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Original Article

Lightweight Multi-Antenna Machine Learning–based Spectrum Sensing for Edge-Centric Cognitive Radio Ad Hoc Networks

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Abstract *- Spectrum sensing in Cognitive Radio AdHoc Networks (CRAHNs) can be framed as a binary hypothesis issue under fading and noise uncertainty. This document introduces a lightweight spectrum sensing framework that utilizes multi-antenna technology and is supported by Logistic Regression, specifically designed for edge-centric secondary user devices. The proposed framework receives the Multi-Antenna Signals and models them under the Noise-Only and Signal-Plus-Noise Hypotheses. Further, to exploit spatial diversity while maintaining low dimensionality, compact covariance- and energy-based statistical features are extracted from every signal. Finally, a Light Weight Logistic Regression model is used for probabilistic classification, whose inference complexity scales linearly with the feature dimension. The proposed framework is evaluated under varying SNR conditions, antenna configurations, and Rayleigh & Rician fading channels. Simulation results show that, for a four-antenna configuration, the proposed approach achieved an average probability of detection of approximately 0.914 over the Signal-to-Noise Ratio (SNR) in the range of −20 dB to 0 dB, providing absolute improvements of 0.277 over SVM-based sensing and 0.322 over deep learning–based approaches, while significantly reducing computational overhead. These results demonstrate that multi-antenna statistical modelling combined with logistic regression offers an effective trade-off between sensing reliability and algorithmic simplicity.*

Keywords *- CRAHNs, Logistic Regression, Multi-Antenna systems, Spectrum sensing, Detection probability, Probability of false alarm.*

1. Introduction

Hasty development of wireless networks in the last 20 years has led to a huge need for a rich source of radio spectrum. With the rapid adoption of handheld devices (wearable sensors, tablets, smartphones and IoT nodes), wireless connectivity has become an integral part of everyday life. Autonomous systems, smart healthcare, smart transportation and mission-critical ad hoc communication are also increasing the demand for reliable and efficient spectrum access [1, 2]. The radio spectrum is finite and restricted resource that is often licensed to one company and almost always wants to make the procedure run in a static manner. Cognitive Radio (CR) is a new paradigm [3] to solve this problem, which allows the communication system to access the spectrum in real time. CR is a perceptive wireless network fit for sense its surrounding radio environment, learn from spectral patterns and adapt transmission parameters so as to opportunistically take advantage of unoccupied licensed spectrum band without interfering to its Primary Users (PUs). This idea has gained interest in recent years, especially in decentralized and infrastructure-less systems such as Cognitive Radio Ad Hoc Networks (CRAHNs) where autonomous nodes need to coordinate their vision and access the spectrum in dynamic environments.

Spectrum sensing is important in cognitive radio operation, as it indicates if there are any users of a given frequency band. Timely Spectrum Sensing with Better accuracy is needed for managing spectrum usage and good protection of licensed users. Several traditional spectrum sensing approaches [6, 7] have been developed in recent years (Cyclo-stationary Feature, Matched Filter and Energy Feature,

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etc.). Energy Detection (ED) remains effective because of its uncomplicated nature and lack of understanding [8, 9]. Although, it is poor in low SNR contexts and is much sensitive to the uncertainty of noise levels. Matched filter detection, while best suited for the typical signal situation, requires all primary user characteristics to be known, which is often impractical in real-world applications. Cyclo-stationary detection of signals is more robust and is computationally more intensive, allowing for longer sensing times, making it less suitable for ad hoc networks with limited resources [10].

Additionally, spectrum sensing is more difficult in CRAHNs because of mobility of nodes, multi-path fading and shadowing, as well as lack of centralized coordination. Single-node sensing decisions are not reliable (missed detection or false alarms) in the context of spectrum utilization, which led to immediate degradation of sensing accuracy and efficiency of utilization. Cooperative sensing approaches [11] proposal was made to overcome such difficulties, but they incur added burden (communications, energy consumption and decision fusion), so their performance can only be used in dense/rapidly changing networks. These issues highlight the need for additional vigorous and adaptive spectrum sensing mechanism can take advantage of different channel conditions to maximize spectrum utilization in CRAHNs. Thus, the practical challenge is not only improving the sensing accuracy but also the sensing must be processed within the processing and memory constraints of secondary-user nodes. Although statistical and learning-based spectrum sensing methods have been extensively investigated, a practical gap remains in balancing multi-antenna sensing reliability with computational simplicity at resource-constrained secondary-user nodes. Conventional low-complexity methods can lose reliability under low-SNR and fading conditions, whereas more sophisticated machine- and deep-learning approaches generally increase feature-processing, training, and inference requirements.

In light of these challenges, we propose a novel and lightweight spectrum sensing approach for improving sensing accuracy and utilization efficiency without adding a high computational or communication cost. The main aids to this paper are as follows.

- Lightweight Logistic Regression-based Spectrum Sensing Framework: We present a LR based low complex spectrum sensing mechanism based for Edge Oriented CRAHNs. The proposed classifier is fast inference and low memory requirements, with reliable detection in secondary user devices.
- Small and Compact Multi-Antenna Feature Extraction: We design low-dimensional covariance and energy-based statistical features to extract spatial diversity and signal presence properties of the signals in presence of fading and noise uncertainty. Our feature extraction approach avoids high-dimensional raw data processing and deep feature learning and is much more efficient.
- Multi-Antenna Diversity Exploitation: We design a multi-antenna SU receiver configuration for spatial diversity gain and study the Antenna's effect on detection performance. The detection probability and sensing error decrease with increasing number of antennas.

The remaining paper is systemized as follows. Section 2 Demonstrates about the literature survey on classical, multi-antenna and ML based spectrum sensing techniques in CRAHNs. Section 3 demonstrates the proposed method on LR based multi-antenna spectrum sensing method. Section 4 describes simulation setup, dataset generation process, performance metrics and results analysis for SNR levels, antenna configurations and fading channels. Section 5 provides conclusion and possible future directions.

2. Literature Survey

Spectrum sensing is essential in CRAHNs as it enables SUs to recognize licensed primary users and make use of unoccupied spectrum. Over the years, various spectrum sensing methods have been reported in existing studies. Spectrum sensing methods differ in terms of sensing accuracy, computational complexity, prior knowledge requirements and robustness to channel impairments (Shadowing, fading, and Noise Uncertainty). Broadly, the early methods are classified into logical (feature-based) methods vs non-logical (blind) methods depending on whether prior knowledge of the PU signal characteristics are considered or not.

2.1. Classical Methods

Logical spectrum sensing techniques make use of the known structures or statistical properties of PU indication to achieve higher detection accuracy. Matched Filtering (MF) [12, 13] is a detection technique when primary user signal is completely known; it has fastest sensing time and maximum detection probability but requires knowledge of modulation type, shape of pulse and frame structure of signal beforehand [14]. WS [15, 16] exploit patterns in primary user signal (e.g., pilot signals, preambles or synchronization sequences), which leads to improved detection accuracy than energy detection, especially at low SNR.

CSD is noise uncertainty tolerant and can distinguish between noise and modulated signals well, but its substantial computational requirements and prolonged sensing duration limit makes it difficult to deploy in resource-limited cognitive radio ad hoc networks [18, 19]. Furthermore, Likelihood Ratio Test (LRT) based sensing methods can be statistically most effective in terms of hypothesis testing but require precise modelling of signal and noise distributions, which is not typically possible in dynamic wireless environments [21].

In contrast, non-logical approaches are based on the received signal energy and do not utilize any information about the source signal of the user. Among them, Energy Detection (ED) [22-24] is effective as it is easy to implement,

low cost and independent of source signal. In ED, the spectrum occupancy is identified by comparison between the Received PU Signal's Energy and a threshold static. Even with ease of implementation, ED is severely affected by low SNR and noise uncertainty and unreliable in dynamic and ad hoc cognitive radio environments. To overcome some of the drawbacks of traditional communication and data processing methods for signal sensing, Eigenvalue-based Spectrum Sensing (ESS) [25] methods have been developed, which exploit the covariance based statistical properties of received signal. ESS methods are robust and also ensure better Accuracy even without knowledge on the signal power under uncertainty in noise and correlated signals. However, matrix operations increase computational overhead, which is not desirable for decentralized ad hoc networks with limited processing capabilities [26].

