International Journal of Computers and Applications

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tjca20

A review of deep learning techniques for enhancing spectrum sensing and prediction in cognitive radio systems: approaches, datasets, and challenges

Noureddine El-haryqy, Zhour Madini & Younes Zouine

To cite this article: Noureddine El-haryqy, Zhour Madini & Younes Zouine (21 Oct 2024): A review of deep learning techniques for enhancing spectrum sensing and prediction in cognitive radio systems: approaches, datasets, and challenges, International Journal of Computers and Applications, DOI: 10.1080/1206212X.2024.2414042

To link to this article: https://doi.org/10.1080/1206212X.2024.2414042

Published online: 21 Oct 2024.

INTERNATIONAL JOURNAL OF COMPUTERS AND APPLICATIONS
https://doi.org/10.1080/1206212X.2024.2414042

A review of deep learning techniques for enhancing spectrum sensing and prediction in cognitive radio systems: approaches, datasets, and challenges

Noureddine El-haryqy, Zhour Madini and Younes Zouine

Department Electrical and Telecommunication, Laboratory of Advanced Systems Engineering (ISA), National School of Applied Sciences (ENSA), Ibn Tofail University, Kenitra, Morocco

ABSTRACT

Cognitive radio (CR) is an emerging wireless technology designed to optimize frequency band usage and address spectrum shortages. Spectrum sensing and prediction are crucial for cognitive radios to make intelligent spectrum access decisions and dynamically alter transmission parameters based on real-time spectrum conditions. These techniques contribute to the efficient use of the spectrum. However, they encounter significant obstacles such as noise uncertainty, low signal-to-noise ratios, channel fading, and more, necessitating robust and intelligent solutions. Deep learning has attracted much attention and displayed great potential in various fields in recent years. This review paper provides a thorough examination of the use of deep learning techniques in spectrum sensing and prediction in the context of cognitive radio. It examines the available literature in depth, highlighting the techniques, the assessment keys, datasets, and limitations of the investigations. The article seeks to provide significant insights and guidance for future developments in harnessing deep learning for better cognitive radio spectrum management by critically assessing the present state of research.

KEYWORDS

Deep learning; cognitive radio; spectrum sensing; spectrum prediction; signal detection; cooperative spectrum sensing; noise; interference; convolutional neural networks; recurrent neural networks; wireless communication

1. Introduction

Over the past few decades, there has been a notable increase in the use of wireless devices due to technological advancements. Moreover, according to recent Federal Communications Commission (FCC) studies, nearly 70% of the spectrum allocated in the United States stays idle [1]. There will always be some gaps in the spectrum and some opportunities. A spectrum hole occurs when a frequency band is unoccupied. As a result, cognitive radio [2] is a technology that allows the radio frequency (RF) spectrum to be used intelligently and adaptively. It seeks to address the problem of spectrum scarcity by allowing unlicensed users, such as secondary users, to opportunistically access and utilize underutilized areas of the spectrum that are predominantly dedicated to licensed users or primary users.

The cognitive cycle in cognitive radio (CR) refers to the series of actions and choices that CRs make in order to efficiently sense, adapt, and use the available radio frequency (RF) spectrum. The various stages of this technique are shown in Figure 1.

This cycle enables CRs to maximize spectrum consumption while ensuring that they do not interfere with primary users (PUs) or authorized transmitters.

Spectrum Sensing (SS): This is the identification and recognition of the present spectrum occupancy in real-time. SS is a major CR service that involves checking a specific frequency band to establish the presence or absence of primary users (PUs). SS techniques can be used to provide the additional required spectrum bandwidth via dynamic spectrum access. It must be faster, more accurate, resistant to noise and interference, simpler, and use less energy [3]. to allow CR to use the available spectrum and dynamically change their operating parameters without interrupting PUs.

Spectrum prediction (SP): CR can use either SS or SP to identify whether a spectrum is occupied or available. Incorporating historical data, CR systems can employ SP (also known as spectrum inference) [4] to adopt a more informed approach in optimizing spectrum utilization and effectively address challenges associated with dynamic spectrum access. The incorporation of SP not only optimizes the energy efficiency of CR operations, but also allows for adaptive adjustments in transmission parameters based on predicted changes in the spectral environment [5,6].

Spectrum Decision: In CR networks, the spectrum decision function is essential for choosing the best spectrum for opportunistic usage while avoiding interference with primary users (PUs). To make intelligent decisions, this function depends on data from the SS function. The spectrum decision function chooses a spectrum band for SUs based on the quality of service (QoS) needs for SUs, including bandwidth, PU usage level, and channel quality [7].

Spectrum Sharing: Spectrum sharing is a crucial feature in CRNs and dynamic spectrum access (DSA) systems. It refers to the practice of efficiently utilizing the radio frequency spectrum by allowing numerous users, both primary users (PUs) and secondary users (SUs), to share the available spectrum resources. It is a method of optimizing the use of the airwaves, or wireless communications channels, by allowing many types of users to safely utilize the same frequency ranges. However, the fundamental goal of spectrum sharing is to optimize spectrum use, maximize network capacity, and improve overall communication efficiency[8].

CONTACT Noureddine El-haryqy noureddine.elharyqy@uit.ac.ma Department Electrical and Telecommunication, Laboratory of Advanced Systems Engineering (ISA), National School of Applied Sciences (ENSA), Ibn Tofail University, Kenitra 14000 Morocco; Zhour Madini Department Electrical and Telecommunication, Laboratory of Advanced Systems Engineering (ISA), National School of Applied Sciences (ENSA), Ibn Tofail University, Kenitra 14000 Morocco; Younes Zouine Department Electrical and Telecommunication, Laboratory of Advanced Systems Engineering (ISA), National School of Applied Sciences (ENSA), Ibn Tofail University, Kenitra 14000 Morocco

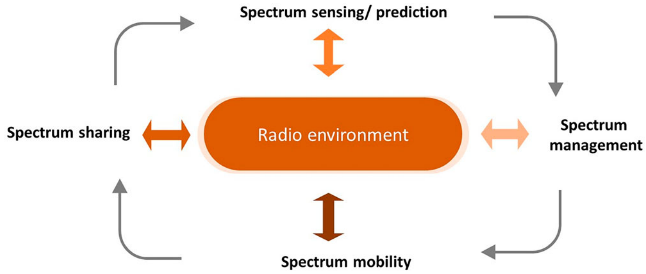


Figure 1. Cognitive radio cycle.

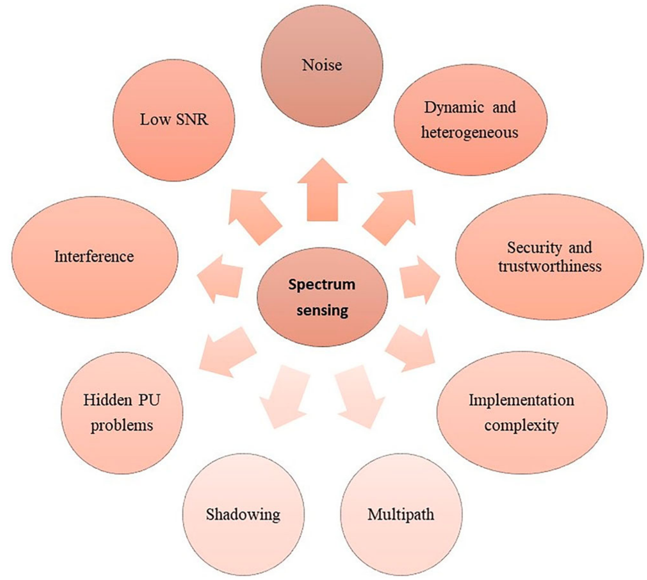


Figure 2. Spectrum sensing challenges.

Spectrum Mobility: The adaptability and flexibility of wireless communication systems are improved through spectrum mobility. When the radio frequency spectrum is crowded, susceptible to interference, or when users have different QoS requirements, it is especially useful. Spectrum mobility makes it possible for users to transfer frequencies carefully, which makes wireless communication more dependable and effective. However, designing and putting in place spectrum mobility methods can be difficult, and it's important to carefully take things like network coordination and interference management into account [9].

Spectrum sensing in CR systems faces several obstacles and limitations that affect its ability to dynamically access and utilize the radio frequency spectrum. Figure 2 provides a visual summary of these challenges. As shown in Figure 2, issues such as multipath fading and shadowing add uncertainty to the received signal strength, which complicates reliable signal classification [10,11]. Environmental factors depicted in the figure highlight the difficulties in adapting spectrum sensing techniques to account for this unpredictability. Addressing these challenges is crucial for improving the effectiveness of spectrum sensing in CR systems. Furthermore, accurate signal recognition is challenging in low signal-to-noise ratio (SNR) environments, where the signal strength either competes with or is lower than the noise [12]. Interference, whether intentional or unintentional, affects the trustworthiness of spectrum sensing results, which could lead to a mistake in the spectrum occupancy status [13]. In the other hand, security and trustworthiness concerns pose vulnerabilities that might compromise the integrity of SS procedures [14]. Malicious actions or illegal access might bias sensing results, leading to incorrect spectrum occupancy estimates. The implementation complexity of robust sensing algorithms adds an extra layer of difficulty, which influences the deployment and operating efficiency of CR systems. In addition to these complexities, PU activity and hidden PU problems [15] bring further layers to spectrum sensing challenges. Detecting PUs in licensed channels, particularly in high-traffic CRNs, requires complex algorithms to reduce energy overhead and wait times for SUs. Simultaneously, addressing hidden PU issues is critical, as inadequate spectrum information may impair the spectrum-sensing accuracy.

Overall,these issues highlight the importance of advanced algorithms and adaptive solutions in CR applications to ensure precise and effective spectrum usage. Addressing these challenges is critical to the growth and practical implementation of CR systems. In the face of these complex obstacles, researchers are constantly searching for novel ideas and algorithmic approaches to improve the robustness and efficiency of spectrum sensing. However, sophisticated data processing techniques have become increasingly necessary in the fields of CR and wireless communications. Although helpful, traditional machine learning techniques sometimes require tedious human feature engineering to extract relevant information from unprocessed data [16]. This is particularly difficult in situations where the dataset comprises high-dimensional inputs with a wide range of characteristics, including channel information, frequency spectrum data, and measures of signal intensity. On the other hand, deep learning models are very good at automatically identifying complex representations from raw data. They handle high-dimensional, complicated information with ease and capture nonlinear correlations with proficiency [17]. Moreover, deep learning models show good scalability for large datasets and are skilled at revealing complex patterns that might be difficult to extract using conventional machine learning methods [18]. Several DL network categories have been investigated in the context of spectrum sensing and prediction in CR systems, in which Convolutional Neural Networks (CNNs) are used to process spatial information [19] and Deep Belief Networks (DBNs) are used for their ability to model hierarchical representations [20]. Recursive Neural Networks (RNNs) have been used because of their sequential learning properties, which are suitable for some SS and SP applications [21], [22]. Furthermore, hybrid models add to the development of deep-learning applications in CR for SS by fusing components from different deep-learning architectures [23,24].

In our review article, we perform a thorough study and examination of recent studies that investigate the application of deep learning approaches in tackling the present issues in CR, with an emphasis on spectrum sensing and prediction. Our goal is to give readers a thorough and in-depth understanding of how deep learning techniques have been successfully applied to resolve the problems that CR systems are currently facing, notably in the area of SS and SP.

The following are the contributions and innovative ideas of this paper:

(1) In this study, we analyze various traditional spectrum sensing methods, delineating their benefits and drawbacks for each technique. Additionally, we present a detailed review of the cooperative spectrum sensing approach.
(2) We provide the widely used assessment metrics for DL-based spectrum sensing and prediction in order to improve understanding of the relevant literature.
(3) We provide a comprehensive overview of spectrum sensing and prediction in the context of CR networks, highlighting the importance of efficient spectrum utilization and the role of deep learning in enhancing sensing and prediction capabilities.

(4) Provide a detailed analysis of the performance of deep learning-based spectrum sensing and prediction models, including their applications in real-world CR systems and their potential impact on spectrum efficiency and utilization.
(5) Additionally, we present a wide variety of datasets utilized in deep learning for SS, as well as the main obstacles that need to be overcome to further advance the spectrum sensing task.
(6) This study provides a comprehensive analysis of a wide variety of deep learning approaches and their noteworthy contributions to the development of spectrum prediction and sensing.
(7) In this paper, we offer a thorough critical examination of the particular difficulties faced by deep learning methods in spectrum sensing and prediction. We go beyond an overview of current approaches to investigate how these obstacles impact model performance, encompassing problems with limited data, model flexibility, and computational effectiveness. We also provide a thoughtful analysis of how these issues affect real-world applications and suggest specific future paths for resolving these issues and developing the field.

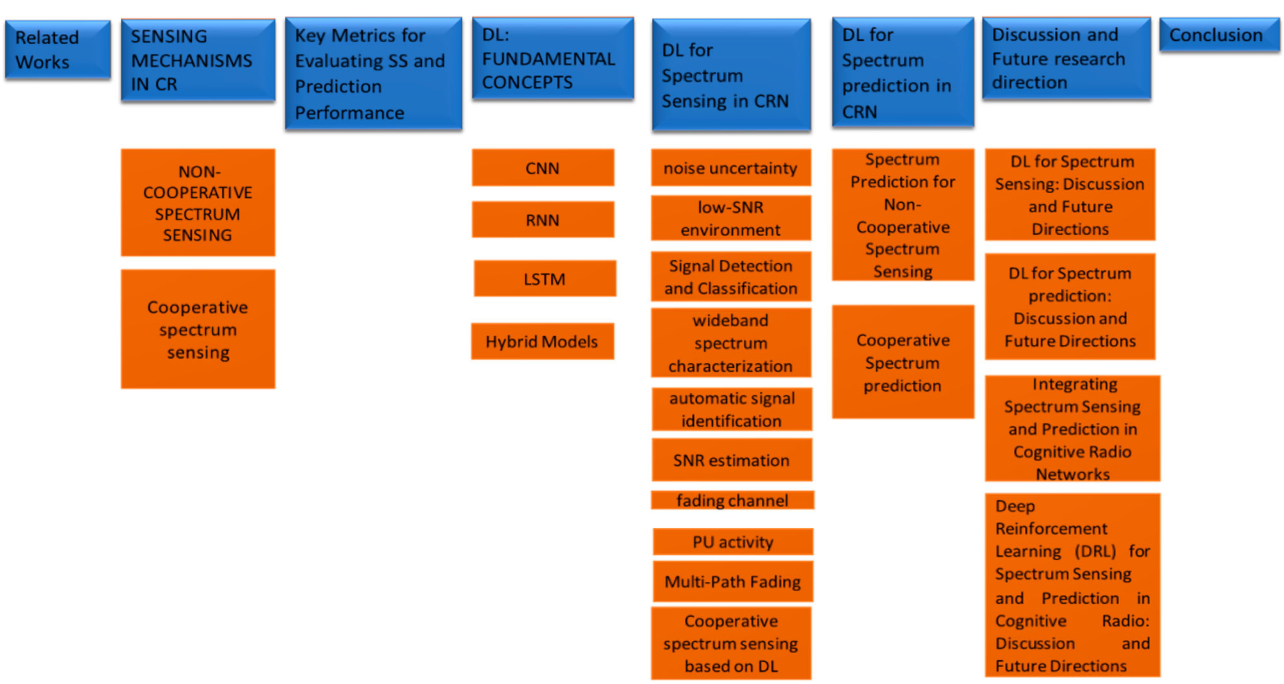
1.1. Abbreviations and acronyms

Abbreviations used in the survey are listed below

Acronyms	Definitions
AWGN	Additive White Gaussian Noise
BPSK	Binary Phase Shift Keying
CRN	cognitive radio network
CR	Cognitive radio
CSP	cooperative spectrum prediction
CSS	Cooperative spectrum sensing
DBN	Deep Belief Network
DL	Deep learning
DNN	Deep Neural Network
DRL	deep reinforcement learning
DSA	dynamic spectrum access
DSS	dynamic spectrum sharing
CNN	convolutional neural network
OFDM	Orthogonal Frequency Division Multiplexing
FCN	Fully Convolutional Network
GFSK	Gaussian Frequency-Shift Keying
HD	Hard Decision
HF	Hard Fusion
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MMSE	Minimum Mean Square Error
MSE	Mean Square Error
MSPE	Mean Square Prediction Error
MU	malicious user
RNN	recurrent neural network
LSTM	long short-term memory
RF	radio frequency
EF	energy detection
PAM	Pulse Amplitude Modulation
PFA	probability of false alarm
PU	Primary User
DNN	deep neural network
FFT	fast Fourier transform
ED	Energy Detection
FC	Fusion Center
QAM	quadrature amplitude modulation
QPSK	Quadrature Phase Shift Keying
QoE	quality of experience
QoS	quality of service
ROC	Receiver Operating Characteristic
RMSE	Root Mean Square Error
SD	Soft Decision
SNR	Signal-to-Noise Ratio
SOI	Signal of Interest
SP	Spectrum prediction
SS	Spectrum sensing
SU	Secondary User
USRP	Universal Software Radio Peripheral

1.2. Paper Organization

The remaining portions of this survey are divided into several parts:



2. Related works

Several research articles and surveys have been published that investigate the use of spectrum sensing (SS) for cognitive radio (CR). These studies frequently provide extensive overviews of the many SS techniques, challenges, and developments in the context of CR networks. Table 1 provides a summary of the key studies, their methodologies, and their findings regarding SS techniques

3. Sensing mechanisms in cognitive radio

The fundamental purpose of cognitive radio (CR) sensing methods is spectrum sensing, which involves continuously scanning the RF spectrum to identify spectrum opportunities

and detect the presence of primary users (PUs). Mathematically, the spectrum sensing problem is expressed as considering that H_1 denotes the presence of the primary

User and H_0 indicates the absence of the primary user.

$$\mathrm{H}_1 :\ \mathrm{x(i)} = \mathrm{s(i)} + \mathrm{u(i)}$$

$$\boldsymbol{H}_0 : \boldsymbol{x}(\boldsymbol{i}) = \boldsymbol{u}(\boldsymbol{i})$$

Where s(i) the signal from the PU, u(i) indicates the additive white Gaussian noise (AWGN) sample and x(i) is received signal.

Various methods are employed for spectrum sensing, including energy detection, matched filtering, cyclostationary feature detection, and others. Additionally, CR devices have the capability to sense the spectrum cooperatively or non-cooperatively.

3.1. Non-cooperative spectrum sensing

In non-cooperative spectrum sensing, each CR or secondary user (SU) senses the spectrum and makes their own spectrum decisions. This type of SS can be detected using a variety of techniques. As shown in Table 2, each technique has its own set of advantages and disadvantages, such as cyclostationary detection, energy detection[31], matched filter detection, waveform-based detection, and covariance-based detection.

Table 1. An overview of existing reviews for spectrum sensing and spectrum prediction.

