

Republic of Iraq
Ministry of Higher Education and Scientific Research
University of Babylon / College of Information Technology
Information networks



A Blind Spectrum Sensing Technique Based on Deep Learning and Linear Cooperation

A Dissertation

Submitted to the Council of the College of Information Technology for
Postgraduate Studies of University of Babylon in Partial Fulfillment of the
Requirements for the Degree of Doctor of Philosophy in
Information Technology / Information networks

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2023 A.D.

1444 A.H.

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Dedication

*The sake of Allah, my Creator and my Master, My great teacher
and messenger, Mohammed (May Allah bless and grant him),
who taught us the purpose of life.*

*To :The soul of my brother, the martyr Naseer, who is the
reason I am here*

*My great parents; who never stop giving of themselves in countless
ways,*

*My dearest husband; Mr. mustafa kamil al_ sammarraie, who leads me
through the valley of darkness with light of hope and support.*

*My beloved brothers and sisters; Mrs. Dounia ,Mrs. Lubna , Mr.Bsheer
,Mr. Moneer, Mr.Atheer and Ali who stand by me when things look
bleak.*

*My beloved kids; RAYAN and Jana , whom I can't force myself to stop
loving.*

I dedicate this research.

Acknowledgement

First of all, I have to express all thanks and gratitude to my God who gives me the ability to achieve such an imperfect work and all what has been done without his blessing and support nothing can be done. I would like to express my sincere gratitude and appreciation to my supervisor (**Prof . Dr . Sattar B. Sadkhan**) for his invaluable guidance, supervision and untiring efforts during my study.

Special thanks go to all the staff members of information Technology College / Information networks for their faithful efforts to give us the utmost scientific topics and endless support in all directions aiming to bring into perfection their scientific followers, and for their unforgettable kind and wise management to our affairs during the research period.

Finally, I apologize to those whose names might be missed. But, I am grateful to all of them for the help that I have received from in various research and day-to-day life matters.

Doaa Jabbar Murdaw

Abstract

Cognitive radio technology has been proposed to improve spectrum efficiency by having the cognitive radios act as secondary users to opportunistically access under-utilized frequency bands. Spectrum sensing enables a cognitive radio to measure, learn, and be aware of its operating environment. The main problem faced is the scarcity of spectrum sensing bandwidth especially in blind spectrum sensing of without prior information about available channels, it plays a crucial role in Cognitive Radio Networks (CRNs) of low signal to noise ratio(SNR) values since it is the first step in allowing un-licensed users (secondary user) to access free licensed channels (primary users). A variable propagation environment and interference created by various secondary users, many primary users will use various modulation techniques, data speeds, and transmission strengths; they can use to build an integrated system to enhance spectrum sensing in cognitive radio.

To enhance spectrum sensing techniques in cognitive radio, Secondary Users (SUs) can use frequency bands when Primary Users(PUs) not present, so that SUs do not interfere with the PUs.

The proposed system based on blind spectrum sensing in CRN to predict the effect of the CR signal to Primary User signal, it depends on multiple dataset as (RML 2016.10b class, 2016.04C.multisnr.tar) and it is an adaptive system to selective channel from top list recommender. It achieves significant accuracy improvements for high or low and both SNR signals.

The results of hybrid approach showed that the proposed spectrum techniques achieved high network performance to be aware with primary user signals with high predication based on deep neural network model to appearance the primary users as the accuracy is 94% measured. Also, it indicated that the proposed method was promising, fast, and very suitable as an initial stage in the reliable or predictive detection of passive PUs signals for enhancement use of the spectrum network.

In addition, the simulation results showed the minimum total packet loss ratio of data signals is 9 of case 6: 10 SU, and 15 PU. The maximum total throughput is 62.933 Bps, and total handover is 18 of Case 1: 5 SU, and 20 PU.

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List of Abbreviations

Symbol	Meaning
AMC	Adaptive Modulation Coding
ACD	Auto-correlation-based Detector
ADCs	Analog to digital converters
AI	Artificial Intelligent
AM	Amplitude Modulation
AMF	Amplitude-Frequency Modulations
AMC	Adaptive modulation coding
ANFIS	Adaptive Neuro-Fuzzy Interference System
AP	Access Point
AWGN	Additive white Gaussian Noise
BER	Bit Error Rate
BPSK	Binary phase-shift keying
BS	Base Station
BSS	Blind Spectrum Sensing
CAF	Cyclic Autocorrelation Function
CAV	Covariance Absolute Value
CCC	Common Control Channel
CE	Cognitive Engine
CFD	Cyclostationary Feature-based Detector
CFN	Covariance Frobenius Norm
CNN	Convolutional Neural Network
CPFSK	Continuous Phase Frequency Shift Keying
CR	Cognitive Radio
CRD	Cognitive radio devices
CSV	Comma-Separated Values
CSD	Cyclostationary Detection
DR	Data Rate
DR	Detection Rate
DSB	Double-sideband suppressed-carrier transmission
ED	Energy detector
EME	Energy with Minimum-Eigen value
FAR	False Alert Rate
FB	Frequency band
FC	Fusion Center
FDMA	frequency division multiple access
FMA	Facilities Management
FN	False Negative
FP	False Positive
GFSK	Gaussian Frequency-shift keying
HWN	Heterogeneous Wireless Networks
IoT	Internet of Things
ITPU	Interference to Primary user

LLC	Logical Link Control
MAC	Media Access Control Layer
MC	Multi-Coset
MED	Maximum-Eigen value-Detection
MF	Matched Filtering
MLP	Multi-layer Perceptron Neural Network
MME	Maximum to Minimum Eigen value
MOD	Modulation Technique
MS	Mobile Station
MSEE	Mean-to-square Extreme-eigen Value
MTSE	Multifaceted Spectral Estimation Methodology
OFDM	orthogonal frequency division multiplex signal
OMNET++	Objective Modular Network Testbed in C++
OODA	Observe, Orient, Decide, Act
OSA	Open Source Access
PAM4	Pulse Amplitude Modulation 4-level
PDA	Personal Digital Assistant
PMU	Power Management Unit
PRSG	Pseudo Random Sequence Generator
PSD	Power Sensitive Density
PSK	Phase Shift Key
PSK	Phase-shift keying
PU	Primary User
PWR	Power Transmitted
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
QPSK	Quadrature Phase Shift Keying
RMT	Random Matrix Theories
SIANN	Shift Invariant Artificial Neural Networks
SNR	Signal to Noise Ratio metric
SOPs	Spectrum Opportunities
SSB	Single-Sideband Modulation
SU	Secondary User
SVD	Singular Value Decomposition
TDMA	Time division multiple access
TN	True Negative
TOI	Transmission Opportunity Index
TP	True Positive
TPC	Transmit power control
TPR	True Positive Rate
WBFM	Wideband Frequency Modulation
WSN	Wireless Sensor Network

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List of Publications

1	Blind Spectrum Sensing Algorithms in CRNs: A Brief Overview. In the 7 th International Engineering Conference(IEC2021), IEEE in 12/07/2021.
2	The Security Challenges with Cognitive Radio Environments For VANETS. International conference on communication and Information Technology (ICICT'21) ,IEEE in 26/10/2021.
3	Generative Adversarial Nets by based multiple methods for Spectrum Sensing in Cognitive radio network / published with journal Bulletin of Electrical Engineering and Informatics, Scopus Q3 .
4	Embedded Hybrid Blind spectrum sensing CRNs algorithm by developed deep learning CNN and Linear Cooperation Techniques , Submitted to: Applied Computing and Informatics, ISSN: 2634- 1964, Scopus Q1 .

1.1 Introduction

A cognitive radio, also known as a CR, can essentially be defined as a high-tech wireless-communication scheme that can detect the electromagnetic environment in which it is working. It can dynamically and independently modify the parameters of its radio operations. In this context, whenever it is determined that a licensed user is not actively transmitting, it is possible for a CR device to get opportunistic access to the frequency band that has been designated for use by that licensed user, within an important concept known as Opportunistic Spectrum Access (OSA). This is because OSA enables opportunistic access to the frequency spectrum, which makes it feasible for this to happen [1].

Cognitive Radio should primarily be characterized by two qualities:

1. The cognitive capabilities of CR equipment may be defined first and foremost as the ability to perceive its radio environment and make sense of the data collected from those sensors, and make a decision concerning the spectrum sharing, depending on the info that has been processed.
2. The re-configurability is defined as the capability of a CR to adjust its operational settings on the fly depending on the information obtained through spectrum analysis.

In a similar line, the design of the CRN decides whether it will be a centralized network (infrastructure) or a infrastructure-less network. The spectrum sensing refers to a method of collecting wireless or spectral response information at a specific place and instant, and it is accomplished via the use of control receivers. This information may be used for a variety of purposes (CRs) [2].

It is possible to use either blind detection approach or the feature detection method to identify spectrum holes. Without any prior knowledge of transmission, the holes in the accessible spectrum may be defined using blind detection

techniques. If both a PU signal and a CR signal are present at the same time, the technique remains unable to tell them apart. The most well-known blind detection approaches that have been explored in relation to CRNs are power identification, correlation sensing, and higher-order-static detection [3].

In addition, Deep learning (DL) algorithms are used as a technique for supporting blind sensing and improving the detecting efficiency, as DL system could mine suitable characterization and patterns through a data-driven way. A remarkable increase has been observed with regards to the research interest and its application in non-cooperative communications [3].

Feature detection methods make use of past information on the main transmission in order to locate gaps in the spectrum. They can tell the difference between signals from primary and secondary users. Furthermore, the weak primary signals are detected in an accurate manner by means of the linear cooperation and in spectrum sensing. Being less computationally complex in comparison with the quadratic detectors, the significance of differences increase with the rise in number of nodes [4].

1.2 Related Works

In this part, the works that are most closely related to the present study in terms of the created blind spectrum sensing method with variable bandwidths in CRNs have been reviewed and overviewed, as follows:

Timothy et al. [5] explored the unsupervised representation learning of radio communication signals by means of raw sampled time series representations. They demonstrated how the basic function of modulation can be learned by means of convolutional auto-encoders, for the visual recognition of their relation to the basis of analysis in digital communication. A proposal and evaluation of quantitative

metrics is presented for evaluating the encoding efficiency and quality via domain-relevant efficiency factors.

Dong et al. [6] presented a new spectrum sensing algorithm for CNNs, whereby the Primary Users (PU) detecting rates is lower within the environment of low signal-to-noise rate. The CNN is used for solving the spectrum sensing, being regarded a binary hypothesis-testing issue. First, the extraction of presence features for PU signals and noise signals takes place, which include the cyclo-stationary and energy features. Next, the extracted features undergo preprocessing so as to function as the CNN model training input. This is followed by feeding the testing data in the CNN model after training. The purpose behind this final process is detecting the PU presence. The results of experiments indicate that the built CNN model is of sufficient reasonability, whereby a higher detection probability is achieved by the suggested algorithm as compared to the cyclo-stationary feature detection (CFD), being approximately 0.5 in -20dB.

Zhuhua Hu et al. [7] introduced a sensing method for the wideband spectrum that is both adaptive and blind and uses the singular value decomposition: ABRMB strategy based on singular value decomposition (SVD) via the Spectrum Sensing Method. Wideband spectrum sensing was the problem that needed to be solved, and the primary benefits of the method include the fact that it needs fewer channels to obtain higher probability reconstruction of spectral support in low SNR ranges. It also enhances the highest number of sub-bands that can be used to reconstruct a signal. Both of these benefits are due to the fact that it reduces the number of channels that are required to achieve high probability reconstruction. The proposed system is similar this work in case of the used SNR values for spectrum sensing.

Kumar et al. [8] proposed a signal distortion correction module (CM) showing how the CM+CNN scheme obtains more accurate results than the current ones. The suggested CM consists of a neural network for estimating the random carrier

frequency and phase offset as presented by the channel, so as to be fed into the unit for undoing the distortions, followed by the CNN-based modulating recognition. The output can be differentiated according to the weight, allowing the end-to-end training by means of the received signals in the CNN modulating recognition. For supervising purposes, the modulating scheme label is necessary, whereas the knowledge of the features or phase offsets is optional.

Ebian et al. [9] utilized spectrum segmentation and minimization recovery for blind compressive sensing in CRN. The used SS method utilized a spectrum segmentation strategy in conjunction with l2-minimization, which served as a CS recovery procedure. The issue that has been resolved estimates the state of the various subchannels, and the primary benefits of using this method include the ability to assess the status of the subchannels with high precision in a variety of (SNR) and in a variety of numbers of CR users on different sparsity levels.

Awin et al. [10] presented a concise course and explanatory tutorial on blind spectrum access for an overlapping cognitive radio system. The Spectrum Sensing Techniques Applied ED technique, MME approach, ME approach, CAV approach, and CFN approach were all used as blind spectrum sensing methods. In low SNR situations, the solved problem provides excellent protection for the licensed user against interference from the unlicensed user, and the main benefits of this Energy detector make it the preferred spectrum sensing approach because it detects the licensed user's presence without any prior knowledge of that user's presence.

Mourad Mabrook et al. [11] proposed an artificial intelligence (AI)-based collaborative spectrum access method for cognitive radio suggesting an adaptable blind MC sampling-based wide spectrum sensing technique. This algorithm is designed to function with cognitive radio networks. It is made up of five SUs, and each user implements an adaptable MC algorithm in order to identify the free channels. After that, a central sensor fusion system is used to collect the detection

findings that were generated by each individual user. Next, the created (AI) detecting technique is based on an Adapted ANFIS structure, and it has a total of fifteen rules and five inputs. The channels power levels PMU were analyzed for adaptive network base fuzzy inference system (ANFIS) identified channels, and it was found that they were the highest as compared to those of other senders with more than five. The main advantages of the system input data are the channels that are detected by the SUs, and the output variable is the channels that are ideally accessible. The designed technique has solved the problem.

Mourougayane et al. [12] proposed a dependable model of spectrum sensing that includes many stages to be used in cognitive radio applications: The method of Spectrum Sensing that was employed made use of two detectors: an ED and a SVD, which were employed in the high SNR band, while a CFD and an ACD were utilized in the low SNR band. The issue that has been resolved causes the detecting process to be more reliable in areas with higher and lower signal-to-noise ratios, as well as the primary benefits of the technology. The multistage detector that has been presented has an enhanced sensitivity, an expanded sensing range, and an optimal sensing mean time, along with the capacity to detect various signals in a dependable manner.

Kai et. al [13] proposed a deep-learning based blind spectrum sensing method whereby three types of neural networks are used: the CNN, long short-term memory, and fully connected neural networks. The experimental results indicated that their proposed method is more efficient than energy detectors, particularly with lower signal-to-noise ratios. Meanwhile, they analyzed how various long short-term memory layers affect the detecting efficiency, exploring the reason behind the improved performance of deep-learning based detectors.

Shishun et al. [14] proposed an iterative unsupervised learning based cooperative spectrum sensing (CSS) algorithm. By increasing the number of

iterations, these individual detectors can be used to cooperatively detect the spectrum status online when there are only slight changes in global labels. The simulating results indicate how the proposed algorithm can realize comparable individual and cooperative detection performance with the existing supervised sensing methods over a wide signal-to-noise ratio (SNR) region.

Chaurasiya and Shrestha [15] proposed a spectrum sensing method VLSI design built on MED, EME, and mean-to-square severe value (MSEE), which are three different spectrum sensing techniques. Blind spectrum sensors are based on the eigenvalue and have a fast sensing time, as they make use of little hardware resources for cognitive radio networks. Recollection and low-latency sensor drawings, as well as recollection and resource-sharing frequency band architectures that make full use of resource sharing, are both utilized in their work. Memory-based spectrum-sensor structures which make extensive use of shared resources are also utilized. Memory-free sensor designs are the most typical type of this technology. The following is an explanation of the issue that was resolved. A shorter sensing time was accomplished while maintaining appropriate efficiency of the hardware. Less hardware was used while maintaining a reasonable sensing time. There are a number of primary benefits that come with using the technique: it operates on real-world applications of the core technology of spectrum sensing, which has the potential to make cognitive radio a reality; it requires a decreased sensing time while maintaining appropriate efficiency in the hardware; and it utilizes a less amount of hardware while maintaining a reasonable sensing time.

De [16] proposed new algorithms for the blind perception of signals with varying bandwidths which are devised and implemented in CR applications. The method for the measurement of spectrum is an angled projection of a received signal, in addition to QR decompositions of possible futures received information matrices of the resampled receiver end. The problem that has since been fixed is

the detection of the pop group PU signals in a CR. The primary benefits of this approach are that it is genuinely blind, meaning that it does not need any previous knowledge, and that it demonstrates greater performance over a broad variety of PU signals available bandwidth. In addition to this, the approach makes use of the subsidiary autocorrelation of the signal, which would be produced as a result of oversampling as well as the use of numerous reception antennas.

