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Optimized Deep Learning Model for Effective Spectrum Sensing in Dynamic SNR Scenario

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Abstract: The main components of Cognitive Radio networks are Primary Users (PU) and Secondary Users (SU). The most essential method used in Cognitive networks is Spectrum Sensing, which detects the spectrum band and opportunistically accesses the free white areas for different users. Exploiting the free spaces helps to increase the spectrum efficiency. But the existing spectrum sensing techniques such as energy detectors, cyclo-stationary detectors suffer from various problems such as complexity, non-responsive behaviors under low Signal to Noise Ratio (SNR) and computational overhead, which affects the performance of the sensing accuracy. Many algorithms such as Long-Short Term Memory (LSTM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) play an important role in designing intelligent spectrum sensing techniques due to the excellent learning ability of deep learning frameworks, but still require improvisation in terms of sensing accuracy under dynamic environmental conditions. This paper, we propose the novel and hybrid CNN-Cuttle-Fish Optimized Long Short Term Memory (COLSTM), an improved version of LSTM that is well suited for the dynamic changes of environmental SNR with less computational overhead and complexity. The proposed COLSTM based spectrum sensing technique exploits the various statistical features from spectrum data of PU to improve the sensing efficiency. Furthermore, the addition of shuttle-fish optimization in LSTM has reduced the computational overhead and complexity which in turn enhanced the sensing performances. The proposed methodology is validated on spectrum data acquired using RaspberryPi-RTLSDR experimental test-beds. The proposed spectrum sensing technique and the existing classical spectrum sensing techniques are compared. Experimental results show that the proposed scheme has shown the brighter enhancement of performance under different SNR environments. Further, the improvised performance has been achieved at low complexity and low computational overhead when compared with the other existing LSTM networks.

Keywords: Spectrum sensing; cuttle-fish; long short term memory; raspberry pi-low SNR; convolutional neural networks

1 Introduction

Cognitive Radio (CR) [1] is an emerging technology, which fulfils the spectrum scarcity due to the exponential growth of 5G and Internet of things (IoT) devices. Cognitive Radio technology [2] has gained the hawk-eye research interest to fulfill the spectrum scarcity. Its goal is to opportunistically reuse vacant spectrum bands or white spaces, ensuring that licensed users are not subjected to collisions and interferences [3]. In the CR network, licensed users are referred to as Primary Users (PU), whereas unlicensed users are referred to as Secondary Users (SU).

The basic goal of CR is to allow secondary users to access underutilized spectrum bands in an opportunistic manner without interfering with prime users. This necessitates the employment of a high-efficiency spectrum sensing system that recognizes the presence of primary users and utilizes the spectrum bands without secondary users overlapping [4–7]. But detection performance in practice is often compromised with multipath fading, shadowing and receiver uncertainty issues. To countermeasure these issues, effective spectrum sensing methods are needed. Many spectrum sensing techniques are used for an effective sensing of spectrum for utilizing the frequency band [8–10]. Although these spectrum sensing techniques are used for allocating the spectrum bands, capturing the primary user activities under environmental noise factors still remains to be challenge [11–14]. The primary user‘s statistical information can be useful in the CR for an effective prediction of spectrum occupancy mechanism and optimization of system performance with improved spectral efficiency. Recent advancements of machine learning [15,16] and deep learning algorithms [17,18] in wireless communication has gained brighter light of research from industry and academia. The key feature of CR network is its learning by itself from the radio environment which makes the machine and deep learning suitable for the CR networks [19–21].

The hybrid combination of Convolutional Neural Networks (CNN) and Long Short Term Memory (LSTM) plays a significant role in constructing an effective spectrum sensing model, according to the existing literature [22]. But these models are designed based on noise free environments without the real time spectral data. To solve this above problem, this paper proposes the novel HOLE-NETS (Hybrid Optimized LSTM Enabled Networks) which ensembles the CNN and Optimized LSTM for the better sensing of the primary users based on the statistical characteristics of primary users under noisy environment. The main contributions of the paper are as follows

1. This paper proposes the Novel Hybrid Combination of CNN and LSTM in which the hyper parameters of LSTM are optimized by Cuttle Fish mechanism to achieve high sensing accuracy.
2. The proposed model has been designed under different levels of noisy environment with less computational overhead.
3. The proposed ensemble model has been tested with the real time datasets obtained from the experimental test bed consist of Raspberry Pi Model 4 and RTL-SDR Tuners.

The rest of the paper is organized as follows: Section 2 presents the related works from different authors. The preliminary views of CNN, LSTM and Cuttle Fish Optimization are presented in Section 3 and it also discusses about the system model with working mechanism of proposed hybrid network based spectrum sensing. The empirical test-bed descriptions are presented in Section 4, experimentation results and comparative analysis are presented in Section 5. Finally the paper is concluded with future enhancement in Section 6.

2 Related Works

The cooperative strategy is incorporated into Dueling Deep Q Networks (DDQN), the deep multi-user reinforcement learning (DMRL) technique [23]. Without prior knowledge of network dynamics, DDQN can effectively learn the relationships between channels and reduce the computing cost in the vast subspace of the multi-user scenario. A cooperative channel strategy based on identifies signals without releasing spectrum information is being researched to reduce conflicts and boost network usefulness. Each user selects a channel and transmits a packet with a defined probability in each time slot.

A new database is developed in [24] for cooperative spectrum sensing. The author adopted the convolutional neural network (CNN) for maximizing the spectrum performance with minimal error rate. OFDM signals are comprised with white Gaussian noise that has been used for generating the dataset. VGG, LeNet, and AlexNet have been designed to obtain the optimum spectrum evaluated with proposed database and results are compared with each other. The limitation of the proposed model is the wireless network which included only 5 nodes in a network which is not suitable for real-time purpose.

