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Bayesian deep learning for collaborative spectrum sensing in 6G mmWave communication systems

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A B S T R A C T

In this paper, we present an innovative approach for spectrum sensing in mmWave massive multiple-input multiple-output (MIMO) systems by leveraging a hierarchical Bayesian model integrated with Stacked Denoising Autoencoders (SDAEs). The proposed method significantly improves the accuracy of spectrum sensing by effectively estimating the unknown covariance of the CSCG noise. By incorporating Bayesian deep learning principles into the model, a robust estimation of noise characteristics is achieved, enhancing the detection performance of weak signals amidst noise with unknown covariance. The use of Collaborative Deep Learning (CDL) allows for adaptive learning of complex noise patterns and provides a more accurate characterization of the spectrum. Extensive simulations are conducted to validate the effectiveness of the proposed CDL-based spectrum sensing method in mmWave massive MIMO systems. The simulations compare the performance of the Bayesian deep learning approach against traditional spectrum sensing techniques and state-of-the-art methods. The results demonstrate superior performance in terms of detection accuracy, noise robustness, and computational efficiency. Detailed performance metrics and analysis are provided to showcase the practical advantages of integrating CDL with SDAEs for spectrum sensing in real-world mmWave scenarios.

Keywords: *Cognitive radio network, Spectrum sensing, Baysian deep learning, Massive MIMO.*

1. Introduction

Efficient utilization of the radio frequency spectrum has become a critical challenge due to the rapid growth of wireless communication services. Spectrum sensing is a fundamental function of cognitive radio networks, enabling secondary users to detect spectrum availability while avoiding harmful interference with licensed users [1]. Reliable spectrum sensing is particularly crucial in emerging wireless systems, where dynamic environments, hardware impairments, and noise uncertainty significantly affect detection performance [2].

With the advent of mmWave massive MIMO systems, spectrum sensing faces new challenges. Although mmWave communication offers large bandwidth and high data rates, it is highly sensitive to noise, blockage, and channel impairments. In practical scenarios, the noise characteristics—especially the noise covariance—are often unknown or time-varying, which severely degrades the performance of conventional spectrum sensing techniques.

Traditional methods typically assume white Gaussian noise with known variance, making them unreliable in realistic mmWave massive MIMO environments.

To overcome these limitations, machine learning (ML) and deep learning (DL) techniques have been increasingly adopted for spectrum sensing. Data-driven approaches enable more flexible modeling of complex signal environments and have shown improved performance compared to classical methods [3, 4]. Supervised learning algorithms such as Support Vector Machines (SVMs) and Decision Trees have been widely used to classify spectrum occupancy based on extracted features. SVMs, in particular, are effective in separating signal classes by constructing optimal hyperplanes in high-dimensional feature spaces [5], while Decision Trees provide interpretability and can efficiently handle mixed data types [6]. However, supervised methods rely heavily on labeled datasets, which are often difficult to obtain in dynamic wireless environments [7-9].

Unsupervised learning techniques, including clustering algorithms such as K-means, alleviate the need for labeled data by discovering inherent structures in received signals [10]. In addition, dimensionality reduction methods such as Principal Component Analysis (PCA) are commonly employed for feature extraction and complexity reduction when dealing with high-dimensional spectrum data [11]. While these approaches improve scalability, they still lack robustness against noise uncertainty and complex interference patterns.

More recently, deep learning methods have demonstrated superior capability in modelling nonlinear and high-dimensional spectrum data. Convolutional Neural Networks (CNNs) have been successfully applied to time–frequency representations to capture spatial features and enhance signal detection and classification performance [12, 13]. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are effective in learning temporal dependencies in dynamic spectrum environments [14, 15]. Furthermore, Generative Adversarial Networks (GANs) have been utilized to generate synthetic spectrum data, improving model generalization and robustness [16, 17]. Despite these advances, most existing DL-based spectrum sensing approaches implicitly assume known or stationary noise statistics, limiting their effectiveness in practical mmWave massive MIMO systems with unknown colored noise.

In this context, Bayesian learning provides a powerful framework for spectrum sensing under uncertainty. By explicitly modeling prior knowledge and uncertainty, Bayesian methods offer probabilistic inference mechanisms that improve robustness in noisy and incomplete information scenarios. Bayesian networks and Bayesian inference techniques enable systematic updating of beliefs regarding spectrum occupancy based on observed data [18]. Recent studies have focused on improving the computational efficiency of Bayesian methods, making them increasingly suitable for real-time spectrum sensing applications [18]. However, traditional Bayesian approaches alone may struggle to scale efficiently in high-dimensional mmWave massive MIMO systems.

Motivated by these observations, this paper proposes a Bayesian deep learning-based collaborative framework for cooperative spectrum sensing in mmWave massive MIMO cognitive radio networks. By integrating hierarchical Bayesian modeling with Stacked Denoising Autoencoders (SDAEs), the proposed approach jointly estimates the unknown covariance of circularly symmetric complex Gaussian (CSCG) noise and performs reliable spectrum sensing. The collaborative deep learning (CDL) framework enables efficient denoising and feature extraction from high-dimensional received signals, thereby enhancing detection performance in challenging noise conditions. The main contributions of this paper can be categorized as follows:

- An innovative approach is proposed for spectrum sensing in mmWave massive MIMO systems by leveraging a hierarchical Bayesian model integrated with Stacked Denoising Autoencoders (SDAEs). This method significantly improves the accuracy of spectrum sensing by effectively estimating the unknown covariance of the CSCG noise. By incorporating Bayesian deep learning principles into our model, we achieve a robust estimation of noise characteristics, which in turn enhances the detection performance of weak signals amidst noise with unknown covariance. The use of CDL allows for adaptive learning of complex noise patterns and provides a more accurate characterization of the spectrum.
- A collaborative deep learning (CDL) framework is introduced specifically tailored for spectrum sensing in massive MIMO

systems. This framework utilizes SDAEs to perform denoising and feature extraction from received signals. The hierarchical Bayesian model embedded within the CDL framework enables the joint optimization of noise covariance estimation and signal detection. By integrating multiple SDAEs in a collaborative manner, our approach efficiently handles the high-dimensional nature of mmWave signals and improves the robustness of spectrum sensing in challenging environments.

