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"ENHANCED THE PERFORMANCE OF SPECTRUM SENSING IN COGNITIVE RADIO NETWORK USING CLASSIFICATION TECHNIQUES"

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ABSTRACT

Cognitive radio networks (CRNs), an assemble of smart schemes intended for permitting secondary users (SUs) to opportunistically access spectral bands vacant by primary user (PU), has been deliberated as a solution to improve spectrum, utilization. Cooperative spectrum sensing (CSS) is a vital technology of CRN systems used to enhance the PU detection performance by exploiting SUs' spatial diversity, however CSS leads to spectrum sensing data falsification (SSDF), a new security threat in CR system. The SSDF by malicious users can lead to a decrease in CSS performance. In this paper we proposed the r spectrum sensing model using the deep neural network classification and gives better result than the existing techniques.

Key Words: Cognitive Radio Network, Classification Techniques, Neural Network, Support Vector Machines, Deep Neural Network.

I. INTRODUCTION

Nowadays the Internet of Things (IoT) is one of the most rising network applications that connects the billions of networking devices across the globe to the Internet world and permits connectivity among devices, all networking appliances can collect and share data continuously over the internet to achieve better value and services. Nevertheless, there are several challenges that abate the outgrowth of IoT networks such as its requires greater bandwidth for connecting a lot number of hybrid communication devices and services, ensuring the security of a massive number of heterogeneous devices and networks, high implementation cost, lack of adequate spectrum and more energy required than the conventional communication systems. Cognitive Radio (CR) technology is developed to solve the spectrum shortage due to increasing wireless devices and networks. It promotes the use of the radio frequency band by permitting Secondary User (SU) to allow the licensed spectrum of the Primary User (PU). In a Cognitive Radio based IoT (CR-IoT) network, each CR-IoT user is conveniently using the idle licensed frequency bandwidth when the licensed user is absent in the CR-IoT networks. Basically, each CR-IoT user detects the unoccupied licensed channels and selects the one that is most appropriate for data transmission. To overcome the unacceptable conflict between the PU and the CR-IoT user, the CR-IoT user leaves the licensed spectrum as soon as possible when the PU returns to transmit data in the network. The unoccupied licensed spectrum detection is a very important part in the CR Network (CRN) to overcome the unacceptable conflict between the PU and the SU. Licensed spectrum detection approaches can be classified into many groups, including non-coherent spectrum sensing, coherent spectrum sensing, Non- Cooperative Spectrum Sensing (NCSS), and Cooperative Spectrum Sensing (CSS). In a non-coherent spectrum sensing, for the purpose of spectrum sensing it is not require any

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previous knowledge about the PU signal. In a coherent detection scheme, PU signal detection requires perfect prior knowledge of the PU signal, e.g. synchronization message, presenter, spectral scattering sequences, training and pilot patterns. In non-cooperative detection, CR-IoT users do not need to exchange sensing information with other CR-IoT users. In this method, the performance of spectrum detection is reduced due to concealed terminal issues, multi-path fading, and shadow impact. In CSS technique, where group of CR-IoT users cooperatively execute spectrum detection to mitigate the multi-path fading, hidden terminal problem, and shadowing effects. In CSS technique, each CR-IoT user sends the spectral detection result of the PU signal to the respective Fusion Center (FC) individually. Thereafter, the FC uses the fusion rule on the collected spectrum detection outcomes of the CR-IoT users to take a final global decision. In the end, the FC transfers a final global decision to all CR-IoT user about the appearance and non-appearance of the PU signal in the CR-IoT networks. Numerous spectrum sensing methods have been investigated under varying conditions, including matched filter method, cyclostationary feature method, entropy-based method, eigenvalue-based method, and Energy Detection (ED) method. The matched filter method and cyclostationary feature method are both easy to understand and execute. However, both require reliant prior knowledge of PU signals, e.g., the carrier frequency, the modulation technique, amplitude, and phase of the PU signal. The ED method is one of the simplest methods to calculate the received signal energy of the PU signal without any previous information about the PU signal [14]. Therefore, it is the most commonly used method for spectrum sensing in CRNs. However, the ED is very susceptible to noise fluctuations and needs a absolutely right understanding of the influence of noise signal power at the receiver side of the CR-IoT user for proper identification of PU signal. As a result, the detection performance of the ED method is degraded in noise uncertainty environments and low Signal to Noise Ratio (SNR) value.

