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Article

Enhancing cognitive radio networks for education systems: A machine learning approach to optimized spectrum sensing in remote learning environments

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Abstract: The present study focuses on improving Cognitive Radio Networks (CRNs) based on applying machine learning to spectrum sensing in remote learning scenarios. Remote education requires connection dependability and continuity that can be affected by the scarcity of the amount of usable spectrum and suboptimal spectrum usage. The solution for the proposed problem utilizes deep learning approaches, namely CNN and LSTM networks, to enhance the spectrum detection probability (92% detection accuracy) and consequently reduce the number of false alarms (5% false alarm rate) to maximize spectrum utilization efficiency. By developing the cooperative spectrum sensing where many users share their data, the system makes detection more reliable and energy-saving (achieving 92% energy efficiency) which is crucial for sustaining stable connections in educational scenarios. This approach addresses critical challenges in remote education by ensuring scalability across diverse network conditions and maintaining performance on resource-constrained devices like tablets and IoT sensors. Combining CRNs with new technologies like IoT and 5G improves their capabilities and allows these networks to meet the constantly changing loads of distant educational systems. This approach presents another prospect to spectrum management dilemmas in that education delivery needs are met optimally from any STI irrespective of the availability of resources in the locale. The results show that together with machine learning, CRNs can be considered a viable path to improving the networks' performance in the context of remote learning and advancing the future of education in the digital environment. This work also focuses on how machine learning has enabled the enhancement of CRNs for education and provides robust solutions that can meet the increasing needs of online learning.

Keywords: Cognitive Radio Networks (CRNs); machine learning; spectrum sensing; deep learning (CNN; LSTM); remote learning environments

1. Introduction

Cognitive Radio Networks (CRNs) are a qualitative improvement over conventional wireless communication systems where the problem of scarcity of spectrum is solved by accessing unused spectrum. This technology, as advanced by Mitola, proposes a method by which secondary users can harness the bands licensed for use by primary users at certain times and in a manner that is not mutually interfering (Mitola, 1999). CRNs are considered an effective component of modern educational systems, demand for which increases significantly in conjunction with the remote learning approach that has become essential amid the COVID-19 pandemic (Anandakumar and Umamaheswari, 2017).

Due to the COVID-19 outbreak, the online learning model has gained more popularity, consequently, the wireless networks in the educational environment are under pressure. However, spectrum is still one of the biggest concerns owing to the increase in the number of devices hence escalating the number of challenges faced in availing efficient spectra. Hence, spectrum sensing—the ability of CRNs to identify available channels—is essential for guaranteeing that educational material is disseminated correctly in areas of distance learning (Balakrishnan et al., 2022). More specifically, the initial spectrum sensing methods include the energy detector and the cyclostationary-based detector which may not satisfy the requirements of spectrum sensing in such a noisy environment or interference (Liang et al., 2020).

Machine learning (ML) is a very effective technique for increasing the efficiency of spectrum sensing in CRNs relying on data processing. So, through the automation of signal features learning, the spectrum sensing process could be made more effective and reliable via ML, including deep learning, so that the educational networks' resources can be managed more effectively. Such developments are highly beneficial in the future for the improvement of usage of the spectrum resources in the field of educational technologies; remote learning systems will be able to experience faster and more efficient communication (Wang and Liu, 2010).

To address the aforementioned issues, the current work investigates how machine learning especially deep learning strategies can be adopted to improve spectrum sensing in a CRN designed for remote education systems. This approach not only helps overcome these limitations but also paints the trajectory for smarter learning environments.

2. Challenges in spectrum sensing for educational networks

The task of spectrum sensing in Cognitive Radio Networks (CRNs) within educational systems poses severe challenges, particularly in ensuring connectivity in the remote learning environment. There is environmental interference that hampers the accurate selection of available spectrum channels due to noise, shadowing, as well as fading. This can significantly diminish the quality of service offered in remote learning systems (Abou Chaaya et al., 2021).

