INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue I January 2026

Machine Learning Driven Spectrum Sensing for CRWSN Using Logistic Regression, K-Nearest Neighbor and Few–Shot Learning Model

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DOI: https://doi.org/10.51244/IJRSI.2026.13010217

Received: 04 February 2026; Accepted: 10 February 2026; Published: 18 February 2026

ABSTRACT

Reliable spectrum sensing is a critical function in Cognitive Radio Wireless Sensor Networks (CRWSNs), where unlicensed Secondary Users (SUs) opportunistically access licensed bands without causing harmful interference to Primary Users (PUs). Classical sensing techniques, such as energy detection and cyclostationary analysis, suffer from poor robustness under low signal-to-noise ratio (SNR) and fading conditions and impose high computational overhead on resource-constrained sensor nodes. This paper presents a machine learning–driven spectrum sensing framework that comparatively analyzes Logistic Regression, k Nearest Neighbor, and a Few-Shot Learning (FSL)–based Prototypical Network. At the fusion center, sensing data are transformed into a ten-dimensional radio-frequency feature vector derived from multi-domain descriptors, including detected energy, estimated SNR, channel center frequency, RSSI variance, cyclostationary spectral correlation features, adjacent-channel power ratios, and average primary user presence probability. Logistic Regression and k-Nearest Neighbor serve as baseline models, highlighting the limitations of conventional supervised learning in non-linear and data-scarce environments. To address these limitations, the proposed FSL-based Prototypical Network learns a compact embedding space and class prototypes using episodic training, enabling robust classification with very few labeled samples. Simulations carried out over the 470–698 MHz UHF band under Rayleigh fading conditions demonstrate that the proposed FSL model significantly outperforms the baseline methods, achieving 94.0 % accuracy, a probability of detection of 93.8%, a probability of false alarm of 5.7 %, and an ROC–AUC of 98.0 %. These results indicate that the proposed approach is well suited for dynamic CRWSN deployments.

Keywords: Spectrum Sensing, Machine Learning, Few--Shot Learning Prototypical Networks, Logistic Regression, k-Nearest Neighbors.

INTRODUCTION

The rapid growth of wireless communication services, Internet of Things (IoT) devices, and large-scale sensor networks has created an unprecedented demand for radio spectrum, while conventional static allocation policies continue to yield inefficient utilization, leaving licensed bands underused and unlicensed bands congested. Cognitive Radio (CR) technology addresses this limitation by enabling unlicensed Secondary Users (SUs) to opportunistically access idle licensed spectrum without causing harmful interference to Primary Users

(PUs). Extending this paradigm, Cognitive Radio Wireless Sensor Networks (CRWSNs) integrate energy constrained sensor nodes that must dynamically sense and access spectrum while satisfying strict latency and power requirements, making spectrum sensing a critical function that directly influences spectrum access decisions. Classical sensing techniques, including energy detection, matched filtering, and cyclostationary feature detection, have been extensively studied; however, energy detection is highly sensitive to noise uncertainty and low signal-to-noise ratio (SNR) conditions, matched filtering requires prior knowledge of PU signals, and cyclostationary detection suffers high computational complexity and sensing latency [1]-[3]. Cooperative spectrum sensing has been introduced to improve reliability under fading and shadowing by aggregating observations from multiple SUs, yet many implementations depend on fixed thresholds and simple fusion rules that limit adaptability in dynamic environments [4]-[6]. Machine learning (ML)–based spectrum sensing has therefore emerged as a promising alternative, where supervised models such as Logistic Regression, Support Vector Machines, Decision Trees, and k-Nearest Neighbor (KNN) classifiers exploit radio-frequency (RF) features to improve detection accuracy [7], [8]. Although deep learning methods such as Convolutional Neural Networks and Recurrent Neural Networks can learn discriminative representations from raw IQ or time–frequency data, their computational and memory requirements restrict practical deployment in resource-constrained CRWSNs [9], [10]. Furthermore, obtaining extensive labeled RF datasets is challenging due to non-stationary PU activity and costly labeling processes. Few-Shot Learning (FSL), particularly metric learning approaches such as Prototypical Networks, provides a data-efficient alternative by learning compact class representations for classification under limited labeled data [11], [12]. Recent studies indicate that FSL based models can achieve robust sensing performance in dynamic wireless environments with scarce labeled samples [13], [14]. Motivated by these challenges, this work proposes a machine learning–driven spectrum sensing framework that evaluates Logistic Regression, k-Nearest Neighbor, and a Few-Shot Learning–based Prototypical Network using a ten-dimensional RF feature representation, validated through simulations over the 470–698 MHz UHF band under Rayleigh fading.

