# A Review of Spectrum Sensing Techniques Based on Machine Learning

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## INTRODUCTION

Wireless communication systems use the radio frequency (RF) spectrum as their propagation medium. RF spectrum is divided into several bands occupying electromagnetic frequencies from 30 kHz to 300 GHz. The necessity of RF spectrum uses increases constantly due to the rapid growth of modern wireless communication systems. Several technologies, especially the deployment of the 5G network and the Internet of Things (IoT), cause high demand for resources from the wireless spectrum for many devices (Xu et al., 2020).

Most of the available RF spectrum has already been assigned to existing wireless systems resulting in only an insignificant part of this spectrum can be given to new applications.

Cognitive radio (CR) aims to reinforce the utilization of the underutilized RF spectrum. These frequency bands are assigned to licensed or primary users (PU) but are not utilized in some locations or time instants. Therefore, unlicensed, or secondary users (SU) can use this spectrum.

One of the principal operations of CR is spectrum sensing (SS), consisting of dynamic monitoring and employing underutilized spectrum without interfering with PUs.

This chapter proposes a survey of current spectrum sensing (SS) research involving the application of machine learning techniques. The extensive review included in this document mainly focuses on deep learning architectures and image processing techniques that can help improve CR systems' detection probability to maximize the underutilized RF spectrum in 5G. This article aims to check the newest research about spectrum sensing techniques reported in the literature, which apply images or time series as input for different deep learning architectures whose main task is to classify the spectrum as occupied or non-occupied.

A current trend, automatic classification modulation (AMC), is also included in this review. It is closely related to SS by recognizing the spectrum availability and classifying the signal type currently using the licensed band of interest. This chapter is helpful for comparison of the current tendencies in spectrum sensing in terms of signal simulation, including different analog and digital modulation types, image-based approaches such as covariance matrix or spectrogram, and wireless channel simulations.

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## BACKGROUND

**Cognitive radio** is a new design paradigm of wireless communications systems that aims to maximize the use of the underutilized RF spectrum. Simon Haykin defines cognitive radio as a wireless communications system that is intelligent and aware of its environment. It uses a methodology by which it learns from the environment and adapts to statistical variations in the input stimulus (Captain & Joshi, 2021; Haykin, 2005). This definition has two main objectives:

- Highly reliable communication when and where needed, and
- Efficient use of the radio spectrum.

Cognitive radio intends to manage and execute real-time operations to adjust its behavior and deal with the increasing demands of RF spectrum and spectrum shortage caused by fixed frequency assignments (Prasad et al., 2008). SU or CR users are allowed access to bands of licensed spectrum assigned to PUs if they do not cause destructive interference. In a cognitive radio network (CRN), the SU or unlicensed user can temporarily access the spectrum not occupied by the PU; therefore, it is critical to determine whether the PU is present or not, and spectrum sensing is a crucial prerequisite for CR (Xu et al., 2020). Three possible cognitive radio implementation models exist: interweave, underlay, and overlay. Due to the popularity of the interweave model and standardization efforts by IEEE on IEEE 802.11 and IEEE 802.11af standards, this type is detailed below (Captain & Joshi, 2021).

**Interweave model:** In this model, secondary users can access the licensed spectrum only when primary users do not use it. A licensed spectrum that is not in use is called a spectrum hole. Secondary users must dynamically identify spectrum holes. Once the primary user begins transmitting on the licensed band again, the secondary user must immediately abandon the licensed spectrum without any interference with PU.

### Spectrum Sensing

One of the purposeful requirements of the SU is to exploit the underutilized spectrum without destructive interference to PU. In addition, a PU is not required to share the spectrum with SUs. Therefore, SUs must be able to detect holes in the spectrum independently of PU before using the licensed spectrum. During the use of that band, the SU needs to monitor constantly if any PU is active in that band, and if that is the case, it needs to abandon that band immediately. As a result, efficient spectrum sensing techniques are required to minimize interference with the PU while maximizing spectrum utilization (Captain & Joshi, 2021). There are three types of spectrum sensing, narrowband spectrum sensing, wideband spectrum sensing, and cooperative spectrum sensing.

#### Narrowband Spectrum Sensing

Narrowband spectrum sensing finds whether a single PU-licensed band is available for SU. The simplified signal detection problem can be explained in terms of two hypotheses $H_0$ and $H_1$. Hypothesis $H_0$ means that only noise is received while the PU signal is missing. Similarly, the hypothesis $H_1$ states that not only noise but also PU signals are observed. Denoting the received signal at the signal detector as $y(n)$ and the PU signals observed by SU as $x(n)$, we have:

$H_0$: $y(n)=w(n)$

$H_1$: $y(n)=x(n)+w(n)$

where $w(n)$ is zero mean additive white Gaussian noise (AWGN), and $n$ denotes the time index.

Due to the unpredictable noise, the probability of detecting PU called a false alarm $P_F$, is increased when it is not present. As a result, the probability of correctly detecting the PU signal when it is present, denoted as $P_D$, is low.

Ideally, it is desirable to have $P_D=1$ and $P_F=0$; however, this is impossible in a low signal-to-noise ratio (SNR) environment. More sophisticated and efficient techniques exist for narrowband spectrum sensing techniques like matched filter, covariance-based, cyclostationary, energy, and wavelet detection (Jain et al., 2019).

## Wideband Spectrum Sensing

Since the wideband spectrum consists of many narrow sub-bands, multiple bands should be evaluated to find spectrum holes. As a result, narrowband sensing techniques cannot be directly used for performing wideband spectrum sensing because they make a single binary decision for the whole spectrum and thus cannot identify individual spectral holes within the wideband spectrum (Ahmad, 2020).

