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Performing Hybrid Spectrum Sensing with an Adaptive and Attentive Multi-stacked Deep Learning Network in a Cognitive Radio Network

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Abstract. Cognitive Radio Network (CRN) includes Secondary Users (SUs) and Primary Users (PUs) to perform better communication. The SUs present in the CRN observe the spectrum band to obtain the white space opportunistically. Employing the white spaces supports enriches the effectiveness of the spectrum. Due to the promising learning capacity of Deep Learning (DL) and Machine Learning (ML) models, various experiments in the previous years have utilised the deep or shallow multi-layer perceptron mechanism. However, these mechanisms do not apply to the time series data because of the memory element's absence. One of the primary issues in spectrum sensing is to model the test statistic. Conventional mechanisms normally employ the model-aided attributes as a test statistic, including eigenvalues and energies. However, these attributes cannot be precisely characterised in the real world. Hence, a DL-assisted hybrid spectrum sensing technique in the CRN is implemented. At first, the data are gathered from appropriate databases. Further, an Adaptive and Attentive Multi-stacked Network (AAMNet) is developed for the hybrid spectrum sensing process. The AAMNet is developed by combining three different deep networks such as Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and autoencoder. The spectrum sensing process by the proposed AAMNet is enhanced further using the Random parameter Improved Duck Swarm Algorithm (RIDSA) for parameter optimisation. The availability of spectrum is identified for better spectrum utilisation with the help of the developed hybrid spectrum sensing process. Throughout, the analysis of the proposed method is checked by evaluating the resultant outcomes with various heuristic approaches and deep learning methods.

Keywords: Cognitive radio network; hybrid spectrum sensing; adaptive and attentive multi-stacked network; attention mechanism; random parameter improved duck swarm algorithm.

1. Introduction

The Cognitive Radio (CR) is a well-known network because of the spectrum sensing approaches. Wireless Sensor Network (WSN) is employed in the spectrum sensing context employing deep learning (DL) (Xie *et al.*, 2020b). The WSNs are networks

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of linked sensor nodes that perform in groups to collect, evaluate, and send the Radio Frequency (RF) spectrum information. When integrated with the DL strategies, the WSNs become an efficient component for enhancing the spectrum sensing accuracy and efficacy (Paul and Choi, 2023a). To automatically recognise and classify signals in the RF spectrum, these sensor nodes collect information that is further given to the DL approaches. This integration makes it possible to monitor the spectrum very dynamically and effectively which makes as a significant module of CR devices with the requirement of constant spectrum usage (Geng *et al.*, 2022). The previous spectrum sensing approaches led the path for the generation of CR. These approaches concentrated on estimating if significant or main candidates are absent or present with particular frequency bands (Pan *et al.*, 2020). Initially, the spectrum is recognised by employing energy identification and connecting the filtering approaches of conventional techniques. However, these techniques had problems concerning accuracy and robustness. A significant part of CR devices is dynamic spectrum access (Rajaguru *et al.*, 2020). According to the real-time spectrum sensing results, the CRs select and employ the frequency bands adaptively (Solanki *et al.*, 2021). The technology of CR is developed as a potential outcome to balance the spectrum availability and its enhancing growth.

The radio spectrum has an important role in everyday life in distinct real-time programs. It employs a range of wireless data transmission through Wi-Fi, laptops, smartphones, and radio broadcasting for critical communication approaches, radar, Global Positioning System (GPS), and baby monitors (Patel *et al.*, 2020). Numerous applications are on the basis of spectrum availability thus it plays a primary role in daily life. Spectrum security highly grows when enhanced data transmission, quick communication, and rapid multimedia applications employ vast spectrum resources (Koçkaya and Develi, 2020). The primary concept of CR is spectrum reuse which enables the Secondary Users (SUs) to employ the authorised spectrum band when the Primary Users (PUs) is idle (Perumal and Nagarajan, 2022). To obtain this, the SUs are needed to continuously perform the spectrum sensing task that recognises the spectrum job's state of the PUs (Uppala *et al.*, 2021). Thus, spectrum sensing is a primary process of CR innovation that can attain deep attention from both industry and academia. The requirement for extra spectrum resources is enhanced highly as many wireless services that are helped and shined the implementation of new rapid data network innovations (Tamuka and Sibanda, 2023).

Nowadays, Machine Learning (ML) approaches for spectrum sensing have attained much attention. Reinforcement learning and DL are the two higher models of ML approaches that relatively enhance the flexibility and precision of spectrum sensing (Mishra and Chaudhary, 2023). The Recurrent Neural Network (RNN) supports tracking the data regarding the overall input sequence and employing it to produce the outcomes and create predictions. The RNN approach handles diverse input sequences and obtains the temporal connections that exist in the data (Solanki *et al.*, 2022). It is complex to recognise the long-term connections employing RNNs because of the expanding or disappearing gradient problem in that the gradients either enhance or vanish highly over time. The primary limitation of spectrum sensing is to develop the experiment statistic to attain better detection probability (Arunachalam and Suresh Kumar, 2023). The energy identification-aided Cooperative Spectrum Sensing (CSS) is considered because of its flexible development, short sensing period, low power usage, and low computing complexity. Especially, in the poor PU signal pattern knowledge, the energy identification is displayed to be very efficient (Yakkati *et al.*, 2021). However, because of the existence of some suspicious SUs, the existing spectrum sensing can be susceptible to misleading the sensing results. Certain problems in the CR Networks (CRNs) are named Spectrum Sensing Data Falsification (SSDF) threats. The Convolutional Neural Network (CNN) and Artificial Neural Network (ANN)-aided approaches have deep or shallow multi-layer perceptron framework (Raghavendra and Manjunatha, 2023a). One of the issues of the deep or shallow multi-layer perceptron framework is its poor ability to store data because of the memory element's absence (Gai *et al.*, 2022). Thus, the multi-layer perceptron models are not applicable for time series and temporal modelling data.

The designed hybrid spectrum sensing in CRN contains the following contributions:

- To present a new hybrid spectrum sensing system in CRN by utilising the multi-stack deep network that automatically improves the accuracy of the data transmissions and minimises the network complexities.
- To construct the new Adaptive and Attentive Multi-stacked Network (AAMNet) by utilising three distinct deep networks such as autoencoder, CNN, and Long Short-Term Memory (LSTM) that support to perform along with attention mechanism for achieving the spectrum sensing accurately. Here, the Random parameter Improved Duck Swarm Algorithm (RIDSA) approach is employed to tune the network parameters.
- To suggest a new RIDSA approach by concentrating on the requisite features of existing DSA and an adaptive idea that increases the performance rates of the hybrid spectrum sensing system in CRN.
- To evaluate the developed hybrid spectrum sensing system in CRN by utilising traditional algorithms and methods that guarantees the superior solutions of the designed system.

Followed by the introduction section, the forthcoming sections are given as follows. Section 2 elaborates on the conventional works of hybrid spectrum sensing mechanisms. Section 3 explains the development of an efficient CRN with hybrid spectrum sensing using a DL approach. Section 4 elaborates on the parameter optimisation using RIDSA and the proposed model description. Section 5 depicts the hybrid spectrum sensing using AAMNet with an objective function. Section 6 elucidates the results and discussions of the implemented hybrid spectrum sensing mechanism. Section 7 explains the conclusion of the designed hybrid spectrum sensing mechanism in CRN.

2. Existing Works

2.1. *Related works*

Liu *et al.* (2019) recommended DNN to perform the data-driven experiment statistic. At first, the DNN was derived to ensure the implemented test statistic's optimality. Further, the sample Covariance Matrix (CM) was employed and recommended a CM-aware CNN-aided spectrum sensing approach that enhanced the functionality. Finally, the simulation findings illustrated that the functionality of the designed framework was close to the optimal detector.

Xie *et al.* (2020a) suggested a CNN-LSTM detector that employed CNN to draw out the features of energy correlation. The consideration of sensing information and energy-correlation attributes related to various sensing times was given to LSTM. Hence, the activity pattern of PU could be learned. With enough experiments, the supremacy of the CNN-LSTM model was proved in situations without and with noise uncertainty.

Soni *et al.* (2020) recommended an LSTM-aided spectrum sensing model that learned the necessary features from the spectrum data. Additionally, the CR devices have exploited the activity statistics of PU using spectrum sensing to improve the sensing functionality. The suggested sensing mechanisms were experimented on the spectrum information of numerous radio technologies. The authors monitored the maximised framework rates of the developed approach.

Kannan *et al.* (2023) combined the two optimisation algorithms to improve the efficient energy usage ability of the spectrum hoes by focussing on distinct sensing situations. The primary objective of the suggested system was to tune distinct attributes such as sensing bandwidth, transmission power, and so on. While estimating the recommended system, the suggested model provided improved solutions.

Vijay and Aparna (2023) implemented a new spectrum sensing mechanism. The model employed the recurrent connections to obtain the temporal dependencies. To develop a spectrum sensing approach, this work cascaded distinct deep networks. The evaluation results provide that the designed method attained higher performance and lower sensing error percentage.

Paul and Choi (2023b) presented a reliable and single model for the CS users. The suggested work employed the time series evaluation via a DL-aided LSTM method for indexing the PU channels. In the end, the authors designed a complex framework and rectified employing a value-iteration-aided approach. The simulation solutions displayed the efficacy of the presented work over the related works.

Nasser *et al*. (2021) employed ANN for performing spectrum sensing. The authors employed cutting-edge mechanisms in the DL sector to obtain accurate solutions. The ANN model was trained to differentiate among two hypotheses. The research outcomes have displayed the efficacy of the presented work, as it performed better than the conventional ANN-aided energy detector.

Rani and Prashanth (2023) explored a DL mechanism and presented an innovative spectrum identification mechanism for CR networks. The integrated feature vector was performed via a reinforcement approach. In the end, these features were employed to train the DL method that engaged the residual blocks. The solutions of the method were contrasted with other DL-aided models and displayed the robustness of the presented work.