Guangliang Pan et al. [17] proposed a technique for perceiving the OFDM signal in the cognitive radio spectrum that is based on deep learning as well as the cyclic spectrum: Deep learning and cyclic spectrum are at the foundation of the ground-breaking spectrum sensing approach, which is now being deployed. This technique applies the advantages offered by the Cns in a picture to a spectrum sensing performed by an OFDM signal. The issue that was fixed successfully increased the frequency sensor performance in wireless situations that are complicated and changeable. When there is a low signal-to-noise ratio, this technique does not only outperform other machine learning approaches, but it also has a greater detecting probability as compared to more conventional ways of spectrum sensing. The advantages include the use of more complex supervised neural models in the area of spectrum sensing with a fixed reference value. The most significant drawbacks of using a single feature as the method's input include the reality that CNNs were not developed with the intention of particularly mitigating the impacts of wireless channel distortions. The proposed system differs from this work with regards to the modulation techniques used, as the adopted system is based on the different modulation techniques with SNR values for each of them, while this work is based on the ODFM to predict the primary user appearance based on deep learning.

Thomas et al. [18] presented a neural network structure that detects the modulating scheme in an efficient way via the portion of I/Q signals. The number

of parameters is not determined by the signal duration, thereby allowing the data streams to be processed resulting in signal-length invariant networks. Besides, a data set is created in light of the simulating impairment, brought to the recorded I/Q signals by the propagation channel and demodulators: random phase shift, delay, roll-offs, sampling rate, and frequency offset. This data set was beneficial in the training of neural networks for ensuring their invariance to impairments and quantifying how accurate its disentangling performance is among modulations in real-life conditions. The data and coding are published to enable the reproduction of the results.

Keunhong et. al [19], introduced a CNN-based deep learning model, namely the deep spectrum sensing (DSS), whereby the autocorrelation curve is adopted as input. The simulating results indicate the relatively high efficiency of the DSS model as compared to the existing deep-learning models using raw signals or spectrogram for input. Besides, DSS models require less data for training as compared to existing models, being much lighter. The efficiency of the DSS implementing process is evaluated with regards to a real test bed that consists of universal software radio peripheral and GNU radio packages, obtaining consistent results of experiments.

Table 1.1 below summarizes the used methodology, goal, and results of the related works.

Table 1.1: The used methods, goals, and results of related works.

Ref. No, Year	Methodology	Goal	Results	Advantages	Drawbacks
[5], 2016	Unsupervised representation learning	Evaluating quantitative metrics for the quality of encoding in spectrum sensing.	Convolutional auto-encoders are suitable in the reduction of parameter space, and the forcing of time-invariance characteristics.	Reducing parameter space, forcing time-invariance characteristics, creating compact radio data front-ends.	The channel variances are removed from the compact data representation criteria.
[6], 2017	CNN	Spectrum sensing	CNN model has an	An improved	Spectrum

		detection rates of the PU signals.	increased detecting probability as compared to cyclo-stationary feature detection (CFD).	training of CNN for enhancing the detecting efficiency.	sensing in low SNR.
[7], 2017	ABRMB Strategy	Wideband spectrum sensing	High probability reconstruction of SNR value of primary users.	Self-adaptive and blind wideband spectrum sensing.	Challenges in multiple measurement vectors.
[8], 2018	CM and CNN	Estimating the random carrier frequencies and phase off-sets presented via the channels.	CM+CNN scheme realizes more accurate results than current schemes.	Improving the modulation recognition accuracy.	Replication of real radio transmission signals is hard.
[9], 2018	Spread Sequence (SS) technique	Utilizing spectrum segmentation and minimization recovery.	High precision in a variety of (SNR)	Determining high accuracy with SNR and different users of CRNs.	Increasing large number of samples to FC.
[10],2019	ED technique, MME approach, ME approach, CAV approach, and CFN approach	Blind spectrum sensing methods, detecting PU presence without any prior knowledge.	Excellent protection for the licensed user against interference.	Blindly detects the existence of the licensed user.	Major interference management
[11],2019	Artificial Intelligence (AI)-based collaborative spectrum access	Channel management with channels that are detected by the SUs.	Ideally accessible of output variable.	Wideband spectrum sensing techniques.	Noise and fading problems.
[12],2019	ED and a SVD	Dependable model of spectrum sensing	Optimal sensing mean time, and the capacity to detect various signals in a dependable manner.	Detecting PU activity via the received signals only, with no need to collect prior knowledge.	Computation processes
[13],2019	CNN, LSTM, and FCNN	Blind spectrum sensing enhancement for Deep Learning	Deep learning is more efficient than an energy detector, particularly with lower signal-to-noise ratios.	Solving the issues of low spectrum resource utilizations.	Signal detection performance.
[14],2020	Cooperative Spectrum Sensing (CSS) algorithm	Online cooperatively detecting spectrum status.	Achieving comparable results with the existing supervised sensing methods over a wide signal-to-noise	Detecting spectrum status channels when there are slight changes in global labels.	Convergence and overheads.

			ratio (SNR) region.		
[15],2020	Spectrum Sensing Method VLSI designs built on MED, EME, and MSEE	Blind Spectrum Sensing of PU signals.	Less amount of hardware while maintaining a reasonable sensing time.	Better sensing time and hardware efficiency.	Computation processes .
[16],2020	Blind perception of signals with varying bandwidths	Genuinely blind, meaning that it does not need any previous knowledge.	Higher measurement of spectrum sensing.	Maintaining constant performing levels at all PU signal bandwidths.	PU signal detection in low-SNR (negative dB) regions.
[17],2020	CNS, and OFDM methods	Perceiving the OFDM signal in the cognitive radio spectrum that is based on deep learning.	Greater detection probability than more conventional ways of spectrum sensing.	A robust multi-stage spectrum sensing.	Spectrum scarcity.
[18],2021	Neural network	Predicting PU spectrum sensing.	High accuracy of prediction.	Detection of spectrum availability.	Predicts the available spectrum with high probability.
[19],2022	CNN, DSS	Auto-correlation enhancement of spectrum sensing in CRN.	More efficient results are obtained as compared to current DL-based models.	To develop and evaluate a machine learning algorithm.	Computation processes.

1.3 Research Problems

When defining the main problem faced, it can be stated that the detecting rate of the PU signals tends to be lower within lower signal-to-noise (SNR) environments during the spectrum sensing procedure. The critical problem is the need to reliably detect the presence of PU. Besides, the quality of spectrum channel of primary user as any collision or interference due to a secondary users with a licensed user channel affect the quality of the spectrum channel used by the primary user. In addition, the sensing utilization of a CR spectrum by secondary users is solved via the early detection of interference of secondary user with primary user to eliminate side effects of interruption, as they lead to the denial of primary access to the spectrum band [12]. The increased number of negative

acknowledgements in traditional blind spectrum sensing of cognitive radio network cycle, which affect the total number of sensing signals is solved by integrating the CNN with efficient linear cooperation training and testing schemes [13].

1.4 Aims of Dissertation

The main aim of this dissertation is the estimation of the impact of bandwidth on the performing efficiency of blind spectrum sensing algorithms, as follow:

- Developing an integrated approach based on CNN with efficient linear cooperation;
- Eliminating or mitigating the interference with primary user through channel allocation for secondary user, which leads to the increase in number of transmitted signals and number of idle channels;
- Enhancing the spectrum sensing in cognitive radio by improvement blind spectrum sensing acquisition;
- Estimating the appearance of previous primary user via a trained SNR model within a hybrid CNN deep learning and linear cooperative approach.

1.5 Contributions of Dissertation

The main contributions can be stated as follows:

- Building an efficient model capable of making reliable prediction blind spectrum sensing within the CRN network based on the Hybrid CNN deep learning and Linear cooperative approach;
- A channel acquisition analyzer for the optimal selection the channel depending on top list recommender of spectrum band as (handoff and handover) in the core engine of the simulated network;
- Dynamic detection of primary users through training the model to automatic work by integrating the CNN training phase with the incoming blind

spectrum using the cooperative SNR value. The output process of the used model is divided into the presence or non-presence of primary users.

1.6 Layout of Dissertation

Following Chapter One, the other sections of this dissertation form the chapters listed below:

Chapter Two: The theoretical background in the second chapter provides a description of the procedures that are used for the primary processes of the system.

Chapter Three: Within this chapter, the proposed system is described, including the procedures for designing and implementing the proposed system. The components of the proposed system are explained in detail.

Chapter Four: The fourth chapter displays the experimental results obtained throughout this study, as it is devoted to presenting the findings of each step of the proposed system as well as the performance assessment of the findings.

Chapter Five: It states the resulting conclusions and describes the future work suggestions.

2.1 Introduction

This chapter presents an introduction to the theoretical background of the used spectrum sensing system handled in one of two ways. The physical layer (PHY) and the media access control layer (MAC) are the two main approaches to the data link layer logical link control (LLC) in the sensing methodology. The principal user signals are the focus of the PHY layer-based spectrum sensing. On the other hand, the MAC layer technique considers the issue of allocating resources to solve the scheduling problem when the channel of interest is best perceived. In addition, it explains the main topics that are related to the proposed system, including the Cognitive Radio Paradigms, Spectrum Sensing techniques, Linear Cooperative Spectrum Sensing, blind spectrum sensing, and hybrid deep Convolutional Neural Network (CNN) with main Convolutional Layers.

2.2 Cognitive Radio

Cognitive radio (CR) can be defined as a type of wireless communication whereby transceivers are able of intelligent detection of the used and unused communicating channels. CR controls the spectrum via cognitive radio cycles performing multiple managing functions like spectrum sensing and assignment. It can be divided into three major mechanism based on how this opens up the licensed spectrum band to secondary users [14]:

2.2.1 Cognitive Radio Mechanism

The main concept of the cognitive radio mechanism is based on managing the spectrum band from both cognitive radio elements as primary user and secondary users, and it is divided into the following mechanisms [15]:

- A- **Underlay Mechanisms:** As long as the interference generated through the secondary user (SU) is below a particular level, the SU will transmit at the same time as the primary user (PU)[16].
- B- **Overlay Mechanisms:** In this mechanism, the secondary user transmitter is also aware of the primary user's channel, along with their unique message and codebook assignments. Interference is lessened as long as there is some collaboration [17]. The proposed system is based on this mechanism.
- C- **Interweave Paradigm:** It can be described as the originally introduced concept of CR for creating opportunistic communications whereby no transmissions take place in the primary system. The main goal is to find unlicensed white spaces or spectrum holes in the licensed spectrum band for data transmission, such as the case of TV white spaces [18]. Three primary mechanisms of cognitive radio are shown in Figure (2.1) below [18].

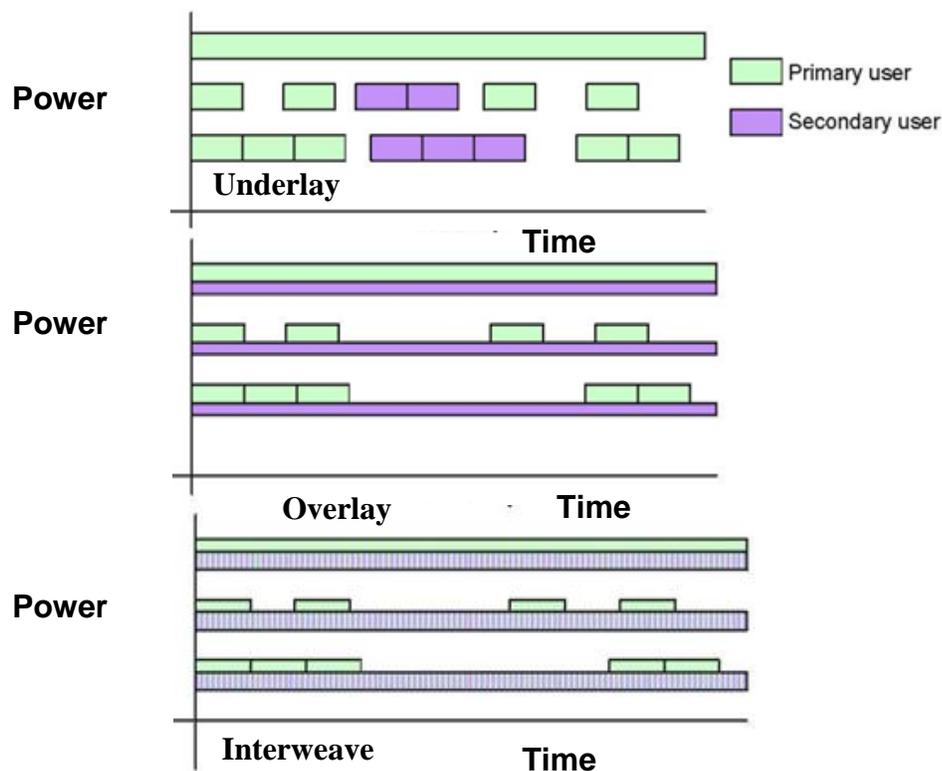


Figure 2.1 The interweave, underlay, and cooperative overlay of cognitive radio [18].

In order to create a better comprehension of CR nodes, the cognitive cycle should be followed to see the classes of cognitive radio nodes depending on cognitive functionality. When the relevant environmental conditions are applied, the self-organized setting is able to develop and adapt to new requirements while remaining transparent and flexible [19].

2.2.2 The Ability of Cognitive Radio

As a brief overview, the ability of Cognitive Radio (CR) may be stated as follows:

- A- Spectrum sensing:** Cognitive Radio nodes are able of locating spectrum holes in the frequency band, as it was demonstrated with regards to whether or not it interfered with the primary user. Finally, this feature was shared with other nearby nodes [20].
- B- Location identification:** Cognitive nodes have the ability to know where they are and where other transmitter nodes are located within the network. There are a variety of alternative methods and models available for collecting information on where something is located. The two most common approaches are to find it through searching or by relying on an additional geographic location system [21].
- C- Network/system discovery:** For the cognitive node to determine which networks are present within its area of influence, it must first locate those networks. Directed multi-hop communication nodes must also have access to the network [22].
- D- Service discovery:** The network services are able to be obtained when discovery and connection within the network has been made, hence this characteristic is tied to network discovery capability, as well as to the network service capability [23].

2.2.3 Reconfigurable Capability

Reconfiguring the Cognitive Radio provides a way to explain its characteristics [24]:

- **Frequency agility:** This cognitive radio can perform a dynamic adjustment of its working frequency in order to choose the signal frequency that is most sensitive, taking into consideration the sensitivities of all other transmitters. However, its unique selling point is the ability to choose frequencies on the fly [25].
- **Adaptive modulation/coding (AMC):** The fading channels took on the form of an approach channel capacity. The CR node's capacity to alter the characteristics of the transmitter provides a wider system compatibility while choosing the best modulation type [26].
- **Transmit power control (TPC):** The data transmission method utilizes a more selective approach to decrease the effective power level, in case power levels must be altered dynamically [27].
- **Dynamic system/network access:** Reconfiguring CR to support heterogeneous wireless networks is absolutely essential in a heterogeneous Wireless Networks (HWN) environment. Therefore, the CR changes its settings to accommodate the various protocols needed to connect to the various /network slicing CS/NS [28].

2.2.4 Self-organized Capability

CR is far more versatile, and it was created to open up additional wireless spectrums. It means that CR is capable of sensing the surrounding environment, and on top of that, is adaptive to it [29]. The radio is capable of determining the most appropriate means of transferring information [30].

There are a variety of Cognitive Radio applications found in different fields including healthcare, transportation, and (environmental) sciences. Some advantages of involving CR in applications can be stated as follows [31]:

- Dynamically accessing the spectrum.
- Autopoietic networks.
- The accuracy of real-time spectrum efficiency.
- Increasing the spectrum use.
- Enhancing the interoperability of new systems
- Reducing unreliability of links, for instance, setting up redundant pathways.
- Cheap radios.
- Preventing cognitive jamming interference.

2.2.5 Cognitive radio and Software-defined radio (SDR)

The core of CR is Software-defined radio (SDR) technology, where SDRs is considered the ideal platform for CRs. This integration is considered the best solution for many types of wireless problems, for instance, spectrum under-utilization, and geographical localization. Figure (2.2) illustrates the relation between cognitive radio network and software defined radar [32].

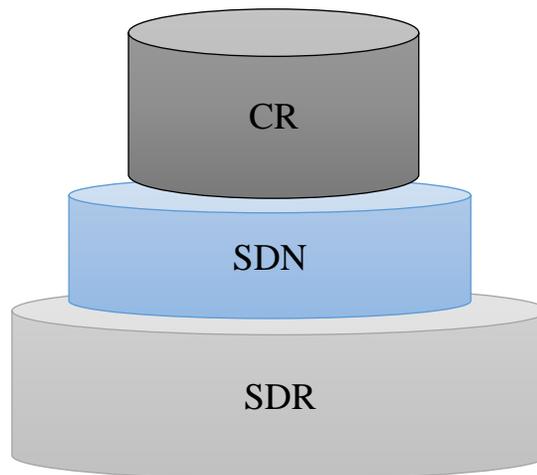


Figure 2.2: The relation between CRN and SDR [32].

The main use of cognitive radio (CR) lies in that it is compatible with software-defined radio (SDR) technology, thereby offering the following benefits to its users [33]:

- Low cost, multi-band;
- Multi-mode operating;
- The flexibility to meet specific Quality of Service (QoS) needs by enhancing the SDR techniques through using an intelligent algorithm known as a Cognitive Engine (CE). It represents an intelligent system background of the CR being a mix of optimizing algorithms and spectrum sensing [34];
- Higher energy efficiency or throughput in WSNs is accomplished when the battery is employed in an application that also makes use of WSN and the IoT. Rural networks in particular have limited environments in restricted condition for communications and channel bandwidth;
- The efficiency and security of computing environments rely on a management system called 'Secure Radio Resource Management [35];

Figure 2.3 shows the main steps of cognitive radio life cycle, which can be in turn stated as follows [35]:

- Network Spectrum Sensing: The assumption is made that all cognitive users are aware of their surroundings. This module makes it possible for cognitive users to identify non-used spectrum bands for the purpose of sharing information to neighboring users.
- Spectrum Decision: For the allocation of cognitive users, several available channels are selected in light of the channel features like data and error rates, PU statistics, and cognitive user QoS criteria.

