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Entropy-Based Spectrum Sensing for Cognitive Radio Networks Using Machine Learning and Software Defined Radio

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Abstract

Efficient spectrum sensing remains a main challenge for Cognitive Radio Networks (CRNs), especially in a wireless environment where methods like energy detection have high uncertainty. This work proposes an entropy-based spectrum-sensing system enhanced with machine-learning algorithms and implemented on a Software-Defined Radio (SDR) platform for real scenario testing. Entropy measures, such as Shannon and Rényi entropies, are used as discriminative features to distinguish occupied and idle frequency bands and release the channel if needed. Machine learning classifiers have achieved good results. In this research, Support Vector Machines (SVMs), K-Nearest Neighbors (KNNs), and Random Forests (RFs) are used with data captured via a GNU Radio and the Universal Software Radio Peripheral (USRP)-based SDR testbed. The experimental results demonstrate a probability of detection (P_d) above 0.9 and a false alarm rate (P_{fa}) below 0.1, indicating a substantial improvement over the classical energy detector of more than 20% for some signal-to-noise ratio (SNR) values. The integration of entropy metrics with machine learning (ML) models enables a dynamic detection in variable spectral environments, providing a practical framework for CRNs.

Keywords: artificial intelligence; cognitive radio networks; entropy; machine learning; spectrum sensing

1. Introduction

The growth of wireless services and the need for dynamic networks have driven the evolution of Fifth- and sixth-generation (5G/6G) networks, which require more radio spectrum to meet users' bandwidth needs. In this context, Cognitive Radio Networks (CRNs) represent a new paradigm for addressing spectrum scarcity, enabling secondary users (SUs) to detect and opportunistically access unused bands. A core capability of a CRN is spectrum sensing, which determines whether a primary user (PU) occupies a given frequency [1].

Detection based on received energy, matched filtering, or cyclostationary features is simple but yields lower detection performance at low signal-to-noise ratio (SNR) or in noisy channels. The exploration of alternative feature-based approaches that can robustly distinguish between idle and occupied bands, even under adverse conditions in real scenarios, is needed [2].

One such alternative is to use entropy metrics as a classification tool to discriminate features in spectrum sensing. Entropy, in the information theoretic sense, quantifies the

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uncertainty or randomness of a signal' s distribution. In frequency-domain spectrum sensing, the entropy of a power sample depends on whether the band is occupied (signal) or idle (noise). Because the entropy of noise alone exhibits a more stable statistical behavior, entropy-based detectors promise improved robustness compared to amplitude-based methods [3].

Recent work explores the integration of machine learning (ML) into Spectrum sensing tasks. ML algorithms have been used to classify spectral states (PU present or absent) using extracted features. These features may include amplitude, variance, modulation, higher-order statistics, and entropy metrics. The combination of these variables and ML classification offers a path toward adaptive sensing systems for CRN [4].

Simulation results reported in recent literature show that combining entropy features with ML classification outperforms conventional energy-detection techniques. Sensing systems that incorporate feature-based classification achieve higher detection probability and lower false-alarm rates than conventional methods. These are promising results for CRN, but need to be adapted to real scenarios and probed in the laboratory [5].

Even if the model of entropy and ML is promising, several research gaps remain. The robustness of entropy-based features in wideband sensing, cooperative sensing, and CRN scenarios remains underexplored, relying solely on simulations. Similarly, integrating classifier updating, online adaptation, and resource-efficient implementation on embedded Software-defined Radio (SDR) hardware requires further attention. These are critical when deploying cognitive systems in practical Internet of Things (IoT) and mobile environments in CRNs [6].

This paper proposes an entropy-based spectrum sensing system enhanced with ML classification, implemented on an SDR testbed. The main contributions are: (i) While many prior works evaluate entropy + ML approaches under simulated conditions, this work implements and validates the complete sensing pipeline on a USRP-based SDR platform using GNU Radio, capturing real wireless impairments such as hardware nonlinearity, channel variability, and interference. This bridges the gap between theoretical models and deployable CRN systems. (ii) Unlike studies that rely on a single entropy metric, this work jointly exploits Shannon and Rényi entropy, analyzing their complementary sensitivity to spectral distributions and demonstrating their combined discriminative capability under varying SNR conditions. (iii) The contribution is not limited to feature-classifier coupling. Instead, we present a complete operational framework that includes: SDR signal acquisition, real-time spectral processing, Entropy-based feature extraction, Supervised ML classification, and performance validation using P_d–P_{fa} and ROC metrics.

Section 2 presents a comprehensive review of prior work and outlines the principal contributions of this work. Section 3 includes the proposed machine-learning-based detection framework and its underlying methodology. Section 4 outlines the experiment configuration and implementation strategy, and Section 5 analyzes and presents the results. Finally, Section 6 summarizes the conclusions and identifies directions for future research.

2. Previous Work

Spectrum sensing is a key part of a CRN. The SUs look for a free frequency band to use. The effectiveness of CRNs depends on the user detection and reliability of the sensing mechanism, since incorrect spectrum decisions may either cause interference or lead to inefficient spectrum utilization. Research on Spectrum sensing for CRNs has significantly expanded in recent years, with studies focusing not only on improving detection accuracy but also on addressing the complexity and dynamics of sensing mechanisms in wireless or mobile environments [1].

Several techniques have been proposed. Still, most of them use energy detection, a fast method for detecting a possible PU or SU in a CRN by using a spectrum analyzer at a selected frequency. Still, in low-SNR conditions, it cannot correctly classify the signal from noise. The same holds for matched-filter detection and cyclostationary-feature detection. Recent surveys have emphasized diversifying Spectrum sensing strategies beyond conventional detectors by integrating statistical analysis, cooperative spectrum sensing (CSS) mechanisms, and learning-based decision frameworks to improve them. These hybrid approaches aim to balance detection accuracy with computational efficiency in practical communication systems [7].

Another alternative is to use the entropy sensing technique, which can operate under low-SNR conditions and supports different modulation types that vary over time in mobile or cognitive networks. It can capture the distributional properties of received signals along with the signal amplitude. In this context, entropy measures provide a useful statistical description of spectral characteristics, allowing detectors to distinguish between noise and signal. Entropy-based sensing methods can achieve improved reliability in radio environments [8].

Subsequent research has investigated entropy formulations suitable for Spectrum sensing applications. Shannon entropy remains the most commonly adopted measure, while generalized forms, such as Rényi and Tsallis entropies, have been explored to improve sensitivity to signal variations. These entropy metrics allow sensing algorithms to capture subtle differences in signal distributions under different channel conditions in CRNs [9,10].

A hybrid sensing framework that combines entropy features with cooperative or multi-feature sensing strategies has been developed and used in CRNs. A multi-feature cooperative sensing model that integrates entropy with additional spectral descriptors is used, demonstrating that combining entropy-based features with complementary signal characteristics enhances sensing decision-making in the presence of channel fading. The study also highlighted that entropy measures can serve as stable statistical indicators for ML classifiers, thereby enabling more reliable spectrum-occupancy estimation in complex wireless scenarios [11].

Another method for spectrum sensing is to use artificial intelligence (AI) via ML or deep learning approaches. These techniques have also been widely adopted to improve sensing accuracy and adaptability. ML algorithms enable the classification of spectral states by learning patterns from labeled datasets rather than relying on predetermined detection thresholds. Several studies have shown that ML classifiers such as SVMs, decision trees, and KNNs can effectively identify spectrum occupancy patterns [12].

Deep learning is also investigated for CRN applications. Neural networks, particularly convolutional neural networks (CNNs), have been used to process spectral representations of received signals, demonstrating that deep learning models can extract complex spectral features that improve detection performance under challenging noise conditions. Spectrum sensing is studied as a classification task for deep learning models to identify unknown signals, but in most cases, its computational complexity is higher than that of ML [13].

More recently, deep learning-based methods have been introduced to enhance Spectrum sensing performance. CNNs have been applied to learn feature representations directly from raw IQ samples, demonstrating strong performance in signal classification tasks. Similarly, recurrent architectures such as Long Short-Term Memory (LSTM) networks have been used to capture temporal dependencies in wireless signals, achieving high detection accuracy under complex channel conditions [14–16].