2.2. Multi-Antenna based Methods

Most existing spectrum sensing techniques target the single-antenna cognitive radio receiver, which limits the sensing reliability in practical wireless environments where multipath fading, shadowing and noise are common, especially under low SNR conditions [27]. These impairments lead to false alarms and missed detections, which negatively affect spectrum utilization efficiency. To address this, multiple-antenna spectrum sensing techniques [28] take advantage of spatial assortment, which offers independent observations for the primary user information. Mehrabian and Zaimbashi [29] studied spectrum sensing in "Single I/p and Multi O/p (SIMO)" CR system with I/Q imbalance between primary user transmitter and CR and formulated the problem as a composite hypothesis test. They derive eigenvalue-based Rao and Wald detectors from likelihood ratio test, which operate at CFAR and have better detection performance (Wald detector outperforms Rao test under most conditions). Despite improved robustness to transmitter I/Q imbalance, the method incurs high computational and hardware complexity due to multi-antenna covariance processing and assumes accurate impairment modelling, limiting its scalability in dynamic ad hoc cognitive radio networks. Some methods combined classical methods with multi-antenna configuration and tried to overcome the problem with classification methods alone [30, 31]. However, in recent years, Machine Learning based methods are quickly becoming popular due to their learning standards.

2.3. Machine Learning (ML) based Techniques

To solve the problems with classical sensing methods, especially under Fading, low SNR, and complicated signal environments, ML/DL techniques have recently emerged as alternate for accurate spectrum sensing in CRAHNs. Unlike traditional hypothesis-testing methods, ML-based approaches [32] treat spectrum detecting as a data-driven classification or prediction tricky, where statistical features of the received signal (e.g., energy measurements and spectral patterns) are used to train models that can generalize to detect primary user activity with more reliability and robustness. ML techniques include supervised learning, Deep Neural Networks, and hybrid models that can adapt to different channel conditions and diverse signal types.

Srinu et al. [33] used a Logistic Regression (LR) with extreme eigen values of the conventional signal covariance matrix as input features. This approach combines classical eigenvalue-based sensing with a machine learning classifier to enhance detection reliability without explicit noise variance estimation. Arkwazee et al. [34] proposed SVM for spectrum sensing in CRAHNs, in which a supervised classification problem is formulated, and the signal features from the received samples are used to train an SVM classifier for primary user activity detection. Additionally, Murti et al. [36] added Energy detection along with SVM for spectrum sensing in CRAHNs. Their method improves the conventional energy detection by training the SVM classifier to distinguish the existence and nonappearance of the main user built on energy-based features from the conventional signal. However, these approaches did not consider the covariance and energy related statistics as significant features, which creates ambiguity on the existence /nonappearance of main User.

Li et al. [37] proposed CEEMDAN and wavelet packet analysis for spectrum sensing in Multi-antenna Configured CRAHNs. In this framework, multi-antenna signals are decomposed into mode functions of signals using CEEMDAN to suppress noise effectively and capture the signal components in nonstationary channels; wavelet packet is decomposed to extract discriminative energy features for primary user detection. ML spectrum sensing method increases our detection performance but also require more training, have higher computational cost and have low generalization in dynamic environments.

Some authors recently used deep learning algorithms to enhance the spectrum sensing capabilities in CRNs. For example, Abdelbaset et al. [9] considered sensing as a classification problem and proposed a CNN model by diverse signal and noise data to enhance sensing precision and adaptability. Similarly, Shachi et al. [38] presented a CNN assisted cooperative spectrum sensing outline that leverages Spatio-temporal features from multiple CR users. Here, spectrum sensing is developed as a classification task using a structured dataset that captures both spatial correlations between cooperating nodes and temporal variations of the received signal. The CNN model learns discriminative features from the spatio-temporal sensing data and is more accurate than cooperative sensing in detecting the signals.

Vijay and Aparna [39] proposed a CNN-Transformer (CNN - Tn) based framework which combines spatial feature extraction with transformer attention to enhance spectrum sensing and utilization efficiency. Chae and Kim [40] also considered Muti-Antenna Configuration and applied a CNN

model for spectrum sensing. CNNs are used to process signals received from multiple antennas so they can jointly exploit spatial diversity and learned signal features in the process of detecting the target of interest. Since no handcrafted feature extraction is required, it outperforms traditional multi-antenna sensing techniques in low SNR settings. Kumar et al. [41] review spectrum sensing approaches based on CNNs and RNNs and show their effectiveness in capturing temporal and spectral patterns for better detection.

Zhang et al. [42] proposed MASSnet, a DL assisted method for multi-antenna configured CR-IoT networks. In their proposed model, signals from multiple antennas are jointly processed by a neural network to exploit spatial diversity and automatically detect discriminative features. Xi et al. [43] proposed cross-attention based DL model in environments where there is non-Gaussian noise and traditional sensing techniques are often not effective. This model uses attention mechanisms to focus on the relevant signal components but suppress noise-dependent features and improve sensing robustness for impulsive and heavy-tailed noise.

Table 1 provides a comparative analysis among proposed and traditional methods. In Summary, the Classical Sensing methods mainly rely on predefined statistical models and are often sensitive to noise uncertainty, fading, and variations in channel conditions, particularly at low SNR. Next, multi-antenna sensing advances reliability in detection through spatial diversity. Nevertheless, the associated RF chains, covariance processing, and eigenvalue computations increase implementation complexity. Further, machine and deep learning methods can provide improved adaptability under varying channel conditions; however, complex learning architectures generally demand greater computational resources and training effort. These limits encourage the advancement of a lightweight spectrum identifying framework that can maintain reliable detection while reducing the computational burden for deployment on resource-constrained cognitive radio nodes.

Table 1. Comparison with existing spectrum sensing approaches

Approach	Main information/features	Classifier / Decision	Computational characteristic	Limitation relative to present work
Srinu et al. [33]	Extreme covariance eigenvalues	LR	Low–moderate	Limited covariance representation
Arkwazee et al. [34]	Signal features	SVM	Moderate	SVM inference/implementation burden
Murti et al. [36]	Energy-based features	SVM	Moderate	Primarily energy-oriented sensing
MASSnet [42]	Learned multi-antenna representation	Deep network	High	Greater model/inference complexity
Proposed	Compact covariance + energy statistics	LR	Low	Designed for edge-oriented sensing

3. Proposed Method

This section provides complete details about the proposed method, which aims to achieve reliable and lightweight spectrum sensing in CRAHNs. The approach consists of two main subsections.

The first part provides a theoretical background for spectrum sensing in terms of hypothesis construction, energy detection for single-antenna receivers, and multi-antenna SU configurations. The second part outlines the spectrum sensing methodology proposed for CR nodes based on multi-antenna dataset generation, compact feature extraction, and logistic regression–based classification.

3.1. Spectrum Sensing Methodology

Spectrum sensing is core purpose of CRAHNs, as it provides important insights about the availability and occupancy of spectrum. By accurately identifying unused frequency bands, spectrum sensing enables efficient detection of spectrum holes, thereby supporting dynamic spectrum access and improved spectrum utilization. The detailed principles and methodologies of spectrum sensing are explained in the subsequent subsections.