The issues of combined spectrum sensing and optimum channel selection in distributed cognitive radio systems were addressed in [25]. For recognizing the unused spectrum in a distributed context, the authors suggested a decentralized based multi-agent Q-learning reinforcement model. The algorithms enable each agent to generate a globally optimal Joint Spectrum Sensing (JSS) strategy, even if the individual agents have limited but complementary channel coverage. In comparison to basic single-agent systems, in the estimated values of interest, there is a faster convergence rate and less noise provides in these algorithm. The limitation of the proposed system is deficiency in privacy and protection of individual usage.

Deep Neural Networks (DNN) was created in [26] for spectrum sensing. A deep learning-based model called "DLSenseNet" is suggested for spectrum sensing that uses structural information from incoming modulated signals. To detect false alarms in Cognitive Radio (CR) users and reduce mistake rates, the suggested model is a modified version of a convolutional neural network. The suggested DNN-based spectrum detector has a learning complexity restriction.

An approach to incorporate opportunistic spectrum sensing into the Nomadic Base Transceiver Station (BTS) architecture, a hybrid Automatic Modulation Classification (AMC) based spectrum sensing model was developed in [27]. Selected analogue and second generation (2G) digital modulation methods were evaluated, and the accuracy of the best model obtained will allow for the most accurate detection of spectrum holes within the bands under consideration]. A unique CNN-based Cooperative Spectrum Sensing (CSS) strategy for CRN was developed in [28], which is the first attempt to apply deep learning for CSS. CNN is used in DCS to learn the technique for combining the binary or real-valued individual sensing outcomes of the SUs.

Multi-feature learning model with enhanced local attention for vehicle re-identification (MFELA) is proposed in [29]. This framework uses global features for vehicle re-identification. But this framework need an improvisation to handle occlusion conditions of vehicle datasets. The CNN based fine grained vehicle classification type method is proposed in [30]. This framework significantly reduced the network parameters to reduce computational overhead. But this framework need improvisation to handle real time dataset to maintain the same accuracy.

3 Proposed Framework

3.1 System Model

Cognitive radio scenario is considered as multiuser. A primary user (PU) transmitter is used for transmitting the primary user signals. The primary signal users are collected and sampled. These sampled signals are used to train and test the proposed design and the architecture can take the decision to determine the unknown samples in the network.

Consider X (k)= $\{\, \mathrm{X}x1(k),\ x2(k),\ x3(k)\ldots\ldots\ldots x(m)k\}t$, where m represents the number of user and k denotes the received signals from m users. X (k) denotes the discrete time sample present at m^{th} users. The paper uses the binary hypothesis testing process for spectrum sensing as mentioned in [31].

$$H1: x(k) = R\_N(k) + Y(k) \tag{1}$$

$$H0: x(k) = Y(k) \tag{2}$$

The signal vector R_N(k) is the one that is affected by channel fading and path loss. The distinct noise vector with aero mean is represented by Y (k). As a result, according to [31], hypothesis H1 denotes the presence of a principal user, while hypothesis H0 denotes its absence. These signal parameters are separated into real and imaginary components which are used to train and test the proposed architecture.

3.2 Preliminaries

This section details about the preliminary working principle of CNN, LSTM and Cuttle fish optimization. Additionally working mechanism of the proposed framework is presented.

3.2.1 Convolutional Neural Network

Convolutional neural network (CNN) is a propelled advancement of Multi-Layer Perception MLP. CNN is popular in the computer vision sector. Fig. 1 shows the different layers employed by the CNN for the feature extraction and classification.

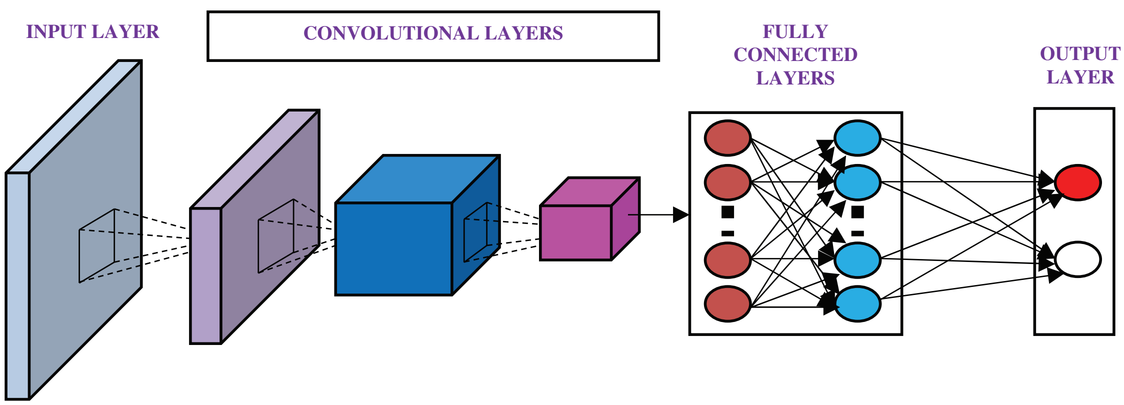

Figure 1: Convolutional neural network–Its layers and working mechanism

From the Fig. 1, it is clear that CNN is supervised feed forward multi-layered networks which usually includes the multi-layer convolutional layers (CL), Layers with a pooling layer (PL) and layers that are entirely connected (FC). These layers are connected from input to output, with one layer's output feature map serving as the input to the next layer, resulting in natural inter-layer flow [31].