Pravin and Sundararajan (2024) developed an efficient Oppositional Function-based Chimp Optimisation Algorithm (OFCOA) for effectively managing the energy and resource allocation in CRN. Here, the OFCOA model was performed to evaluate the optimal solution using an oppositional function. This developed method was validated using the MATLAB platform using several metrics like delay, energy consumption, and so on. The comparative performance was evaluated with existing methods to provide better performance. Liu *et al.* (2024) proposed a hybrid CSS mechanism with the help of a DL method. Further, the energy allocation has been calculated among transmitting of packet and spectrum sensing. Also, the issues of average Age of Information (AoI) have been resolved using the developed model. Shrote and Poshattiwar (2024) implemented a hybrid algorithm spectrum sensing mechanism in CRN to recognise the availability in the channel. The process of feature extraction was performed with the help of the received signal whereas; the spectrum sensing availability was highly detected utilising the designed approach. The resultant simulation of the implemented MIMO method has reached a high performance of extreme flexibility to detection performance. Prabhavathi and Saminadan (2024) developed a resource optimisation framework with a priority pricing technique. With consideration of different PU states, the Hybrid-CRNs (H-CRN) have been detected. Here, the higher priority of the PU and SU were applied in spectral resources using a DL model. Khaf *et al.* (2024) investigated a hybridised model along with a Deep Reinforcement Learning (DRL) model in CRN to maximise energy efficiency. Also, the performance of the developed method has obtained effective performance. Jain *et al.* (2024) implemented an ANN model with a Wireless Regional Area Network (WRAN). For the experimentation, the 2048 samples were taken in the experimental analysis to provide reliable performance. The experimental findings of the proposed method have shown maximised performance than the conventional methods.

Ge *et al.* (2024) developed a Reconfigurable Intelligent Surface (RIS) framework to maximise CSS performance within fixed sensing time. Phase Shift Matrix (PSM) optimisation mechanism was implemented to enhance the cooperative detection probability. Data fusion and decision fusion schemes of CSS could have the ability to remove high tolerance false alarm issues on PSM. The simulation outcomes of the designed framework have demonstrated a better performance compared to other existing approaches.

Wu *et al.* (2024) developed a novel blind spectrum sensing using one-bit Analog-to-Digital Converters (ADCs) to minimise power consumption and hardware costs. The theoretical calculation of simulation outcomes of this developed model has shown better performance. Taherpour *et al.* (2024) developed and derived several detectors based on linear spectral statistics from random matrix theory. Gaussian distribution has been combined with these detectors using the central limit theorem. Performance validation of the designed model has illustrated the effectiveness of the developed detectors in different real-world applications to minimise the average Signal-to-Noise Ratio (SNR) and enhance detection probability.

Ezhilarasi and Clement (2024) proposed a novel technique with the help of blockchain-based technology to detect and prevent several criminal activities using a spectrum sensing mechanism. The iron-out phase and block updation phase were involved in the detection strategy. The simulation outcomes of the developed model were illustrated 3.125%, 6.5%, and 8.8% at −5 dB SNR in the appearance of malicious users.

Vlădeanu *et al.* (2024) developed a novel Energy Detection (ED) model for SS which contains binary activity for detecting the signal to enhance detection performance. The proposed method has been validated with statistical analysis and derives the expressions using diverse methods. The theoretical findings of this model have outperformed better detection outcomes.

Li *et al.* (2024) developed a cryptonym array-based privacy-preserving aggregation approach and data confusion-based privacy-preserving model for SS in cognitive vehicular networks. The implemented method can accurately transmit the confused data in the aggregation process.

2.2. *Research gaps and challenges*

The conventional spectrum sensing methods mostly concentrate on the feature-retrieving process. However, this procedure takes more time to elaborate all the sensing data. Sensitivity to noise, inefficiency, and signal representation are some of the issues presented in existing spectrum sensing approaches. Some of the techniques are vulnerable to noise that affects the detection process of spectrums. Table 1 presents the features and challenges of existing spectrum sensing approaches in CR networks using DL. CM-CNN (Liu *et al.*, 2019) has the ability to retrieve test static-based features and it rectified the spectrum sensing problem of multi-antennas. However, it does not solve the spectrum scarcity problems and lots of time is needed for the training process. CNN-LSTM (Xie *et al.*, 2020a) helps to retrieve correlation features from the sensing data and it effectively

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Table 1. Features and challenges of conventional spectrum sensing techniques in CRN using DL.

Author	Methodology	Advantages	Disadvantages
Liu *et al.* (2019)	CM-CNN	• It can retrieve test static-based features. • It rectified the spectrum sensing problem of multi-antennas.	• It does not solve the spectrum scarcity problems. • Lots of time is needed for the training process.
Xie *et al.* (2020a)	CNN-LSTM	• It helps to retrieve correlation features from the sensing data. • It effectively learns the activity patterns of PUs.	• The sensing period is high.
Soni *et al.* (2020)	LSTM-SS	• It achieved high accuracy. • It learns the implicit features efficiently with the help of employed memory elements.	• It does not work well on multiple numbers of PUs and SUs. • The execution time for sensing the spectrum is high.
Kannan *et al.* (2023)	GWO-CS	• It attained high throughput by maintaining the spectrum holes. • It solves the radio spectrum shortage issues.	• It is affected by channel congestion and interference problems. • Convergence is low.
Vijay and Aparna (2023)	RNN-BIRNN-LSTM	• It effectively categorises the sensing data.	• Training each network requires a lot of time. • It has degradation problems.
Paul and Choi (2023b)	DRL	• It solves the channel shortage problems. • It reduces the sensing overload issue.	• It suffers from hidden noise issues.
Nasser *et al.* (2021)	ANN	• It utilises only one detector for the training process.	• Retrieving energy-related features is difficult.
Rani and Prashanth (2023)	DRLNet	• It retrieves energy-correlation features for an efficient spectrum detection process. • It has the capability to capture time-shifted signal correlation.	• The communication of the system is not effective. • It suffers from security and power control issues.

learns the activity patterns of PUs. Yet, the sensing period is high. LSTM-SS (Soni *et al.*, 2020) achieved high classification accuracy at low SNR regimes. It learns the implicit features efficiently with the help of employed memory elements. It does not work well on multiple numbers of PUs and SUs. The execution time for sensing the spectrum is high. GWO-CS (Kannan *et al.*, 2023) attained high throughput by maintaining the spectrum holes and it solves the radio spectrum

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shortage issues. Yet, it is affected by channel congestion and interference problems and the convergence is low. RNN-BIRNN-LSTM (Vijay and Aparna, 2023) effectively categorises the sensing data. But, Training each network requires a lot of time and it has degradation problems. DRL (Paul and Choi, 2023b) solves the channel shortage problems and it reduces the sensing overload issue. But, it suffers from hidden noise issues. ANN (Nasser *et al.*, 2021) utilises only one detector for the training process. However, retrieving energy-related features is difficult. DRLNet (Rani and Prashanth, 2023) retrieves energy-correlation features for an efficient spectrum detection process. It has the capability to capture time-shifted signal correlation. But, the communication of the system is not effective and it suffers from security and power control issues. Therefore, a hybrid spectrum sensing method in a CRN using DL will be implemented.

3. Developing an Efficient CRN with Hybrid Spectrum Sensing Using DL Approach

3.1. *CRN: System model*

The system model of CRN is explained here. Here, a normal multi-antenna CR (Liu *et al.*, 2019) framework is offered. The terminal CR employs an N-factor antenna device to do the spectrum sensing on the basis of M observation attributes. Consider, $y(m) = [y_1(m), y_2(m), \ldots, y_N(m)]^U$, $m = 0,1,\ldots,M-1$ and specify the observation attribute, where the variable $y_j(m)$ specifies the mth discrete time sample at the CR terminal's jth antenna. Hence, the spectrum sensing issue at the multi-antenna CR terminal is derived as a binary hypothesis testing issue as given in the following equation:

$$\begin{aligned} &J_1\colon\ y(m) = d(m) + v(m), \\ &J_0\colon\ y(m) = v(m). \end{aligned} \tag{1}$$

Here, the variable $d(m) \in F^{N\times 1}$ specifies the signal vector $d(m)$ that troubles with channel fading and path loss. Commonly, it is not possible to achieve the previous PUs knowledge at the CR terminal hence, the signal vector is considered to be an identically and independently distributed Circular Symmetric Complex Gaussian (CSCG) factor with CM $S_d = A(d(m)\,d^V(m))$ and zero mean. A variable $x(m) \in F^{N\times 1}$ indicates the noise factor and it is considered as a CSCG arbitrary factor with CM $S_x = A(x(m)x^V(m)) = \sigma_x^2 J_N$ and zero mean, whereas a variable σ_x^2 indicates the noise variance. Moreover, the attributes V_1 and V_0 indicate the hypotheses that PUs are absent and present correspondingly.

According to the observation factors, the test statistic U is developed to make the decisions: if the condition $U > \gamma$ is met, then the PUs are present; or else the PUs are absent. Here, the threshold value is indicated as γ. Based on the Neyman–Pearson (NP) scenario, the primary concept of spectrum sensing is to develop a test

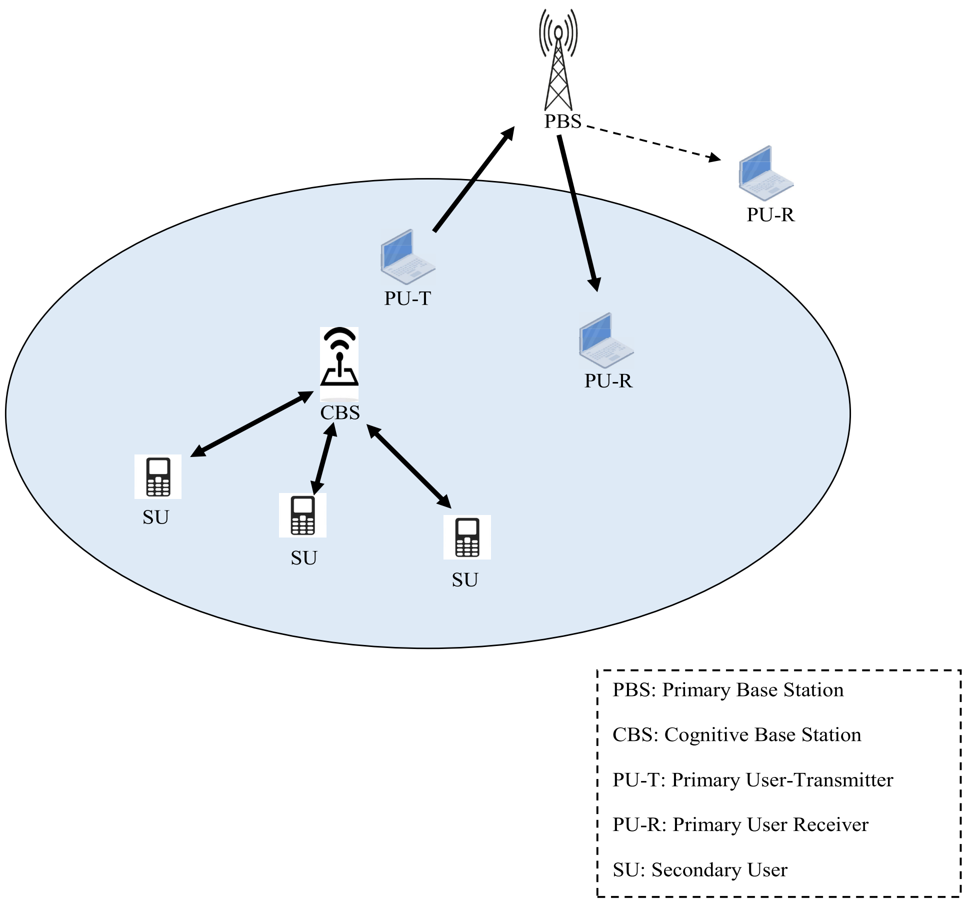

Fig. 1. System model of CRN for suggested hybrid spectrum sensing mechanism.