3.1.1. SU with Single Antenna

During the sensing interval, the cognitive radio receiver collects a finite number of signal samples, denoted by N, to infer the existence of PU. According to the collected finite samples, spectrum sensing is done via formulating it as a binary classification task aimed at identifying the existence or absenteeism of PU; i.e., signal occupies a given frequency band. This decision process is commonly modelled using a hypothesis testing framework with two possible hypotheses [44];

$$S = \begin{cases} \mathcal{H}_0; Main\ user\ is\ absent \\ \mathcal{H}_1; Main\ user\ is\ present \end{cases} \quad (1)$$

Under $\mathcal{H}_0$ where PU does not transmit, the received signal consists solely of noise and can be denoted as [45];

$$y(n) = w(n); \qquad n = 0, \dots, N-1 \quad (2)$$

Where $w(n)$ is complex AWGN (mean = 0 and variance = σ_w^2). Here, the signal samples are assumed as statistically independent and identically distributed. Under $\mathcal{H}_1$, the signal

received at SU includes both PU's signal and noise so that it can be expressed as [46].

$$y(n) = h\,x(n) + w(n); \qquad n = 0, \dots, N-1 \quad (3)$$

Here $x(n)$ denotes signal transmitted by PU, h is channel coefficient amid the PU sender and SU receiver. $x(n)$ is independent of the noise process and, in absence of PU transmission, it is 0.

3.1.2. SU with Multiple Antennas

In this case, spectrum sensing is considered as a binary hypothesis problem exploiting spatial diversity to increase detection reliability.

Assume that the SU receiver has M antennas and collects N signal samples at respective antenna in sensing interval. Under $\mathcal{H}_0$, the signal acknowledged at SU is represented as [27];

$$y_m(n) = w_m(n); \qquad m = 1, \dots, M \;\&\; n = 0, \dots, N-1 \quad (4)$$

Where $w_i(n)$ is AWGN received signal at m[th] antenna with mean = 0 and variance = σ_w^2. The AWGN assumed at SU is independent so that spatial diversity can be exploited for spectrum sensing. Otherwise, when PU is active, signal received at SU with multiple antennas is;

$$y_m(n) = h_m\,x(n) + w_m(n); \qquad m = 1, \dots, M \;\&\; n = 0, \dots, N-1 \quad (5)$$

Where h_m is the channel coefficient amid the mth antenna of the SU receiver and PU transmitter and $w_m(n)$ is the corresponding AWGN component.

3.1.3. Energy Detection

For SU with single antenna, received signal samples $y(n)$ collected over sensing interval N are used to derive test statistic. The output of the ED is then expressed as;

$$T_{SA} = \frac{1}{N}\sum_{i=0}^{N-1} |y(n)^2| \quad (6)$$

The decision derived based on the comparison between test static and a threshold γ.

$$T_{SA} = \begin{cases} < \gamma; \mathcal{H}_0; Main\ user\ is\ absent \\ \geq \gamma; \mathcal{H}_1; Main\ user\ is\ present \end{cases} \quad (7)$$

The threshold γ is usually chosen based on a desired false alarm probability. For SU with multiple antennas, let the receiver have M antennas collecting N samples during sensing time.

The signal received at SU's m^{th} antenna is represented as $y_m(n)$. The energy measured at each branch of antenna is first calculated as [47];

$$T_{MA,m} = \frac{1}{N}\sum_{i=0}^{N-1} |y_m(n)^2|\,; m = 1, \dots, M \quad (8)$$

The individual energy measurements are then combined to form a global test statistic. A commonly used approach is equal gain combining, given by $T_{MA} = \frac{1}{M}\sum_{m=1}^{M} T_{MA,m}$.

The last sensing result is completed by comparison T_{MA} with predefined threshold γ; as follows;

$$T_{MA} = \begin{cases} < \gamma_{MA}; \mathcal{H}_0;\ Main\ user\ is\ absent \\ \geq \gamma_{MA}; \mathcal{H}_1; Main\ user\ is\ present \end{cases} \quad (9)$$

The threshold γ_{MA} is obtained through the converse expression of function Q for a fixed probability of false alarm P_{FA} value, formulated as [47]

$$\gamma_{MA} = \sigma_w^2 + \frac{\sigma_w^2}{\sqrt{MN}}\,Q^{-1}(P_{FA}) \quad (10)$$

Where P_{FA} denotes the probability of declaring the sensing period as employed by PU when, in genuinity, the PU is not present, computed as

$$P_{FA} = \Pr\left(T_{MA} > (\gamma_{MA}|\mathcal{H}_0)\right) = Q\left(\frac{\gamma_{MA} - \mu_0}{\sigma_0}\right) \quad (11)$$

Where $\mu_0 = \sigma_w^2$ and $\sigma_0^2 = {\sigma_w^4}/{MN}$. Inversely, P_{CD} is denoted as the probability of right detection. The Q(.) is the complementary of Gaussian Distributed Function [45]. Mathematically it is given as

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} exp\left(\frac{-u^2}{2}\right) du \quad (12)$$

The P_{FA} and P_{CD} are the performance evaluation parameters for spectrum sensing, and P_{CD} is calculated for a multiple-antenna configuration as follows [48];

$$P_{CD} = \Pr\left(T_{MA} > (\gamma_{MA}|\mathcal{H}_1)\right) \quad (13)$$

3.2. Proposed Model

The proposed spectrum sensing model is designed for cognitive radio ad hoc networks where SUs operates as edge devices. To improve sensing reliability under fading and noise while retaining low computational complexity, the SU receiver is configured with multiple antennas and spectrum sensing is expressed as a lightweight machine knowledge–based classification task.

The proposed model consists of two major stages: (1) multi-antenna dataset generation, and (2) logistic regression–based classification using compact statistical features. Figure 1 demonstrates the proposed Spectrum sensing model for CRAHNs.

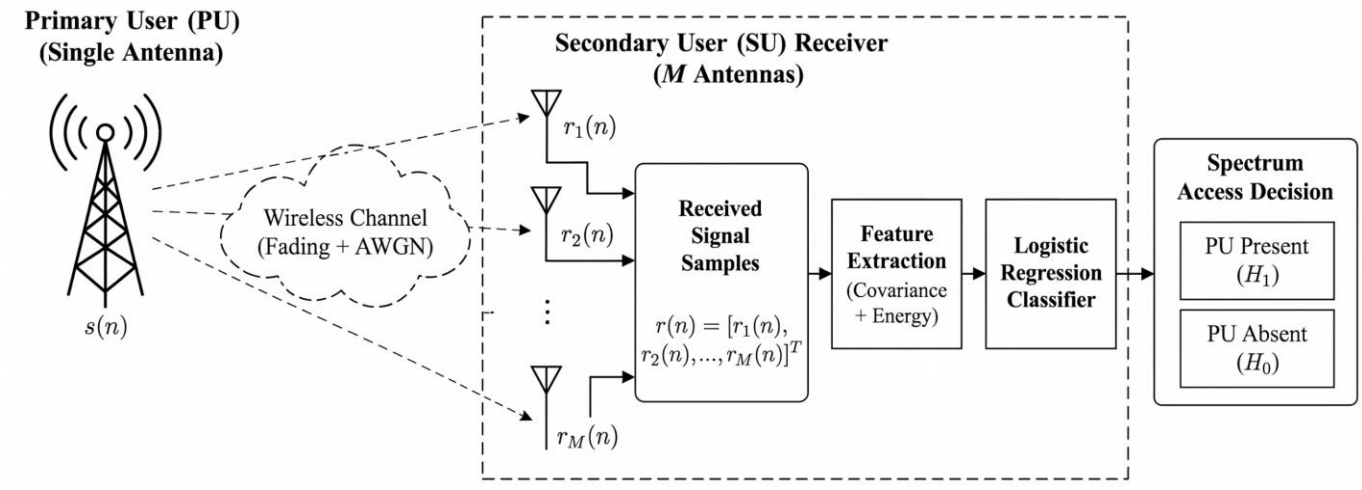

Fig. 1 Block diagram of proposed spectrum sensing model

3.2.1. Multi-Antenna Dataset Generation

Consider an SU receiver fortified with M antennas, collecting N complex base band samples per antenna during each sensing interval. The sensing issue is modelled using the binary hypotheses:

$$\begin{cases} \mathcal{H}_0 : y_m(n) = w_m(n) \\ \mathcal{H}_1 : y_m(n) = h_m x(n)\, w_m(n) \end{cases} \quad m = 1,2,\ldots,M,\ n = 0,1,\ldots,N-1 \qquad (14)$$