3.2.2 Long Short Term Memory-An Overview

As mentioned in [32], Fig. 2 shows the LSTM consists of cell, input gate, output gate, and forget gate make up the network. Cells are well-known for their ability to remember values over long periods of time. The "cell input state is Ct, the cell output state is Gt, and its previous state is Gt-1, and the three gates' states are j_t, T_f, and T0. Both Gt and ht are passed to the next neural network in the RNN, according to the topology of the LSTM cell. The output and forget gates are used to update the memory of the LSTM, which combines the output of the previous unit with the current input state.

We utilize the following equations in order to determine Gt and ht. To begin, determine the states of the three gates as well as the cell input state, input gate: Cell, input gate, output gate, and forget gate make up the network".

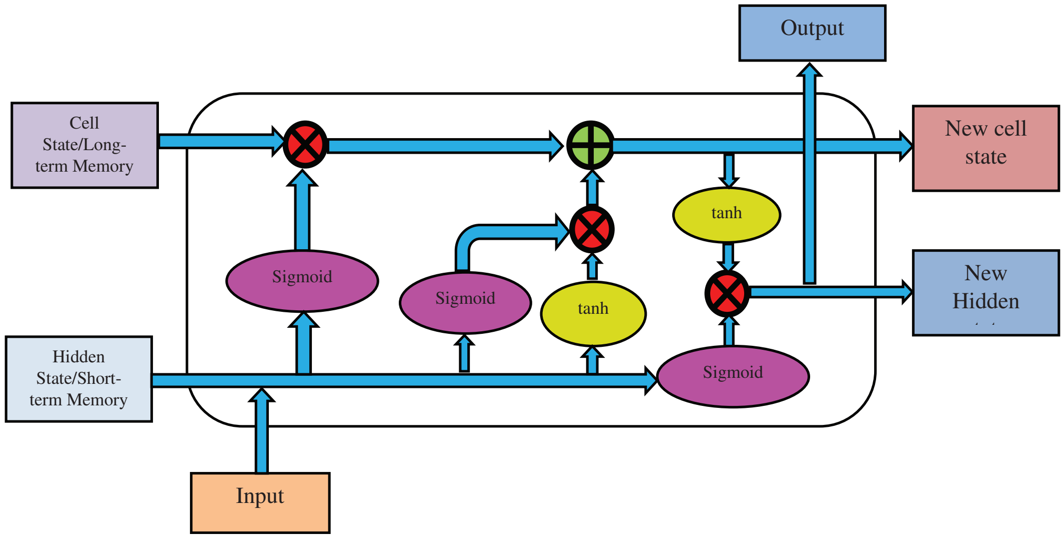

Figure 2: An overview of LSTM

The input gate is given as

$$j_t = \theta(G_l^i.0_t + G_h^i.e_{t-1} + s_i) \tag{3}$$

The forget gate is given as

$$T_f = \theta(G_l^f.0_t + G_h^f.e_{t-1} + s_f) \tag{4}$$

Output gate is calculated as

$$= \theta(G_l^0.0_t + G_h^o.e_{t-1} + s_o) \tag{5}$$

Cell Input is given as

$$\tilde{T}c = \tanh(G_l^c.O_t + G_h^c.e_{t-1} + s_c) \tag{6}$$

where G_l^0, G_l^f, G_l^i, G_l^C are the weight matrices connecting the input gates to the output layers whereas G_h^i, G_h^f, G_h^o, G_h^C are the weight matrices connecting the gate inputs to the hidden layers. Also s_i, s_f, s_o, s_C are the bias vectors and tanh is considered to be hyperbolic function".

3.2.3 Cuttle Fish Algorithm-An Overview

Cuttle Fish Algorithm is a novel approach which is based on the AI-inspired meta-heuristic by the adaptive color characteristics of the Cuttle fishes. Replicated light from dissimilar layers such as chromatophores, iridophores, and leucophores produces diverse colour patterns in cuttlefish. These cells are piled together in cuttlefish, and it is the immediate combination of these cells that produces the wide range of colour patterns. In a summary, this one-of-a-kind technology reproduces the light reflection process over multiple layers, as well as the visibility of the matching pattern that cuttlefish employs to match its chroma background. This method separates the cells into four groups, two of which are utilized for global searching and the other for local searching. Fig. 3 illustrates the functioning algorithm. The detailed working of the proposed cuttlefish algorithm is explained in [33,34].

