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Performance Evaluation of the K-Means-LSTM Hybrid Model for Optimization of Spectrum Sensing in Cognitive Radio Networks

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Abstract – CR (cognitive radio) technology has become an attractive field of research owing to the increased demand for spectrum resources. One of the duties of this technology is spectrum sensing which involves the opportunistic identification of vacant frequency bands for occupation by unlicensed users. Various traditional and state of art Machine-Learning algorithms have been proposed for sensing these vacant frequency bands. However, the common drawbacks of the proposed traditional techniques are degraded performance at low signal-to-noise ratios (SNR) as well as the requirement for prior information about the licensed user signal characteristics. More so, several Machine-Learning / Deep Learning techniques depend on simulated, supervised, and static (batch) spectrum datasets with synthesized features, which is not the case with real-world networks. Hence, this study aims to optimize real-time and dynamic spectrum sensing in wireless networks by establishing and evaluating a K-means-LSTM novice model (artifact) that is robust to low SNR and doesn't require a supervised spectrum dataset. Firstly, the unsupervised spectrum dataset was collected by an RTL-SDR dongle and labelled by the K-means algorithm in MATLAB. The labelled spectrum dataset was utilized for training the LSTM algorithm. The resultant LSTM model's performance was evaluated and compared to other commonly used spectrum detection models. Findings revealed that the proposed model established from the K-Means and LSTM algorithms yielded a *Pd* (detection probability) of 94%, *Pfa* (false-alarm probability) of 71%, and an accuracy of 97% at low SNR such as -20 dB, a performance which was superior to other models' performance. Using our proposed model, it is possible to optimize real-time spectrum sensing at low SNR without a prior supervised spectrum dataset.

Index Terms – Spectrum Sensing, Cognitive Radio, K-Means-LSTM, SNR, Signal–to–Noise Ratio, Detection Probability, Pfa (False-Alarm Probability), Optimization.

1. INTRODUCTION

The global demand for wireless communication services has seen an unprecedented increase due to factors like the expansion of wireless networks such as 5G, IoT, mobile devices, and disruptive technologies [1]. However, this surge in demand has created a significant shortage of available frequency bands, known as spectrum resources, which are essential for wireless networks to function. The scarcity of spectrum resources was recognized as a major challenge for the future of wireless communications by the International Telecommunication Union (ITU), a specialized agency of the United Nations [1]. In their report "The State of Broadband 2019," the ITU highlighted that over 50% of the global population still lacks internet access due to limited spectrum availability [1]. This was confirmed by [2] who revealed that frequency bands are underutilized since the licensed users do not utilize the allocated spectrum to maximum capacity. Spectrum scarcity is primarily caused by government regulatory bodies rigidly allocating the available frequency bands to licensed operators. Surprisingly, despite this shortage, most of the spectrum allocated to licensed users remains underutilized. In the context of Africa where this research was conducted, spectrum scarcity has been reported to be an issue by the Independent Communications Authority of South Africa (ICASA) due to the shortage of techniques for spectrum management [2]. ICASA emphasized the need for dynamic spectrum management techniques to support the country's digital transformation and stimulate economic development. The limited availability of spectrum resources hinders the expansion of wireless services, especially in rural areas, and fails to meet the growing demand for data connectivity. The CR (Cognitive radio) technology has gained remarkable popularity as a solution to the spectrum shortage

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problem. It incorporates spectrum sensing, which involves opportunistically detecting unoccupied frequency bands for data transmission.

1.1. Problem Statement

The efficient utilization of spectrum has become an increasingly important issue in the field of wireless communication. With the ever-growing demand for wireless services and the limited availability of spectrum resources, there is a critical need to explore the proposed spectrum sensing novel techniques. Various spectrum sensing technologies and techniques have been proposed and investigated for optimizing dynamic spectrum utilization. However, some limitations still need to be addressed such as the degraded performance of energy detection at low SNR, the requirement for prior information about the licensed user signal characteristics by both the cyclostationary feature-based and the matched filter-based detectors, the utilization of mostly static labelled datasets for developing and evaluating the proposed machine learning (ML) and deep learning (DL) techniques, which are not reflective of real-world scenarios. Based on these limitations, this research focused on optimizing spectrum sensing in wireless networks by evaluating a novel hybrid model that was robust at low SNR and is entirely blind (doesn't require prior licensed user information / labelled spectrum datasets). The proposed hybrid model developed from the K-means and LSTM (K-means-LSTM) algorithms was validated using a real-world spectrum dataset for real-time spectrum sensing.

1.2. Aim and Study's Objectives

This study aimed at evaluating the performance of an entirely blind (doesn't necessitate prior licensed user information / supervised spectrum datasets) K-means-LSTM hybrid model, using a real-world dataset for spectrum sensing optimization. The study accomplished the following objectives.

1. To identify the limitations of the existing traditional and machine learning spectrum-sensing techniques in wireless networks.
2. To propose an artifact (model) for optimizing spectrum-sensing in wireless networks using machine learning algorithms.
3. To analyze (evaluate) the performance of the proposed spectrum-sensing model in spectrum-sensing optimization.

Efficient techniques should be in place to optimize spectrum sensing (SS). This study's remaining part is as follows: Section 2 covers the study's background and related studies, the study's methods are articulated in Section 3, the findings are presented in Section 4, and Section 5 presents the discussion of the results. Section 6 addresses the limitations inherent to the study. Section 7 concludes the study.

2. RELATED WORK

2.1. Spectrum Sensing

Spectrum sensing, also known as spectrum detection, enables unlicensed users to gain information about a wireless network by detecting the presence of signals from licensed users (primary users) and deciding whether they can transmit within the same frequency band [3]. Spectrum detection (sensing) is represented as follows:

$$x(n) = \begin{cases} a(n) & H_0\text{: } licensed\ user \text{ is absent} \\ y * s(n) + a(n), & H_1\text{: } licensed\ user \text{ is present} \end{cases} \quad (1)$$

n from Equation (1) depicts the sample of spectrum operators [4]. The state H_1 signifies the licensed user's presence, whereas H_0 denotes the absence. From Equation (1), $x(n)$ denotes the signal that the unlicensed (secondary) user received, and $s(n)$ denotes the signal that the licensed user propagates. The additive (mixed) noise signal to the propagated signal $s(n)$ is denoted by $a(n)$. The gain for the transmission channel, for instance, a transmission antenna is signified by y. The licensed user signal's presence is determined by comparing the output of the detector, (often termed the test statistic), and the predetermined threshold [4]. The decision is calculated as shown in Equation (2):

$$\begin{cases} \text{if } T \geq t, & H_1 \\ \text{if } T < t, & H_0 \end{cases} \quad (2)$$

Where t denotes the threshold and T presents the spectrum detector's test statistic. The "*Probability of detection*/P_d" as well as the "*Probability of false alarm*/ Pfa" are the metrics to assess the detector's performance [4].

From Equation (3), P_d is the possibility that T accurately determines H_1

$$P_d = P\{\text{ detector's output } = (H_1/H_1)\} = P\left\{T > \frac{t}{H_1}\right\} \quad (3)$$

From Equation (4), Pfa is the possibility that T determines H_0 as H_1

$$Pfa = P\{\text{ detector's output } = (H_1/H_0)\} = P\{T > t/H_0\} (4)$$

There are two categories of spectrum sensing which are non-collaborative (co-operative) and collaborative (co-operative) sensing approaches [4]. The non-cooperative sensing approach, involves one user scanning the frequency bands and making a decision on vacant or occupied frequency bands. On the other hand, the cooperative approach involves multiple users cooperating to achieve a common decision. The predominant traditional techniques in spectrum sensing encompass MF (matched-filter detection), autocorrelation detection energy detector, and wavelet detection [4]. Considering the energy detector shown in Figure 1, the energy of the received signal is computed as the squared magnitude of the fast Fourier transform (FFT) over N unique samples.

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This value, when averaged over the sample set, is compared with a pre-determined threshold to infer the sensing decision.

If the computed energy surpasses this threshold, the licensed operator is inferred to be present. Conversely, if the energy is found to be below the threshold, the licensed operator is considered absent. Figure 1 indicates the energy detection approach.

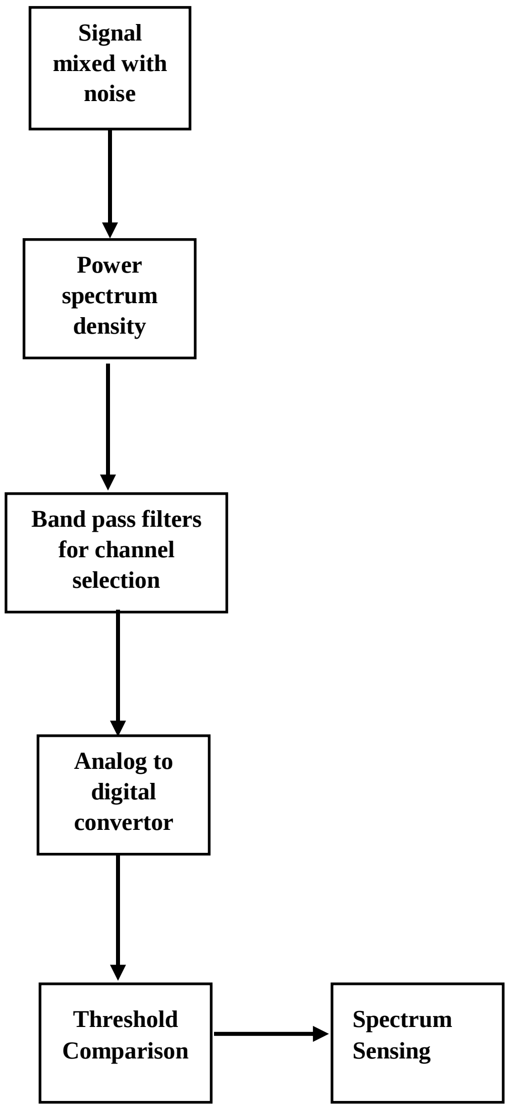

Figure 1 The Energy Detection Approach [5]

This technique is easy to apply because we do not need any prior knowledge about the licensed user (supervised dataset) as opposed to other techniques [4]. Nonetheless, this approach's performance is poor at low SNR (signal-noise ratios).