Year	Reference	Topic	The Contribution
2018	[4]	Spectrum prediction	The paper covers the sources of spectrum occupancy statistics, the models of spectrum usage, and the predictability of spectrum state evolution. It also offers an overview of the existing algorithms and techniques for spectrum inference, including machine learning-based approaches.
2021	[15]	Spectrum sensing	The article reviews the spectrum sensing challenges and solutions within CR-based vehicular networks. It offers valuable insights into the distinctive features of vehicular networks, including the mobility of vehicles, dynamic topological changes, and periodic shifts, which present specific challenges for spectrum sensing in this context
2021	[25]	Spectrum sensing	The paper covers the classification of different spectrum sensing techniques, the review of narrowband and wideband spectrum sensing techniques, and the analysis of the advantages and limitations of these techniques. The authors also discuss the use of machine learning-based approaches for spectrum sensing and the challenges related to spectrum sensing in CRNs.
2021	[26]	Spectrum sensing	The paper presents a comprehensive overview of the application of deep reinforcement learning (DRL) in spectrum sensing for CRNs. It explores the potential applications of DRL, covering cooperative spectrum sensing, anti-jamming communications, dynamic spectrum access, distributed dynamic spectrum access, and reliable SS.
2020	[27]	Spectrum sensing	The article provides insights into the use of machine learning-based methods for cooperative spectrum sensing in CRNs.
2022	[28]	Spectrum sensing and Spectrum sharing	The paper reviews an extensive collection of resources, offering insights into the integration of machine learning in cooperative spectrum sensing and sharing within CRNs. This compilation includes surveys and papers that thoroughly explore the application of machine learning-based algorithms, with a specific focus on the domains of cooperative spectrum sensing (CSS) and dynamic spectrum sharing (DSS)
2023	[29]	Spectrum sensing	The article offers numerous resources pertaining to the application of deep learning in SS for CRNs. These resources encompass surveys, research papers, and practical examples that explore the use of deep learning algorithms, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, in the context of spectrum sensing tasks.
2023	[30]	Spectrum sensing	The paper elucidates the applications of deep learning algorithms, including CNNs, LSTMs, and various neural network types, in radio spectrum sensing. It analyzes the present state of research, applications, and the challenges encountered by deep learning in the realm of cooperative spectrum sensing.

Table 2. Various spectrum sensing technique.

Method	Pons	Cons	Ref
Cyclostationary detection	• Ability to distinguish the primary signal from interference and noise. • It works also at low SNR conditions. • The ability to distinguish between various primary systems.	• Prior knowledge of the PU signal is required • The computational cost is relatively high. • Sensing Is relatively high.	[32,33]
Energy detection	• Knowledge of PU Signal in Advance not required. • The computational complexity is low.	• In the low SNR scenario,ED performs poorly. • Inability to differentiate interference from primary users and noise.	[32–36]
Matched filter detection	• higher sensing accuracy. • Less sensing time.	• Prior knowledge of the PU signal is required. • Implementation complexity is high.	[32,37]
Covariance based detection	• No prior knowledge of PU signal and noise is required. • Blindly detection.	• Increasing computational complexity.	[32,25]
Eigne based detection	• No prior knowledge of PU signal, channel, or noise variance is required	• Implementation complexity is high	[32,38]
Waveform based	• requires short measurement time	• prior knowledge of the PU signal is required.	[36]
machine learning techniques	• No prior knowledge of PU signal and noise is required • higher sensing accuracy.	• the computational power requirements is very high	[39]

3.2. Cooperative spectrum sensing (CSS)

Non-cooperative spectrum sensing involves each CR detecting licensed channels of interest and deciding on the PU's occupancy without the involvement of all other CRs. However, Cooperative spectrum sensing is a technique used in CRNs, where secondary users (CRs) collaborate to enhance the detection of PUs [10,40]. This approach offers several benefits, including improved reliability, accuracy, and the ability to adapt to dynamic radio frequency environments. By sharing individual sensing information, CRs can achieve a more comprehensive understanding of the radio frequency environment, leading to more effective spectrum utilization and interference avoidance. Therefore, cooperative spectrum sensing (CSS) is a technique used in CRNs to address the challenges posed by the unpredictable and dynamic nature of the radio frequency spectrum [41]. CSS leverages spatial and temporal diversity to enhance the detection of primary users [12]. However, CSS is vulnerable to a variety of obstacles, such as multipath fading, shadowing, noise uncertainty, and the hidden PU problem [42,12]. CR users have no prior knowledge of PU actions, which can result in false data being exchanged with other CR users. Despite these challenges, CSS provides a collaborative and dependable mechanism for finding and utilizing available spectrum opportunities in CRNs. It addresses important concerns and helps secondary users make educated decisions, ultimately leading to more efficient and responsible spectrum usage. Different techniques for organizing and conducting spectrum sensing activities in CR networks are illustrated in Figure 3. These techniques include centralized, decentralized, cluster-based hierarchical, and relay-assisted cooperative spectrum sensing [43].

3.2.1. Centralized sensing architecture

In a centralized cooperative SS architecture, a node is selected to serve as a fusion center (FC). The primary function of the FC is to analyze and process the collected local detection statistics or sensing results from SU to reach a final conclusion on the presence of PU in the radio frequency spectrum. To determine PU occupancy, the FC employs various data fusion techniques to combine the local sensing acquired from SS. This approach leverages the spatial diversity in the observations of spatially located CRs to improve sensing performance and reduce reporting error.

Hard Fusion (HF): In centralized cooperative SS, hard fusion involves each SU transmitting a binary decision to the fusion center (FC) based on predefined fusion rules. Some of the most popular fusion rules used in hard fusion are AND, OR, and majority rules [43]. These rules are applied at the FC to combine the binary decisions from the SUs and make a final decision regarding the presence or absence of a primary user in the spectrum. This process helps in improving the overall detection performance and reducing reporting error in CSS.

Soft Fusion (maximum ratio combining): Soft Fusion, also known as maximum ratio combining, is a cooperative decision-making process that involves the transmission of channel sample measurements obtained at the local SU to the fusion center (FC). The local sufficient statistics and their quantized versions are transmitted to the FC. The FC then integrates the collected samples to produce a global PU value, which is then compared to a predetermined threshold. Weighted linear combining, optimal combining, Machine Learning-Based Approaches, and equal-gain combining are all methods for combining data [44–46]. Soft fusion is a more nuanced approach to PU occupancy detection, allowing for a gradual transition between the binary decisions of hard fusion.

3.2.2. Distributed sensing architecture

In distributed cooperative spectrum sensing, SUs work together without the aid of a central coordinator, communicating directly with each other to establish an agreement on the sensing results. This approach reduces deployment costs and enables SUs to share sensing information and make informed decisions about the presence or absence of PUs in the spectrum. Sensing nodes or SUs work together in a distributed cooperative spectrum sensing architecture without the aid of a central coordinator. Within its coverage region, each sensing node separately conducts spectrum sensing. Based on the outcomes of their local sensing, each SU decides locally whether there are any PUs present or not. Following that, these local choices are immediately exchanged between neighboring SUs.

However, several distributed cooperative sensing decision methods have been suggested in the literature, the majority of which fall into the following categories:

Belief Propagation: This method involves SUs exchanging their local decisions and updating their beliefs about the presence or absence of PUs based on the received decisions from neighboring SUs [47].

Weighted: This method combines the local decisions of SUs with predefined weights, taking into account the reliability or confidence of each SU in determining the presence or absence of PUs [33].

Consensus-Based: This method involves SUs iteratively exchanging their local decisions until they converge to a unified decision on the presence or absence of PUs [48].

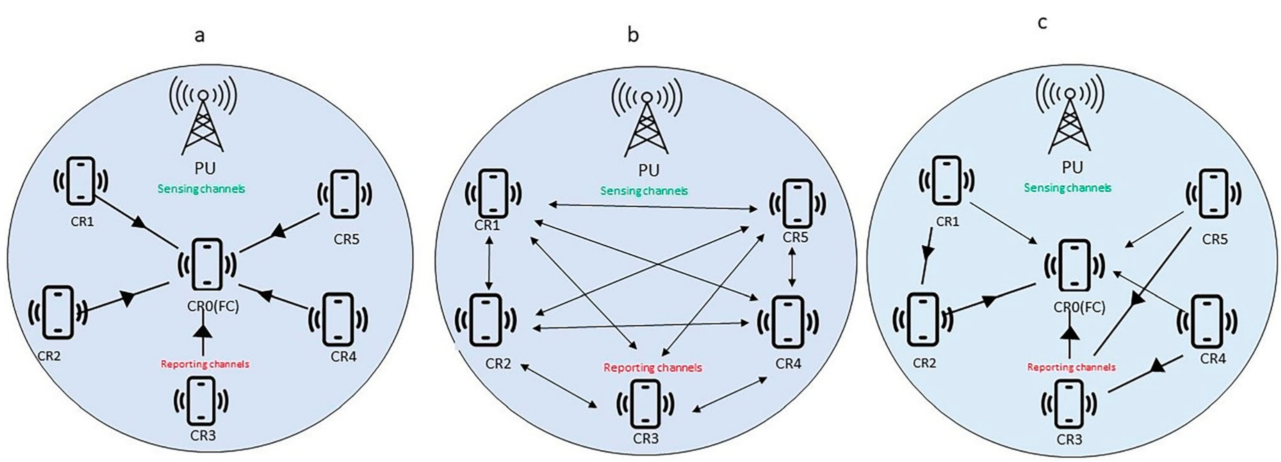


Figure 3. Categorization of cooperative sensing: (a) centralized approach, (b) distributed approach, and (c) relay-assisted approach.

3.2.3. Relay-Assisted Sensing

In CRNs, relay-assisted cooperative spectrum sensing is a technique used to increase the accuracy and effectiveness of spectrum sensing. This approach involves the deployment of strategically positioned relay nodes that collect sensing information from nearby CRs and transmit it to a central fusion hub. The process can be summarized as follows: First, relay nodes are carefully positioned in the network to gather sensing information from surrounding CRs and send it to the fusion hub. Next, the relays exchange their sensing data with each other to validate and enhance the accuracy of the results. The fusion hub then receives the sensing information from the relays and performs data fusion to determine the presence or absence of PUs in the spectrum. Finally, based on the fused data, the system makes a decision regarding the presence or absence of PUs, taking into account the information from multiple relays [49,50].

4. Key Metrics for Evaluating Spectrum Sensing and Prediction Performance

A variety of criteria are used in the assessment of spectrum sensing and prediction approaches in order to determine their efficacy and performance. Furthermore, in order to offer a thorough evaluation of system performance, researchers frequently take into account a variety of metrics. The most commonly used metrics for evaluating the efficacy of spectrum sensing and prediction methods are displayed in Table 3.

5. DL: fundamental concepts

Deep learning (DL) is a subset of machine learning characterized by neural networks with three or more layers, hence the term 'deep.' Inspired by the structure and function of the human brain, deep learning has emerged as a potent tool for solving complex problems in computer vision, speech recognition, and signal processing. In the context of SS, DL has demonstrated remarkable efficacy due to its capacity to automatically extract features. This is particularly advantageous given the varying levels of difficulty associated with traditional SS techniques, as illustrated in Table 1. Some traditional methods necessitate prior knowledge, which may not always be accessible, while others exhibit high computational complexity and prolonged sensing times. Notably, researchers have recently introduced several deep learning-based SS and SP approaches, leveraging models such as CNN, RNN, LSTM, and hybrid DL models to enhance sensing performance.

5.1. CNN

Convolutional neural networks (CNNs) [51] are a type of neural network that learns directly from data to extract the features needed to make a prediction or a classification and has risen to prominence in a wide range of computer vision tasks. A CNN can learn directly from raw data because of its architecture, which is built to take advantage of the temporal or geographical structure of the input. As depicted in Figure 4 [52], a CNN architecture is made up of two major components. Convolutional procedures and pooling layers are applied during the feature extraction process. Using a collection of learnable filters and the input data, the convolutional procedures compute dot products to create feature maps that highlight pertinent spatial patterns in the data.

CNNs use convolutional layers that apply small filters (or kernels) over the input data. These filters scan across the data to detect patterns like edges, textures, or other relevant features. For example, in image processing, a filter might detect edges, while in time-series data (such as radio signals), it could detect frequency patterns. This local connectivity allows the network to focus on small, meaningful portions of the data at a time. Besides, in raw data (like images, signals, etc.), simple patterns (e.g., edges in images or spikes in signal data) appear first. As the data flows through deeper layers of the CNN, more abstract patterns are recognized. CNNs automatically learn a hierarchy of features – from low-level patterns in early layers to high-level representations in later layers – by using multiple layers of convolutions. This eliminates the need for manually designed features and allows CNNs to work directly with raw, unprocessed data. The same convolutional filter is applied across the entire input, which means the network is able to detect the same feature in different parts of the data. This is particularly useful when dealing with raw data where similar patterns might appear at various locations. CNNs use pooling layers (such as max pooling) to reduce the dimensionality of the data [53]. By doing so, they retain the most important features while making the model more efficient and invariant to small shifts in the data, which is crucial when processing raw, noisy inputs. CNNs are trained end-to-end, meaning that the model adjusts the filters during training through backpropagation. This allows CNNs to automatically learn which features are most important for a particular task directly from the raw data without requiring explicit feature extraction steps.

5.2. RNN

Recurrent neural networks (RNNs) [54] are a form of neural network that is built to operate with data sequences, making them ideal for applications like time series analysis [55], natural language processing [56], and speech recognition [57]. RNNs are able to handle sequences of inputs because they preserve an internal state, in contrast to standard feedforward neural networks, which analyze data inputs in a single pass. They are therefore useful for tasks where interpreting the present input requires a comprehension of the context of previous inputs. Moreover, RNNs excel at recognizing patterns and dependencies across time in the context of SP, capturing dynamic variations in the radio frequency spectrum. Their recurrent connections enable information persistence, allowing the model to make predictions while considering the complete temporal environment [22].

5.3. LSTM

The Long Short-Term Memory (LSTM) network [58] was designed primarily to store and handle long-term dependencies seen in sequential data. Consequentially, these networks were purposefully intended to avoid the difficulty provided by the vanishing gradient issue that arises in standard RNNs. Their main advantage over other RNNs, hidden Markov models, and sequence learning approaches is their relatively great resistance to gaps in the data sequence.

The input gate, forget gate, and output gate are the three basic parts that make up the structure of an LSTM unit. These parts form a chain-like design, as shown in Figure 5 [59]. These gates are found in every LSTM unit, and they work together to control the information flow through the unit. The input gate determines how much of the current input is influential, the forget gate determines how much information from the prior state is preserved, and the output gate determines whether or not the information is transferred to the following LSTM unit.

LSTM networks significantly improve the model's ability to make accurate predictions based on historical patterns and trends observed in spectrum data. The integration of LSTM layers improves the ability of CR systems to make well-informed decisions about spectrum

Table 3. The major equations used to assess the effectiveness of spectrum sensing and spectrum prediction techniques.

Parameter	Area	Formula	Equation
Detection Probability (P_d)	Detection probability gauges how well the CR can identify the signals of PUs when they are present in the spectrum. It shows how well the system can recognize occupied channels. To avoid interference with primary users, a high Pd is preferred.	$P_d = P(H_1/H1)$ or $P_d = \frac{\text{True Positives}}{\text{True Positives+False Negatives}}$ where H1 denotes the existence of the PU	(2)
Probability of False Alarm (P_{fa})	False alarm probability is a measure of the possibility that the CR may falsely identify PU signals when they are not actually there. To avoid interference with PUs, a low value of Pfa is preferred.	$P_{fa} = P(H_1/H_0)$ or $P_{fa} = \frac{\text{False Positives}}{\text{False Positives+True Negatives}}$ where H1 denotes the existence of the PU and H0 indicates the absence of a PU signal.	(3)
Probability of Missed Detection (P_m)	Pm is the probability of missing PUs when they are active, and it is the complement of Pd.	$P_m = 1 - P_d$	(4)
Probability of False Alarm (P_f)	Pf shows the likelihood of false alarms when PU's are not present and is complementary to Pfa.	$P_f = 1 - P_{fa}$	(5)
Signal to noise ratio (SNR)	SNR is defined as the ratio of the power of the signal of interest (P_{signal}) to the power of the background noise (P_{noise}). Higher SNR levels indicate better signal quality. However, difficulties occur in low SNR situations, where the signal intensity is equal to or less than the noise. Consequently, this poses a formidable challenge for CR systems.	$SNR = \frac{P_{signal}}{P_{noise}}$	(6)
Receiver Operating Characteristic (ROC) Curve	The balance between Pd and Pfa is graphically represented by the ROC curve. It offers information on how the system performs at various threshold settings. A well-designed ROC curve facilitates the selection of an appropriate threshold for SS.		
Mean Absolute Error (MAE)	MAE is a significant evaluation metric for determining the accuracy of predictive models. MAE calculates the average absolute difference between estimated and actual spectrum state values, offering insight into the prediction model's overall precision.	$\mathrm{MAE} = \frac{1}{\mathrm{T}} \sum_{\mathrm{i}=1}^{\mathrm{T}} \lvert \mathrm{y_i} - \mathrm{y_i'} \rvert$ where T is the total number of samples taken into account, and y' and y_i represent the actual and anticipated values, respectively.	(7)
Mean Absolute Percentage Error (MAPE)	MAPE is a useful statistic for assessing prediction model accuracy. MAPE calculates the average percentage difference between estimated and actual values, providing a percentage-based measure of prediction errors.	$\mathrm{MAPE} = \frac{100}{\mathrm{T}} \sum_{\mathrm{i}=1}^{\mathrm{T}} \left\lvert \frac{\mathrm{y_i} - \mathrm{y_i'}}{\mathrm{y_i}} \right\rvert$ where T is the total number of samples taken into account, and y' and y_i represent the actual and anticipated values, respectively.	(8)
Root Mean Square Error (RMSE)	RMSE is a critical parameter for analyzing the accuracy of SP models in CR systems. It is a quantitative measure that measures the average magnitude of the errors between expected and actual values, offering a comprehensive view of prediction accuracy. A lower RMSE indicates a more exact and reliable prediction model. High accuracy in predicting spectrum conditions is necessary for CR networks to dynamically allocate resources and improve spectrum use.	$RMSE = \sqrt{\frac{1}{T} \sum_{i=1}^{T} (y_i - y_i')^2}$ where T is the total number of samples taken into account, and y' and y_i represent the actual and anticipated values, respectively.	(9)
Mean Squared Error (MSE)	MSE is an important metric for quantifying the average squared difference between estimated and actual data. MSE is useful for analyzing the accuracy and precision of predictive models, as well as providing insights into the overall performance of SP.	$MSE = \frac{1}{T} \sum_{i=1}^{T} (y_i - y_i')^2$ where T is the total number of samples taken into account, and y' and y_i represent the actual and anticipated values, respectively.	(10)
Precision, Recall, F1-score	Precision: Expresses the ratio of true positives to the total of true positives and false positives, demonstrating the accuracy of positive predictions. Recall: determines the ratio of true positives to the total of true positives and false negatives, hence assessing the model's capacity to catch all relevant instances. F1-score: is a balanced metric that combines precision and recall through their harmonic mean.	$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+FP}}\, Recall = \frac{TP}{TP+FN}\, \mathrm{F1\text{ - }score} = 2 \times \frac{\mathrm{Recall \times Precision}}{\mathrm{Precision+Recal}}$ where TP denotes results where the data is positive and is predicted to be positive, TN denotes true negatives (cases where the model correctly predicted the negative category), FP denotes false positives (cases where the model predicts the positive category, but it is actually negative), and FN denotes false negatives (cases where the model predicts the negative category, but it is actually positive).	(11)
Classification Accuracy	Classification Accuracy: It evaluates the ratio of accurately predicted cases to total instances in a classification task to determine the overall correctness of the model.	$\mathrm{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$	(12)

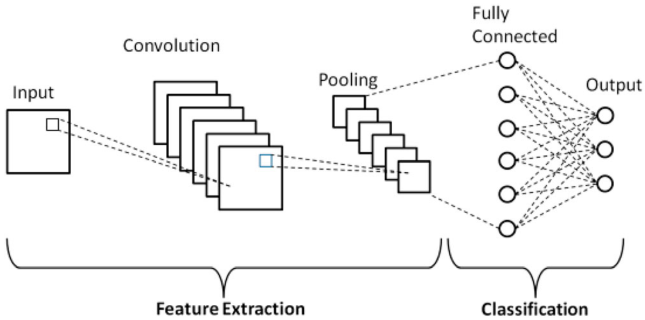


Figure 4. CNN block illustration [52].