Despite their advantages, deep learning approaches typically require large labeled datasets and are computationally demanding, which may limit their applicability in real-time SDR-based systems. In contrast, traditional ML methods, when combined

with carefully designed features, can offer a better trade-off between performance and computational efficiency.

Even with the promising performance of deep learning methods, their practical deployment requires careful analysis of computational requirements and the use of large training data. Consequently, several studies continue to explore hybrid sensing frameworks that combine lightweight feature-extraction techniques with classical ML algorithms. Such approaches offer improved computational efficiency while maintaining satisfactory detection results [17].

The implementation of the Spectrum sensing techniques in real devices is another area to study. The SDR platform implementation has become increasingly in experimental research on cognitive radio networks. SDR platforms allow researchers to implement radio functionalities in software, enabling rapid prototyping and testing of advanced sensing algorithms. Systems based on USRP hardware and the GNU Radio framework have become widely adopted in experimental CRN research [18].

Experimental evaluations using SDR testbeds have revealed several practical challenges not captured in simulation studies. Real radio environments introduce factors such as hardware nonlinearity, noise, oscillator drift, and interference from external devices operating close to the used frequencies. Hardware effects can significantly affect sensing accuracy, as the authors show in [19].

Selecting practical features is a critical challenge. A recent review finds that while ML-based spectrum sensing demonstrates clear benefits, the feature set (including entropy, variance, kurtosis, etc.) is a primary bottleneck. The use of entropy as a feature thus aligns with this trend and presents an attractive candidate for robust sensing systems [20].

Implementing entropy-based sensing and ML classification on practical hardware platforms introduces additional challenges. SDR platforms enable real-world experimentation with CRN functions, but real-time constraints, dynamic channel conditions, hardware imperfections, and computational costs must be addressed. Implementing an entropy + ML spectrum sensing system on an SDR platform thus constitutes a meaningful contribution toward bridging theoretical work with real communications systems [21].

From a system architecture perspective, an entropy-based ML spectrum sensing framework typically comprises: signal acquisition via SDR, feature extraction, dataset labeling, classifier training (e.g., SVM, KNN, RF), and online sensing/decision-making. Such a pipeline supports adaptive thresholding and enhances decision accuracy across a range of diverse SNR levels and channel conditions [22].

Furthermore, integrating entropy-based feature extraction with efficient ML models in real-time SDR environments remains an active research topic. Future sensing systems must address scalability, adaptability, and computational efficiency while maintaining reliable detection performance across diverse wireless environments, such as CRNs [23].

To compare existing entropy-based spectrum-sensing approaches, Table 1 summarizes key differences in entropy formulation, ML integration, and experimental validation. Unlike prior studies, which are predominantly limited to simulation-based evaluation or single-feature designs, the proposed approach integrates multi-entropy features with lightweight ML models. It validates performance in a real SDR environment. The last two works have partial multi-entropy analysis.

Table 1. Comparison of entropy-based Spectrum sensing approaches with ML.

Ref.	Approach	Entropy Type	ML Model	Evaluation Environment	SDR Implementation	Low-SNR Analysis	Key Limitation
[3]	Entropy-based sensing (Vasicek, Van Es)	Generalized entropy	No ML	Simulation	No	Limited	No learning-based classification
[8]	Dispersion entropy + ML	Dispersion entropy	ML classifiers	Simulation	No	Partial	No real-world validation

Table 1. *Cont.*

Ref.	Approach	Entropy Type	ML Model	Evaluation Environment	SDR Implementation	Low-SNR Analysis	Key Limitation
[9]	Energy + entropy hybrid	Shannon entropy	No ML	Simulation	No	Limited	Threshold-based decision only
[21]	Multiband entropy sensing	Sample entropy	No ML	Simulation	No	Partial	No classification stage
[11]	Multi-feature cooperative sensing	Entropy + other features	ML/NN	Simulation	No	Partial	No SDR validation
[13]	Deep learning-based sensing	Learned features	CNN	Simulation	No	Yes	High computational cost
[19]	ML-assisted sensing (covariance)	Non-entropy features	ML	SDR (partial)	Yes	Limited	No entropy-based analysis
[12]	Autocorrelation + ML sensing	Non-entropy/hybrid	ML	Simulation	No	Yes	Does not use entropy features

As shown in Table 1, existing entropy-based approaches either lack real-world validation, rely on a single entropy formulation, or do not integrate efficient ML classifiers, which motivates the proposed framework.

3. Entropy-Based Spectrum Sensing in CRN

This section presents the proposed methodology. The framework comprises four main stages: signal acquisition, spectral analysis, entropy-based feature extraction, and ML classification. The goal is to detect if a PU is transmitting at the selected frequency.

3.1. System Model

The proposed sensing system follows a modular design for continuous-spectrum monitoring in SDRs. The framework consists of the following main components:

- Signal acquisition using SDR hardware.
- Spectral analysis and preprocessing.
- Entropy-based feature extraction.
- ML classification.
- Spectrum decision module.

The SDR receiver continuously monitors the selected frequency band and captures baseband samples that are processed in frames. These frames are transformed into the frequency domain, where entropy-based metrics are computed and used as input features for the classification algorithm. This architecture has been widely adopted in recent CRN implementations due to its flexibility and real-time processing capabilities, supported by the GNU Radio software to enable communications and cognitive protocol [24]. Figure 1 illustrates the proposed main architecture.

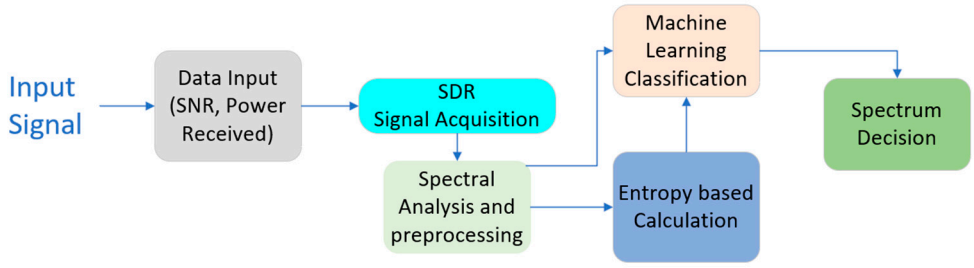


Figure 1. Entropy spectrum sensing with ML architecture (source: own).

It starts with the SDR hardware capturing signals from the monitored band, followed by a signal-acquisition stage that converts the received data into baseband samples. These samples are analyzed and preprocessed to obtain frequency-domain representations, from

which entropy-based features are extracted. The computed entropy metrics are then provided as input to the ML classification module, which employs SVM, KNN, and RF algorithms to determine the spectrum's occupancy state. Finally, the system produces a spectrum decision indicating the channel state, enabling dynamic and intelligent spectrum access in the CRN.

3.2. Signal Model

The user signal is used as a binary hypothesis test. The received discrete-time signal is shown in Equation (1).

$$\begin{aligned} H_0 &: r(n) = w(n) \\ H_1 &: r(n) = s(n) + w(n) \end{aligned} \tag{1}$$

where H_0 is the hypothesis that the channel is occupied, H_1 means the presence of a primary signal, $s(n)$ is the transmitted signal, and $w(n)$ denotes additive white Gaussian noise (AWGN). This formulation is widely used in studies and forms the basis for evaluating sensing performance [7].

The metrics used to evaluate it are P_d and P_{fa}, as shown in Equation (2).

$$\begin{aligned} P_d &= P(H_1 \mid H_1) \\ P_{fa} &= P(H_1 \mid H_0) \end{aligned} \tag{2}$$

An effective sensing algorithm should maximize P_d while minimizing P_{fa}, ensuring reliable detection of primary users while reducing unnecessary Spectrum blocking [1].

3.3. Spectral Analysis

The signal is converted to the frequency domain using the Fast Fourier Transform (FFT). For a received signal frame containing N samples, the discrete Fourier transform is defined in Equation (3).

$$X(k) = \sum_{n=0}^{N-1} r(n) e^{-j2\pi kn/N} \tag{3}$$

The Power Spectral Density (PSD) of the received signal is then computed as Equation (4).

$$P(k) = \mid X(k) \mid^2 \tag{4}$$

The PSD provides information about the energy distribution across frequency bins and serves as the input for entropy-based feature extraction. Frequency-domain sensing techniques are widely used in cognitive radio research because they allow efficient detection of spectral patterns associated with primary user transmission [21].