statistic to enhance the detection probability for the provided Probability of False Alarm (PFA) that is derived in the following equation:

$$\begin{aligned} &\max_{U} Q_c = \int_{\gamma}^{\infty} g_{U|V_1}(t)\,dt, \\ &\text{s.t.} \;\; Q_g = \int_{\gamma}^{\infty} g_{U|V_0}(t)\,dt = \varphi \end{aligned} \tag{2}$$

In this, the test statistic formulated from the observation factors is denoted as U. The attributes $Q_g = Q\{U > \gamma | V_0\}$ and $Q_c = Q\{U > \gamma | V_1\}$ indicate the PFA and Probability of Detection (PD) accordingly. The variable $\gamma | V_j$ indicates the experiment statistic under the hypothesis V_j. The factor $g_{U|Vj}$ indicates the $U| V_j$'s probability density function. Further, the variable φ specifies the needed PFA and the specific detection threshold is given as γ. Figure 1 displays the system model of CRN for the recommended hybrid spectrum sensing mechanism.

3.2. *Input data details*

The recommended hybrid spectrum sensing mechanism's input details are collected from the link "https://github.com/caiotavares/spectrum-sensing: access date:2024-06-08". This is a synthetic dataset. This dataset includes the overall data size as (70,000, 3) and the overall target size as (70,000, 1). And, the collected information is specified as S_d, here $d = 1,2,...,D$, and the overall data is indicated as D.

3.3. *Motivation and significance for hybrid spectrum sensing*

In the present day, the utilisation of wireless systems and its service has been enhanced highly but it leads to spectrum scarcity. The regulatory authority policies utilise the static spectrum allocation techniques and allocate new spectrum bands for providing new categories of services to the candidates. These techniques result in small usage of available spectrum bands. The CR (Vaduganathan *et al.*, 2023) offers better outcomes for these issues and it relatively concentrates on the effective usage of available spectrum bands.

Significance of hybrid spectrum sensing: The idea of CR has developed to minimise the issue of spectrum scarcity. In the modern days, it has been reported that the spectrum can be reutilised by employing CR (Al-Bosham *et al.*, 2024) technology from television or cellular bands. In the CR, the unauthorised candidates, often considered SUs, sense and purposely use the radio spectrum while confirming that the interference to the PU is below several acceptable thresholds. The interference in the PU highly occurs when the SU stops to recognise the activity of the PU as an authorised band. Thus, effective and accurate hybrid spectrum sensing is a significant problem in the CRNs.

Motivation for hybrid spectrum sensing: The wireless communication system's performance could be enhanced by employing the CUs features without affecting PU's performance. Numerous techniques were recommended using experts for the spectrum management function such as estimating spectrum sensing and determining the spectrum for CUs. In CRN (Raghavendra and Manjunatha, 2023b), the sensing platform includes distinct components with low-powered sensors. Thus, an issue occurs in the spectrum sensing and it minimises the functionality of the method. In the conventional mechanisms, some experts have been concentrated on spectrum sensing to enhance the sensing accuracy. In both mechanisms, the accuracy is minimal. In order to enhance the sensing accuracy, a hybrid spectrum sensing was implemented in the recommended work that chooses the suitable spectrum band for the CUs.

4. Parameter Optimisation Using RIDSA and Proposed Model Description

4.1. *Proposed conceptual view of CRN with HSS*

In this day, an ever-enhancing requirement for larger data values demands high spectrum resources. The conventional static spectrum allocation only enables the particular PUs to employ the licensed spectrum, while the SUs are restricted. To enhance the spectrum efficacy, the CR mechanism was recommended. The primary concept of CR is spectrum reuse which enables the SUs to employ the authorised spectrum band when the PUs are idle. To attain this, the SUs are required to perform the spectrum sensing process that recognises the PU's spectrum occupation state. Thus, spectrum sensing is a primary operation of CR innovation that has focussed intense attention from both industry and academia. The important issue of spectrum sensing is to develop the test statistic to attain higher detection likelihood. In the past years, numerous model-driven spectrum sensing techniques have been implemented. However, the noise uncertainty issue varies with time causing the degradation of detection performance. To minimise the noise uncertainty issue, the totally-blind techniques have been implemented. However, the performance of these techniques is worse than that of the other techniques. Considering the traditional method-aided techniques, DL strategy can highly draw out the features of distinct platforms and enhance the performance of traditional communication devices. Although the conventional DL-aided techniques enhance the detection functionality, these features drawn from the conventional techniques are susceptible to noise uncertainty. To rectify the conventional technique's limitations, an effective hybrid spectrum sensing framework is important. Figure 2 displays the implemented hybrid spectrum sensing framework.

An effective hybrid spectrum sensing system is constructed in this work for CRN that improves the spectrum efficiency. First, the data attributes are fetched from the available resources. Further, the hybrid spectrum sensing process is carried out with the support of AAMNet. This network is the integration of CNN, LSTM, and autoencoder. The spectrum sensing approach by the recommended AAMNet is improved by the RIDSA-aided parameter optimisation process. Here, the recommended RIDSA optimally tunes the parameters of the AAMNet hence enhancing the spectrum sensing process. Spectrum availability is recognised for better utilisation of spectrum by the recommended hybrid spectrum sensing process. The effectiveness of the implemented method is evaluated by determining the outcomes with several DL and heuristic approaches.

4.2. *Conventional approach: DSA*

The existing DSA (Zhang *et al.*, 2021) is a swarm intelligence-aided approach motivated by the foraging and searching behaviours of the duck swarm. The

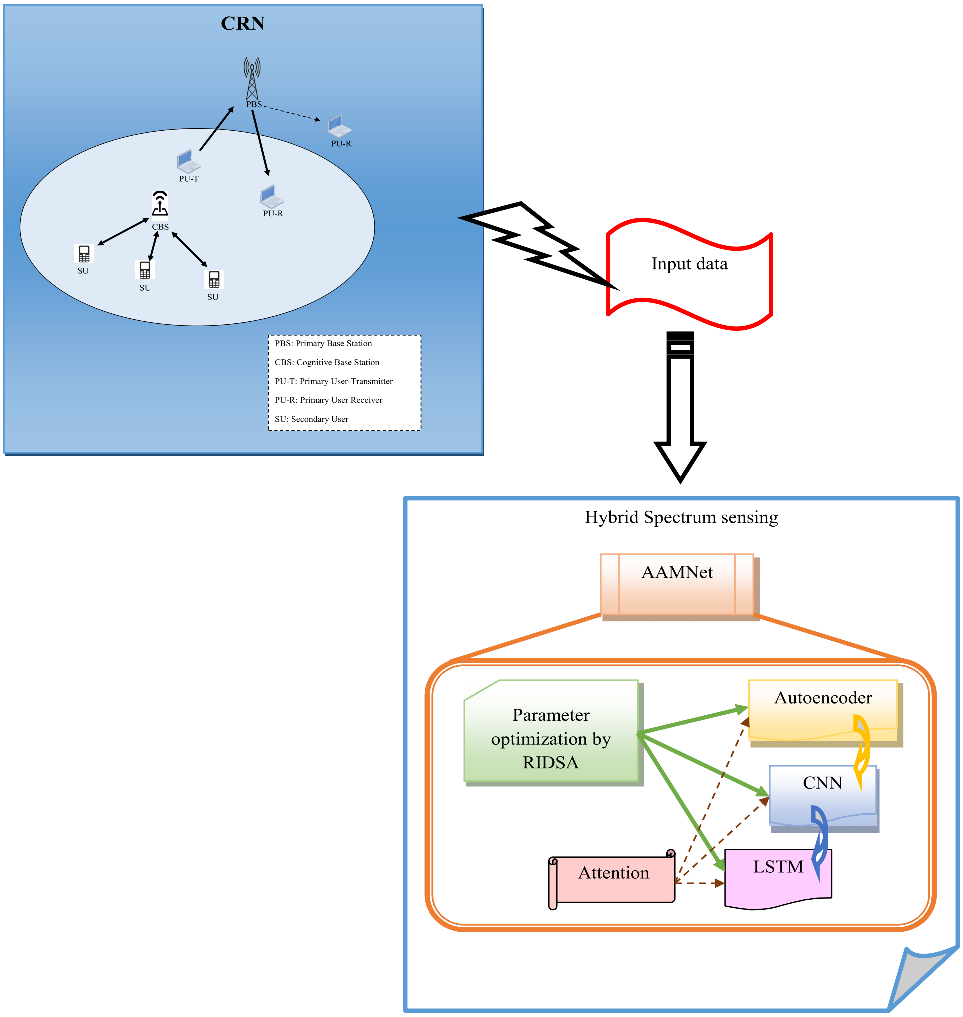

Fig. 2. The architecture of the implemented hybrid spectrum sensing system for CRN.

mathematical process of the DSA is explained here. The DSA includes the following stages.

- Duck swarm's positions after queuing (Initialisation of population)
- Food source searching (Exploration)
- Foraging in groups (Exploitation)

Population initialisation: Consider the derivation of randomly produced starting place in the D-dimensional search area as given in the following equation:

$$P_m = C_r + (X_r - C_r) \cdot v. \tag{3}$$

Here, the mth duck's $m = 1,2,...,F$ spatial region is specified as P_m in the duck group, and the population size number is given as F. The search region's lower and upper regions are considered as C_r and X_r appropriate. The arbitrary integer matrix among 0 and 1 is provided as v.

