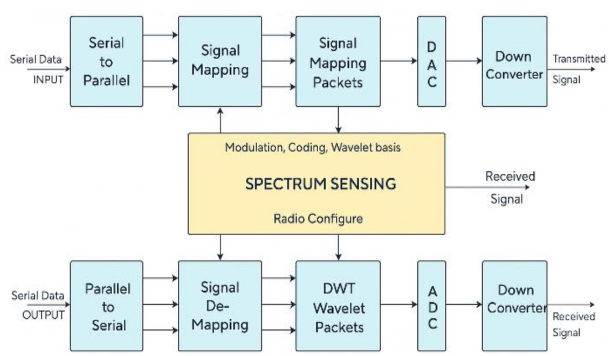
3-Need of Prior Knowledge (Partial)

- CFD calls for awareness of predicted cyclic frequencies—linked to signal characteristics—thus implying a degree of previous knowledge (Harit Mehta, 2014).

3.1.3. Wavelet-Based Spectrum Sensing

Wavelet-based methods find spectral edges the border between populated and unoccupied channels in wideband signals by examining the singularities of the PSD utilizing wavelet transforms (CWT/DWT) as shown in figure-3. Wavelet coefficients demonstrate sharp peaks at these edges, suggesting subband transitions (*Multiband Spectrum Sensing*, n.d.)

Figure No 3: Wavelet-based Spectrum Sensing (Haykin, 2005)



Advantages

- Wideband Efficiency: Detects multiple sub-bands simultaneously no need to scan sequentially (Arjoune & Kaabouch, 2018).
- Fast Edge Detection: By spotting abrupt changes, quickly finds occupancies over the spectrum.

Disadvantages

- Impulsive noise can lead to faulty edge detections; hence, adaptive thresholds are required (*Multiband Spectrum Sensing*, n.d.).
- Relies on Nyquist-rate ADCs and sophisticated wavelet computation, resulting in significant latency and power consumption, high complexity and sampling requirements (Arjoune & Kaabouch, 2018).

- Low-SNR performance that is poor: Difficulties in detecting edges at signal amplitudes close to noise level (Arjoune & Kaabouch, 2018).

4. Results and Analysis

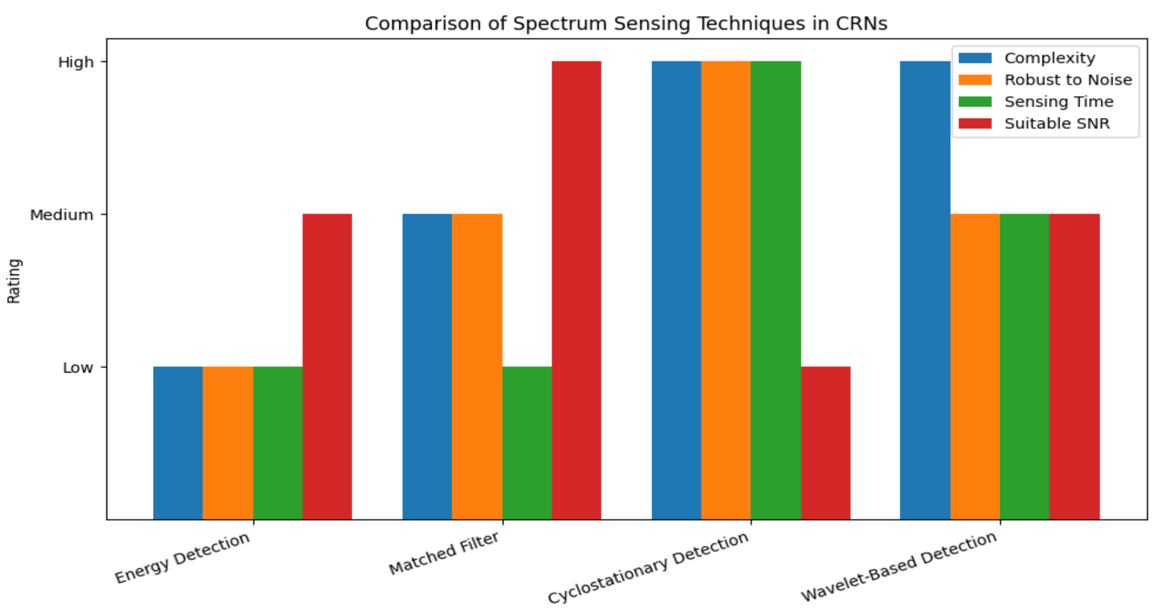
Table 1 presents a comparative evaluation of four key spectrum sensing techniques based on critical performance criteria: prior knowledge requirement, computational complexity, robustness to noise, sensing time, and suitable SNR environment. These metrics provide a clear understanding of the practical strengths and limitations of each approach.