- To validate the effectiveness of our proposed CDL-based spectrum sensing method, we conduct extensive simulations in mmWave massive MIMO systems. The simulations compare the performance of our Bayesian deep learning approach against traditional spectrum sensing techniques and other state-of-the-art methods. Results demonstrate that our approach offers superior performance in terms of detection accuracy, noise robustness, and computational efficiency. We provide detailed performance metrics and analysis to showcase the practical advantages of integrating CDL with SDAEs for spectrum sensing in real-world mmWave scenarios.

Existing spectrum sensing approaches, including classical energy detection and sparse Bayesian learning methods, generally rely on predefined or stationary noise statistics, which limits their robustness in practical mmWave massive MIMO environments characterized by high-dimensional signals and noise uncertainty. Recent deep learning–based techniques, such as CNN- and LSTM-based spectrum sensing frameworks, have demonstrated improved feature extraction capabilities; however, these methods typically operate under implicit noise assumptions and do not explicitly model uncertainty in the noise covariance.

Closely related studies, including prior works by the authors and other recent contributions (e.g., [1, 3, 19]), primarily focus on signal detection under known channel or noise conditions, or consider spectrum sensing without fully exploiting collaborative sensing in the presence of unknown coloured noise. In contrast, the proposed Bayesian collaborative deep learning framework integrates hierarchical Bayesian inference with stacked denoising autoencoders, enabling joint noise-aware feature learning and uncertainty modeling. This design makes the proposed approach particularly suitable for collaborative spectrum sensing in mmWave massive MIMO systems, where noise statistics may vary over time and across sensing nodes.

The rest of this paper is organized as follows. Section 2 presents the system model of the proposed network. In Section 3, the problem formulation and solutions are explained. Numerical results are provided in Section 4, and finally, Section 5 concludes the paper.

1.1. SYSTEM Description

In this paper, we consider large-scale CRN model which is composed of several PUs and SUs, which sense the spectrum using *L* and *K* antennas, respectively. The number of active PUs is unknown to the SUs, and each PU is active or inactive with a certain probability. The network is organized in a cluster topology, so the proposed model, as depicted in Figure 1 is a large-scale cooperative MIMO system.

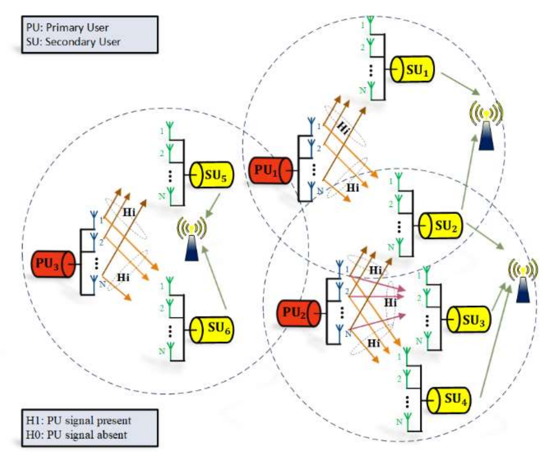

Figure 1. Proposed system model for massive MIMO spectrum sensing

In the proposed system, when an SU requests to use the spectrum, it attempts to find an available channel. Specifically, the SU must sequentially scan all channels until it either finds an available channel or fails. To check the status of the PU in the spectrum, two states H_0 and H_1 are considered, representing the spectrum being occupied by the PU and the spectrum being unused, respectively. The spectrum usage is formulated as follows:

$$y(n) = \begin{cases} w(n) & H_0 \\ Hx(n) + w(n) & H_1 \end{cases} \quad (1)$$

where $x(n) \in \mathbb{C}^{L\times 1}$ represents the n-th sample of the received signal from the PU antennas. It is assumed that this signal is a circularly symmetric complex Gaussian (CSCG) with zero mean and unknown covariance. $w(n) \in \mathbb{C}^{L\times 1}$ denotes CSCG white noise with zero mean and unknown variance. $H \in \mathbb{C}^{L\times K}$ is the channel gain matrix between the PU and SU.

In next-generation networks, the increasing number of users and limited space for antennas lead to the phenomenon of mutual coupling between antennas. Antennas interfere with each other, and the greater the distance between them, the less the interference. The interference between antennas is characterized by a matrix that is applied to the received signals from the transmitting and receiving antennas. It is also important to note that the coefficients of the mutual coupling matrix vary under different temperature conditions, meaning that the coupling matrix is not constant. The system model, assuming mutual coupling between antennas, is defined as follows:

$$\hat{y}(n) = \begin{cases} M_{mc}^{R} w(n) & H_0 \\ M_{mc}^{R}(H\hat{x}(n) + w(n)) & H_1 \end{cases} \quad (2)$$

$$\hat{x}(n) = M_{mc}^{T} z(n) \quad (3)$$

where M_{mc}^{R} and M_{mc}^{T} represent the mutual coupling matrices of the transmitting and receiving antennas, respectively. $z(n) \in \mathbb{C}^{L\times 1}$ is the input signal to the antennas before being affected by mutual coupling. The signal $\hat{x}(n)$ is the transmit signal after applying the mutual coupling of the transmitting antennas.

