Deep Learning Techniques Deployed for Spectrum Sensing in Cognitive Radio Networks: A Review

Abdulkarim Ilyasu, Aliyu[1;] Abel E Aeroborman[2;] Ruqayat Yusuf[3]

Department of Electrical and Electronics Engineering, Nigerian Defence Academy, Kaduna, Nigeria

Abstract

The transformation of wireless radio telecommunications in recent times cannot be undeniable with advancement of technologies such as cognitive radio. The Cognitive radio network has been relied upon to solve the problem of spectrum scarcity from the inefficient utilization and dynamic spectrum access as a result of ever-increasing demand to resource allocation of the radio spectrum. The utilization of artificial intelligence and its subsets such as deep learning for spectrum sensing, has been very crucial to the research in cognitive radio and spectrum works. This document offers an extensive summary of Deep Learning (DL) methods employed in Spectrum Sensing, categorized into: Multilayer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, integrated CNN-LSTM architectures, and Autoencoders (AEs). The studies are examined in terms of the input given to the DL model, the technique used for data collection, the structure of each algorithm, the metrics used for evaluation, the outcomes achieved, and a comparative analysis based on overall characteristics.

Keywords: cognitive radio networks, machine learning, wireless radio, spectrum sensing.

Introduction

The ever increase in demand of mobile communication, which has led to significant increase in usage of communication technologies, especially wireless technology, has resulted in escalation on resource allocation to availability of the electromagnetic spectrum. With recent advent in innovative communication, high-tech networks such as 5G requiring large-scale development been deployed for better services, the research for 6G networks has been researched on ever- since [1]. This rapid development has led to increase in cell phone usage resulting to the growth of wireless communication and the increasing need for spectrum bandwidth.

.At the current time, spectrum management and allocation are handled by governments of across the globe in a more like static-based system.

To address this spectrum demand/scarcity, cognitive radio plays a key role in solving such problems. Cognitive radio performs through the exploitation of the frequency spectrum by dynamic detection and transmission in underutilized bands.

DOI: https://doi.org/10.5281/zenodo.17701671

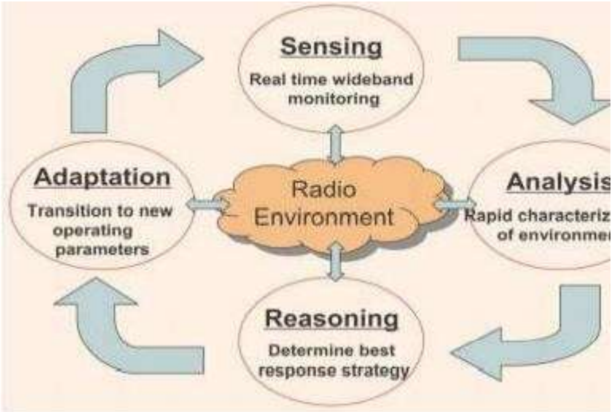

Figure 1. cognitive radio network system. [2]

Spectrum white space

The spectrum white space refers the portions of the frequency spectrum that are unused by licensed users. a typical CR responsibility can identify these spectrum blank areas, through selection of the optimal frequency groups, coordinating spectrum utilization, and relinquishing the frequency when a priority user appears. The ensuing functions facilitate a specific cognitive process: spectrum detection and evaluation, spectrum administration and transition, spectrum allocation and cooperation, and spectrum allocation and cooperation [3].

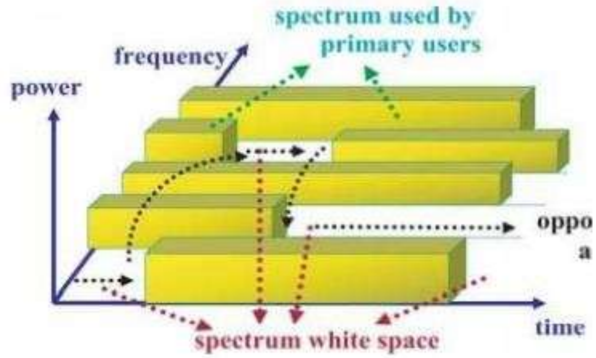

Figure 2. spectrum white space illustration.