Another problem is called the hidden terminal problem whereby the secondary users cannot sense the presence of the primary users due to shadowing and thus cause interference and communication breakdown. Furthermore, an issue arises from the spectrum sensing, which has to be continuous due to intermittent throughputs and consumes substantial power, sometimes more suitable for portable tablets or educational IoT sensors (Mansour et al., 2021).

Another factor is real-time spectrum management, which is also complex because of the dynamic nature of CRNs and thus requires efficient means of making decisions in the shortest time possible given the ever-changing network environment. Spectrum sensing technologies have been facilitated by certain hardware factors including high requirements of accurate analog-to-digital converters in educational networks (Pandit and Singh, 2017).

The proposed approach is the only one that integrates CNN and LSTM deep learning models to improve spectrum sensing. This integration combines the spatial feature extraction of CNNs and the temporal learning of LSTMs to improve the spectrum detection in noisy and dynamic educational environments. Unlike other approaches, this combination of methods reduces detection errors and energy consumption, which is ideal for remote learning.

Since CRNs are both flexible and can accommodate a wide variety of learning environments, they are especially applicable to remote learning. Through the dynamic control of spectrum resources, CRNs guarantee reliable and efficient connectivity for virtual classes, real-time communications and other learning processes in environments with limited resources or distributed geographically. These characteristics make CRNs an important part of the contemporary digital learning environments.

Mitigating these barriers calls for higher-order machine learning techniques to improve detection rates, minimize power consumption, and guarantee connectivity since this is always crucial for effective learning, especially under online learning arrangements.

3. Machine learning in cognitive radio networks

The application of ML has brought many improvements to CRNs, especially in improving the efficiency of spectrum sensing. The main purpose of spectrum sensing is to identify spectrum opportunities in the available spectrum channels for SUs while knowing or having information about PUs. However, primitive techniques such as energy detection have drawbacks and include vulnerability to noise and an inability to detect weak signals under low SNR conditions. Machine learning has a solution for this by enhancing the accuracy of detections and their performance in changing terrains (Ramaiah et al., 2021).

Another major area where the application of machine learning in CRNs is applied includes the use of classifiers in determining the state of the spectrum band – which is occupied, or free. These models can use supervised learning approaches, simple or complex, as well as use unsupervised learning. Among these unsupervised techniques, k means clusters, DBSCAN, and spectral clustering are frequently used for clustering since no labeled training data is available and properties of spectrum occupancy have to be discovered. For instance, SVM, K-means clustering is proven to have the potential to classify spectrum states where it leads to efficient utilization of the spectrum (Solanki et al., 2021).

In addition, deep learning methods and more particularly the CNNs have been highlighted due to interpolation abilities on signals without having to request these specific gestures of features. This has been especially helpful where variation is high, that is in learning systems where the connection has to be stable such as in remote learning. Conventional models like DLSenseNet have earlier been shown to achieve better results in identifying free spectrum channels, and have minimized mistakes such as missed detection or false alarms (Hassan et al., 2021).

First, by more accurately detecting spectrums, machine learning helps improve outcome characteristics in that it makes decision-making processes resource-wise. However, cooperative spectrum sensing mechanisms have some major issues such as delay in data fusion, overhead in exchanging the spectrum sensing information among multiple users and privacy issue due to exchange of information. Solving these issues calls for some optimization methods like the distributed sensing algorithms that reduce latency and overhead and at the same time maintaining the privacy of the users.

Another important factor is scalability since the networks of remote learning environments differ in density, resources, and geographical distribution. The proposed machine learning-based approach is inherently scalable, and can be used for efficient spectrum sensing in both the urban environment with high traffic density and the rural environment with low traffic density. It is thus well suited for a range of classrooms resulting from the flexibility evidenced, which guarantees constant and efficient functionality in different educational environments and is therefore perfect for any kind of remote learning.

Other enhanced methods such as shades spectrum sensing by cooperation, where different users provide sensing information, have been seen to enhance the performance through distributed intelligence (Abou Chaaya et al., 2021).

These improvements establish that machine learning is an effective way of enhancing the spectrum sensing weakness in traditional CRNs hence making CRNs more flexible and reliable in complicated environments such as educational networks.