Exploration: After the duck swarm's queuing process, the ducks come to the region with much food. Each duck moderately disperses and initiates food searching. This operation is explained in the following equation:

$$C_m^{a+1} = \begin{cases} P_m^a + \mu \cdot P_m^a \cdot \operatorname{sign}\left(v - 0.5\right) & B > rd, \\ P_m^a + YY_1 \cdot \left(P_{\text{leader}}^a - P_m^a\right) + YY_2 \cdot \left(P_d^a - P_m^a\right) & B < rd. \end{cases} \tag{4}$$

Here, the term sign has an impact on the task of exploring for food, and it is set either 1 or -1 and the variable μ indicates the global search's control parameter. The exploration stage's search conversion probability is specified as B. The competition and cooperation coefficient between ducks in the search region is indicated as YY_2 and YY_1 accordingly. The present historical value's best duck region is indicated as P_{leader}^a at the ath iteration. The variable P_d^a specifies the agents around P_m^a in exploring for food by the group of ducks in the ath iteration. The variable rd is the updated arbitrary integer using Eq. (9) for enhancing the performance rates. Equation (5) determines the variable μ and Eq. (6) estimates the variable L

$$\mu = L \cdot \left(\frac{1-a}{a_{\max}}\right), \tag{5}$$

$$L = \sin(2 \cdot rd) + 1. \tag{6}$$

Exploitation: After discovering the duck swarm's food, that is, sufficient food can satisfy the duck's foraging. This operation is relatively related to each place of duck's fitness and derived in the following equation:

$$C_m^{a+1} = \begin{cases} P_m^a + \mu \cdot \left(P_{\text{leader}}^a - P_m^a\right) & g\left(P_m^a\right) > g\left(P_m^{a+1}\right), \\ P_m^a + ZZ_1 \cdot \left(P_{\text{leader}}^a - P_m^a\right) + ZZ_2 \cdot \left(P_u^a - P_d^a\right) & \text{else}. \end{cases} \tag{7}$$

Here, the variable μ indicates the global search's control parameter in the exploitation stage. The competition and cooperation coefficient between ducks in the search region is indicated as ZZ_2 and ZZ_1 accordingly in the exploitation stage. The present historical value's best duck region is indicated as P_{leader}^a at the ath iteration. The variables P_d^a and P_u^a specify the agents around P_m^a in foraging of a group of ducks in the ath iteration, where $u \neq d$.

Considering the parameter values YY_2, YY_1, ZZ_2 and ZZ_1 are all in the limit of 0 and 2 also, the evaluation formula is provided in the following equation:

$$YY_m \text{ or } ZZ_m \leftarrow \frac{1}{QQ}, rd \quad (m = 1, 2). \tag{8}$$

Here, the variable QQ is constant, it is set to 0.618. The pseudo-code of the existing DSA is represented in Algorithm 1.

Algorithm 1. Conventional DSA

```
Initial duck swarm positions, population number F, objective function, and
parameter value setting
Estimate the initial region's fitness values and choose the leader agent place
P_leader and best value g_min and population candidate
For a=1 to a_max
    Upgrade the μ parameter value employing Eq. (5) and upgrade the attributes
    B, YY_2, YY_1, ZZ_2 and ZZ_1
    For m=1 to F
        Upgrade the duck swarm places employing Eq. (4) (Exploration)
        Estimate the new place and fitness value g_new
        Upgrade the leader place P_leader and fitness value
        Upgrade the duck swarm to new places employing Eq. (7) (Exploitation)
        Estimate the fitness value
        If g_new < fitness
            Upgrade the place of individual and fitness value
        End if
            Upgrade the place of leader P_leader and fitness value
    End for
    Save the solution of the best individual
End for
Output fitness value and best place
```

4.3. *Proposed approach: RIDSA*

Numerous research worked are explored by analysing the performance of optimisation algorithms. Also, the consideration of existing optimisation algorithms faces several challenges that do not effectively work in our research work. On considering the existing POA algorithm, it restricts the amount of validators, which helps to limit and select the transactions to control in the network. In WOA, it fails by local optima issues during complex optimisation processes. Thus, it has a minimal speed of convergence and accuracy. Also, it has less capability of the exploitation phase. To solve these issues in existing optimisation algorithms, the research work adopts an improved algorithm, named RIDSA. The RIDSA is implemented for performing the optimisation process with the support of the existing DSA mechanism.

Purpose: The RIDSA is the integration of conventional DSA with an adaptive concept. The RIDSA is employed in the AAMNet-based hybrid spectrum sensing process. The AAMNet is the integration of three deep networks such as autoencoder, CNN, and LSTM. In these techniques, the important parameters such as hidden neurons need to be optimised to minimise the computational burden. For performing the optimisation of the hidden neuron counts in the mentioned techniques, the RIDSA is implemented.

Novelty: As mentioned earlier, the RIDSA is developed for optimising the hidden neuron counts in techniques such as autoencoder, CNN, and LSTM. This helps to maximise the performance of the hybrid spectrum sensing process and minimise the computational burdens. The RIDSA is developed from conventional DSA. The DSA has better accuracy value compared to conventional algorithms and also it provides the solutions quickly. However, a random integer from the range of 0 and 1 is involved in the conventional DSA for performing both exploitation and exploration. The involvement of this random integer leads to low convergence when increasing the iteration counts. Also, because of this random integer, there is a possibility that the DSA falls into the local optima issue. In order to mitigate these issues, a new random integer is constructed with the assistance of fitness rates. With the support of this newly designed random integer, the limitations mentioned in the DSA are prevented, and increased the performance and convergence rates. Thus, the RIDSA approach is constructed in this work and employed in the hybrid spectrum sensing process. Equation (9) derives the newly developed random integer

$$rd = \frac{cff}{\sqrt{(bff^2 + wff^2)}}. \tag{9}$$

Here, the newly invented random integer is taken as rd and it is employed in Eqs. (4), (6), and (8) for improving both exploitation and exploration tasks. Additionally, the variables cff, bff and wff specify the current fitness, best fitness, and worst fitness. Algorithm 2 shows the pseudo-code of RIDSA and Fig. 3 depicts the flowchart of implemented RIDSA.

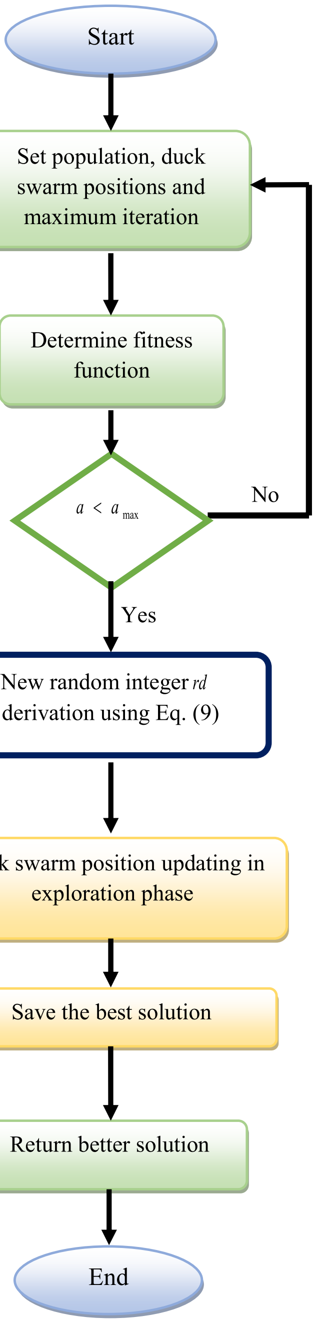

Fig. 3. Flowchart of implemented RIDSA for improving hybrid spectrum sensing process.

Algorithm 2. Developed RIDSA

Initial duck swarm positions, population number F, objective function, and parameter value setting
Estimate the initial region's fitness values and choose the leader agent place P_{leader} and best value g_{min} and population candidate
For $a=1$ to a_{max}
  Upgrade the μ parameter value employing Eq. (5) and upgrade the attributes B, YY_2, YY_1, ZZ_2 and ZZ_1
  For $m=1$ to F
    Derivation of a new random integer *rd* by Eq. (9)
    Upgrade the duck swarm places employing Eq. (4) (**Exploration**)
    Estimate the new place and fitness value g_{new}
    Upgrade the leader place P_{leader} and fitness value
    Upgrade the duck swarm to new places employing Eq. (7) (**Exploitation**)
    Estimate the fitness value
    If $g_{new} <$ fitness
      Upgrade the place of individual and fitness value
    End if
      Upgrade the place of leader P_{leader} and fitness value
  End for
  Save the solution of the best individual
End for
Output fitness value and best place

5. Hybrid Spectrum Sensing using Adaptive and Attentive Multi-stacked Network with Objective Function

5.1. *Models utilised in multi-stacked network*

The MNet is implemented in this work for performing the hybrid spectrum sensing process for CRN. The MNet is the integration of three deep networks such as autoencoder, CNN, and LSTM. These techniques show better performances in the domain of CRN and thus employed in the hybrid spectrum sensing process. These three techniques are explained as follows.

Autoencoder (Subray *et al.*, 2021): It is an unsupervised learning approach that is employed to minimise the input data's dimensionality and regenerate the real data from the compressed format. The autoencoder includes three significant parts such as decoder, latent space, and encoder. The encoder is employed for minimising the input data's dimension and producing an input data's compressed version. The layers of encoding contain a set of layers with a minimised amount of nodes.

If the variable y denotes an original number's S vector of dimension e, $y \in S^e$ further the result of the encoder module i is provided in the following equation:

$$i = g(Xy + c). \tag{10}$$

Here, factors c and X are the related bias unit and the weight matrix of the encoding layer accordingly. The activation function is specified as g. The compressed data generated are i indicated by the latent space. It is also named code space. Finally, the decoder regenerates the input data from the compressed data to be as near to the real data as possible.

If the variable $\bar{y}$ specified as the reconstructed solution, the compressed data's mapping i to $\bar{y}$ be given in the following equation:

$$\bar{y} = g'(X'y + c'). \tag{11}$$

Here, the variables c' and X' are considered as the decoding layer's bias unit and the weight matrix. Further, the activation function is specified as g'. The objective of the autoencoder is to reduce the reconstruction faults while the backpropagation approach is employed to reduce the errors. The loss function among the input and reconstructed data is determined by employing functions such as binary cross entropy and mean square error.

CNN (Wu *et al.*, 2018): It has been employed in numerous applications. It contains three significant layers such as pooling layers, convolutional layers, and Fully Connected (FC) layers. A convolutional layer includes a kernel named filters each of which contains a receptive field. Due to the shared files and the local connectivity, the convolutional layers can handle multi-dimensional data by translation invariance. The convolution task is formulated in the following equation:

$$b_{kl} = g\left(\sum_{n=0}^{N-1}\sum_{m=0}^{M-1} x_{nm} \cdot t_{(j+n)(k+m)} + c\right). \tag{12}$$

Here, the feature representation is given as b, and the convolutional kernel's weight is specified as x. The bias offset is taken as c and the variables M and N specify the kernel height and width, respectively. The position indices are taken as $(j+n)(k+m)$ and the activation function is specified as $g(\cdot)$.

