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Article

Performance Analysis of Wavelet-Denoising Convolutional Neural Networks for Spectrum Sensing under Diverse Modulation Schemes

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A B S T R A C T

Spectrum sensing is a critical function in cognitive radio (CR) systems, enabling dynamic spectrum access while minimizing interference with primary users (PUs). This paper presents a performance analysis of a Wavelet-Denoising Convolutional Neural Network (WD-CNN) for spectrum sensing under diverse modulation schemes and low signal-to-noise ratio (SNR) conditions. The proposed approach integrates wavelet denoising with spectrogram-based deep learning to enhance the discriminative representation of received signals. Extensive simulations were conducted for BPSK, QPSK, and 16-QAM signals across low-SNR scenarios ranging from −5 dB to −20 dB. Comparative evaluation with a pre-trained AlexNet demonstrates that WD-CNN consistently achieves higher classification accuracy and reduced spectrum sensing latency, particularly under severe noise conditions and for higher-order modulation schemes. The results confirm that the proposed WD-CNN framework provides a robust and computationally efficient solution for real-time spectrum sensing in CR networks.

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1. Introduction

Efficient utilization of wireless communication resources is a critical challenge due to the rapid expansion of devices and services operating in licensed frequency bands [1], [2]. Cognitive Radio (CR) networks have emerged as an effective solution, enabling secondary users to opportunistically access underutilized spectrum without interfering with licensed Primary Users (PUs) [3], [4]. Central to the operation of CR systems is spectrum sensing (SS), which detects whether a frequency band is occupied by a PU and ensures reliable and interference-free communication for secondary users [5]. Achieving accurate SS is particularly challenging under low Signal-to-Noise Ratio (SNR) conditions, where conventional detection techniques exhibit significant performance degradation [6].

Traditional SS methods, such as Energy Detection (ED) [7], Matched Filter Detection (MFD) [8], Cyclostationary-Based Detection (CBD) [9], and Eigenvalue-Based Detection (EBD) [10], require prior knowledge of either the PU signal or noise characteristics and typically exhibit significant performance degradation in low-SNR scenarios. These limitations have motivated the exploration of intelligent approaches that rely on signal classification rather than explicit signal models.

Deep Learning (DL), a subset of machine learning, has shown promise in addressing these challenges by automatically extracting hierarchical features from complex signal representations [11]. Convolutional Neural Networks (CNNs) have been effectively applied to spectrum sensing tasks using time–frequency representations such as spectrograms, enabling robust distinction between signal and noise [12]. DL-based methods generally achieve higher accuracy and resilience than conventional techniques, especially in adverse noise conditions [13], [14].

However, conventional CNN-based models are susceptible to feature distortion under severe noise, which limits their performance at low SNR. Hybrid approaches that integrate denoising methods with CNNs have been proposed to enhance input feature quality prior to classification [15]. Building on this concept, this study evaluates a Wavelet-Denoising CNN (WD-CNN) framework, where wavelet-based denoising is employed as a preprocessing stage prior to CNN-based feature extraction. This integration enhances the quality of the extracted features, leading to improved classification accuracy and more reliable spectrum sensing performance, particularly under low-SNR conditions.

In this work, the performance of WD-CNN is systematically compared with a pre-trained CNN model, namely AlexNet, across multiple modulation schemes including BPSK, QPSK, and 16-QAM under low-SNR conditions. The analysis evaluates both detection accuracy and sensing efficiency to demonstrate the practical benefits of the proposed hybrid approach for CR applications. The key contributions of this paper are summarized as follows:

1. Development of a WD-CNN framework for spectrum sensing, combining wavelet denoising and CNN-based classification for robust PU detection under low-SNR conditions.
2. Comprehensive evaluation across diverse modulation schemes BPSK, QPSK, 16-QAM, highlighting the performance advantage of WD-CNN over conventional CNN models such as AlexNet.

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3. Analysis of spectrum sensing efficiency, including detection accuracy and latency, showing the practical benefits of the denoising step.
4. Extensive simulation study across low-SNR scenarios to validate the approach under realistic wireless channel conditions.

The remainder of this paper is structured as follows. Section II reviews the background and related literature on spectrum sensing, including conventional and deep learning–based approaches. Section III describes the proposed framework and methodology. Section IV presents the simulation setup and discusses the obtained results. Section V concludes the paper.

2. Background and Related Work

2.1. Spectrum Sensing Fundamentals

The radio spectrum remains underutilized due to rigid spectrum allocation policies and the continuous increase in user demand [16]. Within CR based dynamic spectrum management (DSM) systems, spectrum sensing (SS) plays a fundamental role in acquiring awareness of the radio environment [17], thereby enabling more efficient spectrum utilization. Spectrum sensing allows secondary users (SUs) to continuously monitor licensed frequency bands in order to identify PU activity and available spectrum opportunities in terms of time, frequency, and spatial dimensions [18]. This sensing task is commonly formulated as a binary hypothesis testing problem, where the hypotheses correspond to the presence or absence of the PU signal [19]. When spectrum availability is detected, subsequent CR functions such as spectrum sharing, decision-making, and resource allocation are activated to support reliable transmission [20]. Figure 1 illustrates the general block diagram of PU spectrum sensing performed by an SU. The received signals are initially subjected to signal processing, feature extraction, and data preprocessing stages before being fed into the spectrum sensing detector. Based on the processed input and any available a priori information, the detector ultimately determines whether the PU is present or absent.