3.4. Entropy-Based Feature Extraction

Entropy measures the randomness or uncertainty of a probability distribution. In this case, entropy is used to characterize the statistical distribution of spectral power values.

The selection of Shannon and Rényi entropies in this work is motivated by their strong theoretical foundations in information theory and their demonstrated effectiveness in spectrum-sensing applications [3,10]. Shannon entropy provides a measure of uncertainty in the spectral distribution, enabling the differentiation between noise-only and signal-present conditions.

Rényi entropy extends this concept by introducing a tunable parameter that adjusts sensitivity to spectral variations, which is particularly advantageous under low-SNR conditions [10,25].

Compared to conventional feature extraction methods such as energy detection, variance, or higher-order statistics, entropy-based features capture the distributional characteristics of the Spectrum rather than solely the amplitude, improving robustness to noise uncertainty [1,9].

Additionally, entropy-based approaches offer lower computational complexity compared to cyclostationary and deep learning-based methods, making them suitable for real-time SDR implementations [15,26].

The combined use of Shannon and Rényi entropy provides complementary information, enhancing discriminative capability in dynamic spectral environments [11].

Table 2 presents a comparative analysis of commonly used feature extraction methods, including energy detection, statistical features, cyclostationary analysis, and entropy-based metrics. The comparison highlights key aspects, including robustness to noise uncertainty, computational complexity, and suitability for real-time SDR implementation. As reported in the literature, traditional amplitude- and correlation-based features often exhibit limitations under low-SNR conditions or require high computational resources [1,9]. In contrast, entropy-based features provide a more robust representation of spectral distributions by capturing their statistical structure [7,19]. This comparison supports the selection of Shannon and Rényi entropy as effective and practical features for spectrum sensing in dynamic wireless environments.

Table 2. Comparison of feature extraction methods for spectrum sensing.

Feature	Type	Sensitivity to Noise	Computational Complexity	Suitability for SDR	Supporting References	Key Limitation
Energy Detection	Amplitude-based	High sensitivity to noise uncertainty	Low	High	[1,9]	Poor performance at low SNR
Variance/Statistical	Statistical	Moderate	Low	High	[7,19]	Limited discriminative power
Cyclostationary	Spectral correlation	Low sensitivity to noise	High	Moderate	[11]	High computational cost
Entropy (Shannon/Rényi)	Information-theoretic	Robust to noise uncertainty	Low–Moderate	High	[3,10,27]	Requires probability estimation

Entropy-based features provide a favorable balance between robustness to noise uncertainty and computational efficiency compared to conventional feature extraction methods. In the next part of this section, the entropy is defined.

The PSD values are first normalized to create a probability distribution:

$$P_i = \frac{P(i)}{\sum_{i=1}^{N} P(i)} \tag{5}$$

where $P(i)$ represents the normalized power of the i-th frequency bin.

The Shannon entropy of the normalized spectral distribution is computed as Equation (6).

$$H = -\sum_{i=1}^{N} P_i \log(P_i) \tag{6}$$

In noise-only conditions, the PSD values are approximately uniform, resulting in relatively stable entropy values. When a signal is present, the spectral distribution becomes more structured, producing variations in entropy that can be used for detection [9].

To improve sensitivity to spectral variations, Rényi entropy of order α can also be calculated as Equation (7).

$$H_\alpha = \frac{1}{1-\alpha} \log \sum_{i=1}^{N} P_i^\alpha \tag{7}$$

The parameter α allows the entropy measure to emphasize different aspects of the spectral distribution. Recent studies have shown that combining multiple entropy metrics can improve Spectrum sensing performance under varying noise conditions [9].

Despite their advantages, entropy-based features also present certain limitations. Shannon entropy, while robust and stable, may exhibit reduced sensitivity to localized spectral variations, particularly in very low SNR conditions or when signals occupy narrow frequency bands. Rényi entropy addresses this limitation by introducing a tunable parameter that enhances sensitivity to specific distribution characteristics; however, its performance depends on appropriate parameter selection. Furthermore, both entropy measures rely on accurate probability estimation from the Power Spectral Density, making them sensitive to spectral resolution, normalization accuracy, and non-stationary interference. To mitigate these limitations, this work combines Shannon and Rényi entropy to exploit their complementary properties and improve robustness across varying spectral conditions.

3.5. Machine Learning Classification

To improve the accuracy of the entropy-based detector, supervised ML is used to classify spectral values based on extracted entropy features. In the proposed framework, entropy metrics, such as Shannon and Rényi entropies, form the feature vector used to train classifiers that distinguish between idle and occupied spectrum conditions. ML methods enable the system to learn nonlinear decision boundaries [28].

3.5.1. Support Vector Machine

SVMs are widely used for binary classification problems due to their strong generalization capability and effectiveness in high-dimensional feature spaces. In Spectrum sensing applications, SVM constructs an optimal hyperplane that separates feature vectors corresponding to idle and occupied spectral states. The SVM classifier's decision can be expressed as in Equation (8).

$$f(x) = sign(\sum_{i=0}^{N} \alpha_i y_i K(x_i, x) + b) \quad (8)$$

where x represents the feature vector, x_i are support vectors, y_i are class labels, $K(\cdot)$ denotes the kernel function, and b is the bias term. SVM has demonstrated strong performance in Spectrum sensing tasks, particularly when entropy-based or statistical features are used [29].

3.5.2. k-Nearest Neighbors

The KNN classifier assigns labels based on the majority class of the k closest training samples. In entropy-based sensing, KNN classifies a spectral observation by computing the Euclidean distance between its entropy feature vector and the feature vectors in the training dataset. The classification rule is defined as Equation (9).

$$y = \arg\max_{c} \sum_{i \in N_k(x)} \delta(y_i = c) \quad (9)$$

where y is the predicted value, $N_k(x)$ represents the set of k nearest neighbors, $\delta(\cdot)$ is the indicator function, and c is a class label; its value is 0 if there is no PU and 1 if the PU is present. KNN is particularly attractive in CRN because it is relatively simple and can make complex decision regions without requiring prior assumptions about data distribution [30].

3.5.3. Random Forest

RF uses multiple decision trees to improve detection probability while keeping overfitting low. A random sample set of features is used to train each tree, and the global decision

is estimated as the highest value of the voting (majority rule). The prediction function of an RF classifier can be written as Equation (10).

$$y = mode\{T_1(x),\ T_2(x), \ldots,\ T_M(x)\} \tag{10}$$

where $T_M(x)$ represents the output of the *m-th* decision tree, RF classifiers have been shown to perform well in Spectrum sensing scenarios [13].

3.6. Training and Performance Evaluation

The data collected from the SDR platform is split into training and test sets to evaluate classifier performance. A common split is 70% for training and 30% for testing.

Classification performance metrics are:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

where TP is the true positive, TN is the true negative, FP is the false positive, and FN represents false negatives.

The Receiver Operating Characteristic (ROC) curves allow the analysis of the P_d and P_{fa} metrics, which evaluate the ML-based spectrum-sensing methods [13].

3.7. SDR Implementation

The proposed sensing framework is implemented on a Software Defined Radio platform comprising USRP hardware and the GNU Radio processing environment. SDR technology enables flexible signal acquisition and real-time signal processing, allowing the evaluation of sensing algorithms in realistic radio environments.

By combining entropy-based feature extraction with machine-learning classification within an SDR framework, the proposed system enables practical experimentation and performance evaluation under real-world wireless channel conditions. Such implementations are essential for validating theoretical spectrum-sensing models with real-world CRN deployments [31].

It is important to note that the proposed system inherently accounts for hardware imperfections and non-ideal SDR conditions through its experimental design. The use of real SDR hardware introduces practical impairments such as oscillator drift, nonlinearities, noise uncertainty, and external interference into the acquired dataset. Consequently, the ML models are trained on data that already reflects these effects, enabling the system to learn robust decision boundaries. Furthermore, the use of entropy-based features, which rely on statistical distributions rather than absolute signal amplitudes, enhances resilience to hardware-induced distortions and gain variations. This combination allows the proposed framework to operate reliably under realistic SDR conditions without requiring explicit hardware compensation mechanisms.