Wideband spectrum sensing can be classified into two classes based on the sampling rate: Nyquist wideband spectrum sensing and sub-Nyquist wideband spectrum sensing.

In wideband spectrum sensing, the wideband signal is obtained using an analog-to-digital converter (ADC), which samples the broadband signal at the Nyquist sampling rate. Next, signal processing techniques are used to detect the spectrum holes. However, the problem arises because the required sampling rate is very high and requires high computational complexity and detection time. Consequently, Nyquist wideband sensing imposes significant challenges for required hardware operating at a high sampling rate and efficient high-speed algorithms (Yang et al., 2018).

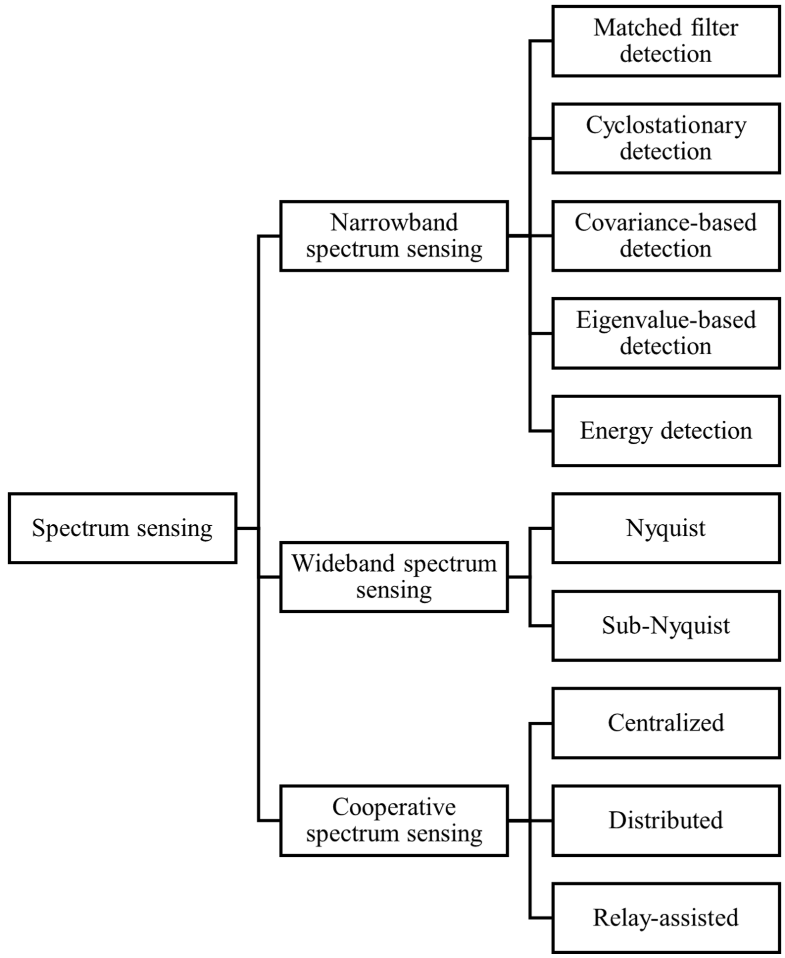
Sub-Nyquist wideband spectrum sensing samples only a fraction of the entire bandwidth and ignores the remaining part. This behavior is applied when the SU might only be interested in finding various spectrum holes rather than all spectrum opportunities in a wideband cognitive radio network (Sun & Laneman, 2014).

## Cooperative Spectrum Sensing

Cooperative spectrum sensing (CSS) enhances the sensing performance by exploiting the spatial diversity of multiple CR users at the expense of cooperation overhead. Multiple SUs, also called cooperating secondary users (CSU), collaborate by sharing their information to detect spectrum opportunities. CSS is divided into three categories: centralized, distributed, and relay-assisted (Akyildiz et al., 2011).

In summary, the following figure presents a diagram with all the mentioned classifications on spectrum sensing.

*Figure 1. Spectrum sensing classifications*




## REVIEW OF MOST RECENT TECHNIQUES

Recently, there has been an increasing interest in applying machine learning methods to different engineering problems for which the development of conventional solutions is challenged by modeling or algorithmic complexity (Simeone, 2018). Machine learning (ML) is a branch of artificial intelligence (AI) and computer science that develops algorithms to learn from data. These algorithms can solve problems by learning from data and creating a model or set of rules to predict an outcome based on features (Rebala et al., 2019).

Deep learning (DL) is a subset of ML where feature extraction is performed along the training process (Chew & Cooper, 2020). DL is, at this time, one of the most popular research directions from ML and has reached great achievement in many fields, such as natural language processing, computer vision, and speech recognition (Yang et al., 2019). Artificial neural networks (NN) are the most popular supervised ML models; they can be divided into two variants, traditional and deep architectures (Khamayseh & Halawani, 2020). Traditional NN is constituted of three layers, input, hidden, and output; however, this type has the problem of an excessive number of parameters (Xu et al., 2022).

Deep structures have a feature learning part in their inner layers, so the network selects features by itself (Xu et al., 2020). Convolutional neural networks (CNN) are deep NN used extensively for image classification and analysis (Nair & Narayanan, 2022).

Spectrum sensing is a binary classification task where secondary users must classify the presence or absence of the primary user. As a result, the most recent SS methods generally use ML techniques to perform this classification. Three main types of ML-based include unsupervised learning, supervised learning, and reinforcement learning.

The literature review demonstrates that authors mainly used supervised machine learning-based approaches, i.e., ML first generates a model based on processing the dataset and then predicts the label of a new input data point by executing that model (Rebala et al., 2019). The classification of supervised machine learning-based techniques included in this survey is presented below.

