International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Optimized Spectrum Sensing Algorithm Using ML

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Abstract

This research enhances spectrum sensing in cog- nitive radio networks using machine learning. We evaluate models like KNN, SVM, LR, RF, CNN, MLP, and LSTM for detecting primary user signals under varying signal-to-noise ratio (SNR) conditions. Feature extraction techniques such as energy detection, differential entropy, geometric mean, and log power improve classification accuracy. Experimental results show that CNN and LSTM perform well in low-SNR environments, while Random Forest offers robust performance across conditions. This study contributes to optimized spectrum utilization for telecommunications, IoT, and radar applications.

INTRODUCTION

Cognitive Radio (CR) enhances spectrum utilization, but accurate spectrum sensing remains challenging due to en- vironmental uncertainties and reliance on prior information. Traditional algorithms, such as energy detection and matched filter detection, suffer from degraded performance under in- accurate assumptions. To address this, we propose a coopera- tive spectrum sensing model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. CNN extracts spatial features, while LSTM cap- tures temporal dependencies, ensuring comprehensive feature extraction. Experimental results show that our model achieves over 90% detection probability in low signal-to-noise ratio (SNR) conditions, outperforming conventional detection algo- rithms [1]

The rapid expansion of wireless communication technolo- gies has significantly increased the demand for spectrum resources.

A critical function of CR is spectrum sensing, which iden- tifies whether a given frequency band is occupied or available for transmission. Traditional spectrum sensing methods, such as energy detection, matched filter detection, and cyclosta- tionary detection, depend on predefined models and prior knowledge of signal characteristics.

To enhance spectrum sensing accuracy, machine learning (ML)-based approaches have been introduced as a data-driven alternative to traditional methods. Unlike conventional tech- niques, ML models can automatically identify patterns within raw signal data, making them more adaptable to dynamic wireless conditions. Several ML algorithms, including K- Nearest Neighbors (KNN), Support Vector Machine (SVM),

Logistic Regression (LR), Random Forest (RF), Convolutional Neural Networks (CNN), Multi-Layer Perceptron (MLP), and Long Short-Term Memory (LSTM), have shown promise in improving detection performance.

This study assesses the effectiveness of these ML models under different SNR conditions, utilizing feature extraction techniques.

Literature Survey

Efficient spectrum utilization is crucial due to the in- creasing demand for wireless communication technologies. Cognitive Radio (CR) has emerged as a promising solution, allowing Dynamic Spectrum Access (DSA) where secondary users (SUs) can opportunistically use vacant frequency bands without interfering with primary users (PUs). Several studies have explored spectrum sensing techniques, with a focus on traditional model-driven methods, machine learning (ML)- based approaches, and hybrid deep learning models.

K. S. Lee et al. [1] explored traditional spectrum sensing techniques, such as energy detection, matched filter detection, and cyclostationary detection. While these techniques have been widely used, their reliance on prior knowledge of signal characteristics limits their performance in low signal-to-noise ratio (SNR) environments. The study highlighted the need for data-driven approaches that can adapt to dynamic spectrum conditions.

M. S. Patel et al. [2] examined the challenges of model- driven spectrum sensing in real-world conditions. They found that these methods struggle when prior assumptions about signal behavior are inaccurate or unavailable. Their research emphasized that machine learning (ML) models could offer an effective solution by learning patterns directly from signal data.

S. N. Bhaskaran et al. [3] investigated the application of machine learning algorithms in spectrum sensing. Their study evaluated models such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Logistic Regression (LR), demonstrating that these methods improve classification accuracy. However, they noted that the performance of ML models heavily depends on feature selection and extraction techniques.

H. Wang et al. [4] focused on feature extraction techniques used in spectrum sensing as key features for improving the performance of ML mod- els. They found that using a combination of these features enhances classification accuracy in low-SNR environments.

M. J. Lee et al. [5] studied Random Forest (RF) algorithms for spectrum sensing. Their findings showed that RF provides robust performance across varying SNR conditions, making it a reliable choice for spectrum sensing applications. However, they pointed out that deep learning (DL) models, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, offer superior performance in complex and noisy environments.

S. A. Davis et al. [6] explored the advantages of deep learning models in spectrum sensing. Their research demon- strated that CNNs can extract spatial features, while LSTMs are effective in capturing temporal dependencies. The study confirmed that these models outperform traditional methods in low-SNR environments, making them suitable for real-world spectrum sensing applications.