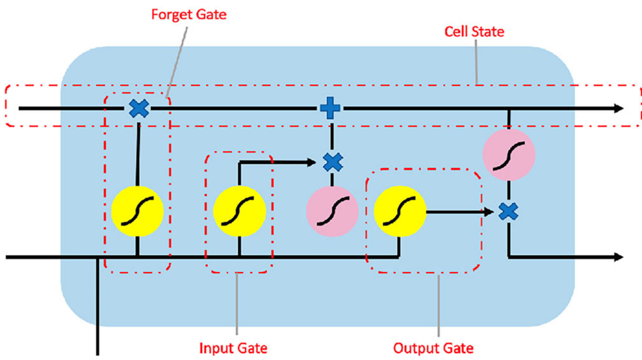


Figure 5. The LSTM unit is made up of a forget gate, an output gate, and an input gate. The sigmoid activation function is shown by a yellow circle, while the tanh activation function is denoted by a pink circle. In addition, the '' and '+' symbols represent the element-wise multiplication and addition operators, respectively [59].

utilization in dynamic and changing environments, as these systems progress toward more predictive and adaptive functionalities.

5.4. *Hybrid Models*

For CR, hybrid models take advantage of the complementary features of CNN-RNN or CNN-LSTM architectures in the application of spectrum sensing and prediction. With regard to feature extraction and sequential pattern recognition in particular, this clever combination seeks to leverage the advantages of both CNNs and RNNs or LSTM networks. The first convolutional layers in these hybrid frameworks retrieve important information from the spectrum signals first. These features are subsequently passed on to the subsequent RNN or LSTM layers, which are critical for comprehending the spectrum dynamics. The convolutional layers play a major role in the preliminary extraction of significant spectral features in this collaborative approach, while the RNN or LSTM layers focus on recognizing sequential patterns within the feature maps, hence improving the model's overall predictive capabilities [21,23,24].

Generally, one of the key advantages of hybrid models, such as CNN-LSTM or CNN-GRU models, is their ability to handle both spatial (or spectral) and temporal data. For example, CNNs excel at feature extraction from raw data, identifying patterns in the spectral domain, such as frequency changes or modulation types. This addresses challenges like low SNR or multipath fading by focusing on localized patterns in the input. RNNs or LSTMs capture temporal dependencies, which is crucial for tracking dynamic changes in the radio environment, such as PUs activity. These architectures are particularly adept at handling sequential data, allowing the model to predict future spectrum states more accurately based on past observations. Consequentially, by combining these architectures, hybrid models improve the system's ability to detect and predict spectrum availability and usage patterns more effectively than standalone models [23,24].

6. DL for spectrum sensing in cognitive radio networks

In this section, we examine at the issues of SS and the use of DL approaches to improve and optimize SS capabilities. DL models have the unique capacity to learn from data and change dynamically, making them an effective tool for addressing noise, interference, and other difficulties in CR and wireless communication systems. Figure 6 depicts a full DL model for SS [60]. However, SS is commonly approached as a classification task, focusing on identifying the presence, absence, and modulation types of signals. To address these challenges effectively, traditional model-driven SS frameworks are combined with advanced DL. In this context, several studies have explored the application of DL techniques for SS, demonstrating the potential of DL for improving the efficiency and accuracy of SS in CRNs. These studies provide valuable insights into the practical application of DL in SS, showcasing its potential to enhance the performance of CR systems [61,[62]]. However, in this section, we delve into each issue encountered in SS for CR and explore their resolutions through DL techniques.

6.1. *Noise uncertainty*

DL approaches offer potential solutions for modeling, estimating, and adjusting to noise situations. Noise uncertainty is a common concern in CRNs. These methods can improve the adaptability and dependability of CRs in complex and dynamic RF environments, which will ultimately result in better communication and more effective spectrum use. For instance, The study [63] tackles the difficulty of reliable SS in the context of the space-air-ground integrated network (SAGIN), which intends to deliver wide-area connectivity with improved quality of experience (QoE). The study offers a DL-based SS strategy that uses a deep neural network to extract characteristics from received signals based on the covariance matrix. This method is intended to increase SS performance, particularly in low SNR settings. The paper presents a blind threshold setting approach to limit the impact of noise uncertainty in lack of prior system knowledge. In the other hand, when pink noise appears, the efficiency of the classic techniques, such as the conventional max–min eigenvalue ratio-based technique and the frequency domain entropy-based approach, noticeably declines. To overcome this limitation, the authors [64] reformulated the SS task as a binary classification issue and added a brand-new SS method with roots in DL. The intrinsic ability of DL to autonomously identify noise features from data have been leveraged in this method. The input to a CNN is specifically the signal's power spectrum. The network has been trained using a varied dataset that includes a range of signal kinds and noise levels in order to ensure robustness. Notably, the suggested method outperforms existing strategies in terms of detection accuracy and reliability in experimental evaluations that include colored noise settings. The authors built a deep unsupervised learning-based detector (UDSS) for spectrum sensing in this study [65]. The UDSS did not require any prior knowledge of signal or noise distributions. The UDSS requires far less labeled training data than supervised learning-based SS systems. Experiments revealed that UDSS beat the benchmark non-deep learning algorithms and performed similarly to the CNN-based supervised DL method. Furthermore, the UDSS algorithm's efficiency in the presence of non-Gaussian noise was demonstrated. Furthermore, the authors [66] suggested using the matching network (MN) for environment-robust spectrum sensing (MN-ERSS),

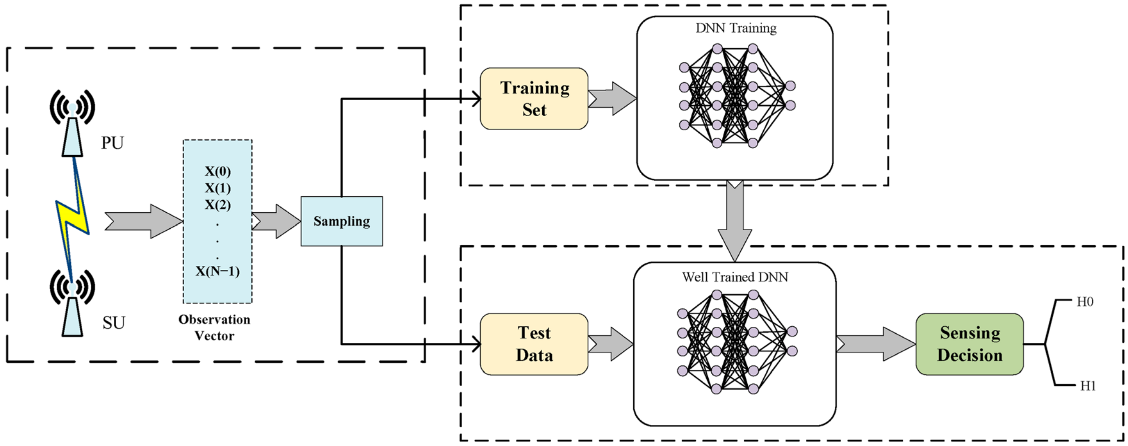


Figure 6. Illustrates the conventional framework for spectrum sensing driven by traditional models [60]

which would solve the problem of environment-sensitivity in current DL-based sensing techniques. They presented a novel method that uses cross-correlation characteristics of the cyclic prefix (CP) of orthogonal frequency division multiplexing (OFDM) signals as input data along with a sophisticated one-shot learning strategy. Furthermore, they developed a customized training technique that efficiently makes use of the information from the prior environment, enabling successful SS using just one sample from the prior environment and data from one previous environment. Extensive simulations were used to validate the proposed MN-ERSS, proving that it outperformed state-of-the-art sensing techniques in a wide range of SNR situations.

For blind signal detection, the conventional energy detector is an acceptable choice, however it suffers from the well-known SNR wall caused by noise uncertainty. The authors of the research [61] suggested a DL-based signal detector that makes use of the modulated signals' underlying structural information. The authors used a powerful CNN and LSTM layer combination known as the DetectNet neural network architecture. DetectNet makes use of the structural data that modulated signals have underlying. In addition, the DL classification approach for SS is enhanced in this research [67]. The strategy incorporates This study [68] advocates using the potential of DL, specifically neural networks such as AlexNet, SqueezeNet, ResNet101, and LSTM, to reduce the negative impacts of noise and interference on detection ability. A comparison of these neural networks is performed to assess their effectiveness in various contexts, with the goal of improving SS capabilities. While acknowledging the benefits of these detectors over simpler energy detection approaches, the article emphasizes the significance of adjusting detection thresholds to maintain a consistent probability of false alarms. It also recognizes the effect of interference and the importance of training detectors to reduce its impact.

With their STFT-CNN approach, the authors [69] created a revolutionary new SS technology. In this approach, the temporal and spectral features of signal samples are utilized by combining the Short-Time Fourier Transform (STFT) with CNN in a fluid manner. Comparatively to traditional methodologies, it allowed flexibility across various PU signals and didn't require any prior knowledge. The generalization and SNR resiliency skills it showed were particularly impressive.

Based on a stacked autoencoder (SAE) architecture, the authors of this study [70] provide SAE-SS, a robust SS technique. This method successfully addresses issues that traditional approaches typically encounter, such as timing delay, noise uncertainty, and carrier frequency offset (CFO). In contrast to other models like RNN and CNN, SAE-SS excels at gleaning information from received signals that is not readily apparent, hence improving its overall sensing accuracy. In addition to being more robust to different signal conditions, the approach does not require previous information from incumbent users (IUs) that use OFDM modulation.

For CR systems functioning in the TV band, the authors of the reference [71] suggest and examine a machine learning-based non-CSS method. In order to provide effective SS across a range of locations, wireless settings, and frequency bands, the paper presents a deep CNN-based transfer learning architecture. Through the use of transfer learning, the model seeks to ensure good performance in TV signal detection while minimizing computing complexity, reducing the amount of data needed for training, and shortening the sensing time. Studies carried out in various parts of Thailand show how well the suggested approach meets the SS specifications while cutting down on training and sensing times. The authors [72] introduce a groundbreaking approach to SS by leveraging deep CNNs, departing from conventional model-driven methods depicted in Figure 7. This innovative framework exploits CNNs' inherent abilities to extract key features autonomously from raw spectral data. At its core lies a carefully designed CNN-based detection architecture that is sensitive to the covariance matrix, divided into offline training and online detection stages. By optimizing the maximum a posteriori probability criterion, the method demonstrates resilience to environmental variables such as correlated PU signals and varying SNRs, showcasing its robustness and suitability for real-world CR applications.

The Linear Support Vector Machine (SVM) as a classification layer into the already used DetectNet-based DL method. When compared to the standard DetectNet technique, simulation results show that the suggested approach performs better overall, especially in the detection of low SNR signals.

In order to meet the urgent demand for precise and speedy primary signal detection, this research [73] offers a novel hybrid SS technique for CR systems. The approach uses Zhang test statistics from LRS-G2 and energy data from energy detection as input features for training the ANN. The ANN component assures consistent performance and offers adaptive learning capabilities. Real-world main signals from several radio technologies are used to evaluate the proposed sensing method. The findings show that the suggested technique consistently outperforms both traditional energy detection and enhanced energy detection methods.

In addition, Table 4 presents a comprehensive overview of key studies that focus on reducing noise uncertainty in CRNs. The table summarizes various works by detailing the model or framework

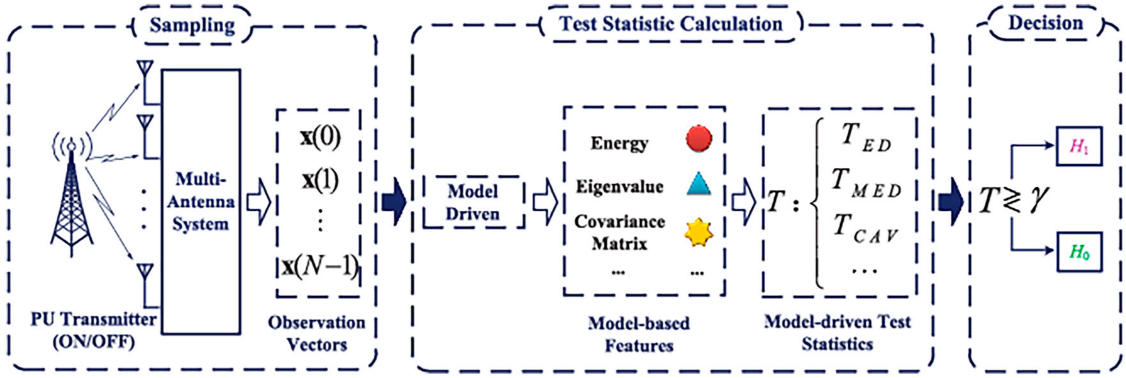


Figure 7. Illustrates the conventional framework for spectrum sensing driven by traditional models [72]

used, input and data sources, modulation types, SNR range, evaluation metrics, future research directions, and results. This overview highlights the diversity of approaches and metrics used to assess performance, while also pointing out the common challenges and future research directions identified by these studies

6.2. low-SNR environment

To address the significant issue with CR-based detection in low SNR scenarios that plagues traditional SS techniques. It was suggested in [62] to use the DL approach for passive signal detection. To extract the frequency and time domain elements of the signal, a CNN and the LSTM algorithm are utilized. In this context, Insufficient spectrum utilization caused by low SNR in SS is a problem that is addressed in this study [75]. In order to detect signals without prior information, it introduces a revolutionary DL-based method that integrates CNNs, LSTM, and fully CNNs. However, the suggested approach works better than conventional energy detectors, particularly under low SNR circumstances. It makes use of an end-to-end deep neural network that directly learns signal properties from raw data. The contributions include enhanced detection performance, an examination of the influence of LSTM layers, and understandings of why the DL model performs so well. However, this work [76] introduces a powerful DL technique to handle the frequent problem of poor SNR in SS. The main objective is to improve a CNN model built on the LeNet-5 architecture using the cyclic spectrum properties of OFDM signals as the training dataset. Particularly in difficult SNR circumstances, simulation results highlight the substantial performance gain realized by this approach when compared to conventional SS techniques. Moreover, Two cutting-edge SS frameworks for orthogonal frequency division multiplexing (OFDM) signals are built in this study [77] Robust Deep Sensing Through Transfer Learning in CR by utilizing DL networks. The first, called stacked autoencoder-based spectrum sensing (SAE-SS), outperforms traditional OFDM sensing techniques because to its resistance to timing jitter, carrier frequency offset, and noise uncertainty. Without prior signal expertise, SAE-SS excels at resolving these difficulties, making it a useful tool for SS. By combining characteristics from both the time and frequency domains, the second, stacked autoencoder-based SS technique using time–frequency domain signals (SAE-TF) provides even greater accuracy, especially in low SNR conditions. These techniques offer significant improvements over current methods and can be a key tool for dynamic spectrum sharing, effectively addressing spectrum shortages.

For CRNs, where unlicensed users opportunistically access the licensed spectrum, the authors of this research [78] presented a reliable SS technique. This approach uses a parallel CNN-LSTM network built on DL methods to enable SS without knowing the licensed user or channel condition beforehand. They created a diversified dataset for the model's training that contained a range of modulated signals and noise data, enabling the recognition of many signal types even in difficult low-SNR circumstances. The strategy makes use of the complimentary feature extraction abilities of CNNs and LSTMs, with CNNs emphasizing spatial features and LSTMs emphasizing temporal elements. To deal with spectrum resource shortages and temporal correlations in spectrum data, the authors [60] created a DL-based technique. To extract regional features and world correlations from time series data, the researchers utilized a 1D CNN, a bidirectional long short-term memory network (BiLSTM), and a self-attention mechanism. The SA layer highlights critical characteristics while the BiLSTM promotes feature extraction in opposite directions. Particularly in low-SNR conditions, the model performed better than the best-performing DNN models. The study also investigated modulation schemes and sample length impacts on detection performance, offering insightful information for further investigation and real-world applications.

To determine if the PU is active or inactive, the authors of the research [79] view sensing as a binary classification problem. The suggested method uses likelihood ratio test statistics and energy detection as features to train the neural network. This research offers insightful information on how to optimize ANN hyperparameters for CR networks, how well they function in various SNR settings, and the crucial effects of hyperparameter tuning and training time. The low PU signal detection rates in surroundings with low SNR are a problem that this study [80] addresses by presenting a unique SS approach that uses CNNs. The method comprises extracting features, including cyclostationary and energy properties for both PU and noise signals. These features are extracted, pre-processed, and used as training data for a CNN model. With a significant 0.5 improvement in detection probability at -20 dB SNR, experimental data show that our CNN-based methodology outperforms the conventional cyclostationary feature detection (CFD) method. A promising option for SS, CNNs are known for their strong classification performance and noise reduction capabilities. This is especially true in tough low-SNR conditions. The DLSenseNet model [81] is optimized for the specific goal of identifying PU signals, which is crucial for optimizing the spectrum utilization by SUs in CR. Using a combination of CNN and LSTM layers, the model investigates incoming modulated signals in both spatial and temporal dimensions. Furthermore, while the paper discusses the effects of various modulation schemes, its major focus is on demonstrating the performance and assessment outcomes of various forms of modulated signals.

Table 4. An overview of works that use deep learning for spectrum sensing, with a focus on reducing noise uncertainty.