The idea with regards to Cognitive radio networks (CRN) was first conceived in a doctoral research in 1999 in Sweden by Dr. Joseph mitola, widely known as the "father of software radio". Cognitive radio networks are defined as wireless communication systems programmed to select appropriate channels options for spectrum utilization. The system is designed to communicate intelligently with other cognitive devices to enhance the efficiency and effectiveness of the frequency spectrum and achieve dependable communication. A conventional cognitive radio system consists of four main components: spectrum sensing, spectrum analysis, spectrum judgment, and spectrum reconstruction. Spectrum sensing is the most essential amongst the four, which is the core prerequisite for realizing Cognitive radio applications. Spectrum sensing technology improves the efficiency of spectrum usage by continuously monitoring and analyzing radio frequencies. It quickly recognizes and makes use of available frequency bands when previously assigned or fixed frequencies are not accessible, thereby addressing the demand for spectrum resources. Spectrum sensing has numerous applications and has been extensively researched. It can observe the usage of the radio spectrum to identify which bands are unoccupied by primary users, facilitating improved allocation of spectrum resources and dynamic sharing.

This con-current policy of fixed spectrum allocation by which a designated portion of radio spectrum is allocated to licensed Primary Users (PU), while only a smaller portion of licensed Secondary Users (SU) has led to result in spectrum scarcity.

The spectrum has historically been analyzed using well-known methods like Energy Detection (ED), Matched Filter Detection

DOI: https://doi.org/10.5281/zenodo.17701671

(MFD), and Cyclostationary-based Detection (CBD). These conventional approaches have often led to suboptimal utilization of radio resources due to both the failure to detect the Primary User (PU) and the occurrence of false alarms. A high probability of missed detection do occur when there is a failure in identifying (PU) by the system, resulting in performance degradation. Conversely,

As a result of these drawbacks by these conventional Spectrum Sensing techniques and surge in high emergence in use of Artificial Intelligence (AI), many recent works have adopted traditional Machine Learning (ML) algorithms which has the likes of Support Vector Machines (SVMs) and K-Nearest Neighbor (KNN) for Spectrum sensing. Nevertheless, the traditional machine learning algorithm's technique manual feature extraction usually demand specialized expertise and is often lengthy in carrying out[25]. Deep Neural Network (DNN) methods, which are highly adaptable, show resilience to unpredictable radio environments. The spectrum is segmented into several distinct parts, each accommodating different authorized users within the licensed frequency range. A recent investigation in the United States revealed an uneven usage rate of licensed frequencies, with certain areas exhibiting a very low percentage of utilization. Consequently, dynamic management of spectrum resources and allocation to enhance efficiency has emerged as a challenge that needs addressing [22]. This paper intends to summarize the current state of research, contextuality of usage, and prospective development pathways for deep-learning-based spectrum sensing technology.

Related works

In recent research works, various solutions have been suggested to solve the spectrum sensing challenges in cognitive radio problems in different applications or context of usage. Survey papers have reviewed those solutions in view of different scopes, and have discussed the research challenges and future directions associated with it. For instance, a survey by [18] reviewed the deep spectrum sensing techniques, which incorporate deep-learning frameworks for 5G networks. The paper talked about the standardization for advanced sensing methods in relation to forthcoming generation of extensive connectivity that tackles the issues related.
Furthermore, [19] carried out a review on the optimization resources with respect adding AI techniques on spectrum allocation. This AI-enabled feature helps in distinguishing favorable methods for applying the techniques, while [20] outline machine learning techniques and it impacts dynamic and intelligent spectrum management. A valid point of view showed that, deep-learning techniques are highly essential for CRN in a wider range of use. Authors [21] focused on the application of deep reinforcement learning (DRL) and deep neural networks in spectrum sensing but lacks overview on the methodologies of the main algorithms. In summary, it can be said that some existing papers have provided insight on deep learning and machine learning techniques from a collaborative perspective, this enable us to present a more recent review on the works carried out so as

DOI: https://doi.org/10.5281/zenodo.17701671

to give researchers up to date trends of deep learning applications to spectrum sensing oversights in cognitive radio networks.

3.1 **Deep-learning spectrum sensing**

Deep learning is characterized as a branch of machine learning that can automatically identify intricate patterns and attributes within the input data.[2]. The development of deep learning is widely but not only known to be applicable in the areas of large language modeling and computer vision, but also relevant to the domain of communication engineering. These has resulted in increased number of researches been conducted in-depth. deep learning has been applied in domain of communication to mainly the branches optimization, and cognitive radio networks.