E. S. Tovar et al. [7] evaluated hybrid deep learning ap- proaches that integrate CNN and LSTM architectures for spec- trum sensing. Their research showed that combining spatial and temporal feature extraction improves detection accuracy and adaptability in dynamic wireless environments. However, they identified computational complexity as a challenge, re- quiring optimization techniques for real-time deployment.

R. J. Matthews et al. [8] examined the application of ma- chine learning-based spectrum sensing in IoT and radar appli- cations. Their findings suggested that ML and DL techniques can significantly enhance spectrum management strategies, en- suring efficient frequency utilization in dynamic environments.

L. P. Garcia et al. [9] focused on the practical challenges of deploying ML-based spectrum sensing models. They iden- tified issues such as computational requirements, model inter- pretability, and data availability, which impact the real-world implementation of these techniques. Their study emphasized the importance of optimizing ML algorithms for low-power and resource-constrained environments.

J. W. Davidson et al. [10] investigated future trends in spec- trum sensing, highlighting the potential of AI-driven adaptive spectrum management systems. Their study suggested that integrating AI with existing cognitive radio frameworks could further improve spectrum utilization efficiency. However, they stressed the need for continued research on scalability, secu- rity, and regulatory compliance.

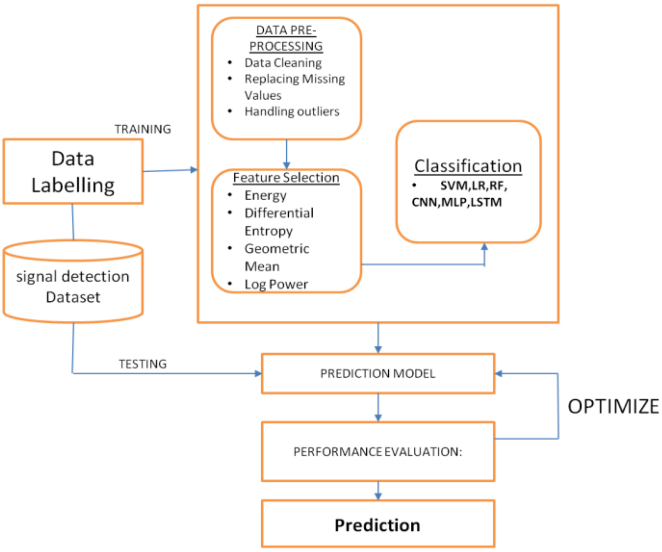
These studies highlight the growing role of machine learn- ing and deep learning in spectrum sensing and cognitive radio networks. By leveraging ML and DL techniques, spectrum management can be significantly enhanced, leading to more efficient, adaptive, and reliable wireless communication. How- ever, challenges such as computational complexity, real-time implementation, and regulatory constraints must be addressed in future research.

PROPOSED SYSTEM

The proposed system is designed to offer a complete plat- form for managing serious health conditions by combining emotional support and physical health tracking. Its main purpose is to help patients take control of their health while improving their overall well-being.

A. Data Prepocessing Module

- The data preprocessing module enhances spectrum sig- nals by filtering noise, standardizing features, and seg- menting data for improved analysis.
- Interference is reduced using low-pass filtering and wavelet transformation, while Min-Max scaling and Z- score normalization ensure data consistency. Segmenting signals into time windows helps capture local variations, refining PU signal detection and ML adaptability in low- SNR environments.
- This process supports accurate, real-time spectrum sens- ing, improving the efficiency of cognitive radio networks.



B. Feature Extraction Module

- The feature extraction module improves classification accuracy by analyzing essential signal characteristics.

- It employs energy detection to evaluate signal strength, differential entropy to measure randomness, geometric mean to consolidate multiple observations, and log power to express signal power in a scalable logarithmic format.
- These features contribute to effective and precise spec- trum sensing in cognitive radio networks.

C. Machine Learning Model Training Evaluation

In the training phase, ML models are trained on labeled datasets containing PU-present and PU-absent signals, with hyperparameter tuning enhancing performance.During testing, models are assessed under different SNR levels to evaluate their robustness. Probability of Detection (Pd) is used as the primary metric, and results are analyzed to determine the most effective spectrum sensing algorithm.