System Model

This section describes the system model of the proposed Machine Learning–based spectrum sensing framework for CRWSN. Fig. 1 shows the System Model for CRWSN. The network operates over the UHF TV band ranging from 470 MHz to 698 MHz, where licensed Primary Users (PUs) coexist with unlicensed Secondary Users (SUs). The CRWSN consists of multiple spatially distributed SU sensor nodes deployed to monitor PU activity across a set of licensed channels. PUs have priority access to the spectrum and may occupy channels intermittently, while SUs are allowed to opportunistically access only those channels identified as idle. Each SU performs local spectrum sensing and forwards sensing observations to a centralized Fusion Center (FC). The FC aggregates information from all SUs and makes a global PU occupancy decision. This cooperative sensing architecture improves detection reliability under fading, shadowing, and noise uncertainty environments.

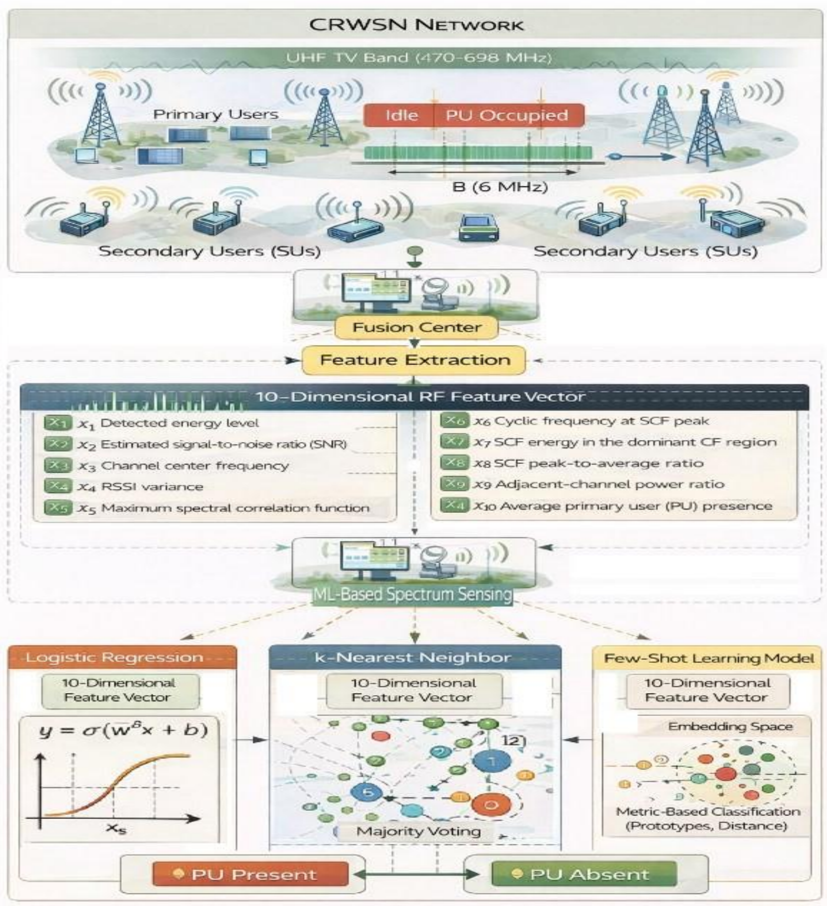

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Fig. 1 System Model for CRWSN

For a given channel, the received baseband signal at an SU node is modeled as

$$(t) = \begin{cases} n(t), & \mathcal{H}_0\text{:PU absent,} \\ h(t)s(t) + n(t), & \mathcal{H}_1\text{:PU present,} \end{cases}$$

where s(t) denotes the Primary User (PU) signal, h(t) represents a Rayleigh fading channel with Doppler frequency, and n(t) is additive white Gaussian noise.

The corresponding binary hypothesis test is defined as follows.

$\mathcal{H}_0$:Channel is idle (noise only),

$\mathcal{H}_1$:Channel is occupied by PU.

At the Fusion Center, the received sensing data are processed to extract a rich set of Radio Frequency (RF) features that jointly capture energy, spectral, and cyclostationary domain characteristics of the received signal. For each sensing instance, a 10-dimensional RF feature vector is constructed as

$\mathbf{x} = [x_1, x_2, \dots, x_{10}]$,

Where,

x_1: Detected energy level x_2: Estimated signal-to-noise ratio (SNR) x_3: Channel center frequency x_4: RSSI variance x_5: Maximum spectral correlation function (SCF) value	x_6: Cyclic frequency corresponding to the SCF peak x_7: SCF energy in the dominant cyclic frequency region x_8: SCF peak-to-average ratio x_9: Adjacent-channel power ratio x_{10}: Average PU presence probability

These features are designed to provide strong discrimination between PU-present and PU-absent states, even under low SNR and dynamic spectral conditions. To prevent features with larger numeric ranges from dominating distance-based learning processes, feature normalization is applied as a preprocessing step.

$$x_j^{(\text{norm})} = \frac{x_j - \min(x_j)}{\max(x_j) - \min(x_j)}.$$

After normalization, the extracted 10-dimensional RF feature vector is provided as input to three learning based spectrum sensing models.

