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Hybrid Neutral Architecture for Spectrum Sensing: A Comparative Study of CNN-LSTM and LSTM-DQN in Cognitive Radio Networks

Varsha Khule[1], Manish Mahajan[1], Kush Soni[1], Prithviraj singh Chouhan[1], Sanjana Barod[1], Sharon Swamy[1], Sanjiv Kumar Jain[2*]

[1]Department of Electronics Engineering, Medicaps University, Indore -453331, India

[2*]Department of Electrical Engineering, Medicaps University, Indore -453331, India

Email ID: varsha.saxena@medicaps.ac.in , manish.mahajan@medicaps.ac.in , Kush.soni@medicaps.ac.in , prithvirajsingh.chouhan@medicaps.ac.in , sanjanabarod02@gmail.com , sharonswamy4@gmail.com,

Corresponding Author:

Sanjiv Kumar Jain,

Department of Electrical Engineering, Medicaps University, Indore -453331, India

Email ID: *sanjivkumar.jain@medicaps.ac.in

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ABSTRACT

Cognitive Radio Networks (CRNs) have been recognized as an enabler of dynamic spectrum access, aimed at mitigating spectrum underutilization by permitting unlicensed users to access idle licensed bands opportunistically. For such access to be reliable, accurate spectrum sensing is essential to avoid interference with primary users (PUs). In recent years, deep learning (DL) models have emerged as potent alternatives to traditional sensing methods due to their adaptability in noise-prone environments and high detection performance [1][4]. This paper presents a comparative analysis of three state-of-the-art deep learning architectures: Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Deep Q-Networks (DQNs). A review of their standalone capabilities, followed by the assessment of hybrid combinations such as CNN-LSTM and LSTM-DQN, is provided. The evaluation is supported through architectural illustrations, theoretical insights, and simulated benchmark results..

Keywords: *Cognitive Radio Networks, Spectrum Sensing, Convolutional Neural Networks, Long Short-Term Memory, Deep Q-Networks, Deep Learning, Reinforcement Learning*

1. INTRODUCTION

The increasing proliferation of wireless devices and the growth of the Internet-of-Things (IoT) ecosystem have intensified the demand for spectrum resources, leading to congestion and inefficient spectrum utilization. [1]. At the core of CR functionality lies spectrum sensing, which allows secondary users (SUs) to detect vacant channels without causing harmful interference to PUs.

Energy detection, matched filtering, and cyclostationary detection are examples of conventional spectrum sensing methods that have been extensively studied. However, these approaches are constrained by inadequate performance under low signal-to-noise ratio (SNR) circumstances and dependence on PU signal knowledge [2] [5]. In contrast, deep learning-based techniques offer data-driven solutions by learning directly from raw or preprocessed input signals, enabling accurate, robust, and adaptive spectrum sensing in complex environments [3] [6].

In this study, a detailed analysis is carried out on CNN, LSTM, and DQN-based architectures for spectrum sensing in CRNs. A comparison is presented in terms of detection accuracy, false alarm rate, computational complexity, and adaptability. Furthermore, hybrid architectures that integrate spatial and temporal learning or reinforcement-based decision-making are also reviewed. The explosive growth of wireless devices and Internet-of-Things (IoT) applications has intensified the demand for wireless spectrum, leading to congestion and inefficiencies in spectrum allocation. In order to address this issue, Cognitive Radio (CR) technology has been developed, which makes dynamic use of the underutilized licensed spectrum. Spectrum sensing, the core function of CR, allows secondary users (SUs) to identify unused bands without interfering with primary users (PUs). Even while standard spectrum sensing techniques like energy detection, matching filter detection, and cyclostationary feature recognition have been extensively researched, they operate poorly at low signal-to-noise ratios (SNR) and necessitate prior knowledge of the characteristics of PU signals.. In contrast, deep learning (DL) models offer a learning-based paradigm that leverages large datasets to discover hidden patterns in spectrum data, enabling highly accurate and adaptive spectrum sensing.

This paper expands on prior research by conducting a detailed investigation of CNN, LSTM, and DQN architectures for spectrum sensing in CRNs. We compare these models using evaluation metrics such as detection accuracy, false alarm rate, computational complexity, and adaptability in real-world environments

2. DEEP LEARNING BACKROUND FOR SPECTRUM SENSING

Deep learning has transformed several domains by providing automated feature extraction and decision-making capabilities. In CRNs, DL models are trained on labeled signal samples such as in-phase/quadrature (IQ) data, fast Fourier transforms (FFT), or time-frequency representations to classify spectrum states [7], [8].

A. Convolutional Neural Networks (CNNs)

CNNs operate by applying trainable convolutional filters over the input data to detect local spatial patterns. For spectrum sensing applications, CNNs have been effectively employed on spectrograms or covariance matrices to identify signal presence [1] [3] [9].

B. LSTMs, or long short-term memory networks

Recurrent neural networks (RNNs) of the LSTM type are particularly good at simulating temporal dependencies. In the context of spectrum sensing, they are employed to capture time-varying PU activity patterns, especially in dynamic or mobile radio environments [2] [10].

