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A Comprehensive Review on Cognitive Radio Networks: Applications, Challenges and Research Trends

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Abstract: - The exponential growth in wireless communication demand, driven by mobile devices and emerging technologies, has revealed the limitations of traditional spectrum management strategies, which often result in inefficient spectrum usage and increased interference. Cognitive Radio (CR) technology has emerged as a promising solution, enabling dynamic and intelligent spectrum utilization through the ability to sense, analyze, and adapt to the radio frequency environment. A key challenge in CR networks is Wide Band Spectrum Sensing (WBSS), crucial for identifying and evaluating available spectrum across a broad frequency range. While traditional spectrum sensing techniques are effective in narrowband scenarios, they struggle with the complexities of wideband analysis. Recent advancements in Machine Learning (ML) offer new opportunities to enhance WBSS capabilities by improving spectrum sensing accuracy and efficiency. This research explores the application of various ML algorithms, including Artificial Neural Networks (ANN), Naive Bayes, Random Forest, Decision Trees, K-Nearest Neighbor (KNN), Support Vector Machines (SVM), and Convolutional Neural Networks (CNNs), to address these challenges. Additionally, the study highlights the potential of a non-parametric dual transfer framework for Cooperative Spectrum Sensing (CSS), which significantly improves performance without extensive parameter tuning. This paper provides a comprehensive analysis of ML approaches applied to WBSS, comparing their effectiveness against conventional techniques and discussing the implications for CR systems. It also includes a literature review on Wireless Body Sensor Systems (WBSS) using ML in Cognitive Radio Ad-hoc Networks (CRAHNs), emphasizing ML applications in optimizing spectrum sensing and management. The reviewed studies demonstrate significant advancements in detection accuracy, particularly in low Signal-to-Noise Ratio (SNR) environments, through innovative approaches like deep learning, transfer learning, and cooperative sensing. The paper concludes by discussing the integration of ML into CR systems, highlighting its potential to enhance spectrum management, reduce interference, and improve wireless communication system performance in dynamic and complex environments, with specific focus on healthcare and other critical applications.

Keywords: Cognitive Radio, Spectrum Sensing, Wireless Communication, Ad Hoc Network, Machine Learning

I. INTRODUCTION

In recent years, the demand for wireless communication has skyrocketed, driven by the proliferation of mobile devices and emerging technologies. This surge in demand has exposed the limitations of traditional spectrum management strategies, which often result in inefficient spectrum usage and increased interference. CR (Cognitive Radio) technology takes emerged as a promising solution to address these challenges by enabling more efficient and dynamic spectrum utilization. CRs are intelligent systems capable of sensing, analyzing, and adapting to the radio frequency environment, which allows them to operate opportunistically in unused spectrum bands. One of the critical challenges in CR networks is wide band spectrum sensing, which involves identifying and assessing the availability of spectrum across a broad frequency range. Accurate and timely spectrum sensing is crucial for ensuring effective spectrum management, minimizing interference, and maximizing the performance of CR systems. Traditional spectrum sensing techniques, while effective in narrowband scenarios, often struggle with the complexities and demands of wide band spectrum analysis. Recent developments in machine learning (ML) provide an achievable approach to enhance Wide Band Spectrum Sensing (WBSS) capabilities [2].

Due to their ability to identify patterns and make predictions from massive datasets, machine learning algorithms hold great promise for increasing the precision and effectiveness of spectrum sensing. CRs may more effectively detect chances for using spectrum, adjust to changing circumstances, and lessen the chance of interference by utilizing ML approaches. WBSS in CRANs is a critical task to identify available frequencies efficiently. Various ML (ML) algorithms such as ANN (Artificial Neural Network), Naive Bayes [1], Random Forest, Decision Tree, K-Nearest Neighbor (KNN), and Support Vector Machine (SVM) [2] have been employed to enhance spectrum sensing accuracy under challenging conditions like low SNR scenarios and hidden node problems.

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This figure 1 represents a conceptual overview of CR Ad Hoc Networks (CRAHNs) and their interaction with licensed spectrum bands. The diagram shows the electromagnetic spectrum divided into Licensed Band I and Licensed Band II. These bands are allocated for specific uses, controlled by regulatory bodies, and licensed to certain users. Primary Users(PUs), depicted in blue ellipses, have priority access to these bands and must not be interfered with by other users. Primary Networks consist of infrastructure and devices like cellular towers that use these dedicated frequencies for communication. CRAHNs are represented within the dotted ellipse.

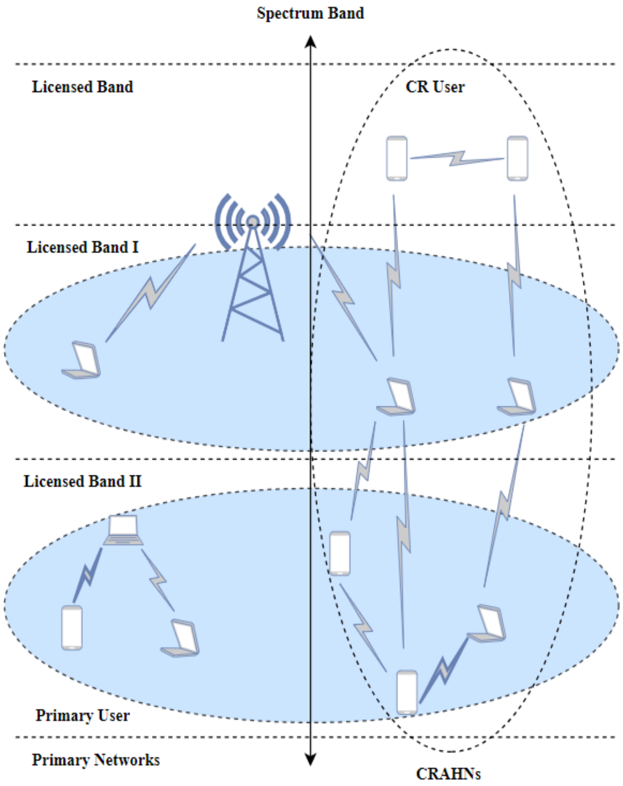

Figure 1. The CR ad hoc network architecture [33].