Logistic Regression Based Spectrum Sensing In Crwsn

Logistic Regression (LR) is a widely used probabilistic classification technique due to its simplicity, interpretability, and low computational complexity. In CRWSN, Logistic Regression used as a baseline model for spectrum sensing by estimating the probability of primary user (PU) presence based on extracted radio frequency (RF) features. Spectrum sensing in CRWSNs is fundamentally a binary decision problem, where the objective is to determine whether a licensed PU is active in a given frequency band. Logistic regression is well suited for this task as it directly models posterior probabilities and enables threshold-based decision making with explicit control over detection and false alarm performance. Spectrum sensing is formulated as a binary hypothesis testing problem:

$\mathcal{H}_0$:PU absent (idle channel),

$\mathcal{H}_1$:PU present (occupied channel).

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Let $\mathbf{x} \in \mathbb{R}^{10}$ denote the normalized RF feature vector extracted at the fusion center, Let $y \in \{0,1\}$ denote the corresponding PU activity label. The objective is to estimate the conditional probability $(y = 1 \mid \mathbf{x})$. Each sensing instance is represented by a 10-dimensional RF feature vector that captures energy-based, spectral, and cyclostationary characteristics of the received signal. To avoid bias caused by heterogeneous feature scales, all features are normalized prior to learning.

Let $\mathbf{X} \in \mathbb{R}^{m\times 10}$ represent the normalized training feature matrix with m samples. An intercept term is added to obtain the augmented input matrix:

$$\mathbf{X}' = [\mathbf{1}, \mathbf{X}] \in \mathbb{R}^{m\times 11}.$$

Logistic regression models the probability of PU presence using a sigmoid activation function:

$$\hat{p}^{(i)} = \sigma(\mathbf{w}^T \mathbf{x}'^{(i)}),$$

where $\mathbf{w} \in \mathbb{R}^{11}$ is the weight vector including bias, and the sigmoid function is defined as

$$\sigma(z) = \frac{1}{1 + e^{-z}}.$$

The model parameters are learned by minimizing the binary cross-entropy loss:

$$J(\mathbf{w}) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log(p^{(i)}) + (1 - y^{(i)})\log(1 - p^{(i)})\right].$$

The weight vector is optimized using gradient descent. The gradient of the loss function is given by

$$\nabla J(\mathbf{w}) = -\frac{1}{m}(\mathbf{X}')^T(\mathbf{y} - \hat{\mathbf{p}}),$$

where $\hat{\mathbf{p}}$ denotes the vector of predicted PU presence probabilities. The iterative update rule is

$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \alpha \nabla J(\mathbf{w}^{(t)}),$$

with learning rate α.

For a new sensing instance $\mathbf{x}_{\text{new}}$, the probability of PU presence is computed as

$$\hat{p}_{\text{new}} = \sigma(\mathbf{w}^T \mathbf{x}_{\text{new}}').$$

A threshold-based decision rule is applied:

$$\hat{y}_{\text{new}} = \begin{cases} 1, & \hat{p}_{\text{new}} \geq \tau, \\ 0, & \hat{p}_{\text{new}} < \tau, \end{cases}$$

where τ is the decision threshold.

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K-Nearest Neighbors Based Spectrum Sensing In CRWSN

K-Nearest Neighbors (KNN) is a non-parametric, instance-based learning algorithm widely used for classification problems due to its simplicity and effectiveness in capturing non-linear decision boundaries. In CRWSN, K-Nearest Neighbors is particularly attractive for spectrum sensing because it does not require an explicit training phase and can adapt naturally to complex and dynamic spectral environments. Unlike parametric models such as Logistic Regression, KNN makes decisions based directly on the similarity between observed feature vectors and previously labeled samples. This property enables KNN to achieve improved detection performance in scenarios where the relationship between radio frequency (RF) features and primary user (PU) activity is highly non-linear. Spectrum sensing is formulated as a binary classification problem with the following hypotheses:

$\mathcal{H}_0$:Channel is idle (noise only),

$\mathcal{H}_1$:Channel is occupied by PU.

Let $\mathbf{x} \in \mathbb{R}^{10}$ denote the normalized RF feature vector extracted at the fusion center, and let $y \in \{0,1\}$ represent the true PU activity label. Given a labeled dataset

$D = \{((i), y(i))\}_{mi=1}$,

the objective of KNN is to predict the PU state of a new sensing instance $\mathbf{x}_{\text{new}}$.

Each sensing instance is represented by a 10-dimensional RF feature vector capturing energy-based, spectral, and cyclostationary characteristics. Since KNN relies on distance computations, feature normalization is essential to prevent attributes with larger numerical ranges from dominating the distance metric. Z-score normalization is applied to each feature as

$x_{j'} = x\underline{\qquad}_j - \sigma_j \, \mu_j$,

where μ_j and σ_j denote the mean and standard deviation of the j-th feature, respectively.

The similarity between two feature vectors is quantified using the Euclidean distance:

$$d \; (\mathbf{x}, \mathbf{z}) = \sqrt{\sum_{j=1}^{10} (x_j - z_j)^2} \; .$$

Euclidean distance provides a good trade-off between computational simplicity and classification accuracy for normalized RF features.