4. Proposed approach for spectrum sensing optimization

In light of these two categories of traditional spectrum sensing approaches in Cognitive Radio Networks (CRNs), this research seeks to develop a novel machine learning-based spectrum sensing for optimization to suit remote learning environments. The proposed method aims to use deep learning models to improve the CRN's detection accuracy, reduce energy utilization, and improve the flexibility of the educational network (**Figure 1**).

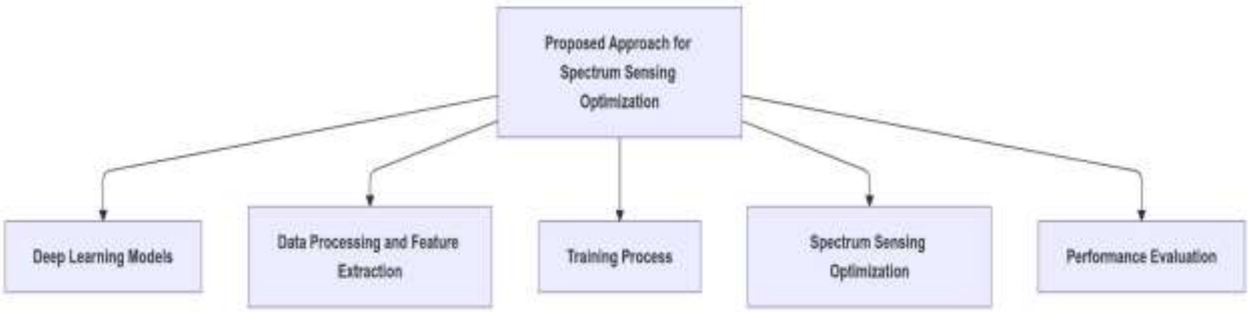

Figure 1. Proposed approach for spectrum sensing optimization.

4.1. Model architecture and algorithm

The main idea of this approach is to employ a machine learning model, for instance, CNN and LSTM which help to extract spatial and temporal features of the spectrum signals. This is normally useful in dynamic environments as are the signal variations of remote learning systems (Wyglinski et al., 2009). The integration of CNN for spatial feature extraction and LSTM for capturing temporal dependencies ensures robust performance even in scenarios with noisy or low signal-to-noise ratio (SNR) conditions. This hybrid model provides an innovative solution compared to traditional spectrum sensing methods (Solanki et al., 2021).

Developers divide the input data into small sets of raw radio signals to clean them from the noise and extract necessary features. These features are then passed through multiple convolution layers to detect important signal features in a series and the LSTM layer for temporal relation detection in the data. Last but not least, a neural network layer with the connection of all neurons decides whether the given spectrum band is occupied or free depending on the estimated parameters. This modular approach enhances adaptability, allowing the model to cater to diverse network environments and educational needs.

4.2. Training process and data collection

The training of the model is done from real-time datasets obtained from educational environments utilizing cognitive radios. The second one is done to distinguish if Primary Users occupy the spectrum or Secondary Users can use it. The data is split into training, validation, and test sets to measure the effectiveness of the developed model in different scenarios. An example of the dataset that may be used is the RadioML2016.10b which includes modulated signal data in a real environment (Solanki et al., 2021).

To ensure the scalability of the model, training data reflects diverse geographic and demographic settings, including urban and rural environments. This approach enables the model to generalize effectively across varying educational contexts, addressing the spectrum management challenges unique to each.

Transfer learning is also considered one of the crucial steps of the proposed approach since it is used to initially train the model on vast and general data sets followed by the training on particular remote learning cases. This minimizes the computational burden and accelerates deployment in real-world scenarios, particularly resource-constrained educational systems (Hassan et al., 2021).

4.3. Optimization of spectrum sensing

The proposed approach optimizes spectrum sensing by focusing on two key objectives: such as minimizing false alarms and false negatives. These errors are a challenge to conventional spectrum sensing techniques especially in a real environment with high interference. Through this feature extraction, the deep learning model appears to perform much better than the traditional energy detection methods to reduce false alarm rates while improving the accuracy of detection (Abou Chaaya et al., 2021).