For instance, the effectiveness of spectrum sensing in cognitive radio networks can be enhanced through the use of deep learning techniques by effectively leveraging the non-linear relationships present in the training data [3]. Deep learning approaches offer greater accuracy and reliability compared to conventional spectrum-sensing techniques. Additionally, the spectrum sensing method based on deep learning is recognized for its ability to extract higher-order statistical features from the received signal to facilitate classification. A deep neural network learns by processing features from a specific signal, enabling the trained network to achieve perceptual recognition without needing prior knowledge of the received signal. The deep learning spectrum-sensing model is illustrated in figure 3.

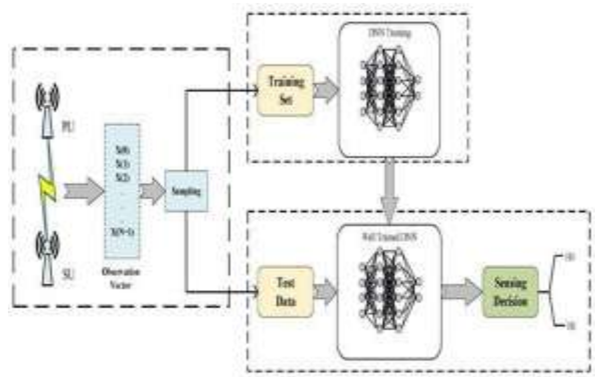

Figure 3. deep-learning model for spectrum sensing. [2]

Ongoing research on deep learning for spectrum sensing primarily concentrate on networks with high performance. The following section discusses the classification of common techniques of deep learning neural networks in spectrum sensing for cognitive radio networks (CRNs), including MLPs, CNNs, RNNs, LSTMs, and Autoencoders.

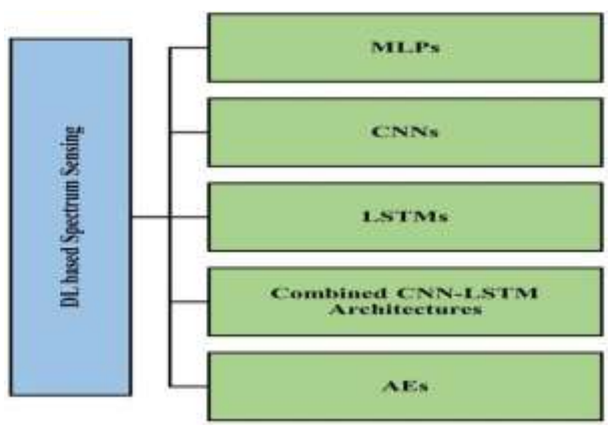

Figure 4. deep-learning-based techniques used in spectrum sensing. [3]

Convolutionalneuralnetworks

Convolutional Neural Networks (CNNs) are specific techniques utilized within deep learning that are often applied in spectrum sensing. A basic CNN architecture includes convolutional layers, pooling layers, and fully connected (fc) layers, in addition to the input and output layers [7]. The applications

DOI: https://doi.org/10.5281/zenodo.17701671

of CNN-based spectrum sensing include signal-time and frequency domain information. Through the relation of how energy and frequency relate to each other, spectrograms are often used to show analysis. The examination of the signal features in both the time and frequency domains is typically conducted using the short-time Fourier transform (STFT) to generate the signal's spectrogram. Consequently, the issue of spectrum sensing can be redefined as an image recognition challenge addressed by a CNN.

CNN method of spectrum-sensing can be applied for signal time domain sensing as proposed and worked by introducing an efficient CNN-based Spectrum sensing model that directly uses spectrogram of the received signal as the input to the CNN for feature extraction, with the use of PU signals at different levels to train the network. the experimental model was further sectioned. The study was divided into two parts to determine the ideal number of epochs and convolutional layers. In the first part, a model with a layer of 32 convolutional kernels was trained for 40 epochs, and its accuracy was evaluated at SNR levels ranging from −5 dB to −20 dB, resulting in a decline in accuracy from 65% to 52%. The second part of the model improved upon the first by incrementally increasing the number of layers to achieve higher accuracy. Results demonstrated that the model's accuracy remained stable even as the SNR of the primary user signal decreased, achieving an impressive 98% accuracy at SNR = −20 dB, marking a notable enhancement compared to the first approach [10]. For the spectrum-sensing method, the researchers utilized the extraction of features from the signal through Short-Time Fourier Transform (STFT), providing a time–frequency matrix of the received signal [6].