II. SMART GRID COGNITIVE RADIO

Conventional power grids are large interconnected networks that widely distribute energy from suppliers to consumers. The electric power only flows from the power generating stations to the consumers and information monitoring is handled only in the distribution networks that distribute electrical power within a city to the individual consumers. These power grids face new challenges, such as growing energy demands, aging infrastructure, emerging renewable energy sources, as well as reliability and security problems. To overcome these challenges, the Smart Grid (SG) paradigm has been introduced with a variety of state-of-the-art enabling information technologies [5]. These technologies cover the areas of embedded sensing, broadband wireless communication, pervasive computing, adaptive control, as well as automated and intelligent management. These SG technologies can achieve significant improvements in the efficiency, effectiveness, sustainability, reliability, security, and stability of the electrical grid.

III. SPECTRUM SENSING TECHNIQUES

Due to the rapid growth in the field of communication, there is an increasing demand for higher data rates. Static frequency assignment cannot fulfill the requirements of higher data rates. In CR communication, spectrum sensing is performed before an SU starts using the spectrum. By spectrum sensing, the white holes are determined and these holes are used efficiently. There are certain methods for sensing the unused spectrum. Spectrum sensing techniques (Cooperative detection, Transmitter detection and Interference-based detection) are shown in below figure.

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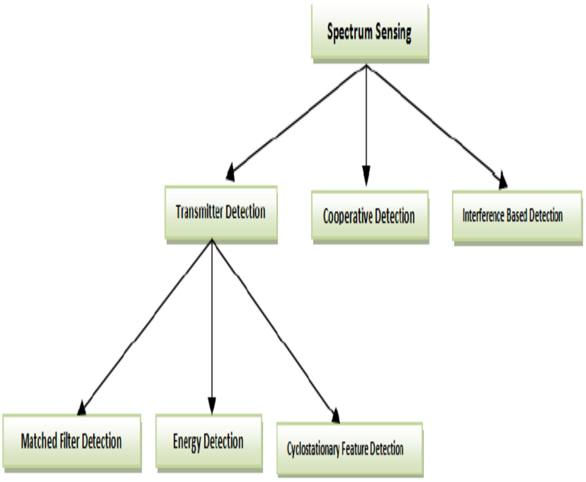

Figure 1: Different Spectrum Sensing Techniques.

IV. PROPOSED WORK

The rapid development of wireless communication technology has led to more and more wireless network services. The radio spectrum, as the most valuable resource in wireless networks, cannot meet the requirements of wireless services at present and in the future. The existing fixed spectrum allocation method makes the spectrum utilization low and seriously uneven. According to the investigation, the average spectrum utilization is less than 5% at any time or place. Dynamic spectrum access (DSA) is considered to be the main technical solution to the contradiction between supply and demand. As the basis of DSA, cognitive radio (CR) technology has become one of the most cutting-edge research topics in the field of wireless networking. Note that the proposed schemes here balance sensing performance and sensing complexity. Although the considered CNN networks are classical, they are easy to implement due to their high popularity. Both the data acquisition and the network structure have low complexity. However, the sensing performance is at a high level according to the results of the simulation experiments. In summary, the proposed schemes in this paper are necessary and useful for the possible performance improvement of SS.

System Model

Sensing Scenario

As shown in below figure, each SU directly transmits the local sensing information to the FC, and the FC makes the final decision and then sends it to each SU for the centralized CSS. The details of centralized CSS are as follows:

1. The energy vector of each sensing node is obtained by the sampling and signal processing.
2. The obtained energy vector of each node is sent to FC over the reporting channel, where the reporting channel obeys the Rayleigh distribution.
3. After the reporting channel, a two-dimensional matrix is obtained with the energy vector of each sensing node. Then, the mean value of the covariance of the two-dimensional matrix is removed by each matrix element. Finally, the updated two-dimensional matrix is input to the CNN module for the final decision.
4. The final decision result at FC is sent to each local sensing node.