- Spectrum Sharing: Given the nature of wireless communications, the users tend to share the same channels when communicating.
- Spectrum Mobility: The users in wireless networks are aware of the available channels, however in CR the users are not aware of the idle channels.

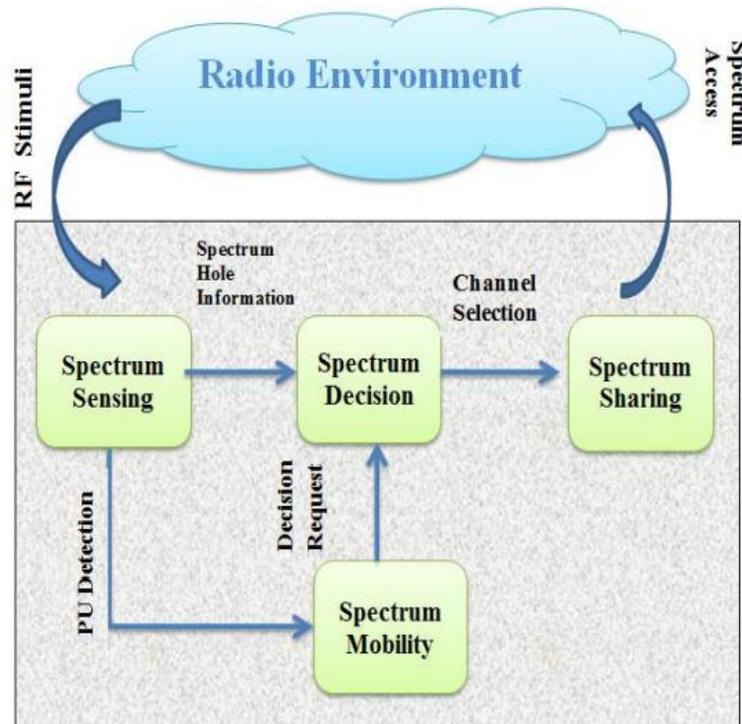


Figure 2.3: Cognitive Cycle [35]

2.2.6 Main Issues in Cognitive Radio Networks

There are a number of issues found in the application of CR networks. These can be summarized as follows:

1. It is critical and specific to prevent secondary users from harming primary users, which is one of the core CR issues. One conceivable method for spectrum access is overlay, and the other is underlay [36]. The proposed system addresses this issue in particular.
2. Accurate sensing is also necessary, whereby primary user behavior is used to identify whether a channel is idle or busy.

3. Scenarios with control information interchange between CR devices for spectrum sensing and sharing necessitate the use of signaling. To enable rapid signaling and neighbor discovery in ad hoc networks, the vast majority of CR MAC protocols utilize a control channel called the common control channel (CCC) [37].
4. When secondary consumers are allowed to dynamically select the optimum channels and transmission characteristics, this leads to optimized spectrum decisions.
5. Spectrum handover schemes must have seamless transitions with little quality deterioration. This issue is related to the proposed system.
6. Also known as cross-layer design, obtaining a greater performance typically requires the strict layer-based design to be ignored, and the cross-layer interactions to be used instead [37].
7. To reduce energy and time consumption, a high priority is given to the number of channels being detected.
8. Spectrum under-utilization is a challenging topic, but cognitive radio provides a new approach to addressing this issue. Sub bands of the wireless spectrum that appear to be underused by the PU are identified and made available to secondary users through two separate mechanisms employed by the device: (1) identifying and trying to highlight the under-used sub bands of the radio spectrum; and (2) managing the configuration methods so as to enable multiple users to utilize underused sub bands of radio spectrums [38].
9. To solve the hidden terminal issue within Cooperative Spectrum Sensing, it is necessary to resolve the complexity issue for the Network lifespan.

10. The operations that require matched filtering must have prior information of the principal user in place. This information is more difficult to obtain, particularly in tactical environments [39].

2.2.7 Relation to Other Radios

Radios that are not yet aware of the local optimizing features can exchange learning with radios which have already undergone learning to the local spectrums, channels, waveforms, or protocol conditions [40].

- Since network operators care about their networks' performance, it is suggested that networks should be consistent, predictable, and within FCC regulations.
- Since learned behaviors are beneficial to the community, it is appropriate that they are made available to the community in a database, where they can be vetted. Net benefits can be calculated before implementation.
- The Radio Environment Map seems to be a representation of how these services are delivered.
- Cognitive radio learning technology has not yet been described by market studies. However, it will be of great use if a person can efficiently utilize spectrum.
- Programming radios or even a whole network to learn how to adjust in real time, is beneficial to the user, the network, and/or the owner of the spectrum.
- Capabilities provided by cognitive radios will be economically valuable because of existing telecommunications infrastructure, which can be used to provide them [41].

2.3 Cognitive Radio Networks Architecture

Most generally, cognitive radio nodes can boost both the network capacity and channel capacity in a notable manner. As heterogeneous network compounds, the cognitive network has numerous communication systems within it. Technologies, networks, user terminals, applications, and service providers related to wireless access,

and the various locations of each, occur at different communication system levels such as the layer and network architecture. The design of the CRN architecture is primarily focused on increasing the network utilization. To the user, the network usage indicates that it can satisfy its requirements at any time and place, because it may leverage several CRNs simultaneously [41].

A- Infrastructure Architecture: The three network components form the framework of this architecture. As shown in the situation depicted in Figure (2.4), MS can only connect to a BSs / APs via a single hop (A). The MSs can communicate via the BS/AP illustrated in scenario (B). When looking at the connections among cells, backbone/core networks are often used [42].

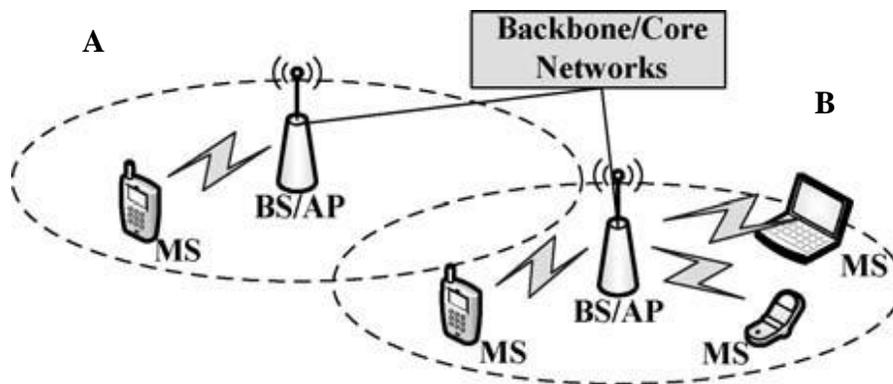


Figure 2.4: CRN Infrastructure architecture [42]

B- Ad-hoc Architecture: These kinds of designs are put up on the fly, not relying on infrastructure assistance. In Figure (2.5), it can be noted that two MS nodes inside each other's range of radio waves (RF) seek to link up and exchange information using the established protocols and norms for such exchanges such as Wi-Fi or Bluetooth. In situations where the need for communication arises, it enables instant communication links [43].

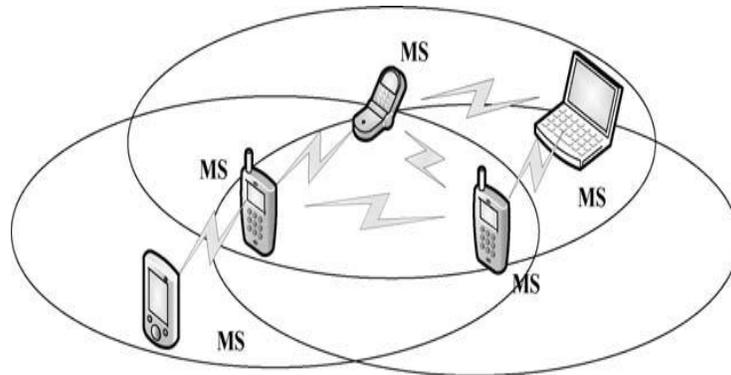


Figure 2.5: CRN Ad-hoc architecture [43]

C- Mesh Architecture: It incorporates infrastructure from the past, as well as infrastructure-less (ad-hoc) designs. In this scenario, the node closest to the BSs / APs is directly connected to it using a relay node. This design is more versatile, allowing many sorts of structures to be built. Certain APs have a gateway function, while some are linked to the core network via a gateway. It can also make use of the channel spectrum hole to see what others are doing, resulting in the greatest effectiveness. The architecture is shown in Figure (2.6) for the CR-Mesh Network [44].

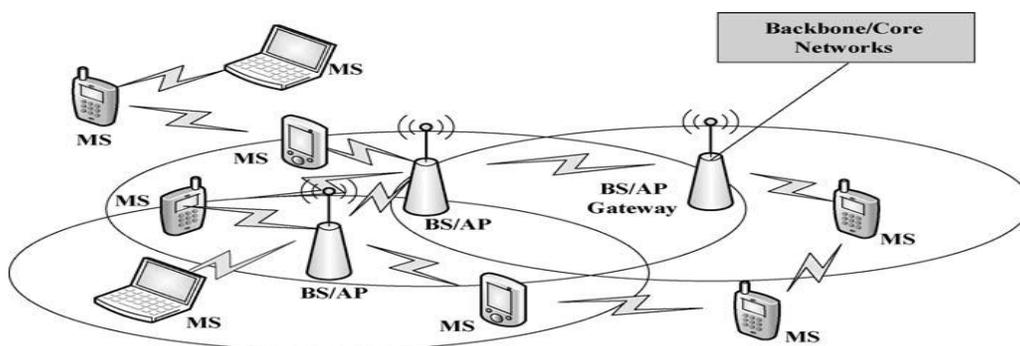


Figure 2.6: Architecture of a CR-mesh network [44]

2.4 Popular Uses for Cognitive Radio Networks

CRNs have a number of uses, including in the applications of WSNs. The devices could include facilities management (FMA), precision agriculture (PDA), machine surveillance (WMS), defensive maintenance (SMD), and medicine (MDM) [45]. Leased

networks represent the vast majority of CRN applications whereby the SU is used for resources while there is no PU network available in the normal scenario. Primary Network operators gain by having a piece of their spectrum leased to the SU, which is responsive to spectrum access opportunities. In conclusion, it can be said that improving general cognitive network performance by enhancing spectrum sharing capability is rendered largely insignificant due to network connection failure and channel capacity. SU leases of half of the timeslot from the PU at the cost of relaying the PU's data transmission employed in this arrangement [46].

Cognitive radio devices (CRD) are responsible for tracking spectrum bands via the spectrum sensing technique. The cognitive network nodes (CRN) share the same call management (CP). Despite that, CRD and CRN utilize different algorithms and jobs [47].

2.5 Spectrum Sensing

When it comes to spectrum sensing, there are a number of critical factors to be considered, namely dimension space, hardware problems, and approaches to spectrum sensing [48]:

2.5.1 Radio Spectrum Space

In order for the secondary user to transfer data over the open section of the band, spectral gaps are required in each of the n dimensions of this space. Various approaches to the radio spectrum are outlined in [49]:

- Frequency domain utilization: The use of Frequency Division Multiple Access (FDMA) within cellular communications enables the usage of small band parts that are not used.

- Time domain utilization: The use of Time Division Multiple Access (TDMA) within cellular communications makes the non-used spectrum parts available for a short period of time to be used by SUs.
- Spatial domain utilization [50]: As for spatial dimensions, the location (longitude, latitude and elevation) as well as distance of the PU are sensed, enabling the use of vacant spectrums.
- Code dimension: The sensing parameters used to manage radio spectrum space in this dimension are [51] [52]:
 - (i) Having the code disseminated (Spreading code)
 - (ii) Frequency hopping.
 - (iii) Time jumping or hopping.

The orthogonal code is utilized in parallel with the primary user's code without interfering with the PU. The dimensions of the sensing parameter angle are [53]:

- (i) PU azimuth and elevation angles.
- (ii) Specificity of PU.

To avoid interference, the spectrum is divided so that the PU transmits in one direction and the SU transmits in another.

2.5.2 Challenges of Spectrum Sensing Based on Node Components

- **Software Requirements**

Higher-resolution ADCs and quicker signal processors are required for CR users, driving up the system cost [54].

- **The hidden problem with CR's primary users**

This aspect is comparable to the CSMA's hidden node problem. Cognitive radio is unable to communicate with the primary user transmitter because it is outside the radio

communication range. All of the secondary users' lines of communication are in constant dialogue with the principal user. The range of CR and PU emitters is inadequate, which means that they could transmit properly at the same time. In case interference occurs at PU, the cooperative sensing forms a solution to the PU problem since it ensures that it remains hidden [55].

1- Detecting primary users

As it makes use of spread spectrum methods to achieve its goals, it is difficult to distinguish between the normal and primary users as the strength of PU when distributed over a wide frequency range [56].

2- SU channel Allocation

When an unused band is found, the band must be cleared for the SU. To begin with, implementing it in real time has significant obstacles. The length of time for detecting, as well as the period of time for transitioning, must be shortened. All SUs select different channels through the determination of the channels that are in the spectrum hand-off [57]. Table (2.1) below shows the main signal processing techniques, along with the advantages of secondary user channel allocations [58].

Table 2.1 The advantages and downsides of various signal processing techniques [59].

Techniques	Advantages	Disadvantages
Matched Filtering	Higher performance and cost-efficient implementations	Requires primary user's previous information
Energy Detector	Does not require previous information, and has a lower implementing budget	Susceptible to noise and difficult to distinguish PU from SU
Cyclostationary feature	Applicable in low SNR area with no interferences	Requires previous information, and has a higher implementing cost
Multichannel	Smaller sampling amounts, withstanding model disparity	Needs numerous channels for sampling.

Compressing	Small sample amounts, and affordable signals.	Deficient design.
Filter Sampling	Small number of samples, with a wide and flexible coverage.	Computational complexity.

A system that can detect both radio and electro-magnetic spectrums at a certain location and time is known as spectrum sensing. PUs' idle channels, monitoring interference faced by the PU, understanding the PU traffic state to boost CRN activity, and calculating channel gains among CRs are all pieces of radio knowledge that can be gained via spectrum sensing. The CRN collects the information sensed and analyses it to decide whether or not there is a suitable spectrum available. The spectral sensing technique can be utilized to address the following aspects [60]:

- The CRs have designated sensing windows to be used in order to identify the spectrum choices. Depending on how long it takes for a cognitive response to be learned, spectrum sensing may either be proactive or reactive. In proactive sensing, sensors are used on a daily basis, whereas in reactive sensing, sensors are used on an individual basis [61].
- A CR wants to be knowledgeable of and aware of all of the idle networks a PU has, in order to locate and intercept such networks [62].
- Where to sense: With CR hardware like this, the question 'where to sense' can only be asked. Each sensor's maximum number of bands depends on the selected operating mode. To accomplish concurrent spectrum sensing in the wideband mode, CRs need more hardware, whereas CRs operating in the narrowband mode require much less hardware [63].

- How to experience: This is dependent on the usage of spectrum sensing regulations like the number of spectrum bands that are monitored in use, the way the algorithm is programmed, or if learning spectrum sensing is utilized [64].

The method utilized for sensing a spectrum varies with the length of time needed. With attribute detection, the sensing time is longer than for blind detection techniques [65].

A key part of CR networking is the capacity to locate the radio spectrum. CR could potentially use this information and alter their strategies to co-transmit via primary recipients. Equation (2.1) shows that Spectrum sensing is critical for improving the precision of CR networks [66]:

$$y(k) = \begin{cases} \eta(k) & : H_0 \\ s(k) + \eta(k) & : H_1 \end{cases} \quad (2.1)$$

At every given time instant k , access is provided to the samples $y(k)$ and the additive noise $\eta(k)$, but not the sent signal $s(k)$. There are two possible interpretations of the data, respectively designated as alternative hypothesis H_0 (no noise) and alternative hypothesis H_1 (noise plus signal). Changes in broadcast signal strength due to fading and shadowing may be accounted for in a rewritten version of the algorithm [67].

The samples $y(k)$ and the additive noise $\eta(k)$ are available at each instant k , while the transmitted signal $s(k)$ is not. Alternate hypothesis H_0 and alternate hypothesis H_1 are alternative hypotheses: no noise and noise plus signal. To a certain extent, they

could be rewritten to account for fluctuating broadcast signal levels due to fading and shadowing, as shown in Equation (2.2) [68].

$$y(k) = \begin{cases} \eta(k) & : H_0 \\ h \cdot s(k) + \eta(k) & : H_1 \end{cases} \quad (2.2)$$

The difference between these two equations is that eq. (2.1) is the calculation of present of primary user without noise, while eq. (2.2) is the state of calculation of primary user with noise.