These networks include CR users equipped with cognitive radio capabilities, allowing them to opportunistically access and use underutilized spectrum segments without interfering with major users. CR users operates the spectrum to identify unused frequencies or "spectrum holes," dynamically accessing these frequencies for communication and optimizing spectrum usage. They also coordinate among themselves to ensure efficient spectrum sharing, minimizing interference and maintaining throughput. In the event that a PU begins using a frequency, CR devices will vacate the band to avoid interference. The diagram illustrates how CRAHNs operate as an overlay on licensed bands, demonstrating their flexibility in using the same spectrum as primary networks without a predefined infrastructure. This ad hoc communication model allows nodes to connect and disconnect dynamically, facilitating decentralized and adaptable network structures. CRAHNs improve spectrum utilization by leveraging frequencies that might otherwise be idle, addressing spectrum scarcity. Their ad hoc nature provides flexibility and scalability, making them suitable for dynamic environments where infrastructure-based networks are impractical. However, they present challenges, such as ensuring reliable spectrum sensing, avoiding interference with primary users, and maintaining secure communications. CR technology introduces the concept of intelligent, spectrum-aware communication systems that dynamically adapt to their environment. By leveraging advanced spectrum sensing and management techniques, CRs can opportunistically access unused or underutilized frequency bands, thereby improving spectrum efficiency and reducing interference. Ad-hoc Networks, on the other hand, are decentralized and self-organizing networks that do not rely on a fixed infrastructure. In these networks, nodes communicate directly with one another, forming a flexible and scalable network topology [10]. [50]-[54] elaborates the various CR use cases and proposed hybrid spectrum sensing algorithm and its superiority compared to existing energy detection (ED) and Covariance Absolute Value (CAV) algorithms. The use of Multiple Input Multiple Output(MIMO) in CR network with different combining methods has been studied well in [55] .The 'Angle' dimensions using Direction of Arrival (DoA) techniques for dynamic spectrum access has been investigated in[56]. The integration of ML techniques, particularly convolutional neural networks (CNNs), into wireless communication systems has shown significant promise. CNNs have shown to be quite successful in detecting and classifying wireless signals without any prior knowledge. Recent research demonstrated that CNNs can achieve over 90% testing accuracy at a signal-to-noise ratio (SNR) of 15 dB. This high level of accuracy highlights the potential of CNNs to revolutionize CR network spectrum sensing by automating the identification of available spectrum, thereby enhancing the efficiency and reliability of wireless communication systems. Furthermore, a groundbreaking non-parametric dual transfer framework for cooperative spectrum sensing (CSS) has been developed. This framework addresses the prevalent issue of insufficient labeled data in spectrum sensing tasks. Traditional spectrum sensing methods often struggle with data scarcity, which can limit their performance and applicability. However, the dual transfer framework provides a robust solution by demonstrating strong performance without the need for hyper parameter tuning. This means that the framework can adapt to various scenarios and environments, offering a significant advantage over conventional methods that require extensive parameter adjustment [4].

The study looks at the potential applications of several machine learning algorithms, such as unsupervised, supervised, and reinforcement learning methods utilized to improve the accuracy and reliability of spectrum sensing. By employing these advanced algorithms, the paper aims to address some of the significant limitations of traditional spectrum sensing methods, which often rely on predefined models and assumptions that may not hold in real-world scenarios. The research discusses both the challenges and opportunities associated with integrating ML into spectrum sensing, highlighting potential obstacles such as computational complexity, data requirements, and model generalization, as well as the potential benefits, including increased accuracy, adaptability, and efficiency. A comprehensive analysis of different ML approaches applied to wideband spectrum sensing is presented, showcasing their effectiveness in various scenarios. The study examines a wide range of spectrum sensing methods, comparing conventional techniques with newer, ML-driven approaches. This includes a detailed evaluation of how narrowband and wideband communication systems can benefit from these advancements, offering insights into the potential improvements in detecting and utilizing available spectrum [5].

The prime contribution of this research is:

1. This study provides an extensive overview of the spectrum sensing methods proposed so far, covering both narrowband and wideband communications systems.

2. To provide valuable insights into how ML can be used to address the inherent limitations of traditional spectrum sensing methods, which are often based on statistical models that may not capture the complexities of real-world wireless environments.

3. To discussed the various CR standards and its application.

4. To have insight on how ML can facilitate more adaptive and responsive spectrum management, enabling more efficient use of the radio frequency spectrum in CR systems,. This is particularly important in today's increasingly crowded wireless landscape, where the demand for bandwidth continues to grow.

5. By considering conventional techniques alongside cutting-edge ML approaches, the paper offers a balanced perspective on the current state of spectrum sensing research. The findings underscore the potential of ML to transform spectrum sensing in CR networks, paving the way for more robust, efficient, and adaptable wireless communication systems capable of thriving in dynamic and complex environments

The remainder of the document is structured as follows: Section 2 provides a background on CRs and common nomenclature. It covers the basic principles of CR technology, such as how CRs enable dynamic spectrum access by sensing and adapting to the radio environment. Section 3 covers the literature review and includes a thorough analysis of the most recent methods and relevant research in the field. Section 4 presents the standards for CRANs. Finally, Section 5 contains the conclusion.

II. BACKGROUND

Dynamic spectrum management (DSM) has become a crucial strategy to overcome these challenges. Unlike traditional fixed spectrum allocation, this approach seeks to optimize spectrum usage by enabling flexible, real-time adjustments based on current demand and availability. By using strategies like sharing, reallocation, and spectrum sensing, wireless systems are able to better use existing spectrum resources and adjust to changing environmental conditions [7]. CR technology is a breakthrough in dynamic spectrum management. CRs are smart systems that sense the radio environment, find available spectrum opportunities, and adapt their transmission parameters. By using unused or underutilized spectrum bands, CRs help alleviate spectrum scarcity and reduce interference, improving wireless communication networks' efficiency. [Integrating machine learning (ML) techniques further enhances CR capabilities by analyzing large datasets, identifying patterns, and predicting spectrum availability. This data-driven approach enables more accurate and efficient spectrum sensing and management. CR technology allows unlicensed users to access underutilized spectrum, ensuring efficient spectrum utilization. [8]. CRAHNs extend this capability by enabling dynamic spectrum management in decentralized, infrastructure-less environments. WBSS is a fundamental task in CRAHNs, involving the detection of available spectrum across a wide frequency range. Traditional spectrum sensing techniques face limitations in terms of accuracy, speed, and energy efficiency. ML (ML) offers potential solutions to these challenges by leveraging data-driven approaches for more efficient spectrum sensing [9].

A. Introduction to Cognitive Radio Ad-hoc Networks (CRAHNs)

In the evolving landscape of wireless communication, the need for more flexible and efficient network architectures has never been greater. Traditional network models, which rely on fixed infrastructure and predefined spectrum allocation, are increasingly strained by the rapid growth of wireless devices and the demand for high-bandwidth applications. In response, CRANs have become a viable solution to address these challenges and enhance the overall efficiency of wireless communication systems. CRANs represent a sophisticated convergence of two transformative technologies: CR and Ad-hoc Networks. When CR and Ad-hoc networks are combined, it creates CRANs. CRANs harness the adaptability and spectrum-awareness of CRs within the decentralized framework of ad-hoc networks. This integration offers several advantages, including enhanced spectrum utilization, increased network flexibility, and improved resilience to dynamic and unpredictable environments. Figure 2 shows the CR cycle.

