FUZZY CONVOLUTION NEURAL NETWORK AND CONVERGENCE IMPROVED BAT OPTIMIZATION FOR AN ENERGY EFFICIENT AND SECURED SPECTRUM ACCESS IN COGNITIVE RADIO NETWORK

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ABSTRACT: Certain frequency bands are frequently used in traditional wireless communications systems but few are not utilized in specific time slots. The imbalanced spectrum allotments and service or traffic dynamics may be the reason for improper utilization of scarce spectrum resources. Cognitive radio (CR) technology is regarded as the prominent solution for mitigating spectrum under-utilization concern where secondary user can utilized the unused spectrum resources whenever primary users (PUs) is not using it. This is greatly achieved by the concept of spectrum sensing. A better-quality model work for optimum Spectrum Utilization of wireless systems with Cognitive Radio Networks has been suggested in existing work. Ensemble Adaptive Neuro Fuzzy Inference System (EANFIS) is greatly deployed for spectrum access control and Intrusion Detection is acquired through Enhanced support vector machine. The Particle Swarm Optimization (PSO) is also exploited for power allocation for secondary users. Conversely, there arises high ANFIS computational cost because of complex structure and gradient learning. In addition, PSO may easily fall into local optimum in high-dimensional space and low convergence rate in iterative processes which are considered as PSO drawbacks. An enhanced model is presented for mitigating these problems through Fuzzy Filter Convolutional neural network (FFCNN) for spectrum access control and antecedents are regarded for spectrum selection of secondary user with trivial likelihood. Weighted fuzzy c means clustering plays a major role in detecting DOS and Replay attacks which is detected on basis of normal protocol operation behaviour, traffic flow and primary user access time. Kernel Cumulative Sum (KCUSUM) method is presented furthermore for detecting Primary User Emulation Attack (PUEA). Convergence Improved Bat Optimization (CIBAT) is deployed too for secondary user's power allocation and thereby diminishing energy consumption. The suggested spectrum access control and power allocation model efficiency are validated by experimental outcomes pertaining to throughput, packet delivery ratio and energy efficiency.

KEYWORDS: Cognitive Radio, Secondary Users, Adaptive Neuro Fuzzy Inference System, Spectrum Utilization, Convolutional Neural Network, Support Vector Machine and Power Allocation.

1. INTRODUCTION

Wireless technologies and its application have been tremendously growing and highly demanded for various services which in turn greatly necessitate spectral proficient and energy-efficient communication systems. Conversely, attaining high spectral efficiency (SE) is a great challenge because of fixed spectrum allocation approach. As per Federal Communications Commission report, merely 30% of licensed spectrum in United States is completely utilized. For improving SE, Cognitive Radio (CR) has been greatly suggested for enabling primary user for sharing its frequency band with secondary user in a network. Specificially CR helps in spectrum sharing for secondary user without interfering PUs whenever it is idle [1,2].

CR is regarded as possible solution for improving SE since it is greatly exploited in various traditional cellular networks, relay networks, and wireless sensor networks. There exist various classification of spectrum sensing technique such as cyclostationary detection, matched filter detection, Eigenvalue based detection and energy detection (ED). Cyclostationary detection provides improved detection performance when PU cyclic frequencies is known, but is greatly desires higher sensing time in a frame structure. The matched filter detection offers necessary value of detection gain in contradiction with other techniques with short sensing time [3,4,5]. But, it necessitates PU's signaling features entire information.

The test statistics computation is done from eigenvalues of received signal sample covariance matrix in case of Eigen value based detection. Furthermore, prior information of sampling signals is not required. Energy detection technique is considered to be very simple approach since no sampling signals prior information is not required and the approach is less complex. Conversely, detection gain is conceded under different channels i.e., fading, shadowing, uncertainty and hidden terminal issue [6,7].

A better-quality model work for optimum Spectrum Utilization of wireless systems with Cognitive Radio Networks has been suggested in existing work. Ensemble Adaptive Neuro Fuzzy Inference System (EANFIS) is greatly deployed for spectrum access control and Intrusion Detection is acquired through Enhanced support vector machine. The Particle Swarm Optimization (PSO) is also exploited for power allocation for secondary users. Conversely, there arises high ANFIS computational cost because of complex structure and gradient learning. In addition, PSO may easily fall into local optimum in high-dimensional space and low convergence rate in iterative processes which are considered as PSO drawbacks.

An enhanced model is presented for mitigating these problems through Fuzzy Filter Convolutional neural network (FFCNN) for spectrum access control and antecedents are regarded for spectrum selection of secondary user with trivial likelihood. Weighted fuzzy c means clustering plays a major role in detecting DOS and Replay attacks which is detected on basis of normal protocol operation behaviour, traffic flow and primary user access time. Kernel Cumulative Sum (KCUSUM) method is presented furthermore for detecting Primary User Emulation Attack (PUEA). Convergence Improved Bat Optimization (CIBAT) is deployed too for secondary user's power allocation and thereby diminishing energy consumption.

This paper structure is organized as specified: Spectrum sensing activity in Cognitive Radio Network is presented in section1. Various reviews on methodologies adapted for spectrum sensing is given in section 2. The suggested energy efficient and spectrum sensing research strategies are explained in section 3. Simulation results are discussed in section4. Conclusion and future scope are elaborated in section 5.

2. LITERATURE REVIEW

The various power allocation approaches for spectrum sensing is given an outline in this segment.

Jin, et al [8] suggested a model for predicting network environment status through Hidden Markov model (HMM)-based cooperative spectrum sensing (CSS). It is assumed that all CR nodes possesses same network environment in case of conventional prediction algorithms for cooperative spectrum sensing. Conversely, numerous CR nodes channel availability might be reasonably diverse and low prediction accuracy in a complex radio environment is achieved for conventional algorithms. The suggested algorithm effectiveness is validated by in terms of its energy efficiency and spectrum utilization which is enhanced by about 13% and 15%, respectively.

Sudhamani [9] enhanced cognitive radio network energy efficiency by optimization of number of secondary users (SUs) in a cooperative spectrum sensing. Also, mathematical formulation for number of SUs by OR and AND fusion rules at fusion center is also attained. In addition, it is proved that OR rule performance is better than AND rulethrough analysis.

Karimi, et al [10] suggested an approach for optimal disjoint, joint spectrum sensing and downlink power allocation by Probabilistic Spectrum Access (PSA) scheme in CR network. Spectrum sensing is attained by cooperative framework where cognitive sensors is cooperated by energy-detection-based soft spectrum sensing. Various experimental outcomes helps in validating the suggested method.

Ozcan et al [11] utilized EE maximization quasi-concave property for original problem transformation into an equivalent parameterized concave problem by suggesting a Dinkelbach's iterative power allocation algorithm. The optimal power levels identification is done in diverse levels of channel side information (CSI) existence dealing transmission and interference links at secondary transmitter, namely, perfect CSI of both transmission and interference links, perfect transmission link CSI , imperfect interference link CSI, imperfect both links CSI , or only both links statistical CSI. By experimental outcomes, sensing performance, different CSI availability categories and transmit and interference power constraints on secondary users EE is analysed Through numerical results, the impact of sensing performance, different types of CSI availability, and transmit and interference power constraints on the EE of the secondary users is investigated.