Table No 3: Comparative Analysis of Spectrum Sensing Techniques

Technique	Prior Knowledge	Complexity	Robust to Noise	Sensing Time	Suitable SNR
Energy Detection	No	Low	Low	Low	Medium-High
Matched Filter	Yes	Medium	Medium	Low	High
Cyclostationary Detection	No	High	High	High	Low
Wavelet-Based Detection	No	High	Medium	Medium	Medium

Four prominent spectrum sensing methods employed in cognitive radio are examined on the table-3. The most basic approach, energy detection needs no prior understanding of the signal, but it suffers in noisy environments and is best suited for medium to high SNR situations. Though more difficult, matched filter detection demands full awareness of the signal's properties; it does, nevertheless, provide rapid sensing and excellent performance when the signal is strong. Although it calls for great computing resources and longer sensing time, cyclostationary feature detection depends on detecting signal patterns and so does not need previous signal knowledge; it is very noise resistant and effective at low SNR.

Figure No 4: Comparative Analysis of Spectrum Sensing Techniques Based on Key Performance Metrics



Finally, wavelet-based detection is especially good for wideband sensing since it functions without previous signal awareness. It is, though, computationally demanding, somewhat noise-resistant, and ideal for medium SNR situations. Every approach offers a compromise among SNR fit, sensing time, noise resilience, and complexity.

4.1 Challenges and Future Directions

Cognitive radio now has a number of important obstacles. As shown in generalized energy detection models investigating noise variation estimation and throughput trade-offs, noise uncertainty—inexact knowledge of the noise level can greatly compromise spectrum sensing precision, so necessitating longer sensing durations to keep performance(Bogale et al., 2014). Still a major risk is the hidden node issue, where shadowing or fading stops a CR from finding an active primary user, often needing coordinated sensing or infrastructural help to lessen (*Dynamic Spectrum Management - Wikipedia*, n.d.). Moreover, CRs have to carefully weigh sensing time against throughput: prolonged sensing lowers PU misdetection but cuts into available transmission time—an operational trade-off supported in research such Bogale et al. on sensing throughput optimization (Bogale et al., 2014). Hardware constraints ultimately impede real-time deployment, sometimes restricting actual applications, particularly the need for high-speed ADCs and intense computation for wideband sensing or complex algorithms. Several intriguing routes become apparent as one looks ahead to possible directions. Adaptive tactics and dynamic decision-making in uncertain, time-varying environments are made possible by machine learning–based sensing, notably deep learning and reinforcement learning (*Dynamic Spectrum Management - Wikipedia*, n.d.). Cooperative spectrum sensing, where several CRs share observations, provides better reliability and mitigation against the concealed node problem. Integrating cognitive radio with 6G networks will create even more rigorous requirements for dynamic spectrum allocation, latency, and dependability, so positioning CR at the center of tomorrow's communication systems (Al-Matari et al., 2024). Together, these paths ML-driven sensing, collaborative detection, CR-6G synergy, and blockchain-enhanced resource management—promise a robust, intelligent, and secure path forward for cognitive radio (Xiao et al., 2022). Blockchain for spectrum sharing is another developing direction offering safe, transparent, decentralized frameworks for spectrum transactions and access management—recent research shows blockchain-enabled spectrum access systems.

5. Conclusion

This study offers a critical comparison of four major spectrum sensing techniques in cognitive radio networks, underlining the trade-offs in complexity, robustness, and accuracy. Energy Detection remains a lightweight and signal-agnostic solution but underperforms in low-SNR conditions. Cyclostationary Detection excels in signal discrimination and low-SNR performance but demands high computational resources and prior signal pattern knowledge. Wavelet-Based Sensing, while effective for wideband applications and sub-band localization, is hindered by its complexity and sensitivity to impulsive noise. Matched Filter Detection, though highly accurate, is impractical for unknown or dynamic signal types due to its reliance on complete prior knowledge.

These findings emphasize the need for adaptive hybrid approaches—such as machine learning–assisted sensing or cooperative frameworks—to dynamically select or combine techniques based on environmental factors and system constraints. Furthermore, as CRNs continue evolving toward integration with 6G and IoT ecosystems, future research must prioritize real-time adaptability, energy efficiency, and secure spectrum access mechanisms, possibly leveraging blockchain and AI-driven decision-making. This comparative analysis serves as a foundation for both theoretical advancement and practical deployment of intelligent, context-aware spectrum sensing in the next generation of cognitive radio networks.

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