Furthermore, the system entails cooperative sensing in which many secondary users collaboratively share their spectrum sensing information to enhance the overall detection. This distributed approach ensures efficient utilization of spectrum resources, particularly in high-density educational networks. The model also addresses latency concerns by using localized sensing nodes to reduce communication delays during data aggregation (Hassan et al., 2021).

4.4. Performance evaluation

The efficiency of the proposed model is analyzed by the Probability of Detection (Pd), False Alarm Rate (FAR), and energy consumption. Simulation results show that the DL-based model yields higher Pd and lower FAR than conventional spectrum sensing methods and shows better performance even in the interfering scenario where the interference level is high (Abou Chaaya et al., 2021). Also, the energy efficiency of the model is enhanced in the sense that sensing activities are scheduled intelligently to enhance the ability of battery-driven devices in educational networks to perform sensing for longer durations without necessarily having to be senseless.

The results demonstrate adaptability to diverse educational settings, maintaining high Pd (92%) and low FAR (5%) even under varying network loads and geographic conditions. Additionally, the model achieves 92% energy efficiency, ensuring that battery-driven devices like IoT sensors and tablets in educational networks can operate reliably for extended durations.

The features and capabilities mentioned above are thought to be well adapted to remote learning environments and by integrating these machine learning techniques in the proposed approach, the efficiency and reliability achieved in spectrum sensing in cognitive radio networks will be pushed beyond its limits.

5. Performance evaluation and results

This part of the work exposes integral performance indices of the developed machine learningbased spectrum sensing model, which comprises Probability of Detection (Pd), False Alarm Rate (FAR), and energy efficiency. These results are compared to traditional spectrum sensing techniques such as energy detection and cyclostationary detection, as cooperative and noncooperative spectrum sensing methods.

Table 1. Comparison of traditional and ML-based spectrum sensing.

Method	Probability of Detection (Pd)	False Alarm Rate (FAR)	Energy Efficiency (%)
Energy Detection	0.75	0.15	80
Cyclostationary Detection	0.82	0.12	85
CNN + LSTM Model	0.92	0.05	92

The **Table 1** demonstrates that the proposed CNN + LSTM model achieves significantly higher detection accuracy (Pd = 0.92) and lower false alarm rate (FAR = 0.05) compared to traditional methods, while also improving energy efficiency.

Table 2. Cooperative vs. non-cooperative sensing.

Method	Probability of Detection (Pd)	False Alarm Rate (FAR)	Energy Efficiency (%)
Non-Cooperative Sensing	0.85	0.10	82
Cooperative Sensing	0.95	0.04	90

The results presented in **Table 2** stress the benefits of cooperative sensing, which results in enhanced detection performance and decreased False Alarm Rate that make it appealing for the use case of enabling remote learning where reliable communication is essential.