**Image-based approaches:** This approach consists of using any image as input. An image is a 2-D signal or matrix with information in two coordinates. Many types of images can be created to be applied as input for spectrum sensing systems, including spectrograms, covariance matrices, constellation maps, etc.

**Time series-based approaches:** This approach applies 1-D signals as input for spectrum sensing systems. This signal or vector could be a direct measurement of the amplitude of a wireless signal or any type of transformation, such as the power spectrum through the Fourier transform. Many authors apply other kinds of transformations intending to extract relevant features for classification.

**Automatic modulation classification:** Spectrum sensing addresses the problem of detecting the presence or absence of a signal by analyzing the frequency spectrum. A similar concept is automatic modulation classification (AMC). This process detects the presence of a signal and classifies the signal modulation type from the spectrum samples or images. AMC approaches could be image-based or time series-based.

In summary, the following figure presents a diagram with all the mentioned approaches to machine learning-based spectrum sensing and their subdivisions in terms of spectrum sensing types.

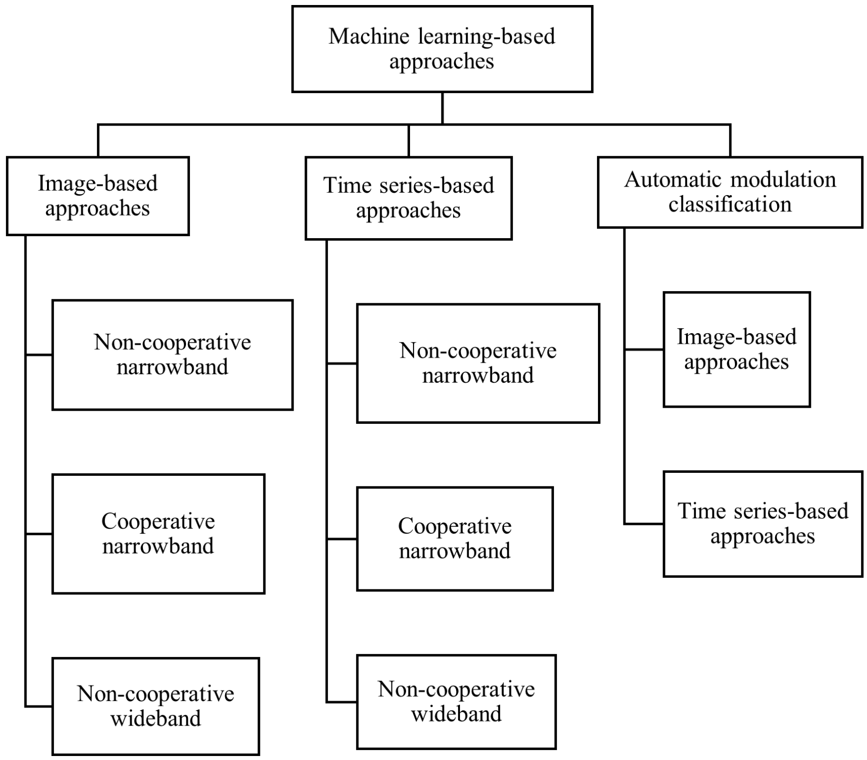
## Image-Based Approaches

From the point of view of machine learning for images, several works have been reported in the literature.

### Non-Cooperative Narrowband

Pan et al. (2020) proposed a spectrum sensing method based on deep learning and cyclic spectrum, which applies the benefits of a CNN to an image obtained from an orthogonal frequency division multiplexing (OFDM) signal. The OFDM signal was analyzed, and the cyclic spectrum was obtained using a smoothing fast Fourier transform (FFT) accumulation algorithm (FAM). This spectrum is normalized to process the gray-scale image corresponding to the cyclic autocorrelation. A CNN based on a classic LeNet-5 model was applied for the learning phase. The novelty of this method was the application of the cyclic spectrum, which is an inherent feature of OFDM signals. Another CNN-based approach is presented by Xie et al. (2019), which does not require information regarding the probabilistic model of the signal, noise, or pattern of PU activity. This work takes advantage of the present and historical data, which are represented through covariance matrices (CM) used as the input for a CNN to train the algorithm with both current information and the pattern of PU activity originating from a semi-Markov model approach. CMs are considered images in this work. Another work that applies the sample covariance matrix as the input for a CNN is reported by C. Liu et al. (2019), proposing a covariance matrix-aware CNN (CM-

*Figure 2. Machine learning-based spectrum sensing techniques*




CNN)-based spectrum sensing algorithm. This paper formulates the structure of the CM-CNN method and theoretically proves that this approach is equivalent to the optimal estimator-correlator (E-C) detector.

A combination between CNN and Long-Short Term Memory (LSTM) has been proposed by Xie et al. (2020), which applies the CNN to extract energy-correlation features from the covariance matrices (images) generated by the sensing data. Then the series corresponding to multiple sensing periods are input into the LSTM to learn the PU activity pattern. The purpose of learning the PU activity pattern is to promote the detection probability further. This algorithm is evaluated in scenarios with and without noise uncertainty. A similar combination reported by Chen et al. (2022) employs the covariance matrix of the signals received into an LSTM classification model (CM-LSTM) to achieve fusion learning of spatial correlation and temporal correlation features of the signals. The CM-LSTM algorithm can simultaneously learn the spatial correlation features of multiple signals received by an antenna array and the temporal correlation features of single signals providing two options that work together for classification purposes.