This DSM capability allows CRANs to operate efficiently even in spectrum-constrained or highly variable conditions. Additionally, the ad-hoc nature of CRANs allows for rapid deployment and reconfiguration, making them well-suited for a variety of applications, from emergency response to autonomous vehicle networks [11].

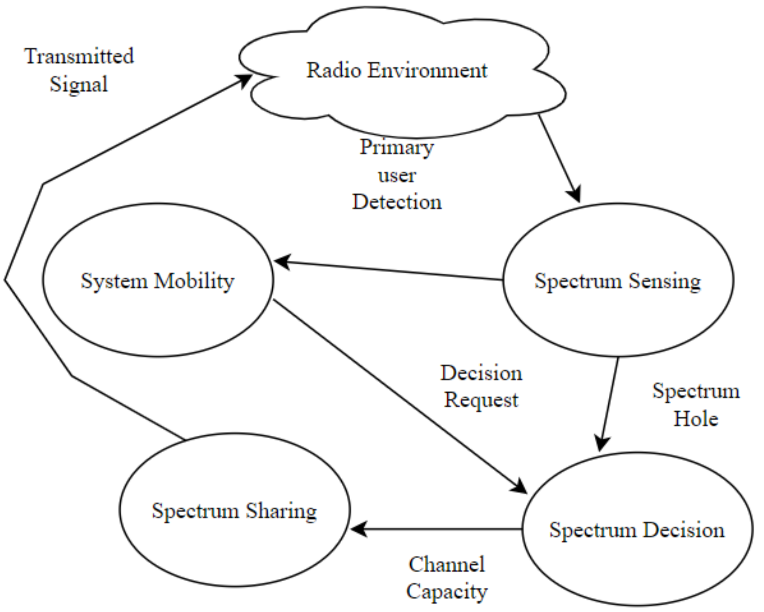

Figure 2: Cognitive cycle.

The capacity of CRAHNs to dynamically adapt to shifting spectrum settings is one of their defining characteristics. CRAHNs' essential elements include [12]:

(a) Spectrum Sensing (SS): Detecting Unused Spectrum Bands

Finding out which ranges of the radio frequency (RF) spectrum are now in use or accessible for use is a technique known as spectrum sensing. Finding unused or idle spectrum bands that CR systems or other secondary users can use without interfering with primary users that have licensed rights to those bands is the aim. Using spectrum sensing, one may measure the presence or absence of signals in various frequency bands by keeping an eye on the radio frequency surroundings. Energy detection, matched filtering, and cyclostationary feature identification are a few methods for spectrum sensing. To maximize spectrum efficiency and enable dynamic spectrum access, accurate spectrum detection is essential [12].

(b) Spectrum Management: Allocating Detected Spectrum to Users

Spectrum Management involves the strategic allocation of detected spectrum resources to various users or applications. Once spectrum sensing identifies available frequency bands, spectrum management ensures that these bands are allocated efficiently and fairly among users. This process involves determining which users can access which bands, for how long, and under what conditions. Spectrum management aims to optimize spectrum utilization, minimize interference, and balance the needs of different users. This can be done through mechanisms such as dynamic spectrum access, where spectrum allocation is adjusted in real-time based on current demand and availability [6].

(c) Spectrum Mobility: Ensuring Seamless Communication During Spectrum Handoff

Spectrum Mobility refers to the ability of a wireless system to maintain seamless communication while switching between different spectrum bands. In scenarios where a CR system or user needs to move from one frequency band to another—often due to the primary user's reoccupation of the band—spectrum mobility ensures that the communication session continues without interruption. This involves managing the transition process to avoid service disruptions and maintain quality of service. Effective spectrum mobility requires mechanisms for detecting spectrum availability, reestablishing connections, and managing handoffs in a way that minimizes impact on ongoing communications.

(d) Spectrum Sharing: Coordinating Spectrum Access Among Users

Coordinating access to spectrum resources among various users in order to minimize disputes and maximize use is known as spectrum sharing. In environments where spectrum is a limited resource and multiple users or systems need access, spectrum sharing mechanisms ensure that users can coexist and operate without causing harmful interference to each other? This coordination can be managed through various approaches, including time-division, frequency-division, and spatial-division multiplexing. Spectrum sharing requires effective communication and negotiation among users, as well as mechanisms to monitor and manage interference. The goal is to increase the overall usefulness of the spectrum while ensuring fair and efficient access for all parties involved [13].

B. Wide Band Spectrum Sensing (WBSS)

In terms of wireless connectivity, effective management of the RF (radio frequency) spectrum is crucial for ensuring efficient and reliable communication. With the increasing demand for wireless services and the growing number of devices, the need for advanced spectrum management techniques has never been more pressing. In order to solve the issues related to spectrum scarcity and poor spectrum usage, WBSS has become an important technology [14].

WBSS refers to the process of monitoring and analyzing a broad range of frequency bands to identify and evaluate available spectrum resources. Unlike narrowband sensing, which focuses on specific frequency bands, WBSS encompasses a wide frequency range, enabling the detection of unused or underutilized spectrum across a larger portion of the RF spectrum. This approach is essential for CR systems, which rely on the ability to access and utilize spectrum opportunistically based on real-time conditions. The primary goal of WBSS is to enhance spectrum utilization by providing a comprehensive view of spectrum availability [15].

Traditional spectrum sensing methods, which often operate within limited frequency bands, may not fully capture the dynamic nature of the RF environment. WBSS, on the other hand, offers a more holistic perspective, allowing for more informed decisions regarding spectrum access and management. Implementing WBSS involves several key challenges, including the need for high-speed data acquisition, efficient signal processing, and accurate detection algorithms. Wide band sensing systems must be capable of handling large volumes of data and distinguishing between signal and noise across a wide frequency range. Advanced techniques such as compressed sensing, ML, and adaptive filtering are often employed to address these challenges and improve the performance of WBSS systems. The benefits of WBSS extend beyond improved spectrum utilization. By identifying available spectrum across a broad range, CR systems can more effectively adapt to changing conditions, reduce interference, and optimize communication performance. This is particularly valuable in environments where spectrum is highly congested or variable, such as urban areas or in dynamic scenarios like emergency response or military operations [16].