The author/Year	ref	Model/Framework	Input/Data Sources	modulation	SNR range	Evaluation Metrics	Future Directions	Results
Zheng et al. (2020)	[64]	CNN	the signal power spectrum and noise data as input sources	BPSK, QPSK, 2FSK, 4FSK, 16QAM, 32QAM, 4PAM, and 8PAM.	-20 dB to 20 dB	P_d, P_f	Experiments with large-scale real-world signal data collected over the air	Generalization ability, Adaptability to untrained signals, Robustness to noise power uncertainty and colored noise
Gao et al. (2019)	[61]	DetectNet	RadioML2016.10a [74]	BPSK, QPSK,8PSKCPFSK QAM16, QAM64, GFSK, PAM4	-20 dB to 20 dB	Pd, Pf	research could focus on techniques such as transfer learning and domain adaptation to enhance the generalization of DL models across diverse environments, signal conditions, and modulation schemes.	the proposed method successfully achieves high Pd and low Pf simultaneously.
Sabrina et al. (2022)	[67]	DetectNet [61] with Linear SVM	RadioML2016.10a [74]	BPSK, QPSK,8PSKCPFSK QAM16, QAM64, GFSK, PAM4	-20 dB to 20 dB	Pd, Pf	the proposed DL-based detection framework can be extended to handle more complex scenarios, such as dynamic spectrum access in heterogeneous environments with multiple PUs and varying signal characteristics.	Improved detection at low SNR compared to DetectNet
Vyas et al. (2017)	[73]	Artificial Neural Network Model	Real-world primary signal data captured using USRP	– – –	-20 dB to 4 dB	Pd, Pf, Accuracy	Incorporation of additional relevant features	Improved performance compared to classical method
Liu et al. (2019)	[72]	Deep CM-CNN	Sample covariance matrix		+18 dB to −20 dB	PD, PFA, ROC curves	Investigate the performance of the proposed model under different scenarios.	Achieved a detection probability of 96.7% with a false alarm probability of 1.9% at SNR = -18 dB; Close performance to the optimal detector.
Ouamna et al. (2022)	[68]	AlexNet, SqueezeNet, ResNet101, and LSTM	Spectrograms	BPSK	-9 dB to 0 dB	Pmd, Pfa	Hybrid algorithms, latency reduction	Presented various Pfa and Pmd values at different SNRs for different detectors.
Chen et al. (2021)	[69]	STFT-CNN	Short-time Fourier transform (STFT)	QPSK, PAM	-20 dB to 0dB	PD-SNR, ROC	The dataset's robustness may be increased by integrating real-world PU signal data from various sources and situations, allowing for more accurate detections and classifications.	Detection probability of 90.2% with a false alarm probability of 10% at SNR = -15dB
Cheng et al. (2021)	[66]	matching network (MN) for environment-robust spectrum sensing (MN-ERSS)	Cross-correlation feature of CP of OFDM signals	BPSK	−20 dB to −10 dB	Sensing Accuracy	Exploring transfer learning, more efficient training techniques	MN-ERSS significantly outperforms SSDL and SAE-based methods in spectrum sensing with minimal testing samples
Xie et al. (2020)	[65]	unsupervised DL. The UDSS algorithm utilizes a Variational Auto-Encoder (VAE) and Gaussian Mixture Model (GMM) for cluster identification and threshold determination.	The algorithm utilizes an unlabeled set for deep unsupervised learning and a labeled set for cluster identification. It processes raw data collected during the PU's inactive period.	QPSK	with −5 dB to −15 dB SNR.	ROC curves, Pd, Pfa.	The authors suggest that the UDSS algorithm has the potential for further improvement and can adapt to various data distributions, including non-Gaussian noise.	The UDSS algorithm outperforms other benchmark algorithms under both Gaussian and Laplace noise
Cheng et al. (2020)	[70]	Stacked Autoencoder Based Spectrum Sensing Method (SAE-SS)	Received OFDM signals		−20 dB to −8dB	P_m, ROC curves	Explore implementation on practical OFDM systems	Significant reduction in miss detection probability compared to existing methods
Man Pati et al. (2020)	[71]	deep CNN based linear SVM	Spectrograms collected in UHF TV band		10 dB to 30 dB	Pd, Pfa	- Improve the method to handle severe channel quality deterioration.-Investigate the applicability of the pre-trained model to different radio systems for multi-radio integration.	Reduced the training data requirements and sensing time

Moreover, Table 5 provides an overview of early studies on DL for SS, particularly highlighting research conducted in low SNR environments

6.3. Signal Detection and Classification

In CR systems, signal detection plays a crucial role in determining if primary users are present or absent from the spectrum. DL models like CNNs and RNNs have demonstrated promising outcomes. By learning intricate patterns and features from the input signals, these models are able to distinguish between the main user signals and other competing signals or noise. In this regard, the authors of this paper presented a hybrid model of CNN-RNN for SS to detect the presence or absence of a signal at a predetermined time interval in order to improve the accuracy of sensing for low SNR signals [85].

6.4. Wideband spectrum characterization

This paper proposes [86] a deep learning framework for automatic wideband spectrum characterization (ASCW) at sub-Nyquist sampling speeds. However, Figure 8 illustrates the proposed deep learning-based architecture for an end-to-end ASCW framework, facilitating wideband spectrum characterization at sub-Nyquist rates. Especially for wideband signals, the suggested architecture successfully addresses problems with modulation categorization, spectrum reconstruction, and SS. The framework eliminates the drawbacks of traditional Nyquist sampling techniques by utilizing a single pipeline to directly characterize wideband signals collected using sub-Nyquist techniques. The enhanced SS and modulation classification accuracy of the framework is demonstrated by the study's assessment under various wireless channel conditions, SNRs, and modulation schemes. Furthermore, the article suggests the potential of the proposed architecture for reconfigurable platforms and underscores the need for further research in intelligent spectrum characterization and its integration with hardware for practical implementation in next-generation networks.

6.5. Automatic signal identification

The benefits of employing DL for wideband spectrum characterization and automatic signal identification in the context of SS are substantial. In our prior research [87], we provided an extensive and thorough overview of research articles and methods related to automatic signal identification using DL. It describes the many approaches and strategies used over time by diverse researchers, as well as their distinctive contributions and uses. In addition, the paper promotes the use of object detection techniques for signal classification and location and presence identification within a specific bandwidth. Additionally, they emphasize the significance of using object segmentation tasks to separate signals of interest (SOI) from interference and noise, as well as to extract other characteristics, including carrier frequencies, bandwidths, start-stop times, center frequencies, and modulation types. When combined, these techniques help to approach wideband as an image segmentation problem, which makes signal processing and analysis more precise and efficient.

6.6. Interference

Interference in SS can indeed be a significant issue in wireless communication systems. It can lead to reduced signal quality, dropped calls, and slower data speeds, impacting the overall performance of telecommunication networks. Interference occurs when multiple devices share the same spectrum, resulting in signal degradation and reduced performance. This interference can be both intentional and non-intentional, arising from various factors such as neighboring networks, overlapping frequencies, equipment malfunction, improper antenna placement, and environmental conditions. To address interference issues in SS, various strategies and technologies have been proposed.

A brand-new adversarial attack was introduced by the authors [88] with the intention of lowering the precision of SS in DL-based systems. This attack increased its interference capabilities by utilizing a brand-new jamming waveform design that was strengthened by data poisoning. In addition, the authors presented the Embedded Communication Method (ECM) waveform, which, in contrast to conventional techniques, produces imperceptible disruptions while maintaining particular interference capabilities. In addition, they suggested a new data poisoning attack technique called the Poisoned Data Label Hidden Attack (PLHA), which was designed specifically for the binary classification scenarios used by DL. The authors proposed the embedded poisoning method (EPM) as a means of targeting SS devices utilizing DL, building on the ECM waveform and PLHA. The security implications of EPM were assessed, and simulation results showed that it was more effective, secretive, and robust than typical white-box algorithms. The issue of spectrum congestion and the necessity for effective SS were addressed in this study [89] by repurposing the CNN in an innovative way. The CNN detector shows amazing effectiveness in detecting signals amid noise and interference by changing the SS problem into an image recognition job. Notably, the CNN detector outperformed traditional energy detectors in terms of robustness under various noise levels and in the presence of interfering signals. The experiments proved the CNN detector's effectiveness even further, emphasizing its independence from noise floor estimations and capacity to retain performance despite fluctuations in the received signal's power.

6.7. SNR estimation

The estimation of the SNR using DL and constellation diagrams was successfully solved in this work [90]. Due to considerable estimation errors, traditional SNR estimation methods have limits, especially in low SNR settings. This research suggests a DL-based method that makes use of the distinctive patterns seen by constellation diagrams at various SNR levels. The method offers precise SNR estimates, even in low SNR circumstances, by identifying these patterns using DL. This SNR estimation was performed using three DL networks: AlexNet, InceptionV1, and VGG16. The method successfully addressed this obstacle by recasting SNR estimates as a constellation diagram recognition problem. This innovative method not only performs better than conventional approaches, particularly in low SNR circumstances, but also provides quicker execution and effective GPU-based calculations. This algorithm's unique combination of constellation diagram representation and CNN-based regression shows promise for solving a variety of communication issues and parameter estimation tasks in communication systems, extending its applicability to fields like channel recognition and interference analysis as well as frequency offset and time delay estimation.

6.8. Fading channel

Fading channel problems in the context of SS have been addressed using SS techniques to improve the accuracy and robustness of SS

Table 5. An Overview of Early Studies on Deep Learning for Spectrum Sensing, with a Focus on Low SNR Environments.

The author/Year	ref	Model/Framework	Input/Data Sources	modulation	SNR range	Evaluation Metrics	Future Directions	Results
Da Ke et al. (2019)	[62]	CLDNN-based method	Synthetic and Real-world Communication Signals	DQPSK, QPSK, BPSK, 16QAM	6 dB to -15 dB	Pd, Pfa	Generalization of the method, Performance evaluation for cooperative communication	4.5-5.5 dB better performance compared to traditional blind detection algorithms at different SNR levels
Pan et al. (2020)	[76]	improved CNN model	Cyclic Autocorrelation, FAM Algorithm. The OFDM signal cyclic spectrum feature		-12 dB to High SNR	Pfa, P_m, Detection Rate, Training Time, Test Time	Integration with multi-feature inputs, Real-time implementation	Higher detection probability compared to traditional methods under low SNR
Yang et al. (2019)	[75]	1D CNN, LSTM, and FCNN	RF signal from a digital radio		-11 dB to 6 dB	Pd, False alarm rate	Improvement of detection performance with reduced computing resources	25-38% performance improvement over the energy detector method
Patel et al. (2020)	[79]	ANN with Energy Detection	Real-world radio technology signals		-20 dB to 5 dB	Pd, Pfa	Incorporation multiple PU and SU scenarios	63% improvement over classical energy detection methods
Xu et al. (2020)	[78]	Parallel CNN-LSTM Network	Generated modulated signals and noise	4ASK,8ASK, BPSK, QPSK, LFM, QAM16, QAM32, QAM64	-20 dB to 20 dB	Pd, Pf, ROC curves	Incorporating real-world signal data for evaluation	effective detection of multiple modulation types, especially in low SNR conditions
Cheng et al. (2019)	[77]	Stacked Autoencoder Based Spectrum Sensing Method (SAE-SS) and Stacked Autoencoder Based Spectrum Sensing Method with time-frequency domain signals (SAE-TF)	Received signals from OFDM system	BPSK	-20 dB to -8dB	PM, PFA, Computational complexity, Training time	Further optimization of computational complexity; exploration of additional input features for improved accuracy	SAE-SS and SAE-TF exhibit superior performance compared to conventional OFDM sensing methods, achieving significantly lower PM values under varying SNR, timing delay, and CFO conditions. SAE-TF outperforms SAE-SS in accuracy but comes with higher computational complexity.
Dong Han et al. (2017)	[80]	CNN	Cyclostationary features and energy features extracted from PU signal and noise	BPSK	-20 dB to -5dB	Pd, Loss function	Further feature extraction and improvement of CNN training for better detection performance	Higher detection probability than cyclostationary feature detection (CFD) about 0.5 in -20dB
Xing et al. (2021)	[82]	1D Convolutional Neural Network (1D CNN), Bidirectional Long Short-Term Memory Network (BiLSTM) and Self-Attention (SA) layer	Time-series data of received raw signals from [83] data created using the GNU radio	BPSK, QPSK, 8PSK, CPFSK, GFSK, QAM16, QAM64, PAM4	[-20, 5] dB	Missed detection, False alarm, ROC curves, Computational time	Integration of real-time applications	Improved performance over existing DNN models in terms of missed detection and false alarm rates, especially at low SNR.
Solanki et al (2021)	[81]	DLSenseNet (Deep learning-based spectrum sensing network)	RadioML2016.10b dataset [84]	8APSK, BPSK, CPFSK, GFSK, PAM4, AM16, QAM64, QPSK	-20 dB to +18 dB	Pd, Sensing error (SE), Pf	Incorporating real-world scenarios, Enhancing detection efficiency	Outperforms other sensing models, achieving better probability of detection and lower probability of false alarm in cognitive radio SS applications.
Solanki et al (2022)	[85]	CNN-RNN, Transfer Learning	RadioML2016.10b dataset [84]	QPSK, QAM16, QAM64, GFSK	-20 dB to +18 dB	Pd, Sensing error (SE), Pf	Enhance the robustness for real-time deployment.	The findings indicate considerable improvements in both the Pd and the Pf, highlighting the effectiveness of the proposed CNN-RNN model in SS.

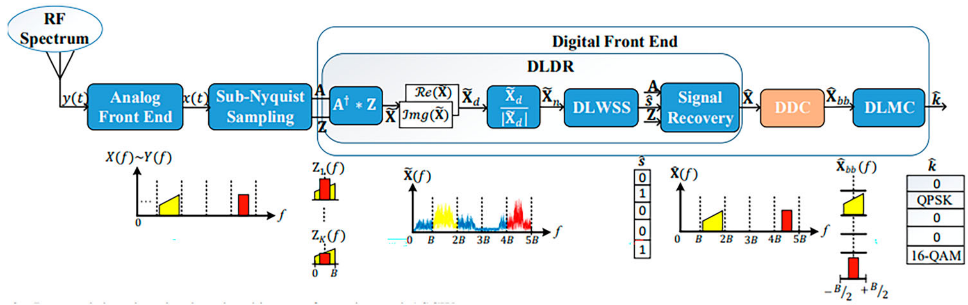


Figure 8. Proposed ASCW Architecture Overview [86].

in CR systems. DL algorithms have been proposed to tackle fading scenarios, such as Rayleigh fading, in non-cooperative and CSS. For non-cooperative SS, a robust algorithm based on DL has been proposed to handle Rayleigh fading channels [91]. In CSS, DL techniques are used to classify signals under generalized fading scenarios [92]. One approach is to transform the RF one-dimensional signal into an image using the General Linear Chirplet Transform (GLCT) and then combine it with CNN. This combination of GLCT with CNN has been shown to outperform the direct application of CNN and the combination of spectrogram and CNN. This approach has been applied to a dataset of RF weather radar signals, where different fading conditions are created [93]. Moreover, the Spectral Correlation Function (SCF) is used as a crucial input to a specially created CNN in this study [94] to provide a unique DL-based strategy for SS and signal identification in CR networks. The technique operates in joint and sequential modes and has the distinct advantage of flexible spectrum detection and signal categorization without the need for prior information. Comparative investigations show that the SCF is superior to conventional features for DL network training. Comparing the results to those obtained with existing DL models and traditional cyclic frequency domain approaches, significant performance gains are also shown, particularly in difficult channel conditions.

The authors [95] generated a varied dataset of OFDM signals using QPSK and QAM with a CNN. Glow worm swarm optimization (GWSO) was used in the suggested method to automatically optimize CNNs, minimizing the requirement for user intervention. Additionally, the k-Nearest Neighbors algorithm was used in place of the conventional Softmax to handle noisy signals with better performance. The investigation of the suggested improved CNN-GWSO approach's classification performance in comparison to existing machine learning classifiers, such as support vector machines and decision trees, made it abundantly evident how superior these capabilities were. In both fading and non-fading scenarios, simulation results showed that this strategy outperformed other approaches, demonstrating its improved efficiency in terms of error rates and optimization of data transmission opportunities.

6.9. PU activity

Traditional SS methods call for prior knowledge of both the PU signal and noise, and only then is optimal performance possible. In this context, to increase the likelihood that SS will be detected in CR, knowing PU activity patterns is important. In paper [19], a CNN-LSTM approach is used, in which the energy correlation features are first extracted via the covariance matrices produced by the sensing data using the CNN, followed by a series of energy-correlation characteristics related to various sensing periods being input into the LSTM in order to discover the primary user activity pattern. In all instances regardless of noise uncertainty, the CNN-LSTM detector's superiority is demonstrated. The issue of hidden terminals emerges in traditional SS approaches like energy detection or cyclostationary detection algorithms when CR is shaded by extremely low SNR values and detection methods are unable to detect the PU's presence. This study [21] used an ensemble CNN and RNN to detect and classify statistics like PU and SU. The suggested approach (ECRNN) estimates spectrum availability at 5G base transceiver stations by learning spectrum data characteristics. ECRNN looked at PU statistics, which enhanced SS. On the other hand, the deep belief networks (DBN) is used to predict the behavior of PU agents by classifying their performances[96]. In Figure 9 of paper [97], the authors introduce an LSTM-based Spectrum Sensing (LSTM-SS) approach designed to extract crucial insights from spectrum data, particularly focusing on the correlation between current and past timestamps. By leveraging this approach, CR systems enhance their performance by integrating PU activity statistics. However, a CNN-LSTM network is suggested by the authors in their research [98]. The CNN-LSTM network is capable of obtaining complex spatial and temporal features. The LSTM layer can perform appropriate modeling with the temporal information and provide a solution for preserving long-term memory. This place temporal features in long-term order, and the CNN can extract features from multiple variables. This approach is predicated on the notion that every PU signal will have a modulation format attached to it, and that detecting the presence of a modulation format proves the presence of a PU signal. With the use of this method, PUs can be detected. Additionally, in this paper [99], the authors suggested a SS method for CR systems that relies merely on the energy of the received signal and doesn't necessitate special knowledge of the PU transmission. They created a 2-dimensional spectrogram using FFT to effectively determine channel occupancy. With fewer parameters and performance that was equivalent to other CNN-based algorithms, this approach did away with the necessity for the free channel assumption.

6.10. Multi-Path Fading

Multipath fading is a phenomenon in wireless communication where signals transmitted from a transmitter to a receiver take multiple paths due to reflections, diffractions, and scattering in the environment. These multiple paths can result in variations in the received signal strength at the receiver. In the context of SS, the accuracy of sensing can be affected because the fading can lead to fluctuations in the signal strength, making it challenging to reliably detect the presence or absence of signals in the spectrum. This study [100] proposes a DL-based SS scheme (DS2MA) using a multi-antenna receiver to mitigate the effects of multipath fading. The proposed scheme uses a DL-based signal detector to detect the presence of primary signals,

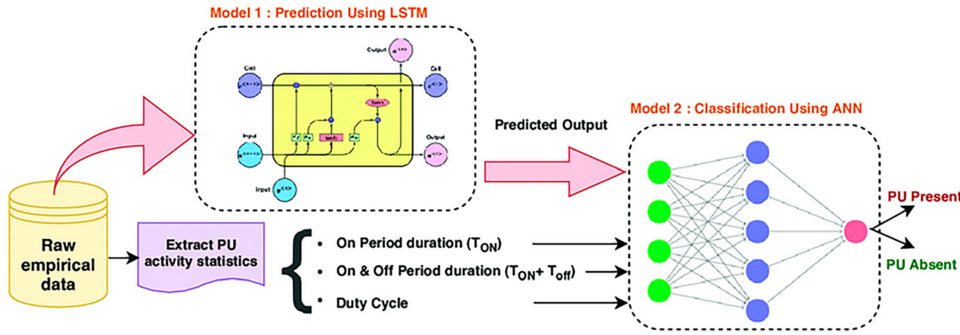


Figure 9. A spectrum sensing scheme for cognitive radio utilizing LSTM models and primary activity statistics [97].

which are usually very weak, without prior knowledge of channel state information or background noise.