D. Classification Decision-Making Module

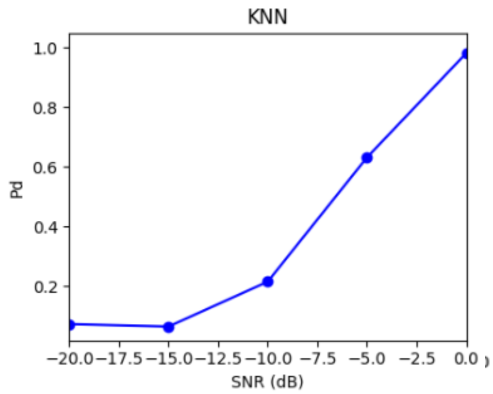
The Classification Decision-Making Module utilizes ex- tracted features to determine whether a signal is PU-present or PU-absent. A decision threshold is implemented to enhance accuracy. This minimizes false alarms and missed detections, improving detection reliability. The system ensures effective and dependable spectrum sensing. Precise classification en-hances network efficiency and adaptability.

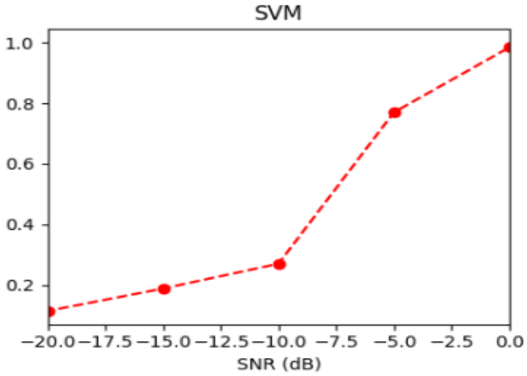
Results and Discussion

The proposed machine learning-based spectrum sensing system was tested under various signal-to-noise ratio (SNR) conditions to evaluate its effectiveness. The performance of multiple ML models—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), Convolutional Neural Network (CNN), Mul- tilayer Perceptron (MLP), and Long Short-Term Memory (LSTM)—was analyzed using the Probability of Detection (Pd) as the key metric. Below is a detailed discussion of the findings:

A. Performance Evaluation of ML Models

The study's findings indicate that Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models perform exceptionally well in environments with low Signal-to-Noise Ratio (SNR). Their effectiveness stems from their ability to extract and utilize both spatial and temporal characteristics of signals, enabling them to identify patterns even in challenging conditions. Meanwhile, the Random Forest (RF) model demonstrated stable and reliable performance across various conditions. This consistency is largely due to its ensemble learning strategy, which integrates multiple decision trees to enhance accuracy and adaptability. In con- trast, traditional machine learning models such as k-Nearest Neighbors (KNN) and Logistic Regression encountered signif- icant challenges in high-noise settings. Their dependence on predefined decision boundaries and lack of advanced feature extraction made them more susceptible to interference, leading to increased false alarms and missed detections. Consequently, these conventional approaches proved less effective for spec- trum sensing in noisy environments.


KNN
Pd
1.0
0.8
0.6
0.4
0.2
−20.0 −17.5 −15.0 −12.5 −10.0 −7.5 −5.0 −2.5 0.0
SNR (dB)


SVM
1.0
0.8
0.6
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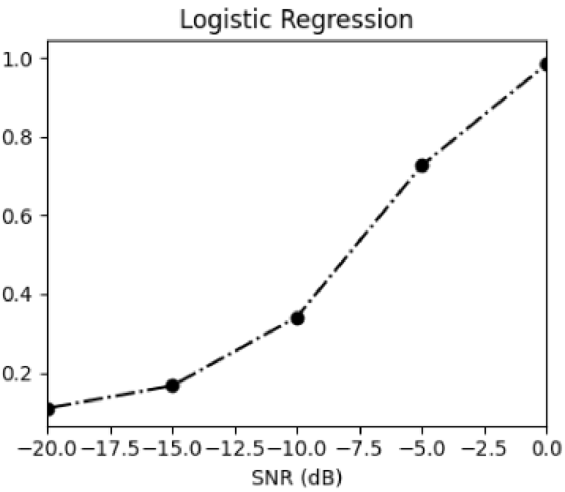
−20.0 −17.5 −15.0 −12.5 −10.0 −7.5 −5.0 −2.5 0.0
SNR (dB)