Yadav et al [12] exploited energy harvested from ambient sources and spectrum sensing information for analysing energy-efficient power sharing arrangement in CR networks. The optimization problem formulation is given as ratio of spectral efficiency (SE) to total energy consumption under energy and battery causality restrictions which is mitigated through iterative algorithm for attaining optimal solutions. Lastly, extensive simulation outcome helps in validating the suggested power allocation scheme which enhances network average energy efficiency (EE) and SE performance.

Thangaraj and Aruna [13] suggested an approach namely orthogonal frequency division multiplexing based heterogeneous cognitive radio network (HCRN) for energy efficient resource allocation system under imperfect spectrum sensing setup with definite quality of service (QoS). The HCRN energy efficiency (EE) maximization is the main research objective pertaining to total transmission power, interference and QoS Constraints. The suggested EEPA algorithm greatly attains greater EE than traditional equal power allocation technique which is validated by numerical outcomes.

Eappen and Shankar [14] presented a novel approach namely Hybrid PSO-GSA which is nothing but article Swarm Optimization (PSO) hybridization with Gravitational Search Algorithm (GSA). A balanced trade-off amid exploration and exploitation abilities of PSO-GSA algorithm can be greatly achieved by this method. PSO-GSA efficacy is also substantiated through simulation outcome in optimizing energy efficiency for spectrum sensing in terms of transmission power, spectrum sensing bandwidth and power spectral density in contradiction with prevailing PSO and Artificial Bee Colony (ABC) algorithms.

3. PROPOSED METHODOLOGY

The model for spectrum sensing with security and energy efficiency is proposed which encompasses three modules. DOS and replay attack detection using weighted fuzzy c means clustering and primary user emulation attack detection using Kernel Cumulative Sum method is the first module. Convergence improved BAT optimization (CIBAT) for energy monitoring by power allocation to optimal users is the next module. Lastly, Spectrum access control using Fuzzy Filter Convolution neural network (FFCNN) is the third module which is revealed in figure 1.

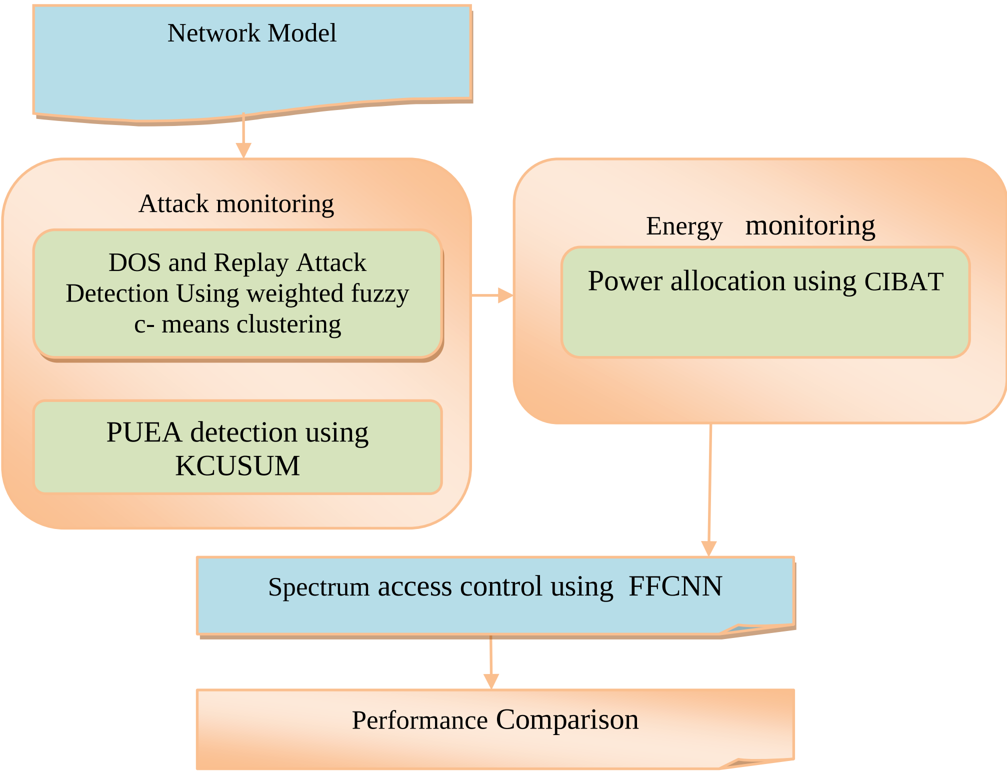

Figure: 1.Overall architecture of the proposed model

3.1. System Model

The system model is assumed to consist of N number of SUs as transmitters in a CRN with a SBS (Secondary Base Station) as the common receiver for uplink communication. PU's transceiver pair with a primary BS as receiver and OFDM (Orthogonal Frequency-Division Multiplexing) technology licensed spectrum band is utilized by transmitter for both transmissions. The degradations in primary users transmission quality are evaded by setting threshold value denoted by I^{th} should be below interferences from secondary transmitters to primary BS. OFDM helps in dividing licensed spectrum band into K sub-channels or every wireless link on a su- channel allocation is done on a fixed time slot in which slot can be varied in succeeding allocation. Various sub-channels are gained by every link which does not dependent on each other. Threats in CRN are given below in detail.

3.2. Threats in CRN

Security threats are mainly inherited by CRNs which is nothing but elementary WNs. This threat categorization is on the basis of layers for attack taxonomy. TCP (Transport Control Protocol) is vulnerable to transport layer threats and largely "Lion" attack. Network layer attack comprises Sinkhole and HELLO flood attacks which is distinct from CRN attacks. Link layer attacks ensue on sensing spectrums which accompanies Byzantine attacks related to ad hoc networks, DOS (Denial of Service) attacks by CRN controls. Additionally, physical layer attacks are considered as challenging factors in CRNs and comprise PUE (Primary User Emulation), jamming and objective function attacks, Replay attack. DOS, replay and Primary User Emulation attacks (PUEA) are detected by this suggested methodology. Now certain information about those attacks which are to be detected is discussed in this work.

DOS Attack

A denial-of-service attack (DOS attack) is a cyber-attack in which perpetrator try to find for making a network resource unapproachable to its intentional users via temporarily or indefinitely disrupting host services connected to Internet. Therefore detection can be done by transmitted and received signal length.

Replay Attack

A replay attack (also termed as playback attack) is a form of network attack in which a valid data transmission is malevolently or fraudulently repeated or delayed. This execution is done either by originator or an adversary who helps in data interception and re-transmitting it. This detection can be done by computing transmitted signals delay rate by weighted fuzzy c means clustering for DOS and Replay Attacks detection**.**

Primary User Emulation Attack

In the Primary Users (PU) absence, attackers mimic PUs' signal characteristics for fooling legitimate Secondary Users (SU) which makes channel evacuation for them which exploits channel selfishly through Kernel Cumulative Sum. Weighted fuzzy c means clustering is utilized in succeeding step for DOS and replay attack detection.

3.3. DOS and Replay Attack Detection using Weighted Fuzzy C Means Clustering

3.3.1. Conventional Fuzzy C Means Clustering (FCM)

A sort of clustering namely Fuzzy clustering where every data point might be appropriate to more than one cluster. Clustering or cluster analysis is nothing but data points allotment to clusters such that items in same cluster are as identical as probable, whereas items belonging to dissimilar clusters are as disparate as possible. Cluster identification is done through similarity measures which involve distance, connectivity, and intensity. The different similarity measures choice is dependent on data or application.