C. Cooperative Spectrum Sensing (CSS)

One essential component of CR technology is cooperative spectrum sensing where multiple CR users collaborate to accurately detect available spectrum opportunities. By leveraging collective information from various users, cooperative sensing improves the reliability of detecting spectrum holes (unused bands), enhancing the performance of wireless networks. This approach significantly boosts detection accuracy by combining data from multiple sources, even in noisy or interference-heavy environments. It also helps mitigate fading and shadowing effects because different CRs experience varying channel conditions. As a result, cooperative sensing reduces false alarms, leading to more efficient spectrum utilization [34].

Every CR in CSS carries out local spectrum sensing to detect primary users and identify potential spectrum holes. The sensing information is shared among CRs in the network, either through a centralized approach (where data is sent to a fusion center) or a decentralized approach (where CRs communicate directly). In the centralized method, a fusion center aggregates data from all CRs and uses algorithms to determine spectrum availability, while in the decentralized method, CRs combine their information to make a joint decision. This helps ensure that spectrum bands are available for use with minimum disruption to the main users. The benefits of cooperative spectrum sensing include increased reliability, particularly in environments with fluctuating signals, and enhanced spectrum utilization by making better use of underutilized bands. It is also more robust against challenges like noise, interference, and user mobility, making it well-suited for dynamic environments [35].

However, there are challenges to this approach. Sharing sensing data introduces communication overhead, which needs to be managed efficiently. Synchronizing CRs for accurate data fusion can be complex, especially in decentralized networks. Additionally, there's a risk of malicious users providing false sensing information, potentially compromising the cooperative sensing process's integrity.

D. Cognitive Radio in 325 GHz Band

The 325 GHz band, part of the Terahertz (THz) frequency range, holds great potential for CR technology due to the rising demand for wireless communication. This band can enhance wireless systems by offering new spectrum opportunities and increasing network capacity. It provides abundant bandwidth, high data rates, and effective short-range communication, making it ideal for massive data transmission applications like HD video streaming and real-time processing. Additionally, its suitability for short-range communications with line-of-sight paths makes it perfect for indoor settings and point-to-point links. CRs can efficiently identify available spectrum in the 325 GHz band, improving spectrum efficiency because of its sparse usage. CR technology in the 325 GHz band supports 5G and beyond by offering additional bandwidth and faster data speeds. It's also ideal for wireless backhaul applications, enabling efficient network data transfer and supporting high-resolution imaging and sensing, such as security screening and medical imaging. The short range and directionality of 325 GHz transmissions also enhance security by reducing the risk of eavesdropping.

However, there are challenges with the 325 GHz band. High frequencies experience propagation losses due to atmospheric absorption, limiting communication range and requiring advanced techniques for signal integrity. Developing efficient hardware like antennas and amplifiers remains challenging, and the THz spectrum's regulation requires international coordination, as it's relatively new for commercial use. Even with low congestion, interference management is crucial as more devices use this band, necessitating cognitive radios to adapt to changing conditions. To utilize the 325 GHz band effectively, several CR techniques can be employed. Dynamic Spectrum Access (DSA) allows CRs to dynamically access available spectrum, enhancing utilization and reducing interference. Adaptive modulation and coding enable CRs to adjust based on channel conditions, optimizing performance. Beam forming and MIMO technology enhance signal strength and coverage, addressing propagation challenges. Advanced spectrum sensing techniques allow CRs to detect primary users and share the spectrum efficiently, minimizing interference.

E. Machine Learing(ML) in Spectrum Sensing

The creation of algorithms that enable computers to learn from data and make judgments or predictions is known as machine learning (ML), a subset of artificial intelligence. Large-scale spectrum data may be analyzed by ML algorithms in the context of spectrum sensing in order to spot trends, spot abnormalities, and forecast spectrum availability. CR systems may greatly increase the precision and effectiveness of spectrum sensing by utilizing ML. ML in Spectrum Sensing encompasses several key aspects as shown in figure 3 [18]:

Received Signal: This block processes raw data, which can come in the form of radio waves, audio signals, or various other analog or digital signals requiring analysis. In a spectrum sensing scenario, this could refer to the raw RF signals captured by an antenna.

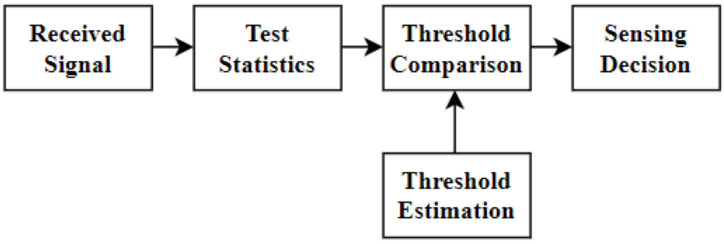

Figure 3. ML Spectrum Sensing

Feature Extraction: ML algorithms can extract relevant features from raw spectrum data, such as signal strength, frequency occupancy, and temporal patterns. This preprocessing step is crucial for transforming complex data into meaningful inputs for ML models.

Trained ML Algorithm: This is a machine learning model trained to recognize patterns or make decisions based on features extracted from input data. The algorithm has been trained with a dataset that includes examples of possible outcomes. Supervised Learning involves algorithms like SVM, Random Forest, or Neural Networks, which require labeled data. Unsupervised Learning includes clustering methods such as K-means, which find patterns without labeled data. Reinforcement Learning uses models that learn optimal actions through trial and error. The trained model outputs predictions or classifications of input data based on the learned features.

Sensing Decision: This block makes a final decision based on the predictions from the ML algorithm. The decision could be binary, such as determining whether a signal is present or absent, or it could be more complex, depending on the analysis. In signal detection, it determines if a specific signal is present in the spectrum. For spectrum allocation, it decides on the usage of bands of spectrum in CR networks.

Training Data: By giving the model instances to learn from, this data is utilized to train the ML model. The quality and size of the training dataset are crucial for the model's accuracy and performance. Features are the input data attributes used for training, while labels are the known outcomes corresponding to each feature set, used specifically in supervised learning [19].

The integration of ML into spectrum sensing offers numerous benefits. It enhances the ability of CRs to adapt to dynamic and complex RF environments, reduces the probability of false detections, and improves the overall efficiency of spectrum utilization. Additionally, ML-driven spectrum sensing can operate in real-time, providing timely and accurate information for spectrum management decisions [20].