In this paper, our goal is to explore the use of neural networks (NN) and machine learning (ML) classification to detect the status of the primary user in the context of cooperative spectrum sensing.

2. Proposed Solutions

2.1. Neural Netwoks

Deep learning usually refers to neural networks with more than two layers. To better understand deep learning, we will examine multi-layer perceptrons (MLPs), which are one of the simplest types of neural networks. Essentially, an MLP is a sequence of parametric nonlinear transformations. We want to train an MLP for regression that maps an \$ M\$-dimensional input vector to a *D*-dimensional output vector. The input matrix is denoted as X_0 (where 0 denotes the 0-th layer of the perceptron), and the *M*-dimensional vector X_{0,j^*} represents the *j*-th row of the input matrix. The output of the problem is denoted by *Y*, and similarly, Y_{j^*} is a *D*-dimensional row vector. The MLP problem with *L* layers can be formulated as follows [19, 20]:

$$\min_{W_l, b_l} \| X_L - Y \|_F + \lambda \sum_l \| W_l \|_F^2$$
$$\text{Subject to } X_l = \sigma(X_{l-1}W_l + b_l), \quad l = 1, \dots, L-1 \quad (4)$$
$$X_L = X_{L-1}W_L + b_L$$

where $\sigma(.)$ is the sigmoid function, given by $\sigma(x) = \frac{1}{1+\exp(-x)}$. λ is the regularization parameter, and $\| . \|_F$ denotes the Frobenius norm. Instead of the sigmoid function, functions like $\tanh x$ and $\max(x, 0)$ can also be used to provide nonlinear transformations.

The network's output X_L can be easily computed using the input data, coefficients, and bias values. However, the coefficients and biases are unknown to us. In reality, we have selected a configuration of neurons across different layers, but what drives the network's training is adjusting the weights and biases of the neurons. Next, a cost function *E* is defined according to the problem type, and ultimately, the network weights are adjusted using the Backpropagation algorithm and stochastic gradient descent. Gradients are calculated as follows using the chain rule:

$$\frac{\partial E}{\partial X_L} = 2(X_L - Y)$$
$$\frac{\partial E}{\partial X_l} = (\frac{\partial E}{\partial X_{l+1}}) \circ X_{l+1} \circ (1 - X_{l+1}) \cdot W_{l+1}$$
$$\frac{\partial E}{\partial W_l} = X_{l-1}^T \left(\frac{\partial E}{\partial X_l} \circ X_l \circ (1 - X_l) \right) \quad (5)$$
$$\frac{\partial E}{\partial b_l} = mean\left(\frac{\partial E}{\partial X_l} \circ X_l \circ (1 - X_l), 1 \right)$$

where X_l for $l = 1, \dots, L-1$ represents the hidden units. The regularization term has been omitted. The only free parameters in conventional deep learning models are b_l and W_l, which are obtained through training algorithms, while other parameters are computed using these two parameters.

2.2. Hierarchical Bayesian Model

2.2.1. Generalized Bayesian Model

In the introduced MLP network, suppose the network input is the noisy version of the data X_0 and the output is the clean version of the data X_c [9]. The process of generating the generalized Bayesian model is as follows:

For each layer l of the network:

- For each column n of the weight matrix W_l:

$$W_{(l,*n)} \sim \mathcal{N}\left(0, \lambda_w^{-1} I_{K_t}\right) \quad (6)$$

- For the bias vector b_l:

$$b_l \sim \mathcal{N}\left(0, \lambda_w^{-1} I_{K_t}\right) \quad (7)$$

- For each row j of X_l:

$$X_{(l,j^*)} \sim \mathcal{N}\left(\sigma\left(X_{(l-1,j^*)} W_l + b_l\right), \lambda_s^{-1} I_{K_t}\right) \quad (8)$$

- For each j of X_c:

$$X_{(c,j^*)} \sim \mathcal{N}\left(X_{(L,j^*)}, \lambda_n^{-1} I_B\right) \quad (9)$$

If λ_s tends to infinity, the Gaussian distribution in (8) becomes a Dirac delta distribution centered at $\sigma\left(X_{(l-1,j^*)} W_l + b_l\right)$. In this model, the first $L / 2$ layers of the network are used for encoding and the last $L / 2$ layers are used for decoding. Maximizing the posterior probability is equivalent to minimizing the reconstruction error while considering weight decay.

2.2.2. Collaborative Deep Learning

Using the generalized Bayesian model as a step, the process for generating Collaborative Deep Learning (CDL) is defined as follows:

- Generate generalized Bayesian variables.
- For each item j:
- Set the hidden item deviation vector $\epsilon_j \sim \mathcal{N}(0, \lambda_v^{-1} I_K)$
- Set the hidden item vector $V_j = \epsilon_j + X^T_{(L/2,j^*)}$.
- Set the hidden user vector for each user i:

$$u_i \sim \mathcal{N}(0, \lambda_u^{-1} I_K) \quad (10)$$

- Set the ranking R_{ij} for each pair (i, j):

$$R_{ij} \sim \mathcal{N}\left(u_i^T v_j, C_{ij}^{-1}\right) \quad (11)$$

where $\lambda_w, \lambda_n, \lambda_u, \lambda_s, \lambda_v$ are the problem parameters. Note that the middle layer $X_{(L/2)}$ acts as a bridge between ranking and content information. This middle layer, along with the hidden deviation ϵ_j, is key for CDL to simultaneously learn effective features and capture relationships between items and users. For computational efficiency, λ_s can be made to tend to infinity.