6.11. Cooperative spectrum sensing based on DL

The integration of DL into CSS offers numerous advantages for CRNs. DL enhances accuracy by autonomously learning intricate signal characteristics, reducing false positives and negatives in CSS outcomes. Its adaptability to dynamic signal environments allows effective handling of changing spectrum conditions [101]. DL's automatic feature learning capabilities provide versatility, reducing reliance on predefined features. Furthermore, DL models excel in processing complex datasets, mitigating interference, and optimizing decision latency in CSS applications. However, several papers propose CSS methods, providing valuable contributions to the advancement of this methods. This study [102] gave specific attention to how SUs might support PUs in an efficient manner. The estimation of specific exposure samples required careful consideration of both spatial and spectral correlations. A CNN-based framework known as cooperative spectrum sensors was successfully used to guide these exposure samples for SUs. The weight function of the CNN was properly determined by integrating the Improved Whale Optimization Algorithm (IWOA), which significantly improved accuracy. An inertia weight was intelligently introduced to better simplify the way the Whale Optimization Algorithm (WOA) is used within IWOA. This painstakingly planned strategy ultimately enabled the primary user within the CNN framework to obtain an incredibly precise perception. In an OFDM system, these studies [103] and [104] propose ensemble learning (EL) frameworks for CSS in CRNs. Both papers leverage multiple DL models, including CNNs and RNNs, to classify received signals into different modulation types. The outputs of these models are then combined using stacking fusion centers or semi-soft stacking fusion centers, which involve a weighted average of the predicted probabilities. These approaches allow for the incorporation of uncertainty in the predictions, leading to improved accuracy and robustness in spectrum detection.

To integrate the outcomes of each separate sensing operation, a self-taught approach based on training samples is utilized [105]. They suggested that deep DCS is capable of operating independently of the kind of sensing data shared with particular secondary users, e.g., both hard decision (HD) and soft decision (SD) sensing are supported, as are the spectral and spatial correlations of the channels, in a manner that does not require explicit mathematical equations [106]. In this paper [107], the challenge of energy efficiency in distributed cooperative sensing is discussed as a combinatorial optimization problem. It provides a DL framework that blends reinforcement learning with graph neural networks to improve overall system energy efficiency. The efficiency of this suggested technique is

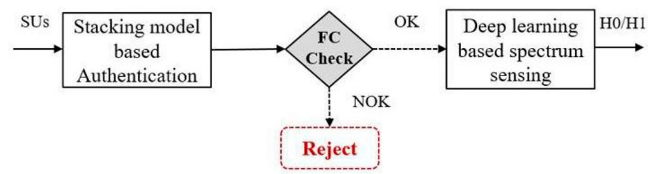


Figure 10. Proposed method for the authentication process in malicious user detection and secure spectrum sensing for primary user classification [108].

demonstrated by simulation results performed across different network scales. The authors [61] present SoftCombinationNet, which utilizes soft information from distributed sensing nodes. SoftCombinationNet is designed to learn the optimal fusion rule through training, achieving a high probability of detection with a low probability of false alarm, thereby outperforming conventional cooperative sensing methods.

The authors [108] presented two separate approaches for cooperative CRNs to protect the privacy of sensed data and improve the precision of SS decisions. They first presented a stacking model-based solution for detecting malicious users (MUs), which combined chaotic compressive sensing-based authentication with stacking ML techniques. Second, they suggested a DL method to categorize the spectrum of PUs based on scalogram plots. The suggested method, however, has two main goals: one focuses on the comparative study of different DL models for the SS process, while the other is specifically intended to automatically reject MUs through ensemble ML. The accompanying Figure 10 illustrates the essential system model blocks, highlighting the authentication process for MU detection and the intelligent, secure SS for PU classification.

In order to improve flexibility in changing radio environments, the authors [109] presented a CNN-based classification model for cooperative SS. They created a spatiotemporal dataset while taking into account several situations of primary and secondary users, and they assessed CNN's performance at various noise floor levels. Because the system model was dependent on user geographical positioning, numerous datasets were generated, including those for low SNR regimes with shadowing effects. In this study [110], the performance of CNN-based CSS is examined in dynamic channel situations. The dataset synthesis takes into account different fading situations, such as Rayleigh and Nakagami-m fading, path loss with log-normal shadowing, and spatial correlation among secondary users. The comparative evaluation places particular emphasis on the performance of CNN-CSS in comparison to the conventional decision fusion methods used in CSS, as well as the influence of various noise floors and fading scenarios. The results highlight CNN-CSS's flexibility and effectiveness, especially in circumstances with low-noise floors and Rayleigh fading. To enable multiband spectrum sensing in cognitive vehicular networks, the research [111] presents a learning-based CSS technique. To extract temporal characteristics from the incoming data, the suggested approach combines an LSTM network with a covariance matrix-aware CNN model. Interestingly, the technique shows resilience in low SNR conditions and shortens sensing time by doing away with the requirement for predetermined choice criteria. Comprehensive models illustrate the method's superiority over conventional techniques, obtaining increased detection accuracy and surpassing benchmark techniques like energy detection (ED) and SVM in SS performance. The suggested classifier performs well, especially in demanding dynamically topological and highly mobile vehicle networks.

By presenting a hybrid CNN-LSTM model that enables precise and effective spectrum perception without the need to compute decision thresholds, the work [24] advances SS approaches in CR. The suggested model performs better and has better detection accuracy, especially in situations where there are several cooperating users. According to the simulation results, the CNN-LSTM network is effective at obtaining high detection probabilities even at low SNR levels, which improves spectrum consumption and protects the principal user in CR environments.

7. Deep learning for Spectrum prediction in CRN

7.1. Spectrum Prediction for Non-Cooperative Spectrum Sensing

spectrum prediction (SP) provides valuable information about upcoming spectral conditions, thereby empowering CR to make informed decisions concerning resource allocation, transmission strategies, and spectrum utilization. Accurate SP can lead to enhanced system throughput, reduced energy consumption, and improved quality of service. SP has numerous applications in wireless communication and CR systems. For instance, the researchers [5] created a SP framework for two real-world spectrum datasets using DL techniques, notably the LSTM neural network. They developed the Taguchi approach for optimum configuration determination, which significantly reduced time and processing needs. The trials highlighted the importance of different design hyper-parameters as well as the improved stability of the LSTM network over the traditional Multilayer Perceptron (MLP) network. The results highlighted the LSTM network's superior performance in both regression and classification, outperforming the MLP network's capabilities. Overall, the study advanced SP techniques by demonstrating the effectiveness of the LSTM network in tackling time series challenges in CRNs. The authors of this research used [22] the structure of the deep recurrent neural network (DRNN)-based spectrum predictor and the multiple-input and multiple-output (MIMO) technique to allow multiple-time slot SP. The continuous channel state was separated into many time slots to simplify multiple-slot SP, and only the largest value of the signal energy in each time slot was chosen to produce the channel state's time series. Through training and SP experiments, the results indicated that the extended Kalman filter (EKF) has a shorter training time compared to the stochastic gradient descent method. Moreover, this study [112] effectively demonstrates the ability of advanced DL techniques, such as DNN, CNN, and LSTM, trained on real RF traces from various coexistence scenarios, to accurately predict the presence, types, and numbers of users in complex RF environments. This can help optimize spectrum efficiency in future wireless networks. This is especially important when it comes to shared spectrum use by several users and systems and dense network deployment.

Xue Wang et al. [113] offer the Back Propagation-Long Short-term Memory Time Forecasting (B-LTF) approach, a fusion of Back Propagation-Long Short-term Memory (BP-LSTM) network models, for efficient SP. In comparison to traditional models such as BP, LSTM, and GRU, their research highlights the improved performance of the B-LTF algorithm and highlights the importance of time spectrum occupancy features and sequence length on prediction accuracy. The research clearly shows the transformational influence of DL on traditional SP approaches, allowing for the construction of a more complex and efficient prediction model. CNNs and RNNs are examples of DL techniques that have shown promise in SP tasks. These models are suitable for capturing temporal or spatial dynamics because they are able to learn complex patterns and dependencies in the spectrum data. Large amounts of historical data can be analyzed by DL models, which can also be used to learn representations that allow precise SPs. Given the presence of T historical time slots of spectral data, the process of SP entails the utilization of these historical spectral data points, commonly indicated as [113] :X_{t-T+1}, X_{t-T+2}, and so on up to X_t, to train a network. This network training permits the discovery of internal connections within the data, simplifying the calculation of the anticipated value of X_{t+1} for the next time slot, generally indicated as $t + 1$. Figure 11 provides a comprehensive illustration of the prediction model.

To predict spectrum availability in cognitive aerospace communications, the authors [114] used a DL system based on LSTM networks. They used simulation data sampled from Share Spectrum Company, covering the spectrum from 3 MHz to 5.4 MHz and divided into 26 channels. The system achieved exceptional performance with up to 98% overall prediction accuracy by utilizing Softmax activation and RMSprop optimization. Notably, the LSTM-based method outperformed a fundamental ANN model, highlighting the importance of LSTM networks in predicting spectrum availability.

In order to accurately predict frequency-hopping sequences, the authors [115] built a complex prediction model including LSTM layers. The model defined the idle or occupied state precisely by establishing an ideal threshold. LSTM's better predictive ability was shown through comparison assessments with the Back Propagation (BP) neural network. The investigation also looked into the effects of various network widths and depths on prediction accuracy, with a focus on the significant impact of network width.

To achieve to enhance SP in high-frequency communication systems, the paper [116] introduces a DL-based method called a temporal-spectral residual network. Several future time slots of several spectrum points can be effectively predicted simultaneously by this strategy. The study [117] aims to develop a multi-channel, multi-step SP system based on LSTM, seq-to-seq modeling, and an attention mechanism. The suggested method provides an alternative by focusing on multi-channel and multi-step predictions. The authors proved the higher prediction performance of their algorithm through simulations when compared to standard single-channel prediction approaches. However, optimizing the training convergence of LSTM models for SP within the framework of CR applications is challenging. The study [118] introduces the 'Kandeepan-Niranjana (K-N) initialization' approach, which utilizes previous statistical insights from the input data to mitigate the computational complexity and delays related to LSTM training. The paper highlights how to reduce prediction delays and speed up training by concentrating on Markov model-based spectrum use data. This will increase both prediction accuracy and spectrum efficiency. In addition, this work [119] adds to a better understanding of the underlying mechanics of LSTM-based SP by examining and modeling the prediction performance of an LSTM-based system model for SP. The research studies the prediction scores of a two-state discrete-time Markov model using spectrum occupancy data and recommends the use of mixes of truncated Gaussian distributions to represent these

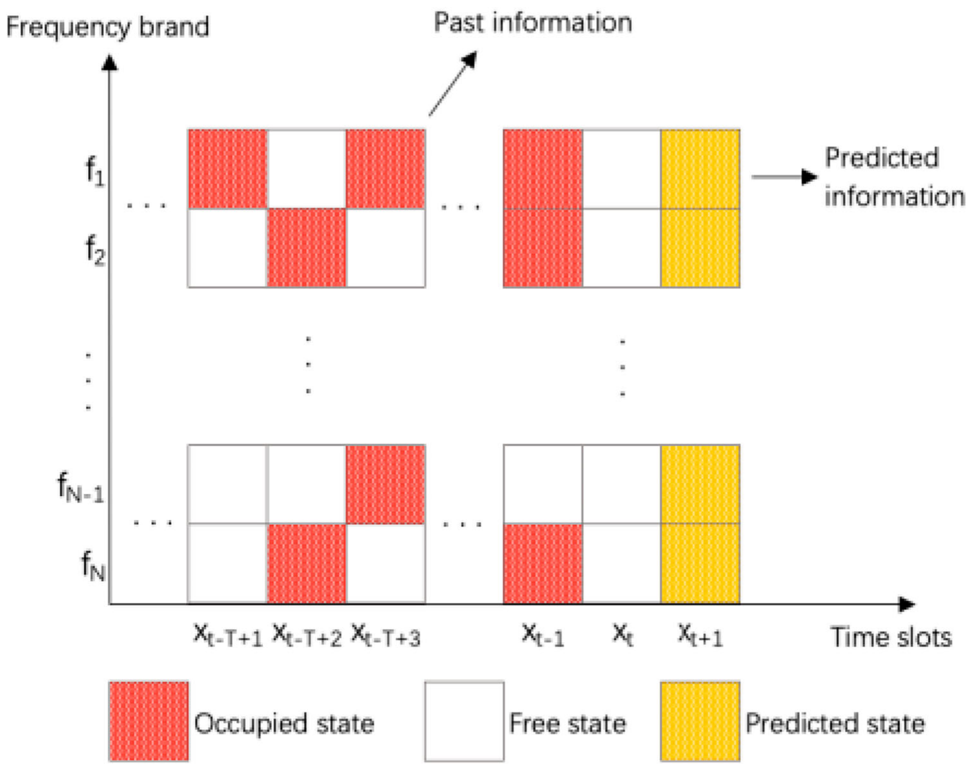


Figure 11. A comprehensive demonstration of a spectrum prediction model [113].

scores. Time, frequency, and space are correlated in several dimensions, and the study [120] highlights the importance of spectrum occupancy prediction in CR systems. With less computational complexity and reliable predictions, the suggested approach, Composite 2D-LSTM, efficiently divides the multidimensional correlation issue into smaller, more manageable subproblems. When full data is not available, the proposed approach may estimate spectrum occupancy with high accuracy without requiring a lot of retraining. The study's extensive testing and validation over real-world spectrum measurements demonstrate this. In reference [121], researchers provide an enhanced deep-learning model called STS-PredNet that can concurrently predict different frequency band states at many locations. The model is able to capture the temporal, spatial, and spectral relationships included in the spectrum data by utilizing the predictive recurrent neural network (PredRNN). The findings of the experiments confirm that the STS-PredNet performs better than the current baselines, suggesting that it has the capacity to forecast spectrum accurately and steadily over a wide variety of prediction ranges.

Anovel model for long-term SP tasks, the Autoformer-CSA, is introduced in this letter [122]. The traditional 2-dimensional (2D) convolution is replaced with a 1-dimensional (1D) convolution by the use of a series channel-spatial attention module (CSAM). With this improvement, the Autoformer-CSA may further improve its learning capabilities by assigning various concentrations to distinct characteristics inside the high-dimensional space. Comparing the Autoformer-CSA to current state-of-the-art benchmarks, it shows better performance by adhering to the original Autoformer architecture's series decomposition block and auto-correlation mechanism. The Autoformer-CSA model has been shown to be successful for long-term SP tasks based on results from experiments and a real-world dataset. This study [23] presents a novel method for long-term SP utilizing a convolutional LSTM (ConvLSTM) DL neural network. This approach captures the simultaneous spatial-spectral-temporal relationships found in spectrum consumption effectively, in contrast to prior models that only concentrated on short-term predictions. Evaluation is conducted using real-world data from Electrosense, which shows the network's strong predictive performance over a long-time horizon and across multiple spectrum channels.

The authors [123] used DL as a data-driven approach for SS, more specifically a generative adversarial network (GAN). They were able to predict spectrum occupancy directly thanks to this innovative strategy, completely dodging the need for traditional energy detection techniques. Through the use of DL and the promotion of neural network competition, the ground-breaking deep compressive spectrum sensing GAN (DCSS-GAN) takes a different approach and is able to recover the spectrum from time-domain data that has been under sampled. In contrast to conventional methods, this data-driven methodology does not require prior understanding or a priori statistical insights into the radio environment. As a comprehensive end-to-end method, DCSS-GAN successfully avoids the energy detection requirement by anticipating spectrum occupancy directly from raw data. On other hand, to address issues with SP caused by a lack of data. This research study [124] proposes a cross-band data augmentation strategy that blends generative adversarial network (GAN) techniques and deep transfer learning. By pre-training a GAN model with the most similar historical data to the target frequency band, this technique allows data augmentation for the target band.

7.2. Cooperative Spectrum prediction (CSP)

Cooperative spectrum prediction (CSP) has emerged as a promising strategy for enhancing spectrum utilization efficiency in CRNs. This research [125] compares the performance of MLP neural network predictors and hidden Markov models (HMM), as well as the spectrum and energy efficiency of CSP. As shown in Figure 12, it studies a centralized CRN with N PUs with different channels and multiple SUs doing pre-fusion CSP operations. Every SU frame involves the

SUs employing an HMM or MLP predictor to do local single-user spectrum prediction (SSP) on the PU channels. The study also evaluates the impact of various fusion schemes (AND, OR, and majority rule) on CSP performance, particularly in terms of spectrum efficiency (SE) and energy efficiency (EE). The results underscore the substantial enhancement in SE with CSP, albeit with a slight trade-off in energy efficiency compared to conventional approaches. In a similar investigation, this work [126] investigates CSP using neural network predictors, specifically in the context of a heterogeneous CR network. Soft cooperative fusion is used to extract spatial relationships from spectrum measurement data and provide accurate occupancy predicts for nearby secondary users. The study shows how non-CR users might benefit from better energy use and improved spectrum use. Furthermore, the research [127] looks at soft fusion approaches for CSP using LSTM models. It highlights the benefits of CSP employing several local predictors, which has been shown to be more accurate than single local predictors. The study successfully minimizes prediction errors compared to local prediction methods and most hard fusion approaches by using soft fusion and hard fusion methods.

To solve the sequence dependence concerns in time series prediction problems that come out in MLP-based prediction models [125], the work [128] adopts a local prediction model based on an LSTM network. The three main stages of the suggested plan are joint prediction and sensing, CSP, and local SP. Every SU makes an individual forecast based on its past sensing data during the first local SP phase, which it then sends to the FC. Afterwards, during the cooperative prediction stage, the FC works together on the combined predictions from every SU in order to reach a consensus on whether or not a PU exists. Lastly, the FC uses an ED framework in the joint prediction and sensing phase to determine the condition of channel slots that the cooperative method was unable to reliably predict. Figure 13 provides a graphic representation of the full procedure for better comprehension. This framework is crucial in recognizing channel conditions prior to physical sensing, significantly improving total network energy efficiency. Furthermore, the proposal provides a parallel fusion-based cooperative prediction model that reduces mistakes in local prediction while also offering adaptive capabilities for dealing with network environment changes.

Additionally, Table 6 summarizes some early studies on DL for SP. This table highlights the authors, models used, input datasets, performance metrics, key results, and identifies limitations and future directions for each study

8. Dataset

The RadioML2016.10a dataset: is a widely utilized synthetic dataset in the research community for radio signal classification and modulation recognition. It is generated with GNU Radio and comprises 11 modulations, with each sample typically consisting of complex-valued IQ (In-phase and Quadrature) samples, fundamental for characterizing modulation features. The dataset contains a diverse set of modulated signals, noise, and interference scenarios, making it suitable for training and testing DL models for SS. The dataset is available on the RadioML website and can be downloaded as pickle files.

RadioML2016.10b Dataset: It a continuation of the RadioML2016.10a dataset, contains IQ samples from 11 modulation classes (8 digital and 3 analog) over 20 SNR values ranging from -20 dB to 18 dB. The dataset is synthetic and generated with GNU Radio, and each sample typically consists of complex-valued IQ (In-phase and Quadrature) samples, fundamental for characterizing modulation features. While the dataset was primarily designed for automatic modulation recognition (AMR) tasks, it can be used for a variety of machine learning and signal processing tasks, including SS and modulation recognition [85].