There are four possible cases of signal detection can be depicted:

Case 1. Declaring H_0 when H_0 is true ($H_0 H_0$)	}	Correct Detection
Case 2. Declaring H_1 when H_1 is true ($H_1 H_1$)		
Case 3. Declaring H_0 when H_1 is true ($H_0 H_1$)	}	Missed Detection
Case 4. Declaring H_1 when H_0 is true ($H_1 H_0$)		
	}	Negative Acknowledge

Cases 1 and 2 could be considered as correct detections. Case 3 represents the missed detections, and Case 4 is the negative acknowledge. In essence, detectors tend to target the highest number of correct detections meanwhile the negative acknowledge and missed detection rates are kept to a minimum [68].

2.6 Local Spectrum Sensing Techniques

The spectrum hole discovery is done while avoiding unwanted interference to the PU terminals [69].

2.6.1 Matched Filtering Detection Method

This technique, known as MF, requires perfect synchronization between the PU and SU, as well as comprehensive understanding of the PU signal and the channel between them. According to the sources, the MF approach has been called the best

detection strategy since it enhances the SNR while suppressing additive noise and decreases decision errors [69].

2.6.2 Method for Detecting Cyclo-stationary Features

The CD takes advantage of the fact that particular signals will often have unique patterns that can be utilized to identify them. In the majority of basic signals, the carrier frequency is sinusoidal, the period is constant, or the cycle of a prefix precedes the modulation. For a very low SNR, the PU signal can be distinguished from other modulated signals and background noise [70].

2.6.3 Energy Detection Method

Among the most frequently explored spectroscopic sensing methods is energy detecting (ED), mostly because of its simplicity in both calculation and implementation. It is a non-coherent methodology, since no prior understanding of the parameters of the main signal is required in advance. Therefore, it may be used to determine whether or not the PU signal is there. Determinations are reached by adding up the squares of the receiver sensitivity strengths during a certain time interval, and comparing it to a pre-determined threshold [71].

2.6.4 Prior Information Needing

A- Matched Filtering (MF)

The matching filter detection is employed in this process. A series of filters on an unknown signal $x(t)$ is used to convolve a filtered impulsive signal, $h(t)$. In order to fully utilize the network's resources, one must first understand how bandwidth is allocated, what frequency is utilized, and how the frames are formatted. This technique has an advantage in that it increases the chance of detecting with less sensing time. In this category, it is often regarded to be the optimal approach. Even if the system only detects fewer signal samples, the detecting remains sufficient, as it withstands

environmental noise. Furthermore, it is capable of effective detection even when SNR is low [72].

B- Cyclo-Stationary Detection (CSD)

By integrating several properties from the received signal, this method capitalizes on cyclo-stationary aspects, including specifications such as the frame format, modulation types, operating frequency, and required bandwidth, as well as statistical measurements like the mean, cyclic correlation, and autocorrelation [73].

C- Coherent Detection

It is a typical practice for coherent detection to include the passing on of intros, transitions, and pilots. A sequence that is sent before each slot is called a preamble (that is already known). The area in the center of the slot is referred to as the mid-amble. Received signals correlate with their own known duplicate when information about these known patterns is provided [74].

D- Radio Identification Based Detection

This strategy makes use of known technology in order to establish a communication link. If the major user has already revealed their transmission technique, then good spectrum knowledge can be obtained. It can also increase the precision. The fact that Bluetooth functions in the range of 10 meters was utilized here. Bluetooth may be used by CR devices to connect to different Bluetooth-enabled applications at a permitted range. It is highly effective, taking an average of 10 seconds to perform [75].

2.7 Blind Detection

Non-explosive Energy Detectors are the most often utilized approach in commercial energy detection. A signal detector's output is compared to a threshold value to determine whether or not the PU is present. This methodology's advantage is that it is simple and straightforward to adopt. This feature is useful for cutting the

sensing time and power usage. However, the increased noise uncertainty raises the likelihood of a false alert. It has a very low SNR reliability in the low SNR condition. In addition, it does not recognize PU as a separate signal source. As opposed to other procedures, this methodology has a lower accuracy. Using an energy detector to search for spread spectrum signals is therefore considered to be rather useless [76].

The comparison between signal and noise covariance is key to the covariance-based spectrum sensing approach. Even with low signal-to-noise ratios, it is nearly impossible to reliably discriminate between signal and noise. The power consumption is low, but the complexity and processing overhead are not ideal. Besides, the low detection capacity and difficulty in dealing with spread spectrum signals also form problems [77].

In the table below, the different approaches are compared on various critical aspects. Selecting a strategy for a given application could be aided by this comparison [78].

Table 2.2 Comparison of Spectrum Sensing Techniques [78].

	Prior Information needed				Blind Sensing	
	CD	MF	CF	RB	ED	Co
Prior information needing	Yes	Yes	Yes	Yes	No	No
Sensing Time	***	***	***	**	*	**
Robustness against SNR	***	***	***	**	*	**
Detection Performance	**	***	*	**	*	*
Complexity	**	***	**	**	*	**
Accuracy	***	***	*	**	*	**
Power Consumption	**	***	***	***	*	*
*** High ** Medium *Low						
CD-Coherent Detection; MF-Matched Filter; CF-Cyclostationary Feature detection; RB- Radio Identification Based ED- Energy Detector; Co- CoVariance Based						

2.7.1 Blind Spectrum Sensing (BSS)

Either blind detection itself or the technique adopted for spectral hole identification might be applied. Without prior primary transmission information, blind identification algorithms can separate the spectrum gaps, being not able to differentiate PU signals from co-existing CR signals. This results in the interference between the two. CRN has well-known blind detection techniques, including the detection of electricity, auto-correlation, and high order statistics [79]. The previous understanding of primary propagation is employed in finding spectrum hole detection techniques, and the PU signals (which contain just Primary Signals) may be separated from CR signals (which, among others, contain the Primary Signals). Feature detection techniques, such as paired filter and cyclo-stationary detection, serve as good examples [80].

Several investigations in the spectrum sensing field have occurred over the past few years. The currently most prevalent spectrum sensing methods include functional detection processes, value-oriented approaches, and matched filtering methods. When the local noise power is identified, the most effective energy detector is determined in terms of how well it can detect that energy [81].

An unstable signal may interfere with the energy detector, but it is not sufficiently robust to deal with it. The cyclo-stationary detector is used to sense a PU's spectrum with the detection method, which is a matter of the modulation signals' periodicity properties. Finding when pilots and training sequences of the PU signals are made totally available to the SU makes it possible to efficiently and optimally identify PUs [82].

This may allow for PUs to be detected, but the information obtained from the PUs is not always crucial as it depends on the type of data contained in the PUs (TV,

wireless microphones, cell phones). The feature detection or filter technique in real cognitive radio network spectrum sensor output can form a considerable impairment [83]. This proposed method has several phases:

- A- The first phase involves the combination of the linear prediction and QR decomposition (reveal distinctive features) for the matrices of received signals [84].
- B- In the next phase, the computation of two signal statistics takes place using the over-sampled signals that are received. Signal statistic S1 is an estimation of the of the primary signal found within the received data. Signal statistic S2 is an estimation of the noise variance, even in the case that the received signal includes signals and noise together. This enables the sensing algorithm of operating with no information about the noise statistics [85].
- C- The ratio between these two statistics indicates whether or not the primary signal is present within the signals that secondary user receives [86].

The signal was oversampled and contained components of both signal and noise. Most of the overdubbed branches have a very poor connection between noise components. With such low SNR, the signal can be easily distinguished from the noise. Because there is no principal signal, the signals measured in this approach will have a higher disparity in value, and an improved technique of identification would be accompanied by anti-discrimination.

Algorithm 2.1 shows the used spectrum sensing steps of frequency for the blind spectrum sensing approach [86].

Algorithm 2.1: The blind spectrum sensing algorithm**Definitions :**

- m: Number of degrees of freedom
- Number_SUs: Set of sizes of the CRN Network
- N_Simulations : Number of simulated modules
- N_SNR_Changes : Number of times SNR
- dg : Group decision using majority logic

Begin :

1. Initialize m ,Number_SUs,N_Simulations,N_SNR_Changes,SNR_Distribution-mean,dg
2. **For** i=1 length (Number_SUs)
3. **Set** primary User Usage Pattern
4. **For** j =1: N_Simulations
5. **For** k=1: length (Number of data samples)
6. **Check** SNR estimate update count
7. **If** true estimate SNR and optimal Lambda **then**
8. Y \leftarrow sum of square of m input data samples
9. Dec \leftarrow Sigmoid (Y- optimal Lambda) // dec is an SU's SoftDecision
10. mu \leftarrow 500 set empirically
11. error \leftarrow dg-dec
12. Lambda \leftarrow Lambda-mu *error *dec(1-dec)
13. FinalDec \leftarrow ((Y- Lambda)>0)*1
14. **End_if**
15. Error (cnt) \leftarrow mean (abc (Usage Pattern- FinalDec)
16. cnt \leftarrow cnt +1;
17. **End_for**
18. **Net Error** \leftarrow mean (error)
19. **End_for**
20. **End_for**

End_Algorithm

2.7.2 Other Sensing Techniques

The wave surface-based sensing in the PSD of a wideband channel makes use of wavelets to detect the edges. The edges relate to transitions from a region of empty music to a region of full music, and vice versa. Estimating the amount of power available between the two edges once these edges have been identified is known as edge detection. The band's status as either occupied or unoccupied may be determined in a binary approach by accessing this information and also having knowledge of the edge positions. Sub-Nyquist sampling is used in order to increase the accuracy of the wavelet-based detection. A coarse spectrum can be achieved via a sub-Nyquist sampling in case of signal spectrum sparsity. The eigenvalue based sensing is determined by the two prominent eigenvalues [86]:

A- Maximum-Minimum Eigenvalue Detection (MME): It is comparable to the sensing of energy, except that the formula involves minimum rather than maximum values. In order to implement the Random matrix theories (RMT), the RMT is implemented with random matrices. To determine the value that defines the threshold, the ratio is quantized [86]. Through the ratio of the signal energy to the eigenvalue of the least significant bit, the EME is used for detection. To help calculate the SNR, the ED measures the signal power to the noise power [87].

B- Multifaceted Spectral Estimation Methodology (MTSE). The complexity of the estimator is less when compared to the maximum likelihood PSD estimator, which results in an approximation of maximum likelihood PSD [87].

2.8 Radio Frequency Environment

The knowledge gained from the radio environment should be used to form an optimized solution because the Cognitive Radio operates in observe, decide, and act cycles. The RF environments are listed below [88].

2.8.1 Operating Frequency Band

This is the first gene on the chromosome. Each transmitter requires a frequency spectrum for its operation in wireless communication. While other technologies have set spectrum bands, Cognitive Radio is allowed to operate on any available frequency band. The range of operating frequency band is 54MHz to 862MHz, with a step size of 8MHz, as stated in the IEEE 802.22 specifications. The total number of bits required for frequency band encoding is seven bits. This results in different numbers, such as from 0000001 to 1100110 [88].

2.8.2 Modulation Technique

This chromosome contains the second gene. It describes the relationship between two different types of waveforms in wireless communication. There are a variety of different modulation techniques, including the Binary Phase Shift Keying (BPSK), being one of the more simple forms of modulating. It consists of two stages split by 180 degrees. In BPSK, the system changes in the sinusoidal carrier of the phase, referring to the data, after which the phase shifts by 180 degrees. These shifts are in fact an alteration in the state of data: Quadrature Phase Shift Keying (QPSK) takes place in four phases at 0, 90, -90 and 180 degrees. It is considered to be more effective than BPSK due to its higher spectral efficiency, as well as the use of 2 modulating symbols simultaneously. The Quadrature Amplitude Modulation (QAM) combines both amplitude modulating and phase shift keying. The transferring of data takes place through the modulation of two individual carrier signals (sin, cos) which are out of phase by 90 degrees. This process involves different kinds and states: 4-QAM, 8- QAM, 16- QAM, 32- QAM and 64- QAM. All QAM symbol states determine certain phases and amplitudes. The increase in levels and complexity lead the QAM to become more efficient [89].

2.8.3 Bit Error Rate

Bit Error Rate (BER) is one of the more critical RF parameters for wireless communication. The decoded data includes amendments caused by interference or a noisy channel. In each case, the BER can be tolerated up to a particular threshold. Inclusive BER ranges can be calculated between 10^{-1} and 10^{-15} , using a step size of 10^{-1} . In the case of encoding, the total number of bits used is equal to four. Variable encodings have values that range from 0001 to 1111 [90].

2.8.4 Data Rate

The data rate is another critical RF characteristic that needs to be taken into consideration. The information describes the number of bits that are transmitted each unit of time. The data rate varies from one application to another. When discussing the pace at which data travels, the range extends from 50 kbps to 1.55 Mbps, with a step size of 50 kbps. To express the whole amount of bits of DR, 5 bits are required. As such, the variable for encoding is a decimal number ranging from 00001 to 11111 [90].

2.8.5 Power Transmitted (PWR)

The fifth RF parameter for the wireless communication system is power. This experiment has power values that range from 3 dbm to 45 dbm, with step sizes of 3 dbm. Due to this, the total number of bits required for encoding is 4. Variable encoding has values ranging from 0001 to 1111 [91].

2.8.6 Interference to Primary user

It is an essential RF factors within CR networks. It is taken into consideration because the primary user is unaffected due to the transmission power of the CR. There is a significant increase in ITPU from 0.0625 to 0.9375, with a step size of 0.0625. To correctly reflect the total number of bits in which the ITPU can be expressed, the total number of bits in which it can be encoded is 4. The variable encoding has values ranging from 0001 to 1111 [91].

2.8.7 Transmission Opportunity Index (TOI)

Among the various parameters used for channel selection, TOI is particularly crucial. TOI is a direct result of the primary user's activity matrix. The CR uses the Transmission Opportunity Index to predict the future use of a channel. The probability of channel utilization by the cognitive user increases as the value of TOI increases. There is a significant value between 0.3679 and 0.9394 for time on interest. The initial value of the number of time slots employed by the principal user in each individual channel is 0.3697, and it goes up to 0.9297 with a step size of 0.04. This shows that the numbers calculated are within the parameters [91].

2.9 Variable Bandwidth

Variable bandwidth allows the shaping of the traffic flow, and guaranteeing the minimum bandwidth. The traffic source regulates its traffic generation to meet the current network conditions.

It is crucial to administrators that the network's flexible bandwidth is in place. One of the most critical functions of monitoring bandwidth is the providing of information. It is crucial for administrators to be able to monitor their bandwidth so that they can ensure that their applications have the appropriate bandwidth. Once they have had the opportunity to inspect this data and locate any network bottlenecks, they may use that knowledge to address other problems which, in turn, further enhances its overall performance [92].

2.10 Convolutional Neural Network (CNN)

CNNs are deep neural networks commonly employed in DL to process visual data. Such "shift invariant" or "space discrete wavelet transform" artificial neural networks (SIANNs) create feature maps that are highly translation-invariant by using a shared-weight design for convolution or filters which slide along input features and offer translation equivariant outputs. In general, many convolutional neural networks are

simply translation invariant; however there are a few exceptions. Among the various applications of these systems is image and video recognition, as well as recommender systems, picture segments, and medical image interpretation [93].

Regularized multilayer perceptrons are essentially CNNs with additional layers. A multilayer perceptron network will have its neurons connected at all layers. Because of the unrestricted access of these networks which exposes them to overfitting, they are highly vulnerable. Among the many methods used for minimizing overfitting is the punishing of parameters throughout preparation, like weight loss, or reducing the overall number of connections (skipped connections, dropouts) [93]

In contrast to traditional regularization techniques, CNNs leverage the hierarchical pattern in data and employ embossing filters to construct increasingly complicated patterns. Because of this, CNNs have a lower connection and complexity than their counterparts. The organization of a convolutional network's neurons in their communications is inspired by the structure of the visual cortex in animals. Only individual cortical neurons in the receptive field respond to inputs. Due to the overlapping receptive fields of many neurons, all of the visual field can be occupied by them [93].

CNNs can do the majority of the image categorization processing with a minimal amount of work. Conventional algorithms need the use of hand-engineered filters, while the network's algorithms can automatically learn and improve the filters (or kernels). An important benefit of automating extraction of features is that now the system does not just dependent on human knowledge. CNNs consist of an input layer, many hidden layers, as well as an output layer. As a result of the input signal and final convolution, the inputs and outputs of a few of the different layers of a fodder neural network are kept secret. The convolutional layers used in deep neural networks are their secret weapon [93].

Convolution involves sliding a kernel over an input matrix in order to create a feature map, which is then used as an input for the following layer. Once this step is completed, more layered models such as pooling models, entirely connected models, and normalizing models are applied. Convolutional neural networks are layered one on top of the other. The CNN's input is a tensor that can be described as follows: one hundred thousand percent multiplied by the input height, multiplied by the input width, multiplied by one hundred thousand percent, and then multiplied by the input height, multiplied by the input width, again multiplied by one hundred thousand percent, and then multiplied by the height of the input (input channels). Activation maps, also called as feature maps, can be illustrated as follows: after going through a convolutional layer: the (output numbers) \times (feature map height) \times (output numbers) (feature map width) so \times . (number of inputs) the number of inputs is \times . (feature map channels). Convolutional layers in CNNs typically have convolutional filters/kernels with particular width and height specifications (hyper-parameters) [94].