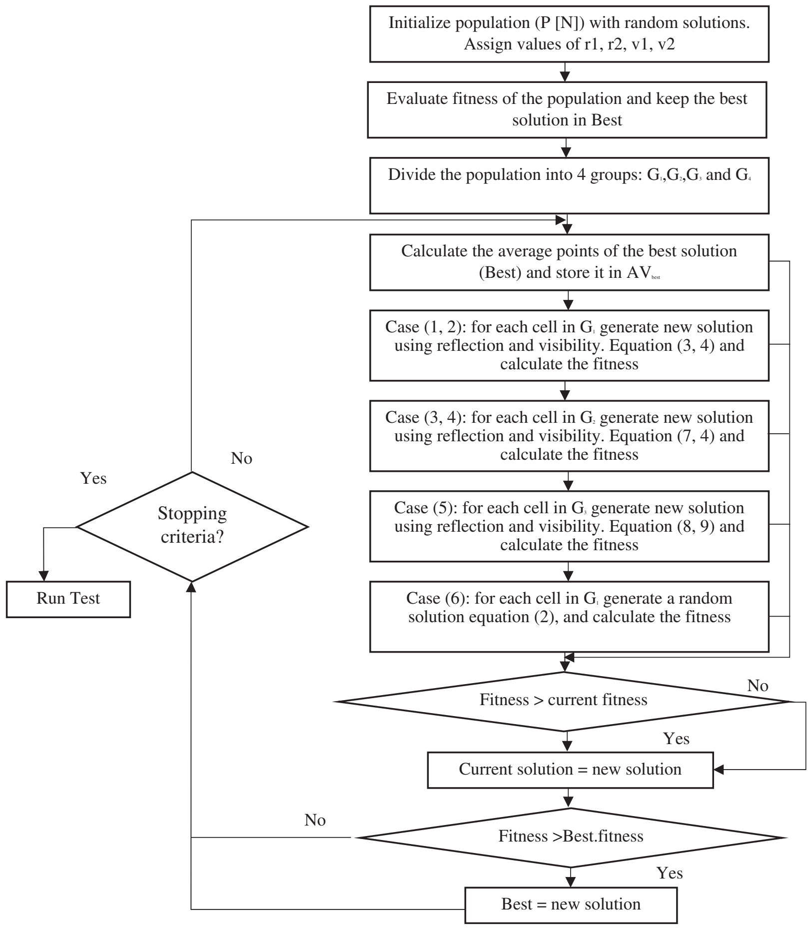

Figure 3: General principle of CFA

3.3 Proposed Framework

3.3.1 System Overview

Fig. 4 shows the proposed overall block diagram for the proposed framework. It works in the three different phases such as Spectrum data collection, Convolutional Feature extraction and finally spectrum sensing by the optimized LSTM networks. The detailed working mechanism of the proposed framework is presented in preceding section.

3.3.2 Dataset Collection

In this phase, empirical test bed consists of Raspberry Pi 3 and RTL-SDR are used for collecting the spectrum data with the different communication frequencies. Since our research work is proposed for the sensing of primary users in noisy environment, signal captured from the test beds are added with Gaussian white noise. The signal Y is represented as 2N samples which is represented below

$$Y = [Y^1, y^2, y^3 \ldots\ldots\ldots x^{2N}] \tag{7}$$

Each sample is used as a source of information for the suggested architecture. Tab. 1 illustrates the number of raw data collected from the empirical test bed.

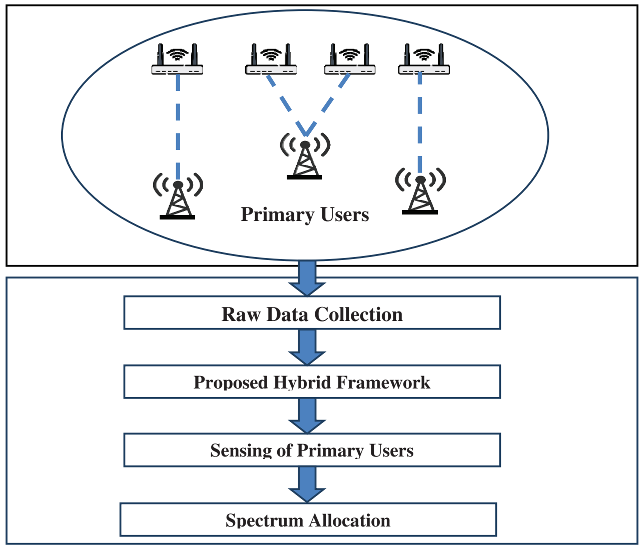

Figure 4: Overall block diagram for the proposed framework

Table 1: Raw data collected form the empirical test bed

Sl.no	Number of data collected	SNR levels(db)
01	4, 76, 402	−20 to 0
02	4, 76, 000	0 to + 20

3.4 Hybrid Ensemble Learning Based Spectrum Sensing

The raw data collected from the empirical test bed is considered as input to proposed optimized hybrid learning algorithm. These data are considered as the input matrix which comprises of real and imaginary elements that are scattered across the H0 and H1. To visualize the difference between the data scattered across H) and H1, CNN is used for an efficient feature extractor. The parameters of CNN used for extracting the energy and correlation features. The CNN's output is vectorized according to the sensing period and fed into the appropriate LSTM cells.

According to the sensing periods, these LSTM cells can extract time-dependent characteristics. Finally, the dense layer receives the LSTM cells' outputs, which include energy, correlation, and time-dependent features, which are used to alter the output dimension according to the label classes. Since the number of classes and data are high, these network leads to high computational complexity and low sensing accuracy. In order to overcome this drawback, the proposed framework uses the Cuttlefish Optimized LSTM layer for further processing in order to reduce the computational complexity which in turn increases the spectral efficiency. In this method of training, hyper parameters such as epoch, hidden layers, learning rate are optimized in accordance to Cuttlefish lighting mechanism. The proposed framework accuracy is coined with the fitness function. The above mentioned hyper parameters are iterated until it meets its fitness function given in Eq. (8).

$$Fitness\ Function = Maximum\ of\ (Accuracy,\ \ Precision,\ \ Recall\ and\ F1 - score) \tag{8}$$

In the proposed framework, first the local solution is calculated using Eq. (8). Once the local solution is calculated then it is again used as input of proposed framework to calculate the global solution using same Eq. (8) to increase the accuracy.