The spectrum sensing problem is transformed into an image recognition problem by Chew and Cooper (2020), employing a well know CNN, AlexNet. This CNN is re-purposed to sense the energy spectrum using a small training set of a few hundred samples. Another advantage of this detector is that it does not require noise floor measurements. This work demonstrates how fine tuning can quickly re-purpose an existing CNN to perform a new task seemingly unrelated to the original one. Similarly, the paper reported by Liu et al. (2021) utilizes a Deep convolutional generative adversarial network (DCGAN) to expand the training set to overcome the shortage of sample data. The sampling covariance matrix of the received signal is transformed into a true color image. After that, the obtained training set is expanded with the DCGAN. Finally, the LeNet network (a CNN) is trained based on this extended data.

Regarding spectrograms used as input for SS systems, Lees et al. (2019) investigate the performance of thirteen methods for SPN-43 radar detection using a library of over 14,000 3.5 GHz band spectrograms. Comparing classical methods from signal detection theory and machine learning to several deep learning architectures demonstrates that ML algorithms outperform classical signal detection methods. A three-layer CNN offers a superior tradeoff between accuracy and computational complexity. Similarly, Chen et al. (2021) exploit the time-frequency domain information of signal samples using the short-time Fourier transform (STFT) and CNN. This blind spectrum sensing STFT-CNN method has no requirements for the PU signal and considerable SNR-robustness.

Gai et al. (2022) proposed an interesting approach that utilizes a residual cellular network (ResCelNet), involving a dual-branch convolution structure, improving the feature extraction ability. The addition operation enhances the micro-feature information, and residual learning is adopted to facilitate training of the deep spectrum sensing network. The received signals are reshaped into a matrix, normalized to gray levels, and used as the network's input (images). Then the feature information of gray-scale images is extracted, and the network is trained through dual-branch convolution and residual learning. The following table presents a comparison between the works detailed in this subsection.

## Cooperative Narrowband

The cooperative sensing approach in Nair and Narayanan (2022) introduces a technique to check the availability of spectrum based on spectrograms received from the primary user. It trains a CNN model to detect whether it is a signal or noise. Regularization methods helped to increase the model's generalization ability, and they could discriminate the newer untrained signal patterns from the noise signal patterns. Another cooperative sensing method presented by Lee et al. (2019) combines the individual sensing results of the SUs who learn autonomously with a CNN using training sensing samples. Both spectral (frequency bands) and spatial correlation (SUs received signal strength (RSS)) of individual sensing outcomes are considered such that an environment-specific CSS is enabled in deep cooperative sensing (DCS).

The ensemble approach by H. Liu et al. (2019) for CSS in an OFDM signal-based cognitive radio system also utilizes images as input for a CNN architecture. In this case, images are created through spectral coherence density (SCD), visualizing second-order correlation features, which will be used for classification. The PU detection of an OFDM signal is transformed into an SCD plane, i.e., image processing. The bagging strategy was employed to establish the training database between CSUs.

The Deep Reinforcement Learning (DRL) based algorithm proposed by Sarikhani and Keynia (2020) applies cooperative spectrum sensing using reinforcement learning to choose the needed SUs to cooperate and DL in each SU to sense the presence or absence of the PU locally. The reinforcement part of the algorithm determines the required SU to share its measurements and local sensing results.

Adversarial transfer learning is applied to spectrum sensing in Miao et al. (2022), where the model is pre-trained at the central node first and fine-tuned at the local nodes. This work constructs a 2D dataset of the observed signal under various SNRs. Then a part of the samples with multiple SNRs in the dataset is employed to pre-train the CNN model. After that, the pre-trained CNN model is distributed to local nodes with different SNRs, and the pre-trained model is fine-tuned, resulting in more robust adaptability at the local node. The following table presents a comparison between the works detailed in this subsection.

*Table 1. Comparison of non-cooperative narrowband works (image-based)*

| Article | Year | Simulated signals | Input | Deep learning approach | Highest detection performance | Average detection time | Comment |
|---|---|---|---|---|---|---|---|
| Lees et al. | 2019 | 60-second, complex-valued (i.e., I/Q) waveform | Spectrogram, time slices | CNN, LSTM | 99.7% | 1.89 ms | 3.5 GHz spectrograms “For Official Use Only” (FOUO) by the US Department of Defense (not publicly available) |
| C. Liu et al. | 2019 | Signal vector (IID) circularly symmetric complex Gaussian (CSCG) | Covariance matrix | CNN | 96.7% at -18 dB | 2.6 ms | The real and imaginary parts of the covariance matrix are treated as two input channels |
| Xie et al. | 2019 | Uncorrelated and correlated signals | Covariance matrix | CNN | Not specified | Not reported | A CM matrix composed of stacked CMs is used for pattern learning |
| Chew and Cooper | 2020 | BPSK signal oversampled at 4 samples per symbol | Spectrogram | CNN | 100% at 0 dB | Not reported | Fixed and variable noise floor, environment with interference |
| Pan et al. | 2020 | OFDM signal | 2D cyclic autocorrelation gray map | CNN | Not specified | 0.3841 s | Five different CNN structures |
| Xie et al. | 2020 | QPSK modulated with unit energy | Covariance matrix | CNN, LSTM | Not specified | Not reported | The noise on each antenna (SIMO channel) is identically and independently complex Gaussian or complex Laplace distributed |
| Liu et al. | 2021 | OFDM signal | Covariance matrix | CNN, DCGAN | 90% at -4 dB | Not reported | Lenet-5 based on CNN and Deep Convolutional Generative Adversarial Network (DCGAN) |
| Chen et al. | 2021 | QPSK | Time-frequency matrix | CNN | 90.2% at -15 dB | Not reported | Short-Time Fourier Transform (STFT) to create spectrograms |
| Gai, et al. | 2022 | QPSK | Received signal observation matrix | Residual Cellular Network (ResCelNet) | 98% at -10 dB | 3.76 s | ResCelNet is based on CNN and Residual cellular block (RCB) |
| Chen, et al. | 2022 | QPSK | Covariance matrix | LSTM | 100% at -10 dB | Not reported | Multiple signals received by an antenna array to extract temporal correlation features |