The other application is based on statistical features of signals as inputs to the CNN for network training, and the network is tested for sensing based on the data test sets [8] proposed a CNN-based spectrum sensing model utilizing the spectrum correlation function in their work. The SCF is used as input to the proposed CNN model. To enable signal.

In the recognition for test carried out spectrum-sensing across two distinct scenarios, the initial scenario entails training a Convolutional Neural Network (CNN) for classifying signals by extracting the cyclic spectra from GSM, UMTS, LTE, and the spatial spectrum. The resemblance between covariance matrices and images makes CNN an appropriate method for spectrum sensing. Covariance matrices provide crucial insights into the second-order statistics of a signal, serving as a statistical attribute of the signal itself. An innovative study was performed using covariance matrix samples as a statistical test with a CNN to extract essential features. A classifier was developed as the input for a support vector machine (SVM) within the fully connected layer, which further enhances performance, representing one of the novel aspects of the research. The objective is to substitute the softmax loss function in the original CNN with a support vector machine SVM, subsequently utilizing the feature vectors derived from the CNN's covariance matrix as training data for the SVM to develop the classifier. The findings indicated that the detection probability of the

DOI: https://doi.org/10.5281/zenodo.17701671

spectrum-sensing model stabilized at 96%, as the training iterations of the suggested model increased to approximately 45, while the performance concerning false alarm probability remained constant.

This resulted further in improvement of performance by enhancement of the detection at a low SNR when compared with Support vector machine (SVM) algorithms and the separate CNN [9].

Multilayer Perceptrons (Mlps)

A Multilayer Perceptron (MLP) is a type of feedforward Artificial Neural Network (ANN) which includes one or more hidden layers in it. The number or set of neurons in the input layer is determined by the dataset dimensions which aim in optimizing the MLP (Sadaf Nazneen syed *et al*, 2023). The architecture of a simple MLP having multiple hidden layers is depicted in figure 5.

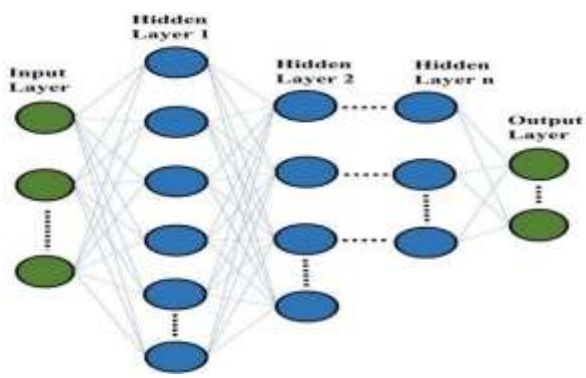

Figure 5. an MLP with multiple hidden layers [21]

MLP containing more hidden layers can be used for centralized Spectrum Sensing of the primary users PU spectrum integrating information geometry with Deep Learning techniques. The input method known as 'IG-DNN' uses a dataset composed geodesic distances gotten from sensing signals covariance matrices, along with noise. The energy levels of both noise and signals, incorporated with various SNR levels are sensed by multiple Sus to design the MLP input[5].

In another research work by [28], an MLP featuring two hidden layers is developed after fine-tuning the number of hidden layers, the neurons count in each layer, optimization algorithm, activation function and learning rate for SS. The PU data is created from four distinct radio technologies gathered through an empirical setup akin to that in work.

MLP contains certain parameters or features which include hidden layers, number of neurons, learning rate and hyperparameter tuning.

Long Short-Term memory networks

An additional frequently utilized class of deep neural network employed in the area of spectrum sensing is the Recurrent neural network (RNNs). This method is mostly adept at processing time-series signals. The process involves a feedback A process where the output from a layer is given back as input to assess the output of that same layer [21]. (RNNs) application in cognitive radio provides a better channel selection through exploiting a certain band information for future utilization prediction. Long short-term memory networks (LSTMs) are a special type of RNNs which can process and capture long term time dependencies, and generate learning can exploit correlation from the time series spectral data. This helps create better prediction of spectrum dynamics.