2.2.3. Learning

Based on the above CDL model, all parameters can be considered as random variables to apply fully Bayesian methods such as Markov Chain Monte Carlo or Variational Inference methods [21, 22]. However, such solutions typically have high computational costs. Consequently, CDL uses an Expectation-Maximization (EM) model algorithm to obtain MAP estimates, such as in [7]. To maximize the posterior probability, we maximize the joint log-likelihood of the variables $U, V, \{X_l\}, X_c, \{W_l\}, \{b_l\}, R$ with respect to the parameters $\lambda_w, \lambda_n, \lambda_u, \lambda_s, \lambda_v$:

$$\begin{aligned} L = & -\frac{\lambda_u}{2} \sum_i \| u_i \|_2^2 - \frac{\lambda_w}{2} \sum_l \left(\| W_l \|_F^2 + \| b_l \|_2^2\right) \\ & -\frac{\lambda_v}{2} \sum_j \| V_j - X^T_{(L/2,j^*)} \|_2^2 \\ & -\frac{\lambda_n}{2} \sum_j \| X_{(L,j^*)} - X_{(c,j^*)} \|_2^2 \\ & -\frac{\lambda_s}{2} \sum_l \sum_j \| \sigma\left(X_{(l-1,j^*)} W_l + b_l\right) - X_{(l,j^*)} \|_2^2 \\ & -\sum_{i,j} \frac{C_{ij}}{2} \left(R_{ij} - u_i^T V_j\right)^2 \end{aligned} \quad (12)$$

If λ_s tends to infinity, we have:

$$\begin{aligned} L = & -\frac{\lambda_u}{2} \sum_i \| u_i \|_2^2 - \frac{\lambda_w}{2} \sum_l \left(\| W_l \|_F^2 + \| b_l \|_2^2\right) \\ & -\frac{\lambda_v}{2} \sum_j \| V_j - f_e(X_{(L,j^*)}, W^+)^T \|_2^2 \\ & -\frac{\lambda_n}{2} \sum_j \| f_r(X_{(0,j^*)}, W^+) - X_{(c,j^*)} \|_2^2 \\ & -\frac{\lambda_s}{2} \sum_l \sum_j \| \sigma\left(X_{(l-1,j^*)} W_l + b_l\right) - X_{(l,j^*)} \|_2^2 \end{aligned} \quad (13)$$

$$-\sum_{i,j}\frac{C_{ij}}{2}\left(R_{ij}-u_i^T V_j\right)^2$$

The encoding function $f_e(\cdot, W^+)$ takes the noisy content vector $X_{(0,j^*)}$ of item j as input and computes the encoding of the item. The function $f_r(\cdot, W^+)$ also takes $X_{(0,j^*)}$ as input, computes the encoding, and then reconstructs the content vector of item j. For example, if the number of layers $L = 6, f_e(X_{(0,j^*)}, W^+)$ is the output of the third layer, while $f_r(X_{(0,j^*)}, W^+)$ is the output of the sixth layer.

$$p\left(W_{(l,*n)}^+ \middle| X_{(l-1,j^*)}, X_{(l,j^*)}, \lambda_s\right) \propto \mathcal{N}\left(W_{(l,*n)}^+ \middle| 0, \lambda_w^{-1} I\right)\mathcal{N}\left(X_{(l,*n)} \middle| \sigma\left(X_{(l-1)}^+ W_{(l,*n)}^+\right), \lambda_s^{-1} I\right) \quad (14)$$

$$p(X_{(l,j^*)} | W_l^+, W_{(l+1)}^+, X_{(l-1,j^*)}, X_{(l+1,j^*)}, \lambda_s) \propto \mathcal{N}(X_{(l,j^*)} | \sigma(X_{(l-1,j^*)}^+ W_l^+), \lambda_s^{-1} I)\mathcal{N}(X_{(l+1,j^*)} | \sigma(X_{(l,j^*)}^+ W_{(l+1)}^+), \lambda_s^{-1} I) \quad (15)$$

2.3. *Bayesian Collaborative Deep Learning*

In addition to MAP estimates, a sampling-based algorithm for solving Bayesian CDL explained here. This algorithm is a Bayesian and generalized version of the well-known backpropagation algorithm. We list the key conditional densities as follows:

- For W^+: We denote the connection $W_{(l,*n)}$ and $b_l^{(n)}$ as $W_{(l,*n)}^+$. Similarly, $X_{(l,j^*)}^+$ denotes the connection $X_{(l,j^*)}$ and 1. Ignoring the subscripts *I*:
- For $X_{(l,j^*)}$ where $l \neq L / 2$: Similarly, we denote the connection W_l and b_l as W_l^+:

Note that for the last layer $l = L$, the second Gaussian distribution is replaced with $\mathcal{N}(X_{(c,j^*)} | X_{(l,j^*)}, \lambda_s^{-1} I)$.

- For $X_{(l,j^*)}$ where $l = L / 2$:

2.4. *Variable ADAM Method*

Recent deep learning methods have achieved significant successes in areas where prediction accuracy is critical, such as computer vision and speech recognition [23]. However, for these methods to be useful across various domains, they must be aware of the uncertainty in their predictions. One of the goals of Bayesian inference is to provide uncertainty estimates using the posterior distribution obtained via Bayes' theorem. Unfortunately, using this theorem in large models, such as Bayesian neural networks, is impractical. In this section, we use natural gradient methods to address the problem of Bayesian neural networks with a natural movement approach, combined with a series of approximations. The main modification involves perturbing the network weights during gradient computation. Uncertainty estimates can be easily obtained using vectors that adapt the learning rate. This method requires less memory, computation, and implementation effort compared to existing methods while yielding uncertainty estimates of comparable quality.