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### Non-Cooperative Wideband

A signal localization task performed by West et al. (2021) addresses the problem of wideband spectrum sensing, which requires detecting potentially multiple signals within the sample bandwidth at arbitrary center frequencies, offsets, and time bounds. This research applies semantic segmentation directly analogous to the radiometer task of detecting whether a time/frequency bin contains a signal or no signal. In image processing, the input image (in this case, a log-magnitude spectrogram) is classified per pixel on the output with the exact resolution as the input image.

The research by Nguyen et al. (2018) presented an energy detector applied to the STFT of a wideband signal to produce a binary spectrogram. Bounding boxes for narrowband signals are then identified using image processing techniques on a block of the spectrogram at a time. These boxes are also tracked along the time axis and fused with the newly detected boxes to provide an online system for spectrum sensing. Fast and highly accurate detection is achieved in simulations for various signals with different hopping patterns and speeds. Another work based on a spectrogram is presented by Li et al. (2019), which proposes a temporal-frequency fusion network for precise spectrum energy level prediction considering heterogeneous data from multiple domains. This system detects signals from the raw spectrogram using an image processing-based robust signal detection procedure based on a modified Otsu thresholding algorithm. The temporal and frequency data for the prediction model automatically capture the intra-spectrum correlations employing an LSTM network. Finally, Zha et al. (2019) proposed a DL framework capable of detecting and recognizing signals. Time-frequency spectrograms are exploited for wideband spectrum sensing, and eye diagrams and vector diagrams are used for the modulation classification task. Their network model includes single-shot multi-box detectors (SSD), CNN, and ResNet. The following table presents a comparison between the works detailed in this subsection.

## Time Series-Based Approaches

The literature review of recent articles from 2018 to 2022 showed that although images have been used extensively for spectrum sensing, time series are still applied in multiple projects compiled in this section.

### Non-Cooperative Narrowband

The research reported by Xu et al. (2020) employs a one-dimension time signal instead of an image as the input to a parallel CNN-LSTM network; this approach does not require prior knowledge about the information of the licensed user or channel state. A combination of CNN, LSTM, and fully connected neural networks proposed by Yang et al. (2019) found that the trained deep neural network learned from typical radio signals and its filters behaved like a matched filter. This work also analyzed the kernel size, the number of filters for the 1D-CNNs, and the effect of multiple LSTM layers obtaining the optimal signal detection performance when this number is 2. The following table presents more details regarding these papers.

*Table 2. Comparison of cooperative narrowband works (image-based)*

| Article | Year | Simulated signals | Input | Deep learning approach | Highest detection performance | Average detection time | Comment |
|---|---|---|---|---|---|---|---|
| H. Liu, et al. | 2019 | OFDM signal of 802.11g protocol with 16QAM | Spectral coherence density (SCD) plane | CNN | Not specified | Not reported | Ensemble learning framework |
| Lee, et al. | 2019 | Fixed-power signal | Matrix of the accumulated RSS of all SUs from different bands | CNN | 95.2% | 0.5 ms | Received Signal Strength (RSS) |
| Sarikhani and Keynia | 2020 | Fixed-power signal | Energy measurement matrix | CNN, DRL | 96.1% | Not reported | Deep Reinforcement Learning (DRL) |
| Nair and Narayanan | 2022 | BPSK, GFSK, PAM4, QAM16, QPSK | Spectrogram | CNN | 91.2% | Not reported | Cognitive radio signals are simulated using GNU Radio, an open-source software development kit |
| Miao, et al. | 2022 | OFDM signal | Covariance matrix | CNN | Not specified | Not reported | Adversarial transfer learning |

*Table 3. Comparison of non-cooperative wideband works (image-based)*

| Article | Year | Simulated signals | Input | Deep learning approach | Highest detection performance | Average detection time | Comment |
|---|---|---|---|---|---|---|---|
| Nguyen et al. | 2018 | Fixed frequency (FF), frequency hopped (FH) | Spectrogram | N/A | 97.98% at 4 dB | Not reported | Box lists indicate the spectrum holes, distance-based metric detection |
| Li et al. | 2019 | FM, TV broadcast, GSM uplink/downlink | Spectrogram | LSTM | 98.02% | Not reported | Adaptive thresholding by modified OTSU |
| Zha et al. | 2019 | BPSK, QPSK, OQPSK, 8PSK, 16QAM, 16APSK, 32APSK, 64QAM | Spectrogram, eye diagrams, vector diagrams | SSD, CNN | 90% at 4 dB | 50.5 ms | Single-shot multi-box Detector (SSD) networks |
| West et al. | 2021 | PSK2, PSK4, PSK8, QAM16, QAM64, QAM256, OFDM, FSK2, FSK4, GMSK, OOK, AM-DSB, AM-SSB, FM | Log-magnitude spectrogram | U-net | 100% at 8 dB | Not reported | U-net is a popular choice for segmentation tasks due to its ability to gather features at multiple scales with minimal distortion |

## Cooperative Narrowband

A combination between CNN and the gate recurring unit (GRU) has been reported by Xu et al. (2022). This work first applies CNN to extract spatial features and GRU for temporal characteristics; then a combination network receives these data to obtain a cooperative result based on a mixture of both types. The final network, called Combination-Net, improves the reliability of spectrum sensing by merging perception information from multiple collaborative nodes. Another approach that uses 1-D signals instead of images is presented by Gao et al. (2019), proposing a DL-based signal detector that exploits the underlying structural information of modulated signals requiring no prior knowledge about channel state information or background noise. Additionally, this research proposes a DL-based cooperative detection to take advantage of the soft information from distributed sensing nodes. The following table presents more details regarding these papers.