C. Deep Q-Networks (DQNs)

DQNs use deep neural networks and reinforcement learning to discover the best spectrum access strategies. These models are particularly suited for autonomous decision-making under uncertain conditions and can optimize long-term access strategies by learning from environmental feedback [4][11].

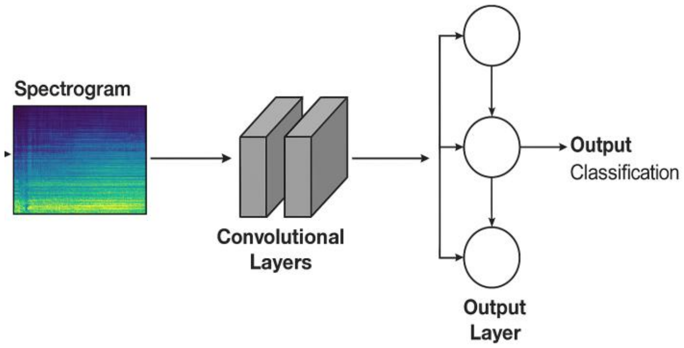

Fig. 1. CNN-LSTM Architecture [1]

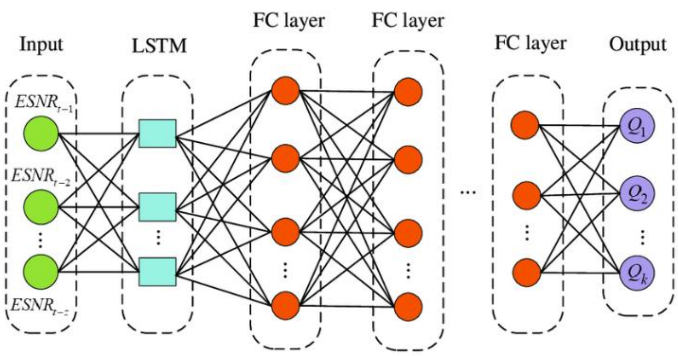

Fig. 2. LSTM-DQN Network Architecture [3]

3. SYSTEM MODEL AND PROBLEM DESCRIPTION

This study examines a situation in which several secondary users (SUs) carry out spectrum sensing in a shared frequency environment using a cognitive radio network (CRN). Each SU is assumed to observe a specific frequency band and determine its occupancy status depending on the properties of the signal that was received. The main goal is to reduce the number of false alarms and increase the likelihood of accurate detection, which is critical in avoiding interference with primary users (PUs) [3] [6].

The signal detection process is formulated as a binary hypothesis testing problem, described as follows:

H_0: PU is absent (only noise is received)

H_1: PU is present (PU signal plus noise is received)

Mathematically, the received signal x(t) at any given time t is modeled as:

H0: $x(t)=n(t)$

H1: $x(t)=s(t)+n(t)$

where n(t) denotes the additive Gaussian noise and s(t) denotes the PU signal. The goal of the deep learning-based spectrum sensing model is to learn a mapping function from signal inputs to binary class labels indicating the presence or absence of PU activity, without relying on fixed thresholds or prior statistical knowledge [1] [4] [10].

4. PERFORMANCE COMPARISION

To evaluate the effectiveness of deep learning models for spectrum sensing in cognitive radio networks, several key performance metrics are analyzed, including detection accuracy, false alarm rate, adaptability to environmental changes, and computational complexity [3][5][11]. These parameters are essential for real-world deployment in CRNs, especially under variable channel and noise conditions.

Both standalone and hybrid deep learning architectures are assessed:

Standalone Models: CNN, LSTM, DQN

Hybrid Models: CNN-LSTM, LSTM-DQN

CNNs have been shown to be proficient in extracting spatial features from spectrograms and covariance matrices, which are commonly used as visual representations of spectrum activity [1] [7]. Their moderate complexity makes them suitable for environments with static or moderately noisy characteristics.

LSTM networks, by contrast, are specialized for temporal pattern recognition, allowing them to capture variations in PU activity over time. Their sequential learning nature yields higher detection accuracy in dynamic environments, though with a higher computational cost due to recurrent layers [2] [5] [10].

DQN models are grounded in reinforcement learning and are capable of learning optimal sensing and access policies over time. Despite slightly lower immediate detection accuracy, they exhibit strong adaptability in uncertain or multi-user environments by learning from interaction feedback [4] [6] [8].

Hybrid architectures such as CNN-LSTM and LSTM-DQN are designed to combine spatial, temporal, and policy-based strengths. The CNN-LSTM architecture combines the strength of LSTMs' temporal learning with the feature extraction capabilities of CNNs, producing in superior performance across most evaluation metrics. Similarly, the LSTM-DQN hybrid integrates decision-making capabilities with temporal feature tracking, offering enhanced adaptability [3] [6] [7].