Here, we propose a natural movement method that provides updates similar to Adam. The typical natural gradient methods are as follows, utilizing the Polyak heavy ball method:

$$\theta_{t+1} = \theta_t + \bar{\alpha}_t \nabla_\theta f_1(\theta_t) + \bar{\gamma}_t(\theta_t - \theta_{t-1}) \quad (16)$$

where f_1 is the function we want to maximize, and the last term represents the movement term. A natural gradient version of this algorithm has been proposed in [24], which uses the natural gradient instead of the gradient. Assuming q is an exponential-family distribution with natural parameter η, the natural movement method in the natural parameter space is given by:

$$\eta_{t+1} = \eta_t + \bar{\alpha}_t \tilde{\nabla}_{\tilde{n}} L_t + \bar{\gamma}_t(\eta_t - \eta_{t-1}) \quad (17)$$

where $\nabla_{\tilde{n}}$ represents the natural gradient in the natural parameter space. In [25], it is shown that for $q(\theta)$ being Gaussian, the above update can be expressed as a VON update with momentum:

$$\mu_{t+1} = \mu_t - \bar{\alpha}_t \left[\frac{1}{s_{t+1} + \tilde{\lambda}}\right] \circ \left(\nabla_\theta f(\theta_t) + \tilde{\lambda}\mu_t\right)$$
$$+\bar{\gamma}_t \left[\frac{s_t + \tilde{\lambda}}{s_{t+1} + \tilde{\lambda}}\right] \circ (\mu_t - \mu_{t-1}) \quad (18)$$
$$s_{t+1} = (1 - \bar{\alpha}_t)_{s_t} + \bar{\alpha}_t \nabla_\theta \theta^2 f(\theta_t) \quad (19)$$

where $\theta_t \sim \mathcal{N}(\theta|\mu_t, \sigma_t^2)$ with $\sigma_t^2 = \frac{1}{N(s_t+\tilde{\lambda})}$. This is a similar update to equation (3-20), but here the learning rates are adaptive. Notably, this update is very similar to Adam. Specifically, Adam's update can be expressed as an adaptable version of equation (3-20) as follows:

$$\theta_{t+1} = \theta_t - \bar{\alpha}_t \left[\frac{1}{\sqrt{\hat{s}_{t+1}} + \delta}\right] \circ \nabla_\theta f(\theta_t)$$
$$+\tilde{\gamma}_t \left[\frac{\sqrt{\hat{s}_t} + \delta}{\sqrt{\hat{s}_{t+1}} + \delta}\right] \circ (\theta_t - \theta_{t-1}) \qquad (20)$$

$$\hat{s}_{t+1} = \gamma_2 \hat{s}_{t+1} + (1-\gamma_2)[\hat{g}(\theta_t)]^2 \qquad (21)$$

where $\tilde{\alpha}_t$ and $\tilde{\gamma}_t$ are defined in terms of Adam's learning α and the following relationships:

$$\tilde{\gamma}_t \triangleq \gamma_1 \frac{(1-\gamma_1^{t-1})}{(1-\gamma_1^t)} \qquad (22)$$

$$\tilde{\alpha}_t \triangleq \alpha \frac{(1-\gamma_1)}{(1-\gamma_1^t)} \qquad (23)$$

Using a method similar to the Vprop derivative, we can express the update as an Adam-like update, which we call Variable Adam or simply Vadam. The pseudocode for the Vadam algorithm is shown in Algorithm 1.

Algorithm 1 Pseudocode for the Vadam Algorithm

Repeat
$\theta \longleftarrow \mu + \sigma \circ \epsilon$ where $\epsilon \sim \mathcal{N}(0,1)$ and $\sigma \longleftarrow \frac{1}{\sqrt{N_s + \lambda}}$
Randomly sample data for example D_i
$g \longleftarrow -\nabla \log p(D_i|\theta)$
$m \longleftarrow \gamma_1 m + (1-\gamma_1)(g + \frac{\lambda_\mu}{N})$
$s \longleftarrow \gamma_2 s + (1-\gamma_2)(g \circ g)$
$\widehat{m} \longleftarrow \frac{m}{1-\gamma_1^t}$ and $\hat{s} \longleftarrow \frac{s}{1-\gamma_2^t}$
$\mu \longleftarrow \mu - \frac{\alpha \widehat{m}}{\sqrt{\hat{s}} + \frac{\lambda}{N}}$
$t \longleftarrow t + 1$
Until Convergence

3. Problem Formulation

In this section, we model the problem presented in (2) as a binary classification problem with two classes: signal and noise, and we solve it using deep learning (DL). During the training phase, we use a variety of signal types and noisy data to train the network as much as possible, with the expectation that the trained network model can adapt to different unknown signals. The input in this method is the received signal power, and this approach is essentially robust for scenarios with uncertainty in noise power. Additionally, most traditional spectrum sensing methods assume that channel noise is additive white Gaussian noise (AWGN), which does not necessarily align with real-world conditions. Since DL can automatically learn noise characteristics based on input data, our proposed method is expected to detect non-Gaussian noise effectively. We will then evaluate the performance of our proposed method.

Here, we approach solving the binary classification problem using maximum likelihood estimation (MLE). Given that we do not have access to the channel and noise, or in other words, these parameters are ambiguous to us, we use a Bayesian framework. The Bayesian framework helps us to view the problem as an unknown function. On the other hand, there are situations where the noise is not Gaussian or where the number of network users is high, complicating the problem. The proposed solution to this challenge is the use of a NN. Employing a convolutional neural network (CNN) at this stage helps us solve the problem quickly; to increase the accuracy and precision of the solution, the number of hidden layers and neurons can be increased.

To solve the MLE problem and obtain the distribution of the unknown parameters (mean and variance of the unknown parameter), we use the Adam method. However, the results indicate that this method performs poorly. To obtain a more accurate solution, we introduce changes to the mean and variance in this method; in other words, we add a degree of uncertainty to the parameter. These changes cause the algorithm to be less confident in its initial results and to search for the best solution in surrounding areas as well. In fact, the algorithm defines a region for decision-making; depending on the type of problem, this region is identified very quickly or through various iterations. Given that the problem under consideration here is a binary classification problem, the solution is found quickly using the Vadam method.