Algorithm-1 presents the working mechanism of the Optimized LSTM network .The working of the proposed training network is presented in **Algorithm-2**

Algorithm 1: Cuttle Fish Optimization Based Training network(CFLSTM)

```
Input: Hyper parameters : Epochs, hidden layers, Bias Weights, Learning Rate
Output: High Spectral Sensing Efficiency
Initialize the hyper parameter
Calculate local solution 1 using fitness function Eq. (8)
Calculate global solution 2 using fitness function Eq. (8)
Find the best global solution
while stopping criteria not meet to do
      Select hyper parameters in a random manner.
Calculate local solution 1 using fitness function Eq. (8)
Calculate global solution 2 using fitness function Eq. (8)
      Calculate the best global solution
      Update the hyper parameters
End while
```

Sl.no Algorithm-2// Working Mechanism of the Proposed algorithm

```
Input:     Raw Spectral Data   D(n)   where n =
Output:    Sensing of Users
While True:
        [Energy, Correlation] = CNN(Y, t) where t = Sensing period
         Time-Dependent Features T = LSTM(Energy, Correlation)
                  Sensing = Optimized_LSTM(T)
End
```

4 Empirical Experimental Test Bed

The testbed consist of RTL-SDR dongle interfaced with Raspberry Pi Model 3 and Windows 10 based computer system for running the software. The software includes GNURADIO and Python 3.8. The GNURADIO is used to capture the different spectrum data and Python 3.8 is used for implementing the proposed spectrum sensing technique .The different frequencies of RTL-SDR configuration on raspberry pi 4 is shown in Tab. 2. The captured spectrum data from the different frequencies are used in offline mode for validating the proposed spectrum sensing

Table 2: Specifications for the RTL_SDR for different frequency bands

Tuners	Elonics E4000	Rafael micro R820T	Rafael micro R828D	Fitipower FC0013	Fitipower FC0012	FCI FC2580
Specifications	52–2200 MHz with a gap from 1100 to 1250 MHz (varies)	24–1766 MHz	24–1766 MHz	22–1100 MHz (FC0013B/C, FC0013G has a separate L-band input, which is unconnected on most sticks)	22–948.6 MHz	146–308 MHz and 438–924 MHz

5 Results and Discussion

The experimental findings for the suggested algorithm are reported in this section. To train and test the models, the proposed technique is built with Keras libraries and a TensorFlow backend. Nearly 9, 52, 402 datasets were collected under different SNR conditions that are used for training and testing the proposed technique. The performance metrics such as Prediction accuracy (Pa), Precision (P), Recall (R), Probability of detection (Pd), and Probability of False Alarm (Pf) are the performance measures used for evaluation (Pf). The chance of announcing the presence of the primary user when the spectrum is actually occupied is Pd, while the likelihood of declaring the existence of PU when the spectrum is truly vacant is Pf. For varying SNR values of the received signals, both probabilities were determined. The averaged value of the chance of false alarm and the probability of miss detection was used to generate the performance metric SE (Pm). The likelihood of miss detection is the chance of declaring the spectrum empty when the PU is actually there. The mathematical expression used for calculating above performance metrics is given in Tab. 3.

Table 3: Mathematical expression for calculating the different performance metrics

Sl.no	Performance metrics	Mathematical expression
01	Prediction accuracy(P_a),	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Recall	$\frac{TP}{TP+FN} \times 100$
03	Precision	$\frac{TP}{TP+FN}$
04	Probability of detection(P_d)	Total number of primary user(PU)/Total number of users (PU + noise signals)
05	Probability of missing ratio(Pm)	1–(P_d)
06	Probability of false alarm(P_f)	Number of noise signals diagnosed/Total number of users (PU + noise signals)

5.1 Model Validation and Hyper Parameter Tuning

70% of the total samples are fed in batches to train the proposed network, while 30% of the data is used to test the network to validate the suggested model. The hyper parameters are tuned in accordance to the proposed optimization algorithm as mentioned in Algorithm-1. Tab. 3 gives the mathematical expression for calculating the different performance metrics and Tab. 4 presents the optimized hyper parameters used for training the network. To start with, to exhibit the attributes of the proposed enhanced locator, we determined the diverse presentation measurements, for example, exactness, accuracy, review, particularity and F1-score at various SNR conditions for various recurrence innovations of exploratory proving grounds. Figs. 5, 6 and 7 shows the performance metrics of the proposed algorithm using different frequency technologies under low and high SNR scenario. Tab. 5 shows the comparative analysis of time complexity with existing systems.

Table 4: Hyper parameters optimized used for training and testing the proposed network

Sl. no	Hyper parameter details	Optimized parameters
01	Epochs	400
02	Hidden layers	20
03	Batch size	42
04	Learning rate	0.001

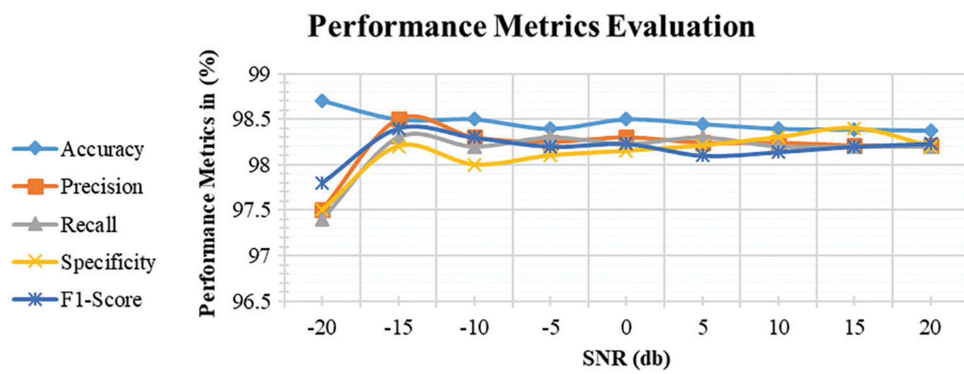

Figure 5: Performance metrics of the proposed algorithm under 1100 to 1250 MHz & 438–924 MHz