RadioML2018.01A dataset: It is an important resource in the field of DL for SS. This dataset contains 24 different forms of digital and analog radio modulations that were synthesized and recorded over-the-air. It is a useful tool for training and assessing DL models that recognize and classify signals in a wideband spectrogram. The RadioML 2018.01A dataset has been validated and formatted to include synthetic simulated channel effects, making it more useful in training models for SS applications [131].

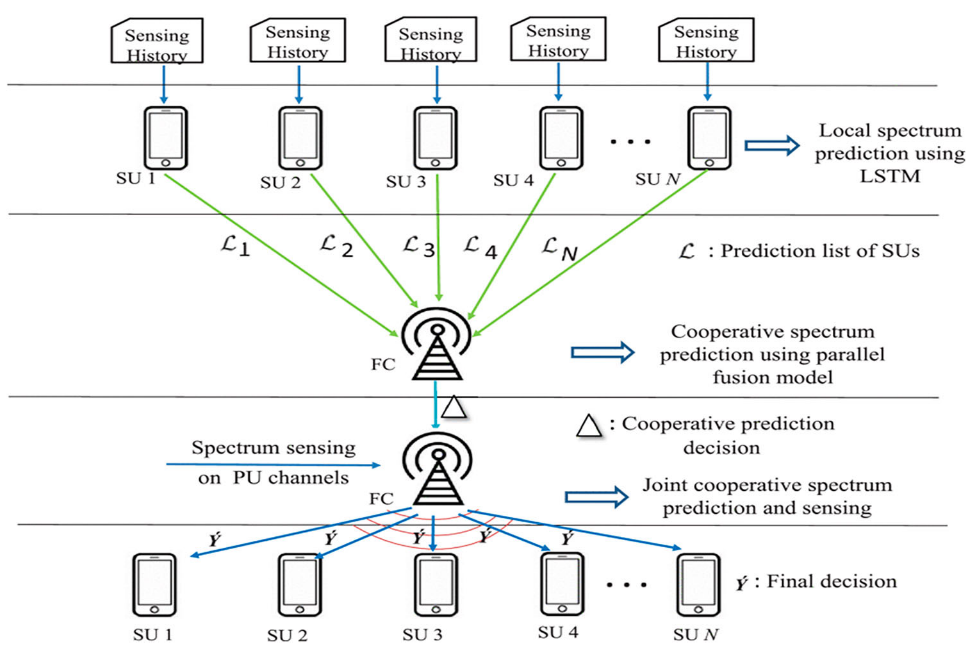


Figure 12. The different phases of the proposed scheme, Cooperative Spectrum Prediction-Driven Sensing [125].

Table 6. A summary of some early studies on deep learning for spectrum prediction.

Author/year	ref	model	Input/Datasets	Performance Metrics	Results	Limitations and Future Directions
Wang et al. (2023)	[113]	B-LTF algorithm with Back Propagation-Long Short-term Memory (BP-LSTM) network model	Historical spectrum occupancy data in time and frequency dimensions	RMSE and MAE values	Improved prediction performance; B-LTF outperforms other models	Explore methods to minimize operating time while improving prediction performance with greater sequence lengths.
Tang et al. (2017)	[22]	Deep Recurrent Neural Network (DRNN)	Spectrum data from multiple time slots.	Convergence speed, NMSE	Reduced energy consumption, higher channel utilization	Longer training times are caused by an increase in hidden layers.
Yu et al. (2017)	[114]	LSTM Network	Historical spectrum availability data	True positive rate, true negative rate, overall accuracy	Overall prediction accuracy up to about 98%.	Comparison with basic ANN model
Meng et al. (2020)	[123]	Deep Compressive Spectrum Sensing GAN (DCSS-GAN)	Sub-sampled spectrum data captured at a rate lower than the Nyquist rate.	ROC, area under the curve (AUC)	DCSS-GAN achieved 12.3% to 16.2% higher prediction accuracy compared to conventional LASSO approach	Reviewing architecture to maximize performance
Ling Yu et al. (2018)	[5]	LSTM Network	Real-world spectrum data from terrestrial and satellite networks.	RMSE and Classification Accuracy (CA)	LSTM network outperforms MLP network in both case studies	Generalization to various frequency bands examined
Ling Yu et al (2017)	[115]	LSTM and BP Networks	Constructed frequency hopping pattern with length of 160 time slots for ten channels.	Accuracy, Prediction Performance	LSTM network outperforms BP network	Optimizing model architecture and network parameters to further enhance prediction accuracy. the absence of validation using real-world channel data as a limitation
Omotere et al. (2018)	[112]	DNN LSTM CNN	the dataset was generated from a tunable Universal Software Radio Peripheral (USRP) based testbed for distributed spectrum monitoring and surveillance [129].	Classification Accuracy	All models achieve accuracies above 90% for most scenarios	LSTM requires more training time;
Xi Li et al. (2021)	[121]	spatial-temporal-spectral prediction network (STS-PredNet)	real-world spectrum measurement dataset.	(MAPE, MAE, MSE)	The model demonstrated superior predictive performance, indicating its effectiveness in capturing complex dependencies in spatial, temporal, and spectral dimensions.	exploring techniques to address potential challenges associated with longer prediction ranges is a potential avenue for future research
Bethelhem S. Shawel et al. (2019)	[23]	Convolutional Long Short-Term Memory (ConvLSTM)	Real environment measurement data from Electrosense.	RMSE	the 95% average RMSE value	
Ling Yu et al. (2018)	[116]	Deep temporal-spectral residual network	HF spectrum data from RWTH Aachen University [130]	RMSE	Superior prediction performance compared to benchmarks (SVR, CNN, FC_LSTM, DTS-Resnet-nofusion)	consider additional factors (e.g., time, geographical location, weather) and explore applications in dynamic spectrum access and cognitive radio network
Mehmet Ali Aygül et al. (2021)	[120]	Composite 2D-LSTM Models	Real-world spectrum measurement data. Time, frequency, and space correlations in spectrum measurements provided by a leading mobile network operator in Turkey.	Precision, Recall, F1-score	Superior detection performance with more robustness and less complexity compared to tensor-based methods. Results validated over real-world spectrum measurements in different scenarios	Requires further investigation into the generality of the proposed method and potential scalability
Niranjana Radhakrishnan et al. (2021)	[118]	LSTM	Markov model-based spectrum utilization data	Training convergence, prediction performance	The proposed 'K-N initialization' significantly improves LSTM training convergence for spectrum prediction.	Extension to other input data models for optimal initialization methods, Further exploration of training convergence in different scenarios
Niranjana Radhakrishnan et al. (2021)	[119]	Long Short-Term Memory-Based Markovian Spectrum Prediction	Simulated Markov-model-based spectrum data, Spectrum measurements data	Mixtures of truncated Gaussian distributions, Probability of error, RMSE, MAE.	The predicted scores of the LSTM model are modeled using mixtures of truncated Gaussian distributions. The probability of error is characterized theoretically and compared with observed values over simulated and measured datasets.	Extension to multi-step ahead spectrum prediction, Further exploration of LSTM model performance
Fandi Lin et al. (2021)	[124]	GAN and deep transfer learning	Historical data of similar frequency band	RMSE	The suggested methodologies have the potential to enhance SP performance, particularly in scenarios with limited historical data or when leveraging transfer learning techniques.	validate the framework for real-world deployment and to explore its scalability and generalization to different spectrum scenarios.

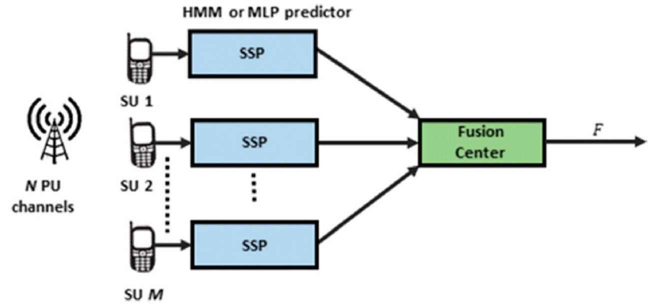


Figure 13. The cooperative spectrum prediction model for pre-fusion [128].

spectrogram data set : This dataset [132] for training machine learning models to perform tasks such as frame detection, classification, and collision detection in RF communications systems. It provides a labeled dataset with a variety of RF frames and their corresponding spectrogram representations.

2D dataset: The authors constructed a 2D dataset [133] by adding noise to the signal post Rayleigh fading channel simulation. The dataset spans an environment with SNR varying from -10 to 4 dB in steps of 1. The signal, received by ten antennas, undergoes computation of the sampling covariance matrix derived from its real and imaginary parts, yielding a matrix size of $10 \times 10 \times 2$. For every SNR, two scenarios are considered: one with both signal and noise, and another with noise alone, each comprising 3000 samples.

MATLAB SpectrumSense Dataset: The dataset created by MATLAB [134],for SS in DL is useful for training deep neural networks to recognize specific signals in a wideband spectrogram. MATLAB provides a comprehensive set of tools for data collecting, DL model training, and signal synthesis. By leveraging trustworthy channel models and signal synthesis, MATLAB makes it easier to generate training data for neural networks to effectively recognize and categorize radar, wireless communication, and other signals in the received spectrum.

Panoradio HF: The RF dataset provided by Panoradio SDR [135] is a robust repository of radio RF signals captured through advanced SDR technology. Engineered for a multitude of applications in RF signal processing, including spectrum analysis, modulation recognition, and signal classification, this dataset offers an extensive array of RF signals spanning diverse frequency bands and communication standards. The RF dataset provided by Panoradio SDR is a robust repository of RF signals captured through advanced SDR technology. Containing 172,800 signal vectors, each vector comprises 2048 complex IQ samples, each possessing distinct attributes such as random frequency offsets, random phase offsets, and a range of SNR values. These SNR values, namely 25, 20, 15, 10, 5, 0, -5, and -10 dB, represent varying levels of signal clarity amidst AWGN, thus simulating a spectrum of real-world signal conditions.

9. Discussion and Future research direction

9.1. DL for Spectrum Sensing: Discussion and Future Directions

The limitations and future works identified in the existing articles for SS based on DL provide valuable insights into the current state of research and the potential areas for improvement. These findings can guide future works and research efforts in the field of CR spectrum management. The identified limitations and future works can be categorized and discussed as follows:

Data Limitations and Generalization Challenges:

The limitations associated with the dataset's performance sensitivity to variable SNR levels and its limited generalization for certain modulation types underscore the necessity for more diverse and representative datasets. Additionally, SS in CRNs demands a substantial amount of annotated data to capture complex channel and emitter characteristics and to train DL algorithms. To overcome these challenges, various approaches have been proposed, such as training data augmentation and domain adaptation using generative adversarial networks (GANs) with DL structures. These approaches are designed to generate synthetic training data, thereby improving classifier accuracy and enabling the adaptation of training data to spectrum dynamics. Notably, the results demonstrate a significant increase in classifier accuracy through training data augmentation, and this improvement is sustained with domain adaptation as spectrum conditions change [136]. Therefore, future research efforts should be directed toward conducting experiments with large-scale real-world signal data collected over the air [81,61]. Moreover, the integration of data augmentation and domain adaptation is crucial to address the identified limitations effectively. For instance, the system [137] effectively incorporates transfer learning approaches to enhance its resilience. These techniques harness additional data for optimizing the learnt models' ability to adapt to new communication settings.

Model Robustness and Latency:

Existing DL algorithms for SS face challenges related to latency and lack of robustness in sensing weak signals over different channel conditions. These challenges arise due to the excessive resource consumption, poor real-time performance, and limited detection accuracy of conventional SS models [138]. To address these issues, researchers should focus on developing DL algorithms that are robust to noise uncertainty, timing delay, and carrier frequency offset. Additionally, efforts should be made to reduce latency in DL-based SS methods. This requires a comprehensive and multifaceted approach, incorporating advancements in algorithm design, training strategies, and system optimization. Researchers are encouraged to explore innovative solutions that not only address the intricacies of real-world, dynamic wireless environments but also significantly elevate the reliability and efficiency of these algorithms. By integrating advancements across these domains, the pursuit of cutting-edge techniques will likely yield substantial improvements, fostering a more resilient and responsive spectrum sensing framework for diverse and challenging wireless scenarios.

Training Efficiency and Adaptability:

The existing DL algorithms for SS face challenges related to complexity. In future research, researchers should concentrate on enhancing training efficiency and adaptability to address these challenges. The search results offer insights into the use of DL for SS, highlighting its potential to improve detection performance and speed. To enhance the efficiency and adaptability of DL algorithms for SS, researchers should explore methods such as developing novel training algorithms, optimizing existing algorithms for faster convergence, and investigating hardware acceleration techniques to expedite the training process. Furthermore, enhancing the adaptability of DL models for SS is crucial. This can be achieved by exploring techniques for domain adaptation, transfer learning, and meta-learning to ensure that the models can effectively handle various modulation types and real-world scenarios.

Practical Implementation and System Integration: The need to explore the implementation of DL models on practical OFDM systems and the investigation of the applicability of pre-trained models to different radio systems highlight the importance of practical implementation and system integration. Future research should focus on improving the methods to handle severe channel quality deterioration and investigating the applicability of pre-trained models to different radio systems for multi-radio integration [139,140].

9.2. DL for Spectrum prediction: Discussion and Future Directions

The limitations and future directions identified in the existing articles for SP based on deep learning provide valuable insights into the current state of research and the potential areas for improvement. These findings can guide future works and research efforts in the field of CR spectrum management. The identified limitations and future works can be categorized and discussed as follows:

Model Architecture and Performance: Efficient and adaptable DL models are needed for SP in CR systems. The need to minimize operating time while improving prediction performance with greater sequence lengths, the absence of validation using real-world channel data, and the higher time and space complexity highlight the importance of developing more efficient and adaptable DL models for SP. DL-based SP methods have attracted extensive attention due to their superior accuracy. There are various DL architectures for SP, such as Composite 2D-LSTM Models, and ConvLSTM [120,23]. The architecture can be reviewed to maximize performance and optimize model architecture and network parameters to further enhance prediction accuracy.

Training Efficiency and Adaptability: The limitations related to longer training times caused by an increase in hidden layers, the need to compare with basic ANN models, and the requirement to explore transfer learning and more efficient training techniques emphasize the importance of developing adaptive and efficient DL models. This includes exploring transfer learning and efficient training techniques to improve the adaptability and efficiency of DL models for SP. Various strategies, including data-centric, model-centric, optimization-centric approaches, budgeted training, and system-centric approaches, have been investigated to hasten training and enhance efficiency [141]. Additionally, techniques like Neural Architecture Search (NAS), Hyper Parameters Optimization (HPO), and Data Augmentation have been shown to enhance the performance of deep neural networks under limited resources [142]. Furthermore, frameworks like DeepSpeed Data Efficiency have been proposed to make better use of data, increase training efficiency, and improve model quality by combining novel data efficiency techniques [143,144]. These advancements in training efficiency and adaptability contribute to the development of more effective deep learning models for spectrum prediction.

Generalization and Multi-step Ahead Prediction: The need to generalize the method to various frequency bands, explore extension to multi-step ahead spectrum prediction, and further explore the LSTM model performance highlights the importance of developing more robust and adaptable deep learning models for spectrum prediction. This includes exploring other input data models for optimal initialization methods and further exploring training convergence in different scenarios [145].

9.3. Integrating Spectrum Sensing and Prediction in Cognitive Radio Networks

CSP and sensing for CR is a key aspect of dynamic spectrum access, offering several advantages. Spectrum prediction enables CR to anticipate future spectrum availability, while sensing provides real-time information about current spectrum occupancy. By integrating these approaches, CRs can optimize their spectrum access strategies for both current and future conditions, leading to improved overall efficiency. SP can be particularly useful in scenarios where real-time sensing is challenging or impractical. For instance, predicting spectrum availability in advance allows CRs to plan their activities and reduce the need for frequent SS, which can be resource-intensive [146]. Furthermore, the combination of SP and sensing can lead to reduced sensing burden. Continuous spectrum sensing can be energy-consuming and may lead to increased overhead. By incorporating SP, cognitive radios can minimize the frequency of sensing operations, focusing on critical times when predictions might be less accurate or when real-time information is essential [147]. In addition, predictions and sensing can complement each other to enhance reliability. For example, if there is uncertainty in prediction due to dynamic changes, real-time sensing can provide accurate information to make more informed decisions [148]. Overall, the integration of SP and sensing enables dynamic spectrum management, allowing CRs to adapt to changing network conditions, interference scenarios, and user requirements in a more responsive and intelligent manner [149].

investigate innovative prediction approaches, and perform real-world tests to confirm the feasibility and adaptability of the integrated SP and sensing strategy. Practical implementations and validations across a variety of scenarios will be critical in determining the feasibility of this paradigm in real-world CRNs. This comprehensive and collaborative strategy is poised to play a critical role in the growth of dynamic spectrum management, ushering in a new era of adaptability and efficiency for CR systems.

9.4. Deep Reinforcement Learning (DRL) for Spectrum Sensing and Prediction in Cognitive Radio: Discussion and Future Directions

Reinforcement learning (RL) is an area of ML where an agent learns how to act in an environment in order to maximize some notion of accumulated reward. The agent learns a policy, which represents a mapping from states to actions, with the goal of maximizing the total reward over time. The agent must learn to interact with an environment: the agent takes an action, the environment changes state, and the agent receives some feedback. This feedback consists of a reward signal that informs the agent of the implications of its action choice. The agent's goal is to maximize the total reward by selecting actions that reach a goal state or achieve some tasks. In other words, the agent must determine an optimal policy that maximizes long-term rewards by trial and error, without the expectation of an immediate reward [150].

In DRL, the agent learns to balance exploration (trying new actions to discover better strategies) and exploitation (making the best decisions based on what it has already learned). This balance is crucial in spectrum sensing, where the agent must explore different channels to identify the best ones for communication, while also exploiting known spectrum opportunities to maintain efficient transmissions [131]. While traditional DL excels at pattern recognition and feature extraction from large datasets, DRL extends this capability by incorporating decision-making processes. This integration allows DRL to not only recognize patterns but also to make optimal decisions based on those patterns in real-time. In CRNs, the spectrum environment is highly dynamic, with varying levels of interference and availability. DRL algorithms can learn to adapt their strategies in real-time, enabling them to select the best channels for transmission based on current conditions [132]. DRL can be extended to multi-agent systems, where multiple cognitive radios or agents work together to sense and access the spectrum. DRL allows these agents to learn cooperative strategies to maximize overall spectrum utilization while minimizing interference. This is particularly useful in scenarios where multiple users are sharing the same spectrum [133]. Furthermore, DRL excels at optimizing long-term rewards rather than focusing only on immediate outcomes. In spectrum sensing and prediction, this is important because actions taken now (e.g., selecting a specific channel) can impact future spectrum availability or the quality of communication. DRL can evaluate the consequences of its actions over time and adjust accordingly to maximize spectrum efficiency [134]. In addition to handling noisy or imperfect information about the spectrum environment, DRL models may function efficiently in uncertain environments. In real-world situations, when complete spectrum knowledge is frequently unavailable, they can, for example, base their choices on incomplete observations of the radio environment [135].

In summary, DRL has a lot of promise for spectrum sensing and prediction tasks in the future, especially in dynamic contexts where decisions need to take long-term outcomes and current observations into account. In light of this, it is particularly useful in CRNs, where effective spectrum management is essential.