Once the unknown parameter is obtained, it is multiplied by the received signal from the antenna, $\hat{y}(n)$ (as per (2)), resulting in the signal $\hat{z}(n)$. To detect the presence or absence of the PU, the signal $\hat{z}(n)$ is compared with a decision threshold. If the signal value is greater than the decision threshold, it indicates the presence of the PU; otherwise, it indicates the absence of the PU. The decision threshold is determined based on the probability of false alarm (P_{fa}).

4. Performance Evaluation

In this section, simulation results are presented to evaluate the performance of the proposed Bayesian deep learning (BDL)–based spectrum sensing framework. The impact of channel conditions and the number of receiving antennas on detection performance is investigated. The proposed method is compared with several benchmark approaches, including CNNs, LSTM networks, and SBL.

4.1. Simulation Setup

A cognitive radio network is considered with two primary users (PUs) and four secondary users (SUs) randomly distributed across three clusters. Each user is equipped with four receiving antennas and performs cooperative spectrum sensing. To rigorously assess detection robustness, simulations are conducted under both AWGN and Rayleigh fading channels.

The dataset used for training, validation, and testing is synthetically generated to accurately reflect realistic mmWave massive MIMO spectrum sensing scenarios. All simulations are conducted using MATLAB. For each realization, the received signal samples are generated under two hypotheses, namely H_0 (absence of the primary user) and H_1 (presence of the primary user), considering both AWGN and Rayleigh fading channels. The noise is modeled as CSCG with unknown and potentially time-varying covariance to reflect practical uncertainty in noise statistics.

The input to the deep learning models consists of received signal power vectors with fixed sample lengths (128 and 256 samples), collected from multiple antennas in a cooperative sensing setting. Corresponding binary labels are assigned to indicate spectrum occupancy. The dataset includes multiple modulation schemes, including BPSK, QPSK, and 64-QAM, and spans a wide range of low signal-to-noise ratios (SNRs) from −30 dB to 10 dB. In total, 20,000 samples are used for training, 8,000 samples for validation, and an independent test set is generated for performance evaluation.

Since power-based spectrum sensing performance degrades significantly at low signal-to-noise ratios (SNRs), simulations are carried out over a low SNR range to highlight the effectiveness of different methods in challenging conditions. The main simulation parameters are summarized in Table 1 , which is consistently used across all experiments.

All deep learning models were trained using standard training procedures with early stopping to prevent overfitting. Default activation functions and regularization strategies commonly adopted in the literature were employed to ensure fair comparison across models.

Table 1. Simulation Parameters [27]

Parameter	Value
Number of filters in each Conv layer	60
Filter Size	16
Number of cells in each LSTM layer	128
Number of neurons in each FC layer	128
Optimizer	Adam
Initial learning rate	0.001
Modulation scheme	BPSK, QAM, 64 QAM
Number of samples per symbol	8
Sample length	256, 128
SNR range	−30 ~ 0 dB in 1-dB increments
Number of training samples	20000
Number of validation samples	8000

4.2. Performance Under AWGN Channel

Figure 2 illustrates the detection accuracy of different spectrum sensing methods for 128-sample QAM signals in an AWGN channel. As shown, both the proposed BDL approach and the CNN-based method outperform LSTM and SBL across the entire SNR range.

At low SNR values, the performance gap becomes more pronounced. For example, at −10 dB SNR, the proposed BDL method achieves a detection accuracy of approximately 92%, compared to 89% for CNN, while LSTM and SBL exhibit significantly lower accuracy. This improvement can be attributed to the Bayesian modeling of noise uncertainty, which enhances robustness in low-SNR environments.

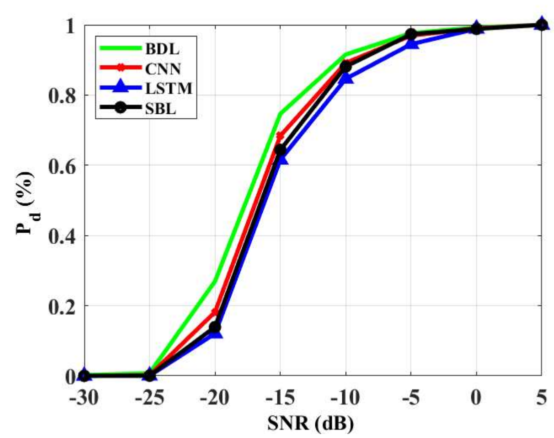

Figure 2. Detection performance of different DL models in the AWGN channel

4.3. *Performance Under Rayleigh Fading Channel*

To evaluate robustness against channel fading, detection performance under Rayleigh fading is presented in Figure 3. Compared with the AWGN scenario, all methods experience performance degradation due to multipath fading. However, the proposed BDL method maintains a clear advantage over competing approaches.

At an SNR of −10 dB, the proposed method achieves approximately 89% detection accuracy, whereas the best-performing benchmark (CNN) reaches only about 81%. This result demonstrates that the proposed method effectively captures the statistical relationships among received samples rather than relying solely on raw signal characteristics, making it particularly robust in fading environments.