The matched filter shown in Figure 2, matches the received unknown signals with the test primary user signals, convolves them over N samples, and compares the output with the predefined threshold. The licensed user is present if the predefined threshold is lower than the convolution output [5]. The licensed user is deemed absent if the threshold value exceeds the convolution output. At low SNR, this technique performs well relative to the energy detector although increasing the sample degrades the performance.

The drawback of the matched filter is it necessitates prior knowledge concerning the licensed user. In practice, this previous information on the licensed users is not always available, rendering this technique impractical and unreliable. Figure 2 presents the matched filter process.

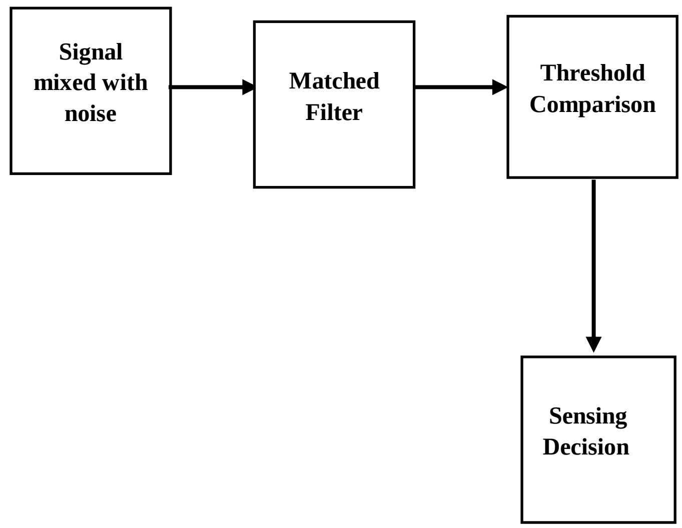

Figure 2 The Matched Filter Detection [5]

The cyclostationary detection (autocorrelation detector) shown in Figure 3 computes a correlation function using a time-shifted form of the N samples for the signal it received [6].

If the correlated function's output exceeds the predefined threshold, the licensed user signal's presence is portrayed; otherwise, the licensed user's signal is absent if the threshold value exceeds the correlated function [6].

However, this technique is computationally complex as opposed to other traditional techniques. The waveform detection (wavelet-based) method presented in Figure 4 is one of the most reliable traditional spectrum detection techniques [7]. This method functions by correlating the reference and incoming signals' waveforms [7].

The drawback of this method is highly accurate information on licensed operators is required. Nevertheless, this is a mammoth task in reality since the licensed users have no prior knowledge concerning these licensed operators' signals.

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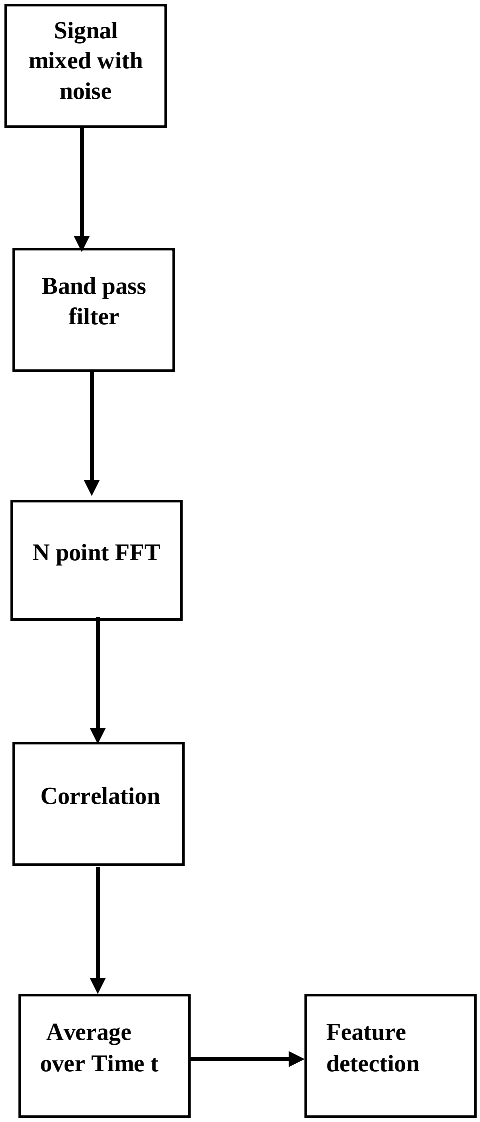

Figure 3 The cyclostationary Detection Approach [5]

2.2. Related Studies on Spectrum Sensing

A related study by [8] adopted a novel energy detector incorporating multiple antennas and a dynamic threshold selection to optimize spectrum detection performance. The authors evaluated the performance of their proposed approach through extensive simulations. They compared their approach with an existing energy detection technique in terms of *Pfa* and *Pd*. Their findings delineated that the proposed method displayed a significant detection accuracy, in conditions characterized by noise uncertainty and fading channels where two or more antennas were adopted. Despite yielding the *Pd* of 1 at SNR below -15 dB, the evaluation of the proposed method was solely based on simulation results, which may not fully represent real-world scenarios. The work by [9] improved the traditional energy detector by integrating it with the matched filter detector.

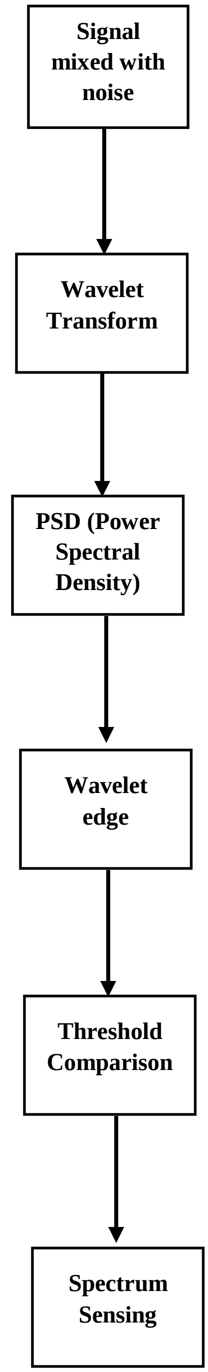

Figure 4 Wavelet-Based Spectrum Detection [5]

The ROC curves, *Pd*, accuracy, and the *Pfa* false-alarm probability were adopted for evaluating the model's detection performance. Their findings revealed that the enhanced energy detector was superior to the traditional energy detector