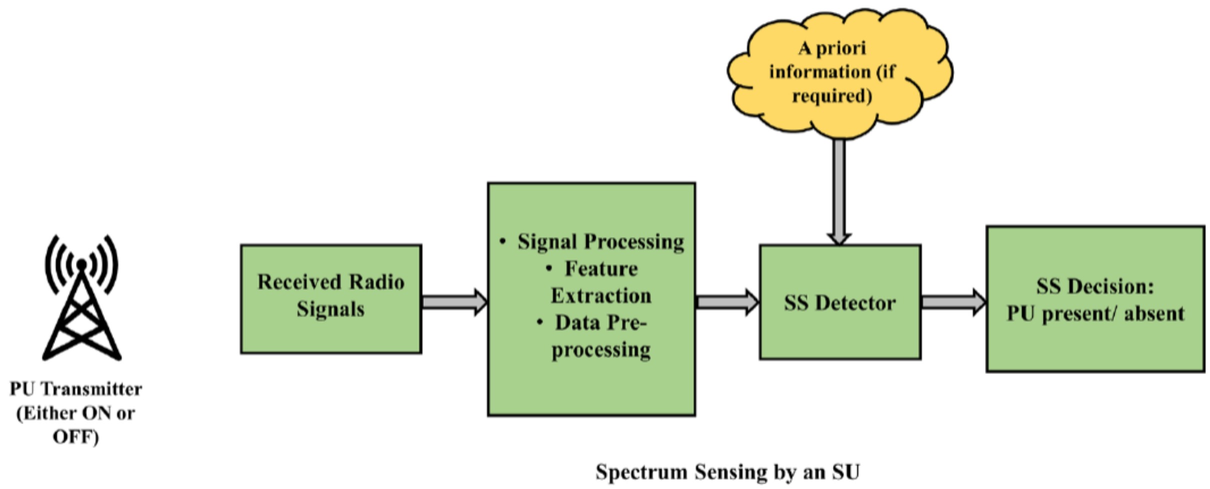

Figure 1. Block diagram illustrating PU spectrum sensing performed by SU.

2.2. Conventional Spectrum Sensing Techniques

Traditionally, spectrum sensing of the PU has been performed using widely adopted techniques such as ED, MFD, EBD, CBD, and Wavelet-Based Detection (WBD). These conventional spectrum sensing approaches have been comprehensively investigated in the literature, as outlined in Section I. Nevertheless, their practical deployment often leads to inefficient utilization of radio resources due to issues such as missed detection of licensed users and an increased probability of false alarms [21].

For example, although ED does not require prior knowledge of the PU signal, it suffers from a high false alarm rate and demonstrates poor performance under low SNR conditions [22]. In contrast, MFD achieves optimal detection performance but is generally impractical, as it relies on accurate prior information about the PU signal characteristics [23]. The EBD approach is associated with high computational complexity [24], while CBD-based spectrum sensing incurs considerable power consumption, processing complexity, and sensing time [20]. Furthermore, WBD-based methods are susceptible to synchronization errors, which can degrade sensing reliability [23].

To mitigate harmful interference, spectrum sensing techniques are required to maintain a low Probability of False Alarm (PFA) while achieving a high Probability of Detection (PoD) [22]. However, the effectiveness of conventional sensing methods degrades significantly in dynamic and low-SNR environments, motivating the adoption of learning-based approaches that can extract more discriminative features from received signals.

2.3. Deep Learning-Based Spectrum Sensing

With the limitations of conventional spectrum sensing techniques under low SNR conditions, recent research has increasingly focused on deep learning (DL) approaches to improve detection performance. DL models, particularly Convolutional Neural Networks (CNNs), are capable of automatically extracting hierarchical features from received signal representations, such as spectrograms, without requiring explicit feature engineering. This allows CNN-based methods to distinguish between PU signals and noise more effectively, providing enhanced robustness and accuracy in adverse channel conditions [15], [25], [26].

Pre-trained CNN architectures, such as AlexNet, have been successfully applied in spectrum sensing tasks, benefiting from transfer learning to accelerate training and leverage previously learned feature representations [27]. However, standard CNN models can still suffer from performance degradation at low SNR due to noise interference, which may obscure discriminative features in the signal representation.

To address this challenge, hybrid frameworks that integrate signal denoising techniques with CNNs have been proposed. In particular, wavelet-based denoising (WD) can be applied as a preprocessing stage to reduce noise while preserving essential signal characteristics. This enhances feature quality, allowing CNNs to achieve higher classification accuracy and reduced sensing latency in real-time spectrum sensing applications. These limitations motivate the development of hybrid spectrum sensing frameworks that combine signal denoising techniques with deep learning models. In particular, integrating wavelet-based denoising as a preprocessing stage can enhance the quality of signal representations, enabling convolutional neural networks to better extract discriminative features under low-SNR conditions. Such frameworks are especially promising for improving spectrum sensing performance across multiple modulation schemes in CR systems.

