

Deep Learning-Based Spectrum Sensing Techniques for Cognitive Radio Networks

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Abstract

Spectrum sensing plays a pivotal role in Cognitive Radio (CR) systems by allowing secondary users to identify and utilize unused spectrum bands without causing interference to licensed primary users. However, traditional sensing techniques often perform poorly under low signal-to-noise ratio (SNR) conditions and struggle to adapt to rapidly changing environments. With the rise of deep learning (DL), spectrum sensing has undergone significant transformation. DL models can autonomously extract meaningful patterns from raw signal data, making them highly effective for this task. This paper explores the use of various DL architectures—such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer models—for enhanced spectrum sensing. It examines their design, training methodologies, input feature strategies, and performance across different SNR scenarios. The analysis demonstrates that DL-based methods considerably outperform conventional approaches, positioning them as essential tools for future intelligent and adaptive spectrum management systems.

Keywords: cognitive radio, Spectrum Sensing, Deep learning, internet of things.

1. INTRODUCTION

Cognitive Radio (CR) technology has emerged as a transformative solution to address the growing demand for wireless spectrum caused by the proliferation of mobile devices, IoT, and next-generation networks like 5G and beyond. A core feature of CR systems is spectrum sensing, which enables unlicensed secondary users (SUs) to identify available frequency bands without disrupting the communication of licensed primary users (PUs). By dynamically detecting idle channels, CR systems enhance spectral efficiency and alleviate the problem of spectrum underutilization [1-3].

Conventional spectrum sensing techniques—such as energy detection, matched filtering, and cyclostationary analysis—are widely used due to

their simplicity. However, they often fall short in challenging environments, particularly under low signal-to-noise ratio (SNR) conditions or in the presence of non-stationary signals. These traditional methods typically rely on manually crafted features and fixed detection thresholds, making them less adaptable to dynamic and complex wireless environments.

To overcome these limitations, deep learning (DL) has emerged as a powerful tool in spectrum sensing. DL algorithms can automatically learn intricate features from raw signal data, enabling more accurate and flexible detection [4]. Techniques involving CNNs, RNNs, LSTMs, and Transformers have demonstrated significant potential in improving sensing accuracy, especially in low-SNR conditions [5]. These models offer enhanced adaptability and

scalability, making them highly suitable for modern cognitive radio networks where real-time decision-making and robustness are critical.

II. MOTIVATION FOR DEEP LEARNING IN SPECTRUM SENSING

The demand for spectrum sensing methods that offer high accuracy, real-time adaptability, and resilience to noise and interference has driven interest in deep learning (DL) within cognitive radio (CR) networks. Traditional techniques often rely on predefined features and static thresholds, which limits their effectiveness in dynamic wireless environments. In contrast, DL models have the ability to learn complex and discriminative features directly from raw signal inputs, eliminating the need for manual feature engineering. These models can adapt to various modulation schemes and channel conditions, making them highly flexible. Moreover, deep learning approaches maintain robust performance even in scenarios with low signal-to-noise ratios or significant fading. As wireless systems grow in complexity, DL architectures also scale efficiently, enabling them to handle large datasets and diverse signal characteristics encountered in real-world applications.

III. SYSTEM MODEL FOR SPECTRUM SENSING

Spectrum sensing can be modeled as a binary hypothesis testing problem:

H_0 : PU is absent \rightarrow received signal consists of noise only.

H_1 : PU is present \rightarrow received signal includes PU signal + noise.

Mathematically:

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

H_1 : $y(n) = h \cdot s(n) + w(n)$

Where:

$y(n)$: received signal at time n

$s(n)$: transmitted signal from PU

h : channel gain

$w(n)$: additive white Gaussian noise (AWGN)

The objective is to decide between H_0 and H_1 with high probability of detection (P_d) and low probability of false alarm (P_{fa}).

IV. DEEP LEARNING ARCHITECTURES FOR SPECTRUM SENSING

Recent advances in deep learning have introduced a range of neural architectures that are highly suitable for spectrum sensing tasks in cognitive radio networks. These models excel at capturing spatial, temporal, and contextual relationships in signal data, which are often too complex for traditional algorithms to handle effectively. Fig.1 shows the Deep-learning-based general model for spectrum sensing Depending on the structure of the input and the sensing requirements, different architectures offer unique advantages.

