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Physics-Informed Neural Networks for Sensing Radio Spectrum for NextGen Wireless Networks

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Abstract**:** ***Sensing radio bands to improve the spectrum sharing capability for emerging wireless networks is crucial. In recent years, numerous data-driven models have been applied to detect radio bands. However, these approaches often suffer from poor generalization due to limited and noisy training data. To address this, domain-specific physical knowledge is incorporated into the neural network training through a physics loss term that regularizes feature representations towards an ideal feature vector extracted from reference (noiseless high-SNR) signal. The feature vector comprises higher-order moments, including energy metrics derived from the received signal samples. The proposed physics-informed neural network (PINN) jointly minimises a standard binary cross-entropy loss and a physics-based squared Euclidean distance loss, balancing empirical risk with physical consistency via a tunable hyperparameter. Extensive simulations over a wide range of SNR values and multiple physical regularization strengths demonstrate that PINN significantly outperforms conventional energy and artificial neural networks-based sensing models. The proposed PINN model can sense signals down to -12 dB at Pd ≥ 90% with a lower dataset size compared to traditional data-driven models, achieving the same performance. The proposed work highlights the benefit of integrating physical priors into neural network models for spectrum sensing. It opens pathways for enhanced cognitive radio designs capable of reliable signal detection under practical channel impairments.***

Index Terms**:** ***Physics-Informed Neural Network, Spectrum Sensing, Signal-to-noise ratio, Detection accuracy, ROC curves***

Abbreviations:
PINN: Physics-Informed Neural Network
NNs: Neural Networks
DL: Deep Learning
CR: Cognitive Radio
PDEs: Partial Differential Equations
ROC: Receiver Operating Characteristic

I. INTRODUCTION

The exponential growth of wireless networking technologies and the increasing number of connected devices have dramatically altered the demand for radio spectrum resources.

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Advanced wireless networks, including cognitive radio (CR) systems, aim to support spectrum sharing by enabling dynamic spectrum access [1]. Sensing radio channels is critical for cognitive radios to opportunistically exploit underutilized spectrum without causing harmful interference. Accurate and reliable spectrum sensing is therefore crucial for enhancing spectrum efficiency, improving network capacity, and ensuring coexistence among heterogeneous wireless systems [2]. This capability is particularly vital for emerging fifth-generation (5G and beyond) wireless networks [3], where massive device connectivity and diverse service requirements demand flexible and efficient spectrum utilisation [4].

Traditional statistical-based sensing techniques have been extensively studied and deployed due to their relative simplicity and low implementation complexity [5]. However, these models are critically limited due to their uncertain detection threshold [6]. Alternatively, in recent years, threshold-independent data-driven models have been applied to sense radio bands [7]. Neural networks (NNs) have shown superiority by learning complex features and non-linear relationships from data, enabling improved detection accuracy [8]. These approaches can exploit subtle patterns in received signal characteristics that classical detectors often miss. While these models demonstrate superior performance under certain conditions, their effectiveness heavily depends on the availability of large, labelled datasets that accurately represent diverse wireless scenarios [9]. The authors in [10] performed deep learning (DL)-based sensing under low-SNR conditions using multiple features extracted from the received signal, which can sense only a signal with a -13 dB signal with 90% accuracy [11]. A Few Hybrid models that can improve sensing accuracy using a combination of ML, CNN, LSTM, RNN, and Auto-encoders in [12], [13]. However, the complexity of these models is high. Additionally, the most existing ML-based sensing methods treat the problem as a black-box learning task, ignoring the underlying physical features of wireless propagation, namely path loss, fading, and noise statistics [14].

A significant research gap exists in effectively combining domain-specific physical knowledge with data-driven learning to enhance spectrum sensing performance, particularly under limited training data and a challenging SNR environment. Reliable sensing ensures that cognitive users can adaptively access the spectrum, maintaining coexistence with primary users and preventing interference. The effectiveness of spectrum sensing has a direct impact on the overall network performance, including throughput, latency, and energy efficiency. Consequently, developing robust and accurate spectrum sensing techniques is critical for realizing the full potential of advanced wireless networks.

By embedding known physical relationships as regularization in terms of constraints in the loss function, Physics-Informed Neural Networks (PINN) models effectively guide the learning process toward physically consistent solutions [15]. This approach not only improves model generalization but also reduces dependence on large, labelled datasets, which are especially valuable in scenarios with limited or noisy training samples. PINNs can leverage prior knowledge about signal features, propagation effects, and channel impairments to regularize the neural network's feature representations. Integration combines physical laws with data learning to improve signal detection. It increases accuracy and reliability, even in low signal or hostile environments.