3.3.2. Disadvantages of FCM

In high dimensional signal scenario, certain features ought to be irrelevant and relevant however might possesses diverse significance in clustering. For improved clustering, it is necessary to include these features in the clustering method.

A weighted fuzzy c means clustering algorithm is suggested for mitigating these issues.

3.3.3. Weighted Fuzzy c-Means Clustering

In this divergence amid traffic flows, SS (Signal Strengths), primary user access times, PDR (Packets Received/Packets Sent) contained by clusters computation can be done by weight function where weight allotment is done to every traffic flows, SS (Signal Strengths), primary user access times, PDR[15,16,17].

Fuzzy c-means helps in data set $X = \{x_1,\ldots, x_i,\ldots x_n\}$ $(1\leq i\leq n)$ apportioning into c clusters based on membership degree matrix $U=(u_{ti})c*n$ when objective function J attains minimum value. The $x_i$of X is p dimensional; u_{ti} denotes membership degree measures in which sample x_i belongs to cluster center v_t. Here, c clusters are marked by cluster centers $V=\{v_1,\ldots v_t,\ldots v_c\}$ $1\leq t \leq c$, V is always set arbitrarily initially. Then membership degree u_{ti} computation is as follows:

$$u_{ti} = \frac{1}{\sum_{Z=1}^{c} (d_{ti}/d_{zi})^{2/(m-1)}} \tag{1}$$

Where d_{ti} denotes Euclidean distance amid sample $x_i$to cluster center v_t, m represents power exponent. In iteration, cluster centres computation is as follows:

$$v_t = \frac{\sum_{i=1}^{n} u_{ti}^{m} d_{ti}}{\sum_{i=1}^{n} u_{ti}^{m}} \quad (2)$$

The objective function *J* is specified below

$$J = \sum_{i=1}^{n} \sum_{t=1}^{c} u_{ti}^{m} \, d_{ti}{}^{2} \quad (3)$$

The feature-weight learning is on the basis of weighted Euclidean distance. $d_{ij}$is frequently used Euclidean distance and d_{ij}^{w} denotes weighted Euclidean distancegiven below:

$$d_{ij}^{w} = \sqrt{\sum_{k=1}^{s} w_k \left(x_{jk} - v_{tk}\right)^2} \quad (4)$$

Thus, t objective function *J* specified in Eq. (2.1) will becomes:

$$J^{w} \; (U, v_1, \; \ldots \; v_c\, ; X) \; = \sum_{i=1}^{C} \sum_{J=1}^{n} u_{ij}^{m} \; (d_{ij}^{w})^{2} \quad (5)$$

Then updated u_{ij}, $w_k$and $v_{ik}$are obtainedas follows:

$$u_{ij} = \frac{n\left(m \sum_{k=1}^{s} \; w_k \left(x_{jk} - v_{tk}\right)^2\right)^{\frac{1}{m-1}}}{\sum_{h=1}^{c} \; \sum_{r=1}^{n} \; \left(m \sum_{k=1}^{s} \left(x_{jk} - v_{tk}\right)^2\right)^{\frac{1}{m-1}}} \quad (6)$$

$$w_k = \frac{\left(\sum_{t=1}^{c} \sum_{j=1}^{n} \; u_{ij}^{m} \left(x_{jk} - v_{tk}\right)^2\right)^{-1}}{\sum_{h=1}^{s} \left(\sum_{t=1}^{c} \sum_{j=1}^{n} \left(x_{jk} - v_{tk}\right)^2\right)^{-1}} \quad (7)$$

$$v_{ik} = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_{jk}}{\sum_{j=1}^{n} u_{ij}^{m}} \quad (8)$$

The resultant W-FCM algorithm summary is as follows

Step 1: Fix maximum number of clusters *c* and a threshold value . Consider *m* be a proper constant.

Step 2: Initialize memberships and centers by FCM.

Step 3: Calculate w_k based on Eq. (7).

Step 4: Calculate u_{ij} based on (5). Thus update the v_{ik} according to (8) by new computed u_{ij} .

Step 5: Calculate objective function $J_w$by means of (5).

If it converges or difference amid two adjacent computed values of objective function *J w* is less than specified threshold then stop. Or else go to step 3[18,19, 20].

The detected DOS and replay attacks are there in one cluster. Subsequent step is identifying primary user emulation attack via kernel cumulative sum technique.

3.4. Primary User Emulation Attack Using Kernel Cumulative Sum

3.4.1. Traditional Cumulative Sum

Cumulative sum (CUSUM) control charts are widely regarded tools, as they are capable of monitoring the change detection in an effective manner. Since the CUSUM statistics entirely relies on past information and current data points, it strategically provides a composed process control that enables initial detection of changes during the normal process. Moreover, the scheme has found applications in monitoring the sequence of discrete count data while monitoring continuous data. Generally, the computation of the average run length (ARL) of CUSUM control charts helps evaluate them. ARL has been defined as the average number of observations plotted on a control chart before the out-of-control signal.

3.4.2. Limitation in CUSUM

In the statistical elements of incoming observations, online change detection includes monitoring a stream of data for changes. Nevertheless, the practicality of CUSUM is limited due to its strict dependency on the specifications as regards relevant probability distributions. A kernel cumulative sum is presented to resolve this issue.

3.4.3. Kernel Cumulative Sum

In accordance with a kernel statistic based probability distribution, the Kernel CUSUM (KCUSUM) algorithm compares the samples of incoming data from a reference distribution rather than using the probability ratio as it is a parametric quantity.

The CUSUM (cumulative sum) test is known as a sequential analysis method that is intuitively sequential. Because the analysis is made as a result of each sum. Thresholding of a statistic, S is sequentially summed until the value S crosses a threshold value. At the time of initial crossing of this threshold, it reaches the stopping time which infers and change occurs.

Consider $Y_n$as a sequence of observations that is derived from the monitoring of network. Let$p_0$be the probability distribution before change; $p_1$be the probability distribution after change; and n * denotes the change occurs at an unknown point in time.

In this way, p_0 $(Yn|Y1, Y2,\ldots,y_{n-1})$ signifies the conditional probability density function (PDF) before change if n < n*; whereas $p1(Y_n|Y_1, Y_2,\ldots, y_{n-1})$ indicates the conditional PDF after change, if n $\geq$ n*. If the input converges p_0, it indicates the non-existence of attack in network. If the input converges $p_{1,}$ it indicates the existence of attack.

The estimation of probability density kernel p is formulated as follows

$$F(x) = \frac{1}{n}\sum_{i=1}^{n} k(x - x_i) \tag{9}$$

In which, a distributed samples and k means kernel are signified by $(x_1, x_2, \ldots, x_n)$

n_d represents the detection time that defines the point, when the occurrence of change is declared. $r = n_d - n^*$ denotes the detection delay. For assessing the faster detection performance, two ARLs have been defined as follows,

$$\bar{T}_1 = \text{ess sup } E_1 [r/n_d \geq n^*] \tag{10}$$

$$\bar{T}_0 = E_0 \; [n_d] \tag{11}$$

Here, the expectation under the assumption that the change happens at time n* is signified by E_1; the expectation under the assumption that the change never occurs is indicated by E_0. Remember that the worst-case delay is notated by the esssup in $\bar{T}_1$. A small $\bar{T}_1$and a large $\bar{T}_0$ need to be acquired, as regards fastest detection. At this point, detected of PUEA in the network is accomplished. Besides, CIBAT will be exploited to execute the Power allocation process for secondary user [21,22] in the following step.