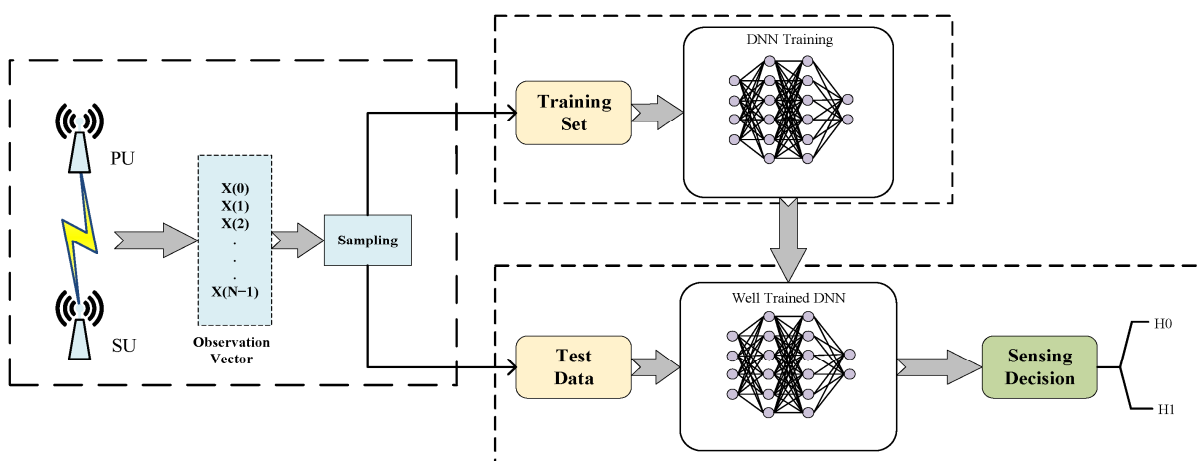


Fig1. Deep-learning-based general model for spectrum sensing [6]

Convolutional Neural Networks (CNNs) are particularly effective for extracting spatial features from structured input representations such as spectrograms or IQ samples. By using filters to learn localized patterns, CNNs can identify modulation characteristics and signal features even in the presence of noise. They are computationally efficient and well-suited for real-time inference. [7-9]

Recurrent Neural Networks (RNNs) and their advanced variants like Long Short-Term Memory (LSTM) networks are designed to handle sequential data, making them ideal for tracking time-varying signal behaviors. These models can capture temporal dependencies in wireless signals, which is critical for detecting subtle variations in PU activity across time [10].

Bidirectional LSTMs (BiLSTMs) enhance the standard LSTM model by processing input in both forward and backward directions. This dual-perspective allows the model to learn both past and future contexts within a signal sequence, resulting in more accurate classification and decision-making in dynamic spectrum environments [11,12].

Transformer Networks, known for their attention mechanisms, offer a powerful alternative to recurrent models by capturing long-range dependencies without relying on sequence-based recurrence. Transformers enable parallel processing of signal data, improving both training efficiency and accuracy. Their self-attention layers make them highly effective in modeling global relationships across signal features, particularly in complex or multi-user environments.

By leveraging these architectures—either individually or in hybrid combinations—deep learning-based spectrum sensing systems can achieve remarkable improvements in detection accuracy, noise robustness, and adaptability, making them a cornerstone of next-generation cognitive radio systems.

V. FEATURE INPUT TECHNIQUES

Despite The performance of deep learning models in spectrum sensing is heavily influenced by the type and quality of input features. One commonly used input is raw IQ (in-phase and quadrature) samples, which retain essential amplitude and phase

information, allowing models to learn signal structures directly from the baseband representation. Another effective input format is the spectrogram, which captures the signal's energy distribution across both time and frequency domains. This representation is particularly useful for identifying patterns in modulated signals and time-varying interference. Additionally, statistical features such as energy, cyclostationary properties, and higher-order moments like kurtosis can be used either independently or in combination with other inputs to enrich the model's feature space. Regardless of the feature type, preprocessing techniques—including normalization, filtering, and windowing—play a crucial role in enhancing model robustness and generalization, especially under varying channel conditions and noise levels.