The application of LSTMs can be based on different inputs and combination of algorithms. In a work carried out by [11], spectrum realization through signal recognition and detection was experimented

DOI: https://doi.org/10.5281/zenodo.17701671

by learning the cyclostationary attributes of time-discrete signals are analyzed using LSTM, along with the original signal data. The classification of various signals is achieved by highlighting distinct cyclostationary features, which are derived from the spectral correlation function and the cyclic profile of the signals, formatted as sequences fed into the LSTM. Meanwhile, the original signal data is utilized for learning the raw data.

in the experiment, the performance of the LSTM based on the raw data is compared to that of the work's method. The result showed a 93.5% classification accuracy for the time-discrete signals, and 99.8% for original data. These proves that LSTM has greater efficiency in original data learning.

For combination of algorithm base method, [12] consider improving the performance of LSTM-based spectrum-sensing methods under a dynamic signal-to-noise ratio by firstly, extracting spectral features of the signal as LSTM inputs through CNNs, and the optimizing it hyperparameters by introducing a cutting fish algorithm. Experiments were conducted with comparing the research detection probability method with CNN-LSTM, energy detection and cyclostationary feature detection method. The results showed that the work method was slightly better than the CNN-LSTM at different frequencies for the spectrum

Combined CNN-LSTM architectures

Convolutional neural networks (CNNs) and Long short-term memory (LSTM) can be combined to create a deep learning technique known as CNN-LSTM model. This combination technique is used to extract complex data features by leveraging CNN's ability to extract special features from input data, and LSTM's ability to capture temporal variations, and handling of sequential data for sensing efficiency and optimization.

In a study conducted by [13], the authors seek to improve spectrum sensing in multi-user cooperative cognitive radio systems by utilizing a hybrid model that incorporates the CNN-LSTM algorithm. The central concept of the paper involves a groundbreaking model for multi-user cooperative spectrum sensing developed, utilizing the CNN's feature extraction, and LSTM's data sequence handling. They further introduced a multi-head self-attention mechanism to improve the data in-flow, thereby enhancing the model's adaptability and robustness complex environments. Experimental simulations were carried out to evaluate the proposed model's performance, and the result The CNN-LSTM model demonstrated low error rates in sensing across various configurations of secondary users (16, 24, 32, 40, 48), achieving a notably low error rate of 9.9658% with 32 users. Furthermore, the proposed model consistently outperformed others, exhibiting a 12% reduction in sensing errors under low-power conditions (100 mW) compared to other deep learning models' sensing errors. In another study conducted by [15], a cooperative spectrum sensing technique was introduced that relies on a channel attention mechanism alongside a parallel (CNN-LSTM) network. This approach leverages the combined framework models of CNN and LSTM to capture spatial and temporal attributes from the spectrum sensing data. Initially, a channel attention mechanism is incorporated into the CNN to improve focus on crucial features within the

DOI: https://doi.org/10.5281/zenodo.17701671

spectrum sensing data during the spatial feature extraction phase, while the LSTM is subsequently used to extract the temporal features from each secondary user's spectrum sensing data. afterwards, the features obtained from both models are merged and flattened, undergoing a feature-level fusion via a fully connected layer to generate the final spectrum sensing output. Findings from the simulations demonstrated that, this approach achieved a high detection probability, particularly with the low Signal-Noise-Ratio (SNR) scenarios. When the SNR drops below a level -10 dB, the average detection probability of the proposed method rises by 5.83% compared to alternative methods, relative to parallel CNN and LSTM methods at a false alarm probability of 0.1, and by 7.09%.

Auto-Encoders

Auto-encoders are a type of a feed-forward, unsupervised neural algorithm that are designed for reduction of dimension in data. They do so by reducing the input's dimension and reconstruction of the data. the two main parts: encoder and decoder, process with the former functioning by learning from input to hidden representation and vice-versa for the latter. Auto-encoder architectures consisting of two or more layers have been used for spectrum sensing.