## Non-Cooperative Wideband

Two methods based on Wavelets and the Higuchi fractal dimension (HFD, a non-linear measure) were applied by Molina-Tenorio et al. (2019) to address wideband spectrum sensing. The multiresolution analysis (MRA) approach detects edges on 1D signals obtaining the available holes in the wideband spectrum. The classification procedure in this study utilized a simple decision threshold based on HFD applied over a frequency version of the input data.

The non-cooperative wideband detection approach proposed by Lin et al. (2022) jointly detects the signal presence and estimates their center frequencies and bandwidths. The DL architecture called SigdetNet includes signal preprocessing, enhancement, feature extraction based on neural networks, and postprocessing. This system comprises a convolutional encoder-decoder network with an embedding pyramid pooling module (CNN and residual block-based) constructed to extract informative features related to signal detection from multiscale. The following table presents more details regarding these works.

# Automatic Modulation Classification

This survey also includes the following works because they provide essential insight regarding spectrum sensing and its possibility to classify the signal type using multiple signal processing and deep learning techniques.

*Table 4. Comparison of non-cooperative narrowband works (time series-based)*

| Article | Year | Simulated signals | Input | Deep learning approach | Highest detection performance | Average detection time | Comment |
|---|---|---|---|---|---|---|---|
| Yang et al. | 2019 | Intermediate Frequency (IF) data | Time series | CNN, LSTM | 99.46% at -3 dB | Not reported | Filters from the deep network behave like a matched filter |
| Xu et al. | 2020 | 4ASK, 8ASK, BPSK, QPSK, LFM, QAM16, QAM32, QAM64 | Time series | CNN, LSTM | Not specified | Not reported | Parallel CNN-LSTM network |

*Table 5. Comparison of cooperative narrowband works (time series-based)*

| Article | Year | Simulated signals | Input | Deep learning approach | Highest detection performance | Average detection time | Comment |
|---|---|---|---|---|---|---|---|
| Gao, et al. | 2019 | BPSK, QPSK, 8PSK, CPFSK, QAM16, QAM64, GFSK, PAM4 | Normalized time domain complex signal | CLDNN | 90% at -8.5 dB | Not reported | Convolutional Long short-term Deep Neural Network (CLDNN) |
| Xu, et al. | 2022 | 4ASK, 8ASK, BPSK, QPSK, LFM, QAM16, QAM32, QAM64 | Time series | CNN, GRU | 93.9% at -20 dB | Not reported | Multifeatures Combination Network extracts features exploiting the complementary modeling capabilities of CNN and GRU |

*Table 6. Comparison of non-cooperative wideband works (time series-based)*

| Article | Year | Simulated signals | Input | Deep learning approach | Highest detection performance | Average detection time | Comment |
|---|---|---|---|---|---|---|---|
| Molina-Tenorio et al. | 2019 | OFDM, NRZ-CDMA, real symbols | Time series | N/A | 98% at 0 dB | Not reported | Classification performed using a Higuchi Fractal Dimension (HFD) decision threshold |
| Lin, et al. | 2022 | 2ASK, BPSK, QPSK, 2FSK, MSK, GMSK | Time series | SigDetNet | 90% at 0 dB | Not reported | SigDetNet receives RF data as the input and predicts the number, carrier frequencies, and bandwidths of signals |

## Image-Based Approaches

An exciting approach of DL for detecting and classifying RF signals was presented by Elyousseph and Altamimi (2021). The main advantage is identifying a signal presence without complete protocol information and detecting or classifying non-communication waveforms such as radar signals. In this work, a hybrid image is proposed taking advantage of both time and frequency domain information and facing the classification as a computer vision problem. Another AMC-based work reported by Yakkati et al. (2021) proposes a multiscale DL-based approach. The method considered the fixed boundary range-based empirical Wavelet transform (FBREWT) based multiscale analysis technique to decompose the radio signal into sub-band signals or modes. The sub-band signals computed from the radio signal combined with the CNN are used to classify modulation types. The approach is tested using the radio signals of different SNR values and four different channel types including AWGN, a combination of Rayleigh fading and AWGN, a combination of Rician flat fading and AWGN, and a combination of Nakagami-m fading and AWGN. A different approach utilizing the benefits of collaborative spectrum sensing and deep learning has been reported by Chen et al. (2020). Although this work does not directly deal with the spectrum sensing problem; it provides more insight into image processing approaches such as semantic segmentation to identify the coverage range of RF emitters converting three-dimensional sensing data into a series of two-dimensional image slices. The following table resumes these works and includes more details.

## Time Series-Based Approaches

Soltani et al. (2019) proposed a software implementation that utilizes Android smartphones with TensorFlow Lite for modulation classification. This system runs a GPU-trained deep CNN for an SNR-based classification scheme to characterize modulation codes for spectrum management. This implementation also proposed a labeling mechanism derived from the insight about confusion matrices of modulation classes learned from previous training procedures.