F. ML Techniques for Wide Band Spectrum Sensing

The rapid expansion of wireless communication technologies has led to an unprecedented demand for radio frequency (RF) spectrum resources. Effective use of the electromagnetic spectrum is critical to accommodate the growing number of devices and applications. When it comes to locating underused or unused spectrum, WBSS is essential across a broad range of frequencies, enabling dynamic spectrum access and mitigating spectrum scarcity. Traditional spectrum sensing methods, however, often face limitations in terms of accuracy and scalability when applied to wide band scenarios. This is where ML techniques come into play, offering sophisticated tools to enhance the performance of WBSS [21]. WBSS involves the detection and analysis of available spectrum resources over a wide frequency range. The challenge lies in accurately identifying spectrum holes (unused spectrum segments) while dealing with the high-dimensional and complex nature of wide band data. Artificial intelligence's ML field allows systems to learn from data and make defensible conclusions and provides powerful methodologies to address these challenges and improve the efficiency of WBSS. ML Techniques for WBSS encompass various approaches, each offering unique capabilities to enhance spectrum sensing:

Supervised Learning: Labeled spectrum data may be used to train supervised learning algorithms like SVM, Decision Trees, and Neural Networks to classify different spectrum states (e.g., occupied or vacant). By learning from historical data, these models can predict spectrum occupancy with high accuracy, enabling more effective spectrum utilization.

Unsupervised Learning: Principal component analysis (PCA) and clustering are two examples of unsupervised learning approaches and they can be used to identify patterns and structures in spectrum data without requiring labeled training data. These methods are useful for discovering hidden relationships and grouping similar spectrum usage patterns, facilitating better spectrum management.

Reinforcement Learning: Through interaction with the environment, reinforcement learning algorithms, such Q-learning and Deep Reinforcement Learning (DRL), allow CRs to develop optimal spectrum access techniques. These models can enhance decision-making in uncertain and dynamic contexts by adaptively optimizing spectrum consumption and getting feedback in the form of incentives or penalties.

Deep Learning: Convolutional and recurrent neural networks (RNNs) are two examples of deep learning approaches and are capable of handling large-scale and high-dimensional spectrum data. These models can automatically extract relevant features and learn complex representations, enhancing the accuracy and robustness of WBSS.

Transfer Learning: Transfer learning allows models trained on one set of spectrum data to be adapted for use in different but related spectrum environments. This technique is particularly useful when labeled data is scarce, enabling the reuse of knowledge and improving the generalization capabilities of spectrum sensing models [22].

Compressed Sensing: Compressed sensing techniques, combined with ML algorithms, can efficiently reconstruct sparse spectrum signals from a reduced number of measurements. This approach reduces the computational burden and data acquisition time, making WBSS more practical and scalable. The integration of ML techniques into WBSS offers several advantages. ML-driven spectrum sensing can significantly enhance detection accuracy, reduce false alarms, and adapt to varying spectrum conditions in real-time. These capabilities are essential for optimizing spectrum usage and ensuring reliable communication in increasingly congested RF environments [23].

III. LITERATURE SURVEY

This section presents a literature review of several existing WBSS using ML in CRAHNs. The review papers are from recent publication years and focus on WBSS using ML in CR Ad-hoc network.

In a paper [1] addresses the challenge of spectrum sensing in CR networks (CRNs) by monitoring and utilizing underused frequencies, thereby improving spectrum efficiency. Unlike several other initiatives that integrate CRNs into generic IoT applications, our research uniquely focuses on maintaining connectivity for connected healthcare applications using CRNs. We emphasize leveraging the robustness of ML (ML) algorithms in CRN to identify idle channel states for spectrum sensing within the 10MT application scenarios. We train various ML algorithms, such as SVM, KNN, Decision Tree, Random Forest, and Naive Bayes, to detect primary users and identify vacant bands for optimal allocation. The data for secondary users is generated considering factors like received signal strength, path loss, and different fading effects. We evaluate system performance using metrics like accuracy, precision, recall, and F1 score across all ML approaches. Our numerical results show a significant enhancement in cooperative spectrum sensing accuracy, with a notable 20% reduction in false positives.

[2] Proposes a spectrum sensing scheme based on ML (ML) that improves detection accuracy in low SNR scenarios while minimizing the computational complexity typically associated with threshold computation in conventional energy detection methods. Methods like SVM and ANN are used as binary classifiers to divide incoming signal

samples into two groups and identify if the primary user is present in a specific frequency range. As the results of simulations show, criteria like error rate, accuracy, and probability of detection are used to assess the sensing performance. [3] introduces a convolutional neural network (CNN) architecture that leverages the cyclo-stationarity characteristics for enhanced spectrum detection and signal recognition in wireless environments. This method surpasses both traditional sensing techniques and various deep learning networks for signal classification while examining actual over-the-air data in cellular bands.

Two methods are proposed: Simultaneous signal detection and classification and Sequential sensing and classification processes. The CNN with spectral correlation function (SCF) achieves over 90% testing accuracy at 15 dB. The proposed method outperforms conventional sensing techniques and other deep learning networks. In contrast, IQ tests perform poorly due to signal blurring, and in fading situations, spread-spectrum signals' energy detection rates are insufficient. The CNN with SCF significantly improves wireless signal detection accuracy, especially for signals exhibiting cyclo-stationary properties. This model underscores the importance of CR network spectrum sensing, demonstrating the effectiveness of the CNN architecture for signal detection and classification.

[4] proposes a novel non-parametric dual transfer framework for cooperative spectrum sensing (DTCSS) to address the issue of poor generalization presentation caused by insufficient labeled information in target environments with varying wireless signals and propagation characteristics. DTCSS features a unique design with a two-stage learning approach. During the offline training stage, the framework transfers domain-level and class-level knowledge from an existing environment to the target environment and trains a target detector. In the online sensing phase, the trained detector is used to determine the spectrum status of the target environment. DTCSS is robust and effective without the need for hyperparameter tuning. Simulation results demonstrate that DTCSS achieves competitive sensing performance.

[7] introduce a SS algorithm using a multilayer perceptron, which operates without needing prior knowledge of the licensed user's traffic characteristics. The proposed model is evaluated based on accuracy, loss across various epochs, and its performance in terms of detection and false alarm probabilities. Traditional methods for spectrum sensing rely on energy detection, but when compared to these traditional methods, the suggested model shows better detection performance. Metrics including accuracy, loss, detection, and false alarm probability are all evaluated. While the PU signal's detection rate is poor in low signal-to-noise ratio situations, standard energy detection methods show even lower detection rates in these circumstances.

A new approach to Hybrid Spectrum Sensing (HSS) in CR Networks (CR) using deep learning has been developed in [8] to address the inefficiencies in utilizing allocated frequencies, providing superior energy detection compared to current radio technologies. This methodology incorporates HSS with multiple detectors and employs a Deep Temporal Convolutional Network (DTCN) for predictive tasks. The proposed model demonstrates enhanced energy detection capabilities and utilizes deep learning to improve overall performance. By addressing the need for efficient and rapid signal detection, this approach significantly improves spectrum sensing in CR Networks through the use of DTCN.