Here $x(n)$ denotes the PU signal sample, h_m represents channel coefficient between PU transmitter and m^{th} antenna of SU, and $w_m(n)$ is complex AWGN. The unwanted signal processes are assumed to be independent across antennas with $w_m(n) \sim \mathcal{CN}(0, \sigma_w^2)$. For each sensing interval, the received samples across all antennas are arranged into an observation matrix:

$$\mathrm{X} = \begin{bmatrix} y_1(0) & y_1(1) & \cdots & y_1(N-1) \\ y_2(0) & y_2(1) & \cdots & y_2(N-1) \\ \vdots & \vdots & \ddots & \vdots \\ y_M(0) & y_M(1) & \ldots & y_M(N-1) \end{bmatrix} \in \mathbb{C}^{MxN} \qquad (15)$$

A labelled dataset is constructed by generating multiple sensing instances under both hypotheses: as Class 0 (H0): noise-only observations and Class 1 (H1): PU's Signal + noise observations. To ensure robustness, dataset generation is performed over a range of operating conditions by changing SNR levels (e.g., from −20 dB to 0 dB), channel realizations (Rayleigh / Rician fading), sensing interval length N and number of antennas M. This produces a dataset as $D = \{(\mathrm{X}_i, l_i)\}_{i=1}^{K}$, where $l_i \in \{0,1\}$ is the label indicating PU absence or presence. Working model of dataset generation is shown in Figure 2.

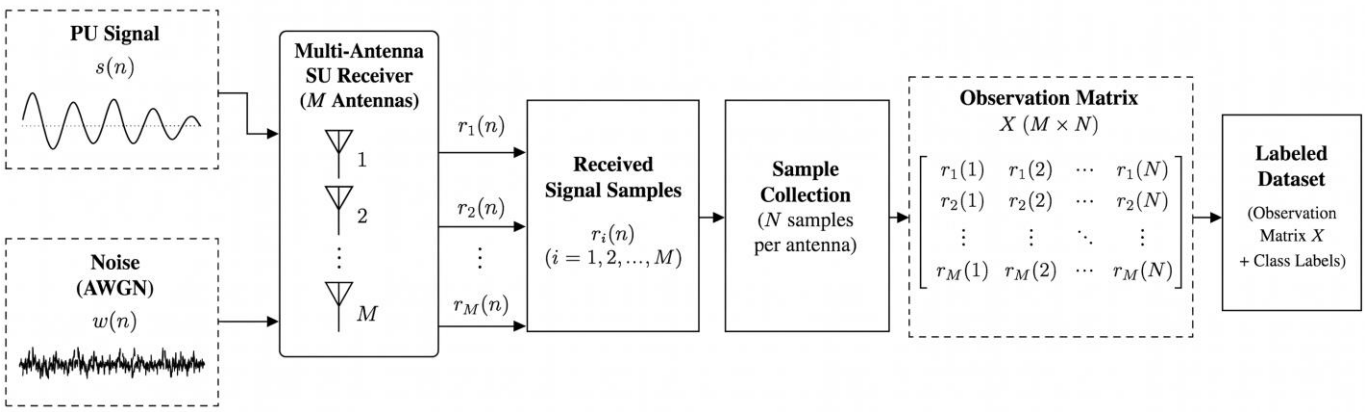

Fig. 2 The working model of dataset generation at SU with multi-antenna configuration

3.2.2. Compact Feature Extraction

Since raw samples are high-dimensional and costly to process on edge devices, each observation matrix X is mapped to a compact real-valued feature vector f. The key objective of feature design is to retain strong discriminative power while maintaining low computational cost.

(a) Covariance Matrix Features: The covariance matrix sample is computed as follows.

$$R = \frac{1}{N}\mathrm{X}\mathrm{X}^{H} \in \mathbb{C}^{MxM} \quad (16)$$

Let the eigenvalues of R be $\lambda_1 \geq \lambda_2 \geq \lambda_3 \ldots \geq \lambda_M$. From R, five lightweight features are extracted, namely the highest Value ($\lambda_{max} = \lambda_1$), Lowest Eigen Value ($\lambda_{min} = \lambda_M$), Eigen Value Ratio ($\rho = \frac{\lambda_{max}}{\lambda_{min}}$), Trace ($\tau = tr(R) = \sum_{i=1}^{M} \lambda_i$) and Off-Diagonal energy ratio ($\eta = \sum_{i \neq j} |R_{ij}|^2 / \sum_i |R_{ii}|^2$). These features capture spatial correlation changes caused by PU activity and are effective under fading and noise uncertainty.

(b) Energy Statistical Features: Additionally, low-cost energy features are computed as follows;

$$E = \frac{1}{MN}\sum_{m=0}^{M}\sum_{n=0}^{N-1}|y_m(n)|^2,\ \log(E), Var(E) \quad (17)$$

Finally, the extracted values are concatenated to form:

$$f = [\lambda_{max}, \lambda_{min}, \rho, \mathrm{Tr}(\mathbf{R}), \eta, \mathrm{Mean}(E), \mathrm{Max}(E), \mathrm{Var}(E)\ ]^T \quad (18)$$

resulting in a low-dimensional feature vector (typically 8–20 features).

3.2.3. Logistic Regression–based Spectrum Sensing Classification

In proposed framework, spectrum sensing is expressed as a binary classification task and addressed using LR, which is well suited for edge-based cognitive radio ad hoc networks due to its low computational complexity and fast inference capability. Logistic regression established the relationship between the obtained feature vector and the probability of the presence of PU, enabling reliable decision-making without requiring deep architectures or extensive training resources. By operating on compact covariance- and energy-based features, the classifier attains an effectual balance between sensing accuracy and computational efficiency. Spectrum sensing is achieved by modelling the decision as a binary classification problem as per Equation (1). Logistic regression is adopted owed to its lightweight structure and appropriateness for real time edge deployment. Given a feature vector f, logistic regression estimates the posterior probability of PU presence as:

$$P(y = 1|\mathrm{f}) = \sigma(\mathrm{w}^T\mathrm{f} + b) = \frac{1}{1+e^{-(\mathrm{w}^T\mathrm{f}+b)}} \quad (19)$$

Where b denotes bias term, and w is the weight vector. The sensing decision is obtained using a probability threshold δ:

$$\hat{S} = \begin{cases} 1, & P(y = 1|\mathrm{f}) \geq \delta \\ 0, & P(y = 1|\mathrm{f}) < \delta \end{cases} \quad (20)$$

Typically, $\delta = 0.5$ is used, though δ can be tuned to regulate the false alarm probability.