An AMC method using a waveform-spectrum multimodal fusion (WSMF) method based on deep residual networks (ResNet) is reported by Qi et al. (2020). After extracting features from multimodal information using Resnet, this approach adopts a feature fusion strategy to merge multimodal parts of signals, such as IQ data, envelope data, and spectrum data, to obtain more discriminating features. Another AMC approach by Han et al. (2021) uses time-series signals which are transformed into multiple domains, including the frequency domain, by FFT and Welch power spectrum analysis. A stacked auto-encoder (SAE) was used for detailed and stable frequency-domain feature representations (feature fusion). A probabilistic neural network (PNN) was implemented for automatic modulation classification for a complex electromagnetic environment with high noise levels and significant dynamic inputs.

A convenient way to perform continuous spectrum sensing is the prediction of spectrum occupancies, which is addressed in Aygül et al. (2022) by employing a DRL algorithm. This system exploits DRL algorithms to teach the base station (BS) how to independently predict spectrum occupancies straight from power spectral density data (time series and images). The following table resumes these works and includes more details.

*Table 7. Comparison of image-based works for AMC*

| Article | Year | Simulated signals | Input | Deep learning approach | Highest detection performance | Average detection time | Comment |
|---|---|---|---|---|---|---|---|
| Chen et al. | 2020 | Three-dimensional sensing data | Two-dimensional image slices | N/A | N/A | N/A | Semantic segmentation network to get the corresponding coordinate positions of RF emitters |
| Elyousseph and Altamimi | 2021 | BPSK, QPSK, 16QAM, GFSK | Raw IQ time-series images and PSD images combined in RGB | CNN | 100% | Not reported | Classification of RF signals based on hybrid images |
| Yakkati et al. | 2021 | BPSK, QPSK, 64-QAM, PAM4, GFSK, CPFSK, B-FM, DSB-AM, SSB-AM | 16 sub-band signal matrix | CNN | 97% at 10 dB | Not reported | Fixed Boundary Range-based Empirical Wavelet Transform (FBREWT) based multiscale analysis technique |

*Table 8. Comparison of time series-based works for AMC*

| Article | Year | Simulated signals | Input | Deep learning approach | Highest detection performance | Average detection time | Comment |
|---|---|---|---|---|---|---|---|
| Soltani et al. | 2019 | AM-DSB-WC, 256QAM, QPSK, AM-SSB-WC, 64QAM, 16APSK, 32QAM, 32APSK, OQPSK, 8ASK, 16PSK, 64APSK, 128QAM, AM-DSB-SC, 16QAM, OOK, 32PSK, FM, GMSK, BPSK, 8PSK, AM-SSB-SC, 4ASK, 128APSK | I/Q samples | CNN | 95% | Not specified | Android smartphone implementation with TensorFlow Lite that can run GPU-trained deep CNNs |
| Qi et al. | 2020 | BPSK, QPSK, OQPSK, 8PSK, 2FSK, 4FSK, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, 1024QAM, 4PAM, 8PAM, 16PAM, 32PAM | Multimodal data (time series in multiple domains) | CNN, Resnet | 95% | Not reported | Waveform-Spectrum Multimodal Fusion (WSMF) |
| Han et al. | 2021 | 2PSK, 4PSK, 2ASK, 4ASK, 8ASK, 2FSK, 4FSK, 8FSK, 32QAM, 64QAM | FFT, statistical analysis, power spectrum | CNN, SAE, PNN | 99.8% at 0 dB | Not reported | Stacked Auto-Encoder (SAE) and Probabilistic Neural Network (PNN) |
| Aygül et al. | 2022 | LTE signals (measured signals between 832-862 MHz) | Measured power spectral densities (times series and images) | 1D-DRL, 2D-DRL | N/A | N/A | Signals acquired from the 832-862 MHz frequency bands, (leading Turkish telecom providers as private uplink bands) |

## SOLUTIONS AND RECOMMENDATIONS



Since this work was mainly developed to obtain insight into the image processing techniques currently applied for spectrum sensing and automatic modulation classification, this section presents more information regarding this specific area of digital signal processing.

In general, authors apply images as input for a spectrum sensing system. One of the main choices is the spectrogram, which provides information in both time and frequency domains in a matrix form. This method utilizes the STFT and has been proven efficient in several works in both narrowband and wideband spectrum sensing (Chen et al., 2021; Chew & Cooper, 2020; Lees et al., 2019; Li et al., 2019; Nair & Narayanan, 2022; Nguyen et al., 2018; West et al., 2021; Zha et al., 2019). Another popular image used for spectrum sensing is the covariance matrix, applied in multiple works (Chen et al., 2022; C. Liu et al., 2019; Liu et al., 2021; Miao et al., 2022; Xie et al., 2020; Xie et al., 2019). This matrix represents the correlation between signals received in multiple time slots or by multiple receptor antennas (cooperative SS). The main idea behind applying the covariance matrix is to discriminate signal correlation from noise correlation, which usually tends to have higher values. Other types of images used for SS include the 2-D cyclic autocorrelation gray map proposed by Pan et al. (2020), and the received signal observation matrix in Gai et al. (2022), both used for non-cooperative narrowband SS. For cooperative approaches, the spectral coherence density (SCD) plane was proposed by H. Liu et al. (2019), the matrix of accumulated received signal strength (RSS) of SUs from different bands by Lee et al. (2019), the energy measurement matrix by Sarikhani and Keynia (2020), and eye diagrams and vector diagrams in Zha et al. (2019). These works create matrices from wireless signals taking advantage of their energy, spectral, or spatial properties (constellation), which will inherently be related to a difference between the transmitted signal and the background noise.