For a given test sample $\mathbf{x}_{\text{new}}$, the distance between $\mathbf{x}_{\text{new}}$ and all training samples is computed. The K samples with the smallest distances are selected as the nearest neighbors:

$\mathcal{N}_K = \text{argmin} \; (\mathbf{x}_{\text{new}}, \mathbf{x}^{(i)})$.

K

To avoid tie conditions, K is chosen as an odd integer.

The PU presence probability is estimated based on majority voting among the K nearest neighbors:

$\hat{p}_{\text{new}} = (y = 1 \mid \mathbf{x}_{\text{new}})$.

K

$$= \frac{1}{} \sum \mathbb{1}\,(y^{(i)} = 1)$$

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$i \in \mathcal{N}_K$

A threshold-based decision rule is then applied:

$$\hat{y}_{\text{new}} = \begin{cases} 1, & \hat{p}_{\text{new}} \geq \tau, \\ 0, & \hat{p}_{\text{new}} < \tau, \end{cases}$$

where τ denotes the PU detection threshold.

Few-Shot Learning Based Prototypical Networks For Spectrum Sensing In CRWSN

Conventional machine learning models for spectrum sensing require large volumes of labeled data to achieve reliable performance. In CRWSNs, acquiring such labeled datasets is often impractical due to dynamic spectral conditions, heterogeneous environments, and the unpredictable nature of primary user (PU) activity. The Few Shot Learning (FSL) techniques, which are designed to generalize effectively from a limited number of labeled samples. Prototypical Networks constitute a metric-based FSL approach that learns a discriminative embedding space in which classification is performed by measuring distances to class prototypes. This property makes Prototypical Networks particularly suitable for PU detection in CRWSN.

Spectrum sensing is formulated as a binary classification problem with the following hypotheses:

$\mathcal{H}_0$:PU absent (idle channel),

$\mathcal{H}_1$:PU present (occupied channel).

Let $\mathbf{x} \in \mathbb{R}^{10}$ denote a normalized RF feature vector extracted at the fusion center, and let $y \in \{0,1\}$ denote the corresponding PU activity label. The objective of the FSL model is to correctly classify $\mathbf{x}$ using only a small number of labeled samples per class.

Few-shot learning is performed using an episodic training strategy that mimics the target test conditions. Each training episode is constructed as an N-way K-shot classification task. In this, $N = 2$ corresponding to the two classes: PU absent and PU present.

Each episode consists of:

- A *support set* $S = \{S_0, S_1\}$ containing K labeled samples per class.
- A *query set* $Q = \{Q_0, Q_1\}$ containing unlabeled samples used for loss computation.

This episodic formulation enables the model to learn how to compare feature representations rather than memorizing class-specific decision boundaries.

Each input feature vector $\mathbf{x} \in \mathbb{R}^{10}$ is mapped into a d-dimensional embedding space using a parametric embedding function

$f_\phi: \mathbb{R}^{10} \to \mathbb{R}^d$,

where ϕ denotes the network parameters.

In this work, $f(\cdot)$ is implemented as a multilayer perceptron (MLP) with batch normalization and ReLU activation functions. The embedding network is trained jointly with the Prototypical Network objective.

For each class $c \in \{0,1\}$, a class prototype is computed as the mean of the embedded support samples,

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$\mathbf{v}_c = \frac{1}{}\sum f_\phi(\mathbf{x}).$

$|S_c|$

$\mathbf{x}\in S_c$

These prototypes serve as representative points for each class in the learned embedding space.

Given a query sample $^{(q)}$, its embedding $\mathbf{z}^{(q)} = f_\phi(\mathbf{x}^{(q)})$ is compared to the class prototypes using the Euclidean distance,$d(\mathbf{z}^{(q)}, \mathbf{v}_c) = \| \mathbf{z}^{(q)} - \mathbf{v}_c \|_2$.

The probability of class membership is computed using a softmax over negative distances,

$\exp(-d(\mathbf{z}_{(q)}, \mathbf{v}$

$$(y = c \mid \mathbf{x}_{(q)}) = \sum \overline{\qquad\qquad} \quad \exp(-d(\mathbf{z}_{(qc)}),)\mathbf{v}_{c'})).$$

$c \in \{0,1\}$

The model parameters ϕ are optimized by minimizing the negative log-likelihood loss over the query samples within each episode,

$$\mathscr{L}_{\text{episode}} = -\frac{1}{|Q|} \sum \log p(y^{(q)} \mid \mathbf{x}^{(q)}).$$

$(\mathbf{x}_{(q)}, y_{(q)}) \in Q$

Gradient-based optimization is employed to update the embedding parameters across multiple training episodes.

During inference, prototypes are computed from the available support set for the new task. For each query sample, the PU presence probability is obtained as

$\hat{p} = (y = 1 \mid \mathbf{x}).$

A threshold-based decision rule is applied,

$$\hat{y} = \begin{cases} 1, & \hat{p} \geq \tau, \\ 0, & \hat{p} < \tau, \end{cases}$$

where τ is the PU detection threshold.