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at diminished SNR levels. Degraded energy detection's performance at very low SNR and the requirement of the licensed user information by the matched filter detector were the study's drawbacks, [10] introduced a matched filter detector with a dynamic threshold to optimize spectrum sensing. The proposed matched filter was compared to other techniques, including the autocorrelation technique and energy detection. The evaluation was conducted based on two metrics: *Pd* and *Pfa*. The results showed that the proposed matched filter outperformed the other techniques. It achieved a detection probability of 0.5, whereas the autocorrelation technique and the matched filter detector achieved 0.15 and 0.12, respectively. Simulation findings pinpointed that the energy detector was easy to implement and did not require prior information about the licensed user. However, its performance degraded at low signal-to-noise ratios (SNRs) such as -20 dB and -15 dB, leading to increased false alarm probability. The dynamic threshold employed in the matched filter showed reliability at low SNRs. However, it had the drawback of requiring previous information on the occupied frequency bands of the licensed user, which is not practically feasible in wireless networks [11]. Argued that hybrid techniques outperform single-existing techniques when it comes to spectrum sensing. The authors combined two detection techniques, the cyclostationary, and the energy detector, for bolstering the spectrum sensing capabilities. Cyclostationary detection was adopted in low SNR environments for compensating the energy detection's poor performance at low SNR. The authors also adopted a time domain cyclostationary detector, which had a simpler structure and lower computational complexity compared to a frequency domain detector. The findings of their study revealed that the proposed hybrid detector outperformed both the cyclostationary and energy detection-based schemes in terms of *Pd* and *Pfa*. The authors also evaluated cooperative (collaborative) spectrum sensing (CSS) using the hybrid method and demonstrated its superior performance compared to CSS using only cyclostationary or energy detection-based schemes. While the study highlighted the simulation results to evaluate the proposed approach, the absence of real-world validation or experimental validation with hardware as well as the requirement of prior data about the licensed user limits the assessment of its practicality under real-world conditions. A related study by [12] introduced a ResNet model for spectrum classification. The authors implemented normalization to the received signal for removing irregularities. The simulation results indicated that the proposed ResNet method outperformed traditional approaches in terms of both Pd and Pfa. However, It is worth noting that the model was established upon simulated signals rather than real-world ones. This limitation should be taken into account when considering the applicability of the findings in practical scenarios. Hybrid models that integrate various techniques have been proposed to address the limitations of individual methods for the optimization of spectrum sensing [13]. Argued that hybrid techniques were superior to single techniques for optimizing spectrum sensing. The study employed a non-cooperative spectrum sensing technique that integrated the cyclostationary feature and energy detectors. MATLAB was adopted to simulate the spectrum dataset and the proposed algorithm. The findings presented a higher Pd and a lower Pfa as opposed to traditional techniques. Despite promising findings from this study, the study focused only on MATLAB simulations, lacking real-world validation. A related study by [14] echoed the argument by [13] by combining a clustering technique with reinforcement learning and expected maximization (EM) techniques. The proposed approach sought to optimize the sensing performance at low SNR. The authors argued that their proposed hybrid approach minimized energy consumption in spectrum sensing and enhanced the spectrum allocation efficiency. While simulation findings revealed that the established hybrid model outperformed the existing traditional techniques at low SNR values, the absence of real-world experiments restricted the approach's evaluation outside of simulation environments. The study by [15] conducted a comparative analysis of the SVM as well as the KNN for spectrum detection. The authors applied *Pd* and *Pfa* to evaluate the techniques' detection performance. The KNN demonstrated superior detection of vacant frequency bands as opposed to the SVM. However, one limitation of their study was the lack of emphasis on the models' performance in unsupervised (unlabelled) datasets. The study by [16] sought to optimize spectrum sensing by proposing the CNN-LSTM hybrid approach. The CNN was adopted for feature extraction and the LSTM was for learning the licensed user activity and detecting whether frequency bands were occupied or vacant. The study evaluated the efficiency of the CNN-LSTM detector through extensive simulations conducted in scenarios without and with noise uncertainty. Simulation findings showed that the proposed hybrid model was superior to the existing spectrum sensing detectors. The findings presented that the detector's ability to extract spatial and temporal features improved the detection probability at low SNR. Although the hybrid CNN-LSTM detector performed well at low SNR, its drawback was that it focused on evaluating its performance through extensive simulations but did not provide real-world validation. Their study was deficient in empirical data from practical deployments of the CNN-LSTM detector.

The review of the related studies revealed that spectrum sensing plays a crucial role in enabling efficient spectrum utilization and dynamic spectrum access. However, several limitations still need to be addressed including, the degraded performance of energy detection at low SNR, the requirement for previous information about the licensed user signal characteristics by both the cyclostationary feature-based and the matched filter-based detectors, the evaluation of most

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proposed ML and DL techniques using static labeled (supervised) datasets which are not available in real-world scenarios and the lack of real-world validation by widely proposed hybrid techniques. Based on these limitations, this research focuses on establishing a novel K-means-LSTM hybrid model that is robust at low SNR and is entirely blind (doesn't require prior licensed user information / labeled spectrum datasets).

The proposed approach will be validated using a real-world spectrum dataset for real-time spectrum sensing. To the best of our understanding, no related work has explored these techniques for the optimization of spectrum sensing. LSTM automatically selects features and reduces detection error, therefore reducing noise. The K-means algorithm does not require primary user information before spectrum detection since it learns from unsupervised data.

2.3. Contribution

Three key contributions were made by this study. To begin, it offered a novel K-Means-LSTM hybrid model that did not rely on prior licensed user signal information or supervised spectrum data, hence full blind operation. Furthermore, even at low SNR settings, our model displayed robust detection ability. Second, rather than using simulated data, the hybrid model was developed with a real-world spectrum dataset received from the RTLSDR dongle.

The application of this dataset increased the applicability and realism of the study. Third, utilizing the aforementioned real-world spectrum dataset, the study performed real-time spectrum sensing to test the performance of the proposed K-means-LSTM model. This validation process was a significant improvement compared to most related studies' approaches.

3. METHODS

This research proposed a novice model (artifact) that was robust at low SNR and doesn't necessitate prior licensed user information (supervised spectrum dataset) from the K-means and LSTM algorithms, for optimizing spectrum sensing. Algorithm 1 presents the pseudocode for implementing the proposed model. K-Means is an unsupervised learning technique that divides an unlabelled dataset into classes [17].

The algorithm starts with an unlabelled spectrum dataset, divides it into k clusters, and then repeats till it does not identify the best clusters [17]. LSTM a variant of RNN possesses a capacity to learn extended sequences [18]. Every LSTM network consists of three gates that regulate information flow and cells that store information. The cell shown in Figure 5 carry information from the beginning to the end of the time step without vanishing. Figure 6 presents the design framework of the proposed model. The implementation steps are discussed in the following subsections:

3.1. Data Collection

Firstly, the unsupervised spectrum dataset was gathered using the RTL-SDR dongle Sandton, Johannesburg. Figure 7 presents the data collection setup. The dongle was connected to the antenna that was used to capture the spectrum dataset. The antenna receives the radio signals and then transmits them to the RTL-SDR Dongle. For this study, an RTL-SDR scanner was utilized for scanning the frequency bands. The RTL-SDR scanner is a spectrum analyzer that was used for scanning, capturing, and analyzing radio signals. The spectrum analyzer which was open source was installed in the Proline desktop with 2GB RAM, a core i3 processor, and 500GB storage. The spectrum dataset was saved in CSV format for analysis.

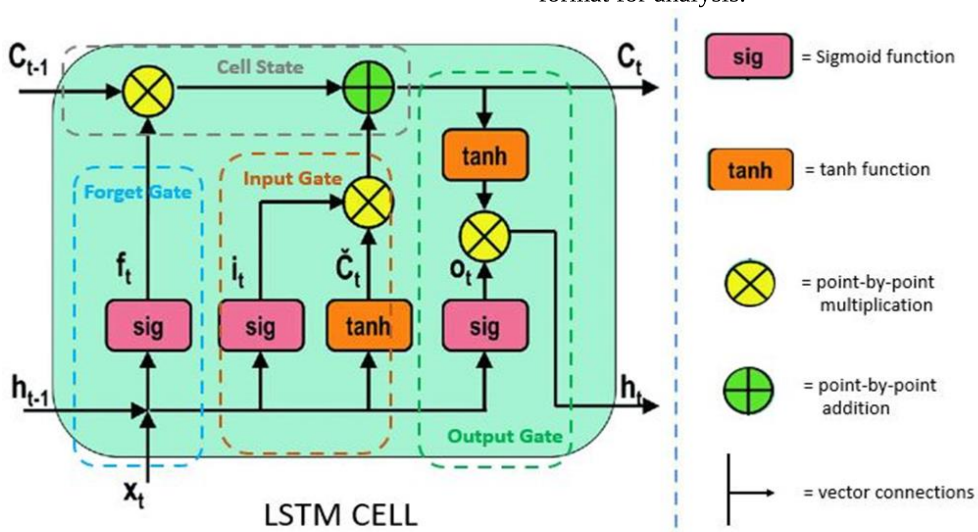

Figure 5 LSTM cell [18]

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START

K-means

Input: unsupervised spectrum dataset

Output: labelled spectrum dataset

Step 1: Choose k to determine the number of clusters from the unsupervised spectrum dataset

Step 2: At random, select k instances, then assign them to the clusters.

Categorize the dataset using k instances.

Step 3: The centrorids for the clusters can be computed

Step 4: Repeat the next steps till the best centroid is identified, which involves the assignment of instances to non-varying clusters.

a. Firstly, squared distances sum between the data instances and the centroids would be computed.

b. Each instance is assigned to the cluster nearest to others.

c. Lastly, the clusters' centroids is computed from the clusters' all of the data instance average.

LSTM

Input: spectrum dataset labelled by the K-means

Output: spectrum sensing (vacant and occupied frequency bands)

Step 5: procedure TRAIN(Epochs, Batch size, normalised X, normalised y, α) X is an independent variable and y is a dependent variable of the lablelled spectrum dataset

Step 6: for $i \leftarrow 1$ to Epochs do

Step 7: spectrum_sensing, label ← extract(Dataset, Batch_size)

Step 8: Random training examples are extracted according to the batch size.

Step 9: Output ← Forward Propagate (LSTM_model, spectrum_sensing) [19].

Step 10: Error ← Backward Propagate (LSTM_model, label, output) [19].

Step 11: Parameters ← Update(error, LSTM_model, α) α is the learning rate.

Algorithm 1 Proposed K- Means-LSTM Model

3.2. Data Description

Table 1 Presents an Overview of the Spectrum Dataset

Time (UTC)	Frequency(MHz)	Power/ dB
1388354774.95	400.000000	-102.74
1388354774.95	400.009765	-104.23
1388354774.95	400.019531	-103.44
1388354774.95	405.029296	-102.92
1388354774.95	407.039026	-103.57

The sample spectrum dataset presented in Table 1 which consisted of 1700 frequencies at various amplitudes (power) was considered for this study. It consisted of 1700 rows and 3 attributes. Rows contained the frequency band instances. Frequency ranged from 400 MHz to 700 MHz. The attributes were Time (UTC), Frequency (MHz), and Power (dB). The Time (UTC) was dropped in Microsoft Excel as it was not used by the models for frequency band detection. Table 1 presents an overview of the spectrum dataset. After dropping the UTC attribute, the dataset remained as shown in Table 2.