10. Conclusions

In conclusion, spectrum sensing and prediction are crucial approaches in cognitive radio, as they improve spectrum usage efficiency and support the rational and effective deployment of spectrum resources. These methods have high research value and strong application potential in wireless communications. This study provides an overview of the system models that implement spectrum prediction and sensing algorithms. Neural network-based DL approaches have demonstrated remarkable success in SS and SP tasks, outperforming other conventional SS techniques and ML techniques. However, there are still challenges, such as the limited training data and hyperparameter fine-tuning, facing the DL-based acoustic event detection. Future research should focus on addressing these challenges and further exploring the potential of DL in CR spectrum management. This includes developing more robust and efficient deep learning models, expanding the available training data, and fine-tuning hyperparameters to improve the performance of DL-based spectrum and prediction systems.

Notes on contributors

Noureddine El-Haryqy is a researcher who graduated in 2021 with a master's degree in embedded electronics from the Faculty of Science at Ibn Tofail University in Kenitra, Morocco. His PhD research is focused on the application of artificial intelligence for dynamic spectrum management. Located in the Department of Electrical and Telecommunications at the National School of Applied Sciences, Ibn Tofail University, Kenitra, Morocco.

Zhour Madini received her Master of Engineering degree from the Optical and Microwave Communications Research Institute, Limoges France. She received her Ph.D degree from University of Limoges in High Frequency Telecommunications and Optic in 2008. She is now an assistant-professor in Electronics and Telecommunications at National School of Applied Sciences of kenitra. Her current research interests include electronic devices, digital signal processing for communications, fiber-optic communication systems and cognitive radio technology.

Younes Zouine received his Master of Engineering degree from the National School of Engineers of Limoges (ENSIL) in 2002. He received his Ph.D in High Frequency Telecommunications and Optics from the University of Limoges in 2005. He joined the National School of Applied Sciences of kenitra, Ibn Tofail University, as Professor of Electronics and Telecommunications. His current research interests deal with digital signal processing for communications and especially with theory and implementation of signal processing for Optical systems.

ORCID

Noureddine El-haryqy http://orcid.org/0009-0002-8837-2935
Zhour Madini http://orcid.org/0000-0002-5684-4005
Younes Zouine http://orcid.org/0000-0002-3023-8453

References

[1] Kolodzy P, Avoidance I. Spectrum policy task force. Federal Commun Comm. 2002;40(4):147–158.
[2] 'Cognitive radio: making software radios more personal | IEEE Journals & Magazine | IEEE Xplore' [accessed 2023 Oct. 24. Available from https://ieeexplore.ieee.org/abstract/document/788210
[3] Captain KM, Joshi MV. Spectrum sensing for cognitive radio: fundamentals and applications. Boca Raton: CRC Press; 2021. doi:10.1201/9781003088554
[4] Ding G, et al. Spectrum inference in cognitive radio networks: algorithms and applications. IEEE Commun Surv Tutorials. 2018;20(1):150–182. doi:10.1109/COMST.2017.2751058
[5] Yu L, Chen J, Ding G, et al. Spectrum prediction based on taguchi method in deep learning With long short-term memory. IEEE Access. 2018;6:45923–45933. doi:10.1109/ACCESS.2018.2864222
[6] Xing X, Jing T, Huo Y, et al. Channel quality prediction based on Bayesian inference in cognitive radio networks. 2013 Proceedings IEEE INFOCOM, April 2013: 1465–1473. doi:10.1109/INFCOM.2013.6566941
[7] Saleem Y, Rehmani MH, Zeadally S. Integration of cognitive radio technology with unmanned aerial vehicles: issues, opportunities, and future research challenges. J Netw Comput Appl. 2015;50:15–31. doi:10.1016/j.jnca.2014.12.002
[8] Macdonald S, Popescu DC, Popescu O. A hybrid framework for spectrum sharing in cognitive radio systems With dynamic users. IEEE Commun Lett. 2019;23(10):1871–1874. doi:10.1109/LCOMM.2019.2926461
[9] Preetha K, Kalaivani S. Analysis of spectrum handoff schemes for cognitive radio networks considering secondary user mobility. Int J Grid Util Comput. 2020;11(4):443–456. doi:10.1504/IJGUC.2020.108448
[10] Godugu KK, Nallagonda AK, Nallagonda S. Performance of energy-efficient cooperative cognitive radio system over erroneous Nakagami-m and Weibull fading channels. Wireless Netw. 2020;26(4):2623–2638. doi:10.1007/s11276-019-02018-2
[11] Atawi IE, Badarneh OS, Aloqlah MS, et al. Spectrum-sensing in cognitive radio networks over composite multipath/shadowed fading channels. Comput Electr Eng. 2016;52:337–348. doi:10.1016/j.compeleceng.2015.12.014
[12] An energy detection-based spectrum-sensing method for cognitive radio. [accessed 2024 Jan. 08]. Available from https://www.hindawi.com/journals/wcmc/2022/3933336/
[13] Okegbile SD, Maharaj BT, Alfa AS. Stochastic geometry approach towards interference management and control in cognitive radio network: a survey. Comput Commun. 2021;166:174–195. doi:10.1016/j.comcom.2020.12.011
[14] Salahdine F, Kaabouch N. Security threats, detection, and countermeasures for physical layer in cognitive radio networks: a survey. Physical Communication. 2020;39:101001. doi:10.1016/j.phycom.2020.101001
[15] 'Spectrum sensing challenges & their solutions in cognitive radio based vehicular networks - Hossain - 2021 - International Journal of Communication Systems - Wiley Online Library'. Available at https://onlinelibrary.wiley.com/doi/abs/10.1002dac.4748
[16] Yao Q, et al. Taking Human out of Learning Applications: A Survey on Automated Machine Learning', 2019, *arXiv*: arXiv:1810.13306. doi:10.48550/arXiv.1810.13306
[17] Selmy HA, Mohamed HK, Medhat W. Big data analytics deep learning techniques and applications: a survey. Inf Syst. 2024;120:102318. doi:10.1016/j.is.2023.102318
[18] Dargan S, Kumar M, Ayyagari MR, et al. A survey of deep learning and Its applications: a New paradigm to machine learning. Arch Computat Methods Eng. 2020;27(4):1071–1092. doi:10.1007/s11831-019-09344-w
[19] Xie J, Fang J, Liu C, et al. Deep learning-based spectrum sensing in cognitive radio: a CNN-LSTM approach. IEEE Commun Lett. 2020;24(10):2196–2200. doi:10.1109/LCOMM.2020.3002073
[20] Hlophe MC. *A model-based deep learning approach to spectrum management in distributed cognitive radio net*works [thesis, University of Pretoria], 2020. Accessed Jan. 08, 2024. [Online]. Available: https://repository.up.ac.za/handle/2263/75644.
[21] Goyal SB, Bedi P, Kumar J, et al. Deep learning application for sensing available spectrum for cognitive radio: an ECRNN approach'. Peer-to-Peer Netw. Appl. 2021;14(5):3235–3249. doi:10.1007/s12083-021-01169-4

[22] Tang Z, Li S. Deep recurrent neural network for multiple time slot frequency spectrum predictions of cognitive radio. KSII Transactions on Internet and Information Systems. 2017;11(6):3029–3045.
[23] Shawel BS, Woldegebreal DH, Pollin S. Convolutional LSTM-based long-term spectrum prediction for dynamic spectrum access. 2019 27th European Signal Processing Conference (EUSIPCO). 2019: 1–5. doi:10.23919/EUSIPCO.2019.8902956
[24] Li L, Xie W, Zhou X. Cooperative spectrum sensing based on LSTM-CNN combination network in cognitive radio system. IEEE Access. 2023;11:87615–87625. doi:10.1109/ACCESS.2023.3305483
[25] Arjoune Y, Kaabouch N. A comprehensive survey on spectrum sensing in cognitive radio networks: recent advances, New challenges, and future research directions. Sensors. 2019;19(1):126. doi:10.3390/s19010126
[26] 'An overview of deep reinforcement learning for spectrum sensing in cognitive radio networks - ScienceDirect' [accessed 2023 Aug 23]. Available from: https://www.sciencedirect.com/science/article/abs/pii/S1051200421000531
[27] Khamayseh S, Halawani A. Cooperative spectrum sensing in cognitive radio networks: a survey on machine learning-based methods, 2020 [accessed 2024 February 04]. Available from http://scholar.ppu.edu/handle/123456789/8086.
[28] 'Machine learning for cooperative spectrum sensing and sharing: a survey - Janu - 2022 - transactions on emerging telecommunications technologies - Wiley Online Library' [accessed 2024 Feb 04]. Available from : https://onlinelibrary.wiley.com/doi/abs/10.1002ett.4352
[29] Syed SN, et al. Deep neural networks for spectrum sensing: a review. IEEE Access. 2023;11:89591–89615. doi:10.1109/ACCESS.2023.3305388
[30] Zhang Y, Luo Z. A review of research on spectrum sensing based on deep learning. Electronics (Basel). 2023;12(21):4514. doi:10.3390/electronics12214514
[31] Lee W, Akyildiz IF. Optimal spectrum sensing framework for cognitive radio networks. IEEE Trans Wireless Commun. 2008;7(10):3845–3857. doi:10.1109/T-WC.2008.070391
[32] 'Spectrum sensing for cognitive radio: fundamentals and applications', Routledge & CRC Press. [accessed 2023 Mar 24]. Available from https://www.routledge.com/Spectrum-Sensing-for-Cognitive-Radio-Fundamentals-and-Applications/Captain-Joshi/p/book/9780367542931
[33] Lunden J, Koivunen V, Huttunen A, et al. Collaborative cyclostationary spectrum sensing for cognitive radio systems. IEEE Trans Signal Process. 2009;57(11):4182–4195. doi:10.1109/TSP.2009.2025152
[34] Zhao Y, Paul P, Xin C, et al. Performance analysis of spectrum sensing with mobile SUs in cognitive radio networks. 2014 *IEEE International Conference on Communications (ICC)*. 2014: 2761–2766. doi:10.1109/ICC.2014.6883742
[35] Nallagonda S, Bhowmick A, Prasad B. Throughput performance of cooperative spectrum sensing network with improved energy detectors and SC diversity over fading channels. Wireless Netw. 2021;27(6):4039–4050. doi:10.1007/s11276-021-02685-0
[36] Yucek T, Arslan H. A survey of spectrum sensing algorithms for cognitive radio applications. IEEE Commun Surv Tutorials. 2009;11(1):116–130. doi:10.1109/SURV.2009.090109
[37] Riyahi A, Bah S, Sebgui M, et al. Classification and analysis of spectrum sensing mechanisms in cognitive vehicular networks. EAI Endorsed Transactions on Smart Cities. 2018;3(7):e4. https://eudl.eu/doi/10.4108eai.12-2-2018.154105
[38] S. Dikmese, J. L. Wong, A. Gokceoglu, E. Guzzon, M. Valkama, and M. Renfors, 'Reducing computational complexity of eigenvalue based spectrum sensing for cognitive radio', *8th International Conference on Cognitive Radio Oriented Wireless Networks*, Jul. 2013, pp. 61–67. doi:10.1109/CROWNCom.2013.6636795
[39] Muzaffar MU, Sharqi R. A review of spectrum sensing in modern cognitive radio networks. Telecommun Syst. 2023;85(2):347–363. doi:10.1007/s11235-023-01079-1
[40] Balam SK, Siddaiah P, Nallagonda S. Optimization analysis of cooperative spectrum sensing system over generalized $\kappa - \mu$ and $\eta - \mu$ fading channels. Wireless Pers Commun. 2021;116(4):3081–3100. doi:10.1007/s11277-020-07836-8
[41] Nallagonda S, Mamidi R, Bhowmick A. Analysis of energy-efficient cooperative spectrum sensing with improved energy detectors and multiple antennas over Nakagami-/ fading channels. Int J Commun Syst. 2021;34(5):e4731. doi:10.1002/dac.4731
[42] 'Optimized cooperative spectrum sensing network analysis in nonfading and fading environments - Ranjeeth - 2020 - International Journal of Communication Systems - Wiley Online Library' [accessed 2024 Sep. 17]. Available from https://onlinelibrary.wiley.com/doi/abs/10.1002dac.4262
[43] Akyildiz I, Lo B, Balakrishnan R. Cooperative spectrum sensing in cognitive radio networks: a survey. Physical Communication. 2011;4:40–62. doi:10.1016/j.phycom.2010.12.003
[44] Alvi SA, Younis MS, Imran M. A weighted linear combining scheme for cooperative spectrum sensing. Procedia Comput Sci. 2014;32: 149–157.
[45] Borota D, Ivkovic G, Vuyyuru R. On the delay to reliably detect channel availability in cooperative vehicular environments. In: 2011 IEEE 73rd Vehicular Technology Conference (VTC Spring); 2011. pp. 1–5. doi:10.1109/VETECS.2011.5956717
[46] Mikaeil AM, Guo B, Wang Z, et al. Machine learning to data fusion approach for cooperative spectrum sensing. In: 2014 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery; 2014. p. 429–434. doi:10.1109/CyberC.2014.80
[47] Li H, Irick DK. 'Collaborative spectrum sensing in cognitive radio vehicular ad hoc networks: belief propagation on highway', 2010 *IEEE 71st Vehicular Technology Conference*, 2010, pp. 1–5. doi:10.1109/VETECS.2010.5494005
[48] Wei Z, Yu FR, Boukerche A. 'Cooperative spectrum sensing with trust assistance for cognitive radio vehicular ad hoc networks', *Proceedings of the 5th ACM Symposium on Development and Analysis of Intelligent Vehicular Networks and Applications*, in DIVANet '15. New York, NY, USA: Association for Computing Machinery, Nov. 2015, pp. 27–33. doi:10.1145/2815347.2815350
[49] 'A novel relay-aided centralized cooperative spectrum sensing scheme using radio frequency energy harvesting - Majumdar - 2023 - International Journal of Communication Systems - Wiley Online Library'. [accessed 2024 Feb 19]. Available from https://onlinelibrary.wiley.com/doi/abs/10.1002dac.5356
[50] Sahu AK, Mahapatro A, Patra R. 'Relay assisted spectrum sensing in presence of in-phase and quadrature-phase imbalance in multi-channel system', 2023 *International Conference on Microwave, Optical, and Communication Engineering (ICMOCE)*, 2023, pp. 1–4. doi:10.1109/ICMOCE57812.2023.10166060
[51] '[1511.08458] An introduction to convolutional neural networks [accessed 2023 October 23]. Available from: https://arxiv.org/abs/1511.08458
[52] Rhee EJ. A deep learning approach for classification of cloud image patches on small datasets. Journal of Information and Communication Convergence Engineering. 2018;16(3):173–178.
[53] Akhtar N, Ragavendran U. Interpretation of intelligence in CNN-pooling processes: a methodological survey. Neural Comput & Applic. 2020;32(3):879–898. doi:10.1007/s00521-019-04296-5
[54] Hopfield JJ. Neural networks and physical systems with emergent collective computational abilities. Proc Natl Acad Sci USA. 1982;79(8):2554–2558. doi:10.1073/pnas.79.8.2554
[55] Gamboa JCB. Deep learning for time-series analysis, Jan. 07, 2017, *arXiv*: arXiv:1701.01887. doi:10.48550/arXiv.1701.01887
[56] Li H. Deep learning for natural language processing: advantages and challenges. Natl Sci Rev. 2018;5(1):24–26. doi:10.1093/nsr/nwx110
[57] Graves A, Jaitly N. Towards end-to-end speech recognition with recurrent neural networks, Proceedings of the 31st International Conference on Machine Learning, PMLR, Jun. 2014, pp. 1764–1772 [accessed 2023 Oct 24]. Available from https://proceedings.mlr.press/v32/graves14.html.
[58] Hochreiter S, Schmidhuber J. Long short-term memory. Neural Comput. 1997;9(8):1735–1780. doi:10.1162/neco.1997.9.8.1735
[59] Rengasamy D, Jafari M, Rothwell B, et al. Deep learning with dynamically weighted loss function for sensor-based prognostics and health management. Sensors. 2020;20(3):723. doi:10.3390/s20030723
[60] Spectrum sensing in cognitive radio: a deep learning based model - Xing - 2022 - transactions on emerging telecommunications technologies - Wiley Online Library'. [accessed 2024 Sep. 21]. Available from https://onlinelibrary.wiley.com/doi/abs/10.1002ett.4388
[61] Deep learning for spectrum sensing. [accessed 2023 Sep. 26]. Available from https://ieeexplore.ieee.org/abstract/document/8824091/
[62] Blind detection techniques for non-cooperative communication signals based on deep learning | IEEE Journals & Magazine | IEEE Xplore. [accessed 2023 Sep. 30]. Available from https://ieeexplore.ieee.org/abstract/document/8753512
[63] Liu R, Ma Y, Zhang X, et al. Deep learning-based spectrum sensing in space-Air-ground integrated networks. Journal of Communications and Information Networks. 2021;6(1):82–90. doi:10.23919/JCIN.2021.9387707
[64] Spectrum sensing based on deep learning classification for cognitive radios [accessed 2023 Sep. 26 Online]. Available from : https://ieeexplore.ieee.org/abstract/document/9020304/
[65] Xie J, Fang J, Liu C, et al. Unsupervised deep spectrum sensing: A variational auto-encoder based approach. IEEE Trans Veh Technol. 2020;69(5):5307–5319. doi:10.1109/TVT.2020.2982203
[66] Cheng Q, Shi Z, Yuan J. Spectrum sensing in full-duplex OFDM systems using one-shot learning. in *ICC 2021 - IEEE international conference on communications*. 2021: 1–6. doi:10.1109/ICC42927.2021.9500575