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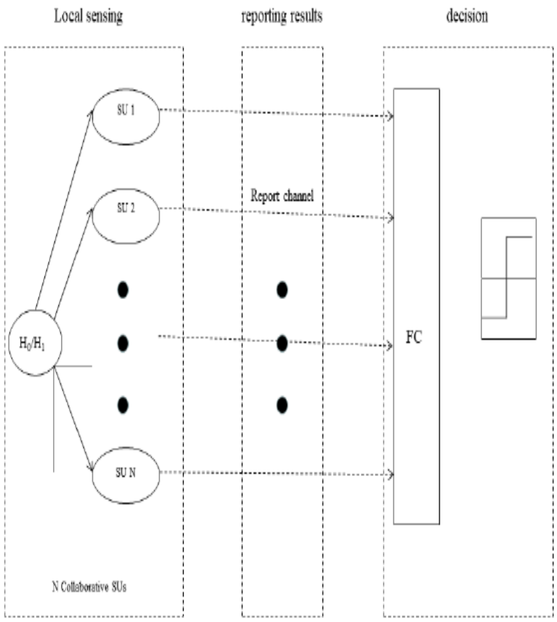

Figure 2: The flowchart of centralized CSS (cooperative spectrum sensing).

V. EXPERIMENTAL WORK

Different performance metrics are used to check the performance of proposed model in various network environments. In our experiment we have some standard performance parameters like channel ratio, accuracy and the throughput for the efficient communication, The reason for the selection of these performance metrics is to check the performance of proposed model for the energy efficiency in the wireless sensor networks.

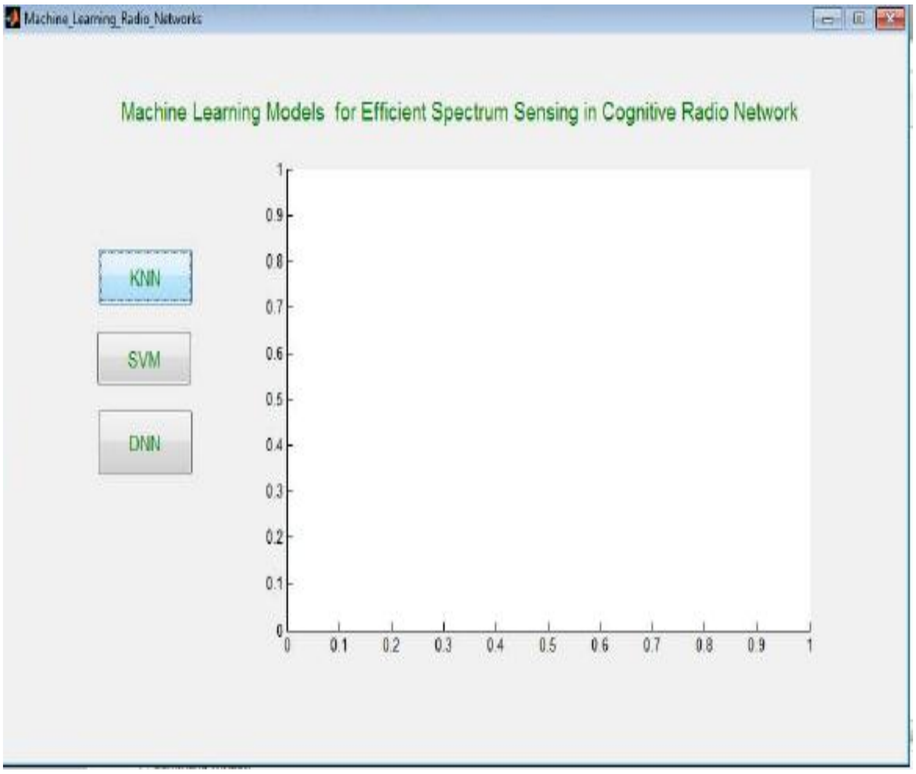

Figure 3: The above figure shows that the simulation graphical user interface window for the KNN classification.

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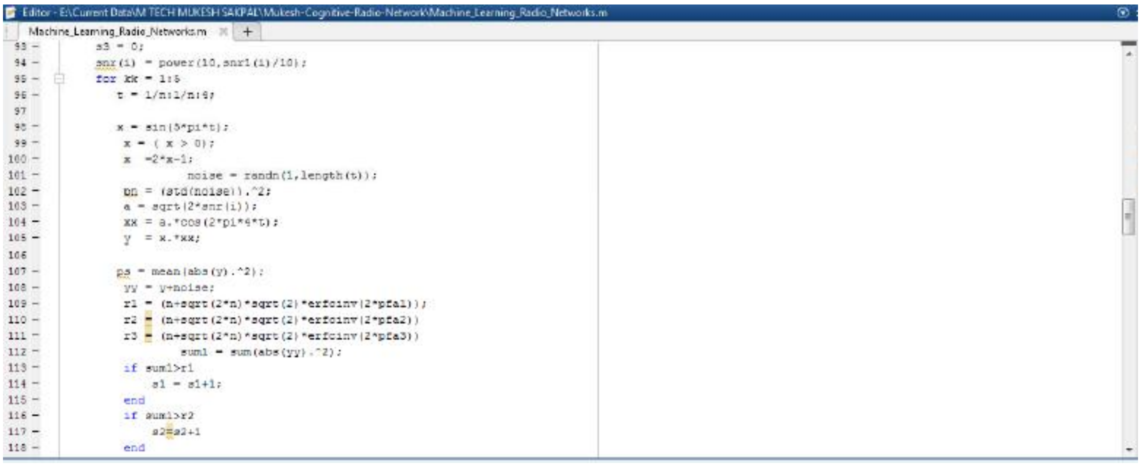