3.5. Power allocation using Convergence Improved BAT

In this step, taken the Power allocation of secondary transmitters in each time slot. If P_k^i is transmitted power of SU i over subcarrier k (k = 1 , 2 , . . . , K) in a time slot and G_k^{ii} (i = 1 , 2 , . . . , N) is the link gain from i to SBS, then SINR (Signal to Interference Ratio) for i 's communication over k denoted as γ_k^i, which can be formulated as follows,

$$\gamma_k^i = \frac{G_k^{ii} P_k^i}{\sum_{j \neq i} G_k^{jj} P_k^j + \sigma^2} \tag{12}$$

- **Utility function:**This function is signified by U_k^i, which is a SU communications over sub-channel k. This function depictsa quality of service. In order to attain maximal user satisfaction, a sigmoidal utility is adopted in this work.The following equation expresses the value of the service provided by this function to the user,
  - $$U_k^i = \frac{1}{1+e^{-a_i(\gamma_k^i - b_i)}} \tag{13}$$

In which, slope parameter (large value means application has a soft quality in services) is signified by a_i; shift parameter to average data rates in the application is indicated by and b_i. The parameter of energy efficiency referred to as higher utilities with less energy consumptions and is formulated as a ratio of utility to transmission power (utility/Joule), which is given by,

$$E=\frac{\sum_{i=1}^{N} U_k^i}{\sum_{i=1}^{N} p_k^i+P_c} \quad (14)$$

Here, $P_c$denotes the static transmission power consumptions other than wireless networks (circuit power consumptions).

- **Constraints:** Interferences received by the primary BS from secondary transmissions in each sub-channel is bound by a threshold I_{th} and G_k^{oi} (k =1 ,... , K) is the link gain from SU_i to primary BS. This power interference constraint is depicted as given as Equation (15)

$$\sum_{i=1}^{N} G_K^{Oi} p_k^i \leq I_{th} \quad (15)$$

The total transmission power over each sub-channel should also be bound by P_{max}, which is expressed as

$$\sum_{i=1}^{N} P_k^i \leq P_{max} \quad (16)$$

By taking the maximal energy efficiency within power interferences as regards power constraints and overall transmit power constraints, and optimization can be expressed as,

$$\text{Maximize } E=\frac{\sum_{i=1}^{N} U_k^i}{\sum_{i=1}^{N} P_k^i+P_C} \quad (17)$$

$$\text{Subject to } \sum_{i=1}^{N} G_k^{oi} P_k^i \leq I_{th} \quad (18)$$

$$\sum_{i=1}^{N} P_k^i \leq P_{max} (19)$$

$$P_k^i \geq 0 \quad (20)$$

3.5.1. Bat Optimization Algorithm

In past few decades, the animal Bat and its highly dominant echolocation feature turn out to be a crucial topic across researchers. The echolocation feature refers to as the echo sound/signal created by the bat, through which they identify the distance of an object (secondary user) even in complete darkness. By using this echolocation method, the bat differentiates the obstacle in its way (inappropriate secondary user), and a targeted prey (optimal secondary user) and it can hunt even at completely dark place[23].

3.5.2. Limitation

Although the original bat algorithm capable of utilizing the search space, yet it may be inadequate for global search since it may get trapped into local optimal behaviour sometimes. This drawback can be avoided through maximizing the diversity of search. Accordingly, this study proposed a novel Conversion Improved BAT (CIBAT).

3.5.3. Convergence Improved BAT

Aimed at creating a new solution (optimal network behaviour) for each bat, the standard BA is enhanced by using a mutation operator. Considering this strategy, two significant features play a vital role in this model, namely exploitation and exploration, which make it as an efficient optimization algorithm.

In CIBAT algorithm, every bat (secondary user) is referred by its corresponding position x_i, velocity v_i, the emission pulse rate r_i, and the fixed loudness A in a d dimensional search space, which is same as BA. Eqs. (21), (22), and (23) express the new solutions x_i and velocities v_i at time step t.

$$f_i = f_{min} + (f_{max} - f_{min})\beta \quad (21\ )$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_*)f_i \quad (22)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (23)$$

Here,a random vector drawn from a uniform distribution is denoted by $\beta \in [0, 1]$; frequency of each bat is signified by f_i ; the current global best solution (secondary user) is notated as x_*that is positioned subsequent to the comparison of overall solutions (secondary user) that correspond to each n bat, at each iteration.

A random number is generated by updating the position of bats. A new position is createdaround the current best solutions, if the generated random number exceeds the value of the pulse emission rate $r_{i..}$ Eq. (4) expresses this function

$$x_{new}=x_{old}+\in A^t \qquad (24)$$

In which, is a random number is denoted by ∈ [-1,1]. At current iteration, the average loudness of each bat is represented by A^t.

The proposed algorithm predominantly tends to include the mutation operator for maximizing the population diversity, concerning the enhancement of search efficiency, and fast convergence to the best value. In accordance with local search, the original BA and the proposed algorithm are identical, i.e. among the best available solution, a new solution is initially acquired through a local random walk (24). This initially acquired solution is bounded by the criteria that a random real number derived from a uniform distribution needs to be higher than a pulse rate parameter.

In the EBat algorithm, an additional pair of tuning parameters, such as Value1 Best and value2 worst are provided by the new mutation operator. As expressed by the following equations, a solution $x_v$will beselected randomly from the population of NP during the process of mutation operator, if a random value is lower than the Best value1.

$$v_r = rand * NP (25)$$

$$X_v = x_{vr} \qquad (26)$$

Here, the r ∈ (1, 2… NP). Then, more mutations are acquaint with the features of current solution (optimal secondary user), if a random value is lower than worst value2. Consequently, the search back is drawn to an optimal position according to the best and worst solutions derived to this point. In such a scenario of local optimum traps BA component that is distant from the actual global one, this mutation proves to be significant. Eqs. 27, and 28 express the modification of mutation operator.

$$x_v = 7 \times (x_{worst}^t - x_v^t) \times rand[0,1]; \qquad (27)$$

$$x_v = 7 \times (x_v^t - x_{best}^t) \times rand[0,1]; \qquad (28)$$

Here, a new solution (optimal secondary user) of the t^{th} iteration is denoted by x_v; the random solution chosen by Eq. (9) is signified by x^t_v; the best and worst solutions determined so far are indicated by x_t best and x_t worst, correspondingly. Or else the objective of the randomization rule for including the population diversity enables the mutation operator for highly effective exploration across search space. As such, the probability of determining the global optimal solution (secondary user) can be augmented.

Improved Bat Algorithm [IBA]

Objective function (E) $f(x)$, $x = (x_1, \ldots\ldots\ldots x_d)^T$

*Initialize the bat population (*secondary user*)* x_i (i=1,2,….n)and v_i

Assign pulse frequency fi at x_i

Initialize pulse rates ri, loudness A_i, Parameter value 1 and parameter value 2.

While *(t <Max number of iterations)*

Create new solutions (optimal secondary user*) by adjusting frequency,*

and revising velocities and locations/solutions [equations (2) to (4)]

if (*r and* $>r_i$ *)*

Determine a solution from the best solutions

Create a local solution from the selected best solution (optimal secondary user)

End if

Produce a new solution by flying randomly

Mutation operator

If(rand<Value 1)then

$V_r = rand * NP;$

$x_v = x_{vr};$ *where the* $V_r \epsilon (1,2, \ldots . NP)$)

If (rand<Value 2) then

Update the worst solution

Else

Update the Best solution

End if

Else If Generate new mutation solution

Estimate the fitness function f(x) for new solution x_v and x_iIdentify best solution fromx_v,x_i . that possesses Highest Fitness Value.