Table 2 Spectrum Dataset after Dropping the Time (UTC) Column in Microsoft Excel

Frequency(MHz)	Power/ dB
400.000000	-102.74
400.009765	-104.23
400.019531	-103.44
405.029296	-102.92
407.039026	-103.57
410.048828	-102.60
411.058593	-102.74
417.078125	-103.70
415.068359	-103.37

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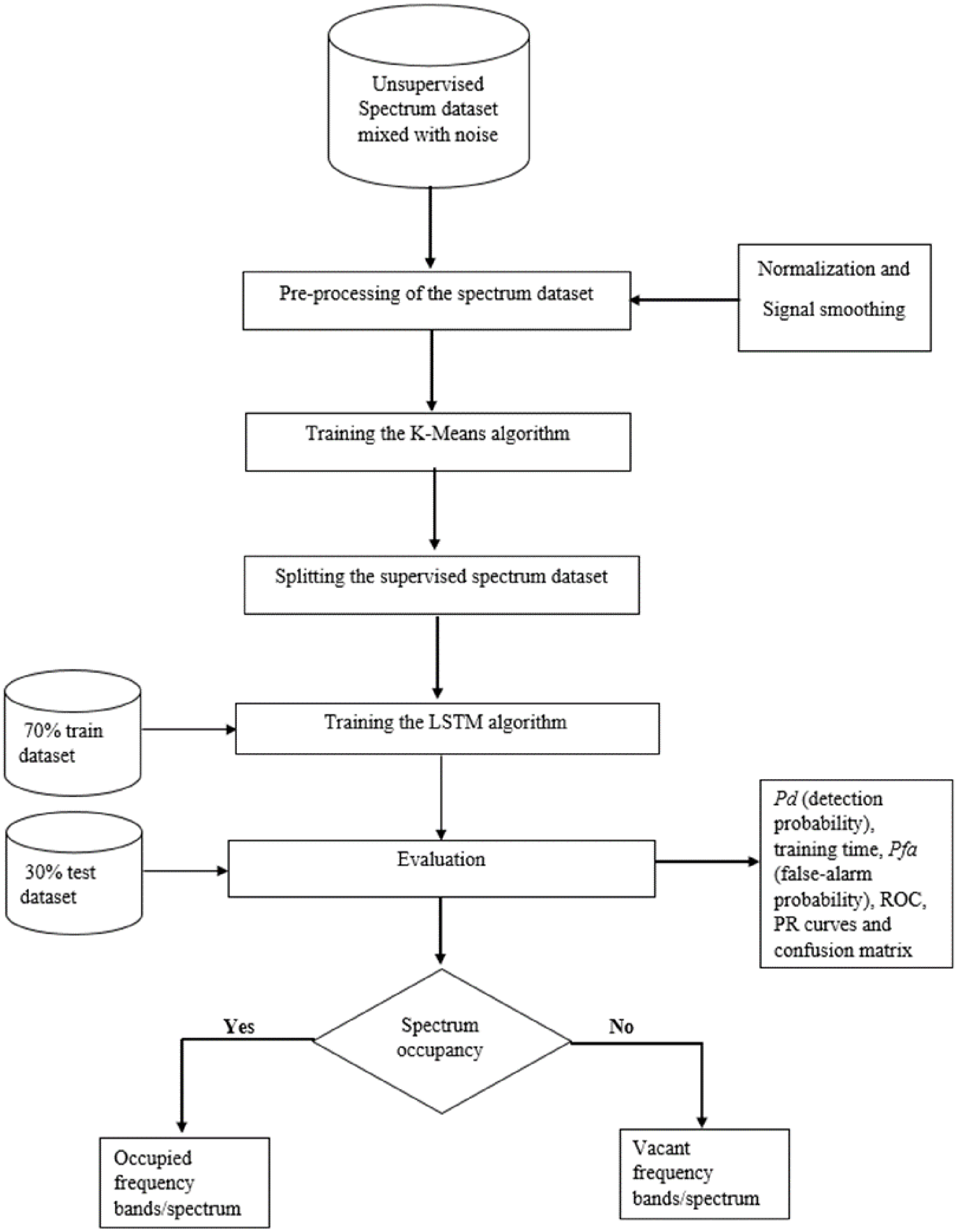

Figure 6 Proposed K-Means-LSTM Model Framework

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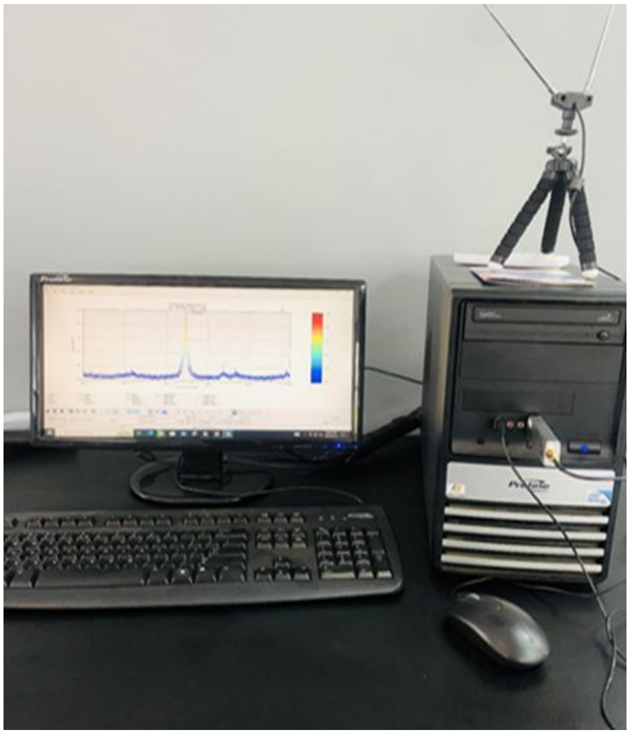

Figure 7 Indicating the Setup for Data Collection

3.3. Dataset Preprocessing

This stage, included spectrum data normalization, signal smoothing, transforming attributes, and splitting the dataset. The spectrum dataset was imported into MATLAB for analysis. The noise signal in the range of -20 dB to 20 dB, mixed with the imported spectrum dataset was emulated using MATLAB's *awgn()* function. After importing the spectrum dataset, the average moving filter of length (window size) 10 was applied for signal smoothing (to remove outliers/irregularities in the dataset). The imported dataset was normalized for features (Power and Frequency) to have a uniform scale (values in the same range). Normalization was an essential procedure for improving the model's accuracy in detecting vacant frequency bands. Pseudocode 1 shows the implementation of the average moving filter and data normalization.

3.4. Training the K-Means Algorithm

Initially, the K-means clustering algorithm was applied for labelling the frequency bands since the spectrum dataset was unsupervised. This algorithm classified unsupervised dataset by analyzing the dataset's patterns such as the power and frequency thresholds. The motive behind adopting this algorithm for labelling the spectrum dataset as it does not require prior supervised spectrum dataset/ licensed user information. The algorithm classified the spectrum dataset into two classes: occupied and vacant. The K-means algorithm classified the spectrum dataset mixed with noise by using a power threshold. Figure 8 shows the spectrum density of the normalized smoothed signal. The frequency bands with power exceeding the threshold power of 0.6 were possibly occupied. The labelled dataset was exported in CSV format for later training of the LSTM algorithm.

```
type = 'linear';
window size = 10;
data = movavg(data,type, windowSize); % apply the moving average filter using a linear window of size 10
normalized_spectrum = (data-mean(data))/std(data);  % z score expression for data normalisation
n_data = normalized_spectrum/max(abs(normalized_spectrum));
```

Pseudocode 1: Implementation of the Average Moving Filter and Data Normalization

3.5. Evaluation of the K-Means Algorithm

Evaluation is the process of checking/testing the capacity of the algorithm to meet the objectives [20]. The widely used evaluation metric for unsupervised ML/Machine Learning algorithms is the silhouette coefficient (value) [20]. The silhouette value measured if frequency bands were correctly classified (belong to their clusters). The silhouette coefficient ranges from -1 to 1. The values near 1 suggest that the frequency bands were correctly classified (in the correct cluster). Values close to -1 indicate that the frequency bands were wrongly classified.

3.6. Splitting the Spectrum Dataset

It was essential to split the spectrum dataset in training as well as testing datasets. The training dataset was utilized to build the spectrum-sensing model from the algorithms. A testing portion was for assessing (evaluating) the model's performance. To avoid bias in the resultant spectrum detection model, the spectrum dataset was stochastically partitioned into 70% training and 30% testing proportions [21].

3.7. Training the LSTM Algorithm

Modeling is the process of developing models by implementing algorithms on a prepared dataset [22]. This stage involves training the LSTM algorithm with 70% of the labelled train dataset. This algorithm was adopted in this research because of its noise-reduction ability.