3. THE PROPOSED MODEL

Spectrum sensing (SS) can be addressed using a Deep Neural Network (DNN), where the received signal is represented in a suitable form such as spectrograms and fed into the network for hierarchical feature extraction and classification. The DNN maps the input representation to a binary output, indicating either the absence H_0 or presence H_1 of PU. A generalized block diagram of the DNN-based spectrum sensing framework is illustrated in Figure 2, showing the main stages: input representation, optional preprocessing, feature extraction through multiple layers, and classification output. In this study, the communication channel between the PU and the cognitive radio (CR) is modeled as an Additive White Gaussian Noise (AWGN) channel. The received signal at the CR is expressed as:

$$y(n) = h * x(n) + w(n) \quad (1)$$

where $x(n)$ is the signal transmitted by the PU, h is the channel gain (set to 1 for a static, non-fading channel), and $w(n)$is zero-mean AWGN modeled as a circularly-symmetric complex

Gaussian random variable with one- sided power spectral density N_0. The corresponding hypotheses are :

$$H_0 : \text{ Primary user is absent,} \quad y_1\,(n) = \; w(n) \tag{2}$$

$$H_1 : \text{Primary user is present,} \quad y_2(n) = h\,x(n) \; + \; w(n) \tag{3}$$

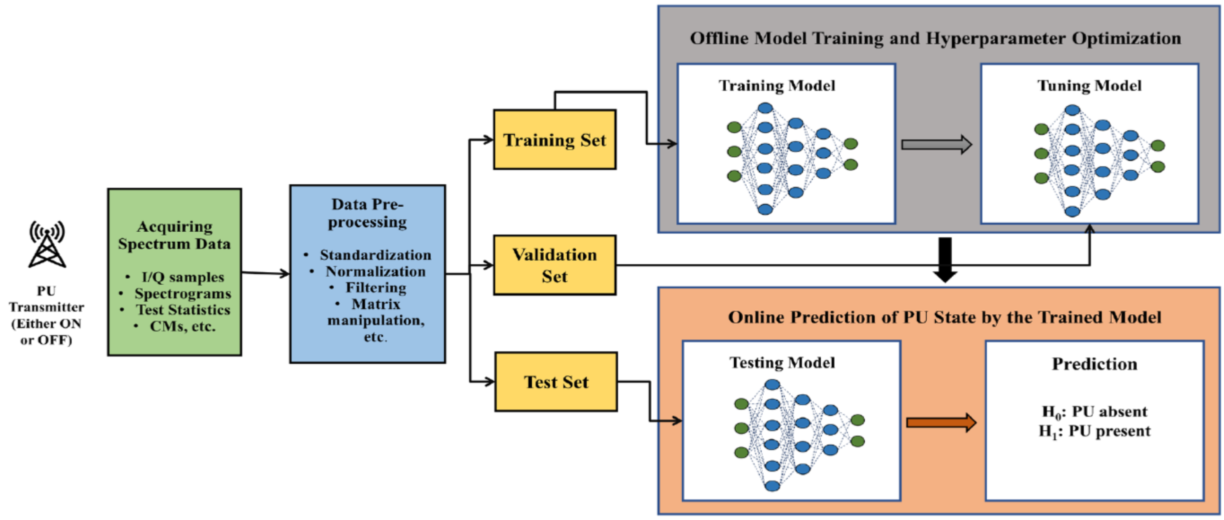

Figure 2. Block diagram of the DNN-based SS system

where H_0 indicates the hypothesis of no PU presence, H_1 indicates the hypothesis of PU presence, $y_1\,(n)$ and $y_2\,(n)$ represent the signals received by the CR. The relationship between SNR and the channel model is explicitly defined as:

$$SNR = \frac{E\left[|h.x(n)|^2\right]}{E[|w(n)|^2]} \tag{4}$$

E[·] denotes the expectation operator (i.e., statistical mean), which reflects the average signal and noise power. To enhance spectral feature clarity under low-SNR conditions, a wavelet-based denoising WD stage is incorporated as a preprocessing step prior to spectrogram generation. Specifically, Daubechies wavelets (db4) with soft thresholding are applied to reduce noise while preserving essential signal characteristics. The selection of wavelet denoising is motivated by its strong capability in processing non-stationary and low-SNR signals, which are typical in cognitive radio environments. Unlike conventional frequency-domain filtering techniques that operate globally, wavelet transform provides joint time–frequency localization, enabling effective separation of noise from transient signal components. This property is particularly important for spectrum sensing, where modulation patterns exhibit localized spectral variations. Furthermore, wavelet thresholding suppresses Gaussian noise while preserving essential signal structures, leading to enhanced spectrogram quality and improved feature extraction by the CNN. Compared to traditional filtering methods such as moving average or Wiener filtering, wavelet-based denoising better maintains discriminative characteristics required for reliable PU detection under severe noise conditions. In wavelet denoising, soft-thresholding is applied to the wavelet coefficients, defined as

$$f_{soft}(c) = \begin{cases} c & |c| \geq TH \\ 2c - TH & TH/2 \leq c < TH \\ TH + 2c & -TH < c \leq TH/2 \\ 0 & |c| < TH/2 \end{cases} \tag{5}$$

where c is a wavelet coefficient and T is the threshold. Coefficients with absolute value below T are set to zero, while larger coefficients are shrunk toward zero by the threshold amount, reducing noise while preserving significant signal features. The denoised signal is then converted into spectrogram images, which serve as input to the CNN. This preprocessing step improves the signal-to-noise ratio in the feature domain, facilitating more accurate PU detection.