[9] elaborates various deep learning algorithms, including Spectrum sensing has made use of Multilayer Perceptrons (MLPs), CNNs, Long Short-Term Memory (LSTM) networks, and mixtures of CNNs and LSTMs. These algorithms are utilized for their effectiveness in different aspects of spectrum sensing, with optimized MLPs achieving high classification accuracy. The paper also explores the enhancement of 6G network performance through robust spectrum sensing methods and proposes the use of grid search to optimize MLP hyperparameters for improved binary classification in spectrum sensing.

Compressed sensing theory is applied to wide-band CR signals, which can lower the sampling rate and reduce computational complexity without compromising system performance [10]. [10]outlines the theoretical framework and key technical aspects of compressive sensing (CS) and demonstrates its application to wide-band CR signals. By addressing challenges such as high hardware costs, complexity, and processing speed, CS offers a solution for spectrum sensing in wide-band CR networks, effectively decreasing the sampling rate and reducing complexity. [11] proposed a spectrogram-aware CNN (S-CNN) algorithm, which uses the spectrogram of signal samples obtained through short-time Fourier transform as the input for a CNN. To enhance the model's performance, a data augmentation technique based on a deep convolutional generative adversarial network (DCGAN) to generate additional training data has been employed. The S-CNN algorithm shows superior detection performance compared to traditional CNN and LSTM-based methods. By using data augmentation, the model's generalization capabilities are significantly improved, making the S-CNN algorithm highly effective for spectrum sensing.

Ahybrid spectrum sensing technique based on a CNN-Cuttle-Fish Optimized Long Short Term Memory (COLSTM) network which leverages various statistical features from the spectrum data of primary users (PU) to enhance sensing efficiency has been investigated in [12]. The COLSTM technique outperforms existing methods in dynamic signal-to-noise ratio (SNR) environments, offering improved performance with lower complexity and computational overhead. Traditional spectrum sensing methods often face issues with complexity and responsiveness, especially under dynamic conditions. By incorporating CNN and LSTM networks, the proposed approach achieves better spectrum sensing accuracy and efficiency in dynamic SNR environments while minimizing computational demands.

In an article [13], the authors analyze various ML (ML) techniques for spectrum sensing in CR, using real-time data collected from a spectrum analyzer. Among the techniques considered—K-Nearest Neighbors (KNN), SVM, logistic regression, and decision tree regression—one was selected for optimal detection performance. This chosen ML technique achieved an accuracy of 99.8% in detecting spectrum holes. Additionally, unallocated channels were effectively utilized by secondary users, as modeled in Simulink. The analysis demonstrates the high effectiveness of the selected ML approach for spectrum sensing in CR environments.

[14] provides a comprehensive analysis of recent advancements in cooperative spectrum sensing (CSS), CR, and ML (ML)-based CSS for CR applications. It highlights how ML has been delivering optimal solutions across various fields, including product recommendations, social media features, sentiment analysis, marine wildlife preservation, heart failure prediction, language translation, automating employee access control, image recognition, healthcare regulation, and the banking sector. The article focuses on how ML-based CSS enhances spectrum sensing efficiency in CR, enabling more advanced wireless applications through optimized spectrum utilization. It details the integration of ML in improving cooperative spectrum sensing techniques.

[15] describes the implementation of multi-band spectrum sensing for primary users using two National Instruments USRP 2943R Transceivers (1 GHz to 6 GHz). The spectrum is monitored through an energy-based spectrum sensing technique on the LabVIEW platform. The threshold values for detection are updated both manually and adaptively, showing promising results, especially for high threshold settings. The study highlights the importance of monitoring neighboring primary user spectrums to ensure continuous communication and mitigate the effects of immediate departure from the spectrum by primary users. This approach enhances the quality of spectrum usage and helps cognitive users effectively manage communication interruptions.

[16] offers a covariance matrix-aware convolutional neural network (CNN)-based multiband joint spectrum sensing method. This method concatenates the multiband sample covariance matrices, which are then fed into the CNN. When compared to cutting-edge spectrum sensing techniques, the suggested algorithm performs better improving overall spectrum sensing capabilities. Notably, this approach does not rely on model assumptions and effectively learns hidden correlation features between subbands, thereby enhancing spectrum sensing in CR networks. Table 2 shows the Applications of Cognitive Radio (CR) Technology. combines a neural network with a multilayer perceptron (MLP) with other deep learning and machine learning techniques for spectrum sensing, such as Gradient Boosting (GB), SVM, Logistic Regression (LR), KNN, and Bagging algorithms.

Among these, the SVM-based approach achieved an accuracy of 94.01% in spectrum sensing. The study compares the performance of different classifiers and highlights that the SVM-based technique notably enhances spectrum utilization in CR Networks, demonstrating a high level of accuracy.

[18] introduces a deep reinforced learning spectrum sensing (DRLSS) algorithm, an unsupervised deep learning method that does not rely on extensive training datasets. Unlike conventional energy detectors, which, to operate at their best, need a lot of training data, the DRLSS algorithm enhances spectrum utilization in CR networks without such a dependency. This approach offers a solution to the limitations of traditional supervised learning methods by reducing the need for large training datasets while improving detection performance. For spectrum sensing, [19] suggested a hybrid model called CNN-RNN, which combines convolutional and recurrent neural networks. Through transfer learning, this model improves low SNR signal detection accuracy. The results demonstrate that

the CNN-RNN model significantly improves spectrum sensing accuracy compared to other models studied in the field.

Table 1. Summary of Current Review Studies

Sr. No.	Review Work	Contribution	Methodology	Focus Area
1	[24], 2015	With an emphasis on security assessment methods that have received little attention in the literature to far, this research offers an overview of current security threats, vulnerabilities, and services in VANETs.	Provides a thorough analysis of recent research on VANET security services, looking at prevalent threats, security specifications, and available mitigation techniques.	Examines typical attacks, security requirements, and current VANET threat mitigation techniques.
2	[25], 2017	This survey examines the difficulties and novel strategies for integrating CR (CR) technology with VANETs. It covers topics including architecture, standards, MAC schemes, spectrum sensing, interference control, and current developments as well as open problems and potential future research areas.	Gives a thorough analysis of CR technologies in VANETs, including their effects, difficulties, and specifications for efficient design and development.	Examines the application of CR technology in VANETs, focusing on design challenges and development requirements.
3	[26], 2017	The main system models utilized in different spectrum sensing strategies are described in this paper, along with a thorough examination of the most recent cooperative spectrum sensing methods for cognitive vehicular networks (CVNs).	Examines the difficulties in using spectrum sensing in CVNs and the methods that are currently in use to solve these problems.	Examines the difficulties and methods associated with spectrum management and sensing in CVNs.
4	[27], 2017	This survey investigates current security aspects in VANETs, identifying vulnerabilities and potential risks through failure modes and effects analysis.	Offers a thorough examination of ongoing developments in security architectures and proposes solutions based on theoretical and practical considerations.	Discusses security issues and solutions within VANETs.
5	[28], 2019	This survey categorizes security threats and privacy concerns in VANETs, providing a detailed analysis of various attack categories.	Reviews advanced security needs and obstacles, proposing solutions for effective security protocol formulation in VANETs.	Explores advanced security attacks and corresponding responses within VANETs.