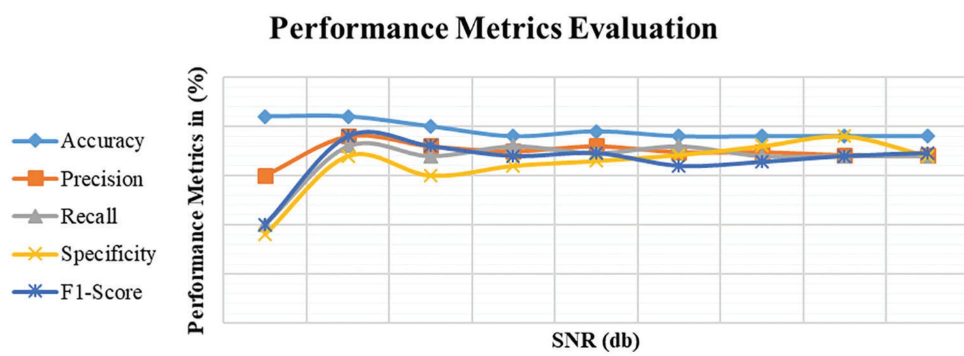

Figure 6: Performance metrics of the proposed algorithm under 22 to 1100 MHz & 146–308 MHz

From the Figs. 5 to 7, performance of the proposed framework is high (98.5% accuracy, 98.4% precision, 98.3%recall, 98.25%specificity, 98.4% F1-score) even under low SNR condition. Besides, to approve the qualities of the proposed detecting method under various Pf, we determined the recipient working attributes ROC bends of the proposed strategy is contrasted and the other learning based spectrum detecting procedures. Figs. 8, 9 and 10 show the ROC curves of the different spectrum sensing techniques under various tuning spectral frequencies at high SNR ratio(SNR = 20 dB).

Table 5: Comparative analysis of computational time

Different algorithms	Time (h)
HOLE-Networks	5
CNN-LSTM (SGD)	9
CNN-LSTM (ADAM)	12
LSTM	14

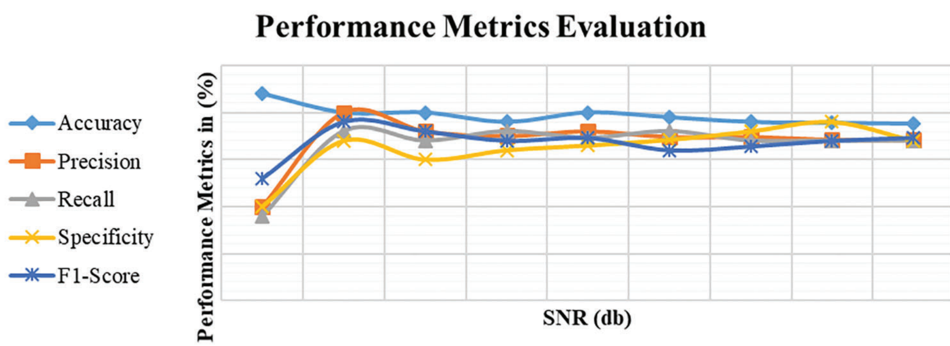

Figure 7: Performance metrics of the proposed algorithm under 52–2200 MHz and 1100–1250 MHz

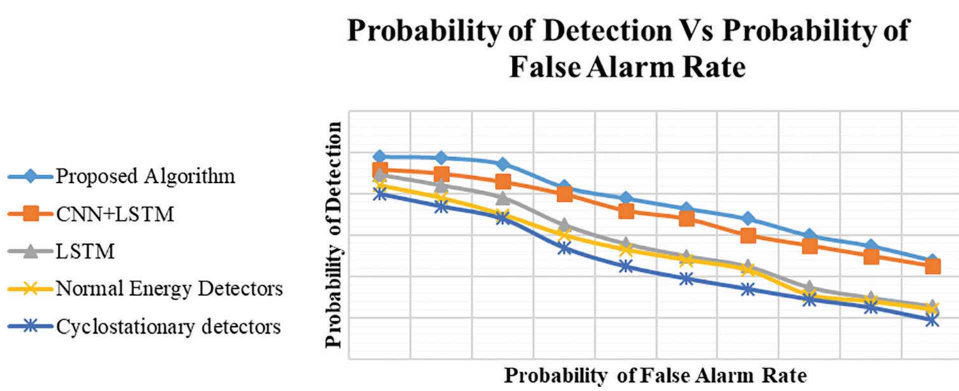

Figure 8: Performance metrics of the proposed algorithm under 1100 to 1250 MHz & 438–924 MHz

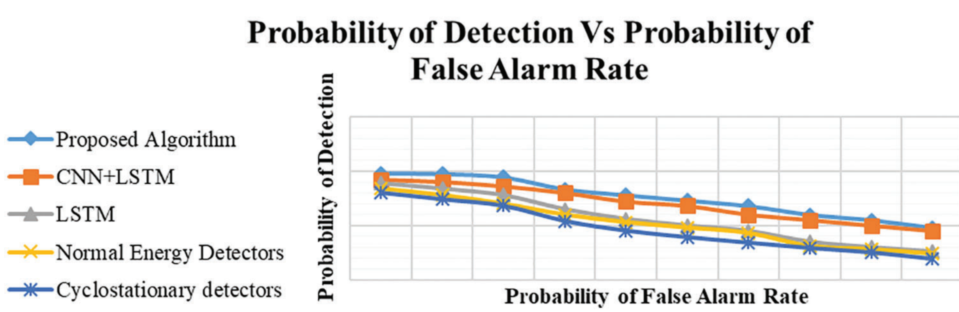

Figure 9: Performance metrics of the proposed algorithm under 22 to 1100 MHz & 146–308 MHz