The proposed WD-CNN architecture is designed to extract hierarchical spectral features from spectrogram images and perform binary spectrum sensing. As illustrated in Figure 3, the network consists of five convolutional layers, each followed by a max-pooling operation, enabling progressive abstraction of discriminative features related to the presence or absence of the PU. To enhance robustness and mitigate overfitting, a global average pooling layer is employed to aggregate spatial information while reducing feature dimensionality. The extracted features are subsequently fed into a fully connected layer, which performs binary classification between the hypotheses H_0 and H_1 , corresponding to the absence and presence of the PU, respectively. Rectified Linear Unit (ReLU) activation functions are adopted in the convolutional layers to introduce nonlinearity and accelerate convergence, whereas a sigmoid activation function is used at the output layer to generate the final detection decision. The network hyperparameters, including filter sizes, stride values, batch size, learning rate, optimizer type, and number of training epochs, were empirically optimized to achieve high detection accuracy under low-SNR conditions while maintaining low computational complexity.

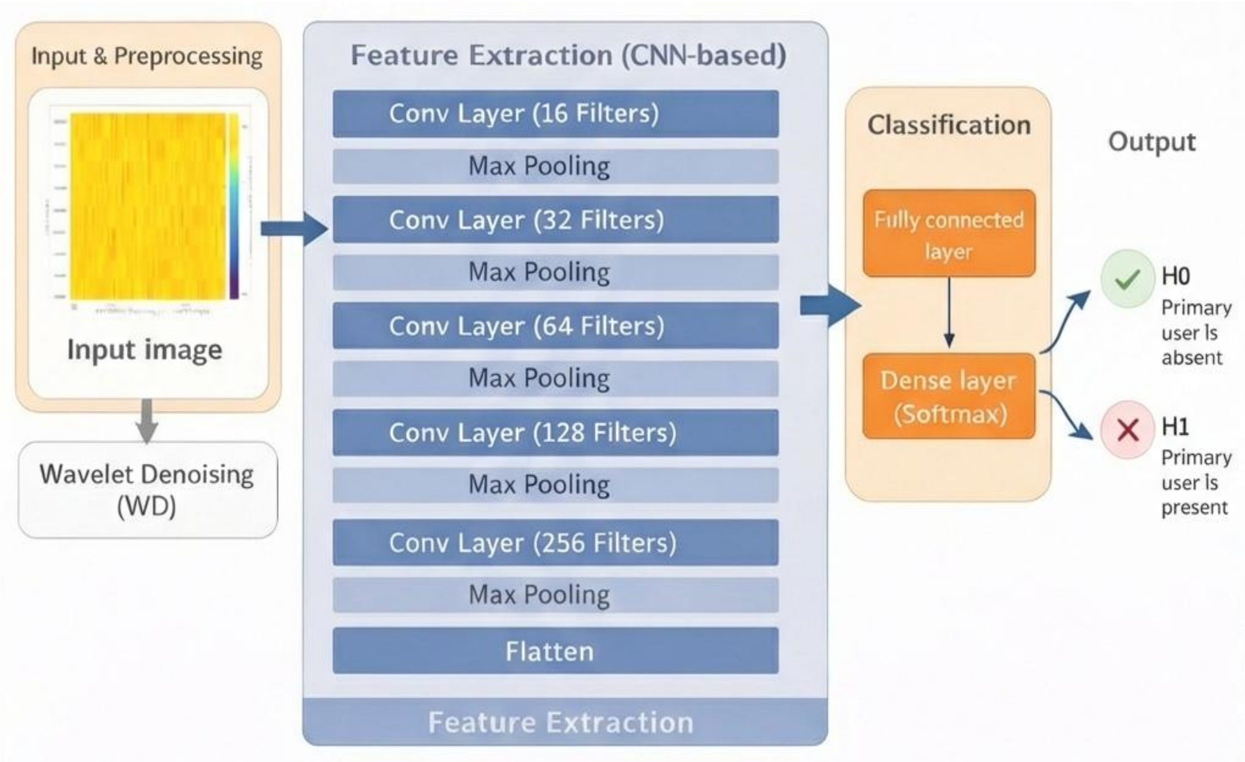

Figure 3. Block diagram of the proposed WD-CNN–based spectrum sensing framework.

The proposed WD-CNN model is evaluated across multiple modulation schemes, including BPSK, QPSK, and 16-QAM, to assess its generalization capability under diverse signaling conditions. For each modulation type, spectrogram representations are generated over a wide range of low SNR) levels, spanning from –5 to –20 dB. This evaluation strategy ensures that the proposed model is capable of accurately detecting the presence of the PU irrespective of the modulation technique employed in the transmission, thereby demonstrating its robustness and practical applicability in cognitive radio environments. Overall, the integration of wavelet-based denoising with hierarchical CNN feature extraction enables the proposed WD-CNN model to achieve robust spectrum sensing and enhanced detection performance under low-SNR conditions.

4. SIMULATION RESULTS

In this section, the simulation setup is described, and the performance of the models under various modulation schemes and SNR conditions is analyzed. Both classification accuracy and spectrum sensing efficiency are investigated to assess the robustness of the proposed approach.

4.1. Simulation Setup

The simulations were conducted on a laptop equipped with a 6th-generation Intel Core i7 processor running at 2.60 GHz with 16 GB of RAM, using MATLAB R2023b. The wireless channel was modeled as an additive white Gaussian noise (AWGN) channel with zero-mean noise. This channel model was selected to focus on the impact of noise on spectrum sensing performance. The performance of the models was evaluated under various SNR levels: −5, −10, −15, and −20 dB.