VI. PERFORMANCE EVALUATION

Assessing the effectiveness of deep learning models in spectrum sensing involves a thorough understanding of the evaluation criteria used to measure their performance. The most widely accepted metrics include the Probability of Detection (P_d), which reflects how reliably a model can identify the presence of a primary user, and the Probability of False Alarm (P_{fa}), which indicates the likelihood of mistakenly detecting activity in an idle channel. An ideal spectrum sensing system aims for a high P_d and a low P_{fa} to ensure efficient and interference-free spectrum access.

In addition to these, the F1 score is often used to provide a balanced measure of precision and recall, particularly in scenarios where the dataset may be imbalanced—such as having more idle slots than occupied ones. Another useful tool is the Receiver Operating Characteristic (ROC) curve, which visually represents the trade-off between P_d and P_{fa} at various decision thresholds, offering insight into the model's sensitivity and specificity.

While deep learning models are theoretically expected to outperform traditional techniques under low signal-to-noise ratio (SNR) conditions, especially in dynamic and noisy environments, actual performance depends on several factors. These include the choice of neural network architecture, the quality and diversity of training data,

and the feature representation used as input. Hybrid models combining CNNs with LSTMs or Transformers, for example, are hypothesized to achieve better generalization and robustness compared to standalone architectures.

A comprehensive performance evaluation, once included, should also consider the model's computational efficiency, inference time, and adaptability to real-time conditions—all of which are essential for practical deployment in cognitive radio networks.

VII. CHALLENGES AND FUTURE WORK

Training deep learning models demands large and diverse datasets to ensure comprehensive learning and avoid overfitting. Acquiring such datasets remains a significant challenge.

TABLE 1: PERFORMANCE METRICS OF DEEP LEARNING MODELS IN SPECTRUM SENSING

Model	Pd @ -20 dB	F1 Score	Pfa	Key Strength
NN-BiLSTM	> 60%	High	~10%	Strong temporal and spatial feature capture
SenseNet	58.8%	Moderate	~12%	Multi-feature fusion from signal characteristics
CNN only	~55%	Moderate	~14%	Fast training and lower complexity
Traditional (ED)	< 40%	Low	>20%	Simple but fails under low SN

Deploying models on edge devices requires lightweight architectures capable of fast, low-latency processing without compromising accuracy.

Ensuring robustness to unseen signals and modulation schemes is critical for practical deployment. Models must generalize well beyond the training data to handle real-world variability.

Deep learning models often function as “black boxes,” providing limited explainability. Enhancing model interpretability is essential for trust, debugging, and regulatory compliance.

The potential of transfer learning across different domains or signal types remains largely untapped. Exploring effective cross-domain adaptation could

significantly reduce training costs and improve performance.

VIII. CONCLUSION

This study investigates the application of deep learning to improve spectrum sensing in cognitive radio (CR) systems, with a particular emphasis on IoT-oriented wireless environments. Conventional spectrum sensing approaches often underperform in challenging conditions, such as low signal-to-noise ratios and rapidly changing channels, due to their reliance on manually extracted features and static detection parameters. In contrast, deep learning models—including CNNs, RNNs, LSTMs, and Transformers—can automatically learn intricate signal characteristics directly from raw data, leading to enhanced detection accuracy and adaptability.

The research also examined various input feature formats, including raw in-phase/quadrature (IQ) samples, spectrogram representations, and statistical signal descriptors. Performance was assessed using standard metrics such as the Probability of Detection (Pd), Probability of False Alarm (Pfa), and the F1 Score. Findings indicate that deep learning models, particularly hybrid designs like CNN-BiLSTM, significantly outperform traditional techniques, delivering scalable and resilient solutions for real-time spectrum sensing in advanced communication networks.

Looking ahead, future developments should aim to create lightweight and interpretable deep learning models that can operate efficiently on edge devices. Efforts should also focus on improving model generalization across unfamiliar signal types and exploring transfer learning methods to streamline the training process. With the continued evolution of wireless communication, deep learning is poised to play a foundational role in enabling intelligent and interference-free spectrum access.

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