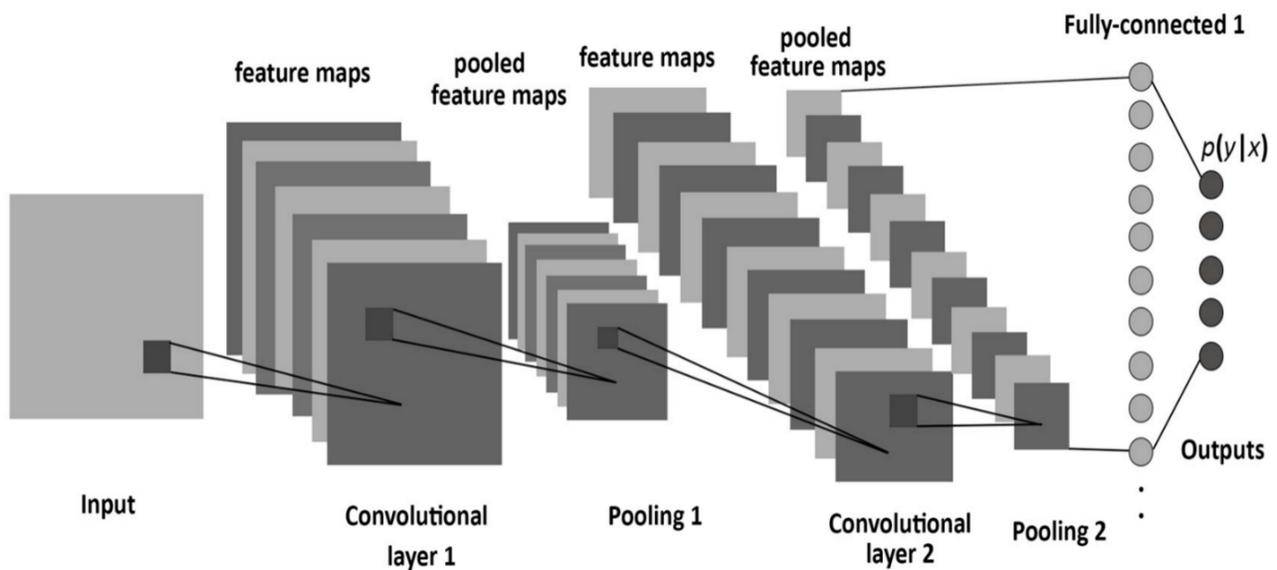


Figure 2.7: CNNs Structure [94].

Input and output channels are equal to the number of inputs and outputs, respectively (hyper-parameters). The number of input channels in one layer in an N-way system should be equal to the number of output channels [94].

2.10.1 Convolutional Layer

It is the central component of a convolutional neural network, where most of the processing occurs. In order to accomplish this, there are a number of components needed, such as the input data, a filter, and a feature map [94]. Even though there are three hyper parameters that determine the volume size of the output, which are required to be established before training the neural network, these hyper parameters must be selected before the training can begin. Some of these include:

- a. Filter design influences output depth. To give another example, a collection of three unique filters will produce three feature maps, resulting in a depth of three.
- b. The stride is the number of pixels or number of blocks that the kernel advances over the input matrix. Although two or more strides are uncommon, a longer step reduces the production [94].

2.10.2 Pooling Layers

Conventional convolutional layers can be included, but global and local pooling layers are available for convolutional networks as well. When neurons are pooled across layers, the outputs of several neurons in one layer are combined into one neuron in the following layer. Typically, clusters with local pooling are sized at 2x2 tiles. Global pooling affects all of the neurons within the map's network [95].

- **Maximum pooling:** When the filter progresses over the input, it collects the pixel with the maximum value and passes it to the output array. In any case, this method is somewhat more common than normal pooling.

- **Middle pooling:** The filter determines the average value found while traveling over the input to be sent to the output array [95].

2.10.3 Fully Connected Layers

In completely connected layers, all neurons within a single layer are coupled to the neurons found within the following layers. Within the context of multilayer perceptron neural networks, the flattened matrix runs via a completely linked layer in order to identify the images. This layer handles the categorization process by utilizing the features acquired by the previous layers and applying various filters [95].

2.10.4 Receptive Field

The various neurons in the previous layer of the neural network all send information to the neurons in the current layer. The receptive region for every neuron in a convolutional layer is known as the neuron's "area of influence." Regions are almost always square, such as 5 by 5 neurons for example. When discussing receptive fields in entirely connected layers, it is useful to mention that the receptive field is the prior layer. With each successive convolutional layer, neurons are processing input from a larger portion of the input as compared to earlier levels [95].

2.10.5 Weights

In order to generate an output value, the neurons in a neural network apply a predetermined function onto the input values that are received from the receptive region of the layer beneath them. A weights vector and bias are used in the procedure for deciding which function will be utilized for the data that is fed into the system (typically real numbers). Learning involves repeatedly altering biases and weights. In mathematical terms, the weight vector and the bias reflect different aspects of the input, and are called filters (e.g., a particular shape). CNNs have the unique property of having numerous neurons utilizing the same filter. With one bias and one weight vector shared by all receptive fields, the memory footprint is reduced [95].

2.11 Linear Cooperative Spectrum Sensing

Spectrum sensing is dependent on users of a CR being able to interact with one another while limiting interference to primary users. Through linearly combining secondary users' recordings and comparing them to a threshold, primary user signal presence may be inferred in linear collaborative spectrum sensing. To study the effect of device characteristics upon the complementary receiver operating characteristics, numerical findings are provided. For a device that has constant local SNRs and channel gain correlation coefficients, a simple calculation may be utilized to represent the optimal likelihood of missed detection [95].

There is a great demand for new wireless networks to be constructed, in both licensed and unlicensed frequency spectrum, because of the exponential growth of wireless communications [95].

Two goals of spectrum sensing are to minimize detrimental interference to PUs and to efficiently detect and use available spectrum holes. One reason spectrum sensing detection accuracy is important to both main and CR networks is the fact that that it is vital to network performance. The metrics of likelihood of false alarm and probability of detection are used in order to calculate the detection efficiency. The detection efficiency is defined as the chance that a CR user will report the presence of a PU while the spectrum is already being utilized by the PU. In most cases, it is preferable to have a high chance of detection while simultaneously reducing the number of false alarms to the greatest extent possible [96].

Working in a cooperative manner to enhance spectrum sensing is necessary if secondary users are present and are spread at different locations. A group of CR users work together to exchange sensing information, which they utilize to come to a better conclusion than making an individual judgment. In order to solve concerns like fading, shadowing, and noise uncertainty, academics have proposed cooperation as a solution.

This significantly minimizes the likelihood of a false alert and a misdetection. Also, it overcomes the primary user problem, which had previously been unknown, and decreases sensing time [96].

The data from each user is transferred to a data fusion center whether it is in its raw or processed form. This acquired data is processed, and finally a choice is made. Classifying cooperative sensing implementation can be done based on the above categories: Centralized, Distributed, External, and Relay-Assisted Sensing [23, 24].

A- In centralized sensing, a single location called the FC is surrounded by numerous CRs. CRs use the local sensing, whereas FC collects sensing information from numerous CR devices and serves as a base station. Decisions about the club are determined by FC [96].

B- Distributed Sensing: Information is shared between all the CR devices. But the decision to either be present or absent of PU is made separately. This technique's core notion is that users who are closer to the transmitter have a better chance of detecting it. Thus, as the user is closer to the recipient, the more the user's information can be shared [96].

C- External sensing: The device takes the place of CR for sensing. In order to communicate the current occupancy of the channel, it broadcasts the channel occupancy information to nearby CRs [97].

D- Relay-Assisted Sensing: It is cooperative communications scheme implemented in a real IEEE 802.15.4 with a beacon-enabled mode and guaranteed time slot (GTS) scheduling. It assists both primary and secondary transmissions in a time-slotted cognitive radio network [97].

2.12 An overview of the planned Cognitive Radio Network's Layers and Modules

When it comes to the five standard communication layers used in wireless networks, the design of the Cr Network is not dissimilar to that of other kinds of networks. Every component of the system will have a representation of its usefulness as the C++ core for the OMNET++ simulation code. The description of the system utilized in each of the levels[98].

2.12.1 Application Layer

True data is not sent. As an alternative, just request signals are sent down through the layers to the MAC layer. It's possible to play about with the models by executing it several time with varied settings. It should be made clear that.ini files should be used to store the values of any parameters that will likely change during testing. Sending it there is an effort to do so. Also, it generates transmission data at random, per the preferences given in the config file. Additionally, depending on the signaling function, it records the number of successful and unsuccessful communications[98].

2.12.2 Transport Layer

Data messages and control messages stand in for the "pipes" via which information travels in a transport layer implementation. It's job is to set up a connection between computers so data may be sent from one to another[98].

2.12.3 Network Layer

The main job of this layer is routing like other traditional network layers, it controls on data coming from upper and lower layer through interfaces to determine destination of packets. As a final destination, it picks a node at random from its immediate network peers. In the network topology file (.NED), the (address, neighbors) parameters must provide the addresses of the one-hop neighbors (source address(own

email) and destination (neighbors)). Within CrNetworks, you'll find the root connection description file (.NED). It responsible to execute network setting and collect all classes and methods from other directory supporting packages by invoking them through namespaces section . In addition, general parameters like sub-modules (address, neighbors, etc.) and full-duplex connections among nodes [98].

2.12.4 Cognitive-Radio-MAC-Layer

Tasks associated with the intelligent selection of spectrum bands are within the purview of medium access control. Furthermore, it offers advanced functionality not available in standard wireless networks[99].

The dynamic channel accessibility, and channel handoff /handover mechanisms with a spectrum sensing provide information about the events of available channels, through selecting the best channel for communication according to a set of parameters that decide efficiency CR-MAC protocol. In addition, the proposed system implements CSMA (RTS, CTS) based MAC protocol with channel dynamically access. This configurable protocol has many parameters which be can changed through the configuration file. It handles physical layer simulation parameters that sent to layer three in order to perform the desired system function known as [send()] method which calls message based on the different procedures[99].

The initial state of the data link layer algorithm describes starting point to get parameters values, while processing state or algorithm body is based on the handler function as the main function of data link layer to building simulation objects and passing frames or data signals to build the results within MAC layer [99].

2.12.5 Physical Layer

The main job of this layer is concerned with the physical component features and channel proprieties. It receives messages from all connections/channels through any physical layer parameters need to be appended to the outgoing messages. This feature

provides dynamically alteration for implementation parameters without need to change the transmission to a new NIC module[99].

INET library: It is a framework installed and uploaded as an open-source OMNET++ scheme for different wired, wireless, and mobile networks. It contains on different features for OSI-layers, communication protocol implementation, routing protocols features and it supports various networking topics [99].

2.12.6 The Supporting Statistics Module

This module is used to collect and extract statistical results related to various variables within layers of cognitive radio nodes architecture. It produces many lines because its objects (subclasses of cStatistic like cStdDev) do so: Average, Variance, and so on, by using the vector, scalar and histogram statistics to explain the results. As well as affected simulation results have based on these modules and each algorithm is implemented to simulate real work for each concern and give the same behavior for the actual module[99].

2.13 Interconnection Links used in Cognitive Radio Network Layers

Application-level C++ code for all of these modules will be explored using our parameters assumed during work for each section[99].

A- Cognitive Engine & Resource Map Modules: This module contains source and header files responsible for interconnection layers and supporting signaling and communication module through core and CrNodes.

B- CrNodes Module: It contains the layer structure and their interconnections like signaling and communication links, statistic and cognitive engine. Moreover it contains the initial default parameters and their data types, gates, definition for sub-modules and some of displays feature related with graphical user interface [99].

- C- PuNodes Module:** It intended to produce PU activity patterns that match the real observed activities for Global System for Mobile Communications (GSM). We summarize general steps for PU activities that simulate PU behavior and these steps of building Primary user units in cognitive radio network inside (puGSM.cc and puGSM.h) files within OMNET++ simulator [99].
- D- PuGSM Module:** It describes behaviors for each primary user using parameters and timers for attendance and absence for primary user that affected on handoff and handover state for secondary user without harmful primary user [99].
- E- RFSpectrum (Radio Frequency Spectrum Module):** Data rate connection processes and determining what form the data rate's operational settings should take constitute this module [99].
- F- SigCommLink(signaling and communication link) :** The purpose of Signaling & Communication Link (SCL) is to provide a connection among all the different components of the CR node architecture. It does not treat data itself but it is a message-based framework implying components, gates and gate connections [99].
- G- DRM Module:** Data from the surrounding environment is to be collected and stored in a database. In addition, it aggregates data signals and stores them in a database-driven knowledge base that can be queried and used by other parts of the CR node architecture for the purpose of optimizing their own performance [99].
- H- Spectrum Sensing:** This component is in charge of monitoring channel activity and reporting its findings to other modules as requested. This implementation is compatible with the "crMacLayer" protocol and feeds the sensing results from a request to it [99].

- I- Core Folder:** It includes message-files (Control messages, Initial, Setting, Text message objects) which are responsible for messages exchange among hierarchical of the proposed cognitive radio network. In addition, it contains core classes and namespaces as global parameters for functions and modules used in all simulation environments [99].
- J- Images Folder:** It contains the images that are used within the layers, background and nodes, as well as changing images during execution time[102].
- K- Out Folder:** This folder (separate directory) contains files resulted from debugging and compiler process to build executable files in OMNET ++ [99].
- L- Results Folder:** This folder contains a set of files for statistical results as vector and scalar type which can be used for analysis file [99].
- M-Omnetpp.ini:** It contains different types of parameters that can change values during running simulation and given initial value for instance total channel, total frames and sensing duration, on the other word, to change default parameters value entered in source code file, which will effect on the all simulation states[100].

2.14 Simulation Tool

The proposed system simulated with OMNeT++, it is considered one of the open-source simulators, which is characterized by the ease of installation and learning, as it is one of the simulations that it has many used the field of information technology as one of the most important academic tools because of its easy-to-use Graphical User interface interfaces and application as well by adding extension tools attached to the implementation of the cognitive radio network such as Castalia and Simulink. In used for different spectrum sensing techniques such as in case of cooperative spectrum sensing under two sensing operating modes: the Constant False Alarm Rate (CFAR) and the Constant Detection Rate (CDR) mode [101].

In addition, the proposed system simulated with OMNET++ simulation tool for network evaluation and system implementation with cognitive radio network elements as primary users, secondary users and Python programming language for deep CNN, machine learning, and linear cooperative. The suggested system network evaluator opted for OMNET ++ due to its intuitive (Tkenv) (Interface) for Windows. This GUI provides different features of tracing, debugging and execution [102]:

- 1- It's recommended in the main development simulation stage, the simulation's status at any moment in time may be examined in great detail.
- 2- It is built on a variety of pre-existing components (Frameworks, Libraries, Models, etc.), reducing the overhead involved in creating realistic simulations of research settings.
- 3- Monitoring the running processes inside the network.
- 4- The adaptability of instruction in areas where C++ is used.
- 5- OMNET++ graphical user interface based on NED topology description language which its trace what happens inside the network.
- 6- Installation prerequisites are to blame. Primary users operate as a base station and secondary users act as cognitive radio nodes in the primary-secondary user model central to the basic network architecture of a cognitive radio network[103].

Many processes are done to build and execute C++ code within OMNET++ simulator, where it based on different simulation parameters that come from a different files header and source and initial files and supporting file for core messages and network description files [104].

2.15 Evaluation Metrics

The proposed system has been evaluated with the deep learning evaluation parameters for dataset and network evaluation for simulation environment.

2.16.1 Accuracy

It is the number of correct predictions which is divided by the total number of predictions. The accuracy can be computed based on Equation (2.1) [104].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (2.1) [104]$$

2.16.2 Detection Rate (DR)

Aka Recall, Sensitivity, Hit rate, or True positive rate (TPR), it is the measure of identified positive (anomaly) instances from all the actual positive instances. This metric can be computed based on Equation (2.2) [104].

$$\text{Detection Rate(DR)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2.2)[104]$$

2.16.3 Throughput

A network's throughput is measured in terms of the proportion of the data packets delivered and processed to the amount of time necessary for the transaction. With the corresponding equation being [105] :

$$\text{Throughput} = \frac{\text{Total Number successful packets}}{\text{Time}} \quad (2.3)$$

2.16.4 Packet Loss Ratio

It is the ratio of the total number of packets that were transmitted to the number of packets that were lost during transmission [106].

2.16.5 F1-score

It is the result of $2 * ((\text{precision} * \text{recall}) / (\text{precision} + \text{recall}))$. It is also called the f1- score or the f1- measure. An equation of this metric can be computed based on Equation (2.4) [106].

$$\text{F1-score} = \frac{2 * \text{TP}}{2 * \text{TP} + \text{FN} + \text{FP}} \quad (2.4)[106].$$

2.16 DataSet

The proposed system is based on two datasets for spectrum sensing model, they are contained on SNR values of primary users in cognitive radio network with different modulation types sorted as follow:

2.16.1 RadioML 2016.10A

The used the RadioML 2016.10A dataset for the proposed system. It consists of radio signals that were synthetically generated using GNU Radio. It consists of 11 modulation types (3 Analog Modulation (AM-SSB, AM-DSB, WBFM) and 8 Digital Modulation [8PSK, BPSK, CPFSK, GFSK, PAM4, QAM16, QAM64, QPSK] schemes) which represent the total attributes and modulation used in this dataset. Which collected at varying signal-to-noise ratios over 20 SNR conditions ranging from -20dB to +18dB . For each combination of modulation type and SNR value, the dataset contains 1000 complex radio signal data examples, each with a length of 128 samples, implying the size of the dataset is (20*11*1000, 2, 128). Dataset consists of the values of SNR and modulation types, and the total records of this dataset are 1200000 records[102].