The application of auto-encoders in spectrum sensing variates with certain modulation, from denoising to modification based on need. [16] carried out a research with Sparse auto-encoders, constraining on the hidden layer which is applied for features extraction from unlabeled data. The authors introduced an innovative modulation classification technique that utilizes a denoising sparse auto-encoder as a classifier to enhance spectrum sensing, thereby minimizing interference with primary users (PU). The application results demonstrated that the denoising method enhanced noise suppression performance by training the network using a corrupted database. In another work by (Subray *et al*, 2021), two variations of spectrum sensing signals were classified using three different auto-encoders algorithms. Namely: variational, deep and LSTM auto-encoders, with the first two consisting of two hidden layers, and LSTM cells LSTM auto-encoder. They further added USRP B210 and GNU Radio to capture the LTE signals while WiFi signals were generated using MATLAB. Both signals were matched by addition of 20 dB. Several combinations of the signals were applied to evaluate the auto-encoders from 802.11ax and 802.11ac Wi-Fi protocols. The result was based on precision and recall metric with the deep auto-encoder with a linear activation unit proven to be more efficient for task classification.

Discussion

In this part, we evaluate and contrast the various deep-learning methods for spectrum sensing found in the literature. The range of deep-learning approaches for spectrum sensing is varied, with each technique architecture offering unique trade-offs through performance and complexity. The choice for a deep-learning model is influenced greatly by input data nature and some specifications of application.

Multi-layer perceptrons do serve as baselines, showcasing the capability of even simple nueral networks outperforming traditional techniques of spectrum sensing

DOI: https://doi.org/10.5281/zenodo.17701671

like energy detection when provided with defined features. However, this dependence on feature engineering, which requires domain knowledge creates the technique fundamental limitation and can subtle disregard signal parameters in raw data. Convolutional neural networks on the other hand, mirrors a great step forward through feature extraction automation process. Its capability to study spatial features from image- like representations of signals, such as spectrograms, makes them outstanding for classification and detection, thereby demonstrating a high impact performance in signal classification. Nevertheless, their primary weakness is a limited capacity to long-range temporal dependencies which an communication inherent.

The subsequent deployment of Long short-term memory (LSTMs) aimed at addressing the temporal modeling challenge. This was done by processing sequential data such as time-series I/Q samples to capture dynamics and signal transmission memory, make it ideal for future spectrum hole prediction, and detecting signal with complex temporal features[30. LSTMs have high computational cost and longer training time as a result of sequential processing which is a main drawback.

The emergence of the combined CNN-LSTM hybrid model, was a far greater powerful framework. With the CNN acting as a spatial feature extractor from time segments, while the LSTM models the temporal evolution. This is suitably applicable for real-world scenarios where signals exhibit both distinct spectral features and temporal modulation, resulting to achieving superior performance by capturing the whole spatio-temporal signal labels. The high cost of increased model complexity and data requirements is a great limitation [29]. In contrast, Auto-Encoders offer a more distinctive pathway. It can detect primary user signals by compressing representations of normal data which can cause high reconstruction error. This approach is valuable to non-cooperative sensing scenarios where labeled training data for specific signals is unavailable. However, the setback lies in setting a robust detection threshold which can dynamically respond to noise (Y. Lin *et al*, 2021).

Provided below, is a comparative analysis of the deep-learning techniques, highlighting their various features for spectrum sensing.

Conclusion and Future Perspective

As the vitality of spectrum sensing and management in cognitive radio cannot be over-emphasized, spectrum sensing is an essential technique for enhancing the effectiveness and efficiency of spectrum utilization for the achievement of efficiency of spectrum resources allocation, which holds significant research values and prospects. CR technology plays a key role in spectrum sensing, enabling secondary users (SUs) to tap into the unutilized frequency bands of primary users (PUs), thus enhancing spectrum efficiency. The application of deep learning (DL) algorithms for spectrum sensing can significantly improve the performance of wireless networks. This paper presents an overview of deep learning methods and techniques employed for spectrum sensing in cognitive radio networks, categorizing them into LSTMs, MLPs, CNNs, combined CNN-LSTM, and

DOI: https://doi.org/10.5281/zenodo.17701671

Auto-encoder architectures. A comparison of these deep learning techniques is provided based on their features, datasets, evaluation metrics, and outcomes. The unique aspects of deep learning methods versus traditional approaches are highlighted.

Ultimately, deep-learning-based spectrum sensing necessitates a considerable amount of research effort and technical support before it can be effectively implemented in practical, complex sensing scenarios to enhance spectrum utilization efficiency, which can positively influence the field of communication. According to the current research landscape, important future research avenues for deep-learning-based spectrum sensing involve further enhancing detection performance and robustness in low signal-to-noise ratio conditions. Furthermore, investigating dynamic threshold configurations and the utilization of self-encoders in spectrum sensing should also be pursued for enhancements.