Generate a new solution by flying randomly

If *(rand <* A_i &$f(x_i) < f(x_*)$*)*

Accept the new solutions (optimal secondary user*)*

Increase r_i *and reduce* A_i

End if

Rank the bats and find the current best x_*

End while

Post process results and visualization

The selection of Global best secondary user that accompanies maximum energy efficiency is carried out through the improved bat algorithm. Best secondary user of the original bat algorithm is retained by the novel mutation, specifically those who possesses fast convergence rate, at the same time the algorithm is enabled to utilize more mutation to attain optimal diversity. The following section confers the implementation of Spectrum access control performed through FFCNN.

3.6. Spectrum access control using FFCNN

Opportunistic Spectrum Access is made by selecting optimal secondary user instances to access free spectrum bands deprived of interferences from primary users. Instance information are collected by FFCNN with the help of following descriptors.

- SUE (Spectrum Utilization Efficiency)
- DM (Degree of Mobility)
- Distance of the Secondary user from Primary User

3.6.1. Traditional CNN

Convolutional neural network (CNN) is known as a class that belongs to deep ANNs. The structure of CNN varies from a general artificial neural network. In the traditional ANN, the input gets flatten out to a vector, conversely the CNN matches the input data spatially as the layers of CNN are selected.

3.6.2. Drawbacks of Traditional CNN

In traditional CNN architecture, there exist the problem of information loss, since it applies pooling operation for reducing the dimension. In this study, a fuzzy filter CNN is utilized to resolve this issue.

3.6.3.Fuzzy Filter Convolutional neural network (FFCNN)

As an improved framework, this fuzzy function is applied in pooling layer for minimizing the dimension. There are four types of layer involved in the proposed FFCNN, namely input layer, convolution layers, the pooling layers and the fully-connected layer [24,25].

Input Layer: This layer is formed as a feature matrix that is made up of extracted features, such as Spectrum Utilization Efficiency, Degree of Mobility, and Distance of the Secondary user from Primary User.

The Convolution Layer: In this layer, convolution kernels and padding are used correspondingly in order to obtain various feature maps.

The Pooling Layer: This layer tends to eliminate insignificant data as well as parameter training.

The weights for the dominant convolved feature set is estimated using fuzzy set is defined as the set of dominant features $G = \{g_1; g_2 \ldots\ldots\}$. Therefore, for each input, the membership value is referred to as GMF, which can be estimated as,

$$m_{avg} = \frac{\sum_{k=1}^{q} m_k}{q} \qquad (29)$$

In which, $m_k$denotes k-middle means that can be derived through (2). The pooled output is taken as the mean of dominant convolved features.

The Fully-Connection Layer: In this layer, Softmax is used as an activation function. The probability value is derived by Softmax as an output, when the M-dimensional vector is entered, through which the data belongs to the category is determined by the maximum probability. Softmax function is referred to as the gradient-log-normalizer of the categorical probability distribution as follows,

$$P\left(y = \frac{j}{x}, \{f_k\}\ k = 1,2, \ldots, k\right) = \frac{e^{f_j\,(x)}}{\sum_{k=1}^{k} e^{f_k(x)}} \qquad (30)$$

Here, a classification function for a j th class is denoted by f_j. Whereas, x and y represent the input and output, correspondingly.

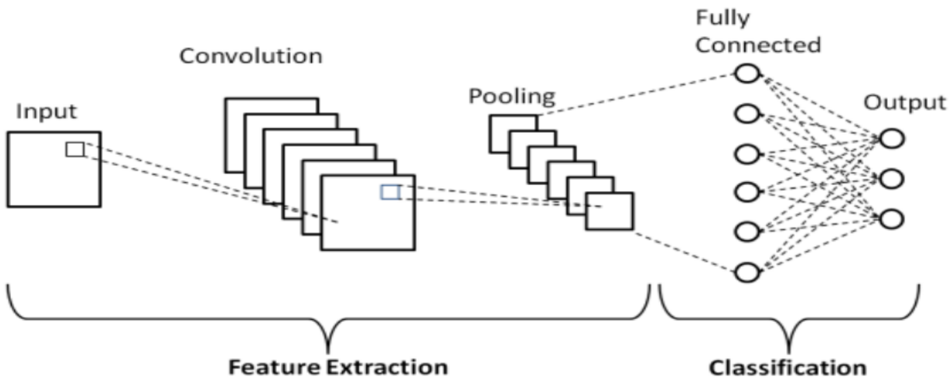

Figure: 2.Convolutional neural network

4. RESULTS AND DISCUSSION

In this segment, the performance evaluation is carried out for the proposed Improved Energy Efficient IDS using IEEE 802.22 WRAN topology. In Table 1, the information corresponding to the WRAN system are provided, where 68 channels have been considered by WRAN CRN model and the maximum limit of secondary users is 12 for simultaneously accessing each channel. From the simulation performed through MATLAB, the effectiveness of the proposed IDS is depicted, concerning the protection of all users from the consequences of attack. Besides, the performance efficiency of the proposed FFCNN method is proved by comparing it with other existing methods, such as MASAS, FLS, ESAC and EESAC.

Table:1.IEEE 802.22 WRAN based cognitive radio network system Parameters.

Chosen Parameters	**Value**
Wireless bandwidth	54 to 806 MHz
Number of channels	68
Individual channel bandwidth	6 MHz
Band ranges	54 to 72 MHz, 76 to 88 MHz, 174 to 216 MHz and 470 to 806 MHz
Maximum number of simultaneous secondary users	12
Minimum peak downlink rate per secondary user	1.5 Mbps
Minimum peak uplink rate per secondary user	384 Kbps
Cell coverage	33 to 100 km
Spectral efficiency	3 bits/s/Hz
Total physical data rate per channel	18 Mbps
Packet size (MTU)	1518 bytes
Minimum frames per second (received per secondary user)	129.51

Table:2.Performance comparison results for Throughput

Methods	Number of nodes				
	10	20	30	40	50
MASAS	40	43	48	51	55
FLS	48	50	54	58	61
ESAC	58	60	63	68	70
EESAC	60	63	65	70	76
FFCNN	62	65	67	72	78