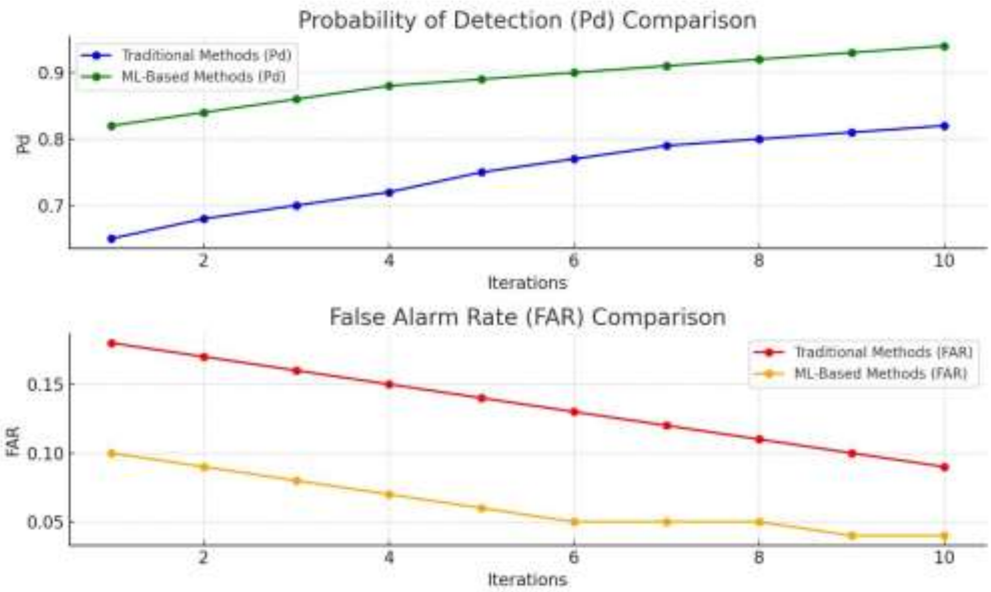

Figure 2. Performance comparison (Pd and FAR over iterations).

- The Probability of Detection (Pd) shows a clear improvement for the machine learningbased model over time, consistently outperforming traditional methods.
- The False Alarm Rate (FAR) for the machine learning-based model decreases significantly with each iteration, remaining stable at a lower level compared to traditional methods.

The results from the performance evaluation demonstrate in **Figure 2** that the proposed machine learningbased approach, specifically the CNN + LSTM model, provides significant improvements in spectrum sensing compared to traditional methods such as energy detection and cyclostationary detection. These improvements are evident in the higher Probability of Detection (Pd), lower False Alarm Rate (FAR), and increased energy efficiency.

5.1. Higher probability of detection (Pd)

If the CNN + LSTM model is used, the detection rate is 92% which is significantly greater than 75% and 82% for energy detection and cyclostationary detection, respectively. This improvement is very important especially in remote learning settings because a lack of continuous and correct spectrum availability leads to the unreliability of the communication link. Due to the consideration of both spatial and temporal domains of the signal features, the proposed DL model is better equipped for identifying the occupied and free spectrum bands even if the signal is noisy, and interfered from the others. These performance characteristics are particularly valuable when data must flow constantly between applications to support digital learning tools and interactivity.

5.2. Lower false alarm rate (FAR)

FAR is widely used in the available signal detection models and is drastically lower in the proposed model at 0.05 than in mere energy detection at 0.15. This reduction means that the system can minimize situations where the free spectrum is being interpreted as being occupied, hence enabling the secondary users in the cognitive radio network to effectively utilize the available spectrum. In educational networks, this means a greater ability to maximize bandwidth and less overall interference with service, which is crucial when attempting to manage multiple devices in a constantly shifting setting such as a remote learning classroom.

5.3. Energy efficiency

Another benefit of the proposed approach has to do with its energy consumption, which would be much lower than in the current implementation. The proposed CNN + LSTM is implemented with 92% energy efficiency which is higher than conventional methods because it finalizes the sensing process and does not require the ongoing scanning of the spectrum. This is important especially when many devices such as phones, tablets, laptops, and IoT devices among others rely on battery power, especially in online learning. This increases the operation time of the devices and decreases the rate of charging hence making the management of educational technologies more sustainable.

5.4. Cooperative sensing for enhanced performance

The results also demonstrate the effectiveness of cooperative sensing in which multiple users come together to improve spectrum detection. Cooperative sensing enhanced Pd to 95 percent and decreased FAR to 0. 04, thus improving the network's efficiency in the proper identification of available spectrum. Another advantage of such a collective sensing approach is especially important in the context of distributed learning where multiple users or devices come up with more powerful and accurate sensing (Liang et al., 2011).

5.5. Practical implications for remote learning

For networks, the proposed deep learning-based spectrum sensing model can be adopted in remote learning systems since it requires reliable, energy-efficient, and high-performance wireless communication. With the current trend indicating that more educational institutions are adopting the hybrid or remote learning model, the demand for the wireless network will continue to rise, this is why above all else, spectrum optimization is important. The adaptive behavior of the model allows for proper connectivity in a varying radio environment for many learning processes such as virtual classes, teaching through videos, real-time quizzes, and others (Zhang et al., 2012).