Raissi et al. [16] initially introduced the concept of PINNs to solve partial differential equations (PDEs) by embedding physical laws into the training process of neural networks. Recently, PINNs have been applied to wireless communications for channel estimation and localization [17], demonstrating improved robustness and accuracy. To the best of our knowledge, the application of PINNs to spectrum sensing, particularly for modulation schemes such as 4-QAM under noisy channel conditions, remains largely unexplored. Existing works do not adequately address how physics-based constraints can regularize feature learning to improve detection accuracy in low SNR regimes.

The goal of this work is to develop a novel PINN-based sensing model for scanning radio bands under noisy wireless channel conditions. The proposed approach aims to integrate physical knowledge about signal features, such as average energy and higher-order moments, directly into the neural network training via a physics loss term. This term regularizes the learned features towards an ideal feature vector extracted from noiseless high-SNR signals, thereby enhancing detection accuracy and robustness against noisy and outlier data environment where traditional data-driven models often fail.

The organization of the remaining paper is as follows: Section II details the problem statement, feature extraction process, and the proposed PINN architecture including the physics-informed loss function. Section III presents simulation results comparing the proposed PINN with baseline data-driven methods across various SNR regimes. Finally, Section IV concludes the proposed work and recommends directions for future studies.

II. Problem Statement and Methodology

The proposed PINN model is illustrated in a block diagram (Fig. 1), which highlights the key stages of sensing radio bands. The process begins with the reception of an in-band signal over the 5G NR FR-1 band at a single cognitive radio node. This received signal is passed through a preprocessing block, where it is segmented into discrete time samples and transformed into a 4-dimensional feature vector comprising average energy and higher order moments (variance, kurtosis, and maximum magnitude). These extracted features are then fed into a PINN model, which consists of a standard feed-forward neural architecture augmented with a physics loss module. During training, PINN minimizes a hybrid loss function, combining binary cross-entropy (for supervised classification) with a physics loss that measures the squared distance between extracted features and an ideal feature vector derived from clean, high-SNR in-band modulation signal. This physics constraint guides the network to learn representations that are not only discriminative but also physically plausible. The output of the network is a binary decision: either an in-band signal is present or not.

We consider the binary hypothesis test:

$$\mathcal{H}_0 : r[n] = w[n] \quad \dots \quad (1)$$

$$\mathcal{H}_1 : r[n] = H_c \cdot \frac{s[n]}{d^{\alpha}} + w[n] \quad \dots \quad (2)$$

Where, d is the transmitter-receiver distance, α is the path loss exponent, $s[n]$ is a digital modulated signal (complex 4-QAM symbol), the vector $w[n] \sim \mathcal{CN}(0, \sigma^2)$ is a channel with a white Gaussian noise signal. $\mathbf{H_c}$ is an ideal channel matrix.

A. Methodology

i. Feature Extraction:

Let $r[n] = [r(0), r(1), \dots, r(N-1)]$ be the received sampled in-band signal. The four-dimensional feature vector, $F \in \mathbb{R}^4$ is extracted as follows:

The average energy (power) feature F_1 can be estimated as [18]:

$$F_1 = \frac{1}{N} \sum_{n=0}^{N-1} |r[n]|^2 . \quad \dots \quad (3)$$

The higher-order moments (F_2, F_3, F_4) can be computed as [19]:

$$F_2 = \frac{1}{N} \sum_{n=0}^{N-1} (|r[n]| - \mu)^2 , \quad \dots \quad (4)$$

where, μ is the mean of a received signal/vector.

$$F_3 = \frac{\frac{1}{N} \sum_{n=0}^{N-1} (|r[n]| - \mu)^4}{\left(\frac{1}{N} \sum_{n=0}^{N-1} (|r[n]| - \mu)^2\right)^2 + \varepsilon} \quad \dots \quad (5)$$

$$F_4 = \max_{0 \le n \le (N-1)} |r[n]| \quad \dots \quad (6)$$

1) ***Energy Detection (ED)***: Under $\mathcal{H}_0$ noise only, the average energy $= \frac{1}{N} |w[n]|^2$ is approximately:

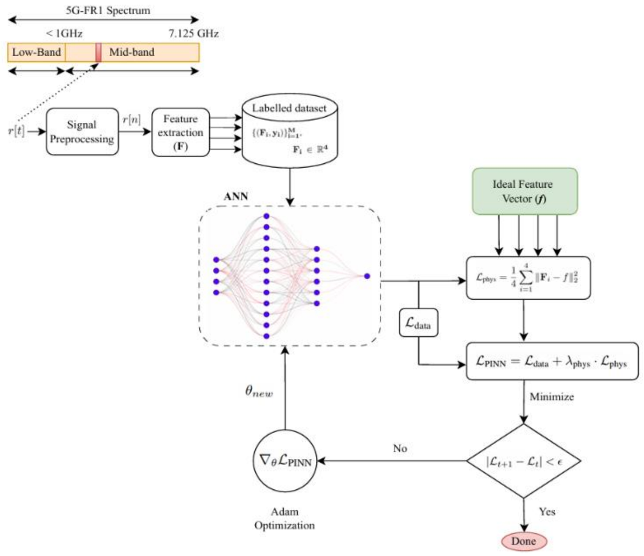
$$F_1 \sim \mathcal{N}\left(\sigma^2, \frac{2\sigma^4}{N}\right) \quad \dots \quad (7)$$

For a false alarm probability P_{fa}, the threshold λ is [21]:

$$\lambda = \sigma^2 \left(Q^{-1}(1 - P_{fa}) \cdot \sqrt{\frac{2}{N}} + 1 \right) \quad \dots \quad (8)$$

The decision rule is,

$$\hat{H} = \begin{cases} \mathcal{H}_1 & \text{if } F_1 > \lambda \\ \mathcal{H}_0 & \text{otherwise} \end{cases} \quad \dots \quad (9)$$



[Fig.1: Proposed PINN Model for Sensing Radio Spectrum Over 5G FR1 Bands]

2. ***Artificial Neural Network (ANN):*** Let the training dataset $\{(F_i, y_i)\}_{i=1}^{M}$,where $F \in \mathbb{R}^4$ is the feature vector size and $y_i \in \{0,1\}$ is the binary-class label corresponding to the i^{th} feature vector. Prediction output of an ANN model based on the training dataset can be represented as [20]:

$$\sigma(z) = \sigma(\theta_2 \cdot \phi(\theta_1 \cdot f + b_1) + b_2) \quad \ldots \quad (10)$$

Where, $\sigma(\cdot)$ is the Sigmoid activation function with a weighted sum z defined as $\sigma(z) = \frac{1}{1+e^{-z}}$.The letter θ_i is a weight vector to the i^{th} hidden layer, $\phi(\cdot)$ is ReLU activation, $\phi(z) = \max(0, z)$.

The decision rule is,

$$\hat{H} = \begin{cases} \mathcal{H}_1 & \text{if } \sigma(z) > 0.5 \\ \mathcal{H}_0 & \text{otherwise} \end{cases} \quad \ldots \quad (11)$$

Binary cross-entropy loss (Data Loss) is given by,

$$\mathcal{L}_{data} = -\frac{1}{M}\sum_{i=1}^{M}\left[z\log(\sigma(z)) + (1-z)\log(1-\sigma(z))\right]. \quad \ldots \quad (12)$$

Where M is the number of entries (records) available for training, $z \in (0,1)$ and $\sigma(z)$is a predicted probability.

The weight parameter update formula using gradient descent optimization (GDO) can be expressed as,

$$\theta_{new} \leftarrow \theta_{old} - \eta \cdot \nabla_\theta \mathcal{L}_{ANN}, \quad \ldots \quad (13)$$

where, θ_{new} is the updated weight (model parameter), η is a learning rate, $\nabla_\theta \mathcal{L}_{ANN}$ is the gradient of the loss function concerning the corresponding weight.

3. ***Physics-Informed Neural Network (PINN):*** This sensing model contains an ANN with a physics loss function [14]. The model is trained with a combined loss:

$$\mathcal{L}_{PINN} = \mathcal{L}_{data} + \lambda_{phys} \cdot \mathcal{L}_{phys} \quad \ldots \quad (14)$$

Where λ_{phys} is a hyperparameter controlling the weight of the physical constraint.

Binary cross-entropy loss ($\mathcal{L}_{data}$) is given by,

$$\mathcal{L}_{data} = -\frac{1}{M}\sum_{i=1}^{M}\left[z\log(\sigma(z)) + (1-z)\log(1-\sigma(z))\right] \quad \ldots \quad (15)$$

Where M represents the number of entries or records available for training.