A synthetically generated dataset was used for training, validation, and testing. Multiple classes were defined, including PU signals modulated using BPSK, QPSK, and 16-QAM, as well as noise-only signals. Each transmitted frame consisted of 10,000 symbols sampled at 1 MHz. The received signals were transformed into time–frequency spectrogram images using short-time Fourier transform (STFT), which were used as input for the deep learning models.

For the deep learning experiments, a pre-trained AlexNet model was employed. Transfer learning was performed over 40 epochs with 16 iterations per epoch, totaling 640 iterations. The cross-entropy loss function was used, which is suitable for multi-class classification tasks.

In the proposed work, the Wavelet-Denoising CNN (WD-CNN) applies wavelet denoising prior to the first convolutional layer to mitigate the impact of noise and enhance PU signal detection accuracy. This preprocessing step results in more discriminative spectrogram features, leading to improved classification performance and a significant reduction in spectrum sensing and testing time. The WD-CNN was trained using the same dataset, SNR values, and modulation schemes as the pre-trained AlexNet, over 40 epochs with 16 iterations per epoch, using the cross-entropy loss function.

Figures 4–7 illustrate the training accuracy and loss progression for both AlexNet and WD-CNN across all modulation schemes. To ensure statistical reliability, Monte Carlo simulations were repeated 10,000 times. Table 1 summarizes the main simulation parameters, including SNR levels, modulation schemes, number of symbols per frame, and training configurations.

Table 1. Description of the Simulation Configuration

Parameters	Values
Modulation Schemes	BPSK, QPSK,16QAM
Spectrogram images	800
Channel Model	AWGN
Convolution layers	5 layers
Number of max pooling layers	5 layers
Training duration	40 epochs
Convolution Activation Function	ReLU
Learning Rate	0.0001
Wavelet Denoising Method	Daubechies (db4)
SNR	-5, -10, -15, and -20 dBs.

4.2. Performance Comparison under Different Modulation Schemes

In this subsection, the classification performance of the pre-trained AlexNet and the proposed WD-CNN is analyzed under different modulation schemes (BPSK, QPSK, and 16-QAM) and SNR conditions. For each SNR value, a single figure presents the accuracy of both models for all modulation types, enabling a direct and fair comparison under identical noise conditions.

At an SNR of −5 dB, as illustrated in Figure 4, the pre-trained AlexNet exhibits noticeable performance differences across modulation schemes. BPSK achieves the highest classification accuracy, followed by QPSK and 16-QAM, reflecting the robustness of lower-order modulation under noisy conditions. The proposed WD-CNN consistently outperforms AlexNet for all modulation schemes at the same SNR. The wavelet denoising step reduces noise and enhances discriminative features in the spectrogram images, thereby improving classification accuracy and reducing spectrum sensing and testing time.

At an SNR of −10 dB, as shown in Figure 5, a general degradation in classification accuracy is observed for all modulation schemes. AlexNet performance decreases more noticeably for higher-order modulations 16-QAM, whereas WD-CNN maintains higher accuracy due to its denoising capability, demonstrating superior robustness under increased noise levels.

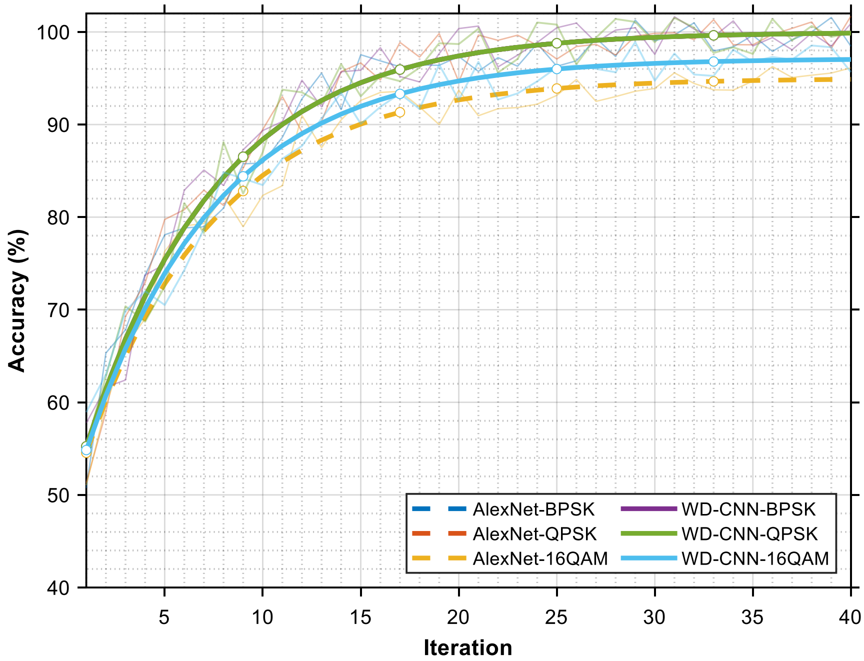

Figure 4. Accuracy versus iteration for AlexNet and WD-CNN across different modulation schemes at SNR = -5 dB.