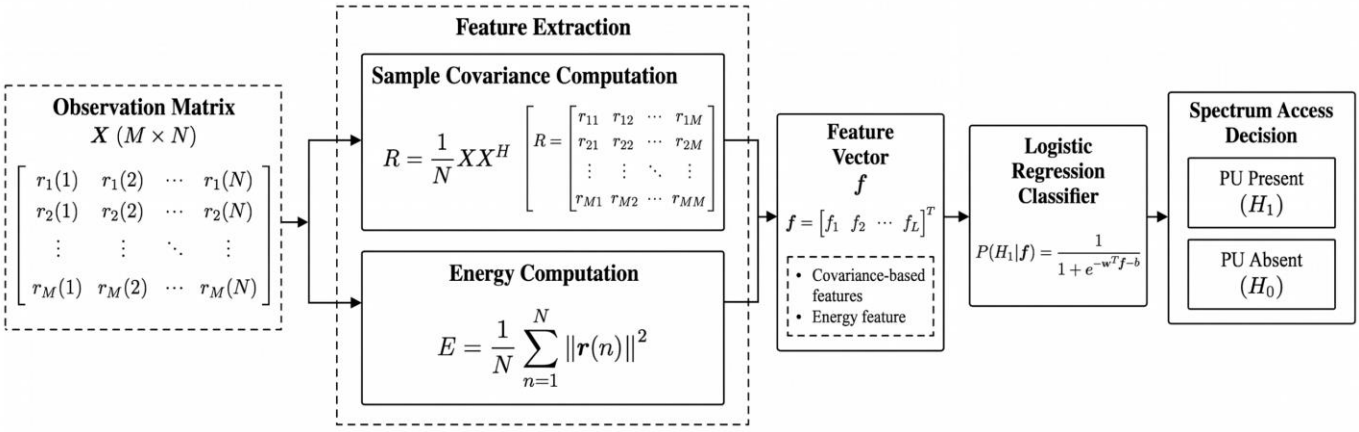

Fig. 3 Working model of LR based spectrum sensing classification

The dataset is divided into subsets for testing, validation, and training (e.g., 70%–15%–15%). Logistic regression parameters $\{\mathrm{w}, b\}$ are obtained based on the minimization of regularized cross-entropy loss, as shown;

$$\mathcal{L}(\mathrm{w}, b) = -\frac{1}{K}\sum_{i=1}^{K}[y_i log\ (\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)] + \lambda_r \|\mathrm{w}\|_2^2 \quad (21)$$

Where $\hat{y}_i = P(y = 1|\mathrm{f}_i)$ and λ_r is the regularization coefficient to reduce overfitting and improve generalization.

The proposed spectrum sensing framework is computationally simple and suitable for deployment on edge-based cognitive radio ad hoc network nodes. Feature extraction involves covariance matrix computation and basic eigenvalue operations over a small number of antennas,

resulting in moderate pre-processing complexity. The logistic regression classifier requires only a linear combination of the feature vector followed by a sigmoid function, leading to low inference complexity and minimal memory requirements. Unlike DL–based approaches, the proposed method does not require complex architectures, iterative feature learning, or GPU acceleration, thereby enabling fast decision-making and energy-efficient operation. These properties make the proposed approach appropriate for real-time spectrum sensing in resource-constrained edge devices. The computational complexity of the proposed system is $\mathcal{O}(MN^2 + M^3 + d)$ where M tells no of antennas, N is the number of samples per sensing interval, and *d* is the size of feature set. The main cost is for covariance computation and eigenvalue extraction, while logistic regression inference is linear in *d*.

4. Experimental Analysis

4.1. Simulation Setup & Dataset Generation

The proposed method is tested through simulations that simulate a practical CRAHNs scenario: the PU signal is generated with standard digital modulation schemes and passed over fading wireless channels in Additive White Gaussian Noise (AWGN) background. SU with multi-antenna configured receiver is considered to exploit spatial diversity; number of antennas varies in order to check sensing performance. Dataset is generated offline for different SNR levels and channel realizations so robustness is guaranteed and simulations are done on a standard desktop computer without GPU acceleration, so approach is very lightweight and edge-friendly (Table 2).

Table 2. Simulation setup

Parameter	Specification
Type of Modulation	BPSK, QPSK
Channel Models	Rayleigh fading, Rician fading, AWGN
Number of SU Antennas (M)	2, 3, 4
SNR Range	–20 dB to 0 dB
Samples per Sensing Interval	Fixed (N samples per antenna)
Dataset Size	Balanced dataset with PU present and absent classes
Learning Model	Logistic Regression
Feature Type	Covariance-based and energy-based statistical features
Simulation Platform	Python
CPU	Intel Core i7
CPU Speed	3.0–3.5 GHz
RAM	16 GB
Storage	512 GB SSD
Operating System	64-bit Windows / Linux

The dataset used to test the proposed framework is generated through a wide-ranging simulation under several realistic environments of CRAHNs. We consider a multi-antenna SU receiver with $M \in \{2,3,4\}$ antennas and sample complex baseband signals during each sensing interval. For every sensing interval, the samples are generated in two different ways: PU absent $\mathcal{H}_0$ and PU present $\mathcal{H}_1$. The no. of samples is set to N =1024, for sensing accuracy and computational efficiency.

The S/N ratio is changed from -20dB to 0dB in 2dB steps. We generate a balanced dataset of around 5000 sensing instances where the presence and absence of users is equally represented. We divided it into subsets for testing, validation, and training (70:15:15). Figure 4 illustrates the distribution of normalized received energy measured at the first and second antennas of the secondary user receiver.

Two distinct clusters can be observed, corresponding to the primary user absent $\mathcal{H}_0$ and present $\mathcal{H}_1$ conditions. The clear separation between the clusters highlights the discriminative nature of multi-antenna energy features and justifies their suitability for lightweight machine learning–based spectrum sensing using logistic regression.

For performance comparison, SVM [34] and MASSnet [42] were considered as ML and DL baselines, respectively, and were evaluated using the same generated sensing dataset, SNR conditions, and antenna configurations as the proposed method. The SVM classifier was implemented using an RBF kernel, with the regularization and kernel parameters selected during validation. For MASSnet-B, the network was trained using SGDM with 45 epochs maximum, 64 sized mini-batch.

Moreover, starting learning rate of 0.01, then reduced by a factor of 0.2 after every seven epochs, and cross-entropy loss was used for binary classification. Both trained models were evaluated on the same test samples at each SNR level, and their predictions were used to estimate the detection probability for comparison with the proposed approach.

4.2. Performance Metrics

To broadly estimate the performance of the proposed approach, standard machine learning classification metrics are employed, namely recall**,** precision**,** F-score, and accuracy. These metrics are particularly suitable for data-driven spectrum sensing models and can be directly mapped to conventional cognitive radio performance indicators such as detection probability (P_d) and False Alarm Probability (P_f).

Spectrum sensing is formulated as a binary classification task, as illustrated by the confusion matrix in Table 3, where True Positive (TP) denotes PU is present and correctly detected, False Negative (FN) denotes PU is present but missed, False Positive (FP) denotes PU is absent but falsely detected as present and True Negative (TN) denotes PU is absent and correctly identified.

Table 3. Confusion matrix

		Predicted Class	
		Class 1 ($\mathcal{H}_1$)	**Class 0 ($\mathcal{H}_0$)**
Actual Class	**Class 1 ($\mathcal{H}_1$)**	True Positive (T_p)	False Negative (F_n)
	Class 0 ($\mathcal{H}_0$)	False Positive (F_p)	True Negative (T_n)

In spectrum sensing, the P_d is a key metric that measures the capability of the system to properly recognize the existence of a main user. The classification model in machine learning methods estimates the target class label from the dataset. In our case, let us consider S as original class and $\hat{S}$ as predicted class, the P_d is measured as $P_d = \Pr(\hat{S} = 1 | S = 1)$. This measures that the PU is existing in the target spectrum when the PU really exists in the spectrum.