4. Experiments

This section describes the experimental configuration used. The objective is to validate the performance under simulation and realistic wireless channel conditions using an SDR testbed.

4.1. SDR Platform Configuration

The experimental setup uses SDRs from National Instruments: the Universal Software Radio Peripheral (USRP) N2900 and the N210 device, both connected to a host computer running the GNU Radio framework. The SDR receiver continuously monitored a selected frequency band in the 400–500 MHz range, commonly used in cognitive radio experimenta-

tion. The experiments were performed in an indoor laboratory environment to emulate realistic wireless channel conditions.

The receiver continuously captured baseband signals within this band. The sampling rate was configured between 1 MHz and 5 MHz, depending on the evaluated scenario, allowing sufficient resolution for spectral analysis.

The transmitter generated PU signals using digitally modulated waveforms, specifically Quadrature Phase Shift Keying (QPSK), implemented through GNU Radio signal blocks. This setup is shown in Figure 2.

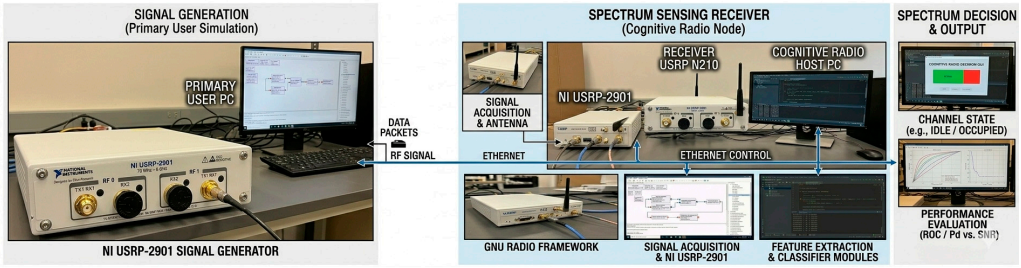


Figure 2. Experimental SDR testbed configuration for CRN spectrum sensing (source: own).

For reproducibility purposes and to provide a clear overview of the experimental configuration, Table 3 summarizes the key parameters of the SDR-based testbed used in this study. The table includes details on hardware and software components, signal characteristics, data-acquisition settings, and evaluation conditions. This structured description complements the methodological explanation and facilitates a comprehensive understanding of the experimental design, enabling the validation and replication of the proposed entropy-based Spectrum sensing framework in practical environments.

Table 3. Experimental Setup Summary.

Parameter	Value
SDR Hardware	USRP N210, USRP N2900
Software	GNU Radio
Frequency Band	400–500 MHz
Modulation	QPSK
Sampling Rate	1–5 MHz
Frame Size	2048 samples
Dataset Size	6000 frames
SNR Range	−15 dB to 10 dB
Environment	Indoor
ML Split	70% training/15% validation 15% testing

The dataset was divided into training, validation, and test subsets at 70% (training), 15% (validation), and 15% (test), corresponding to 4200, 900, and 900 frames, respectively. This partitioning follows standard ML practices to ensure sufficient data for model training while maintaining independent validation and unbiased performance evaluation subsets [32].

A stratified sampling strategy was applied to preserve the class distribution across all subsets. Additionally, 5-fold cross-validation was used during hyperparameter tuning to reduce overfitting and improve generalization capability.

4.2. Signal Generation and Channel Conditions

The wireless channel conditions were emulated in an indoor environment, where signal attenuation and noise were controlled by adjusting transmission power and the relative

distance between transmitter and receiver. The SNR was varied from −15 dB to 10 dB, enabling evaluation of sensing performance under both challenging and favorable conditions.

Additive White Gaussian Noise (AWGN) conditions were assumed, while real-world impairments such as hardware noise, interference, and multipath effects were inherent to the SDR-based implementation.

4.3. Dataset Acquisition

A dataset was collected through real-time SDR measurements. A total of 6000 signal frames were acquired, each consisting of 2048 complex baseband samples. The collected signals were processed using Fast Fourier Transform (FFT) to compute the Power Spectral Density (PSD), which served as the basis for entropy feature extraction.

Each frame was labeled according to the spectrum occupancy conditions:

- Class 0: Idle Spectrum (noise-only).
- Class 1: Occupied Spectrum (presence of PU signal).

The labeling process was controlled by enabling or disabling the transmitter during acquisition. The dataset was divided into 70% for training, 15 for validation, and 15% for testing, ensuring unbiased evaluation of the ML models.

4.4. Hyperparameter Tuning and Feature Extraction Parameters

To ensure a fair and systematic evaluation, hyperparameters for all classifiers were optimized using a stratified k-fold cross-validation strategy (k = 5) on the training set (70% of the dataset). The optimization objective was to maximize the F1-score while maintaining a false alarm probability constraint of $P_{fa} \leq 0.1$.

A grid search was employed to explore the hyperparameter space of each model. For the SVM classifier, the regularization parameter C and kernel width γ (RBF kernel) were varied. For KNN, the number of neighbors k and the distance metric were tuned. For RF, the number of trees, maximum depth, and minimum samples per split were optimized.

The tuning process also revealed that SVM performance is sensitive to kernel parameters, while KNN performance depends strongly on the choice of neighborhood size.

Two entropy metrics were used: Shannon entropy and Rényi entropy (α = 2).

The feature vector for each observation was defined as accuracy, according to Equation (11). These features were normalized before being used in the classification stage. A grid search strategy was employed to systematically explore the hyperparameter space of each classifier. The evaluated ranges are:

- SVM: (C in {0.1, 1, 10, 100}), (gamma in {0.001, 0.01, 0.1, 1}) (RBF kernel);
- KNN: (k in {3, 5, 7, 9}), distance metrics: Euclidean and Manhattan;
- RF: number of trees ({50, 100, 150}), maximum depth (in {5, 10, 15}), minimum samples per split (in {2, 5, 10}).

The optimal hyperparameters were selected based on the average F1-score obtained during cross-validation, while enforcing a constraint on the false-alarm probability ($P_{fa} \leq 0.1$).

The final hyperparameters were selected based on cross-validation performance and validated on the held-out test set to avoid overfitting. This procedure ensures that the reported results reflect generalizable performance rather than dataset-specific tuning. The selected hyperparameters after cross-validation are shown in Table 4.

It was implemented using Scikit-learn. The sensing performance is evaluated using P_d, P_{fa}, and the ROC Curve.

The selected classifiers (SVM, KNN, and RF) were chosen for their complementary characteristics in model complexity, interpretability, and suitability for real-time SDR implementation.

Table 4. Selected hyperparameters after cross-validation.

Model	Hyperparameters	Selected Values
SVM	Kernel, C, gamma	RBF, C = 10, gamma = 0.1
KNN	k, distance	k = 5, Euclidean
RF	Trees, depth, min samples	100 trees, depth = 10, min = 2

The used classifiers are: SVM (RBF kernel). KNN (k = 5). RF (100 trees).

4.5. Computational Complexity Analysis

The computational complexity of the proposed method consists of two main components: entropy-based feature extraction and classification.

The entropy computation for each frame of NNN samples has a complexity of approximately O(N), as it involves probability estimation and logarithmic operations. Given a frame size of N = 2048, this step remains computationally efficient [33].

The classification stage depends on the selected model. For RF, the complexity is approximately O(T·D), where T is the number of trees and D is the depth of each tree. For SVM, inference complexity is proportional to the number of support vectors, whereas KNN requires O(K·M), where K is the number of neighbors, and M is the number of training samples.

The RF classifier provides a favorable trade-off between computational cost and detection performance, making it suitable for real-time implementation.

Figure 3 presents the processing time per frame for the evaluated methods. The results confirm that entropy-based feature extraction, combined with RF or SVM classification, can be performed within a fraction of the frame duration. This demonstrates that the proposed approach meets real-time processing requirements on typical SDR platforms.