Figure 4: The above figure shows that the simulation execution with code environment for the experimental work.

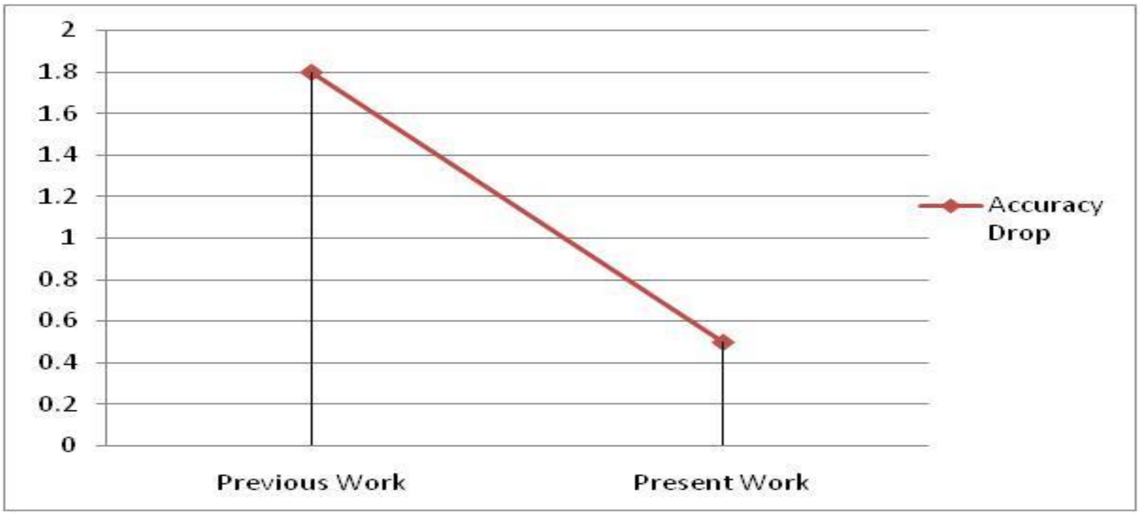

Figure 5: The above picture shows that the experimental work window for the previous work and present work classification with performance parameters like accuracy drop during transmission.