6	[29], 2020	The applications of ML approaches in autonomous vehicle systems are the main subject of this work, which looks at their function in CR-VANET settings.	Surveys the designs, purposes, difficulties, and unresolved problems of ML, CR, VANET, and CR-VANET technologies.	Examines the ways in which machine learning technology may be used to mitigate issues with spectrum sensing, mobility control, security, and other areas in CRE-VANET networks.
7	[30], 2021	In order to improve driver decision-making and road safety, this analysis outlines strategies for assuring prompt and dependable message dissemination among automobiles. It also covers routing and traffic congestion in highway and urban settings.	Gives a thorough analysis of methods for optimizing routing between vehicle nodes utilizing big data, genetic algorithms, and machine learning.	Examines technologies for routing challenges in VANETs.
8	[31], 2021	Reinforcement learning (RL) based routing protocols for VANETs are compared qualitatively in this paper, which also covers their salient traits, optimization standards, and methods for assessing performance.	Analyzes RL-based routing protocols, addressing their advantages, disadvantages, and applications, while identifying open issues and research challenges.	Examines the efficiency gains of RL-based routing protocols for VANETs.
9	[32], 2021	In addition to identifying several security problems such confidentiality, authentication, integrity, availability, and non-repudiation, this research also looks at possible security attacks on VANET services.	Examines new problems in vehicle-to-vehicle and vehicle-to-infrastructure interactions and offers fixes for problems including traffic jams, collisions, time restrictions, and other problems.	Addresses challenges and solutions related to VANET security and trust.
10	[33], 2022	VANET topologies, security protocols, cryptographic methods, and trust-based authentication approaches are all reviewed in this paper.	Provides a comprehensive overview of secure communication in VANETs, including various security services and authentication methods.	Summarizes security services and authentication schemes in VANET.
11	[34], 2021	This review covers fundamental concepts of CR and various CR network paradigms.	Provides an extensive review aimed at optimizing Vehicle-to-Vehicle communication by analyzing various communication protocols and addressing constraints such as latency, bandwidth, mobility, and power consumption.	Focuses on optimizing V2V communication within CR contexts.

12	[35], 2023	This review explores technologies related to VANETs, future advancements, and related challenges, offering solutions for potential future issues.	Covers technology linked to VANETs, with a focus on data protection, integration with new paradigms, and inter-vehicular communication.	Focuses on VANET upgrades and future challenges in vehicular networks.
13	[36], 2023	This survey examines the integration of intelligent CR in modern wireless networks, including VANETs, and details ML (ML) techniques addressing key challenges.	Gives a thorough analysis of the developments in ML-driven CR and how they apply to VANETs, emphasizing the problems that exist now and the areas that future research should go.	Explores advancements in ML-driven CR for VANET communication.

Transfer learning is specifically utilized to boost performance for low SNR signals, and the complexity analysis indicates that this approach leads to better algorithm performance. Overall, the hybrid CNN-RNN model shows notable improvements in spectrum sensing for CR applications.

Table 2. Applications of Cognitive Radio (CR) Technology.

Applications	**Objectives**	**Example**	**Key Features**
Dynamic Spectrum Access (DSA) [34]-[35]	Efficiently utilize underused spectrum bands by dynamically allocating them to secondary users without interfering with primary users.	Allowing devices to access unused TV broadcast frequencies in rural areas, providing better broadband access.	IEEE 802.22: Wireless regional area networks (WRANs) using vacant TV broadcast channels. IEEE 1900.4: Provides a framework for managing spectrum access in dynamic and distributed environments.
Spectrum Sensing [36]-[37]	Detect the presence of primary users in a specific frequency band and avoid interference by vacating the channel when a primary user is detected.	Detecting emergency communication signals to ensure no interference from non-critical devices.	Energy Detection: Measures the energy level in a frequency band to identify active users. Matched Filtering: a more precise approach that necessitates knowing the principal user's signal beforehand.
Interference Management [38]-[39]	Minimize interference among various users sharing the spectrum, enhancing overall communication quality.	Adaptive power control to reduce interference in dense urban environments.	Cognitive Interference Management (CIM): Automatically adjusts transmission parameters based on detected interference levels. Beamforming: Directs signals in specific directions to avoid interfering with unintended receivers.
Cognitive Radio Networks (CRN) [40]-[41]	Create networks where nodes can dynamically configure their operation to optimize performance and spectrum usage.	Ad-hoc networks in disaster recovery scenarios where traditional communication infrastructure is unavailable.	Self-Organizing Networks (SON): Networks that adapt to changing environments without human intervention. Opportunistic Routing: Selects routes based on current network conditions and spectrum availability.
Public Safety Communications[42]	Ensure reliable and efficient communication during	Enhancing communication for first responders by	Project 25 (P25): A collection of digital radio communications

	emergencies by utilizing available spectrum resources dynamically.	accessing unused frequencies during a disaster.	standards utilized by North American public safety organizations.
Cognitive Radio for IoT Applications [43]-[44]	Enhance the connectivity and efficiency of Internet of Things (IoT) devices through adaptive spectrum management.	Smart city applications where IoT devices adjust their communication frequencies to avoid congestion and interference.	Smart Grid: Managing energy consumption and distribution by optimizing communication between smart meters and utility providers. Healthcare Monitoring: Ensuring reliable data transmission for wearable health devices by dynamically selecting less congested frequency bands.
Military and Defense Applications [45]-[46]	Provide secure and reliable communication by dynamically accessing spectrum in contested or hostile environments.	Battlefield communications where cognitive radios adapt to changing environments to avoid detection and interference.	Anti-Jamming: Adapts frequency usage to avoid jamming signals. Secure Communication: Enhances encryption and spectrum hopping to ensure secure transmission.
Cognitive Radio in Vehicular Networks (CR-VANET) [47]-[48]	Enhanced communication between vehicles and infrastructure (V2I) can be achieved through dynamic spectrum access management.	Enhancing safety applications in intelligent transportation systems (ITS) by adapting to varying traffic and environmental conditions.	Dedicated Short Range Communications (DSRC): Utilizes cognitive radio to manage spectrum for vehicular communications. IEEE 802.11p: Supports wireless access in vehicular environments by adapting frequency use.