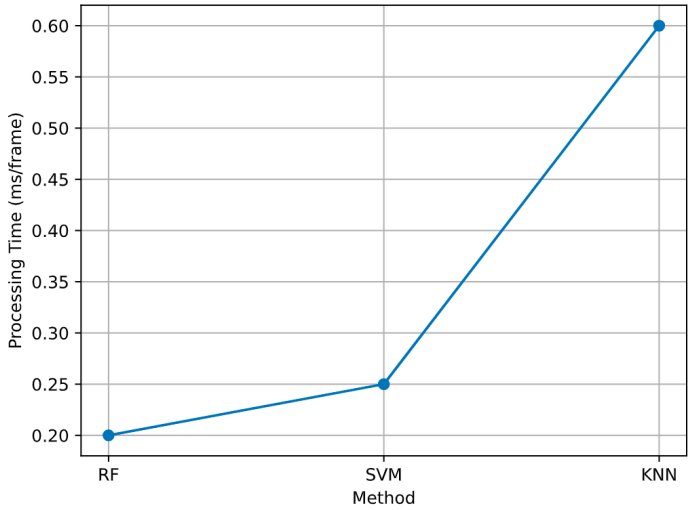


Figure 3. Processing Time per Frame by Method (source: own).

As shown in Figure 3, the entropy extraction stage contributes minimally to the total latency, while classification remains efficient for RF and SVM models. The processing time is dominated by lightweight operations, enabling real-time performance [16]. These results further validate the practical feasibility of the proposed approach for deployment in SDR-based cognitive radio systems.

5. Results

This section describes the evaluation of the spectrum sensing framework. The analysis focuses on entropy behavior, classifier performance, robustness under varying SNR conditions, and comparison with conventional methods.

5.1. Entropy Feature Analysis

The discriminative capability of entropy-based features was first evaluated by analyzing their statistical distributions under idle and occupied-spectrum conditions.

The results indicate that entropy values corresponding to idle conditions (noise-only) exhibit a relatively narrow distribution, reflecting the uniform nature of noise in the frequency domain. In contrast, entropy values associated with occupied states exhibit a broader distribution due to the structured spectral components introduced by the PU signal, as shown in Figure 4.

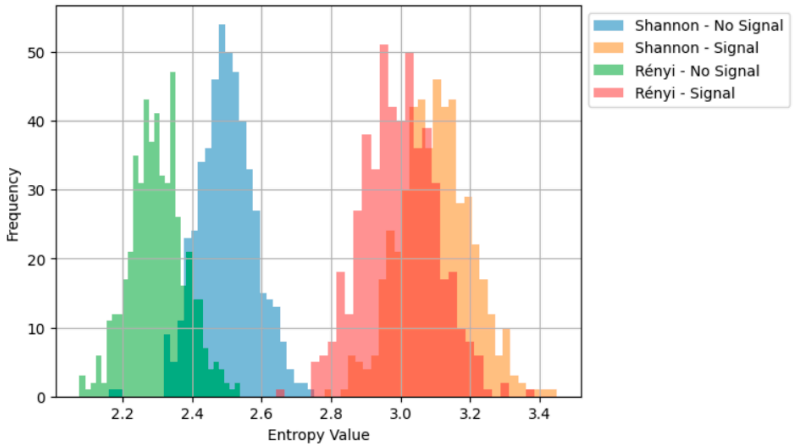


Figure 4. Distribution of Shannon entropy values from the received signal (source: own).

This behavior confirms that entropy provides a meaningful statistical descriptor that distinguishes between spectral states. Moreover, the separation between the two distributions suggests that entropy-based features can effectively reduce classification ambiguity, particularly when combined with ML models.

5.2. Detection Performance

The proposed method was evaluated under different SNR conditions. Figure 5 shows the P_d as a function of SNR for both the proposed entropy-ML method and conventional energy detection.

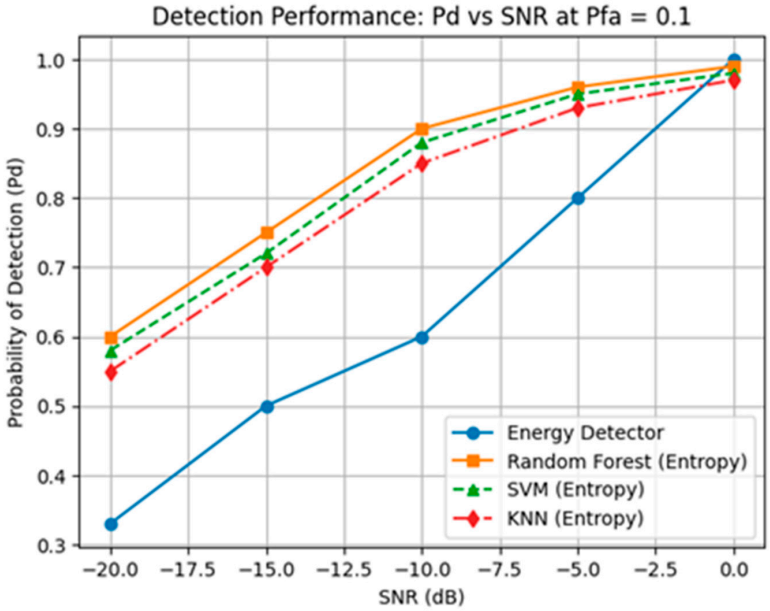


Figure 5. Detection performance, SNR vs. P_d (source: own).

The results show that using the ML model outperforms energy detection across some SNR levels. In particular, at lower SNR values (e.g., −10 dB), the entropy-ML approach maintains a P_d above 0.80, whereas the energy detector drops below 0.60.

5.3. Classifier Performance Comparison

The performance of different ML classifiers was evaluated using accuracy, P_d, and P_{fa}. To provide a comprehensive evaluation, Receiver Operating Characteristic (ROC) curves were generated. These curves illustrate the trade-off between P_d and P_{fa} across different classifiers. as shown in Figure 6.

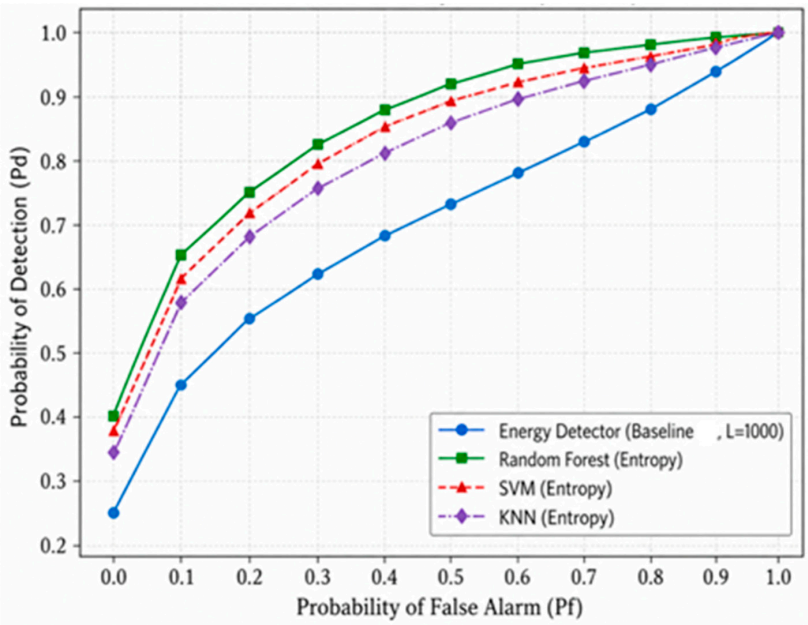


Figure 6. ROC Curve of P_d vs. P_{fa} for −15 dB (source: own).

The results indicate that the ML model dominates the ROC space, achieving higher detection probabilities across all false alarm rates. Among the evaluated models, the RF classifier performs best, followed by SVM and KNN. The baseline energy detector from [9] exhibits lower detection capability, particularly at low P_{fa} values.

For a selected $P_{fa} \leq 0.1$, ML performs better than energy above 20% for P_d. It corresponds to the increase in P_d achieved by the proposed method compared to energy detection under equivalent P_{fa} conditions. Table 5 compares accuracy, P_d, and P_{fa} across several SNR values. A 95% confidence interval was used in experiments.