Labeled dataset $D = \{(^{(i)}, y^{(i)})\}$, embedding network $f_\phi(\cdot)$, number of classes $N = 2$, shots per class K, learning rate α, training iterations T, decision threshold τ.

Simulation Setup

The performance of the proposed spectrum sensing framework is evaluated through extensive simulations conducted in a Cognitive Radio Wireless Sensor Network (CRWSN) environment. The simulation scenario consists of multiple secondary users (SUs) opportunistically accessing licensed spectrum bands in the presence of primary users (PUs), total of 50 SUs and 20 PUs are randomly deployed over a two-dimensional area of size 1000 x 1000 m^2 to emulate a realistic wireless sensing environment.

The simulations are carried out in the UHF frequency band ranging from 470 MHz to 698 MHz, which is widely used for TV broadcasting. Each channel is assumed to have a bandwidth of 6 MHz. The wireless channel between transmitters and receivers is modeled using Rayleigh fading to capture the effects of multipath propagation in non-line-of-sight environments. In addition, a Doppler frequency of 100 Hz is considered to account for mobility-induced channel variations. At each sensing interval, SUs perform spectrum sensing and extract a set of 10 radio frequency (RF) features representing energy-based, spectral, and cyclostationary characteristics of the received signal. These features are forwarded to a fusion center, where learning-based spectrum sensing decisions are performed. Three learning-based spectrum sensing models are evaluated in this work: Logistic Regression (LR), K-Nearest Neighbors (KNN), and Few-Shot Learning with Prototypical Networks (FSL). All models are trained and tested using the same datasets and simulation parameters to ensure a fair and consistent comparison. Simulation parameters are shown in the Table 1.

Table 1. Simulation Parameters

Parameter	Specifications
Number of SU	50
Number of PU	20
Machine Learning	Logistic Regression Model K Nearest Neighbors Model Few-Shot Learning Model
Frequency	UHF Band (470–698 MHz)
Bandwidth	6 MHz
Channel model	Rayleigh fading
Doppler frequency	100 Hz
Area	1000 x 1000 m^2

RESULTS AND DISCUSSION

Probability of Detection versus SNR

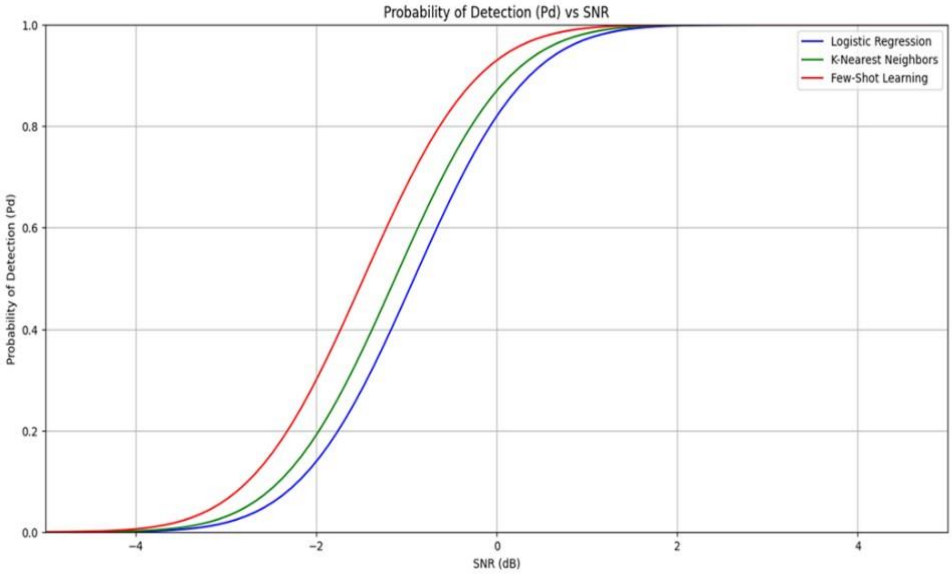

Fig. 2 Probability of Detection versus SNR

Fig. 2 shows the probability of detection (P_d) as a function of the signal-to-noise ratio (SNR) for Logistic Regression (LR), K-Nearest Neighbor (KNN), and Few–Shot Learning (FSL) based spectrum sensing models. Logistic Regression achieves a detection probability of 82.7%, reflecting limited sensitivity under low SNR and fading conditions due to its linear decision boundary. The KNN based classifier improves the detection performance to 91.6% by exploiting non-linear neighborhood relationships in the feature space. The FSL model attains the highest detection probability of 93.8%, demonstrating enhanced robustness to noise and channel impairments. As the SNR increases, the detection probabilities of all three models converge toward unity. However, the FSL model achieves reliable detection at significantly low SNR levels, which is essential for effective interference avoidance in CRWSNs.