References

1. Qin, Z., Ye, H., Li, G. Y., & Juang, B. H. F. (2019). Deep learning in physical layer communications. IEEE Wireless Communications, 26(2), 93–99. https://doi.org/10.1109/MWC.2019.1800155
2. Xing, H., Qin, H., Luo, S., Dai, P., Xu, L., & Cheng, X. (2022). Spectrum sensing in cognitive radio: A deep learning-based model. Transactions on Emerging Telecommunications Technologies, 33(6), e4388. https://doi.org/10.1002/ett.4388
3. Elsaraf, Z., Khan, F. A., & Ahmed, Q. Z. (2021, September). Deep learning-based power allocation schemes in NOMA systems: A review. In Proceedings of the 26th International Conference on Automation and Computing (ICAC) (pp. 1–6). IEEE. https://doi.org/10.23919/ICAC.2021.9594237
4. Ojo, S., Akkaya, M., & Sopuru, J. C. (2022). An ensemble machine learning approach for enhanced path loss predictions for 4G LTE wireless networks. International Journal of Communication Systems, 35(11), e5101. https://doi.org/10.1002/dac.5101
5. Du, K., Wan, P., Wang, Y., Ai, X., & Chen, H. (2020). Spectrum sensing method based on information geometry and deep neural network. Entropy, 22(1), 94. https://doi.org/10.3390/e22010094
6. Chen, Z., Xu, Y. Q., Wang, H., & Guo, D. (2020). Deep STFT-CNN for spectrum sensing in cognitive radio. IEEE Communications Letters, 25(3), 864–868. https://doi.org/10.1109/LCOMM.2020.3048604
7. Cai, L., Cao, K., Wu, Y., & Zhou, Y. (2022). Spectrum sensing based on spectrogram-aware CNN for cognitive radio network. IEEE Wireless Communications Letters, 11(10), 2135–2139. https://doi.org/10.1109/LWC.2022.3183644

DOI: https://doi.org/10.5281/zenodo.17701671

8. Tekbıyık, K., Akbunar, Ö., Ekti, A. R., Görçin, A., Kurt, G. K., & Qaraqe, K. A. (2021). Spectrum sensing and signal identification with deep learning based on spectral correlation function. IEEE Transactions on Vehicular Technology, 70(11), 10514–10527. https://doi.org/10.1109/TVT.2021.3117813
9. Wang, Q., & Guo, B. (2022). CNN-SVM spectrum sensing in cognitive radio based on signal covariance matrix. In Journal of Physics: Conference Series (Vol. 2395, p. 012052). IOP Publishing. https://doi.org/10.1088/1742-6596/2395/1/012052
10. El-Shafai, W., Fawzi, A., Sedik, A., Zekry, A., El-Banby, G. M., Khalaf, A., Abd El-Samie, F. E., & Abd-Elnaby, M. (2022). Convolutional neural network model for spectrum sensing in cognitive radio systems. International Journal of Communication Systems, 35(15), e5156. https://doi.org/10.1002/dac.5156
11. Kassiny, B. M. A. (2022, December 13–14). A deep learning-based signal classification approach for spectrum sensing using long short-term memory (LSTM) networks. In Proceedings of the 2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE) (pp. 667–672). IEEE. https://doi.org/10.1109/ICITISEE56752.2022.10022128
12. Arunachalam, G., & SureshKumar, P. (2023). Optimized deep learning model for effective spectrum sensing in dynamic SNR scenario. Computer Systems Science and Engineering, 45(3), 1279–1294. https://doi.org/10.32604/csse.2023.033848
13. Wang, K., Chen, Y., Bo, D., & Wang, S. (2025). A novel multi-user collaborative cognitive radio spectrum sensing model: Based on a CNN-LSTM model. PLOS ONE, 20(1), e0316291. https://doi.org/10.1371/journal.pone.0316291
14. Bai, W., Zheng, G., Mu, Y., Ma, H., Han, Z., & Xue, Y. (2025). Cooperative spectrum sensing method based on channel attention and parallel CNN-LSTM. **Digital Signal Processing, 158**, 110021. https://doi.org/10.1016/j.dsp.2025.110021
15. Zhu, X., & Fujii, T. (2016). A novel modulation classification method in cognitive radios using higher-order cumulants and denoising stacked sparse autoencoder. In Proceedings of the Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA) (pp. 1–5). IEEE.
16. Kao, H. W., & Wu, E. H. K. (2023). QoE sustainability on 5G and beyond 5G networks. IEEE Wireless Communications, 30(1), 118–125. https://doi.org/10.1109/MWC.001.2300121