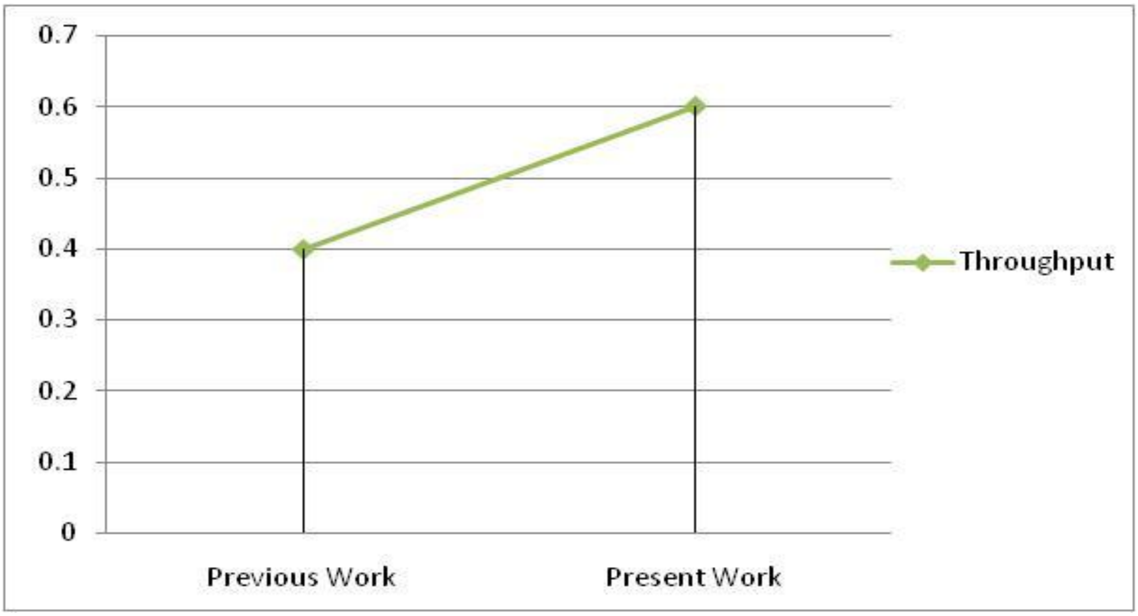

Figure 6: The above picture shows that the experimental work window for the previous work and present work classification with performance parameters like throughput during transmission.

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VI. CONCLUSION

Radio spectrum is naturally a limited resource in wireless communication systems. During the last couple of decades, most of the available spectrum has been licensed for providing high data-rate communication services. This has led to the spectrum scarcity problem for the fifth-generation and beyond wireless communication systems. On the other hand, measurements of the practical spectrum utilization have shown that a large amount of the licensed spectrum is highly underutilized. As a remedy to improve spectral efficiency, communication systems employing cognitive radio (CR) technology have been emerged as a promising paradigm to provide communication services for unlicensed secondary systems without seriously degrading the system performance of the primary network. Cognitive radio is a novel approach that basically improves the utilization efficiency of the radio spectrum. Author presents an extensive analysis of spectrum sensing techniques in cognitive radio. Cooperative spectrum sensing is better than classical spectrum sensing as it overcomes the hidden node problem, reduces false alarm and gives more accurate signal detection. In multiple antenna spectrum technique no prior information of signal is needed. It provides more accurate signal detection in less sensing time than cooperative sensing technique. In this dissertation, we propose a Deep Learning (DL) and Support vector machines (SVM) based channel Estimator. In this work, we propose a novel idea of “Channel Boosting” to improve deep neural networks’ with support vector machines. We have demonstrated that the use of Channel Boosted input can improve the performance of a DNN.

REFERENCES

[1] Manish Kumar Giri, Saikat Majumder, “Extreme Learning Machine Based Cooperative Spectrum Sensing in Cognitive Radio Networks”, 7th International Conference on Signal Processing and Integrated Networks, IEEE, 2020, pp. 636-641.
[2] J. Tlouyamma, M. Velempini, “Investigative analysis of channel selection algorithms in cooperative spectrum sensing in cognitive radio networks”, South African Institute of Electrical Engineers, 2021, pp. 4-15.
[3] A. Manasa, V. Srikanth, “Reinforcement Learning Approach to Reduce Latency for Spectrum Sensing in Cognitive Radio Wireless Networks”, Turkish Journal of Physiotherapy and Rehabilitation, 2021, pp. 3044-3049.
[4] Dongfang Xu, Xianghao Yu, Robert Schober, “Resource Allocation for Intelligent Reflecting Surface-Assisted Cognitive Radio Networks”, IEEE 2020. pp. 1-5.
[5] Amjad Ali, Sikandar Tariq, Muddesar Iqbal, Li Feng, Imran Raza, Muhammad Hameed Siddiqi, Ali Kashif Bashir, “Adaptive Bitrate Video Transmission Over Cognitive Radio Networks Using Cross Layer Routing Approach”, IEEE Transactions on Cognitive Communications and Networking, 2020, pp. 1-13.
[6] Mohammad Amzad Hossain, Michael Schukat, Enda Barrett, “MU-MIMO Based Cognitive Radio in Internet of Vehicles (IoV) for Enhanced Spectrum Sensing Accuracy and Sum Rate”, IEEE 2021, pp. 1-8.
[7] Oluyomi Simpson, Yichuang Sun, “Robust Statistics Evidence Based Secure Cooperative Spectrum Sensing for Cognitive Radio Networks”, IEEE 2020, pp. 1-7.
[8] Youheng Tan, Xiaojun Jing, “Cooperative Spectrum Sensing Based on Convolutional Neural Networks”, Appl. Sci. 2021, pp. 1-13.
[9] Sara A. Attalla, Karim G. Seddik, Amr A. El-Sherif, Tamer ElBatt, “A Reinforcement Learning Approach to ARQ Feedback-based Multiple Access for Cognitive Radio Networks”, IEEE 2021, pp. 1-6.
[10] Shuai Liu, Jiayun Wu, Jing HE, “Dynamic Multichannel Sensing in Cognitive Radio: Hierarchical Reinforcement Learning”, IEEE Access 2021, pp. 25473-25482.
[11] V. Balajia, Pranav Kabrab, P. V. P. K. Saieesh, C. Hota, G. Raghurama, “Cooperative Spectrum Sensing in Cognitive Radios using Perceptron Learning for IEEE 802.22 WRAN”, Procedia Computer Science, Elsevier, 2015, pp. 14- 23.
[12] Shuangyi Zhang, Hua Tian, Xueqiang Chen, Zhiyong Du, Luying Huang, Yuping Gong, Yuhua Xu, “Design and implementation of reinforcement learning-based intelligent jamming system”, IET Commun., 2020, pp. 3231-3238.
[13] Nisha Yadav, Suman Rathi, “A Comprehensive Study of Spectrum Sensing Techniques in Cognitive Radio”, International Journal of Advances in Engineering & Technology, 2011, pp. 85-97.
[14] Akyildiz, I.F.; Lo, B.F.; Balakrishnan, R. Cooperative spectrum sensing in cognitive radio networks: A survey. Phys. Commun. 2011, 4, 40–62.
[15] Na,W.; Yoon, J.; Cho, S.; Griffith, D.W.; Golmie, N. Centralized Cooperative Directional Spectrum Sensing for Cognitive Radio Networks. IEEE Trans. Mob. Comput. 2017, 17, 1260–1274.