2.16.2 2016.04C.multisnr.tar

A synthetic dataset, generated with GNU Radio, consisting of 11 modulations. This is a variable-SNR dataset with moderate LO drift, light fading, and numerous different labeled SNR increments for use in measuring performance across different signal and noise power scenarios, it consists of 11 classes as follow: [8PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, PAM4, QAM16, QAM64, QPSK, WBFM] which represented the total columns and row values for SN and modulation used in this dataset samples, , and the total records of this dataset are 162060 records [100].

3.1 Introduction

In this chapter the proposed system has been explained and sorted with the proposed method is showed, an overview of the planned cognitive radio network's layers and modules is explained. In addition, interconnection links used in cognitive radio network layers of simulated network. The proposed CNN deep learning algorithms and linear cooperative spectrum sensing have been combined as a Hybrid approach and as mentioned, the proposed system provides an embedded way for prediction of SNR as low/high to discover the channel state is present or not present in state of primary user appearance.

3.2 The Embedded Hybrid Approach

It is based on building an efficient model capable of making reliable detection or prediction blind spectrum sensing within CRN network based on the CNN deep within Liner cooperative approach. It built in a way to be an adaptive model to be equivalent with different dataset sources type, and channel acquisition analyzer to optimal selection the channel depending on top list (2.40 - 4.90 GHz) recommender of spectrum band as (handoff, and handover).

The proposed approach is adopt CNN deep learning algorithm to use with linear cooperation to achieve high reliability of blind spectrum sensing in the cognitive radio network to manage the appearance of primary users and eliminate the interference with them. The proposed approach makes use of Deep learning provides access to the necessary libraries and modules to put these models into action within the enhancement model. As a result of using the structural information of the modulated signals that have already been received, this method of blind spectrum sensing reduces the detection error rate to an absolute minimum.

The embedded CNN deep learning algorithm is based on the eight layers and each layer has different number of neurons as (256) and activation function as (Relu, and SoftMax). The proposed GlobalAveragePooling1D layer with Number of Neurons as 256, and activation function as Relu, 256 used due to the effectiveness of this neurons on the accuracy after testing other values which showed less accuracy compared with this state within two dataset used for training approach.

In addition, the data set initialized as radio machine with SNR values dataset of primary user signals. The cognitive radio engine is making a loop that adds all the values of signals with their labels. The data is shuffled to split layers of CNN. Training phase is applied in each SNR separately. Testing using the trained classifier output to evaluate the results into PU present or not present. The simulated environment is generated a dataset contains on the modulation signals used as SNR of PU nodes to simulate the same behavior of the offline radio machine learning dataset.

In addition, the embedded Hybrid approach provides dynamic detection for primary user through automatic trained model integrating the CNN training phase with the blind spectrum of SNR value from cooperative spectrum sensing model. The output results show the present or not present of primary users. Figure 3.1 showed the block diagram of the embedded Hybrid approach structure.

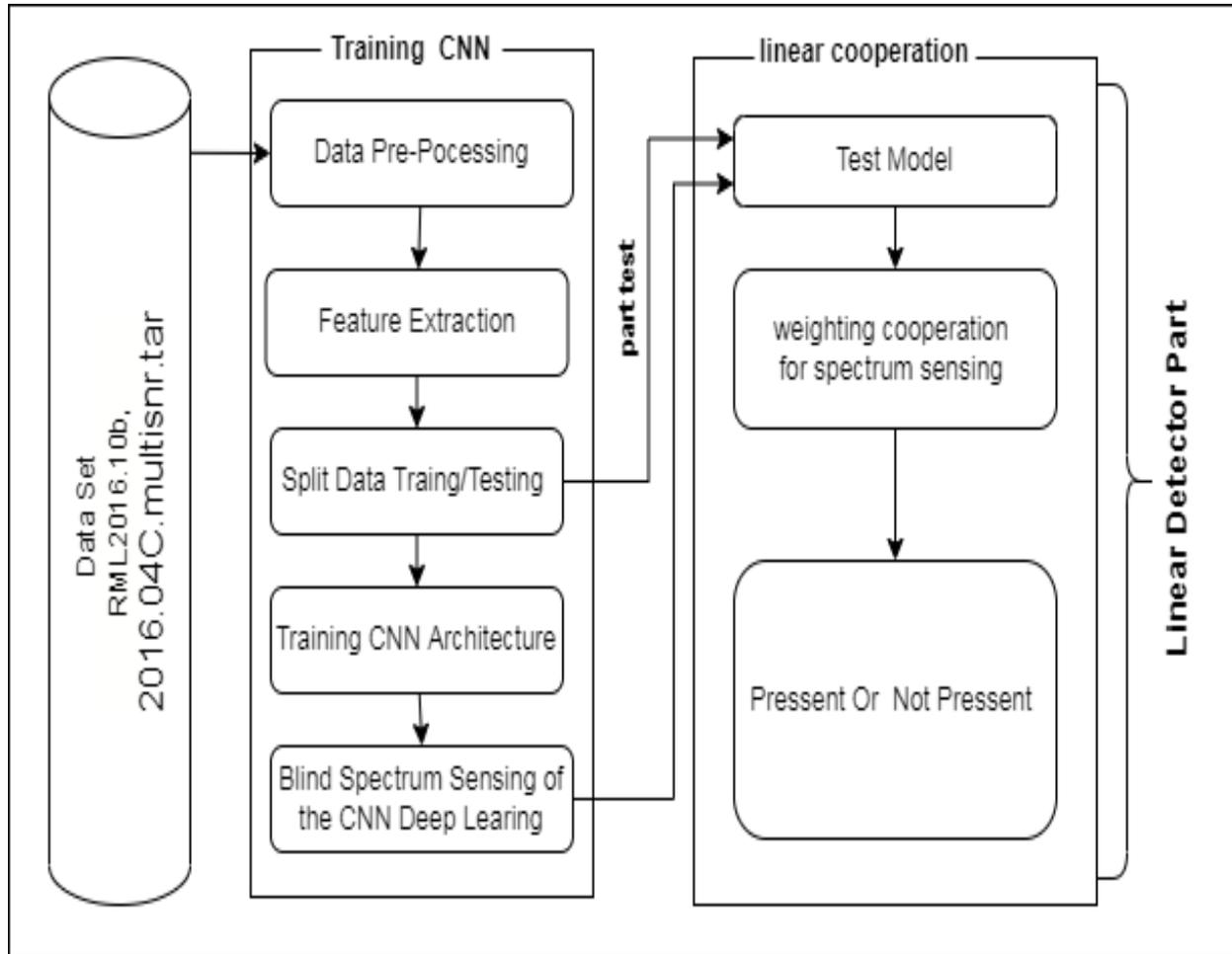


Figure 3.1 The Block Diagram of The Embedded Hybrid Approach Structure.

The embedded Hybrid approach based on the following steps:

3.2.1 The Data Pre-processing

The dataset is preprocessed with the features selection as (256 samples) divided into 128 positive and 128 negative sections. Preprocessing in the proposed system is utilized to convert data into SNR reads. After that, deep learning algorithms are used to get specific SNR data categories from SNR information of primary users by discovering the patterns of each generated SNR values.

The ability of distinguishing different patterns of data represents knowledge in SNR information systems. Additionally, when a system is able to recognize its own mistakes and tries to avoid them in the future, it becomes more sophisticated and adapted. Data preprocessing is applied with the following methods:

3.2.1.1 Data Transformation

Data is Normalized is an essential step in data preprocessing prior to the development of CNN deep learning model. Transformation can enhance the performance of the model. Min-max normalization is used to bind the features values into a certain range. It showed in Algorithm 3.1.

Algorithm 3.1 : Data Transformation method

Definitions:

nReads: SNR reads of PUs

nRange : Range scale of values from (-20, +18)

F: Feature selected

Begin:

1. For each SNR reads do
2. Calculate Min, Max, range Scaler
3. Calculate SNR of feature range $\leftarrow [-20, +18]$ // Range of SNR values for each modulation for all classes.
4. Fitting the data \leftarrow 2D, and 3D arrays.
5. Transforming the dataset \leftarrow (dataset)
6. Normalized the dataset with :

$$\text{Normalized_dataset} \leftarrow ((F1 + ((\text{dataset} - \min(\text{dataset})) * (F2 - F1) / (\max(\text{dataset}) - \min(\text{dataset}))))$$
7. End_for

End_Algorithm

3.2.1.2 Nominal to Numeric

Deep learning is not work with string values in the dataset so it is an important to convert nominal values in dataset into numeric values. In this work, the method is used to convert string value in dataset attribute such as '8PSK', 'AM-DSB', 'BPSK', 'CPFSK', 'GFSK', 'PAM4', 'QAM16', 'QAM64', 'QPSK', and 'WBFM' attributes into numbers (0,1, 2,3,..), the column categories converted into rows and each category is represented as number, each class has a weight to eliminate priority problem in the dataset for selecting the best category.

This method applied as the label encoder (one hot encoding) technique which converted categorical data into numeric data. It takes category value and converts it into numeric data from 0 to n-1.

3.2.2 Feature Extraction

Feature extraction capabilities of CNN Deep learning depend on the amount of information in conjunction with the quality and complexity of signal information present in the primary user SNR reads. A low SNR indicates that the signal information is greatly corrupted by the random noise, higher SNR scores indicate that the signal information is of a higher.

The highly relevant attributes should be used, rest all can be discarded. For performing attribute selected and extracted, one can use level of significance and p- value of the attribute. P-value gives us the probability of finding an observation under an assumption that a particular hypothesis is true.

This probability is used to accept or reject that hypothesis. It used to find relation between two variables. The attribute having p-value greater than significance level can be discarded. new attributes are constructed from the given

set of attributes to help processing. It used to get optimal number of records from dataset to estimate primary user appearance with SNR values.

Feature extraction method is based on the '8PSK' 'AM-DSB' 'AM-SSB' 'BPSK' 'CPFSK' 'GFSK' 'PAM4' 'QAM16' 'QAM64' 'QPSK' 'WBFM' as they explained in Algorithm 3.2.

Algorithm 3.2 : Feature extraction method

Definitions :

Dataset : list the datasets to be analyzed

F: Features and labels of the used datasets

Begin :

1. Analyzed Datasets
2. Selecting configuration file, and Dataset. file ← dataset[ds].
3. Check if the output directory exists, if not, create it ← directory
4. Starting Feature extraction.
5. Create the pre-trained CNN deep learning models with :
 - Select features ← ('8PSK' 'AM-DSB' 'AM-SSB' 'BPSK' 'CPFSK' 'GFSK' 'PAM4' 'QAM16' 'QAM64' 'QPSK' 'WBFM').
6. Check for pre-trained ← weight usage or not.
7. Check for CNN deep learning ← top layers to be included or not.
8. Model ← Model(input ← Model input, Output ← model get layer
9. Training dataset ← train_labels ← train_path
10. Encode the labels ← le ← LabelEncoder()
11. For each labels in the dataset count ← 1 do
 - for I ← label in enumerate(train_labels) do
 - Check how many SNR values are, together with their modulation
 - list_of_SNR_values ← os.listdir(cur_path)
 - Extract features with :
 - feature ← model.predict(x).

```
flat ← feature flatten.  
Features ← append(flat).  
Encode the labels ← Label Encoder.  
Getting the predicted features of training labels.  
Saving features and labels with determined features path  
Return features and labels saved
```

```
End_for
```

```
End_for
```

End_Algorithm

3.2.3 Split Data Training/Testing

It used to split dataset into training and testing sections. The optimal splitting value used is 80% training, and 20% testing after implemented different rate for splitting and the 20% of huge dataset records was acceptable and not effected on the calculation of accuracy for deep learning algorithm.

The split data ratio used as the optimal values of dataset to be better after testing more than states, for example trained classifier tested with 70% and 30 % but the results was less than the cross validation of 80% and 20 % state.

In the proposed approach the cross validation technique in which the model is trained by using the subset of the dataset and then evaluate using the complementary subset of the dataset. Algorithm 3.3 showed the procedure of the cross validation as follows:

Algorithm 3.3: Cross Validation Process.**Definitions:**

SNRDataset: The used Dataset.

Begin:

1. For each SNR reads in Datasets do
2. Shuffle the dataset randomly.
3. Split the dataset ← 80% training, and 20% testing with (10 classes-11 classes categories).
4. For each unique category:
 5. Take the category as a test data set ←20%.
 6. Take the remaining category as a training data set ←80%.
 7. Fit a model training set CNN deep learning and evaluate it on the test set.
 8. Retain the evaluation results.
 9. Validated the trained model with confusion matrix using multi dataset.
10. End_for
11. End_for

End_Algorithm**3.2.4 Data Training phase**

This phase is used to trained the classifier with SNR values from both datasets, which contain on (10 classes of the RML 2016.10b dataset, and 11 classes of 2016.04C.multisnr.tar dataset). It applied to build a prior estimation to PUs signals (licensed users) as the PU present or not present, in addition to use the radio frequency spectrum efficiency in cognitive radio network.

It is built to classify the dataset with SNR. The proposed Deep CNN algorithm in cognitive radio network is showed in Figure 3.2.

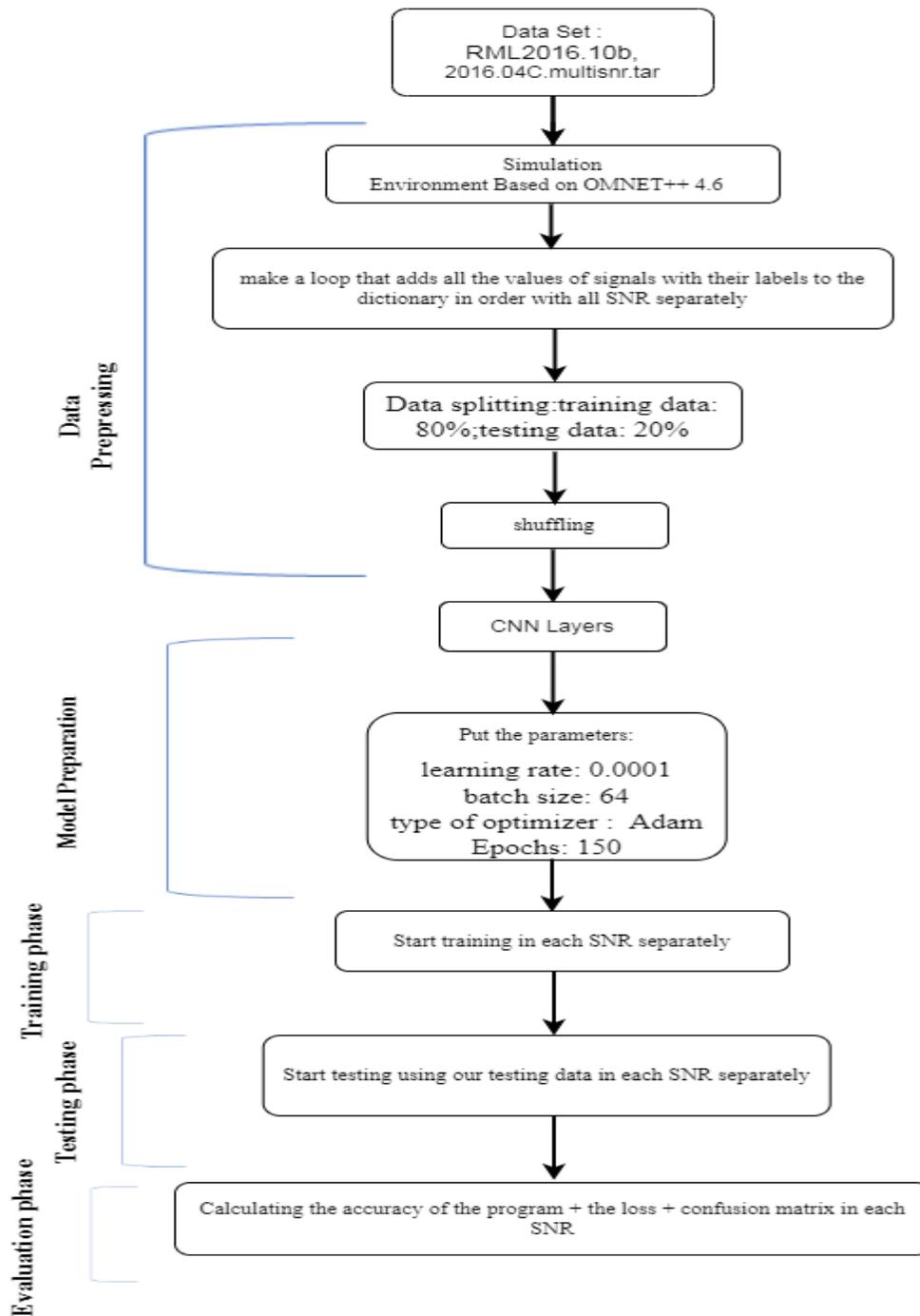


Figure 3.2: The adopt CNN Deep learning block diagram.

The adopt CNN Deep learning steps are sorted as follow:

3.2.4.1 Data preparation

Dataset preparation is used for collecting SNR Dataset for pre-processing events, and it included the following steps:

Step 1: Uploading RML2016.10b and 2016.04C.multisnr.tar.