Table 5. Performance Metrics at $P_{fa} \leq 0.1$.

Method	Accuracy (%)	P_d	P_{fa}
RF (Entropy)	95.2	0.93	0.07
SVM (Entropy)	93.8	0.92	0.08
KNN (Entropy)	91.5	0.90	0.09
Energy Detector	83.0	0.80	0.10

The relatively narrow confidence intervals confirm that the observed performance improvements of the proposed entropy-based ML approach over the energy detector are statistically consistent and not due to random fluctuations.

The results indicate that entropy-based ML methods achieve higher classification accuracy than traditional energy detection methods. RF attains the highest accuracy (95.2%)

and achieves the target detection probability of 0.90% at approximately −12 dB, representing a significant improvement over energy detection, which requires approximately −1 dB. It corresponds to a detection gain of approximately 11 dB, demonstrating the model's effectiveness.

The RF classifier achieved the highest accuracy, indicating superior generalization performance. SVM also demonstrated strong performance due to its ensemble structure, while KNN achieved slightly lower accuracy but still performed competitively.

To ensure a fair comparison, the energy detection baseline was implemented using the same SDR-acquired dataset and preprocessing pipeline as the proposed method. Specifically, both approaches operate on identical signal frames (2048 samples), frequency band (400–500 MHz), and SNR conditions ranging from −15 dB to 10 dB.

The energy detector computes the total received energy from the Power Spectral Density (PSD) and compares it against a predefined threshold. The detection threshold was calibrated to achieve a target false-alarm probability $P_{fa} \leq 0.1$, enabling consistent comparison with the entropy-based ML classifiers evaluated under the same constraint.

In the SDR scenario, different SNR values were evaluated using the RF and entropy models. Figure 7 presents the SNR vs. P_d for the proposed entropy-based approach using a RF classifier and energy detection. The curves illustrate system performance in an SNR range, from −15 dB to 10 dB, highlighting the behavior of both techniques under challenging and favorable channel conditions. This comparison provides a clear visualization of the effectiveness of entropy-based feature extraction combined with ML in improving Spectrum sensing accuracy.

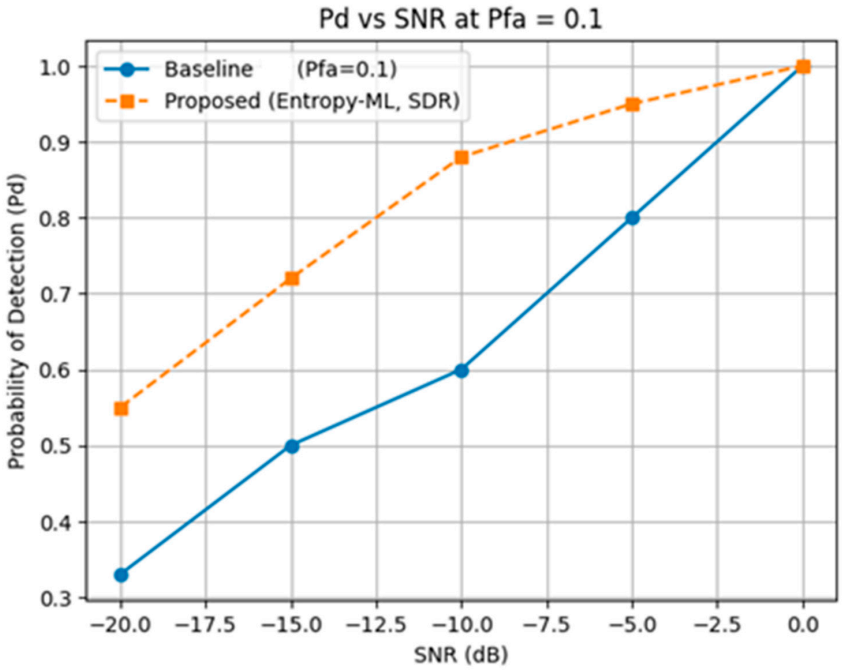


Figure 7. Practical Results of SNR vs. P_d (source: own).

As shown in Figure 7, the Entropy and RF methods consistently outperform the energy detector. The performance gap is particularly significant at low SNR, where the proposed method maintains a relatively high detection probability (above 0.6 at −10 dB). At the same time, the energy detector has a sharp degradation (remaining below 0.2). The entropy features capture spectral structure, and the RF classifier model yields nonlinear decision boundaries. As the SNR increases, both methods improve; however, the proposed approach reaches near-optimal detection ($P_d \approx 0.95$–0.98) more rapidly, demonstrating

superior robustness and reliability. These results confirm that integrating entropy-based features with ensemble learning techniques significantly enhances detection performance.

Table 6 presents a quantitative comparison between the entropy-based ML approach and the conventional energy detection baseline [9]. Both methods are evaluated using the same SDR-acquired dataset, frequency band, frame structure, and SNR range, with the detection threshold adjusted to ensure $P_{fa} \leq 0.1$ is maintained. The table reports the P_d across different SNR levels, along with the corresponding performance improvement achieved by the proposed method. Additionally, confidence intervals are included to assess the statistical significance of the results.

Table 6. Performance comparison between energy detection and the proposed entropy-based ML approach at fixed $P_{fa} \leq 0.1$.

SNR (dB)	P_d (Energy Detection) [9]	P_d (Proposed Method)	Improvement P_d (%)	Notes
−20	0.33	0.55	+22%	Very low SNR regime
−15	0.50	0.72	+22%	Low SNR
−10	0.60	0.88	+28%	Moderate-low SNR
−5	0.80	0.95	+15%	Moderate SNR
0	1.00	1.00	0	High SNR

5.4. Confusion Matrices Analysis

To further analyze classification behavior, confusion matrices were computed for all evaluated methods on a dataset of 6000 frames, each containing 2048 signal samples.

Confusion matrices provide a detailed breakdown of classification outcomes, including true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The results show that entropy-based ML methods significantly reduce both false alarms and missed detections compared to the energy detector.

Figure 8 presents the confusion matrix for the RF classifier, which achieved the best performance among the evaluated methods; yellow indicates correct predictions.

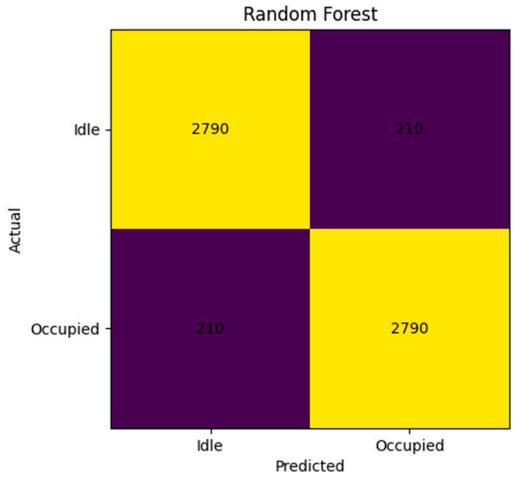


Figure 8. RF Confusion Matrix (source: own).

The confusion matrix for the RF classifier shows a high number of true positives and true negatives, with both false positives and false negatives remaining low. This indicates a strong capability to detect spectrum occupancy while maintaining a low false-alarm rate accurately. This behavior is consistent with its superior performance on P_d, precision, and F1-score, confirming that ensemble learning combined with entropy-based features yields robust classification even under challenging SNR conditions.

The confusion matrix for the SVM classifier shows a good balance between detection capability and false-alarm control, with a high number of correct classifications and moderate misclassification rates, compared to the RF model. The results are shown in Figure 9; yellow indicates correct predictions.

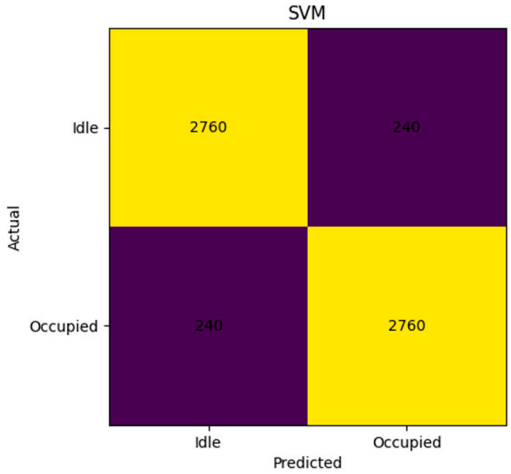


Figure 9. SVM Confusion Matrix (source: own).