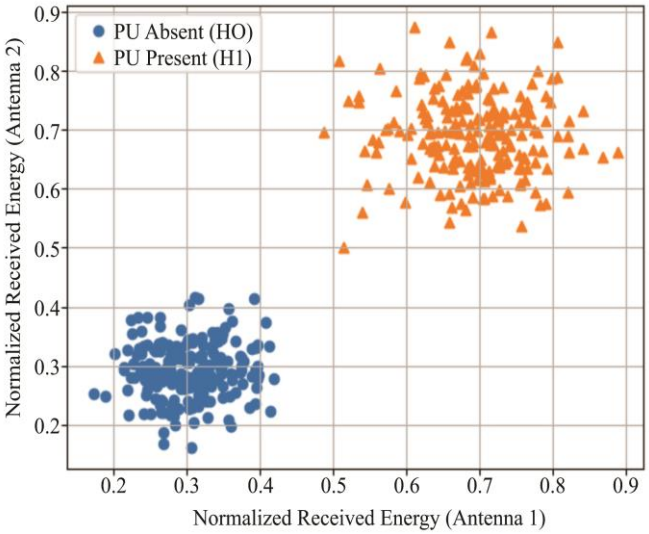

Fig. 4 Scatter plot of normalized received energy at the first antenna versus normalized received energy at the second antenna for PU absent (Class 0: $\mathcal{H}_0$) and PU present (Class 1: $\mathcal{H}_1$) cases

In Contrast, the P_f is one more metric which predicts the PU is present, but it is false. For the given actual and predicted classes, the P_f is measured as $P_f = \Pr(\hat{S} = 1 | S = 0)$. The P_d is equal to recall in machine learning, expressed as

$$P_d = Recall = \frac{T_p}{T_p + F_n} \quad (22)$$

A high recall (or P_d) indicates that the proposed sensing method effectively minimizes missed detections, which is critical for protecting PUs from harmful interference. Next, the precision measures the reliability of positive detections and is defined as

$$Precision = \frac{T_p}{T_p + F_p} \quad (23)$$

Next, the F-score provides a balanced measure that jointly considers detection reliability and false alarms, expressed as

$$F - Score = \frac{2.Recall.Precision}{Recall + Precision} \quad (24)$$

F-score reflects a stable trade-off between Low P_f and high P_d, gives a single and useful metric to measure the total performance of proposed mechanism.
Next, the P_f signifies the misclassifications, expressed as

$$P_f = \frac{F_p}{F_p + T_n} \quad (25)$$

Identically, Precision and P_f are inversely related, lower P_f implies higher Precision.

The probability of misdetection **(P_m)** is another important performance metric and is measured as the probability of failing of sensing algorithm to identify the PU's presence when the PU is actually active. It is known as the complement of the P_d.

$$P_m = 1 - P_d = \frac{F_n}{T_p + F_n} \quad (26)$$

A high P_m means that the SU may mistakenly assume the spectrum to be empty and start to transmit, which could have a negative impact on licensed PUs. Therefore, minimizing P_m is crucial for confirming the protection of PUs and the compliance of CRAHNs with regulations.

Sensing Error **(S_e)** is a composite performance metric that measures the effect of both false alarms and misdetections in spectrum sensing. It is defined as the average of P_f and P_m, which is

$$S_e = {P_f + P_m}/{2} \quad (27)$$

S_e gives an overall measure of sensing reliability by balancing the two main types of sensing errors.

4.3. Results & Comparison

Figure 5 shows the confusion matrix derived from the classification results after the simulation of proposed approach at SNR = -13 dB and M = 3 antennas.

Actual \ Predicted	**Class 1 (PU Present)**	**Class 0 (PU Absent)**	**Total**
Class 1 (PU Present)	TP = 1846	FN = 154	3000
Class 0 (PU Absent)	FP = 240	TN = 2760	2000
Total	2086	2914	5000

Fig. 5 Confusion matrix with M = 3 and SNR = -13dB

It can be seen that our model correctly detects 1846 out of 2000 samples with primary user present and has a recall (probability of detection) of 92.30%. Only 154 are missed, which is very robust at a low SNR.

In case of no primary user present, 2760 out of 3000 samples are correctly detected, and only a few false alarms will occur. The results show that we can find a good balance between high detection and reliable false alarms, and thus good spectrum sensing and better spectrum utilization.

Table 4. Performance metrics of proposed approach with M = {2, 3, 4} antennas at different SNR levels

SNR (dB)	Antennas (M)	P_d	P_m	P_f	S_e
−20	2	0.575	0.425	0.395	0.410
	3	0.602	0.398	0.362	0.380
	4	0.628	0.372	0.331	0.352
−18	2	0.655	0.345	0.312	0.329
	3	0.684	0.316	0.284	0.300
	4	0.712	0.288	0.256	0.272
−16	2	0.732	0.268	0.246	0.257
	3	0.781	0.219	0.210	0.215
	4	0.818	0.182	0.184	0.183
−14	2	0.825	0.175	0.148	0.162
	3	0.882	0.118	0.112	0.115
	4	0.915	0.085	0.082	0.084
−12	2	0.928	0.072	0.065	0.069
	3	0.963	0.037	0.041	0.039
	4	0.982	0.018	0.021	0.020

Table 4 reflects the proposed method's performance through P_d,P_m,P_f, and S_e at several SNR and antenna configurations. At every SNR level, the performance is averaged through antenna configurations M = {2,3,4} to evaluate the overall sensing behaviour. At SNR = -20 dB, the average P_d is low because of the high noise, but the proposed method still provides a meaningful detection with a moderate sensing error and is very robust for low SNR. At -18 dB and -16 dB, the average P_d can be improved significantly, and the average P_m,P_f, and S_e are diminished, indicating it has more reliability. The results are also improved for -14 dB, where the probability of detection is at a high reliability level, and the misdetection probability and false alarm are very low. At -12 dB, our method achieves excellent sensing performance with very high average P_d and low P_m,P_f, and S_e. Our averaged results for different antennas demonstrate that our proposed method always improves detection accuracy and decreases sensing error as SNR increases, proving it is reliable in detecting spectrum in cognitive radio ad hoc networks.

Figure 6 shows the ROC performance of proposed framework for different antenna configurations. The curves show the trade-off between P_f and P_d by diverse no of antennas from M = 2 to M = 4. As expected, increasing the antenna count significantly enhances the detection performance for the entire false alarm range. The AUC values of 0.9656, 0.9789, and 0.9989 for M = 2, M = 3, and M = 4, respectively, show that spatial diversity is useful for the sensing reliability of our proposed method. The near-unity AUC for M = 4 shows good classification ability, which indicates the robustness of our proposed method for low SNR.

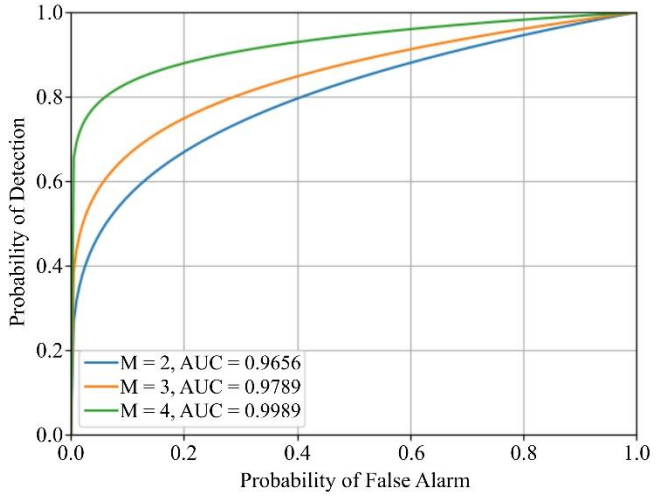

Fig. 6 ROC curve for the proposed approach at different antenna configurations

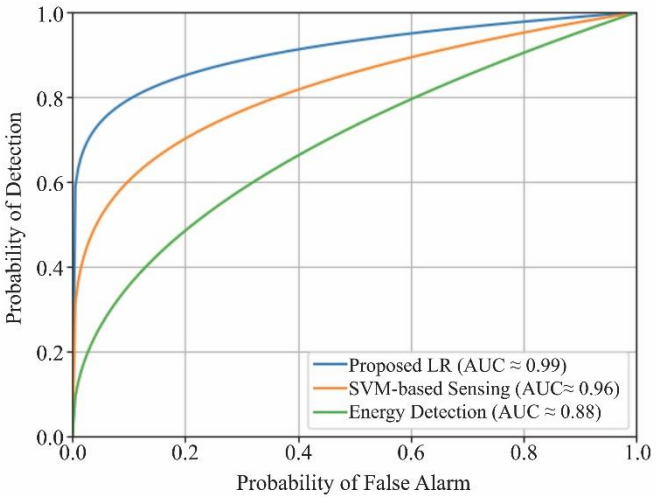

Fig. 7 Comparison of ROC curves for the proposed logistic regression–based spectrum sensing method with SVM-based sensing and conventional energy detection

Figure 7 demonstrates the ROC performance of proposed method versus SVM-based sensing [34] and conventional energy detection [26]. We have shown that our proposed method outperforms both benchmark methods for all false alarm probability ranges. The improved AUC achieved by our LR-based method indicates that our approach exhibits better detection performance with low false alarm rates. In contrast, the SVM-based approach shows that it is a poor detection

platform, as it cannot detect the energy signal owed to uncertainty in the noise and fading effects in spectrum sensing. Our results show that our lightweight machine learning framework is bright to enhance the spectrum reliability sensing and maintain low computational complexity in edge-based cognitive radio ad hoc networks.