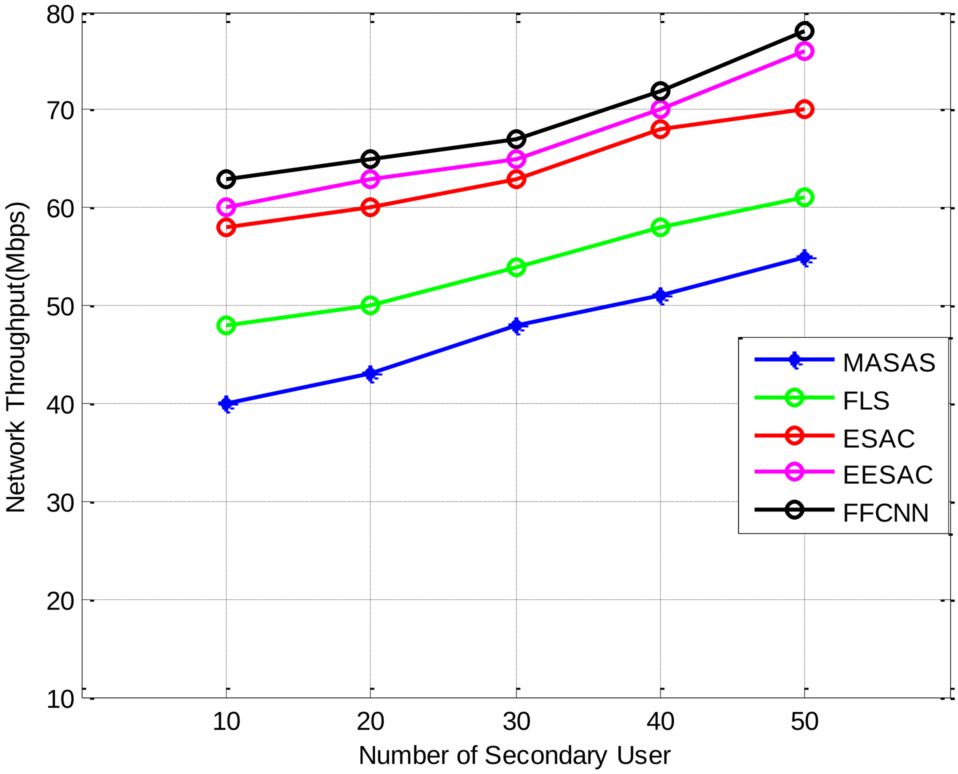

Figure.3. Throughput results vs Number of secondary users

Figure 3 compares the performance of proposed FFCNN and prevailing MASAS, FLS, ESAC and EESAC methods, in terms of Throughput, where the secondary users count lies on X-axis, and Y-axis stands for Throughput values. The results depict the efficiency of the proposed FFCNN method to secure the maximum Throughput of 78 Mbps, whereas, the existing MASAS, FLS, ESAC and EESAC approaches obtain 55 Mbps, 61 Mbps, 70 Mbps and 76 Mbps, respectively. The reason is that, application of Fuzzy C Means Clustering Weight Function enables the optimal clustering of attack, through which the Throughput ratio is considerably improved.

Table: 3. Performance comparison results for system utility rate

Methods	Number of nodes				
	10	20	30	40	50

MASAS	49	52	54	57	60
FLS	50	55	58	60	64
ESAC	61	64	68	71	76
EESAC	63	68	73	72	78
FFCNN	65	70	72	75	81

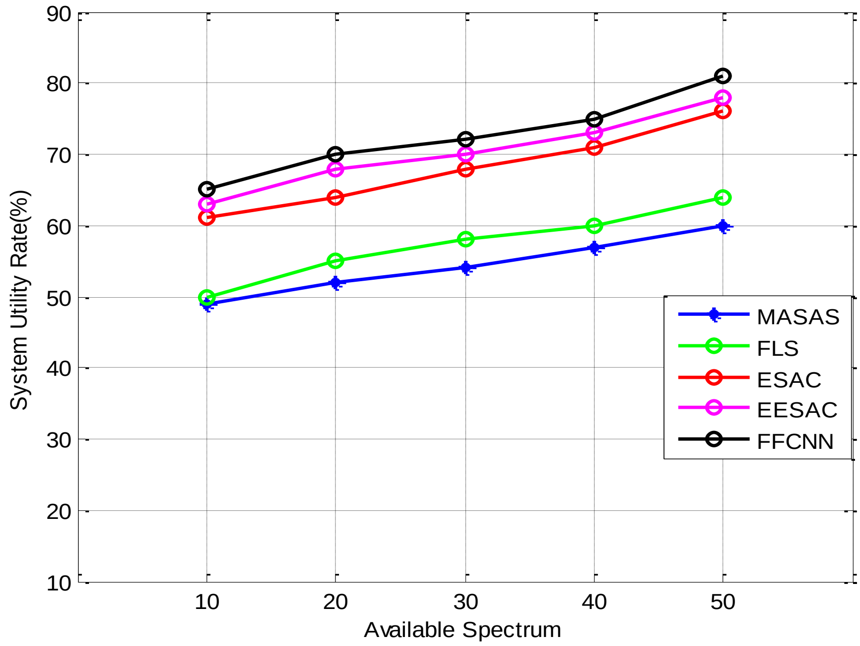

Figure: 4. System utility rate vs. available spectrum range

In Figure 4,the system utility rate of proposed and prevailing methods are compared, where X-axis represents available spectrum range, and Y-axis indicates System utility rate. The results show the efficiency of the proposed FFCNN method to procure 81% system utility rate, which is higher than the existing MASAS, FLS, ESAC and EESAC approaches, as they obtain 60%, 64%, 76%, and 78 %, respectively. Because, in pooling layer of convolutional neural network, Fuzzy Logic is used to select the optimal secondary user, by which the system utility rate is increased.

Table: 4. Performance comparison results for Packet delivery ratio

Methods	**Number of nodes**				
	10	20	30	40	50
MASAS	45	47	50	52	56
FLS	47	50	54	59	62
ESAC	60	65	68	70	74
EESAC	64	68	70	73	79
FFCNN	66	70	73	75	81

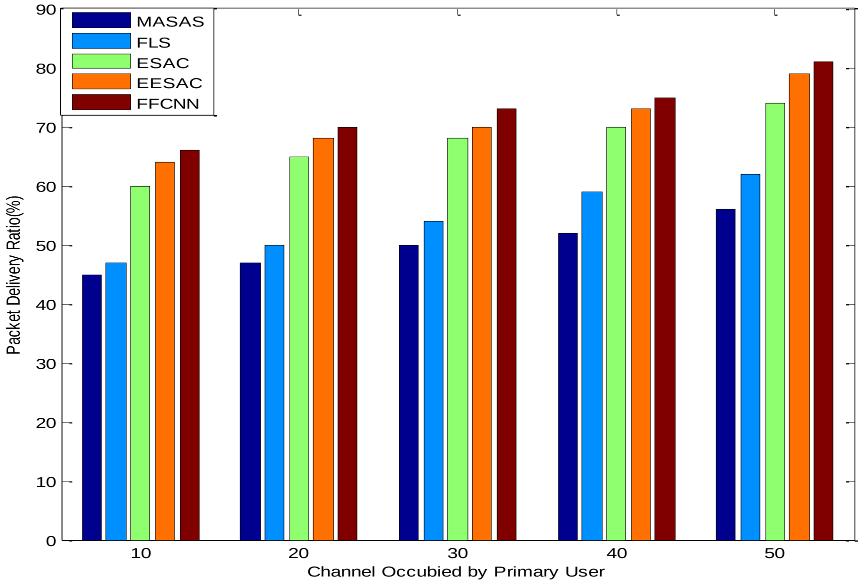

Figure: 5.Packet delivery ratio vs. Channels used by the users

Figure 5 compares the packet delivery ratio individually obtained by the proposed FFCNN and existing MASAS, FLS, ESAC and EESAC methods, in which the number of channels used by the secondary users lies on X-axis, and Y-axis stands for Packet delivery ratio. From the graphs, it is demonstrated that the proposed FFCNN method is efficient to secure 81% Packet delivery ratio, which is higher than the existing MASAS, FLS, ESAC and EESAC approaches as they obtain 56%, 62%, 74%, and 79%, respectively.