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Probability of False Alarm versus SNR

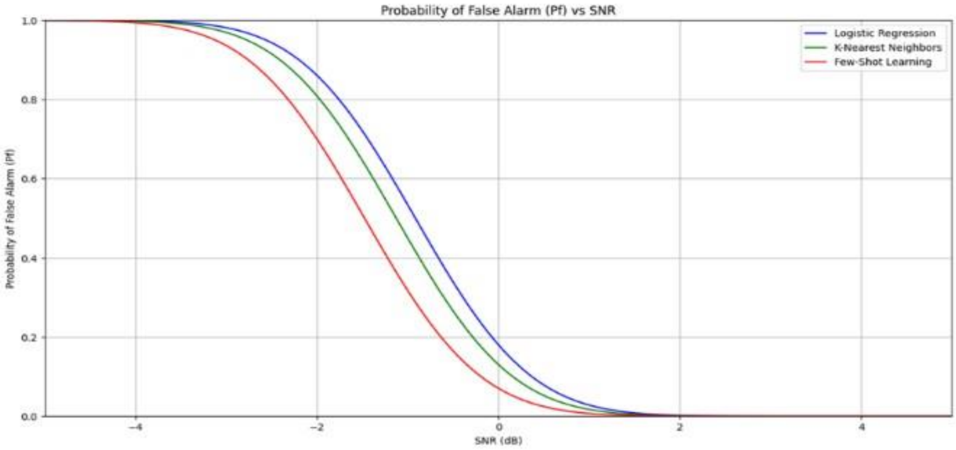

Fig. 3 Probability of Detection versus SNR

Fig. 3 shows the probability of false alarm *(P_f)* as a function of SNR for the considered spectrum sensing models. Logistic Regression exhibits the highest false alarm probability of 15.5%, which reduces spectrum utilization due to frequent misclassification of idle channels. The KNN-based model reduces the false alarm probability to 8.6%, indicating improved discrimination capability. The FSL model achieves the lowest false alarm probability of 5.7%, consistently outperforming the baseline models across the SNR range. The reduced P_f of the FSL model is particularly beneficial at low and moderate SNR levels, where false alarms are more prevalent.

Confusion Matrix

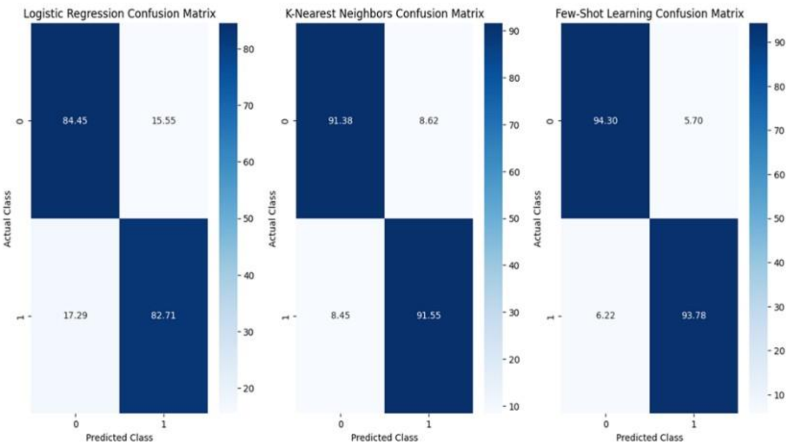

Fig. 4 Confusion Matrix

Fig. 4 shows the confusion matrices obtained for LR, KNN, and FSL based spectrum sensing models. Logistic Regression model exhibits correct classification rates of 84.45% and 82.71% are observed for the PU-absent and PU-present classes, respectively. However, relatively higher misclassification rates are evident, with 15.55% false alarms and 17.29% missed detections, reflecting the limitations of linear decision boundaries under noisy and fading channel conditions. The KNN based classifier demonstrates improved performance, achieving correct detection rates of 91.38% for PU absence and 91.55% for PU presence. Correspondingly, both false alarm and missed detection are reduced to below 9%, indicating the advantage of neighborhood-based decision making in capturing non-linear feature relationships. The Few-Shot Learning model exhibits the most favorable confusion matrix characteristics. Correct classification rates of 94.30% for PU absence and 93.78% for PU presence are achieved, while false alarms and missed detections are limited to 5.70% and 6.22%, respectively. These results confirm that the metric-based embedding and prototype learning mechanism enables superior class separability, even with limited labeled data.