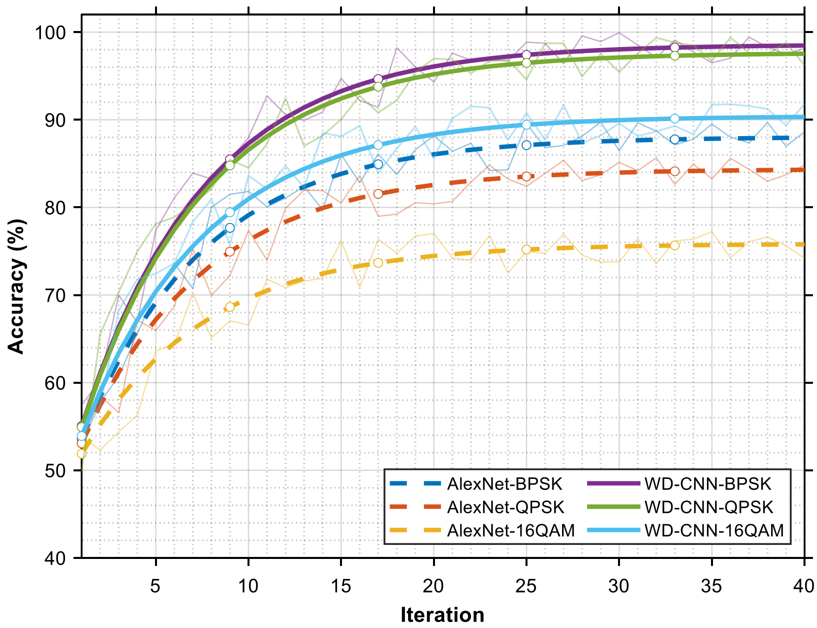

Figure 5. Accuracy versus iteration for AlexNet and WD-CNN across different modulation schemes at SNR = −10 dB.

At an SNR of −15 dB, as depicted in Figure 6, both models show further performance decline. The performance gap between AlexNet and WD-CNN becomes more pronounced, highlighting the advantage of wavelet-based denoising in mitigating severe noise effects, especially for higher-order modulation schemes.

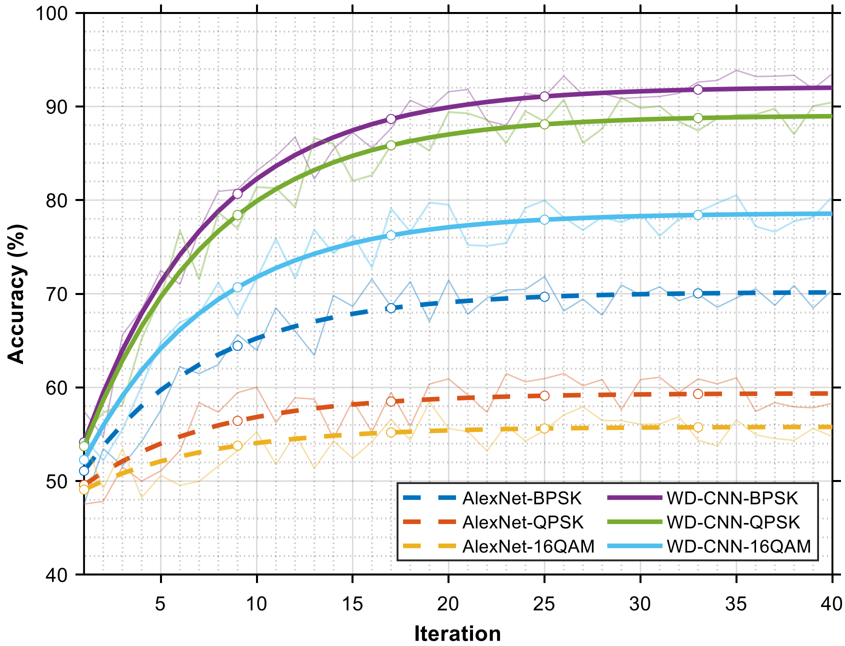

Figure 6. Accuracy versus iteration for AlexNet and WD-CNN across different modulation schemes at SNR = −15 dB.

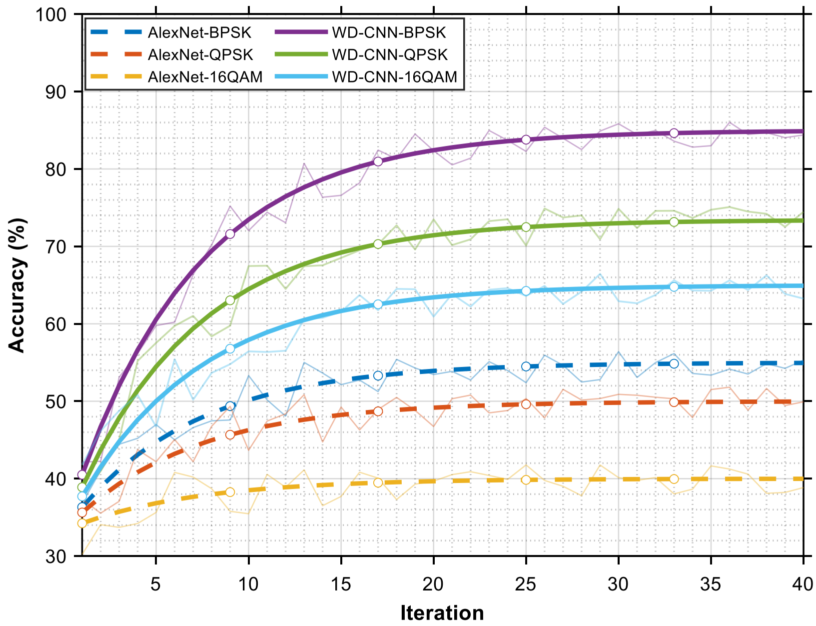

Figure 7. Accuracy versus iteration for AlexNet and WD-CNN across different modulation schemes at SNR = −20 dB.