### Image Processing Techniques Review

The image processing techniques applied to input images (matrices) are usually implemented for wideband spectrum sensing. A robust signal detection procedure based on a modified Otsu thresholding algorithm is proposed by Li et al. (2019). In the research presented by West et al. (2021), the input image, a log-magnitude spectrogram, is classified per pixel on the output with the same resolution as the input image using semantic segmentation, which is directly analogous to detecting whether a time/frequency bin contains a signal or no signal. Image enhancement is utilized by Zha et al. (2019), considering signal aggregation degree and enhancing the traditional eye and vector diagram by using a specific formula and scaling factors. The image details from these diagrams become more prominent utilizing this technique. A wideband SS approach based on image processing is reported by Nguyen et al. (2018), applying several methods, including binarization, morphology operators, and connected components labeling. These algorithms were effective for fixed-frequency and frequency-hopping signals.

### Deep Learning Techniques Review

Deep learning techniques are mainly used for spectrum sensing since they provide accurate results when assessing low SNR scenarios.

Convolutional neural networks (CNN) are the first choice for DL-based systems, as can be noticed in Chen et al. (2021), Chew and Cooper (2020), Lees et al. (2019), C. Liu et al. (2019), Liu et al. (2021), Pan et al. (2020), Xie et al. (2020); Xie et al. (2019), Xu et al. (2020), and Yang et al. (2019) which addressed non-cooperative narrowband SS. In contrast, Lee et al. (2019), H. Liu et al. (2019), Miao et al. (2022), Nair and Narayanan (2022), Sarikhani and Keynia (2020), and Xu et al. (2022) focus on cooperative narrowband SS. In wideband spectrum sensing, only the work of Zha et al. (2019) utilized CNN.

AMC also has multiple examples of CNN-based approaches, such as Elyousseph and Altamimi (2021), Han et al. (2021), Qi et al. (2020), Soltani et al. (2019), and Yakkati et al. (2021).

Long-short-term memory (LSTM) models are less applied since generally they are helpful for 1-D signals or time series inputs, such as the works reported by Yang et al. (2019) and Xu et al. (2020) both these works combine CNN and LSTM. Another combination of CNN and LSTM called CLDNN was applied by Gao et al. (2019) for cooperative SS. However, a 2-D version of LSTM for images is proposed by Chen et al. (2022), Lees et al. (2019), Li et al. (2019), and Xie et al. (2020). Another recurrent model based on a GRU was reported by Xu et al. (2022).

Residual networks have also been proposed in the literature, specifically ResCelNet by Gai et al. (2022) and SigDetNet by Lin et al. (2022). Deep reinforcement learning is also present in this survey (Aygül et al., 2022; Sarikhani & Keynia, 2020). Finally, U-net is another type of DL model applied for segmentation in detecting modulated signals in a log-magnitude spectrogram (West et al., 2021).

## FUTURE RESEARCH DIRECTIONS

The future seems promising for more DL-based approaches, such as residual networks, which are the latest models proposed in current works in the literature. 5G establishes the need for better spectrum utilization since more devices will demand more resources. To address this situation, many authors have proposed SS and AMC systems capable of obtaining a high probability of detection over low SNR scenarios.

An exciting trend found during the development of this paper was a combination of spectrum sensing and spectrum prediction. The latter stands for techniques to learn from the spectrum via LSTM or another type of recurrent network, the PU's spectrum usage patterns. By predicting the subsequent PU frequency band, it would be "easier" for the SU to avoid that band and choose another for their use.

Another future path will be the study and possible implementation of cooperative wideband spectrum sensing, which has yet to be reported in the literature until the development of this document. This has yet to be studied and can be considered a future research direction for interested parties. This SS branch could be helpful for wideband approaches since it exploits the inherent advantages of cooperative SS while covering a broad frequency band. However, it must be noted that the lack of work regarding this branch can also indicate that these types of SS systems are only partially affordable or could be too slow to work on real scenarios.

## CONCLUSION

Spectrum sensing is crucial to cognitive radio and should be as accurate as possible. Deep learning techniques improve the functionality of different spectrum sensing approaches for both narrowband and wideband SS. This paper focused on image processing and deep learning techniques as the main components of spectrum sensing systems. A wide variety of methods have been included in this document, such as narrowband, wideband, and cooperative spectrum sensing approaches. State of art included in this document consists of some of the latest works of spectrum sensing using machine learning from 2018 to 2022.

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## KEY TERMS AND DEFINITIONS

**5G:** The fifth generation of mobile networks.

**Automatic Modulation Classification:** Identifying the modulation type of a signal received over a communication link.

**Convolutional Neural Network:** A deep network architecture widely used for image classification. This deep model extract features directly from input data using its hidden layers.

**Deep Learning:** A subset of machine learning devoted to designing and implementing complex architectures based on neural networks. This approach uses more training resources by including feature extraction techniques on their inner layers.

**Image Processing:** The design and development of algorithms applied to images to transform or obtain information from them.

**Licensed Frequency:** A frequency or range designated for a particular application or wireless communication.

**Machine Learning:** A field of computer science and artificial intelligence devoted to using mathematical models for learning patterns from data without programming specific algorithms.

**Narrowband:** A narrow range of frequencies. A typical range for narrowband signals is 25 kHz or less.

**Neural Network:** An architecture widely used in machine learning inspired by the human brain. A neural network comprises multiple layers with neurons capable of creating models to recognize patterns from input data.

**Primary User:** The user with access to licensed frequencies in the spectrum.

**Secondary User:** The user who does not have access to licensed frequencies but can use them dynamically and opportunistically.

**Spectrum Sensing:** The detection of the presence or absence of a signal in a specific frequency band.

**Wideband:** A broad range of frequencies. Wideband signals generally have a bandwidth greater than 1 MHz.