Step 2: Simulation the CRN environment with different topologies of cognitive radio elements as (primary users and secondary users)

Step 3: Adding values of SNR signals to the dictionary to next step calculation.

Step 4: Dataset splitting into 80% training and 20% testing.

Step 5: Shuffling records to optimal order of dataset to decrease the random reading of SNR of each modulation type.

3.2.4.2 Model Preparation

It used to manage the process of the building the CNN Deep learning layers, and calculated the parameters of CNN algorithm and it included the following steps :

Step 1: Building CNN layers. The embedded CNN deep learning algorithm is based on the eight layers and each layer has different number of neurons as (256) and activation function as (Relu, and SoftMax) .The proposed GlobalAveragePooling1D layer with Number of Neurons as 256, and activation function as Relu. The used 256 Neurons due to the effectiveness of this neurons on the accuracy after testing other values as it showed better accuracy while others which based on 212 Neurons of GlobalAveragePooling1D layer showed less accuracy compared for both dataset used for training approach.

Step 2: Put the model parameters as learning rate, batch size, type of optimizer and Epochs.

3.2.4.3 Training CNN

It used for each SNR values within the used two datasets. The used confusion matrix to evaluate the quality of classifier output over a set of SNR values in the training CNN deep learning is showed in Figure 3.3. The diagonal elements represent the number of points for which the predicted label is equal to the true label, while the non-diagonal elements are the ones wrongly labeled by the classifier. The higher the diagonal values of the confusion matrix, the better, indicating many correct predictions made by the model during training. In addition, it showed each model within all the adopted SNR types ['8PSK' 'AM-DSB' 'BPSK' 'CPFSK' 'GFSK' 'PAM4' 'QAM16' 'QAM64' 'QPSK' 'WBFM'] that were extracted by the proposed Deep CNN implementation of (RML 2016.10b), which calculated 10 models for the dataset.

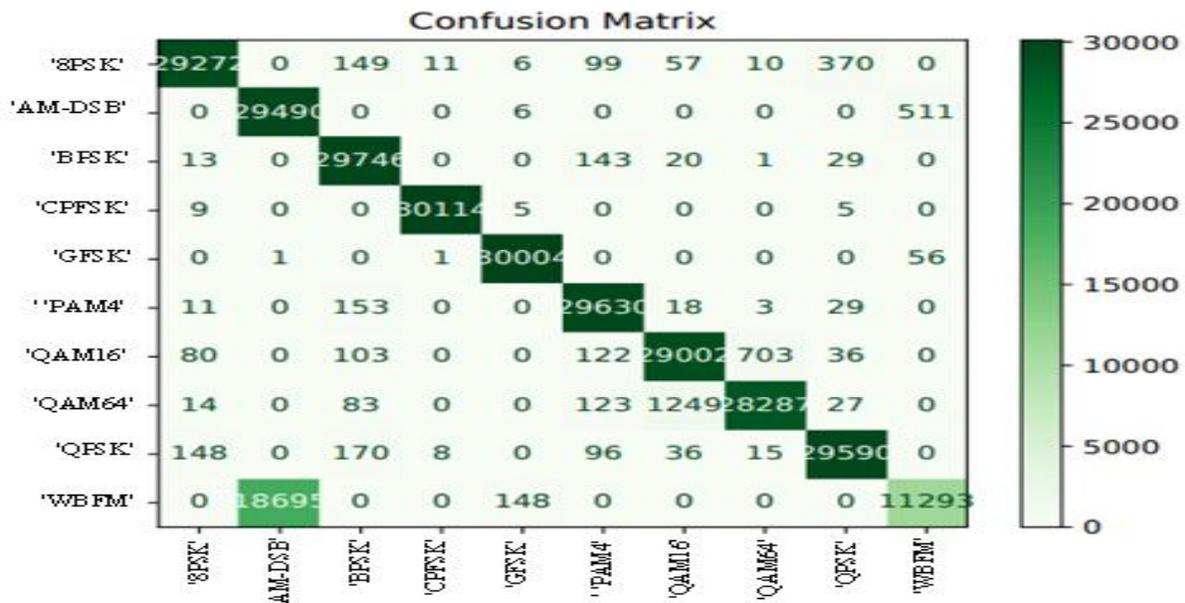


Figure 3.3: Confusion Matrix for deep learning with dataset RML2016.10b.

Furthermore, The Figure 3.4 showed the confusion matrix value for each model within all the adopted SNR types ['8PSK' 'AM-DSB' 'AM-SSB' 'BPSK' 'CPFSK' 'GFSK' 'PAM4' 'QAM16' 'QAM64' 'QPSK' 'WBFM'] that were extracted by the proposed Deep CNN implementation for (2016.04C.multisnr.tar), which calculated 11 models for the dataset.

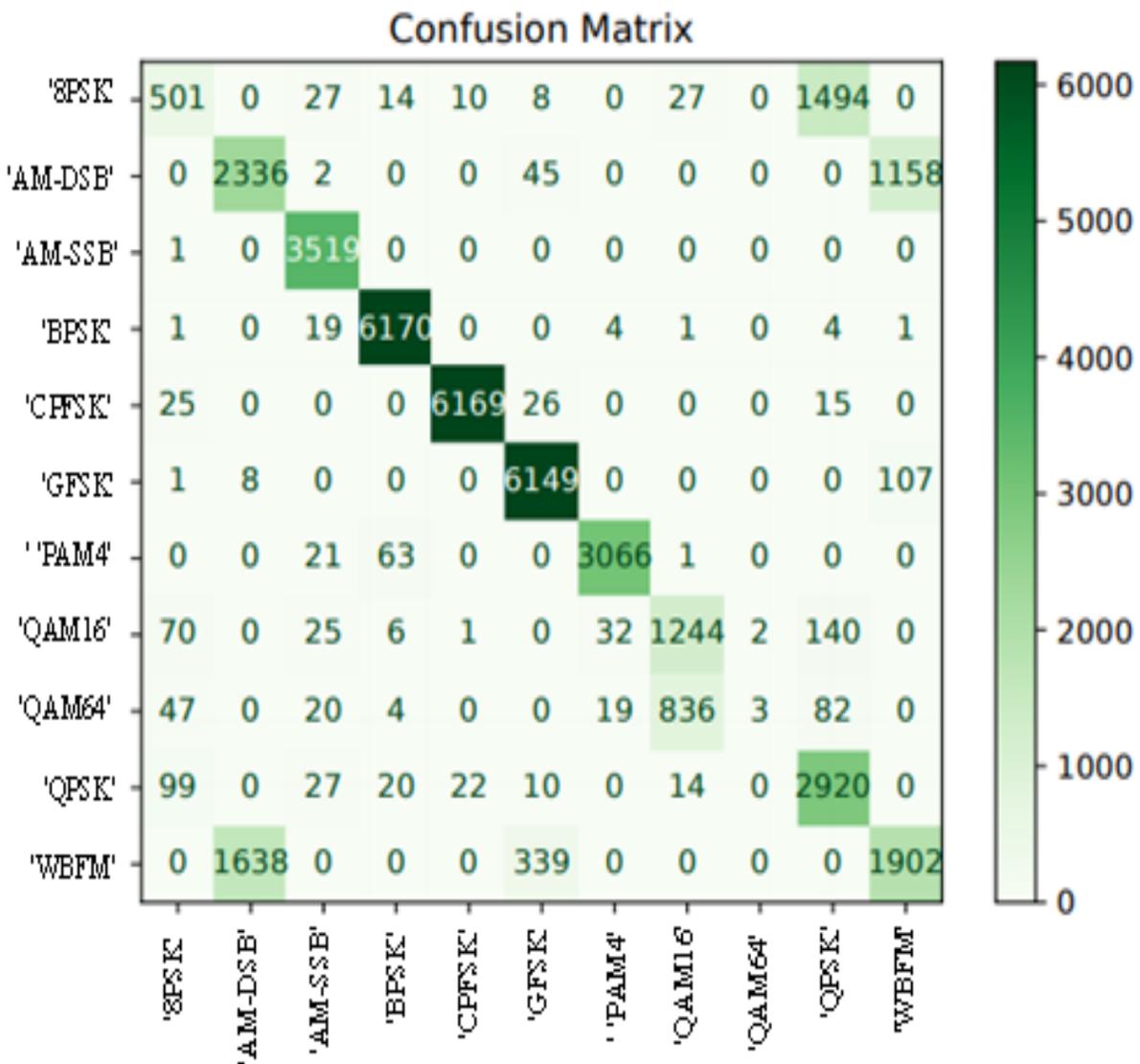


Figure 3.4: Confusion Matrix for deep learning with dataset 2016.04C.multisnr.pkl.

3.2.5 Blind Spectrum Sensing of the CNN Deep Learning

The output value of training CNN through blind spectrum sensing process is used as the input of the testing linear cooperation model, it save the trained SNR reads which it passed to the linear cooperating in the testing section.

3.2.6 Test Model

It used for each SNR in the used datasets. The output of this step is used by linear cooperative to make the final decision of primary user appearance as present or not present.

A- Data testing phased applied with the linear cooperation part and managed with: Test model used to test the output of CNN deep learning.

The main aim of using Linear Cooperative Spectrum Sensing (LCSS) in the proposed system to optimize the detection performance by operating over linear combination of local test statistic from individual secondary users which combat the destructive channel effects between the target primary and opportunistic CRs networks.

It is autonomous detection method to enhance decision making by secondary user to decide if primary user is present or not present. The used LCSS algorithm used as combination method with CNN deep learning approach in cognitive radio network spectrum sensing model . It is based on several considerations:

- First, the proposed linear detector has less computational complexity than does a quadratic detector, and the difference becomes more significant as the number of nodes increases.
- Second, the probabilities of detection and false alarm based on the linear detector have closed-form solutions, which could lead to intuitive system

design guidelines. On the other hand, the performance evaluation and threshold computation of the quadratic detector are mathematically more intractable, since the computation involves many integrals.

- With the linear detector, the designer can use the closed-form expressions to make quick adaptations when some network parameters change during the operation.

As mentioned the input values of this model is from the previous step of the trained classifier as 20% of reads and it showed the model steps to generate signals depending on the time and signal value, and then it collected these reads to generate spectrum power and frequency through specific method in python and then it checked periodically if primary user is present or not present, and it added a level of noise and then it also checked again if the primary user is appear or not. The main steps of linear cooperative spectrum sensing algorithm as follow:

- 1- Input value from testing dataset (20 %) evaluated CNN deep learning algorithm.
- 2- Enter number of Primary User which effected generated SNR values in the dataset after training section.
- 3- Modulation management with :
 - A- Generation Amplitude-Frequency Modulations (AMF) signals for each primary user with parameters (Time, Signal value). It showed in Algorithm 3.4.

Algorithm 3.4 : Amplitude Frequency generation

Definitions:

cAmplitude : Carrier amplitude depending on each layer

Range: Range values line-space(1, 2, 124) to line-space(16, 9, 124)

Begin:

1. For each modulation model do
 - Calculate the modulation index
 - Plotting the signals with Amplitude Frequency modulation features :
 - Label1 ← cAmplitude (Amplitude Frequency)
 - Label2 ← Message signal
 - Label3 ← Amplitude
 - Label4 ← Carrier signal
2. End_for

End_Algorithm

B- Accumulation the generated SNR values from AMF.

C- Generating frequencies bands and related power spectrum signals with specific method in python.

4- Next step is to check power spectrum value for all primary users is:

A. Yes then

- Assign to user as it was not present
- Generation Signals with AMF modulation
- Adding noise

B. No then

-
- Slot empty operation
 - Update AMF modulation signal and return to modulation management Step3.
- 5- Selection Power spectrum for each primary user, and matching power spectrum.
- A. If power spectrum less than γ , it makes the decision as Primary user not present.
 - B. If Power spectrum value is more than γ , it makes the decision as primary user is present.
- 6- Looping with next matching power spectrum.
- 7- Finish the matching and return the results.

Figure 3.5 showed the steps of the of Linear Cooperative Spectrum Sensing algorithm in the proposed system after completion the state of deep CNN learning algorithm as an embedded approach (Hybrid approach). The Hybrid approach improved spectrum sensing in cognitive radio due to the training model for dataset with SNR values which can classify primary user as present or not depending on the SNR values of primary users.

This feature helps cognitive radio or secondary user to work in an accurate manner and used the available channel in reliable with maximum bandwidth and shared channel characteristics with other nodes. Linear cooperative is showed in Figure (3.5)

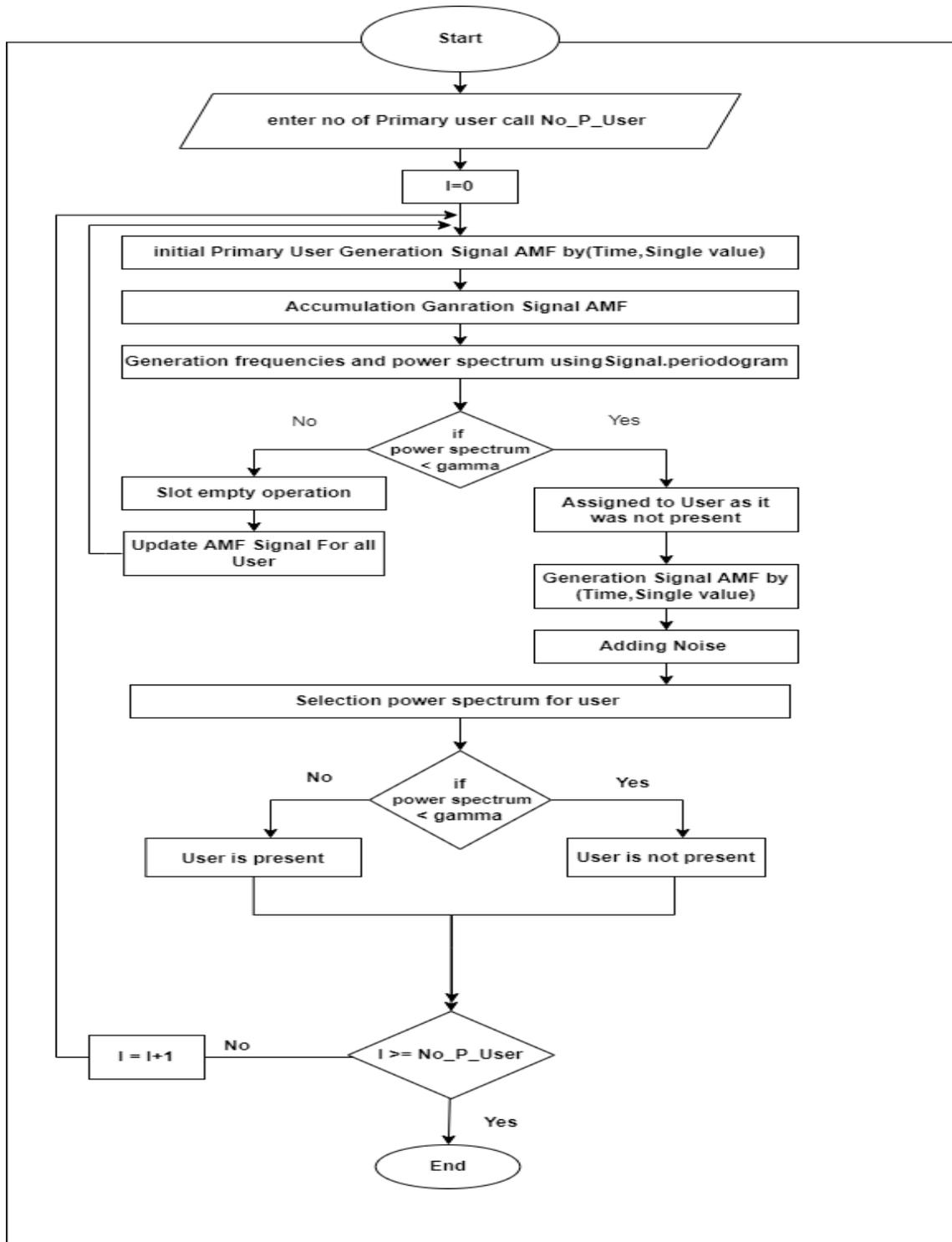


Figure 3.5: The adopt Linear Cooperative Spectrum Sensing (LCSS) flowchart.

- B- Weighting cooperation to spectrum sensing used to calculate the weight values of optimizer.
- C- Collecting data reads of SNR of primary users.
- D- Making the decision to find the results of the collected values.
- E- Classify the results into primary user present or not present

3.2.7 Evaluating the embedded Hybrid approach

In this section, evaluate and analyze the results to ensure that the method is correct and that it reaches its goal. Five scales are used (details in 2.16), including Accuracy, Detection Rate (DR), Throughput, Packet Loss Ratio, and F1-score. They are calculated based on the confusion matrix of SNR values in the dataset to each class which referred as the primary user present with SNR values or not present.

4.1 Introduction

This chapter displays the results of the proposed system that has been presented in chapter three. After the implementation of the proposed system, there is some study cases used to show the capabilities of the system and to prove its feasibility. The proposed system implemented with OMNET++ 4.6, Python, and (Co_Lab , Miniconda) framework used to build the proposed system. To test the performance of the system, the hybrid spectrum sensing has been performed on used original, updated dataset as (RML 2016.10b) and other dataset (2016.04C.multisnr.tar). The dataset is represent in chapter 2, section 2.14.