DOI: https://doi.org/10.5281/zenodo.17701671

17. Shekhawat, G. K., & Yadav, R. P. (2021). Review on classical to deep spectrum sensing in cognitive radio networks. In Proceedings of the Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET) (pp. 11–15). IEEE. https://doi.org/10.1109/WiSPNET51692.2021.9419462
18. Ganesh Babu, R., & Amudha, V. (2019). A survey on artificial intelligence techniques in cognitive radio networks. In Emerging Technologies in Data Mining and Information Security (pp. 99–110). Springer. https://doi.org/10.1007/978-981-13- 1165-9_9
19. Kaur, A., & Kumar, K. (2022). A comprehensive survey on machine learning approaches for dynamic spectrum access in cognitive radio networks. Journal of Experimental & Theoretical Artificial Intelligence, 34(1), 1–40. https://doi.org/10.1080/0952813X.2021.1974560
20. Syed, S. N., Lazaridis, P. I., Khan, F. Ahmed, Q. Z., Hafeez, M., Ivanov, A., Poulkov, V., & Zaharis, Z. D. (2023). Deep neural networks for spectrum sensing: A review. IEEE Access, 11, 89591–89615. https://doi.org/10.1109/ACCESS.2023.3305767
21. Ali, M., Yasir, M. N., Bhatti, D. M. S., & Nam, H. (2022). Optimization of spectrum utilization efficiency in cognitive radio networks. IEEE Wireless Communications Letters, 12(2), 426–430. https://doi.org/10.1109/LWC.2022.3220832
22. Zhao, Y., Wang, C., Hu, M., Wu, H., Lin, F., & Liu, Z. (2022). A cooperative wideband spectrum sensing framework in the frequency domain for resource allocation with 5G-NR. Measurement, 191, 110756. https://doi.org/10.1016/j.measurement.2022.110756
23. Lim, C. H. (2022). Spectrum sensing for a radar signal with pulse compression in cognitive radios. IEEE Communications Letters, 26(12), 3074–3078. https://doi.org/10.1109/LCOMM.2022.3212763
24. Saber, M., Chehri, A., Rharras, A. E., Saadane, R., & Wahbi, M. (2021). A cognitive radio spectrum sensing implementation based on deep learning and real signals. In Innovations in Smart Cities Applications (Vol. 4, pp. 930–941). Springer. https://doi.org/10.1007/978-3-030-66840-2_69
25. Shakeel, T., et al. (2021, November 9-10). [Title of paper]. In Proceedings of the 2021 International Conference on Innovative Computing (ICIC 2021) (pp. 1–528). IEEE.
26. B. Wang and K. R. Liu, "Advances in cognitive radio networks: A survey," IEEE Journal of selected topics in signal processing, vol. 5, pp. 5-23, 2010.

DOI: https://doi.org/10.5281/zenodo.17701671

27. **G. Ding, Y. Jiao, J. Wang, Y. Zou, Q. Wu, Y.-D. Yao, et al**.(2017), "Spectrum inference in cognitive radio networks: Algorithms and applications," IEEE Communications Surveys & Tutorials, 20(1) 150-182, 2017.
28. Soni, B., Patel, D. K., & López-Benítez, M. (2020). Long short-term memory based spectrum sensing scheme for cognitive radio using primary activity statistics. IEEE Access, 8, 97437–97451. https://doi.org/10.1109/ACCESS.2020.2995873.
29. J. Gao, X. Yi, C. Zhong, X. Chen, and Z. Zhang, ‘‘Deep learning for spectrum sensing,’’ IEEE Wireless Commun. Lett., vol. 8, no. 6, pp. 1727–1730, Dec. 2019
30. Yang, Y. (2022, August). Cognitive Radio Spectrum Sensing Technology. In 2022 9th International Conference on Dependable Systems and Their Applications (DSA) (pp. 1002-1003). IEEE.

DOI: https://doi.org/10.5281/zenodo.17701671