Normally, the pooling layer is utilised after some convolutional layers. It offers a nonlinear downsampling form of the input and concentrates on minimising the parameter count in the network. The pooling layer's output is estimated in the following equation:

$$q = \sigma(b'). \tag{13}$$

Here, term q denotes the output of the pooling layer and b' denotes the input of the pooling layer. The downsampling task over the receptive field is indicated as $\sigma(\cdot)$.

After the tasks of convolution and pooling, the diverse feature maps are collected and employed as the input to the FC layer. The FC layer's derivation is given in the following equation:

$$b^o = g(x^o b^{0-1} + c^o). \tag{14}$$

Here, the FC layer's index is represented as o and the output and input of the layer are specified as b^o and b^{0-1} accordingly.

LSTM (Wei *et al.*, 2023): It is the improvement of the RNN. The RNN offered the short-term memory ability that enabled the utilisation of the conventional data to be employed for the current work. The output gates, cell, forget gate, and input gate are presented in normal LSTM.

Forget gate: The primary objective of this gate is to decide which cell gate bits are supported to provide the new input data and the conventional hidden state. The network's forget gate is trained hence results close to zero when an input component is not relevant or else closer to one when it is related. The forget gate fo_t is modelled in the following equation:

$$fo_t = \sigma(we_g[hi_{t-1}, in_t] + bi_g). \tag{15}$$

Here, the activation function is indicated as σ. Variables bi_g and we_g denote the forget gate's bias and weight. Variables in_t and hi_{t-1} refer to the integration of present input and hidden state accordingly.

Input gate: The primary goal of this gate is two-fold. The initial one is to validate if the new data is relevant to keep in the cell stage. One operation includes producing a new memory update attribute specified as $\tilde{D}_t$, by integrating the new input data and conventional hidden state. The operation is formulated in the following equation:

$$\tilde{D}_t = \tanh\left(we_d[hi_{t-1}, in_t] + bi_d\right). \tag{16}$$

Here, the variable bi_d and we_d denotes the input gate's bias and weight. The term tanh is an activation function, which is employed to produce the memory update vector's elements. Same as the forget fate, the input gate is trained to result a value vectors in [0, 1] employing the sigmoid activation function. This operation is provided in the following equation:

$$yy_t = \sigma(we_{yy}[hi_{t-1}, in_t] + bi_{yy}). \tag{17}$$

Here, terms we_{yy} and bi_{yy} denote the input gate's weight bias.

Further, these two tasks are point-wise multiplied. The resulting integrated vector is further added to the cell state as given in the following equation:

$$D_t = g_t \otimes D_t - 1 + yy_t \otimes \tilde{D}_t. \tag{18}$$

Output gate: The primary objective of this gate is calculated in the new hidden stage. The output gate employs three distinct data including new input data, the conventional hidden state, and the newly updated cell state.

It initially employs the conventional hidden state and presents input data via the sigmoid-activated network to attain the filter vector ou_t as given in the following equation:

$$ou_t = \sigma(we_{ou}[hi_{t-1}, in_t] + bi_{ou}). \tag{19}$$

Here, variables bi_{oo} and we_{oo} denoted as the output gate's bias and weight. The cell state is given to the activation function tanh to manage the values into the bound [−1, 1] to generate the compressed cell state that is employed to the filter vector with point-wise multiplication. Along with the new cell state D_t, a new hidden state hi_t is generated, and results as given in the following equation:

$$hi_t = ou_t \otimes \tanh(D_t). \tag{20}$$

The new cell stage D_t becomes the conventional cell state D_{t-1} to the subsequent LSTM module while the new hidden state hi_t changes into the conventional hidden state hi_{t-1} to the upcoming LSTM module.

Thus, by considering these three techniques' improved performance rates, the MNet is constructed for performing the hybrid spectrum sensing process.

Parameter optimisation process: The parameter optimisation process helps to select the best set of hyperparameters in the ML approaches. For initiating the optimisation process, the population of the duck swarm can be randomly generated with the help of prior knowledge. With the help of the objective function in Eq. (22), the hidden neurons in the autoencoder, LSTM, and CNN model gets tuned using the developed RIDSA algorithm to reaches the convergence criteria to make sure better robust performance. Hence in each population of duck, the required parameters are to be encoded and processed over the iteration. At the end of the iteration, the better value is attained for such parameters that are used in the AAMNet model. Thus, it helps to achieve accurate outcomes in the developed model.

5.2. *Attention mechanism*

Nowadays, the attention mechanism (Zhang *et al.*, 2020) is applied in numerous tasks such as object identification, classification, image generation, and so on since it exponentially increases the network performance rates. In this hybrid spectrum sensing process, the attention mechanism is integrated. This attention mechanism is inserted into the network layers that help the network to concentrate on the more necessary features and disregard the inappropriate features and the noise. Moreover, this mechanism supports to concentrate on the important part that has an important effect on the solutions. Equation (21) shows the attention function, which is composed of a mapping query and a pair of keys and values. This function determined the alignment score among the factors from the two modules

$$\text{Attention}(r,t,y) = \text{soft}\max(x(rt^T))\,y. \tag{21}$$

Variables t and y denote the key and value matrices. The query matrix is represented as r.

5.3. *Recommended AAMNet for spectrum sensing*

In the hybrid spectrum sensing process, the AAMNet is constructed in this work. This is a very effective technique since it is developed using DL techniques. The AAMNet includes three deep networks such as autoencoder, CNN, and LSTM. The consideration of these networks provides better outcomes, yet these have several challenges that are mentioned below. Autoencoder is more sensitive, it does not perform in noisy input data. The tuning of several layers in the neural network is complex and it consumes more time. On the other hand, the CNN needs more labeled data; this is expensive and also it causes overfitting issues. In LSTM model, it requires further memory and large time, which can make huge computational complexity. In order to resolve these problems, the attention mechanism is integrated into autoencoder, CNN, and LSTM for improving the hybrid spectrum sensing process in CRN. The advantages of integrating the attention mechanism in autoencoder, CNN, and LSTM are shown below.

Attention-based Autoencoder: The autoencoder can capture the difficult and complex features from the input data. However, when executing more input data, the autoencoder trouble to capture the complex features. Autoencoder contains an attention mechanism, it is used to choose the features effectively. Moreover, it can enhance the performance of the technique.

Attention-based CNN: The CNN minimises the computation process and also extracts the significant features and eliminates the outliers. However, the CNN fails to produce the maximum accuracy when processing small datasets. To maximise the accuracy of the CNN, the attention mechanism is included. This attention mechanism effectively reduces the computational complexities and enhances the performance rates.

Attention-based LSTM: The LSTM can remember the previous data and thus increase efficiency. It minimises the gradient issues also. However, the LSTM faces overfitting issues when the input data increases. Hence, the attention mechanism is included in this network that minimises the overfitting issues, and enhances the efficiency of the LSTM network.

Thus, the AMNet is constructed with the outstanding features of these techniques. This AMNet technique can provide the desired solutions for the hybrid spectrum sensing process. Though the suggested AMNet can provide the desired solutions, the network attributes like hidden neurons in the CNN, LSTM, and autoencoder may cause a computational burden. In order to mitigate this problem, the AAMNet is constructed, where the RIDSA technique helps to tune the hidden neuron count of autoencoder, CNN, and LSTM. Thus, the AAMNet is suggested for performing the hybrid spectrum sensing process. This network highly increases the performance rates and also spectrum efficiency than the other conventional models. The efficiency function of the RIDSA-based parameter tuning is mentioned in the following equation:

$$ob = \underset{\{hn^{\mathrm{AE}}, hn^{\mathrm{CNN}}, hn^{\mathrm{LSTM}}\}}{\arg\max}[A]. \tag{22}$$

Here, hn^{AE} refers to the hidden neuron count in the autoencoder is varying from 5 to 255. hn^{CNN} represents the hidden neuron count in CNN that ranges from 5 to 255. hn^{LSTM} represents the hidden neuron count in LSTM that varies from 5 to 255. Further, the accuracy is indicated as A, and it is maximised by this process. This factor is explained as follows.

Accuracy: It is a performance measure that is utilised to define how the method performs the operation. It is shown in the following equation:

$$A = \frac{xx + cc}{xx + cc + bb + mm}. \tag{23}$$

Here, terms mm and cc denote the true positive and true negative rates. Also, bb and xx represent the false positive and false negative rates.

Thus, the AAMNet is constructed for performing the hybrid spectrum sensing for CRN. The functionality of the AAMNet is explained as follows.

AAMNet: The AAMNet is implemented for performing hybrid spectrum sensing. This network includes three deep networks such as autoencoder, CNN, and LSTM. Initially, the original data S_d are given as input for the autoencoder technique. The autoencoder extracts the complex, requisite, and difficult characteristics in the raw data. Further, the obtained features are given to the CNN method. This approach effectively extracts the optimal features and removes the unnecessary features. After that, the necessary features are forwarded to the LSTM technique. Here, the attention mechanism is integrated to improve the accuracy and performance rates. Moreover, to minimise the computational burdens, the RIDSA algorithm is utilised for tuning the hidden neuron count in the autoencoder, LSTM, and CNN techniques. Thus, a novel hybrid spectrum sensing process is performed for CRN that increases the accuracy and spectrum efficiency than the conventional techniques. The functional diagram of the AAMNet-based hybrid spectrum sensing process is shown in Fig. 4.