3.8. Evaluation of the Resultant LSTM Mode1

This involved testing the model with the test dataset to check its performance. The metrics such as accuracy, learning curves, *Pd* , *Pfa* from ROC curves, precision-recall curve, and training time were adopted for assessing the performance

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of the resultant LSTM model and comparing it with other widely adopted spectrum-sensing models. The proposed model was compared to the matched filter and energy detector, ANN/ artificial neural network, ensemble (random forest), and the support vector machine. The 30% of the spectrum dataset was utilized for evaluation.

3.9. Implementing the Hybrid K-Means-LSTM for Real-Time Spectrum Sensing

To assess the hybrid KMeans-LSTM model's performance, its implementation was carried out in Python to facilitate real-time spectrum sensing. For this purpose, the *pyrtlsdr* library, which is a wrapper, was employed to establish interaction with the RTL-SDR dongle. The rtlsdr() function from the *pyrtlsdr* library was utilized to configure the dongle within the Python environment. Several parameters were configured to ensure the appropriate functioning of the setup. The sample rate was set to 2.4 MHz, the center frequency to 800 MHz, and the gain to automatic. Pseudocode 2 presents the RTL-SDR dongle setup in Python. A while loop was adopted to implement real-time spectrum sensing, enabling the continuous execution of the sensing process at regular intervals of 5 minutes (this can be modified). The implementation of this real-time spectrum sensing framework is demonstrated in Pseudocode 3.

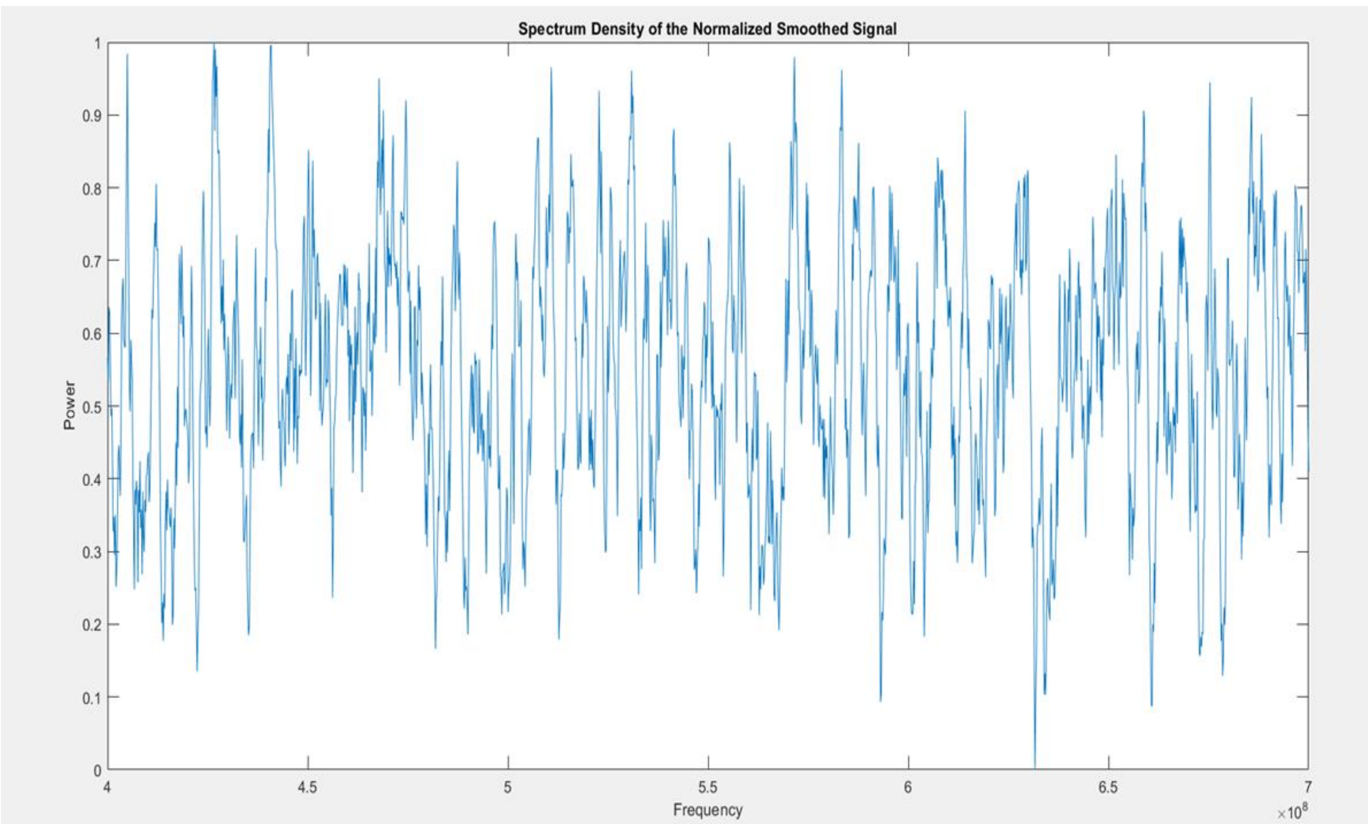

Figure 8 Visualization of the Normalized Spectrum Dataset in MATLAB

```
!pip install pyrtlsdr
from rtlsdr import RtlSdr
# Set up RTLSDR scanner
sdr = RtlSdr()
sdr.sample_rate = 2.4e6
sdr.center_freq = 800e6
sdr.gain = 'auto'
```

Pseudocode 2 RTL-SDR Device Setup in Python

```
# Perform real-time spectrum sensing
while True:   # Starts an infinite loop for continuous spectrum sensing
 # Acquire spectrum dataset from the RTLSDR scanner device
samples = sdr.read_samples(256*1024)          # Reads 256,000 sample from the RTL-SDR device
```