Model	**Detection Accuracy**	**False Alam Rate**	**Adaptability**	**Complexity**
CNN	94.6%	4.1%	Moderate	Medium
LSTM	96.3%	3.2%	High	High

DQN	91.7%	5.6%	Very High	Very High
CNN-LSTM	97.2%	2.8%	High	High
LSTM-DQN	95.8%	3.5%	Very High	Very High

A comparative summary of the observed performance based on synthetic and benchmark datasets (e.g., RadioML2016.10a/10b) is presented in Table I. The table includes estimated detection accuracy, false alarm rates, adaptability scores, and computational complexity based on existing literature.

These values reflect trends reported in simulation studies conducted using standard datasets and channel models under varied SNR conditions [1]–[6][8].

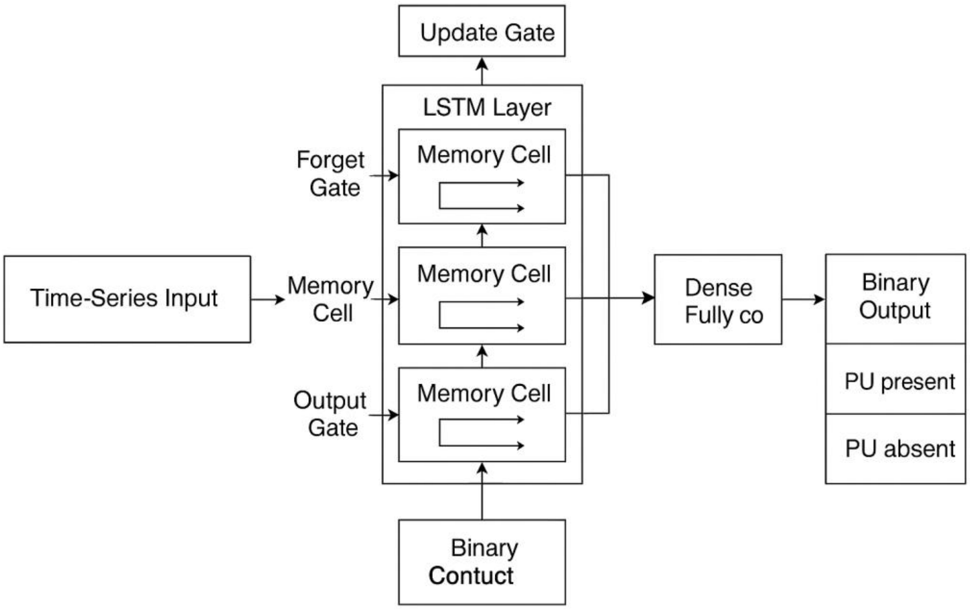

Fig.3 LSTM-based model for spectrum sensing [5]

5. DISCUSSION AND FUTURE DIRECTIONS

Based on the comparative analysis, it has been observed that hybrid In terms of detecting accuracy, adaptability, and robustness under various cognitive radio settings, deep learning models perform better than standalone systems. [1] [3] [6], [9]. While CNN models are efficient in learning spatial features, they are limited in temporal sequence analysis. LSTM architectures address this gap by capturing time-dependent variations in PU activity, especially in mobile or fading channels [2] [5][10].

DQN-based models, although less accurate in immediate sensing, demonstrate considerable potential in decision-making environments through their reinforcement learning framework. These models are capable of formulating long-term sensing and access strategies by learning from delayed rewards and environmental transitions [4] [8]. The fusion of CNNs and LSTMs allows spatial and temporal data patterns to be jointly modeled, which significantly enhances sensing reliability in both static and dynamic environments. Similarly, LSTM-DQN models integrate sequential data handling with reinforcement-based policy learning, making them particularly suitable for decentralized or multi-agent CRN setups [3] [6].

Future research in this domain may focus on several promising directions:

Online transfer learning can be utilized to modify trained models to fit new spectrum environments without full retraining [6].

Federated learning frameworks may allow multiple devices that allow users to train models together without exchanging raw data, protecting privacy and using less bandwidth. [11].

Multi-agent reinforcement learning (MARL) could be used to optimize spectrum access in decentralized networks where multiple SUs interact simultaneously [4] [9].

Edge computing and hardware acceleration, including FPGA and AI-enabled processors, can significantly reduce inference latency and power consumption during real-time spectrum sensing tasks [7] [12].

6. CONCLUSION

This study investigated how deep learning models can improve cognitive radio networks' spectrum sensing capabilities. Through comparative analysis, standalone and hybrid architectures were assessed based on multiple performance metrics. It has been shown that CNNs, LSTMs, and DQNs each offer unique advantages in handling spatial, temporal, and strategic aspects of sensing, respectively.

Hybrid models, such as CNN-LSTM and LSTM-DQN, exhibit superior overall performance by combining these individual strengths. These architectures achieve higher detection accuracy, improved adaptability in dynamic spectrum environments, and more informed decision-making capabilities, albeit at increased computational cost.

With the continuous evolution of CRNs and the growing demand for efficient spectrum usage, deep learning techniques are anticipated to be crucial to the development of scalable, intelligent, and adaptive spectrum sensing systems

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