Table: 5. Performance comparison results for Attack detection rate

Methods	**Number of nodes**				
	10	20	30	40	50
MASAS	44	48	52	56	58
FLS	49	54	58	62	65
ESAC	55	59	63	68	73
EESAC	59	63	65	71	75
FFCNN	61	65	68	72	78

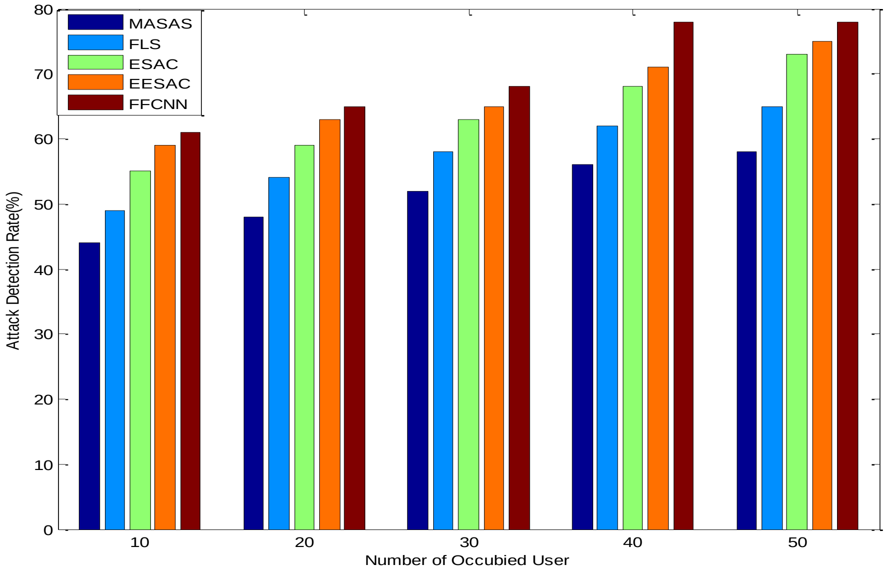

Figure: 6.Attack detection rate vs. Channels used by the users

In Figure 6, the Attack Detection Rate of proposed and existing methods are compared, where X-axis symbolizes the number of utilized Channels, and Y-axis shows the Attack detection rate. From the graphs, the results show the efficiency of the proposed FFCNN method to procure 78% attack detection rate. On the other hand, the existing MASAS, FLS, ESAC and EESAC approaches provide 58%, 65%, 73%, and 75% respectively.

Table: 6. Performance comparison results for Energy consumption

Methods	Number of nodes				
	10	20	30	40	50
MASAS	1.34	2.68	4.02	5.36	6.7
FLS	1.23	2.46	3.69	4.92	6.15
ESAC	1.19	2.38	3.58	4.76	5.96
EESAC	1.02	2.04	3.06	4.08	5.1
FFCNN	0.96	1.92	2.88	3.63	4.8

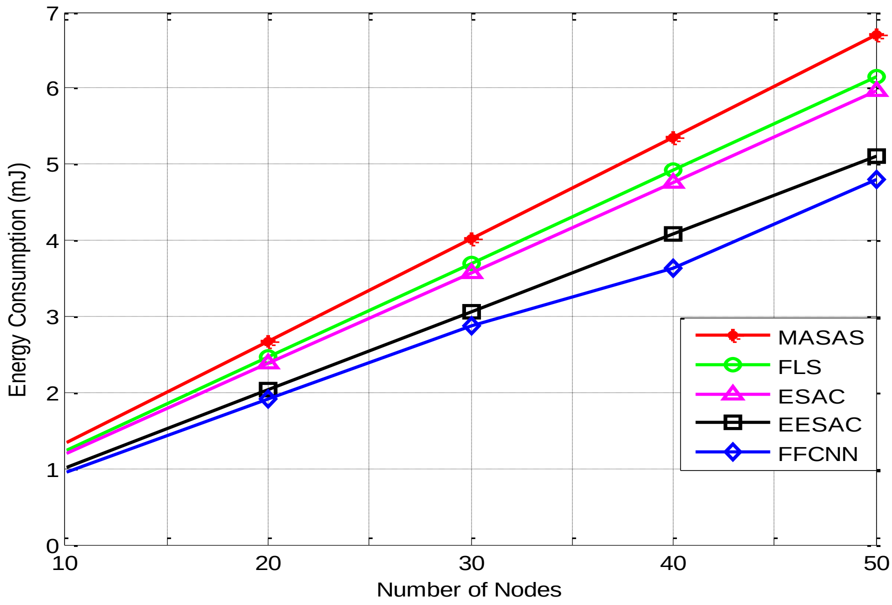

Figure.7. Energy consumption vs. Channels used by the secondary users

Figure 7 compares the individual Energy consumption of the proposed FFCNN and existing MASAS, FLS, ESAC and EESAC methods, where the number of channels used by the secondary users lies on X-axis, and Y-axis stands for Energy consumption values. The graphs reveal that the proposed FFCNN method is energy efficient among all the methods compared, since reduces Energy consumption up to4.8 mj, whereas the existing MASAS, FLS, ESAC and EESAC approaches consume 6.7 mj, 6.15 mj , 5.96 mj, and 5.1.mj, respectively.

Table: 7. Performance comparison results for Error rate

Number of nodes	**Different methods**				
	MASAS	FLS	ESAC	EESAC	FFCNN
10	56	51	45	41	39
20	52	46	41	37	35
30	48	42	37	35	32
40	44	38	32	29	22
50	42	35	27	25	22

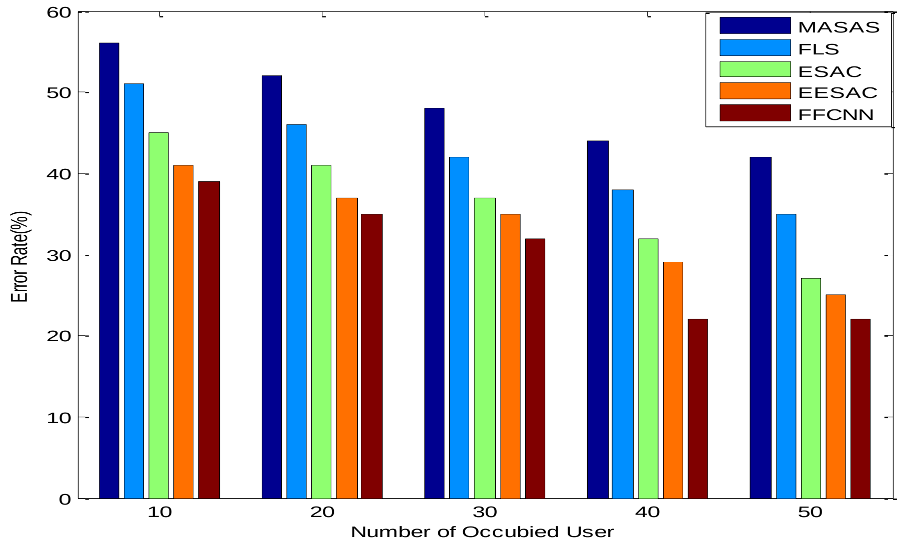

Figure:8.Error rate

In Figure 8, the Error rate of proposed and existing methods are compared, where X-axis represents the number of utilized Channels, and Y-axis indicates the error rate. From the graphs, the results depict the effectiveness of the proposed FFCNN method to reduce the error rate up to 22%. On the other hand, the existing MASAS, FLS, ESAC and EESAC approaches have the ability to reduce only up to 42%, 35% 27% and 25% respectively.