Logistic Regression
1.0
0.8
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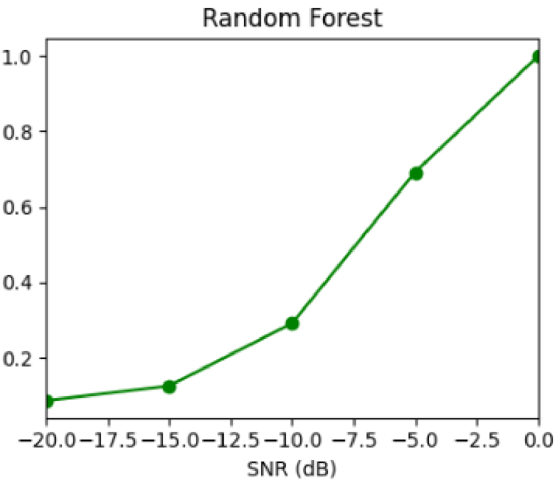
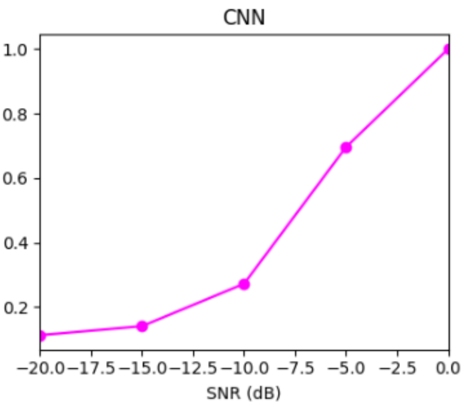
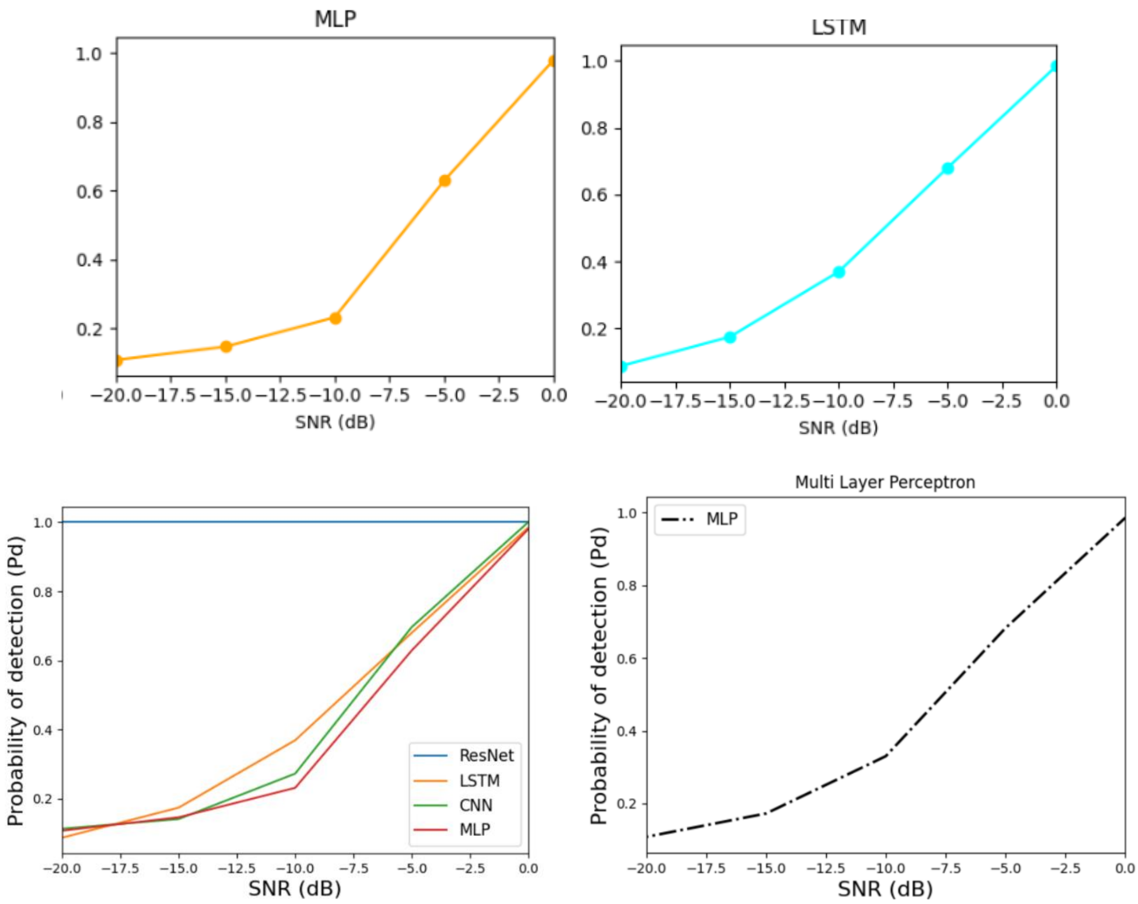
−20.0 −17.5 −15.0 −12.5 −10.0 −7.5 −5.0 −2.5 0.0
SNR (dB)