At an SNR of −20 dB, as can be observed in Figure 7, the proposed WD-CNN continues to outperform AlexNet across all modulation schemes. Even under severely noisy conditions, WD-

CNN achieves significantly higher classification accuracy, whereas AlexNet struggles, particularly with QPSK and 16-QAM signals.

4.3. Comparative Analysis of AlexNet and WD-CNN Models

A comprehensive evaluation was performed to compare the classification performance of the pre-trained AlexNet and the proposed WD-CNN across different modulation schemes and SNR conditions. Table 2 summarizes the accuracy values of both models, providing a clear quantitative comparison. To complement the numerical results, Figure 8, illustrates the accuracy trends across SNR values for both models, highlighting the effectiveness of wavelet denoising in enhancing PU signal detection under noisy environments.

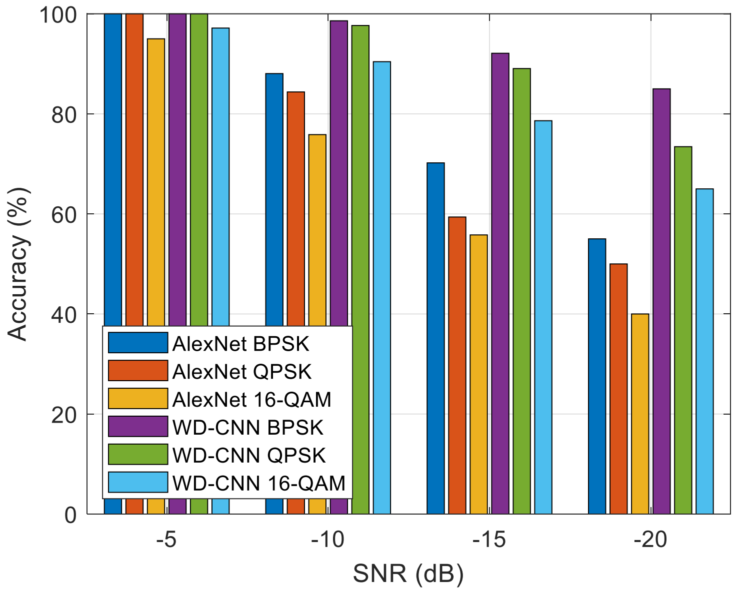

Figure 8. Accuracy versus SNR for AlexNet and WD-CNN across different modulation schemes.

At an SNR of –5 dB, both AlexNet and WD-CNN achieve nearly perfect accuracy for BPSK and QPSK signals. For 16-QAM, AlexNet reaches 95% accuracy, whereas WD-CNN demonstrates slightly higher robustness with 97.15%. These results indicate that while both models perform well at high SNR, WD-CNN provides modest improvement for higher-order modulation.

As the SNR decreases to −10 dB, a performance gap emerges. AlexNet accuracy drops to 88.05%, 84.38%, and 75.85% for BPSK, QPSK, and 16-QAM, respectively, whereas WD-CNN maintains higher accuracy values of 98.6%, 97.66%, and 90.43%. The results, as shown in Table 2 and Figure 8, indicate that the wavelet denoising step effectively mitigates noise impact, particularly for higher-order modulation schemes.

At −15 dB, the difference between the two models becomes more pronounced. AlexNet achieves 70.2%, 59.38%, and 55.8% for BPSK, QPSK, and 16-QAM, respectively, while WD-CNN maintains superior performance with 92.11%, 89.06%, and 78.63%. This highlights the robustness of WD-CNN under moderate noise conditions.

Under severely noisy conditions at −20 dB, AlexNet performance significantly deteriorates, reaching 55.01%, 50%, and 40% for BPSK, QPSK, and 16-QAM, respectively. In contrast, WD-CNN achieves 85%, 73.44%, and 65%, maintaining a clear advantage across all modulation schemes. The results emphasize the importance of wavelet-based denoising in preserving discriminative features, enabling accurate spectrum sensing even at low SNR levels. Overall, the comparative analysis quantitatively confirms that WD-CNN consistently outperforms AlexNet, particularly as noise increases and for higher-order modulations, demonstrating its effectiveness for robust spectrum sensing in CR systems.

Table 2. Classification Accuracy and sensing time for AlexNet and WD-CNN across different modulation schemes and SNR levels.