5. CONCLUSION AND FUTURE WORK

As an potential functionality, Spectrum sensing plays a vital role in cognitive radio networks, as regards spectrum hole detection and opportunistic utilization of under-utilized frequency bands regardless of vulnerable intrusion to legacy networks. In this study, an attainment of spectrum sensing model accompanied by energy efficiency and security is predominantly focused. During the process, Weighted Fuzzy C Means Clustering is employed for identifying the DOS and replay attacks, whereas Kernel Cumulative Sum (KCUSUM) model is utilized to identify the Primary User Emulation Attack (PUEA) in terms of improving the capability of secondary user sensing. Besides, the application of Convergence Improved Bat Optimization (CIBAT) reduces the energy consumption in accordance with utility function, since it eases the task of power allocation for secondary users. In addition, optimal spectrum access were done controlling spectrum sensing of secondary user based on antecedents and Fuzzy Filter Convolutional neural network (FFCNN). Empirical findings depict the proficiency of the proposed framework to diminish the attack detection error rate and increase the packet delivery ratio. Nevertheless, there is a possibility that a deep learning may increase the computational complexities, which can be avoided by experimenting some other learning methods, in future.

REFERENCES

1. Han, D., Sobabe, G.C., Zhang, C., Bai, X., Wang, Z., Liu, S. and Guo, B., 2017, October. Spectrum sensing for cognitive radio based on convolution neural network. In *2017 10th international congress on image and signal processing, biomedical engineering and informatics (CISP-BMEI)* (pp. 1-6). IEEE.
2. Ansere, J.A., Han, G., Wang, H., Choi, C. and Wu, C., 2019. A reliable energy efficient dynamic spectrum sensing for cognitive radio IoT networks. *IEEE Internet of Things Journal*, *6*(4), pp.6748-6759.
3. Kar, S., Sethi, S. and Sahoo, R.K., 2017. A multi-factor trust management scheme for secure spectrum sensing in cognitive radio networks. *Wireless Personal Communications*, *97*(2), pp.2523-2540.
4. Liu, C., Wang, J., Liu, X. and Liang, Y.C., 2019. Deep CM-CNN for spectrum sensing in cognitive radio. *IEEE Journal on Selected Areas in Communications*, *37*(10), pp.2306-2321.
5. Kumar, A., Thakur, P., Pandit, S. and Singh, G., 2019. Analysis of optimal threshold selection for spectrum sensing in a cognitive radio network: an energy detection approach. *Wireless Networks*, *25*(7), pp.3917-3931.

6. Alom, M.Z., Godder, T.K., Morshed, M.N. and Maali, A., 2017, January. Enhanced spectrum sensing based on energy detection in cognitive radio network using adaptive threshold. In *2017 International Conference on Networking, Systems and Security (NSysS)* (pp. 138-143). IEEE.
7. Habib, A.Z.S.B., Mallick, S., Ahmed, A.S., Alam, S.S. and Ahmad, A.S., 2018, September. Performance Appraisal of Spectrum Sensing in Cognitive Radio Network. In *2018 4th International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT)* (pp. 162-167). IEEE.
8. Jin, Z., Yao, K., Lee, B., Cho, J. and Zhang, L., 2019. Channel status learning for cooperative spectrum sensing in energy-restricted cognitive radio networks. *IEEE Access*, *7*, pp.64946 - 64954.
9. Sudhamani, C., 2019. Energy Efficiency in Cognitive Radio Network Using Cooperative Spectrum Sensing. Wireless Personal Communications, 104(3), pp.907-919.
10. Karimi, M., Sadough, S.M.S. and Torabi, M., 2019. Improved joint spectrum sensing and power allocation for cognitive radio networks using probabilistic spectrum access. IEEE Systems Journal, 13(4), pp.3716-3723.
11. Ozcan, G., Gursoy, M.C., Tran, N. and Tang, J., 2016. Energy-efficient power allocation in cognitive radio systems with imperfect spectrum sensing. IEEE Journal on Selected Areas in Communications, 34(12), pp.3466-3481.
12. Yadav, R., Singh, K., Gupta, A. and Kumar, A., 2016, September. Optimal energy-efficient resource allocation in energy harvesting cognitive radio networks with spectrum sensing. In *2016 IEEE 84th Vehicular Technology Conference (VTC-Fall)* (pp. 1-5). IEEE.
13. Thangaraj, C.A. and Aruna, T., 2019. Energy-efficient power allocation with guaranteed QoS under imperfect sensing for OFDM-based heterogeneous cognitive radio networks. Wireless Personal Communications, 109(3), pp.1845-1862.
14. Eappen, G. and Shankar, T., 2020. Hybrid PSO-GSA for energy efficient spectrum sensing in cognitive radio network. *Physical Communication*, p.101091.
15. Kapoor, A. and Singhal, A., 2017, February. A comparative study of K-Means, K-Means++ and Fuzzy C-Means clustering algorithms. In *2017 3rd international conference on computational intelligence & communication technology (CICT)* (pp. 1-6). IEEE.
16. Gu, J., Jiao, L., Yang, S. and Liu, F., 2017. Fuzzy double c-means clustering based on sparse self-representation. *IEEE Transactions on Fuzzy Systems*, *26*(2), pp.612-626.
17. Qiao, W. and Yang, Z., 2019. An improved dolphin swarm algorithm based on Kernel Fuzzy C-means in the application of solving the optimal problems of large-scale function. *IEEE Access*, *8*, pp.2073-2089.
18. Mahela, O.P. and Shaik, A.G., 2017. Power quality recognition in distribution system with solar energy penetration using S-transform and Fuzzy C-means clustering. *Renewable energy*, *106*, pp.37-51.
19. Nguyen, K., Fookes, C., Ross, A. and Sridharan, S., 2017. Iris recognition with off-the-shelf CNN features: A deep learning perspective. *IEEE Access*, *6*, pp.18848-18855.
20. Shen, Y., Han, T., Yang, Q., Yang, X., Wang, Y., Li, F. and Wen, H., 2018. CS-CNN: Enabling robust and efficient convolutional neural networks inference for Internet-of-Things applications. *IEEE Access*, *6*, pp.13439-13448.
21. Wang, W., Wu, B., Yang, S. and Wang, Z., 2018, December. Road damage detection and classification with Faster R-CNN. In *2018 IEEE International Conference on Big Data (Big Data)* (pp. 5220-5223). IEEE.
22. Liu, Z., Hu, J., Weng, L. and Yang, Y., 2017, September. Rotated region based CNN for ship detection. In *2017 IEEE International Conference on Image Processing (ICIP)* (pp. 900-904). IEEE.
23. *A. Prakash and V. Sangeetha.* Review of Opportunistic Spectrum Access Approach in Cognitive Radio Networks. Jour of Adv Research in Dynamical & Control Systems, Vol. 12, 07-Special Issue, 2020.
24. Sangeetha, V. and Prakash, A., 2021. An efficient intrusion detection system for cognitive radio networks with improved fuzzy logic based spectrum utilization. Materials Today: Proceedings.
25. Sangeetha, V. and Prakash, A., Energy Efficient Power Allocation For Cognitive Radio Networks With Optimal Spectrum Utilization Using Ensemble Adaptive Neuro Fuzzy Inference System.