Let $\mathbf{f}$ be the ideal feature vector extracted from a high-SNR signal. Physics loss encourages the extracted feature vector to be close to $\mathbf{f}$:

The physics loss $(\mathcal{L}_{phys})$ is defined as,

$$\mathcal{L}_{phys} = \frac{1}{4}\sum_{i=1}^{4}\|F_i - f\|_2^2 \quad \ldots \quad (16)$$

Where,

$\|\cdot\|_2^2$denotes the squared Euclidean norm,$F \in \mathbb{R}^4$is the feature vector for the received sample/ signal. The feature vector (***F***) contains four values: $F = [F_1, F_2, F_3, F_4]$. The vector $f \in \mathbb{R}^4$is the prior (ideal) feature vector, extracted from a clean, noiseless digital modulated signal at a very high SNR, The squared Euclidean distance to the ideal vector $\mathbf{f}$ is:

$$\|F - f\|_2^2 = (F_1 - f_1)^2 + (F_2 - f_2)^2 + (F_3 - f_3)^2 + (F_4 - f_4)^2 \quad \ldots \quad (17)$$

Update the neural network parameters using the gradient descent (Adam) optimizer:

$$\theta_{new} = \theta_{old} - \eta \cdot \frac{\hat{m}}{\sqrt{\hat{v}} + \varepsilon}. \quad \ldots \quad (18)$$

Where, $\hat{m}$ and $\hat{v}$ are bias-corrected and second-order moments (mean and variance of gradients), respectively. The letters α and ε are the constraints to avoid an unstable condition. The decision rule is

$$\hat{H} = \begin{cases} \mathcal{H}_1 & \text{if } \sigma(z) > 0.5 \\ \mathcal{H}_0 & \text{otherwise} \end{cases} \quad \ldots \quad (19)$$

III. SIMULATION RESULTS

A. Simulation Setup

In this study, we simulate a single-node spectrum sensing scenario for detecting digitally modulated signals under noisy wireless conditions with a carrier frequency in the 5G FR1 range. The transmitted signal comprises randomly generated bits modulated using 4-QAM, which is then passed through a wireless channel characterised by path loss and white Gaussian noise [14]. The received signal is modelled as: $r[n] = H_c \cdot \frac{s[n]}{d^\alpha} + w[n]$, where d is the transmitter-receiver distance, $\alpha = 2$ is the path loss exponent (free space). Sensing radio band is a binary classification problem: detect whether a 4-QAM signal is present (signal + noise) or absent (noise only). For each signal segment, we extract a 4-dimensional feature vector ***F*** that comprises the average energy, variance, kurtosis, and maximum magnitude. Datasets of 10,000 training and 2,000 testing samples per class, featuring vectorised class labels, are derived from high-SNR noiseless signals and serve as the physical prior in the Physics-loss function.

The proposed PINN model is a lightweight feed-forward neural network with two

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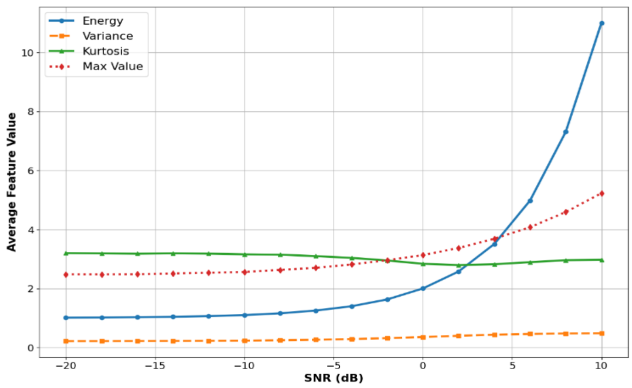
hidden layers consisting of 32 and 16 ReLU-activated neurons, respectively. It is trained using a hybrid loss function: binary cross-entropy (BCE) for label supervision and a physics loss that penalises the squared Euclidean distance between the extracted features and the ideal vector$\mathbb{F}$. A hyperparameter (λ_{phys}) controls the influence of the physical term. The Adam optimizer is eployed with a learning rate η of 0.001, batch (or number of records) size of 64, training the model until 100 epochs, and applied early stopping. Model performance is evaluated based on detection accuracy, receiver operating characteristic (ROC) curves, and the area under the curve (AUC). Comparisons are made between PINN and an ANN (with $\lambda_{phys} = 0$) model. The objective is to demonstrate that incorporating physical constraints enhances the robustness of the neural network model's detection, especially in low SNR and path loss environments.