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```
power = np.abs(samples) ** 2                # Compute the power of the acquired samples
# Reshape data for LSTM input
X = np.column_stack((np.arange(len(power)), power))
X = X.reshape(X.shape[0], 1, X.shape[1])
# Normalize input features
X = scaler.transform(X.reshape(-1, X.shape[-1])).reshape(X.shape)
# Predict cluster labels
y_pred = model.predict(X)
# Extract vacant frequency bands (unoccupied clusters)
vacant_bands = np. unique(frequency[y_pred.flatten() < 0.6])        # Extracting the frequency bands predicted to be unoccupied (labels below the threshold, 0.6)
# Display vacant frequency bands
print("Vacant frequency bands:")
print(vacant_bands)
# Wait for 5 minutes
time.sleep(600)
```

Pseudocode 3 Implementation of Real-Time Spectrum Sensing

4. RESULTS AND DISCUSSIONS

4.1. Findings from an Evaluation of the K-Means Algorithm

The silhouette coefficient (value) was applied to assess this algorithm's performance. The silhouette value measured if frequency bands were correctly classified. This was done by checking the ability of the algorithm to classify the unsupervised frequency bands into occupied (cluster 1) and vacant (cluster 2) using the dataset's attributes. It can be noted from Figure 9 that the two clusters had silhouette values (0.6 or greater), indicating that the clusters were well separated by the K-Means algorithm. Cluster 1 is for the vacant/unoccupied frequency bands from the spectrum dataset. On the other hand, Cluster 2 with few instances is for the occupied frequency bands. This shows that most of the frequency bands were underutilized. This validates related studies which presented that most of the available frequency bands are underutilized.

4.2. Learning Curves (Accuracy and Loss curves) for the LSTM Model

The spectrum dataset labelled by the K-means algorithm was the input for the LSTM algorithm. The learning curves were applied to check the model's performance over increased samples. Figure 10 shows the learning curves of the established LSTM model. The loss curves gradually decreased upon increasing the number of iterations and converged at 180 iterations. This is an indication that increasing the number of iterations was not improving the model's performance on the validation (unseen) dataset. Contrastingly, the accuracy curves gradually increased until converging at 200 iterations. This is an indication that iterating after this point was not improving the model. The learning curves gradually decreased to a point of equilibrium with a minimal gap between the two. This, therefore, implies that the above model was ideal for spectrum sensing since it was neither overfitting nor underfitting.

4.3. Comparison of the Models' Accuracy

To benchmark the performance of the proposed model, the LSTM model's accuracy was compared with other spectrum sensing models proposed in literature such as energy and matched filter detectors, support-vector machines, random forests, and artificial neural networks. Table 3 presents the comparison of the models' accuracy. At the lowest SNR for example, -20 dB, it can be noted that the LSTM outperformed other techniques by yielding an accuracy of 0.9677. The random forest came second with an accuracy of 0.8728, the ANN (Artificial-Neural Network) had the third-best accuracy of 0.8517, and the SVM (Support Vector Machine) came fourth with an accuracy of 0.8463 at a low SNR of -20 dB. The matched filter had the fifth-best accuracy of 0.5135. The energy detector's accuracy of 0.4845 was the lowest. Notably, these findings indicate that at low SNR, the established LSTM model outperformed other spectrum sensing techniques.

4.4. Models' *Pd* at Different SNR (Signal-Noise-Ratios)

The P_d is the possibility of the model correctly detecting the frequency band as occupied when the frequency band is occupied. Maximum P_d implies the highest spectrum detection performance. Figure 11 presents the plot of P_d at varying SNR. Generally, it can be noted that increasing SNR, also increases the P_d , thus improving the model's performance. At low SNR, the performance of the traditional methods (matched filter and energy detectors) was significantly the poorest. For example, at -20 dB the P_d for the matched filter and energy detector was 0 respectively. This means that at low SNR, these traditional models did not have a discriminative ability for spectrum detection using unseen spectrum datasets. The models were incorrectly classifying the frequency bands. Such models are not ideal when dealing with real-world spectrum datasets that are exposed to noise. On the other hand, machine learning techniques outperformed the traditional methods in spectrum sensing as they yielded higher P_d at low SNR. Notably, the proposed LSTM model was the best technique, followed by the SVM, random forest, and lastly the ANN. For example, at -15 dB, the detection probabilities for LSTM, SVM, random forest, and ANN were approximately 0.94, 0.79, 0.7, and 0 respectively. That being said, this reveals that the performance of the ANN was similar to the matched filter and energy detector's performance (poor performance) at the lowest SNR. This validates the findings by [10] that the ANN's classification ability at high noise levels is weak. Above 5 dB the P_d for the matched filter and ANN detectors gradually increased, thus increasing performance at increasing SNR levels. The energy detector's curve was straight from -20 dB to 20 dB. This reveals that the energy detector was randomly guessing from the spectrum dataset (not learning from the spectrum dataset). This indicates the limitation of this technique that it performs well using simulated datasets and not when using real spectrum datasets. Even so, at high SNR for example, 5 dB, the detection probabilities for the LSTM, SVM, random forest, ANN, energy detector, and matched filter detector were approximately 0.94, 0.94, 0.85, 0.87, 0.55, and 0.9 respectively. Again, the performance of the proposed LSTM model came first which shows that this model is capable of optimizing spectrum sensing at low SNR.