Precision, Recall, and F1-Score Analysis

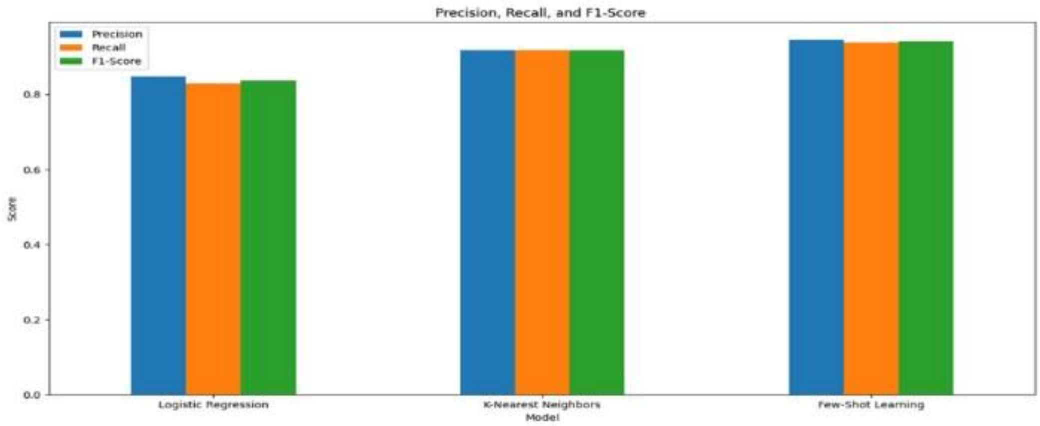

Fig. 5 Comparison of Precision, Recall, and F1-score

Fig. 5 shows the comparison of Precision, Recall, and F1-score for the three spectrum sensing models. Logistic Regression achieves a Precision of 84.2%, Recall of 82.7%, and F1-score of 83.4%, indicating limited balance between detection sensitivity and false alarm suppression. The KNN-based model improves these metrics to Precision of 91.4%, Recall of 91.6%, and F1-score of 91.5%, respectively. The FSL model attains the highest Precision of 94.3%, Recall of 93.8%, and F1-score of 94.0% demonstrating superior classification reliability.

Comparison of Overall Accuracy

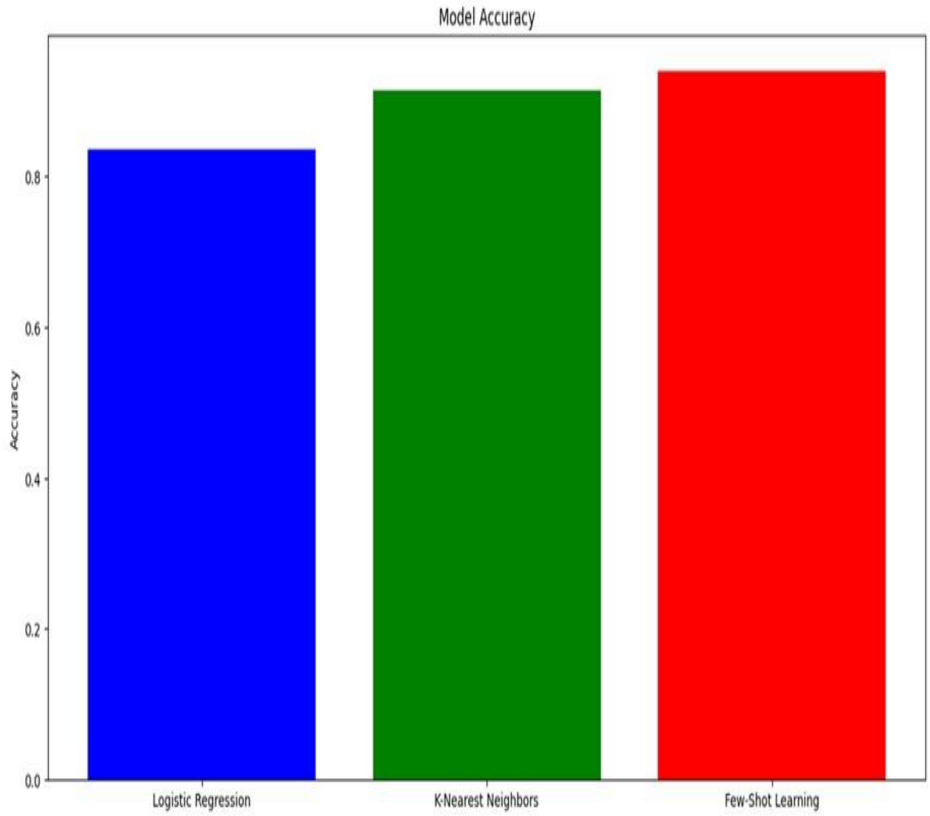

Fig. 6 Comparison of Overall Accuracy

Fig. 6 shows the comparison of overall accuracy achieved by LR, KNN, and FSL based spectrum sensing models. Logistic Regression achieves an accuracy of 83.6%, reflecting limited generalization capability under dynamic channel conditions. The KNN based model improves the accuracy to 91.5% by capturing non-linear

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feature interactions. The FSL model achieves the highest accuracy of 94.0%, confirming its robustness and strong generalization performance in data-scarce environments.