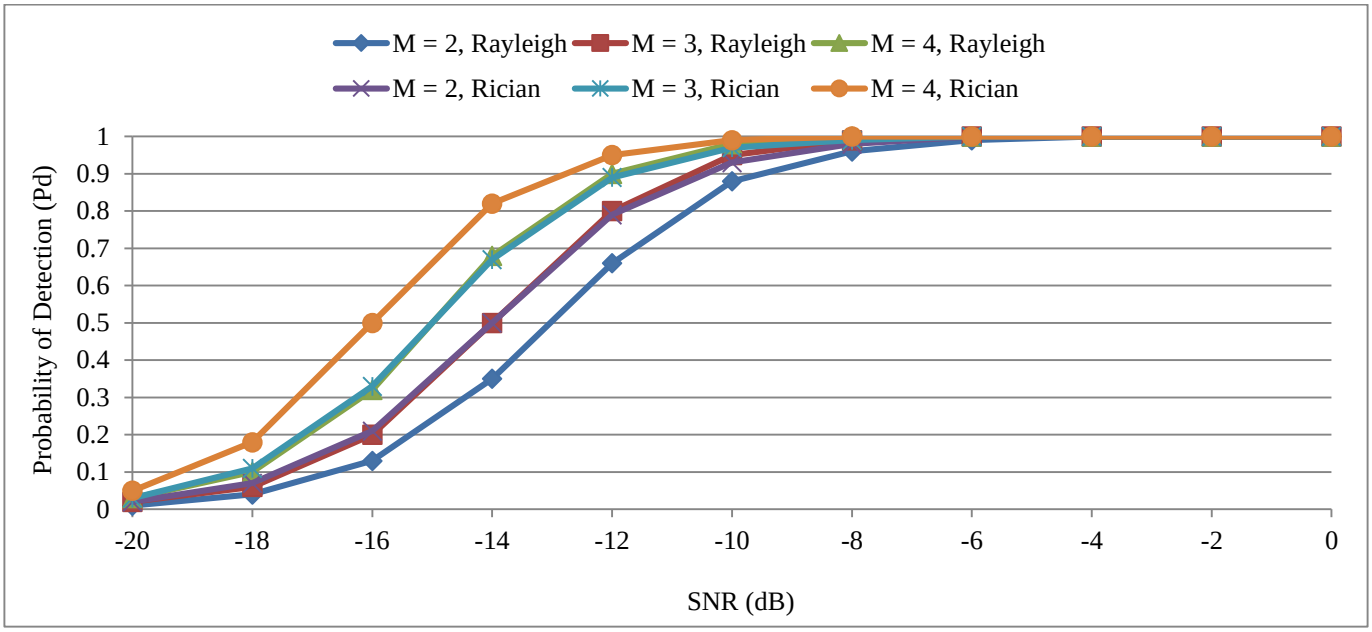

Fig. 8 P_d versus SNR for the proposed approach under Rayleigh and Rician fading channels with different antenna configurations

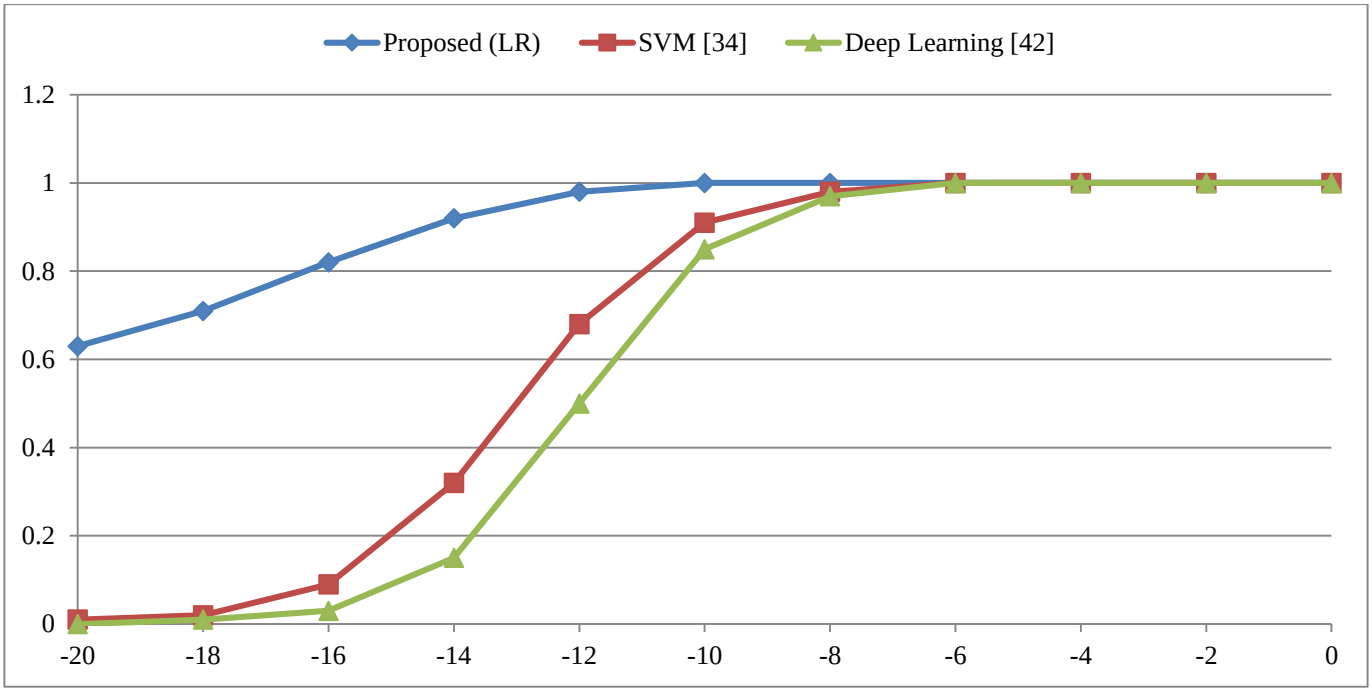

Fig. 9 P_d versus SNR comparisons for the proposed and existing approaches at M=4

Figure 8 shows how the fading channels and antenna diversity are affecting our spectrum sensing method's detection performance. The P_d increases significantly as the no.of antennas increases from M = 2 to M = 4 together Rayleigh and Rician fading, which demonstrates the advantage of spatial diversity. Moreover, Rician fading consistently achieves higher detection probability than Rayleigh fading across the SNR range owed to the existence of a leading line-of-sight factor. These results confirm that combining multi-antenna reception with the proposed lightweight learning framework enhances sensing robustness, particularly in low-SNR environments.

As per Figure 9, the proposed system gains a maximum detection probability across the entire SNR range compared to the SVM [34] and deep learning [42] approaches at M=4. On average, the proposed LR-based method achieved an average P_d of 0.914, compared with 0.637 for SVM and 0.592 for the deep-learning method, corresponding to absolute improvements of 0.277 and 0.322, respectively, demonstrating that the proposed lightweight LR-based model provides superior sensing performance, particularly in the low-SNR rule, while avoiding the computational complexity of deep learning approaches.