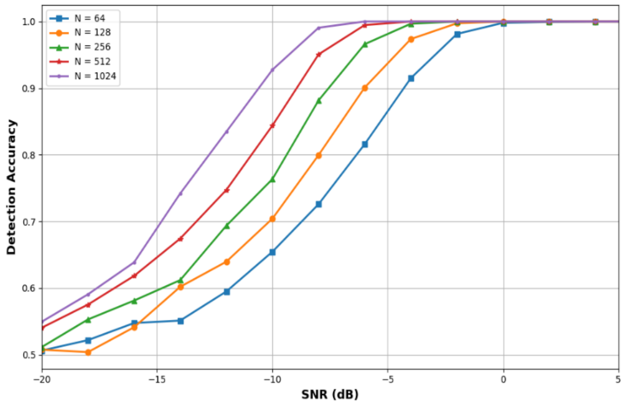
B. Results and discussions

The plotted results in **Fig. 2** demonstrate how the extracted signal features vary across different SNR levels for 4-QAM signals, assuming H1 (i.e., an in-band signal is present) is true. As the SNR increases, the average energy feature F_1 increases, indicating that the stronger signals are more easily distinguishable from noise. Similarly, the variance also increases, reflecting greater dispersion in signal amplitudes with higher signal strength. In contrast, kurtosis decreases with rising SNR, implying a transition from noise-dominated to more structured signal distributions. The maximum magnitude also increases with SNR, showing that signal peaks become more pronounced as the signal becomes clearer. All four features exhibit a consistent monotonic relationship with SNR, indicating their suitability for use as discriminative features in radio band sensing. These results support the design of feature-aware models such as PINNs, which benefit from such reliable feature behaviour across varying SNRs.



[Fig.2: Variation of Extracted Signal Features with SNR for 4-QAM Signals Under Hypothesis H1]

The plotted results in **Fig. 3** illustrate the impact of SNR and sample size N on the detection accuracy of the proposed PINN model based on 4-QAM signals. As the SNR increases from -20 dB to 10 dB, detection accuracy improves consistently across all values of N. Larger values (e.g., N = 512 and 1024) exhibit higher accuracy at low SNRs due to the improved statistical reliability of the extracted features. At higher SNRs, even smaller N values perform well, showing that the PINN effectively leverage both physical prior and data features. The physics constraint contributes to regularising learning, especially in low SNR regimes. Overall, the results validate the applicability of PINN for sensing radio bands.



[Fig.3: Detection Accuracy of PINN vs. SNR for Varying Sample Sizes N]

The ROC plot in **Fig. 4** shows the performance of a PINN model in detecting received QAM signals under varying SNR conditions. As SNR increases from -20 dB to 0 dB, the ROC curves move closer to the top-left corner, indicating improved detection capability. The AUC values increase correspondingly, reflecting better discrimination between signal-present and signal-absent cases at higher SNRs. At low SNRs (e.g., -20 dB), the AUC is approximately 0.5, indicating a random-like performance due to noise dominance. However, as the SNR improves, the AUC approaches 1.0, indicating 100% reliable signal detection. The result highlights that PINN effectively integrates signal features and physical constraints to improve detection accuracy under noisy conditions.

The Precision–Recall plot in Fig. 5 illustrates the PINN's performance in detecting 4-QAM signals at varying SNR levels (-12 dB, -10 dB, and -8 dB). At a lower SNR (-12 dB), both precision and recall are relatively low, indicating a higher frequency of misclassifications due to noise dominance. As SNR improves to 10 dB and 8 dB, the curves shift upward and to the right, reflecting better model confidence and fewer false positives and false negatives. The improvement in recall, accompanied by minimal loss in precision, demonstrates that PINN is effectively learning to detect signals even in moderately noisy conditions. At -8 dB, the curve is significantly higher, confirming that the model becomes more reliable as the signal becomes clearer. This indicates that the physics-informed loss helps reinforce decision boundaries, particularly when signal features are consistent with physical constraints. The plotted results in Fig. 6 clearly illustrate how detection accuracy improves with increasing SNR for all three techniques: average energy, ANN, and the proposed PINN detection models.