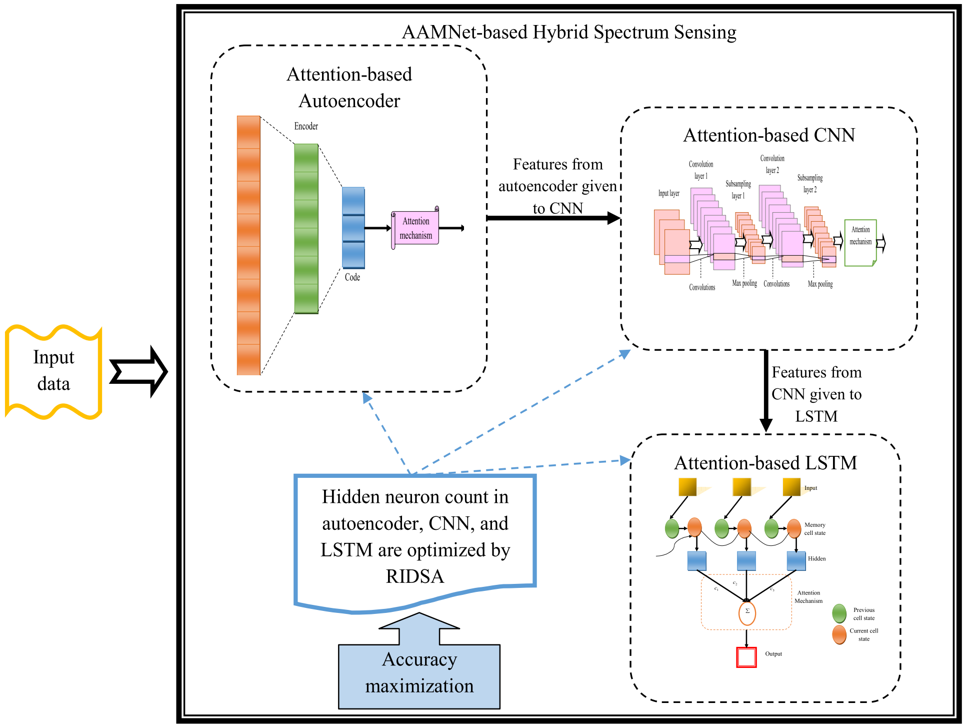

Fig. 4. Functional diagram of AAMNet-based hybrid spectrum sensing process for CRN.

6. Experimental Findings

6.1. *Experimental setting*

The developed hybrid spectrum sensing system in CRN was implemented in the Python platform. On this platform, satisfactory solutions were reached. The proposed RIDSA model's chromosome length was taken as 3, maximum iteration was considered as 50, and total population was taken as 10. In order to prove the designed hybrid spectrum sensing system's effectiveness, the performance analysis was conducted by utilising the traditional algorithms and classifiers such as the Red Deer Algorithm (RDA) (Fathollahi-Fard *et al.*, 2020), Ebola Optimisation Algorithm (EOA) (Oyelade *et al.*, 2022), Squid Game Optimiser (SGO) (Azizi *et al.*, 2023), DSA (Zhang *et al.*, 2021), Autoencoder (Subray *et al.*, 2021), CNN (Wu *et al.*, 2018), LSTM (Wei *et al.*, 2023), and AMNet (Wu *et al.*, 2018; Zhang *et al.*, 2020; Subray *et al.*, 2021; Wei *et al.*, 2023). Table 2 shows the network parameters of the developed CRN and also, the details of system requirements are mentioned in Table 3.

6.2. *Performance measures*

The following approach metrics are used for determining the performance of the designed hybrid spectrum sensing framework.

Table 2. Network parameters of CRN.

Parameter	Value range
Area size	1,000 m × 1,000 m
Number of channels	1
PU interference range (m)	125
Frequency (GHz)	2.4
PU idle time (ms)	10, 20, 40, 80, 160, 320
Effective bandwidth (Mbps)	2
Initial energy (J)	2, 4, 6, 8, 10
SU transmission range (m)	125
Data rate (kbps)	100
Packet size (KB)	1.5
Number of active connections	1, 2, 3, 4, 5
Running time (s)	200

Table 3. System requirements in CRN.

RAM	16.0 GB
Interpreter	MATLAB R2020a
Processor	Intel (R) Core(TM) i3-1005G1
OS	Windows
Development environment	MATLAB
Version	Windows 11 Pro
CPU	1.19 GHz–1.20 GHz
System type	64-bit operating system, x64-based processor

Accuracy: It is derived in Eq. (23).

Sensitivity: It is mentioned in the following equation:

$$\text{Sen} = \frac{xx}{xx + cc}. \tag{24}$$

Specificity: It is shown in the following equation:

$$\text{spec} = \frac{bb}{bb + mm}. \tag{25}$$

Precision: It is calculated in the following equation:

$$P = \frac{xx}{xx + bb}. \tag{26}$$

FPR: It is denoted in the following equation:

$$\text{FPR} = \frac{bb}{bb + xx}. \tag{27}$$

FNR: It is calculated in the following equation:

$$\mathrm{FNR} = \frac{mm}{xx + mm}. \tag{28}$$

NPV: It is derived in the following equation:

$$\mathrm{NPV} = \frac{xx}{xx + mm}. \tag{29}$$

FDR: It is derived in the following equation:

$$\mathrm{FDR} = \frac{bb}{xx + bb}. \tag{30}$$

$F1$-score: It is determined in the following equation:

$$F1\text{-score} = 2 \times \frac{cc \times bb}{cc + bb}. \tag{31}$$

MCC: It is derived in the following equation:

$$\mathrm{MCC} = \frac{mm \times cc - mm \times xx}{\sqrt{(mm + xx)(mm + cc)(xx + bb)(xx + mm)}}. \tag{32}$$

6.3. *Designed RIDSA model's convergence analysis*

The convergence analysis of the RIDSA approach is given in Fig. 5. By comparing the RIDSA method with conventional algorithms, this experiment is carried out whereas; the parameters are effectively tuned to maximise the convergence value. In the convergence analysis graph, the x-axis shows the varying number of iterations,

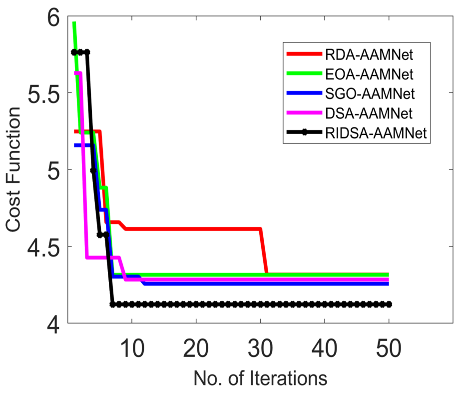

Fig. 5. Convergence analysis of the designed RIDSA method over conventional algorithms.

like 10, 20, 30, 40, and 50. On considering the traditional RDA-AAMNet, it shows low convergence that arise parameter issues. Our proposed algorithm shows good convergence by tuning the necessary parameters using an iteration and population. Based on this evaluation, the optimal solution is reached by considering a predefined value. Thus, it has been reported that the designed RIDSA model obtained a minimum cost function and hence attained higher value convergence than the conventional algorithms. For the 30th iteration, the RIDSA model's cost function is relatively reduced by 7.31% of RDA-AAMNet, 6.58% of EOA-AAMNet, 4.8% of SGO-AAMNet, and 5.12% of DSA-AAMNet accordingly. Additionally, it has been guaranteed that the implemented RIDSA helps to enhance the accuracy rates of the hybrid spectrum sensing approach.

6.4. *Designed RIDSA model's statistical analysis*

The designed RIDSA method's statistical analysis is offered in Table 4. In this statistical analysis, it helps to visualise and analyse complicated patterns to provide better performance. It supports the implemented system can handle effectively works in all types of data. Also, it reduces the scalability problem in the implemented method to enhance the accuracy. By comparing the RIDSA model over related other algorithms, the RIDSA model is improved than the other algorithms by 4.68% of RDA-AAMNet, 4.65% of EOA-AAMNet, 3.22% of SGO-AAMNet, and 3.9% of DSA-AAMNet, respectively, when considering the best factor. Thus, it has been explained that the developed RIDSA approach helps to determine the optimal solutions than the other techniques. Also, it has been clearly indicated that the designed RIDSA increases the accuracy of the hybrid spectrum sensing approach.

6.5. *Implemented hybrid spectrum sensing system's performance analysis*

The developed hybrid spectrum sensing system's performance is verified by employing other recent algorithms and techniques. This experiment is graphically given in Figs. 6 and 7. In Fig. 6(a), the developed hybrid spectrum sensing system accuracy is improved by 2.54% of RDA-AAMNet, 1.8% of EOA-AAMNet, 1.27% of SGO-AAMNet, and 1.06% of DSA-AAMNet appropriately for softmax

Table 4. Statistical report of implemented RIDSA model over conventional algorithms.

Terms	RDA-AAMNet (Fathollahi-Fard *et al.*, 2020)	EOA-AAMNet (Oyelade *et al.*, 2022)	SGO-AAMNet (Azizi *et al.*, 2023)	DSA-AAMNet (Zhang *et al.*, 2021)	RIDSA-AAMNet
Median	4.6135	4.3152	4.2566	4.2843	4.123
Best	4.3168	4.3152	4.2566	4.2843	4.123
Standard deviation	0.27249	0.32921	0.25813	0.26649	0.41261
Mean	4.5609	4.4264	4.3527	4.3552	4.257
Worst	5.2476	5.9631	5.1582	5.6276	5.763