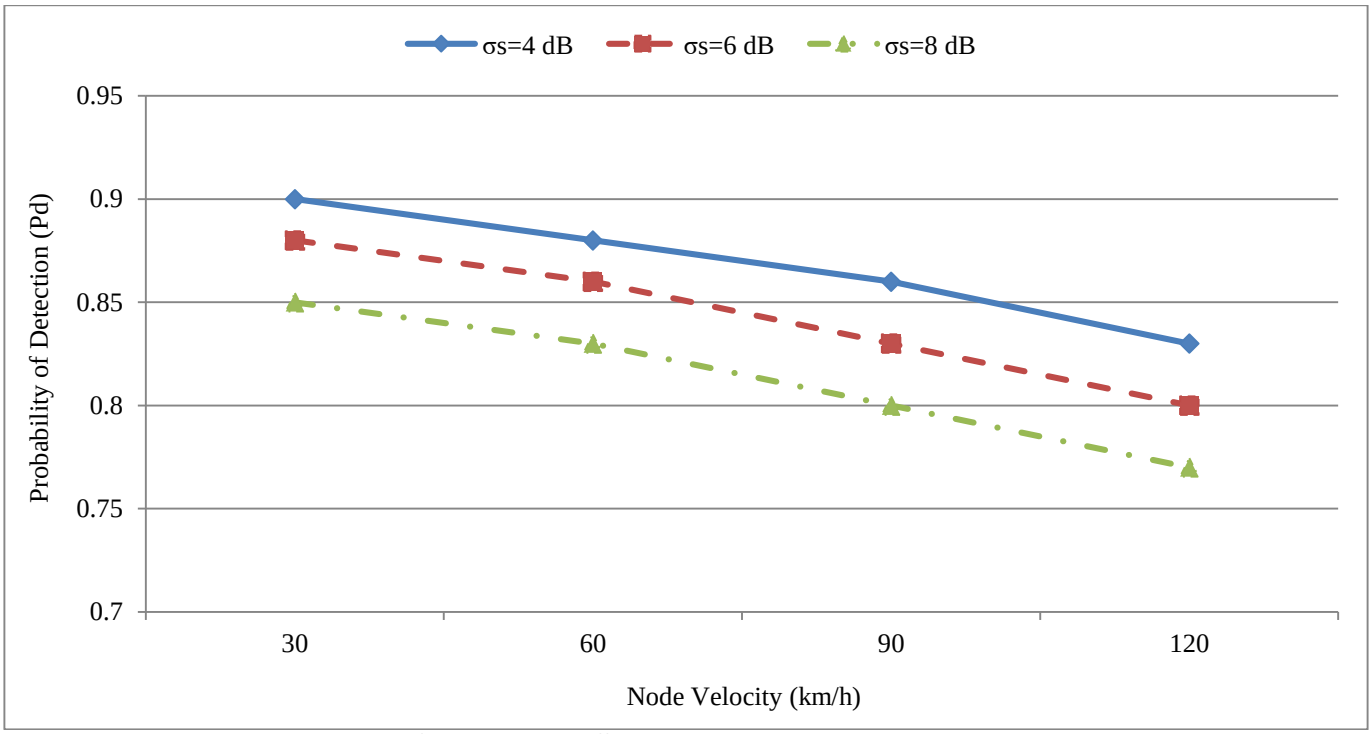

Fig. 10 Probability of detection under different node velocities and log-normal shadowing conditions

Figure 10 illustrates the P_d under different node velocities and log-normal shadowing conditions. The P_d gradually decreases with increasing node velocity and shadowing deviation due to stronger channel variations. For instance, at ($\sigma_s = 4$) dB, P_d decreases from 0.90 at 30 km/h to 0.83 at 120 km/h, whereas under stronger shadowing ($\sigma_s = 8$) dB), it decreases from 0.85 to 0.77. The outcome shows that the proposed multi-antenna sensing framework maintains reasonable detection performance even under increased mobility and shadowing, demonstrating its robustness for dynamic CRAHN environments.

Table 5. Feature importance and ablation analysis

Feature Configuration	P_d	P_m	P_f	S_e
All features	0.914	0.086	0.081	0.084
Without (λ_{max})	0.887	0.113	0.104	0.109
Without eigenvalue ratio (ρ)	0.879	0.121	0.112	0.117
Without off-diagonal ratio (η)	0.893	0.107	0.098	0.103
Without energy features (E)	0.861	0.139	0.127	0.133

Table 5 shows an ablation analysis conducted on proposed approach to inspect the involvement of the major statistical topographies in the sensing performance. With the complete feature set, the average P_d is observed as 0.914, while P_m, P_f and S_e are observed as 0.086, 0.081 and 0.084, respectively. Removal of λ_{max}, ρ, η, reduces P_d to 0.887, 0.879, and 0.893, respectively, accompanied by corresponding increases in missed detection, false alarm, and sensing error. The largest degradation is observed when the energy-related features are removed, where P_d decreases to 0.861 and the sensing error increases to 0.133. These observations indicate that the covariance- and energy-derived features provide complementary information for PU detection, with the energy statistics and eigenvalue ratio having comparatively stronger contributions to sensing performance.

4.3.1. Computational Resource Analysis

The computational requirements of the proposed LR model were assessed against the SVM and MASSnet-B baselines using the same simulation platform fortified with an Intel Core i7 processor functioning at approximately 3.0–3.5 GHz and 16 GB RAM, with the models implemented in Python. The comparison considered model memory footprint

and average inference latency for a single sensing instance. Owing to the compact eight-dimensional feature representation and simple linear decision operation, the proposed LR model requires approximately 2 KB of model memory with an inference latency of about 0.02 ms. In comparison, the SVM requires approximately 150 KB and 0.20 ms, whereas MASSnet-B requires approximately 2500 KB and 2.50 ms, reflecting the higher computational requirements associated with its convolutional and residual processing stages. The substantially lower memory requirement and inference latency of the LR model demonstrate its lightweight computational characteristics and indicate its potential suitability for resource-constrained edge-based spectrum sensing.

4.3.2. Regulatory Compliance and PU Protection

Reliable detection of PU activity is essential in CRAHNs because an incorrect spectrum-access decision may cause harmful interference to licensed users. Therefore, practical spectrum-sensing mechanisms must maintain a high detection probability while restricting secondary-user transmission whenever PU activity is identified. In this context, regulatory and cognitive-radio frameworks such as FCC requirements and IEEE 802.22 emphasize reliable incumbent-user protection and timely spectrum evacuation.

The proposed method achieves probability of detection values exceeding 0.9 under the higher evaluated SNR conditions, demonstrating its potential to support reliable PU protection. Nevertheless, compliance with specific interference-time and spectrum-evacuation requirements depends on the operating frequency band, sensing interval, and target deployment scenario; therefore, these parameters should be configured according to the applicable regional regulatory requirements during practical deployment.

5. Conclusion

A lightweight machine learning–based spectrum sensing framework **is** proposed here for CRAHNs, specifically designed for edge-based SU devices**.** By using a multi-antenna receiver and small statistical feature extraction, spectrum sensing was settled as a binary classification issue and solved in a simple way using logistic regression. However, the proposed method works well in spatial diversity and is not costly to implement in real-time environments. We have demonstrated the effectiveness of our proposed method by running an extensive simulation of the method in different SNR and fading conditions.

For the four-antenna setup, the proposed approach achieved an average P_d of 0.914. This is significantly higher than the existing SVM-based method (average $P_d \approx 0.638$) and deep learning-based method (average $P_d \approx 0.593$. Besides, the proposed method consistently shows lower misdetection probability, fewer false alarms, and less sensing error than existing techniques. The ROC and $P_d - SNR$ analyses also confirm the robustness and reliability of our approach for Rayleigh and Rician fading channels. Overall, our findings show that a simple logistic regression classifier combined with multi-antenna statistical features can provide sensing capabilities comparable to or better than more complex ML and DL models, and can be done at a low computational and energy cost.

Conflicts of Interest

All authors state that there are no competing of interest.

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