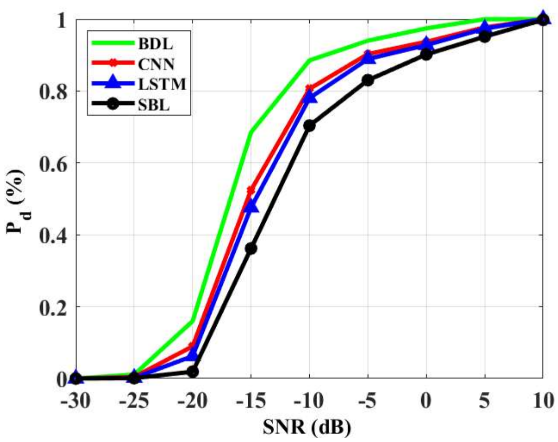

Figure 3. Detection performance of different DL models in the Rayleigh fading channel

4.4. *Impact of the Number of Receiving Antennas*

The effect of the number of receiving antennas on detection performance is investigated in Figure 4. As expected, increasing the number of antennas improves detection accuracy for all considered methods due to the resulting SNR gain and spatial diversity.

The proposed BDL approach consistently outperforms other algorithms for all antenna configurations. However, the results also indicate that beyond a certain number of antennas, performance improvements begin to saturate. This behavior can be attributed to mutual coupling effects among closely spaced antennas, which limit further gains in effective SNR.

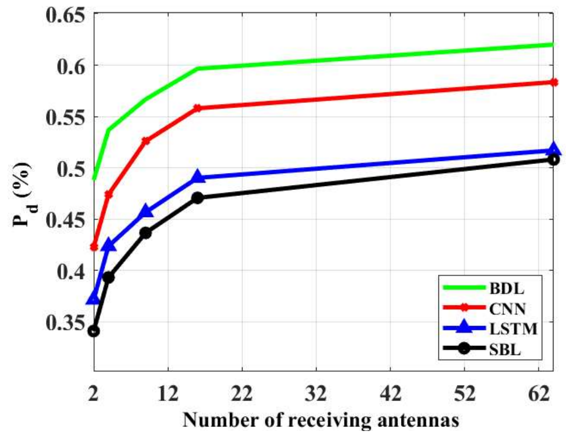

Figure 4. Detection performance of different DL models based on the number of receiving antennas

5. Conclusion

In this paper, a cooperative spectrum sensing framework for cognitive radio networks operating in mmWave massive MIMO environments was investigated. Considering the inherent uncertainty in noise and channel parameters in practical wireless systems, a Bayesian deep learning–based approach was proposed to jointly model noise characteristics and perform reliable spectrum sensing. Simulation results under both AWGN and Rayleigh fading channels demonstrate that the proposed method significantly outperforms conventional CNN-, LSTM-, and SBL-based approaches, particularly in low-SNR regimes. The superiority of the proposed framework is primarily attributed to its ability to explicitly model noise uncertainty and exploit hierarchical Bayesian inference combined with deep feature learning. Additionally, the analysis of antenna scaling confirms that the proposed approach effectively leverages spatial diversity while remaining robust to practical limitations such as antenna coupling.

Overall, the results validate the effectiveness and robustness of the proposed Bayesian deep learning framework for spectrum sensing in challenging mmWave massive MIMO scenarios. Future work will extend this framework to jointly address spectrum sensing and energy efficiency optimization, enabling more intelligent and sustainable cognitive radio network designs.

Authors' Contributions

All authors equally contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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By researchers in Bioinformatics, Computational Biology, Artificial Intelligence and Medicine.

Declaration of Interest

The authors declare that they have no conflict of interest. The authors also declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Ethical Considerations

Not applicable.

References

[1] M. Nouri, H. Behroozi, N. K. Mallat, and S. A. Aghdam, "A wideband 5G cyclostationary spectrum sensing method by kernel least mean square algorithm for cognitive radio networks," *IEEE Transactions on Circuits and Systems II: Express Briefs,* vol. 68, no. 7, pp. 2700-2704, 2021, doi: 10.1109/TCSII.2021.3051087.

[2] E. K. Fard, M. Nouri, H. Behroozi, and S. Sobhi-Givi, "Multi-Agent H-Learning Based Cooperative Spectrum Sensing for Cognitive Radio Networks," in *32nd International Conference on Electrical Engineering (ICEE)*, 2024, pp. 1-5, doi: 10.1109/ICEE63041.2024.10668166.

[3] M. Nouri *et al.*, "Hybrid precoding based on active learning for mmWave massive MIMO communication systems," *IEEE Transactions on Communications,* vol. 71, no. 5, pp. 3043-3058, 2023, doi: 10.1109/TCOMM.2023.3247768.

[4] S. Sobhi-Givi, M. Nouri, M. G. Shayesteh, H. Kalbkhani, and Z. Ding, "Reinforcement Learning Based Joint Resource Allocation and User Fairness Optimization in mmWave-NOMA HetNets," in *2023 31st International Conference on Electrical Engineering (ICEE)*, 2023, pp. 781-786, doi: 10.1109/ICEE59167.2023.10334709.

[5] O. P. Awe, A. Deligiannis, and S. Lambotharan, "Spatio-temporal spectrum sensing in cognitive radio networks using beamformer-aided SVM algorithms," *IEEE Access,* vol. 6, pp. 25377-25388, 2018, doi: 10.1109/ACCESS.2018.2825603.

[6] D. Wang and Z. Yang, "An advanced scheme with decision tree for the improvement of spectrum sensing efficiency in dynamic network," in *2016 9th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, 2016, pp. 1288-1292, doi: 10.1109/CISP-BMEI.2016.7852914.

[7] M. Nouri, S. Sobhi-Givi, H. Behroozi, M. G. Shayesteh, M. J. Piran, and Z. Ding, "Joint Slice Resource Allocation and Hybrid Beamforming with Deep Reinforcement Learning for NOMA based Vehicular 6G Communications," *IEEE Transactions on Network and Service Management,* 2025, doi: 10.1109/TNSM.2025.3561251.