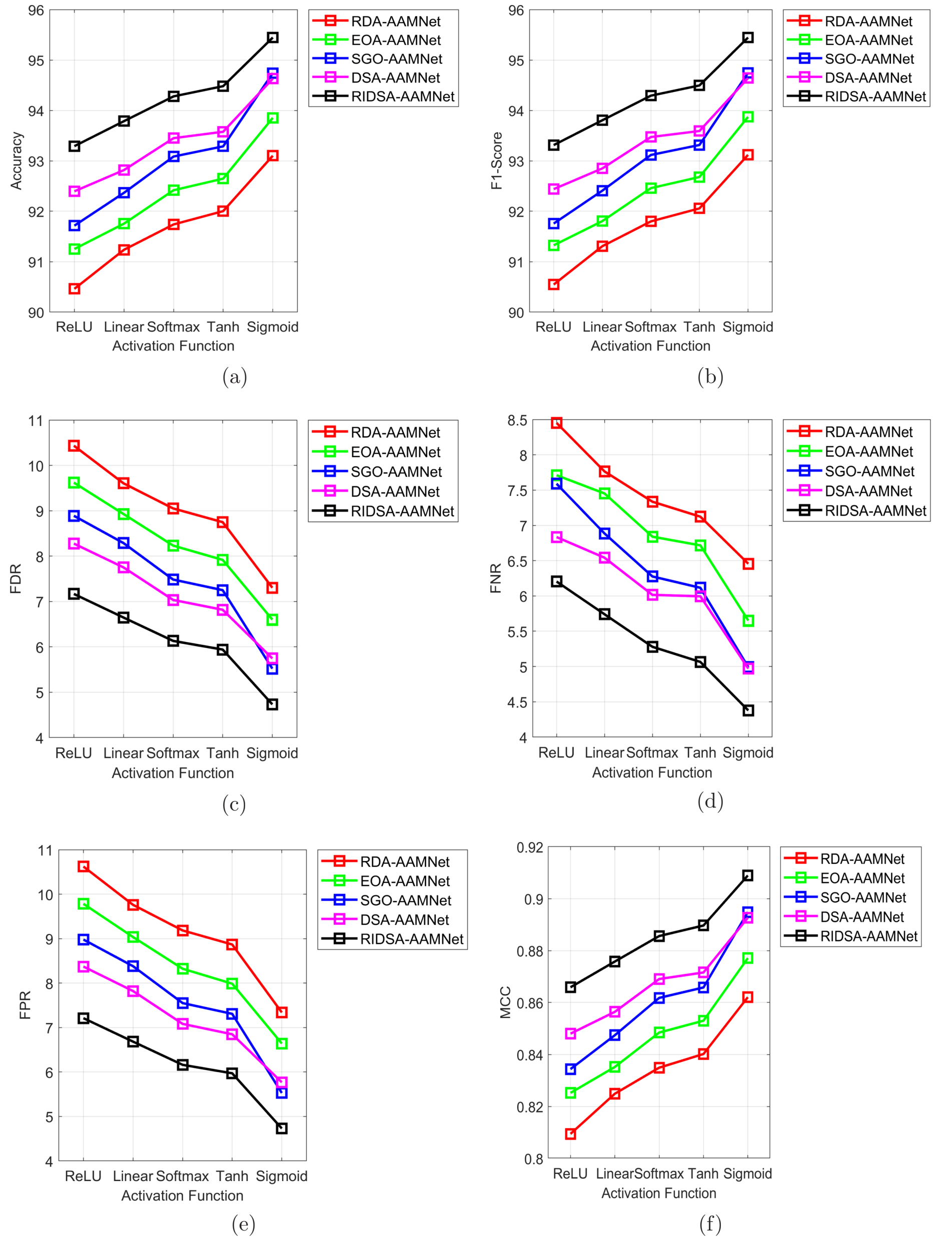

Fig. 6. Performance evaluation of implemented hybrid spectrum sensing system over conventional algorithms in terms of (a) Accuracy, (b) $F1$-score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NPV, (h) Precision, (i) Sensitivity, and (j) Specificity.

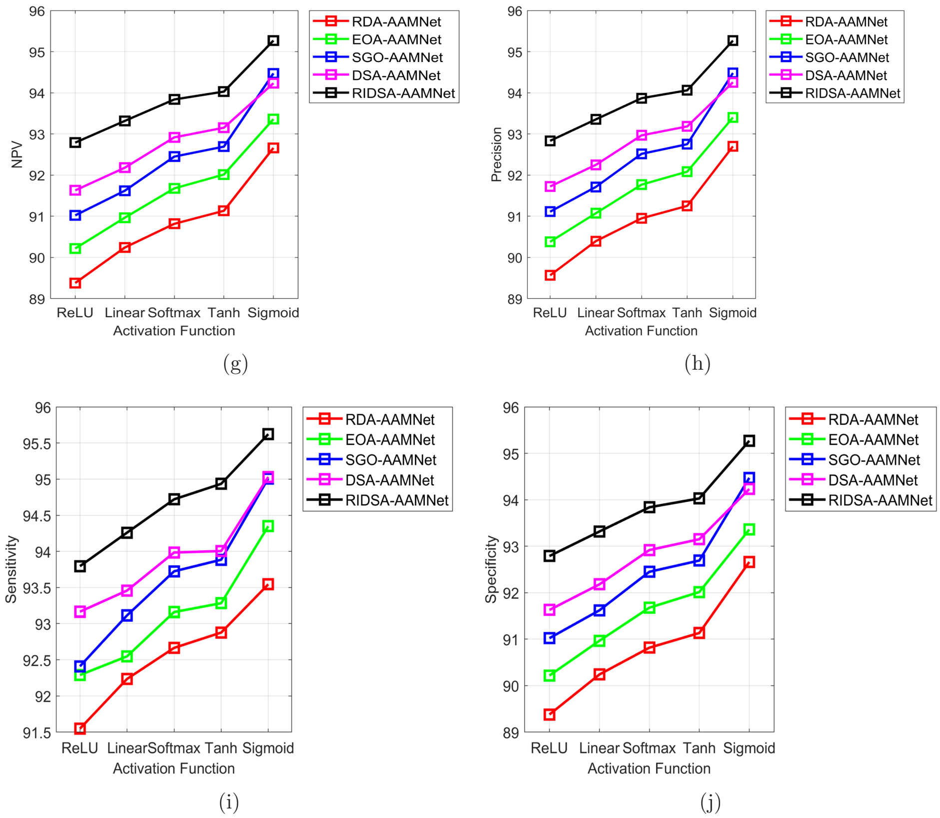

Fig. 6. (*Continued*)

activation function. Considering Fig. 6(h), the precision analysis is focussed on showing a positive outcome in the CRN model. So, this analysis helps to minimise the false positive and false negative errors. The developed RIDSA-AAMNet model reaches maximum precision. In Fig. 7(d), the FNR metric shows a higher error rate in the traditional autoencoder model, yet it affects overall performance in CRN. This causes communication issues while transmitting the data. In the developed method, accurate performance is attained by decreasing the error rate. Moreover, when considering the ReLU activation function in Fig. 7(c), the designed hybrid spectrum sensing system's FDR is minimised by 25.57% of autoencoder, 21.42% of CNN, 14.28% of LSTM, and 14.28% of AMNet, respectively. When focussing on other performance measures, the developed approach produced more effective and superior solutions.

6.6. *Implemented hybrid spectrum sensing system's overall comparative analysis*

The implemented hybrid spectrum sensing system's overall comparative estimation is given in Tables 5 and 6 over the existing methods and models. In Table 5, the error value of FDR in the RDA-AAMNet algorithm is 7.3027 which seems to represent a high error when compared with other techniques. Our developed RIDSA-AAMNet algorithm attains 4.7322 and provides effective performance. In Table 6, while considering the developed RIDSA-AAMNet, the accuracy achieves 95.446 in CRN. The designed hybrid spectrum sensing mechanism's precision is enhanced by 2.33% of autoencoder, 1.31% of CNN, 0.46% of LSTM, and 0.98% of AMNet,

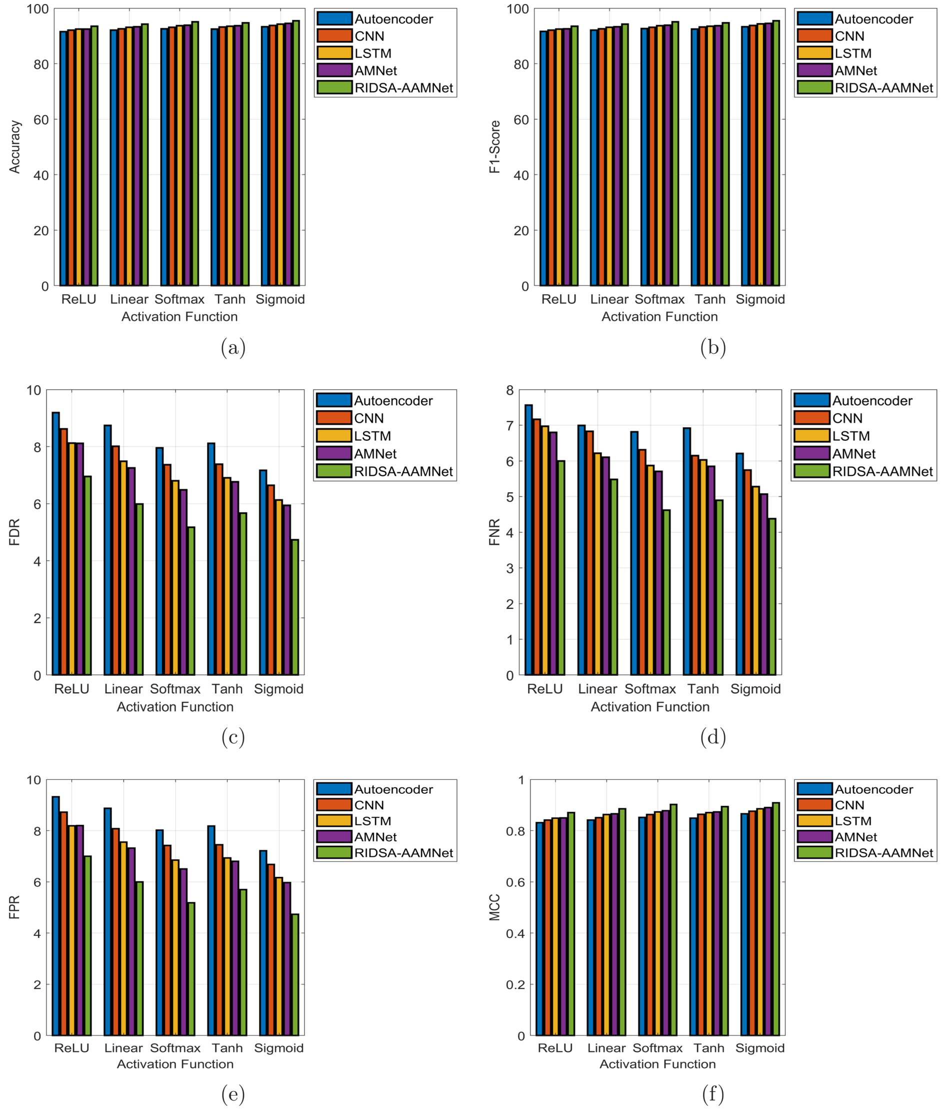

Fig. 7. Performance evaluation of implemented hybrid spectrum sensing system over traditional classifiers in terms of (a) Accuracy, (b) $F1$-score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NPV, (h) Precision, (i) Sensitivity, and (j) Specificity.