At very low SNR values (e.g., -20 dB to 0 dB), average energy detection performs poorly, as expected, due to its inability to distinguish the signal from noise in boisterous conditions. The ANN model outperforms the average energy detection across all SNR values, thanks to its

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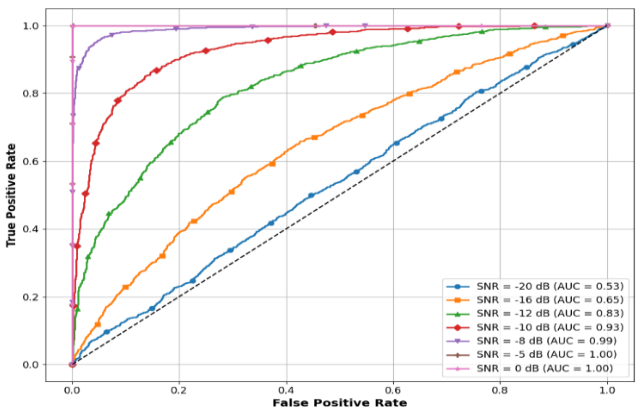
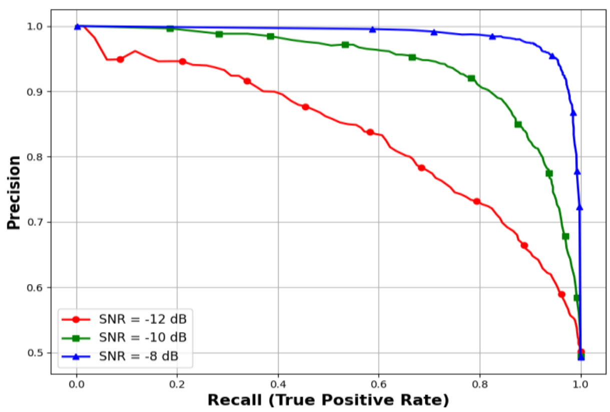
ability to learn complex patterns in the extracted features.



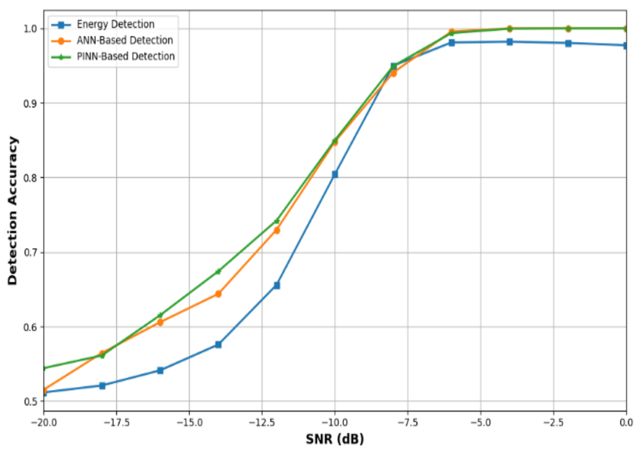
[Fig.4: Detection Performance of PINN Across SNRs: ROC and AUC Analysis]

Notably, the proposed PINN approach consistently outperforms both, especially in the negative SNR range, where physics-informed constraints augment learning. As the SNR approaches 0 dB, the performance gap narrows, with all models reaching high accuracy levels.



[Fig.5: Precision-Recall Performance of PINN for 4-QAM Signal Detection at Low SNR Levels]

This confirms that while data-driven models, such as ANN, are effective, embedding physical knowledge (as in PINN) enhances robustness in challenging noise environments while requiring less data. Therefore, PINN offers a promising approach for spectrum sensing in low-SNR scenarios.



[Fig.6: Comparisons of Detection Accuracy vs. SNR for Energy Detection, ANN, and PINN Models]

IV. CONCLUSION

The study explored the efficacy of the PINN model for sensing 5G NR FR1 radio bands under varying SNR conditions, with a particular focus on detecting digital modulated signals. By incorporating domain-specific physical constraints, such as expected signal average energy, variance, and kurtosis, into the training process, the PINN was able to leverage both data-driven learning and theoretical knowledge to improve detection performance. The results were compared against conventional energy detection and a data-driven ANN approach. Simulation results demonstrate that the PINN-based detector consistently outperforms both energy detection and ANN-based detection, particularly in low-SNR regimes ranging from -20 dB to -6 dB. At extremely low SNRs (e.g., -20 dB), all models struggle, but PINNs still offer a noticeable advantage due to their ability to exploit prior knowledge of signal behaviour. As the SNR increases, the gap between methods narrows, with all models achieving high detection accuracy above -4 dB. Nevertheless, the robustness of PINNs in adverse conditions underscores their potential in practical wireless environments where signals are often weak as the distance increases. These findings highlight the advantage of integrating physical priors into machine learning architectures, especially in signal processing applications where domain knowledge is well-established. Future work will investigate extending this approach to more complex modulation schemes, increasing the feature vector size, and conducting real-world measurements to validate the scalability and generalizability of the proposed PINN-based sensing model.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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