Modulation	Condition SNR (dB)	AlexNet Accuracy Rate%	WD-CNN Accuracy Rate%	AlexNet Sensing time (msec)	WD-CNN Sensing time (msec)
BPSK	-5	100	100	1.55	1.05
	-10	88.05	98.6	1.65	1.25
	-15	70.2	92.11	1.7	1.37
	-20	55.01	85	1.78	1.43
QPSK	-5	100	100	1.6	1.1
	-10	84.38	97.66	1.7	1.3
	-15	59.38	89.06	1.73	1.42
	-20	50	73.44	1.82	1.46
16-QAM	-5	95	97.15	1.62	1.12
	-10	75.85	90.43	1.71	1.33
	-15	55.8	78.63	1.75	1.45
	-20	40	65	1.85	1.5

In addition to classification accuracy, the spectrum sensing elapsed time of both models was evaluated across all modulation schemes and SNR levels. As shown in Table 2, WD-CNN consistently achieves lower sensing times compared to AlexNet. For instance, at −20 dB, WD-CNN requires 1.43, 1.46, and 1.5 ms for BPSK, QPSK, and 16-QAM, respectively, while AlexNet takes 1.78, 1.82, and 1.85 ms. The reduction in sensing time is attributed to the wavelet denoising preprocessing, which enhances feature representation and allows the CNN to converge faster during inference. Figure 9 illustrates the sensing time trends for all modulation schemes, highlighting the efficiency of WD-CNN in real-time spectrum sensing applications.

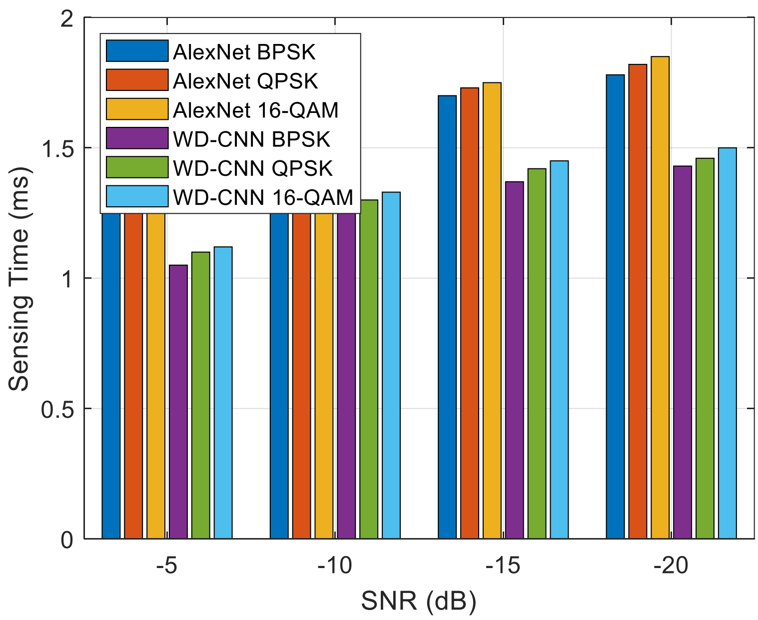

Figure 9. Spectrum sensing time versus SNR for AlexNet and WD-CNN across all modulation schemes.

5. DISCUSSION

Despite the promising detection capability achieved by the proposed WD-CNN framework, several practical aspects merit further consideration. The adoption of wavelet-based denoising introduces an additional preprocessing stage whose effectiveness depends on the statistical properties of the received signal. In practical cognitive radio systems, accurate characterization of channel noise may not always be readily available, which could influence preprocessing efficiency and increase computational burden in time-constrained applications.

Furthermore, the current validation was conducted using spectrogram representations derived from simulated AWGN channels. While such a setup enables controlled performance benchmarking, operational wireless environments are typically more complex. Real channels often exhibit time-varying fading, interference from neighboring users, non-linear distortions, and hardware-related imperfections. These factors may alter the spectral characteristics of the received signal and potentially affect feature consistency during inference.

Another consideration involves computational scalability. Although the proposed architecture enhances detection capability, deployment in resource-limited platforms requires careful optimization of model size, inference speed, and energy consumption. Practical implementation therefore calls for architectural refinement and lightweight model design strategies.

Future investigations should emphasize robustness assessment under realistic propagation scenarios and experimentally collected datasets. Exploring adaptive denoising configurations and alternative wavelet families may also provide further flexibility in handling diverse signal conditions. Additionally, integrating advanced feature adaptation strategies could strengthen resilience against environmental variability.

6. CONCLUSION

This paper presented a comprehensive performance evaluation of a Wavelet-Denoising Convolutional Neural Network (WD-CNN) for spectrum sensing under different modulation schemes and low-SNR conditions. The proposed approach integrates wavelet denoising with spectrogram-based deep learning to enhance PU signal detection in noisy CR environments. Simulation results demonstrate that WD-CNN consistently outperforms the pre-trained AlexNet across all considered modulation schemes, including BPSK, QPSK, and 16-QAM, within a challenging low-SNR range from −5 dB to −20 dB.

At relatively higher low-SNR levels, both models achieve acceptable classification accuracy. However, as the SNR decreases, AlexNet experiences a significant performance degradation, whereas WD-CNN maintains substantially higher accuracy across all modulation schemes, indicating superior robustness against severe noise conditions. This performance improvement is mainly attributed to the wavelet denoising stage, which effectively suppresses noise while preserving essential signal characteristics in the spectrogram representations. As a result, more discriminative features can be extracted.

In addition to accuracy gains, WD-CNN demonstrates improved efficiency in terms of spectrum sensing time, achieving consistently lower sensing latency compared to AlexNet across all evaluated low-SNR conditions. These results confirm that the proposed WD-CNN framework provides a robust and efficient solution for spectrum sensing in adverse noise environments. Future work will focus on extending the proposed framework to more complex channel conditions, such as fading and interference, and investigating its applicability to higher-order modulation schemes and integrated sensing and communication (ISAC) systems for emerging 6G networks.

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