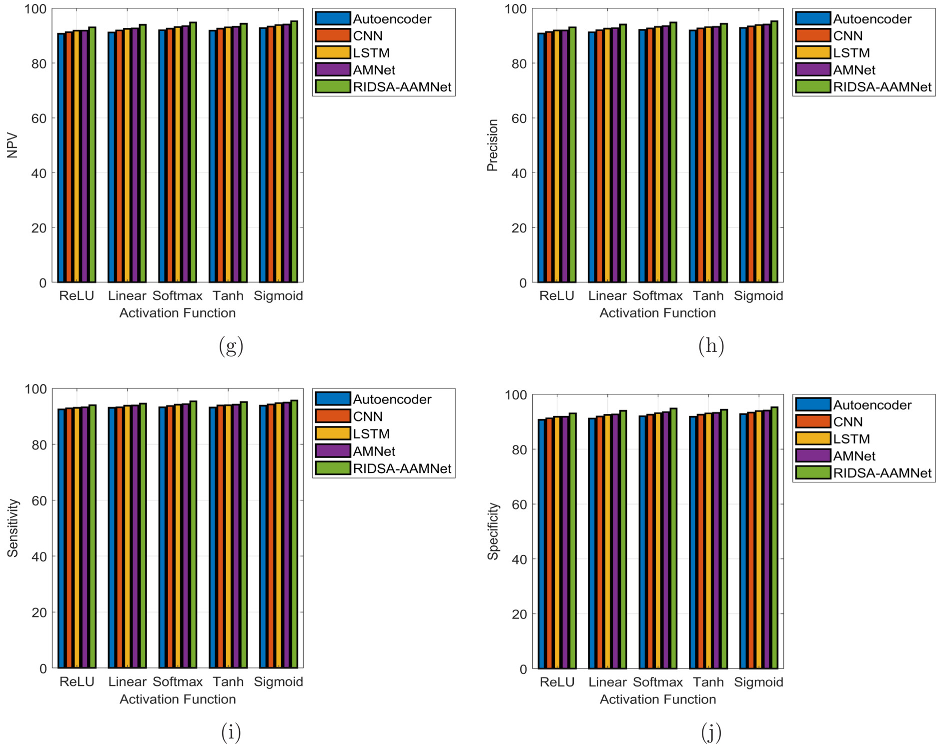

Fig. 7. (*Continued*)

Table 5. Overall comparative estimation of the designed hybrid spectrum sensing system in CRN over conventional algorithms.

Terms	RDA-AAMNet (Fathollahi-Fard *et al.*, 2020)	EOA-AAMNet (Oyelade *et al.*, 2022)	SGO-AAMNet (Azizi *et al.*, 2023)	DSA-AAMNet (Zhang *et al.*, 2021)	RIDSA-AAMNet
Accuracy	93.101	93.853	94.74	94.63	95.446
Sensitivity	93.544	94.348	95.01	95.03	95.622
Specificity	92.661	93.359	94.471	94.232	95.27
Precision	92.697	93.399	94.48	94.255	95.268
FPR	7.3392	6.6406	5.5286	5.7681	4.7303
FNR	6.4561	5.6516	4.9903	4.9702	4.3776
NPV	92.661	93.359	94.471	94.232	95.27
FDR	7.3027	6.6009	5.5204	5.7447	4.7322
*F*1-score	93.119	93.871	94.744	94.641	95.445
MCC	86.207	87.71	89.481	89.263	90.892

respectively, when considering Table 6. Similarly, when considering Table 5, the designed hybrid spectrum sensing approach's specificity is maximised by 2.73% of RDA-AAMNet, 2.01% of EOA-AAMNet, 0.83% of SGO-AAMNet, and 1.09% of DSA-AAMNet accordingly. Thus, it has been ensured that the implemented hybrid

Table 6. Overall comparative estimation of the designed hybrid spectrum sensing system in CRN over conventional classifiers.

Terms	Autoencoder (Subray *et al.*, 2021)	CNN (Wu *et al.*, 2018)	LSTM (Wei *et al.*, 2023)	AMNet (Wu *et al.*, 2018; Zhang *et al.*, 2020; Subray *et al.*, 2021; Wei *et al.*, 2023)	RIDSA-AAMNet
Accuracy	93.503	94.263	95.099	94.703	95.446
Sensitivity	94.005	94.523	95.385	95.101	95.622
Specificity	93.003	94.004	94.814	94.306	95.27
Precision	93.046	94.012	94.823	94.329	95.268
FPR	6.997	5.9962	5.1865	5.694	4.7303
FNR	5.9952	5.477	4.6152	4.8986	4.3776
NPV	93.003	94.004	94.814	94.306	95.27
FDR	6.9542	5.9884	5.1772	5.671	4.7322
$F1$-score	93.523	94.267	95.103	94.714	95.445
MCC	87.011	88.527	90.199	89.409	90.892

spectrum sensing system in CRN reaches highly satisfactory solutions compared to the traditional model.

6.7. *Comparative analysis of the developed model*

The comparative analysis of the implemented method is provided in Table 7. In conventional methods, timely detection is not sufficient this may affect the spectrum sensing performance. By considering Table 7, the developed RIDSA-AAMNet spectrum sensing mechanism of precision is enhanced by 18.50% of CM-CNN, 1.57% of CNN-LSTM, 17.54% of LSTM-SS, 3.01% of RNN-BIRNN-LSTM and 1.57% of DRLNet. In developed RIDSA-AAMNet model, it shows a higher precision value than the existing models thus, it provides better communications without any interference in CRN. It effectively enhances spectrum sensing performance in CRN. In FDR, the performance of the implemented approach shows less error rate when

Table 7. Comparative analysis of the implemented method.

Terms	CM-CNN (Liu *et al.*, 2019)	CNN-LSTM (Xie *et al.*, 2020a)	LSTM-SS (Soni *et al.*, 2020)	RNN-BIRNN-LSTM (Vijay and Aparna, 2023)	DRLNet (Rani and Prashanth, 2023)	RIDSA-AAMNet
Accuracy	80.48	93.44	81.12	92.00	93.76	95.45
Sensitivity	79.87	92.88	80.52	91.29	93.49	95.62
Specificity	81.07	93.99	81.70	92.70	94.03	95.27
Precision	80.39	93.79	81.05	92.48	93.79	95.27
FPR	18.93	6.01	18.30	7.30	5.97	4.73
FNR	20.13	7.12	19.48	8.71	6.51	4.38
NPV	80.56	93.10	81.19	91.54	93.73	95.27
FDR	19.61	6.21	18.95	7.52	6.21	4.73
$F1$-score	80.13	93.33	80.78	91.88	93.64	95.45
MCC	60.95	86.88	62.23	84.00	87.52	90.89

compared with 7.5% of CM-CNN, 2.3% of CNN-LSTM, 7.5% of LSTM-SS, 3.7% of RNN-BIRNN-LSTM, and 2.3% of DRLNet. The traditional method raises a high error rate that can lead to harmful interference and maximise the disruption of transmitting data. However, the developed model has a low error rate, the minimal error rate is crucial for CRN. It can effectively enhance the accurate detection performance and minimise false alarms without any harmful interference. It has been ensured that the implemented hybrid spectrum sensing method in CRN reaches more satisfactory solutions than the traditional models. In Table 5, the existing CM-CNN approach gives a minimal accuracy rate of 80.48 which can degrade the spectrum sensing framework in CRN. The implemented method shows a 95.45 better accuracy value compared to other existing approaches. This comparative analysis in the designed approach helps to handle memory usage and minimise the higher duration of the detection process.

7. Discussion

Figure 5 represents the convergence analysis of the proposed method. This analysis helps to enhance the decision-making process and reduce the processing time. Figure 6 represents the performance evaluation of the implemented hybrid spectrum sensing system with traditional models. Here, diverse performance metrics are utilised to validate the algorithmic analysis process. It can minimise the optimisation process and processing time to detect spectrum sensing in CRN. Figure 7 shows the comparision analysis of the traditional and proposed method detection approaches using diverse measures like FDR, $F1$-score, Accuracy, FNR, FPR, NPV NPV, Precision, NPV, Sensitivity, and Specificity. From Fig. 7(h), the precision value of the existing autoencoder method shows a very low value. However, the developed method shows a better rate compared to other methods. This high precision rate can effectively transmit the data without any communication issues. In Table 5, the developed RIDSA-AAMNet method shows a better accuracy value of 95.446 than the traditional frameworks. It helps to effectively enhance the accurate detection and protect the PU operations. Also, it has the ability to minimise the misclassification and identification process. Based on this evaluation, the designed approach facilitates handling errors in the system. The specificity value of the proposed method can attain 95.62, this high specificity rate can improve the timely detection and maximise SS in CRN.

8. Conclusion

An intelligent hybrid spectrum sensing framework has been recommended in this work for improving the spectrum efficiency in the CRN. In the beginning, from the available resources, the necessary data attributes were aggregated. Further, the hybrid spectrum sensing mechanism was performed by the suggested AAMNet. This network was composed of autoencoder, CNN, and LSTM techniques. In order to maximise the AAMNet-based hybrid spectrum sensing process, the parameters of AAMNet were optimised. For performing the parameter optimisation in AAMNet mode, the RIDSA was utilised due to its better performance rates. The availability of the spectrum was recognised for effective spectrum use with the support of a hybrid spectrum sensing mechanism. The efficacy of the designed mechanism was estimated by estimating the outcomes with conventional techniques. When considering the sigmoid activation function, the implemented hybrid spectrum sensing system's accuracy was enhanced by 4.21% of autoencoder, 3.15% of CNN, 2.10% of LSTM, and 1.05% of AMNet, respectively. From these research findings, it has been revealed that the implemented hybrid spectrum sensing mechanism was more effective and robust than the other related techniques.

Practical implications: The consideration of CRN helps to find sensitive information about patients and also, it prevents malicious activities in the medical sector. CRN can be used for emergency situations and efficiently provides public safety communications. In real-world applications, it is common to effectively detect errors through network nodes. It is highly utilised for identifying interference in spectrum sensing. Also, it is used in several applications like navigation, military, and public safety. Spectrum sensing helps to prevent unauthorised spectrum usage and improve network security in military-based applications. It can effectively handle low-power transmissions; also it is highly suitable for managing large numbers of IoT devices with restricted spectrum requirements. Considering the CRN networks in this applications, it facilitates to maximise the quality of service by reducing the noise present in the signal whereas it can also accommodate more users on the same network. Thus, the CRN networks have the ability to work in numerous applications, including emergency networks, disaster relief, medical, weather forecasting, and traffic control for increasing communications among the networks in rural areas.

Limitations and future work of the developed model: Processing the raw data directly into the AAMNet may cause dimensionality and complexity issues in CRN. Thus, it occurs noisy interference in the developed model. Due to the presence of weak signals, the CRN gets easily affected by the threats, thus it might affect the security. The estimation of the sparsity level of the wideband signal is critical in the developed model. These issues will be rectified in future work. Modern pre-processing methods will be implemented to extract the essential information without any information loss. In future work, the transformer-based model will be considered to improve the spectrum efficiency by analysing the delay and throughput in the CRN network. Time-domain method will be introduced to solve the issues of computational problems to enhance the CRN performance.

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