[20] analyzed various ML (ML) techniques for spectrum sensing in CR, using real-time data collected from a spectrum analyzer. Among the techniques evaluated—KNN, SVM, logistic regression, and decision tree regression—one was selected for optimal detection performance. This chosen ML technique achieved an accuracy of 99.8% in detecting spectrum holes. Additionally, unallocated channels were effectively utilized by secondary users as modeled in Simulink. The paper offers a thorough examination of ML methods for spectrum sensing, highlighting the high accuracy and efficient channel usage achieved with the selected approach.

Various ML-based solutions are explored in [21] to enhance the efficiency of spectrum sensing. These solutions include KNN, SVM, logistic regression algorithms. The study also employs the NOMA (Non-Orthogonal Multiple Access) technique in cooperative spectrum sensing. Performance is evaluated using metrics such as accuracy, sensitivity, specificity, F1 score, and confusion matrix, providing an optimal boundary for detecting the presence or absence of primary users. The analysis is limited to these specific ML algorithms and demonstrates how they can improve spectrum sensing efficiency, particularly when integrated with the NOMA technique for cooperative sensing.

A thorough examination of current developments in cooperative spectrum sensing (CSS), CR, and ML-based CSS for CR applications is given in [22]. It demonstrates how machine learning (ML) has been successfully used to solve a range of computational issues, such as banking, sentiment analysis, language translation, automating employee access control, image recognition, product recommendations, social media features, marine wildlife preservation, heart failure prediction, and more. The paper emphasizes how ML-based CSS improves spectrum sensing efficiency in CR networks, facilitating advanced wireless applications by optimizing spectrum utilization. The detailed analysis focuses on the integration of ML into spectrum sensing techniques, demonstrating its impact on enhancing overall performance.

[23] Introduces a hybrid model that combines CNN and RNN for spectrum sensing. This model significantly enhances the accuracy of detecting low SNR signals through transfer learning. The results demonstrate that the CNN-RNN model outperforms other models studied in this field. Complexity analysis reveals a significant improvement in algorithm performance, with no specific limitations mentioned in the abstract.

IV. CR Standards

CRs need to maintain continuous spectrum sensing, operate over a broad frequency range, and utilize various modulation techniques to compete for spectrum access. This introduces several hardware challenges. The necessary hardware must support high sampling rates, employ high-resolution analog-to-digital converters with a broad dynamic range, and incorporate fast signal processors. On certain CR platforms, it is possible to implement algorithms derived from practical, low-complexity systems that deliver realistic results. GNU Radio is an open-source platform developed using Python and C++. Additionally, several advanced platforms are available: the CR Learning (CORAL) platform from the Canadian Communications Research Centre, which supports research and commercial applications in the License-Exempt ISM bands and complies with IEEE 802.11 standards; the Software Radio (SORA) platform from Microsoft Research Asia, which is intended to effectively implement cutting-edge wireless communication technologies; and the Wireless Open-Access Research Platform (WARP) from Rice University, which is renowned for its programmability and extensibility. The Berkeley Emulation Engine (BEE2), created by the Berkeley Wireless Research Center at the University of California, supports a multiuser environment with performance of up to 500 Giga-operations per second, among other cutting-edge features. It can deliver sub-microsecond latency and achieve a maximum throughput of 16.7 Gbps. The first international standard created for CR networks is IEEE 802.22 [67].

It outlines CR approaches for Wireless Regional Area Networks (WRANs) that enable secondary users to identify and make use of underutilized TV spectrum in the 54 MHz to 862 MHz VHF and UHF bands. Primary networks, which use low bandwidth and lower transmission power, may be difficult to detect and can turn on and off unpredictably. IEEE 802.22 adopts a centralized model, with base stations offering extensive coverage. The IEEE 802.11k standard focuses on radio resource management, including metrics such as station stability reports, noise histograms, and channel load reports. The Bluetooth standard has introduced Adaptive Frequency Hopping (AFH) to minimize interference in the 2.4 GHz unlicensed spectrum [5].

The goal of IEEE P1900, commonly referred to as SCC41 (Standards Coordinating Committee 41), is to provide new standards for next-generation radio systems and improved spectrum management. The scope of this committee's work includes spectrum sensing (P1900.6), dynamic spectrum access (DySPAN) in white space frequency bands architecture and interfaces (P1900.4a), policy languages (P1900.5), and interference management (P1900.2). The goal is to enhance spectrum usage and performance through improved spectrum sensing capabilities.

A. Challenges Associated with CR Technology:

Detecting unused spectrum bands accurately is critical, as false detections can lead to interference with licensed users. Ensuring cognitive radios do not interfere with primary users is complex and requires sophisticated algorithms for dynamic spectrum access and management. CR are susceptible to various security threats such as jamming, eavesdropping, and spoofing, making secure communication a significant challenge. Developing regulatory frameworks that allow the coexistence of cognitive radios with traditional licensed services while promoting innovation is essential [49].

V. Conclusion:

In conclusion, the integration of Cognitive Radio (CR) technology with machine learning (ML) marks a significant advancement in wireless communication, effectively addressing challenges related to spectrum scarcity and inefficient utilization. CR technology's ability to dynamically sense and adapt to the radio frequency environment offers a robust solution for enhancing spectrum efficiency. This paper has explored various spectrum sensing techniques, particularly Wide Band Spectrum Sensing (WBSS), and the application of ML algorithms to improve spectrum detection accuracy. The research underscores the potential of ML-driven approaches, such as supervised, unsupervised, and reinforcement learning, to enhance CR network performance in complex and dynamic environments. These advanced techniques enable CR systems to make more informed and adaptive decisions, optimizing spectrum usage and minimizing interference. The importance of cooperative spectrum sensing (CSS) and the opportunities in the 325 GHz band further highlight the evolving landscape of CR technology.

Moreover, the exploration of wideband spectrum sensing using ML in Cognitive Radio Ad-hoc Networks (CRAHNs) underscores the diverse approaches employed to improve spectrum sensing, focusing on ML techniques to boost detection accuracy, efficiency, and reliability. Studies demonstrate that ML algorithms, including Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and hybrid models, significantly enhance spectrum sensing performance in CR networks. These advancements in CR technology, driven by ML, pave the way for more efficient and adaptable wireless communication systems, capable of thriving in increasingly congested and variable spectrum environments. As wireless communication continues to evolve, the role of CR technology, enhanced by ML, will become crucial in ensuring efficient and reliable spectrum use. This research not only contributes to the current understanding of spectrum sensing methodologies but also sets the stage for future innovations in the field, where intelligent, spectrum-aware systems will play a central role in the next generation of wireless networks.

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