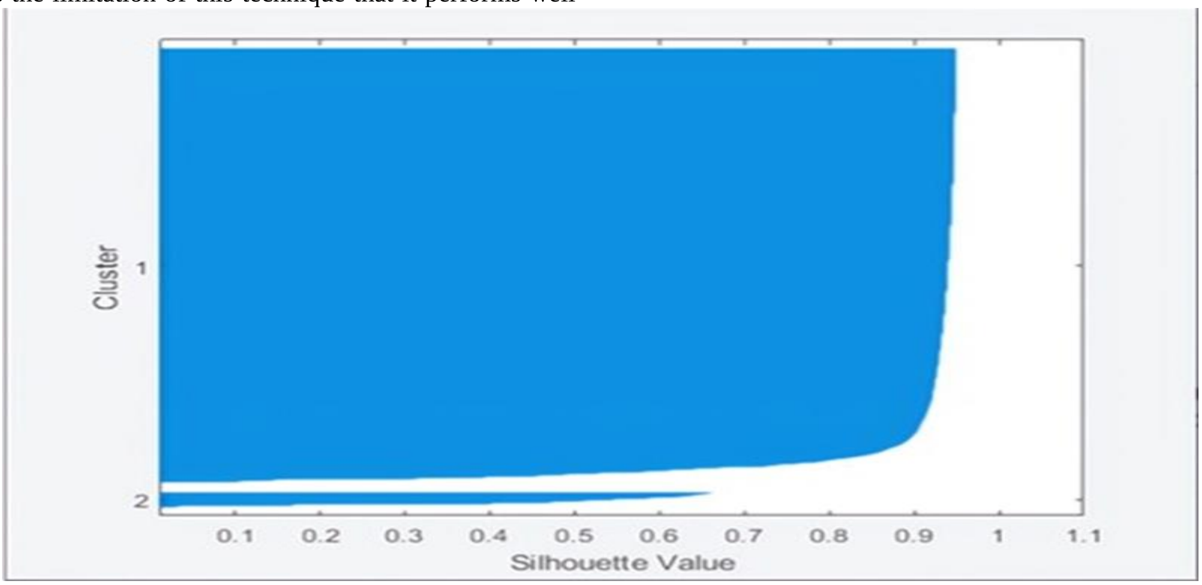

Figure 9 Presents the Classification of the Unsupervised Spectrum Dataset

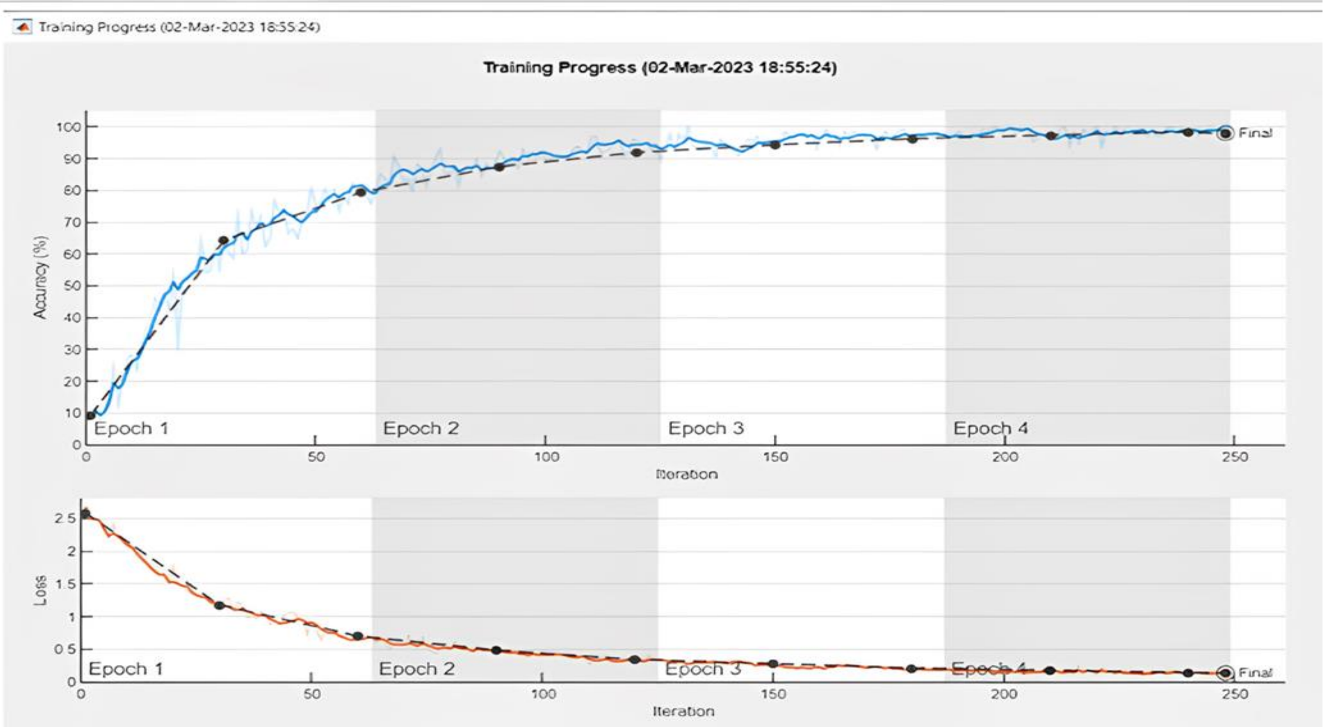

Figure 10 Learning Curves

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Table 3 Comparison of the Models' Accuracy at Various

SNR/dB	Matched filter	Energy detector	LSTM	Random Forest	SVM	ANN
-20	0.5135	0.4845	0.9677	0.8728	0.8463	0.8517
-15	0.5182	0.4870	0.9725	0.8755	0.8480	0.8545
-10	0.5299	0.4915	0.9740	0.8772	0.8523	0.8612
-5	0.5669	0.5423	0.9810	0.8795	0.8587	0.8521
5	0.5669	0.5435	0.9825	0.8891	0.8612	0.8522
10	0.5675	0.5547	0.9828	0.8895	0.8688	0.8523
15	0.5690	0.5602	0.9840	0.8905	0.8750	0.8524
20	0.5752	0.5655	0.9855	0.9157	0.8825	0.8725

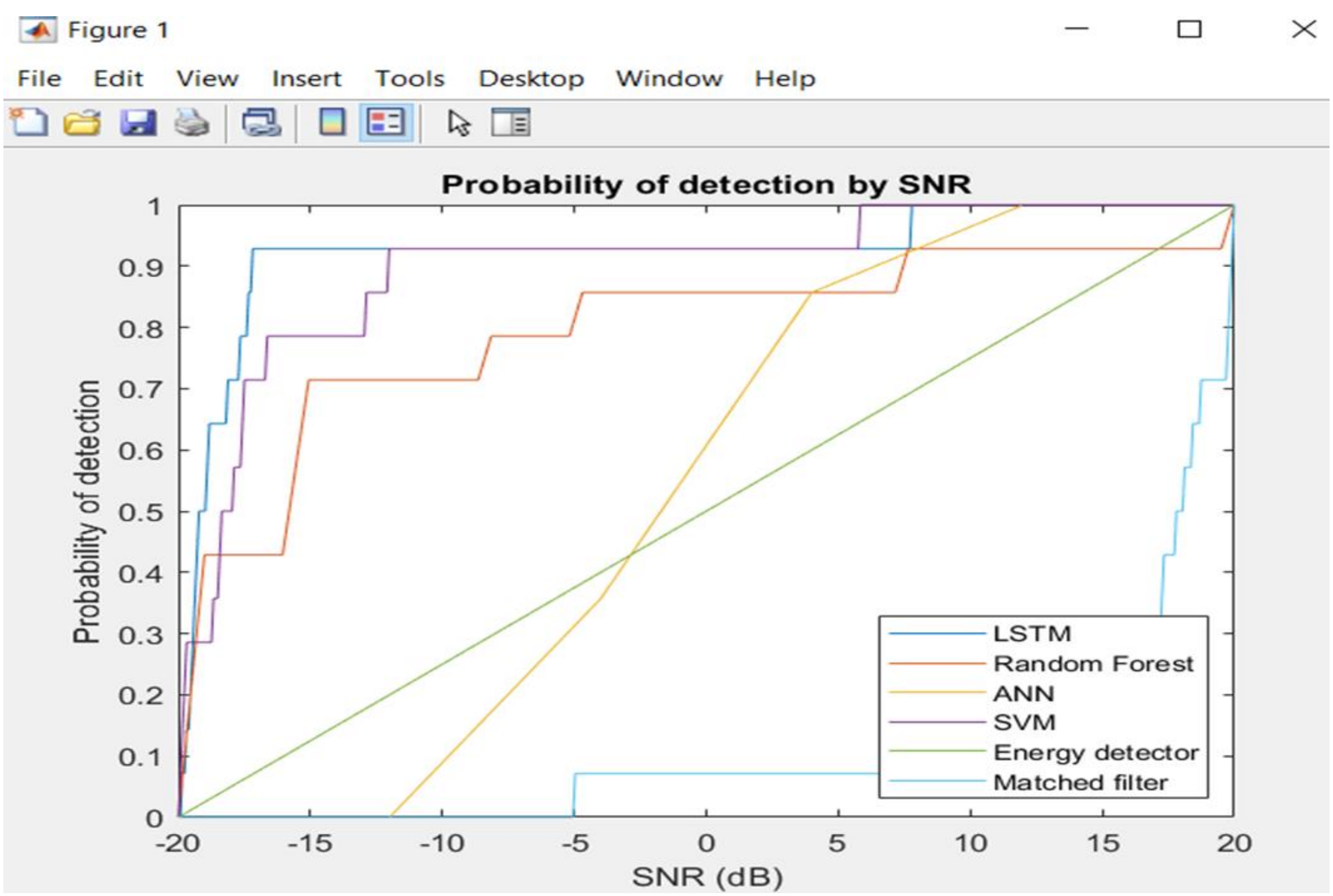

Figure 11 P_d by SNR

4.5. Models' *Pfa* at Different SNR

The Pfa or the false positive rate is the possibility that the model correctly detects the frequency band occupied when it is vacant. A high number of false alarms indicates that several frequency bands are being misclassified, hence to optimize the performance of the model, *Pfa* should be minimized. The plot of *Pfa* at various signal-to-noise ratios is shown in Figure 12. It can be noted that the *Pfa* gradually decreases as the

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SNR levels increase, hence the model's performance increasing. The *Pfa* for the energy detector, matched filter, ANN, random forest, SVM, and LSTM at the lowest SNR of -20 dB were approximately 0.98, 0.98, 0.78, 0.74, 0.73, and 0.71 respectively. Maximum *Pfa* at low SNR for the matched filter and energy detectors reveals that these traditional techniques were misclassifying the majority of frequency bands at low SNR. This supports the findings by [7-9] whose traditional techniques' performance at low SNR was poor. In contrast, the machine-learning techniques were superior to the traditional techniques as they had lower *Pfa* at low SNR. At -20 dB, the proposed LSTM has the lowest *Pfa* of 0.71, which implies that the proposed model was correctly classifying most of the frequency bands than other models. This is because of the LSTM's noise reduction ability and its capability to learn from time series data over a long time. Even at the highest SNR of 20 dB, the proposed LSTM had the lowest probability of false alarm of 0.25 relative to the random forest, SVM, ANN, energy, and matched filter detectors' *Pfa* of 0.28, 0.32, 0.35, 0.45, and 0.42 respectively.

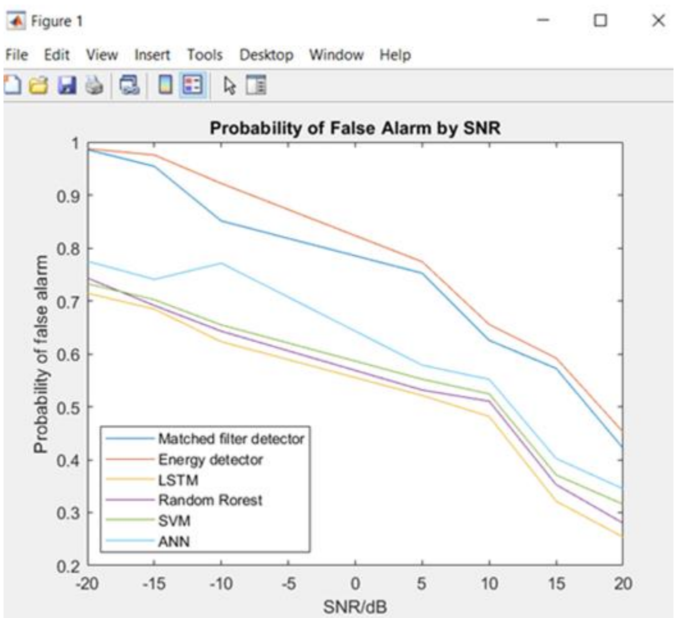

Figure 12 *Pfa* by SNR

4.6. Comparison of the Models' Precision-Recall Curves

Precision is the proportion of total occupied frequency bands that were occupied. Recall is the portion of the occupied frequency bands that were correctly classified as occupied. Figure 13 presents the comparison of the spectrum detection (sensing) techniques using PR curves. The LSTM outperformed other commonly adopted spectrum sensing models with the area under the PR (AUPR) curve of 0.79978. This indicates the technique's highest sensing performance as it correctly classified the majority of the occupied spectrum. The SVM/support vector machine came second best with an AUPR of 0.77345. This presents a decent performance in detecting the occupied spectrum. Again, the energy detector achieved an AUPR of 0. This implies that the energy detector was misclassifying the majority of the frequency bands. Such a model is not reliable for spectrum sensing using real-world spectrum datasets at high noise levels (low SNR). The matched filter detector's AUPR was 0.1768. Again, this model shows poor performance at high noise levels.

4.7. The Comparison of the Models' Training Time

This metric was the time required by the models to predict from the spectrum dataset. An ideal model is one with minimum training time and *Pfa* at low SNR. Such a model is known to be effective and less computationally complex. As shown in Table 4, the energy detector required a training time of 0.007097 seconds. This was the shortest spectrum-sensing time. This was due to the less computational complexity of the technique as indicated by [7] that the energy detector has the shortest sensing time because it is less computationally complex. The second-best was the matched filter detector which required 0.016567 seconds of training time. The random forest was third with a training time of 0.075173 seconds. The Support Vector Machine was fourth with a training time of 0.12897 seconds. The ANN/artificial neural network was fifth and it required 0.23906 seconds. The proposed model which is the LSTM took the longest training time of 1.7144 seconds. The ANN and the LSTM required more training times than the other techniques because of their complex hyperparameters. It was a decent compromise to have more training time for the LSTM which outperformed other models at low SNR.

Table 4 Training Times

Spectrum-sensing model	Training time/ seconds
ANN	0.23906
Random Forest	0.075173
LSTM	1.7144
Support Vector Machine	0.12897
Matched filter detector	0.016567
Energy detector	0.007097

4.8. Real-Time Spectrum Sensing

The proposed hybrid Kmeans-LSTM model displayed the vacant frequency bands at 5-minute intervals to emulate a real-world cognitive radio. It can be shown from Figure 14 that the maximum accuracy attained by the model at the last epoch was 0.9947 (99.4%). On the other hand, the model yielded the least loss of 0.0716 (7.16%) at the last epoch. This revealed that the proposed hybrid model was reliable for optimizing real-time spectrum sensing using real-world spectrum dataset collected by the RTL-SDR dongle.

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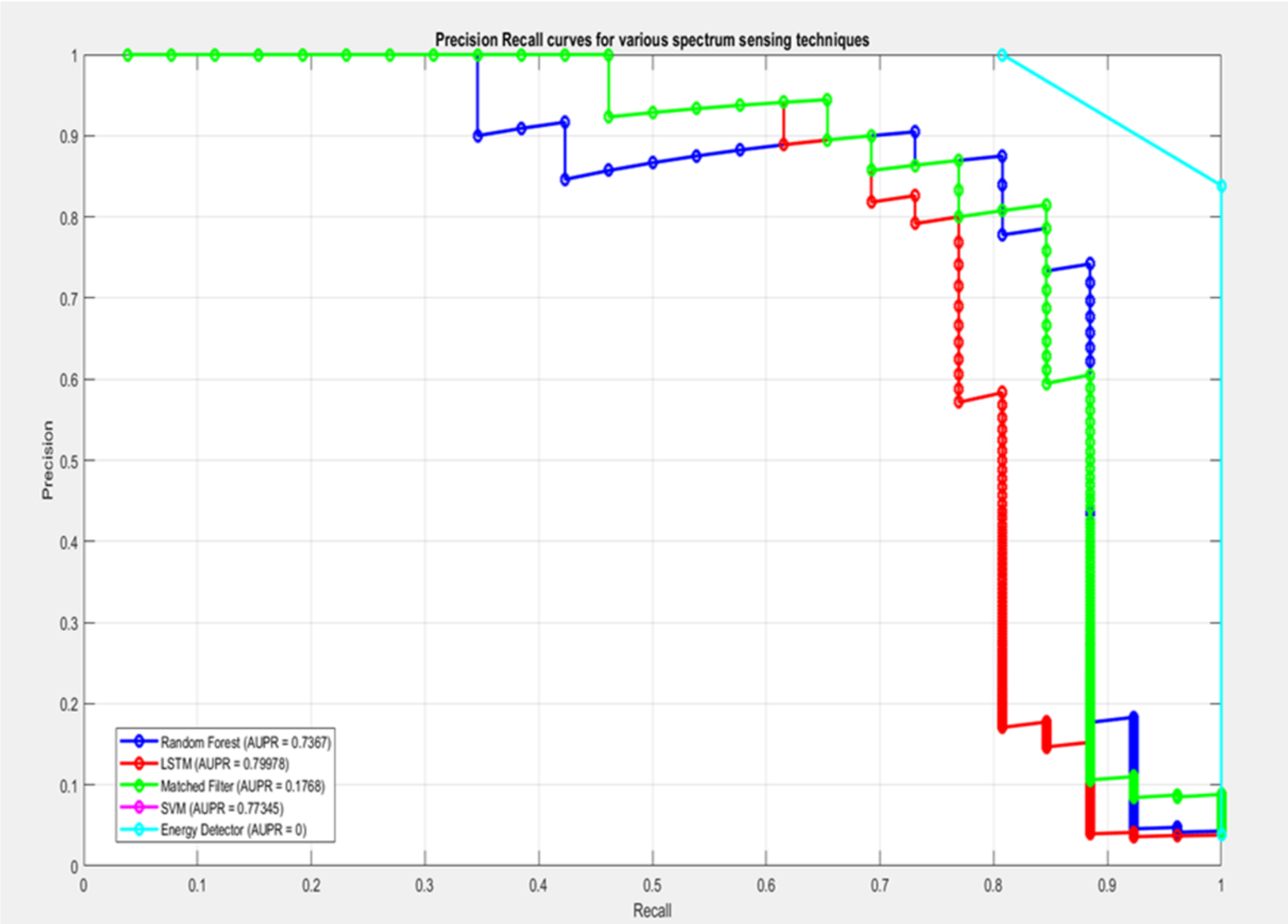

Figure 13 Comparison of the Models' Precision-Recall Curves