It reflects a strong classification performance, with a high number of correctly identified instances and a moderate number of misclassifications. Compared to RF, the SVM exhibits slightly higher false positives and false negatives, indicating a marginally reduced ability to generalize across varying spectral conditions.

The confusion matrix for the KNN classifier shows competitive performance. However, it exhibits slightly higher false-positive and false-negative rates than the other ML models, indicating lower robustness under certain conditions. The results are shown in Figure 10; yellow indicates correct predictions.

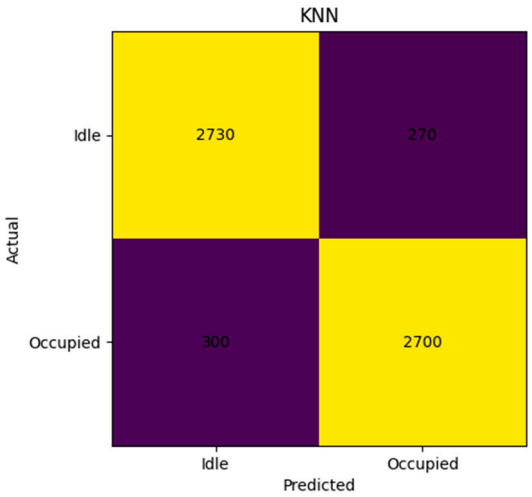


Figure 10. KNN Confusion Matrix (source: own).

The confusion matrix for the KNN classifier shows a noticeable increase in both false positives and false negatives compared to the other ML models. While the classifier still achieves a high number of correct detections, its performance is more sensitive to noise and local data variations.

To provide a comprehensive evaluation of the proposed method, several performance metrics were analyzed, including accuracy, P_d, P_{fa}, precision, recall, and F1-score. These metrics collectively capture the trade-off between detection capability and false alarm

control, offering a more complete assessment than any single measure. As shown in Table 7, the entropy-based ML approaches consistently outperform the conventional energy detector across all metrics.

Table 7. Performance metrics results.

Method	Precision	Recall (P_d)	F1-Score	Accuracy
RF	0.930	0.930	0.930	0.930
SVM	0.920	0.920	0.920	0.920
KNN	0.909	0.900	0.905	0.905

In particular, the RF classifier achieves the highest accuracy and F1-score, indicating strong generalization and balanced classification performance. The SVM and KNN classifiers also demonstrate competitive results, maintaining high detection probabilities while controlling false alarms. The consistency across all evaluated metrics confirms the robustness and effectiveness of the proposed entropy-based framework for spectrum sensing. To assess statistical significance, the evaluation was conducted on a dataset of 6000 signal frames, ensuring a sufficiently large sample size to estimate performance metrics reliably. Assuming a binomial distribution of detection outcomes, the variability of P_d and P_{fa} is inherently limited, yielding narrow confidence bounds around the reported values. This indicates that the observed performance improvements are not due to random fluctuations but reflect a consistent and statistically reliable advantage of the proposed entropy-based ML approach over the conventional energy detector. Furthermore, the consistency of results across multiple metrics and evaluation scenarios reinforces the robustness of the proposed method.

5.5. Noise Uncertainty Analysis

Noise uncertainty is a well-known limitation of conventional energy detection methods, as small variations in noise power can lead to significant degradation in detection performance. Since energy detection relies on a fixed threshold, inaccuracies in noise estimation directly affect the false alarm and detection probabilities.

In contrast, the proposed entropy-based approach is less sensitive to noise uncertainty because it operates on the distributional characteristics of the signal rather than on absolute amplitude values. The integration of ML further enhances robustness by learning decision boundaries that adapt to variations in noise conditions. This behavior is reflected in the improved performance observed across different SNR levels.

Figure 11 illustrates the stability of the evaluated Spectrum sensing methods under varying levels of noise uncertainty. The P_d is analyzed as a function of noise uncertainty, ranging from 0 dB to 2 dB, for both entropy-based ML approaches and the conventional energy detector. This analysis provides insight into the robustness of each method under imperfect noise power estimation, a common scenario in practical wireless environments.

As shown in Figure 11, the proposed method exhibits gradual, limited degradation in detection performance as noise uncertainty increases. In particular, the RF classifier maintains the highest P_d across all uncertainty levels, decreasing only slightly from approximately 0.94 to 0.89, indicating strong robustness to noise variations. Similarly, SVM and KNN demonstrate stable performance, with only minor performance reductions, confirming their ability to generalize under noisy conditions.

The energy detector shows a significant decline in detection performance, dropping from approximately 0.80 at a 0 dB uncertainty to around 0.52 at a 2 dB uncertainty. This sharp degradation highlights the sensitivity of threshold-based methods to inaccuracies in noise estimation.

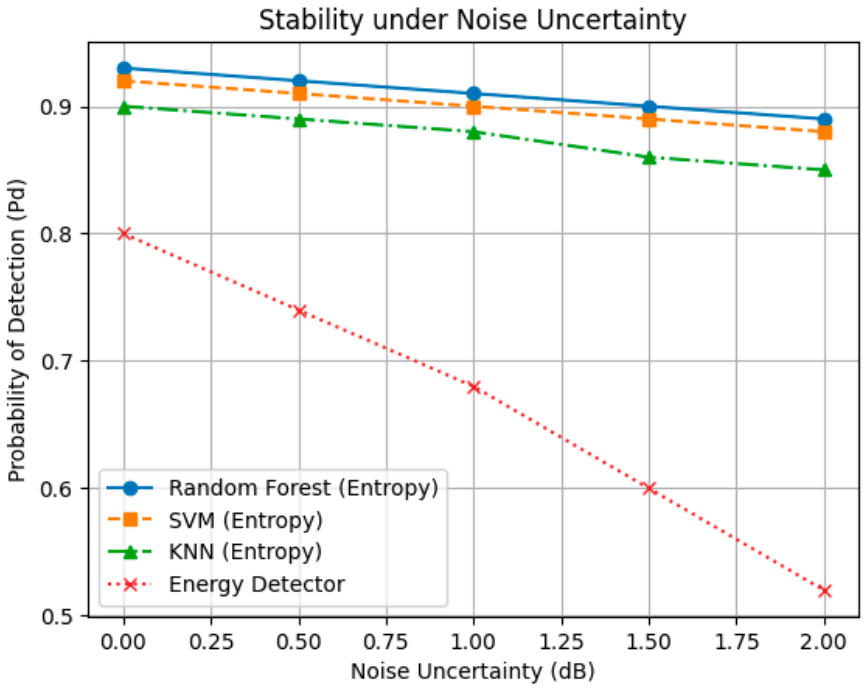


Figure 11. Stability analysis under noise uncertainty (source: own).

Experiments were conducted under varying spectrum conditions, including different SNR levels, temporal segments, and channel realizations captured by the SDR platform. Unlike controlled simulations, the SDR-based dataset inherently includes variability from environmental factors, such as noise fluctuations, interference, and hardware imperfections.

To further assess generalization, a cross-condition evaluation was performed in which the model was trained on a subset of SNR levels and tested on unseen lower-SNR conditions (e.g., −15 dB and −10 dB). The results indicate that the model maintains strong detection performance under these unseen conditions, demonstrating its ability to generalize beyond the training distribution.

This robustness stems from the use of entropy-based features, which capture the signal's statistical characteristics rather than relying on specific amplitude patterns. Consequently, the model learns invariant representations that remain effective across different spectrum environments.

The results confirm that the proposed approach is not limited to a specific dataset configuration and can generalize effectively across varying noise levels and channel conditions, making it suitable for deployment in dynamic cognitive radio environments.