[8] M. Rahimi, S. Sobhi-Givi, M. Nouri, H. Behroozi, and M. Uysal, "A Deep Reinforcement Learning Framework for Joint Bs and Beyond Diagonal Ris Beamforming Design in Isac Systems," in *2025 13th Iran Workshop on Communication and Information Theory (IWCIT)*, 2025, pp. 1-6, doi: 10.1109/IWCIT67595.2025.11073027.

[9] S. Sobhi-Givi, M. Nouri, H. Behroozi, and Z. Ding, "Joint BS and Beyond Diagonal RIS Beamforming Design with DRL Methods for mmWave 6G Mobile Communications," in *2024 IEEE Wireless Communications and Networking Conference (WCNC)*, 2024, pp. 1-6, doi: 10.1109/WCNC57260.2024.10571253.

[10] C. J. Swinney and J. C. Woods, "K-means clustering approach to UAS classification via graphical signal representation of radio frequency signals for air traffic early warning," *IEEE Transactions on Intelligent Transportation Systems,* vol. 23, no. 12, pp. 24957-24965, 2022, doi: 10.1109/TITS.2022.3202011.

[11] F. Pourkamali-Anaraki and S. Becker, "Preconditioned data sparsification for big data with applications to PCA and K-means," *IEEE Transactions on Information Theory,* vol. 63, no. 5, pp. 2954-2974, 2017, doi: 10.1109/TIT.2017.2672725.

[12] S. R. Shebert, A. F. Martone, and R. M. Buehrer, "Wireless standard classification using convolutional neural networks," in *2021 IEEE Global Communications Conference (GLOBECOM)*, 2021, pp. 1-6, doi: 10.1109/GLOBECOM46510.2021.9685799.

[13] L. Wang, J. Hu, D. Jiang, C. Zhang, R. Jiang, and Z. Chen, "Deep Learning Models for Spectrum Prediction: A Review," *IEEE Sensors Journal,* 2024, doi: 10.1109/JSEN.2024.3416738.

[14] W. Lee, M. Kim, and D. H. Cho, "Deep cooperative sensing: Cooperative spectrum sensing based on convolutional neural networks," *IEEE Transactions on Vehicular Technology,* vol. 68, no. 3, pp. 3005-3009, 2019, doi: 10.1109/TVT.2019.2891291.

[15] L. Xu *et al.*, "Spectrum Prediction for Mobile Internet of Things Based on a DB-LSTM Algorithm," *IEEE Transactions on Vehicular Technology,* 2024, doi: 10.1109/TVT.2024.3401144.

[16] K. Davaslioglu and Y. E. Sagduyu, "Generative adversarial learning for spectrum sensing," in *2018 IEEE international conference on communications (ICC)*, 2018, pp. 1-6, doi: 10.1109/ICC.2018.8422223.

[17] R. Zhao, Y. Ruan, Y. Li, T. Li, and R. Zhang, "CCD-GAN for Domain Adaptation in Time-frequency Localization based Wideband Spectrum Sensing," *IEEE Communications Letters,* 2023, doi: 10.1109/LCOMM.2023.3298434.

[18] Y. Fu and Z. He, "Bayesian-inference-based sliding window trust model against probabilistic SSDF attack in cognitive

radio networks," *IEEE Systems Journal,* vol. 14, no. 2, pp. 1764-1775, 2019, doi: 10.1109/JSYST.2019.2936263.

[19] M. Nouri, M. G. Shayesteh, H. Behroozi, and Z. Ding, "Digital/Hybrid Beamforming via KLMS Algorithm in Presence of Mutual Coupling with Experimental Evaluation for 5G and V2V Communications," *IEEE Transactions on Vehicular Technology,* 2023, doi: 10.1109/TVT.2023.3330747.

[20] W. Hao and D. Y. Yeung, "Towards Bayesian deep learning: a framework and some existing methods," *IEEE Transactions on Knowledge and Data Engineering,* vol. 28, no. 12, pp. 3395-3408, 2016, doi: 10.1109/TKDE.2016.2606428.

[21] E. K. Fard, M. Nouri, H. Behroozi, and S. Sobhi-Givi, "Multi-Agent H-Learning Based Cooperative Spectrum Sensing for Cognitive Radio Networks," in *2024 32nd International Conference on Electrical Engineering (ICEE)*, 2024, pp. 1-5, doi: 10.1109/ICEE63041.2024.10668166.

[22] S. Sobhi-Givi, M. Nouri, M. G. Shayesteh, H. Behroozi, H. H. Kwon, and M. J. Piran, "Efficient Optimization in RIS-Assisted UAV System Using Deep Reinforcement Learning for mmWave-NOMA 6G Communications," *IEEE Internet of Things Journal,* 2025, doi: 10.1109/JIOT.2025.3553176.

[23] M. Rahimi, M. Nouri, S. Sobhi-Givi, H. Behroozi, M. J. Piran, and N. K. Mallat, "GAI-Driven Semantic CSI Quantization for Aerial BD-RIS-Assisted NOMA in Future Consumer Networks," *IEEE Transactions on Consumer Electronics,* 2026, doi: 10.1109/TCE.2026.3661397.

[24] M. Khan, D. Nielsen, V. Tangkaratt, W. Lin, Y. Gal, and A. Srivastava, "Fast and scalable bayesian deep learning by weight-perturbation in adam," in *International conference on machine learning*, 2018, pp. 2611-2620. [Online]. Available: https://proceedings.mlr.press/v80/khan18a.html.

[25] S. Sobhi-Givi, M. G. Shayesteh, and H. Kalbkhani, "Energy-efficient power allocation and user selection for mmWave-NOMA transmission in M2M communications underlaying cellular heterogeneous networks," *IEEE Transactions on Vehicular Technology,* vol. 69, no. 9, pp. 9866-9881, 2020, doi: 10.1109/TVT.2020.3003062.