```
Epoch 16/20
54/54 [==============================] - 0s 4ms/step - loss: 0.0896 - accuracy: 0.9912
Epoch 17/20
54/54 [==============================] - 0s 5ms/step - loss: 0.0841 - accuracy: 0.9924
Epoch 18/20
54/54 [==============================] - 0s 5ms/step - loss: 0.0796 - accuracy: 0.9935
Epoch 19/20
54/54 [==============================] - 0s 5ms/step - loss: 0.0753 - accuracy: 0.9930
Epoch 20/20
54/54 [==============================] - 0s 5ms/step - loss: 0.0716 - accuracy: 0.9947
54/54 [==============================] - 1s 2ms/step
Vacant frequency bands:
[400.02173489 400.44070184 400.54584843 ... 668.24925513 668.4607719
 671.31915742]
54/54 [==============================] - 0s 3ms/step
Vacant frequency bands:
[400.04511432 400.09196116 400.21800971 ... 668.53421587 669.18624226
 669.21664535]
54/54 [==============================] - 0s 2ms/step
Vacant frequency bands:
[400.06208454 400.86235368 401.56753142 ... 667.40312472 670.69954926
 671.47313028]
54/54 [==============================] - 0s 2ms/step
Vacant frequency bands:
[400.0499324  400.18995259 400.29191331 ... 669.3962981  670.49617046
 670.57987458]
54/54 [==============================] - 0s 3ms/step
Vacant frequency bands:
[400.28693209 400.3337503  400.45283033 ... 668.71765541 669.50793156
 670.08369017]
54/54 [==============================] - 0s 2ms/step
Vacant frequency bands:
[400.63859321 400.66236689 400.72271949 ... 669.12252685 669.51179885
 669.9459494 ]
54/54 [==============================] - 0s 2ms/step
```

Figure 14 Real-Time Spectrum Sensing

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5. DISCUSSION

The proposed hybrid K-means-LSTM model outperformed other models with the highest accuracy of 97%, *Pd* of 0.94, and the lowest *Pfa* of 0.70 at low SNR. This revealed that our proposed model was reliable for enhancing the spectrum sensing capability as opposed to its counterparts. Furthermore, the model yielded a maximum accuracy of 99.4% and a loss of 7.16% for real-time spectrum sensing. This validates the model's efficacy for real-time spectrum sensing using a real-world spectrum dataset Moreover, the findings revealed that increasing SNR, increased the P_d thus improving the model's performance. This is in line with the notion by [23] who articulated that the *Pd* was directly proportional to the SNR. Compared to [23] deep learning model's detection probability of 0.85 at -15 dB and [24] proposed model's *Pd* of 0.81 at -14 dB, our proposed model yielded a consistently higher detection probability of 0.94 at low SNR within the range -20 dB to -10 dB. More so, our findings generally showed that *Pfa* gradually decreased as the SNR increased, validating the findings by [25], which indicated that increasing the SNR decreases the *Pfa*. This is validated by our model whose *Pfa* was 0.7 at -15 dB, relative to the model by [25] that yielded a probability of false alarm of 1 at -15 dB. The study's findings generally indicated that Machine-Learning (ML) models exhibited a superior performance as opposed to the traditional techniques such as the matched filter as well as the energy detection at low SNR levels, such as -20dB and -15 dB. This was presented by higher accuracy and P_d achieved by ML algorithms at low SNR. This was due to their ability to leverage the statistical properties of the received signal and their capacity to learn from spectrum dataset features. This supports the findings in related studies whose proposed state-of-the-art Machine-Learning algorithms outperformed the conventional techniques at low SNR in terms of probability of detection and probability of false alarm. Therefore, we can conclude that the *Pfa* was inversely proportional to SNR. In light of this, Machine-learning models were found to yield lower *Pfa* at high SNR levels as opposed to the energy and matched filter detectors. However, it was found that achieving the highest P_d at low SNR came at the expense of longer training time. The resultant LSTM model, in particular, had the longest sensing time of 1.7144 seconds compared to other techniques, which was attributed to its complex hyperparameters. Of course, this was expected, as this echoed a study by [26] that postulated that spectrum sensing optimization at diminishing SNR levels is at the expense of longer training times. Furthermore, the findings corroborate the findings by [27] who highlighted that the accuracy of their proposed model was at the expense of high computational complexity. In summary, the proposed artifact established from the K-Means and LSTM algorithms optimized spectrum-sensing in wireless networks without necessitating a supervised spectrum dataset.

6. LIMITATIONS

The scope of the study was inferior to the utilization of a low-cost RTL-SDR dongle which was limited to collecting the spectrum dataset within the range of 25 MHz to 1.7 GHz. Hence the proposed model was not evaluated on high-frequency signals within the 4G to 6G range. In addition, the study assumed the non-cooperative sensing approach, in which one antenna scans the frequency bands and makes a decision on vacant or occupied frequency bands. The study could have presented the performance of the proposed artifact on cooperative sensing where multiple antennas cooperate to reach a spectrum-sensing goal. Despite the scope being inferior to limited frequency range and non-cooperative sensing the results of this study are valid and do not compromise the overall conclusions of the study.

7. CONCLUSION

This research aimed to optimize spectrum sensing in wireless networks by developing a model that did not require a prior supervised dataset (prior information about the occupied frequency bands) and yielded a high level of spectrum detection. Performance at low SNR. The results showed that the proposed model established from the K-Means and LSTM algorithms was robust at low SNR. This implies that using the proposed model, it is possible to optimize spectrum sensing at low SNR without a prior supervised spectrum dataset. The empirical findings underscored that machine learning models are superior to traditional (conventional) models such as matched filter and energy detectors in terms of Pfa and PD. Generally, the established K-Means-LSTM outperformed other models when all the metrics were considered. However, this high level of performance was at a cost of longer training time due to the complex hyperparameter of the model. Based on our findings, there is a lot of room for future research. A low-cost RTL-SDR dongle limited to collecting the spectrum dataset within the range of 25 MHz to 1.7 GHz was utilized in this study. Future research includes the application of an advanced antenna or RTLSDR dongle to collect the spectrum dataset within the 4G to 6G range and evaluate the proposed model in real time. Furthermore, this study assumes the non-cooperative sensing approach. In the future, co-operative sensing where multiple antennas (users) cooperate over a large geographical area to reach a spectrum-sensing goal can be implemented.

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