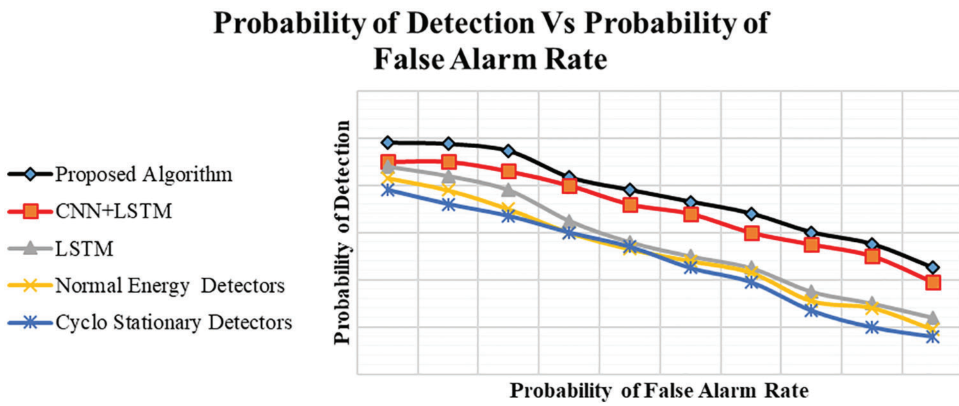

Figure 10: Performance metrics of the proposed algorithm under 52–2200 MHz & 1100–1250 MHz

It can be observed that the deep learning based spectrum sensing technique has outperformed the traditional sensing techniques. In the first two spectrum sensing techniques, CNN is used to extract the signal patterns of the received spectral data corresponding to different sensing periods. Though CNN is good in extracting the signal features, the integration of Cuttle fish optimization on the LSTM has slight edge over the other hybrid learning (CNN + LSTM). Figure shows the ROC curves of the different spectrum sensing schemes under different tuning conditions at Low SNR (SNR = −20 dB). It is evident that the deep learning based spectrum detectors have outperformed the other traditional spectrum sensing techniques. At the Low SNR, optimized hybrid deep learning algorithm has outperformed the other hybrid learning technique. From the above figures, it is found that the both hybrid deep learning based sensing technique has shown equal performances at high SNR scenario but the proposed algorithm has outperformed the other learning schemes at low SNR under various tuning spectral frequencies. Then to prove the effectiveness of the proposed hybrid spectrum sensing techniques under different SNR levels, we demonstrate the Pd-SNR performance of proposed schemes with that of the other deep learning based sensing techniques which are shown in Figs. 11, 12, 13 and 14.

In this evaluation, probability of false alarm rate is set to 0.1 in accordance to IEEE 802.22 standard. From the Figures, it is clear that the proposed schemes exhibits the superior performance than the other existing deep learning and traditional spectrum sensing technique. Although performance degradation is observed HOLE-Networks has outperformed the other learning algorithms even in low SNR conditions. Finally, to prove the efficiency of the proposed optimizer in the hybrid deep learning algorithm, we have compared the other optimizer's performance in sensing the different spectrum users. Fig. 15, presents the computational training time of the networks used for the spectrum sensing From the Fig. 15, it is found that the proposed network consumes less computational time than other existing optimizers and learning model because of COLSTM incorporation and which is highly suitable for low SNR scenarios also.

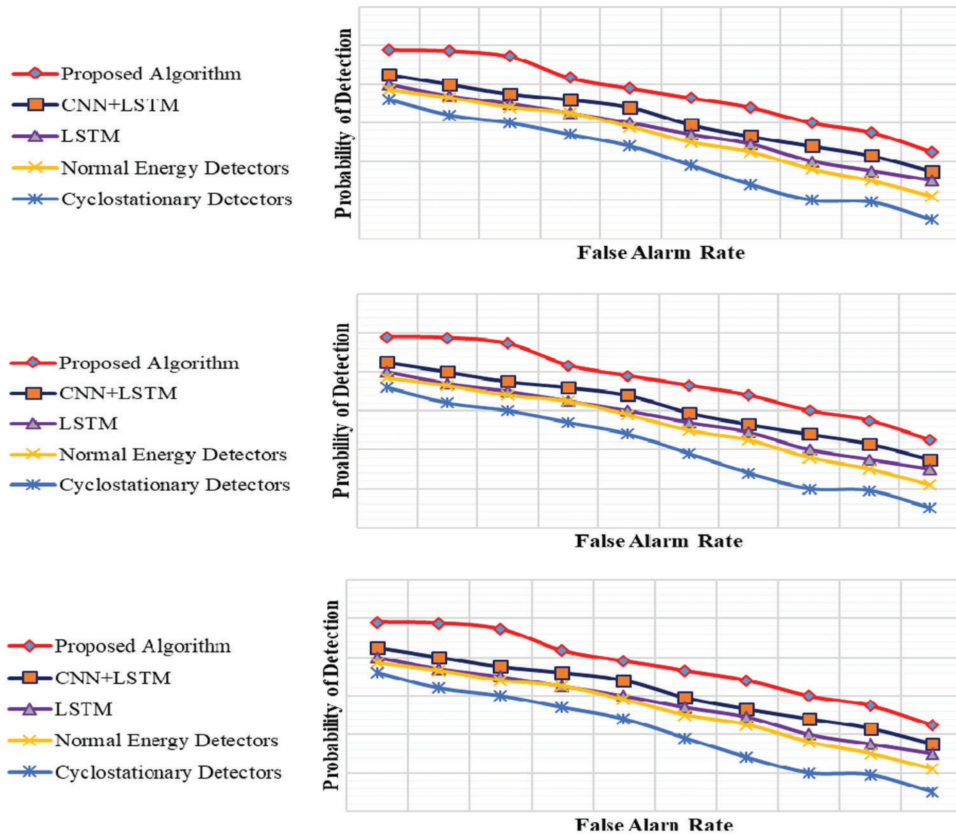

Figure 11: ROC curves: 1100 to 1250 MHz and 438–924 MHz (Top), 22 to 1100 MHz and 146–308 MHz (Middle), 52–2200 MHz and 1100–1250 MHz (Botom)