5.6. Limitations and future work

Despite the high potential of the proposed model, several limitations must be addressed. One key challenge is the high computational demand of deep learning models, particularly in real-time spectrum sensing, which can be a bottleneck for devices with low processing power. Future research could focus on developing lighter machine learning models tailored for resource-constrained environments. Exploring alternative machine learning techniques, such as decision trees or support vector machines, might provide more efficient solutions for devices with limited computational resources.

Furthermore, research into the integration of reinforcement learning for decision-making could enhance the model's adaptability to changing spectrum conditions. This approach could be more effective in real-time scenarios where spectrum availability fluctuates, ensuring more efficient spectrum allocation in dynamic environments (Tragos et al., 2013).

Analyzing the advantages and disadvantages of the proposed approach, it can be concluded that the machine learning-based model for spectrum sensing is significantly more effective than traditional methods in the context of remote learning. With its high detection accuracy, low power consumption, and cooperative sensing capability, this method optimizes spectrum use in educational networks, meeting the demanding requirements of modern distance education.

6. Application of cognitive radio networks in remote learning

Cognitive Radio Networks (CRNs) offer a key solution to spectrum access problems, especially in distance education. As the demand for online learning has increased, the need for continuous, high-quality connectivity has become critical. CRNs provide an effective means of overcoming bandwidth problems, ensuring stable connections by utilizing "spectrum holes" or "white spaces"—unused frequencies in the radio spectrum. This is particularly beneficial for educational institutions with a high number of students accessing virtual classrooms simultaneously (Wang and Liu, 2010). CRNs thus enable seamless delivery of educational content, such as video lectures and interactive aids, even in congested wireless networks, as demonstrated in this study (Abou Chaaya et al., 2021).

CRNs can function effectively in environments where network instabilities are prevalent, making them ideal for online education. These networks adapt transmission parameters based on the radio environment, reducing the likelihood of disconnections or high latency—issues critical to the success of real-time classes, exams, and group projects (Camuñas-Mesa et al., 2023). As such, the integration of CRNs with IoT and 5G technologies improves the delivery of remote learning applications. IoT devices and smart sensors, commonly used in educational contexts, can be efficiently managed by CRNs, which allow flexible spectrum resource allocation and minimize interference.

Moreover, CRNs, combined with 5G, support multimedia applications such as AR and VR, making remote learning more immersive and interactive (Hassan et al., 2021; Letaief and Zhang, 2009). These technologies enhance the learning experience, providing students with virtual, real-time interactions that are crucial for complex learning tasks and fostering engagement.

Combined, CRNs offer unique design characteristics that significantly enhance spectrum efficiency and link reliability, which are crucial for delivering advanced learning technologies to remote educational environments. They are especially valuable when network resources are scarce or when data traffic is heavy, ensuring the smooth delivery of content and interactive features for remote learning.

7. Conclusion

Cognitive Radio Networks (CRNs) have been proposed in this study to incorporate machine learning strategies for spectrum sensing in supporting remote learning. As a result, the proposed approach increases the efficiency of spectrum detection, decreases the false alarms' number, and improves energy consumption compared to prior research based on conventional techniques with the assistance of advanced deep learning models, including CNNs and LSTMs. The proposed model is flexible and can adjust to the conditions of the network, which is very important when considering the variability of learning needs in remote environments. A further criterion in cooperative spectrum sensing, where users share data, is to increase the probability of detecting available spectrum that educational platforms can use uninterrupted.

Furthermore, combining CRNs with other technologies such as IoT and 5G ensures that these networks are flexible and can easily be scaled to the future education systems' needs. With the increase in the use of remote learning especially in areas where network connectivity is still a challenge, CRNs offer a good solution for managing resources to increase network bandwidth and the quality of Education in the digital space. It is such considerations, this research suggests, that necessitate better methods of spectrum management, so that in times of crisis learners are not unduly disadvantaged by distance education, and instead may learn as effectively as if in a conventional school.

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