[67] Z. Sabrina, T. Camel, T. Djamal M., et al. Spectrum sensing based on an improved deep learning classification for cognitive radio, 2022 *International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, Nov. 2022, pp. 1–5. doi:10.1109/ICECCME55909.2022.9987999
[68] Ouamna H, Madini Z, Zouine Y. Deep learning applied for spectrum sensing. Lecture Notes in Networks and Systems. 2023;465:787–797. doi:10.1007/978-981-19-2397-5_70
[69] Chen Z, Xu Y-Q, Wang H, et al. Deep STFT-CNN for spectrum sensing in cognitive radio. IEEE Commun Lett. 2021;25(3):864–868. doi:10.1109/LCOMM.2020.3037273
[70] Cheng Q, Shi Z, Nguyen DN, et al. Non-cooperative OFDM spectrum sensing using deep learning, 2020 *International Conference on Computing, Networking and Communications (ICNC)*, 2020, pp. 704–708. doi:10.1109/ICNC47757.2020.9049678
[71] Pati BM, Kaneko M, Taparugssanagorn A. A deep convolutional neural network based transfer learning method for Non-cooperative spectrum sensing. IEEE Access. 2020;8:164529–164545. doi:10.1109/ACCESS.2020.3022513
[72] Liu C, Wang J, Liu X, et al. Deep CM-CNN for spectrum sensing in cognitive radio. IEEE J Sel Areas Commun. 2019;37(10):2306–2321. doi:10.1109/JSAC.2019.2933892
[73] Vyas MR, Patel DK, Lopez-Benitez M. Artificial neural network based hybrid spectrum sensing scheme for cognitive radio, 2017 *IEEE 28*th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), October. 2017, pp. 1–7. doi:10.1109/PIMRC.2017.8292449
[74] O'Shea TJ, West N. Radio machine learning dataset generation with gnu radio, Proceedings of the GNU Radio Conference, vol. 1, no. 1, Art. no. 1, Sep. 2016, [accessed 2023 Oct. 30]. Available from https://pubs.gnuradio.org/index.php/grcon/article/view/11.
[75] Yang K, Huang Z, Wang X, et al. A blind spectrum sensing method based on deep learning. Sensors. 2019;19(10):2270. doi:10.3390/s19102270
[76] Pan G, Li J, Lin F. A cognitive radio spectrum sensing method for an OFDM signal based on deep learning and cycle spectrum. International Journal of Digital Multimedia Broadcasting. 2020;2020:e5069021. doi:10.1155/2020/5069021
[77] Cheng Q, Shi Z, Nguyen DN, et al. Sensing OFDM signal: A deep learning approach. IEEE Trans Commun. 2019;67(11):7785–7798. doi:10.1109/TCOMM.2019.2940013
[78] M. Xu, Z. Yin, M. Wu, Z. Wu, Y. Zhao, and Z. Gao, Spectrum sensing based on parallel CNN-LSTM Network, 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), May 2020, pp. 1–5. doi:10.1109/VTC2020-Spring48590.2020.9129229
[79] Patel DK, López-Benítez M, Soni B, et al. Artificial neural network design for improved spectrum sensing in cognitive radio. Wireless Netw. 2020;26(8):6155–6174. doi:10.1007/s11276-020-02423-y
[80] D. Hanet al., Spectrum sensing for cognitive radio based on convolution neural network, 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Oct. 2017, pp. 1–6. doi:10.1109/CISP-BMEI.2017.8302117
[81] Solanki S, Dehalwar V, Choudhary J. Deep learning for spectrum sensing in cognitive radio. Symmetry (Basel). 2021;13(1):147. doi:10.3390/sym13010147
[82] Xing H, Qin H, Luo S, et al. Spectrum sensing in cognitive radio: A deep learning based model. Transactions on Emerging Telecommunications Technologies. 2022;33(1):e4388. doi:10.1002/ett.4388
[83] QinHaoXiang1996, Dataset Generation for DL based Spectrum Sensing. (2023). Python. [accessed 2023 October 30]. Available from https://github.com/QinHaoXiang1996/Dataset-Generation-for-DL-based-Spectrum-Sensing.
[84] O'Shea TJ, Corgan J, Clancy TC. Convolutional radio modulation recognition networks. In: C Jayne, L Iliadis, editor. *Engineering applications of neural networks*. Cham: Springer International Publishing; 2016. p. 213–226. doi:10.1007/978-3-319-44188-7_16
[85] Solanki S, Dehalwar V, Choudhary J, et al. Spectrum sensing in cognitive radio using CNN-RNN and transfer learning. IEEE Access. 2022;10:113482–113492. doi:10.1109/ACCESS.2022.3216877
[86] Chandhok S, Joshi H, Subramanyam AV, et al. Novel deep learning framework for wideband spectrum characterization at sub-nyquist rate. Wireless Netw. 2021;27(7):4727–4746. doi:10.1007/s11276-021-02765-1
[87] El-Haryqy N, Madini Z, Zouine Y, et al. A survey on automatic signal detection using deep learning, 2023 9th International Conference on Optimization and Applications (ICOA), 2023, pp. 1–6. doi:10.1109/ICOA58279.2023.10308833
[88] Liu M, Zhang H, Liu Z, et al. Attacking spectrum sensing With adversarial deep learning in cognitive radio-enabled internet of things. IEEE Trans Reliab. 2023;72(2):431–444. doi:10.1109/TR.2022.3179491
[89] Chew D, Cooper AB. Spectrum sensing in interference and noise using deep learning, 2020 *54th* Annual Conference on Information Sciences and Systems (CISS), Mar. 2020, pp. 1–6. doi:10.1109/CISS48834.2020.1570617443
[90] Xie X, Peng S, Yang X. Deep learning-based signal-To-noise ratio estimation using constellation diagrams. Mobile Information Systems. 2020;2020:e8840340. doi:10.1155/2020/8840340
[91] Su Z, Teh KC, Razul SG, et al. Deep Non-cooperative spectrum sensing over Rayleigh fading channel. IEEE Trans Veh Technol. 2022;71(4):4460–4464. doi:10.1109/TVT.2021.3138593
[92] Muthukumar PB, B S, Gurugopinath S. Deep learning techniques for cooperative spectrum sensing under generalized fading channels', 2022 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), 2022, pp. 183–188. doi:10.1109/WiSPNET54241.2022.9767160
[93] Baldini G, Bonavitacola F. Fading channel classification based on convolutional neural network with general linear chirplet transform', 2023 17th European Conference on Antennas and Propagation (EuCAP), Mar. 2023, pp. 1–5. doi:10.23919/EuCAP57121.2023.10133651
[94] Tekbıyık K, Akbunar Ö, Ekti AR, et al. Spectrum sensing and signal identification With deep learning based on spectral correlation function. IEEE Trans Veh Technol. 2021;70(10):10514–10527. doi:10.1109/TVT.2021.3109236
[95] K D, S V. An effective spectrum sensing in cognitive radio networks using improved convolution neural network by glow worm swarm algorithm. Transactions on Emerging Telecommunications Technologies. 2021;32(11):e4328. doi:10.1002/ett.4328
[96] Cui Y, jun Jing X, Sun S, et al. Deep learning based primary user classification in cognitive radios, 2015 *15th International Symposium on Communications and Information Technologies (ISCIT)*, October 2015, pp. 165–168. doi:10.1109/ISCIT.2015.7458333
[97] Soni B, Patel DK, López-Benítez M. Long short-term memory based spectrum sensing scheme for cognitive radio using primary activity statistics. IEEE Access. 2020;8:97437–97451. doi:10.1109/ACCESS.2020.2995633
[98] 'EBSCOhost | 151224257 | improved convolutional neural network based cooperative spectrum sensing for cognitive radio.' Accessed Mar. 26, 2023. Available from https://web.p.ebscohost.com/abstract?direct = true&profile = ehost&scope = site&authtype = crawler&jrnl = 19767277&AN = 151224257&h = 4cJcRF0WgMVizQiN390FFM6nCqpoNd8jsPhL3F19nU5OuBtJ%2f%2f8QBYIdjdxdITnWBO8cvoamW8J9ElvIrh2eiw%3d%3d&crl = c&resultNs = AdminWebAuth&resultLocal = ErrCrlNotAuth&crlhashurl = login.aspx%3fdirect%3dtrue%26profile%3dehost%26scope%3dsite%26authtype%3dcrawler%26jrnl%3d19767277%26AN%3d151224257
[99] Jung T-Y, Jeong E-R. Spectrum sensing based on deep learning to increase spectrum utilization. Turk J Comput Math Educ. 2021;12(6):538. doi:10.17762/turcomat.v12i6.1971
[100] Chae K, Kim Y. DS2MA: a deep learning-based spectrum sensing scheme for a multi-antenna receiver. IEEE Wireless Communications Letters. 2023;12(6):952–956. doi:10.1109/LWC.2023.3250257
[101] Nallagonda S, Bhowmick A, Prasad B. On selection of parameters for cooperative spectrum sensing schemes over κ–μ fading channels. IETE J Res. 2023;69(11):7684–7694. doi:10.1080/03772063.2022.2038700
[102] 'Improved whale optimization algorithm and convolutional neural network based cooperative spectrum sensing in cognitive radio networks: information security journal: a global perspective: Vol 30, No 3'. Accessed Oct. 11, 2023. Available: https://www.tandfonline.com/doi/abs/10.108019393555.2020.1825882
[103] H. Liu, X. Zhu, and T. Fujii, ensemble deep learning based cooperative spectrum sensing with stacking fusion center, 2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), Nov. 2018, pp. 1841–1846. doi:10.23919/APSIPA.2018.8659774
[104] H. Liu, X. Zhu, and T. Fujii, Ensemble deep learning based cooperative spectrum sensing with semi-soft stacking fusion center, 2019 IEEE wireless communications and networking conference (WCNC), Apr. 2019, pp. 1–6. doi:10.1109/WCNC.2019.8885866
[105] Lee W, Kim M, Cho D-H. Deep cooperative sensing: cooperative spectrum sensing based on convolutional neural networks. IEEE Trans Veh Technol. 2019;68(3):3005–3009. doi:10.1109/TVT.2019.2891291
[106] Nallagonda S. Spectrum sensing performance of wireless cognitive radio sensor network with hard-decision fusion over generalized $\alpha-\mu$ fading channels. Int J Commun Syst. 2023;36(10):e5498. doi:10.1002/dac.5498
[107] Deep learning based energy efficiency optimization for distributed cooperative spectrum sensing | IEEE Journals & Magazine | IEEE Xplore'. Accessed Oct. 13, 2023. Available from https://ieeexplore.ieee.org/abstract/document/8752480

[108] Benazzouza S, Ridouani M, Salahdine F, et al. A novel prediction model for malicious users detection and spectrum sensing based on stacking and deep learning. Sensors. 2022;22(17):6477. doi:10.3390/s22176477
[109] P. Shachi, K. R. Sudhindra, and M. N. Suma, Convolutional neural network for cooperative spectrum sensing with spatio-temporal dataset, 2020 international conference on Artificial Intelligence And Signal Processing (AISP), Jan. 2020, pp. 1–5. doi:10.1109/AISP48273.2020.9073175
[110] S. P, K. R. Sudhindra, and S. M. N, 'Deep Learning for Cooperative Spectrum Sensing', 2020 *2nd PhD Colloquium on Ethically Driven Innovation and Technology for Society (PhD EDITS)*, Nov. 2020, pp. 1–2. doi:10.1109/PhDEDITS51180.2020.9315306
[111] Lu L, Li X, Wang G, et al. Multiband cooperative spectrum sensing meets vehicular network: relying on CNN-LSTM approach. Wirel Commun Mob Comput. 2023;2023:e4352786. doi:10.1155/2023/4352786
[112] O. Omotere, J. Fuller, L. Qian, and Z. Han, Spectrum occupancy prediction in coexisting wireless systems using deep learning, 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall), Aug. 2018, pp. 1–7. doi:10.1109/VTCFall.2018.8690575
[113] Wang X, Chen Q, Yu X. Research on spectrum prediction technology based on B-LTF. Electronics (Basel). 2023;12(1):247. doi:10.3390/electronics12010247
[114] Yu L, Wang Q, Guo Y, et al. Spectrum availability prediction in cognitive aerospace communications: A deep learning perspective. In: 2017 Cognitive Communications for Aerospace Applications Workshop (CCAA); 2017. p. 1–4. doi:10.1109/CCAAW.2017.8001877
[115] Yu L, Chen J, Ding G. 'Spectrum prediction via long short term memory', 2017 3rd IEEE International Conference on Computer and Communications (ICCC), Dec. 2017, pp. 643–647. doi:10.1109/CompComm.2017.8322623
[116] Yu L, Chen J, Zhang Y, et al. Deep spectrum prediction in high frequency communication based on temporal-spectral residual network. China Commun. 2018;15(9):25–34. doi:10.1109/CC.2018.8456449
[117] Gao Y, Zhao C, Fu N. 'Joint multi-channel multi-step spectrum prediction algorithm', 2021 IEEE 94th Vehicular Technology Conference (VTC2021-Fall), Sep. 2021, pp. 1–5.
[118] Radhakrishnan N, Kandeepan S. An improved initialization method for fast learning in long short-term memory-based markovian spectrum prediction. IEEE Transactions on Cognitive Communications and Networking. 2021;7(3):729–738. doi:10.1109/TCCN.2020.3046330
[119] Radhakrishnan N, Kandeepan S, Yu X, et al. Performance analysis of long short-term memory-based markovian spectrum prediction. IEEE Access. 2021;9:149582–149595. doi:10.1109/ACCESS.2021.3125725
[120] M. A. Aygül, M. Nazzal, M. İ. Sağlam, et al. Efficient spectrum occupancy prediction exploiting multidimensional correlations through composite 2D-LSTM Models. Sensors. 2021;21(1):135. doi:10.3390/s21010135
[121] X. Li, Z. Liu, G. Chen, Y. Xu, and T. Song, 'Deep learning for spectrum prediction from spatial–temporal–spectral Data', *IEEE Commun Lett*, vol. 25, no. 4, pp. 1216–1220, Apr. 2021
[122] Pan G, Wu Q, Ding G, et al. An autoformer-CSA approach for long-term spectrum prediction. IEEE Wireless Communications Letters. 2023;12(10):1647–1651. doi:10.1109/LWC.2023.3243117
[123] X. Meng, H. Inaltekin, and B. Krongold, End-to-end deep learning-based compressive spectrum sensing in cognitive radio networks, *ICC 2020–2*020 IEEE International Conference on Communications (ICC), June 2020, pp. 1–6. doi:10.1109/ICC40277.2020.9149195
[124] Lin F, Chen J, Ding G, et al. Spectrum prediction based on GAN and deep transfer learning: A cross-band data augmentation framework. China Commun. 2021;18(1):18–32. doi:10.23919/JCC.2021.01.002
[125] Shaghluf N, Gulliver TA. Spectrum and energy efficiency of cooperative spectrum prediction in cognitive radio networks. Wireless Netw. 2019;25(6):3265–3274. doi:10.1007/s11276-018-1720-5
[126] B. S. Shawel, D. Hailemariam Woledegebre, and S. Pollin, 'Deep-learning based Cooperative Spectrum Prediction for Cognitive Networks', 2018 *International Conference on Information and Communication Technology Convergence (ICTC)*, Oct. 2018, pp. 133–137. doi:10.1109/ICTC.2018.8539570
[127] N. Radhakrishnan, S. Kandeepan, X. Yu, and G. Baldini, Soft fusion based cooperative spectrum prediction using LSTM, 2021 *15th International Conference On Signal Processing And Communication Systems* (ICSPCS), Dec. 2021, pp. 1–7. doi:10.1109/ICSPCS53099.2021.9660229
[128] Chauhan P, Deka SK, Chatterjee BC, et al. Cooperative spectrum prediction-driven sensing for energy constrained cognitive radio networks. IEEE Access. 2021;9:26107–26118. doi:10.1109/ACCESS.2021.3057292
[129] O. Omotere, W. Oduola, N. Zou, X. Li, L. Qian, and D. Kataria, 'Distributed spectrum monitoring and surveillance using a cognitive radio based testbed', 2016 *IEEE 37th Sarnoff Symposium*, Sep. 2016, pp. 100–105. doi:10.1109/SARNOF.2016.7846736
[130] '36418663.pdf'. Accessed: Jan. 28, 2024. [Online]. Available: https://core.ac.uk/download/pdf/36418663.pdf
[131] S. N. Syed*et al.*, 'Deep Learning Approaches for Spectrum Sensing in Cognitive Radio Networks', 2022 *25th International Symposium on Wireless Personal Multimedia Communications (WPMC)*, Oct. 2022, pp. 480–485. doi:10.1109/WPMC55625.2022.10014805
[132] Wicht J, Wetzker U, Jain V. Spectrogram data Set for deep-learning-based RF frame detection. Data. 2022;7(12):168. doi:10.3390/data7120168
[133] Miao J, Li Y, Jing X, et al. Spectrum sensing based on adversarial transfer learning. IET Commun. 2022;16(17):2059–2069. doi:10.1049/cmu2.12459
[134] Geng Y, Huang J, Yang J, et al. Spectrum sensing for cognitive radio based on feature extraction and deep learning. J Phys: Conf Ser 2022;2261(1):012016. doi:10.1088/1742-6596/2261/1/012016
[135] Stefan. Machine learning dataset for radio signal classification, Panoradio SDR. [accessed 2024 Mar. 17]. Available from https://panoradio-sdr.de/radio-signal-classification-dataset/.
[136] K. Davaslioglu and Y. E. Sagduyu, Generative adversarial learning for spectrum sensing, 2018 IEEE International Conference on Communications (ICC), May 2018, pp. 1–6. doi:10.1109/ICC.2018.8422223
[137] Peng Q, Gilman A, Vasconcelos N, et al. Robust deep sensing through transfer learning in cognitive radio. IEEE Wireless Communications Letters. 2020;9(1):38–41. doi:10.1109/LWC.2019.2940579
[138] Li L, Lin Y, Liang C, et al. Blind spectrum sensing algorithm based on cyclic spectrum and deep learning. In: International Conference on Intelligent Systems, Communications, and Computer Networks (ISCCN 2023), SPIE; 2023. p. 475–482. doi:10.1117/12.2679555
[139] Li J, Zhang Z, Wang Y, et al. Deep learning-assisted OFDM channel estimation and signal detection technology. IEEE Commun Lett. 2023;27(5):1347–1351. doi:10.1109/LCOMM.2023.3245807
[140] Liu Y, Cao N, Mao M, et al. Radar and communication integrated systems design based on deep neural networks', *IET radar*. Sonar & Navigation. 2023;17(9):1368–1379. doi:10.1049/rsn2.12426
[141] L. Shen, Y. Sun, Z. Yu, L. Ding, X. Tian, and D. Tao, On efficient training of large-scale deep learning models: a literature review, Apr. 07, 2023, *arXiv*: arXiv:2304.03589. doi:10.48550/arXiv.2304.03589
[142] M. Zolnouri, D. Lakhmiri, C. Tribes, E. Sari, and S. L. Digabel, Efficient training under limited resources, Jan. 22, 2023, *arXiv*: arXiv:2301.09264. doi:10.48550/arXiv.2301.09264
[143] C. Li*et al.*, Deep speed data efficiency: improving deep learning model quality and training efficiency via efficient data sampling and routing', Jan. 14, 2024, *arXiv*: arXiv:2212.03597. doi:10.48550/arXiv.2212.03597
[144] G. Menghani, 'Efficient deep learning: a survey on making deep learning models smaller, faster, and better', *ACM comput*. *Surv*., vol. 55, no. 12, p. 251-259:2023
[145] Li K, Li C, Chen J, et al. Boost spectrum prediction with temporal-frequency fusion network via transfer learning. IEEE Trans Mob Comput. 2023;22(6):3209–3223. doi:10.1109/TMC.2021.3136941
[146] Xing X, Jing T, Cheng W, et al. Spectrum prediction in cognitive radio networks. IEEE Wirel Commun. 2013;20(2):90–96. doi:10.1109/MWC.2013.6507399
[147] Abdul Rahim VC, Chris Prema S. A combined spectrum prediction and sensing approach for cognitive radios, in 2021 IEEE 18th India Council International Conference (INDICON), 2021, pp. 1–6. doi:10.1109/INDICON52576.2021.9691541
[148] S. DasMahapatra, S. Patnaik, S. N. Sharan, and M. Gupta, Performance analysis of prediction based spectrum sensing for cognitive radio networks, 2019 2nd International Conference on Intelligent Communication and Computational Techniques (ICCT), 2019, pp. 271–274. doi:10.1109/ICCT46177.2019.8969028
[149] S. M and S. M. G, 'Study of spectrum prediction techniques in cognitive radio networks', 2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS), 2022, pp. 467–471. doi:10.1109/ICACCS54159.2022.9785289
[150] 'Deep Reinforcement Learning | SpringerLink'. Accessed Sep 2024 20. Available from: https://link.springer.com/chapter/10.1007978-981-19-7784-8_10