ISSN : 2455-9679
Impact Factor : 4.256

[16] Chen, Z.; Gao, F. Cooperative-Generalized-Sensing-Based Spectrum Sharing Approach for Centralized Cognitive Radio Networks. IEEE Trans. Veh. Technol. 2015, 65, 3760–3764.
[17] Ling, Q.; Wen, Z.; Yin, W. Decentralized Jointly Sparse Optimization by Reweighted lq Minimization. IEEE Trans. Signal Process. 2013, 61, 1165–1170.
[18] Tsinos, C.G.; Berberidis, K. Decentralized Adaptive Eigenvalue-Based Spectrum Sensing for Multiantenna Cognitive Radio Systems. IEEE Trans. Wirel. Commun. 2014, 14, 1703–1715.
[19] Chaudhari, S.; Koivunen, V.; Poor, H.V. Autocorrelation-Based Decentralized Sequential Detection of OFDM Signals in Cognitive Radios. IEEE Trans. Signal Process. 2009, 57, 2690–2700.
[20] Di Lorenzo, P.; Barbarossa, S.; Sayed, A.H. Bio-Inspired Decentralized Radio Access Based on Swarming Mechanisms Over Adaptive Networks. IEEE Trans. Signal Process. 2013, 61, 3183–3197.
[21] Noorshams, N.; Malboubi, M.; Bahai, A. Centralized and decentralized cooperative spectrum sensing in cognitive radio networks: A novel approach. In Proceeding of the 2010 IEEE 11th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Marrakech, Morocco, 20–23 June 2010; pp. 1–5.
[22] Shinde, S.C.; Jadhav, A.N. Centralized cooperative spectrum sensing with energy detecion in cognitive radio and optimization. In Proceedings of the 2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), Bangalore, India, 20–21 May 2016; pp. 1002–1006.
[23] Misra, R.; Kannu, A.P. Optimal sensing-order in cognitive radio networks with cooperative centralized sensing. In Proceedings of the 2012 IEEE International Conference on Communications (ICC), Ottawa, ON, Canada, 10–15 June 2012; pp. 1566–1570.
[24] Bastami, B.A.; Saberinia, E. A low complexity multi-threshold centralized detection strategy for cooperative spectrum sensing. In Proceedings of the 2011 IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications, Toronto, ON, Canada, 11–14 September 2011; pp. 349–353.
[25] Gao, J.; Yi, X.; Zhong, C.; Chen, X.; Zhang, Z. Deep Learning for Spectrum Sensing. IEEE Wirel. Commun. Lett. 2019, 8, 1727–1730.
[26] He, H.; Jiang, H. Deep Learning Based Energy Efficiency Optimization for Distributed Cooperative Spectrum Sensing. IEEE Wirel. Commun. 2019, 26, 32–39.

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