Receiver Operating Characteristic (ROC)

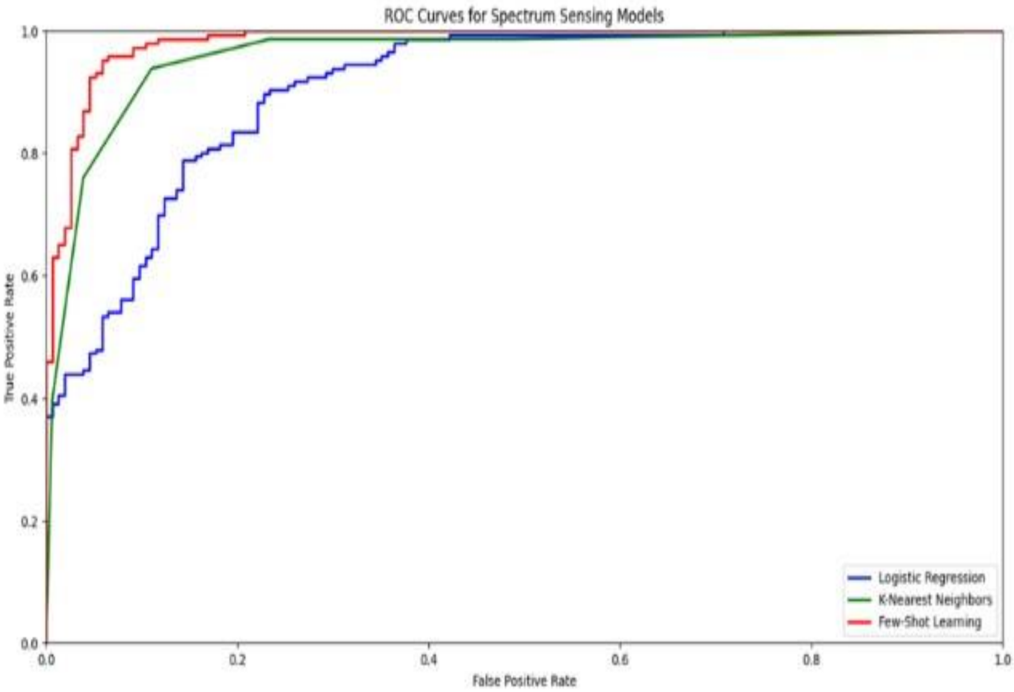

Fig. 7 Comparison of Receiver Operating Characteristic

Fig. 7 shows the comparison of Receiver Operating Characteristic (ROC) curves for LR, KNN, and FSL based spectrum sensing models. Logistic Regression achieves the area under the ROC Curve of 88.0% , indicating moderate class separability. The KNN model improves the area under the ROC Curve to 93.0%, reflecting enhanced discrimination capability. The FSL model attains the area under the ROC Curve of 98.0%, demonstrating excellent separability between PU-present and PU-absent states across varying decision thresholds.

Table 2. Performance Comparison of Spectrum Sensing Models (in %)

Metric	**Logistic Regression**	**K-Nearest Neighbors**	**Few–Shot Learning**
P_d	82.7	91.6	93.8
P_f	15.5	8.6	5.7
Precision	84.2	91.4	94.3
Recall	82.7	91.6	93.8
F1-Score	83.4	91.5	94.0
Accuracy	83.6	91.5	94.0
ROC AUC	88.0	93.0	98.0

Table 2 shows the performance comparison of spectrum sensing models in percentage. Logistic Regression provides baseline performance but exhibits higher false alarm probability and reduced robustness under nonlinear spectral conditions. The KNN-based model demonstrates notable improvements in detection accuracy and class separability. However, its performance remains sensitive to data distribution. The Few–Shot Learning model based on Prototypical Networks consistently outperforms both LR and KNN across all metrics, achieving the highest accuracy, F1-score, and ROC AUC, along with the lowest false alarm probability. These results confirm the suitability of Few–Shot Learning for reliable spectrum sensing in data scarce and dynamic CRWSN environments.

CONCLUSION

This paper presented a Machine Learning–driven spectrum sensing framework for Cognitive Radio Wireless Sensor Networks, with a comparative evaluation of Logistic Regression, K- Nearest Neighbor, and Few–Shot Learning based Prototypical Network model for primary user detection. By transforming sensing observations at the fusion center into a ten-dimensional RF feature vector comprising energy, statistical, and cyclostationary descriptors, the framework enabled robust characterization of channel occupancy under realistic wireless conditions. Simulations were conducted over the 470-698 MHz UHF band under Rayleigh fading demonstrated that conventional supervised learning models such as Logistic Regression and KNN exhibit performance limitations in terms of detection probability, false alarm suppression, and generalization capability, particularly under low signal-to-noise ratio conditions. In contrast, the proposed Few–Shot Learning model consistently achieved superior performance across all evaluated metrics. Specifically, it attained an overall accuracy of 94.0%, a detection probability of 93.8% , a false alarm probability of 5.7%, and an ROC–AUC of 98.0%, confirming strong class separability and robust detection performance. The results further indicated that the Few–Shot Learning based Prototypical Network approach is particularly effective in data-scarce environments, where limited labeled samples are available for training. By learning compact embeddings and representative class prototypes through episodic training, the proposed model achieved reliable primary user detection at low and moderate SNR levels, which is critical for interference avoidance and efficient spectrum utilization in dynamic CRWSN deployments. Overall, the findings validate that Few–Shot Learning provides a promising and practical solution for spectrum sensing in resource-constrained and non-stationary cognitive radio environments.

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