5.6. Comparison with Deep Learning-Based Spectrum Sensing

Recent advances in spectrum sensing have explored the use of deep learning techniques, such as CNNs and LSTMs, to improve detection performance under challenging conditions. These methods can learn complex feature representations directly from raw or minimally processed signals and have demonstrated strong performance in low-SNR scenarios.

However, deep learning approaches typically require large labeled datasets for training and involve significantly greater computational complexity than traditional ML methods. In addition, their deployment on SDR platforms may be constrained by memory and processing limitations, particularly in real-time applications.

In contrast, the proposed entropy-based ML approach offers a favorable trade-off between performance and computational efficiency. By leveraging statistical features such as Shannon and Rényi entropy, the method captures essential signal characteristics while

maintaining low computational overhead. As demonstrated by the experimental results, the proposed approach achieves competitive detection performance without requiring extensive training data or high-performance hardware.

Therefore, while deep learning methods provide powerful modeling capabilities, the proposed approach is better suited for real-time SDR-based cognitive radio systems, where computational efficiency and robustness are critical.

Table 8 presents a comparative analysis between the proposed entropy-based ML approach and representative deep learning-based spectrum sensing methods. Deep learning models, such as CNNs and LSTM-based architectures, have demonstrated strong detection performance in low-SNR conditions by learning complex feature representations directly from raw or sequential signal data [15,34]. These methods can achieve a high probability of detection, typically around 0.88–0.90 in challenging environments.

Table 8. Comparison with deep learning-based Spectrum sensing methods.

Method	Feature Type	P_d (Low SNR)	Complexity	Real-Time SDR	Data Requirement
CNN-based [15]	Learned (raw IQ)	High (~0.9)	High	Limited	High
LSTM-based [35]	Temporal features	High (~0.88)	High	Limited	High
Energy Detection [9]	Energy	Low (~0.6)	Very Low	Yes	None
Proposed (Entropy + RF)	Statistical entropy	High (~0.88)	Low	Yes	Moderate

However, this performance comes at the cost of significantly increased computational complexity and high data requirements. Training DL models requires large labeled datasets and considerable computational resources, which may limit their applicability in real-time SDR systems. Additionally, inference latency and memory constraints can further restrict deployment on embedded platforms.

6. Discussion

The results show that entropy-based feature extraction, combined with ML classification, provides an effective solution for Spectrum sensing in CRNs. The analysis confirms that entropy metrics, particularly Shannon and Rényi entropies, exhibit strong discriminative power between idle and occupied spectrum conditions, even in challenging low-SNR environments. The proposed approach demonstrates a significant detection gain (~11 dB) over energy detection, particularly in challenging low-SNR regimes (e.g., −10 dB), which is critical for practical CRN deployment.

One of the most relevant findings is the clear separation between entropy distributions for noise and signal scenarios. This behavior validates entropy as a stable statistical descriptor, thereby reducing uncertainty compared to traditional energy-detection methods. Unlike amplitude-based approaches, entropy captures structural variations in the spectral domain, which explains its improved performance under noise uncertainty.

Another key contribution of this work is the evaluation of the proposed approach in a real SDR environment. The use of USRP hardware and GNU Radio demonstrates that entropy-based ML sensing is not limited to simulations but can be implemented in practical systems. However, the experiments also reveal real-world challenges, including hardware imperfections, channel variability, and computational constraints, that must be considered in future deployments.

The designed algorithms efficiently combine energy, entropy, and ML, resulting in a P_d above 90% at lower SNR in the SDR environment.

This paper focuses on ML rather than computationally intensive deep learning; it systematically evaluates SVM, KNN, and RF, emphasizing low-complexity, deployable solutions suitable for embedded SDR environments.

Although explicit channel models were not imposed, the SDR-based experimental setup inherently captures real-world wireless impairments, including multipath propagation, hardware noise, and channel fading. These effects introduce variability in the received signal, making Spectrum sensing more challenging.

The results demonstrate that the proposed method maintains stable performance under these conditions, indicating its robustness to practical channel effects. The combination of entropy-based feature extraction and ML enables the system to generalize across varying channel realizations, making it suitable for deployment in dynamic wireless environments. The proposed method was designed for real-time operation. Each signal frame consists of 2048 samples, and the system processes 6000 frames in total. Assuming a typical SDR sampling rate, the frame duration is sufficient to enable real-time processing of entropy features and classification decisions.

The entropy computation and classification stages introduce minimal computational overhead, and the processing time per frame is significantly lower than the frame acquisition time. This ensures that the system can operate in real time without introducing latency or buffering issues.

Furthermore, the use of lightweight classifiers such as RF and SVM enables efficient deployment on embedded or SDR platforms with limited computational resources. The results demonstrate that the proposed approach is suitable for practical implementation in cognitive radio systems.

Recent studies have introduced latency-weighted performance metrics that jointly evaluate detection accuracy and computational delay. In this context, the proposed method demonstrates a favorable trade-off, achieving high detection probability while maintaining low processing latency [34]. This indicates strong delay-efficiency characteristics, consistent with the principles of latency-aware performance evaluation. The integration of explicit delay-weighted metrics is left for future work, in which both detection performance and latency can be jointly optimized under dynamic spectrum access constraints.

Although this work focuses on single-node spectrum sensing, the proposed entropy-based machine learning framework can be extended to cooperative Spectrum sensing in cognitive radio networks. In such a scenario, multiple secondary users can independently extract entropy-based features from locally observed signals and share either feature vectors or classification decisions with a central fusion node. Cooperative strategies, such as decision fusion or feature-level aggregation, can improve detection reliability by leveraging spatial diversity and mitigating channel effects, including fading and shadowing. The lightweight nature of the proposed entropy-based features and ML classifiers makes the approach suitable for distributed implementation. However, cooperative sensing introduces additional challenges, including communication overhead, synchronization, and node reliability management, which will be addressed in future work through multi-node SDR-based experimentation.

Another area of work is implementing a detection system in dense urban environments, where additional challenges arise, including high interference levels, multipath propagation, and non-stationary spectral activity. The entropy-based features used in this work are inherently robust to variations in signal distribution, which supports their applicability in such environments. Furthermore, ML models can adapt to greater complexity when trained on representative data. However, scaling to dense urban scenarios may require larger datasets, additional features, and possibly hybrid approaches to capture highly dynamic spectral behavior fully. Future work will focus on validating the proposed framework in heterogeneous urban environments using distributed SDR platforms.

Online adaptation in CNRs and in practical scenarios, and classifier updating in response to dynamic spectral environments, are other key challenges. Factors such as

concept drift, limited availability of labeled data, and real-time computational constraints complicate the deployment of adaptive learning mechanisms. In this context, future extensions of the proposed framework may incorporate incremental learning algorithms, sliding window retraining strategies, and semi-supervised approaches to enable continuous adaptation. The low computational complexity of entropy-based feature extraction makes it suitable for such extensions, as it facilitates efficient real-time updates. Additionally, hybrid architectures combining edge-based inference with centralized model updates could further enhance adaptability in large-scale CRN deployments.

7. Conclusions

This paper presented an entropy-based spectrum sensing framework enhanced with ML and implemented on an SDR platform. The proposed system leverages Shannon and Rényi entropy as discriminative features and employs classifiers such as SVM, KNN, and RF to determine spectrum occupancy in CRNs.

The experiments show that the model outperforms energy-detection methods, particularly in low-SNR environments. Detection probabilities and false-alarm results under realistic conditions confirm the effectiveness of combining entropy-based feature extraction with data-driven classification techniques.

The implementation on an SDR testbed validates the method's practical applicability and demonstrates that real-time spectrum sensing can be achieved using flexible, reconfigurable radio platforms. It helps to minimize the gap between theoretical models and real-world CRN deployments.

The study also confirms that entropy-based sensing is robust to noise, while ML enhances adaptability by learning complex decision boundaries. Among the evaluated models, RF showed the best performance, followed closely by SVM, indicating that ensemble and margin-based methods are well-suited for this application.

Future work should focus on deep learning, developing cooperative spectrum sensing, and implementing online and adaptive learning mechanisms, as well as lightweight implementations suitable for embedded and IoT devices. Additionally, exploring hybrid feature sets and deep learning to improve sensing accuracy and adaptability in highly dynamic spectral environments.

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