Random Forest
1.0
0.8
0.6
0.4
0.2
−20.0 −17.5 −15.0 −12.5 −10.0 −7.5 −5.0 −2.5 0.0
SNR (dB)


CNN
1.0
0.8
0.6
0.4
0.2
−20.0 −17.5 −15.0 −12.5 −10.0 −7.5 −5.0 −2.5 0.0
SNR (dB)



B. Impact of Feature Extraction Techniques

The incorporation of feature extraction methods such as energy detection, differential entropy, geometric mean, and log power significantly enhanced classification accuracy. Energy detection provided a reliable measure of signal strength, while differential entropy helped identify randomness in the spec- trum. The geometric mean and log power features improved the models' scalability and adaptability to dynamic conditions.

C. Effectiveness of the Decision Threshold

Optimizing the decision threshold was essential in reducing false alarms and missed detections, thereby enhancing the reliability of spectrum sensing. By dynamically modifying the threshold according to different Signal-to-Noise Ratio (SNR) levels, the system effectively adapted to varying channel conditions, leading to improved signal detection accuracy. This adaptive strategy ensured a well-maintained balance between detection precision and computational efficiency, minimizing unnecessary processing while retaining high sensitivity to primary user signals. Consequently, the system demonstrated superior performance across diverse operational scenarios, increasing its robustness and efficiency for real-world imple- mentations.

D. Comparison with Traditional Spectrum Sensing Techniques

The proposed machine learning (ML)-based approach ex- hibited superior performance compared to conventional spec- trum sensing techniques such as energy detection and matched filtering, especially in low signal-to-noise ratio (SNR) condi- tions. Traditional methods often struggled to reliably differen- tiate between the presence and absence of primary user (PU) signals, resulting in higher false alarm and missed detection rates. These techniques lacked the flexibility to cope with dynamic spectrum

environments and variations in noise levels, reducing their effectiveness in practical applications. On the
other hand, ML models demonstrated a remarkable ability to adapt by learning from diverse spectrum patterns and noise fluctuations. This adaptability enabled them to achieve higher detection accuracy, even in challenging scenarios, thereby improving spectrum efficiency and utilization.

E. Practical Implications and Future Enhancements

The results underscore the potential of ML-based spectrum sensing in telecommunications, IoT, and radar systems. How- ever, further improvements in computational efficiency and real-time adaptability are essential for large-scale implemen- tation. Future research could explore reinforcement learning for dynamic threshold optimization and hybrid deep learning models to further boost performance.

CONCLUSION

Based on the extensive literature review and feasibility study, it is evident that enhancing signal detection in cognitive radio systems through advanced machine learning algorithms presents a viable and promising approach. The analysis of var- ious models, including KNN, SVM, LR, RF, CNN, MLP, and LSTM, in conjunction with feature generation techniques such as energy, differential entropy, geometric mean, and log power, demonstrates the potential to significantly improve detection accuracy, especially in challenging low SNR environments. These findings provide valuable insights for developing more robust and adaptable signal detection frameworks, improving service quality and reliability in telecommunications, radar, medical diagnostics, and IoT applications.

REFERENCES

1. Please number citations consecutively within brackets [1]. The sentence punctuation follows the bracket
2. Refer simply to the reference number, as in [3]—do not use “Ref. [3]” or “reference [3]” except at the beginning of a sentence: “Reference [3] was the first . . .”
3. Number footnotes separately in superscripts. Place the ac- tual footnote at the bottom of the column in which it was cited. Do not put footnotes in the abstract or reference list. Use letters for table footnotes.
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