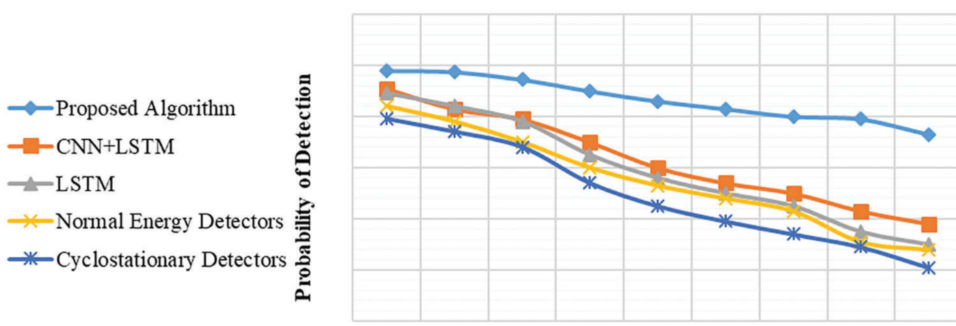

Figure 12: Pd *vs.* SNR Curves for the different spectrum sensing techniques under 1100 to 1250 MHz and 438–924 MHz

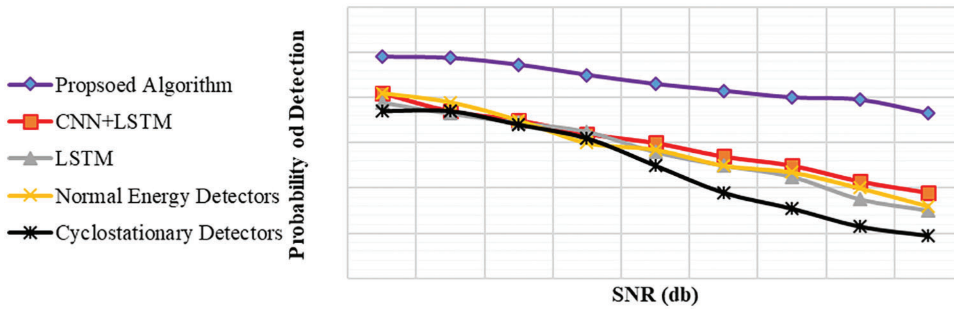

Figure 13: Performance metrics of the proposed algorithm under 52–2200 MHz and 1100–1250 MHz

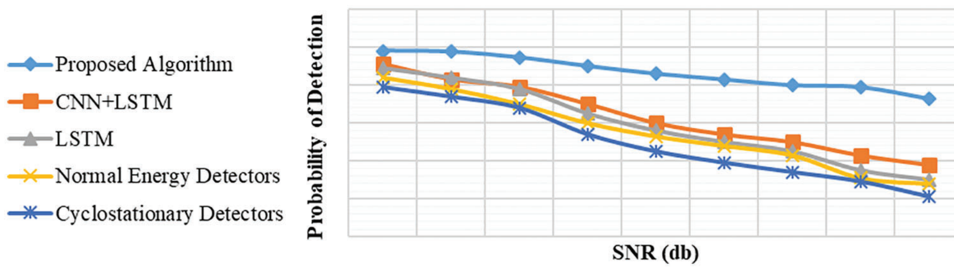

Figure 14: Performance metrics of the proposed algorithm under 52–2200 MHz and 1100–1250 MHz

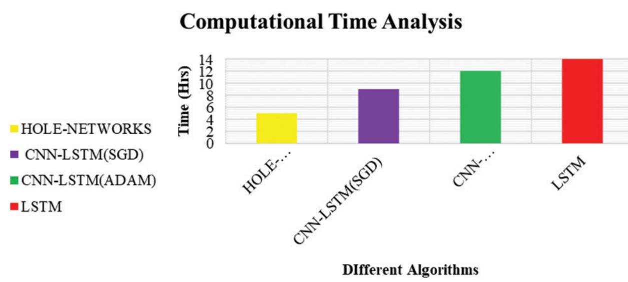

Figure 15: Computational training time analysis for the different algorithms used for the spectrum sensing

6 Conclusions

In this paper, we proposed an ensemble profound learning-based CNN-Optimized LSTM based range detecting method. The proposed HOLE-NETWORK based Sensing technique is designed for an efficient spectrum sensing under dynamic changes of noise environments. The proposed technique indirectly absorbs mandatory features in the noisy spectrum data such as energy, correlation and time-dependent temporal features. Furthermore, to achieve the high spectral efficiency and less computational overhead, we have integrated the Cuttle Fish algorithm for the better optimization of hyper parameters in LSTM layers of training network. The extensive experimentation is carried out using the Raspberry Pi Model 4 interfaced with RTL tuner and performance of the proposed algorithm is evaluated and compared with the other existing hybrid learning based on the sensors information. Implementation results demonstrate that the anticipated algorithm has outperformed other hybrid models in terms of sensing efficiency under different SNR regimes. Hence the proposed framework finds its application in Security applications of IoT. Since the proposed algorithm works in the supervised fashion, adaptive learning in accordance to the dynamic environment still needs the brighter light of improvisation. In future the reinforcement learning is adopted with proposed learning framework to improve the results further to support the secured applications. However, addition of reinforcement with hybrid learning is a lime-light research in recent days.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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