The proposed system implemented with two main sections, the first section is the programming section to test and train the model to be equivalent for incoming sensing in cognitive radio network (CRNs), and train the model using the used dataset, the second section is the simulation which used to simulate CRN with the main network elements as the primary (PU) and secondary (SU) elements, the proposed system simulated with the used topologies are :

- The first case study:
 - A- 5 Secondary Users with 20 Primary Users
 - B- 10 Secondary Users with 20 Primary Users
 - C- 30 Secondary Users with 20 Primary Users
- The second case study :
 - A- 10 Secondary Users with 5 Primary Users
 - B- 10 Secondary Users with 10 Primary Users
 - C- 10 Secondary Users with 15 Primary Users

These numbers are used as the simulated environment depending on idle duration and busy duration. The first case study of fixed primary user as 20 nodes is identified as better case due to the increased number of primary user channel

especially in case of minimum number of secondary user, each secondary user has large number of idle channel (PU) channels to transmit and received though out. Besides, in the second case study of fixed secondary users, the used idle channel is less than compared with the first case study so in the 10 secondary users available to use spectrum bands with 15 primary user channels so it will be scarcity of the spectrum band due to the less number of available channels, and this is the main challenge in wireless system and it must be solved with cognitive radio network. As a result the better case when the primary user number is more than secondary user number, and this ratio is effect on the using spectrum band and network performance in general.

In addition, the main idea of the proposed blind spectrum system is to develop an integrated approach based on deep CNN with efficient linear cooperation to analysis the behavior of both primary user and secondary user and mitigating the interference with primary element by enhanced blind spectrum sensing acquisition in the channel. The system applied and trained with SNR values range [-20 into +18] to predict absence and appearance of primary network element through the shared channel.

4.2 The propose hybrid blind spectrum sensing approach

The proposed hybrid approach is based on both techniques as a blind spectrum sensing technique and deep learning and linear cooperation.

4.2.1 The state of before hybrid approach

The proposed system implementation in linear cooperation case study of before hybrid approach , it based on the 5 cognitive radio nodes as the secondary users SU and 50 Primary User PU nodes as primary user of licensed bands, when adding noise to SNR with the following values in Figure 4.1. It showed the noise and original signals when SNR= [-10]. Noise is added to the original signals due to

the core engine does not has prior information about primary users due to the state of blind spectrum sensing phase. The used (0 –add noise SNR in dB = [-10]) means the round iteration one (0) with SNR (-10) is added for original and noise signals.

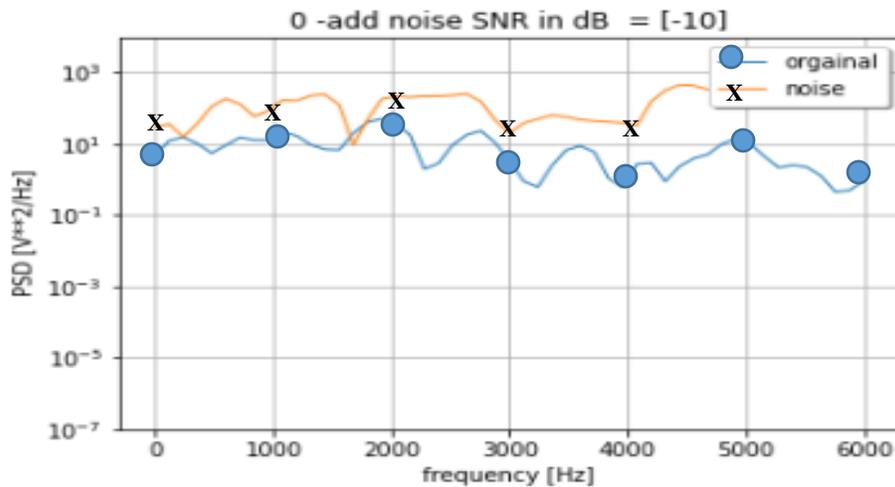


Figure 4.1: Noise added to the original signals of [-10] SNR value.

Figure 4.2 is showed the noise and original signals when SNR= [6]. When Noise is added to the original signals there was a small change and effect by original signals due to the power sensitive module does not has prior information about primary users due to the state of blind spectrum sensing phase.

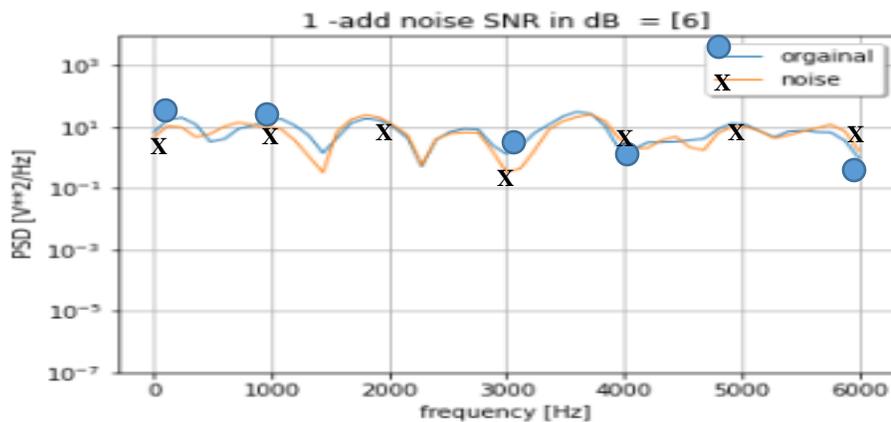


Figure 4.2: Noise added to the original signals of [6] SNR value .

In addition the proposed system is measured other values of SNR as in Figure 4.3 is showed the noise and original signals when SNR= [-16]. When Noise is added to the original signals and effect by original signals due to power sensitive module does not has prior information as mentioned above.

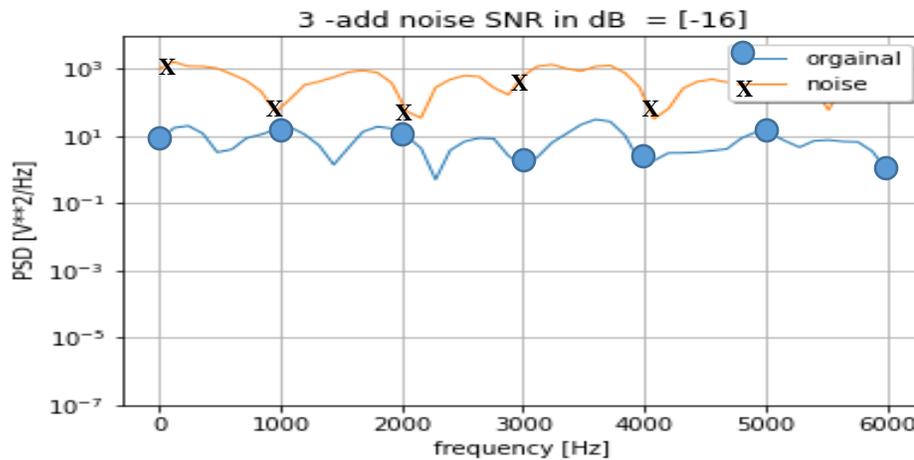


Figure 4.3: Noise added to the original signals of [-16] SNR value.

Figure 4.4 is showed the noise and original signals when SNR= [-20]. When Noise is added to the original signals with this value there was a huge change and effect by noise signals.

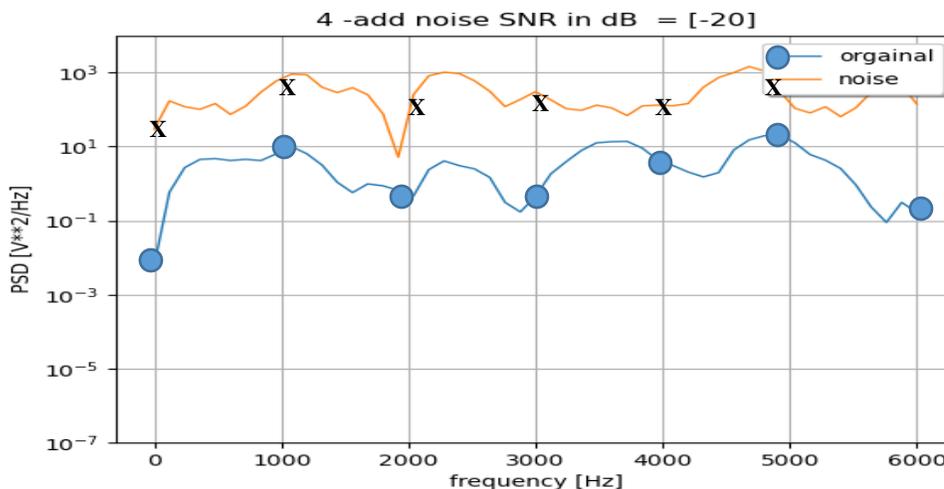


Figure 4.4: Noise added to the original signals of [-20] SNR value.

Figure 4.5 showed how many primary users are appear or not as this model showed the primary user behavior detection. It explained before Hybrid approach and the histogram showed how many channels are idle and how many channels are busy, as the blue color is represent as the primary user present and green color represent the primary user not present as the behavior for free channels in each secondary users. The results showed few available primary user idle channels and high reads for present primary user as busy channel so secondary users cannot use these channel and it cannot harmful primary users.

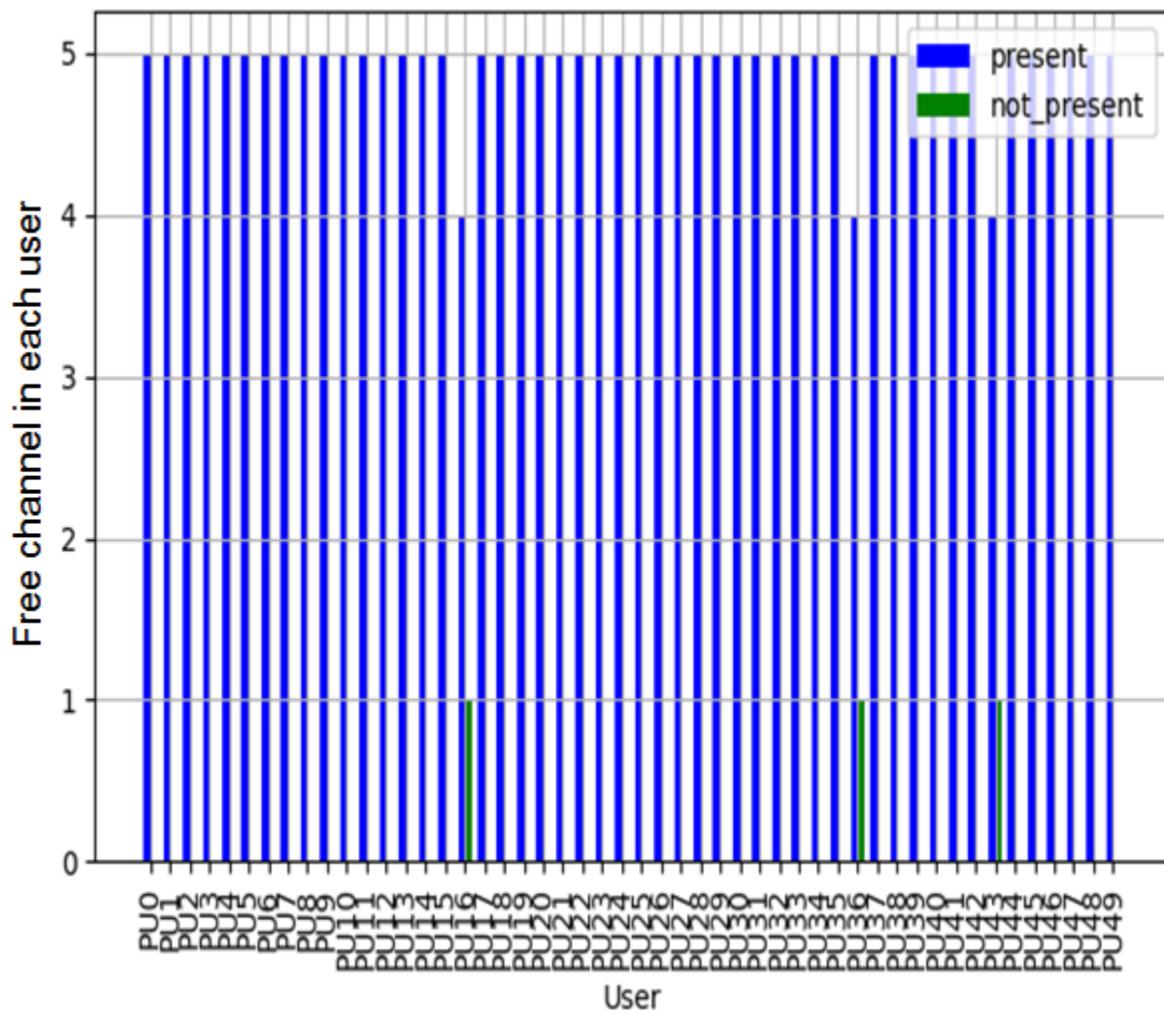


Figure 4.5: PU present or not present in the channel before hybrid model.

4.2.2 The state of hybrid approach

The proposed system applied with CNN deep learning and linear cooperation spectrum sensing, it based on nine rounds used for the model and it showed multiple cases for present and not present of primary user. Table 4.1 showed rounds to find primary user present and not present. The Hybrid approach provides more reliable detection to discover available PU channels and increased capacity of spectrum bands with accurate prediction of idle channels depending on SNR values.

Table 4.1: The primary user present and not present in hybrid and without hybrid blind spectrum sensing approach of the cognitive radio network

Round (R)	With Hybrid	Without Hybrid
R0	All user slots in use. try again later	All user slots in use. try again later
R1	Assigned to User one as it was not present. Assigned to User two as it was not present. Assigned to User three as it was not present. User one is not present. User two is not present. User three is not present. User four is not present. User five is not present.	Assigned to User four as it was not present. User one is present. User two is present. User three is present. User four is present. User five is present.
R2	Assigned to User two as it was not present. Assigned to User three as it was not present. Assigned to User four as it was not present. User one is not present. User two is not present. User three is not present. User four is not present.	Assigned to User one as it was not present. Assigned to User two as it was not present. Assigned to User five as it was not present. User one is not present. User two is present. User three is present. User four is not present. User five is present.

	User five is not present.	
R3	<p>Assigned to User one as it was not present.</p> <p>Assigned to User two as it was not present.</p> <p>Assigned to User four as it was not present.</p> <p>Assigned to User five as it was not present.</p> <p>User one is present.</p> <p>User two is not present.</p> <p>User three is present.</p> <p>User four is not present.</p> <p>User five is not present.</p>	<p>Assigned to User four as it was not present.</p> <p>User one is present.</p> <p>User two is present.</p> <p>User three is present.</p> <p>User four is present.</p> <p>User five is present.</p>
R4	<p>Assigned to User one as it was not present.</p> <p>Assigned to User two as it was not present.</p> <p>Assigned to User three as it was not present.</p> <p>Assigned to User four as it was not present.</p> <p>Assigned to User five as it was not present.</p> <p>User one is not present.</p> <p>User two is not present.</p> <p>User three is present.</p> <p>User four is not present.</p> <p>User five is not present.</p>	<p>Assigned to User four as it was not present.</p> <p>User one is present.</p> <p>User two is present.</p> <p>User three is present.</p> <p>User four is present.</p> <p>User five is present.</p>
R5	<p>Assigned to User four as it was not present.</p> <p>Assigned to User five as it was not present.</p> <p>User one is present.</p> <p>User two is not present.</p> <p>User three is not present.</p> <p>User four is not present.</p> <p>User five is not present.</p> <p>Assigned to User one as it was not present.</p>	<p>Assigned to User one as it was not present.</p> <p>Assigned to User three as it was not present.</p> <p>Assigned to User five as it was not present.</p> <p>User one is not present.</p> <p>User two is present.</p> <p>User three is not present.</p> <p>User four is present.</p> <p>User five is present.</p>

	<p>Assigned to User two as it was not present.</p> <p>Assigned to User three as it was not present.</p> <p>Assigned to User four as it was not present.</p> <p>Assigned to User five as it was not present.</p> <p>User one is present.</p> <p>User two is not present.</p> <p>User three is present.</p> <p>User four is present.</p> <p>User five is present.</p>	
R6	<p>Assigned to User one as it was not present.</p> <p>Assigned to User two as it was not present.</p> <p>Assigned to User three as it was not present.</p> <p>Assigned to User four as it was not present.</p> <p>Assigned to User five as it was not present.</p> <p>User one is not present.</p> <p>User two is not present.</p> <p>User three is not present.</p> <p>User four is not present.</p> <p>User five is not present.</p>	<p>Assigned to User four as it was not present.</p> <p>User one is present.</p> <p>User two is present.</p> <p>User three is present.</p> <p>User four is not present.</p> <p>User five is present.</p>
R7	<p>Assigned to User one as it was not present.</p> <p>Assigned to User two as it was not present.</p> <p>Assigned to User three as it was not present.</p> <p>User one is not present.</p> <p>User two is present.</p> <p>User three is present.</p> <p>User four is not present.</p> <p>User five is present.</p>	<p>Assigned to User four as it was not present.</p> <p>User one is present.</p> <p>User two is present.</p> <p>User three is present.</p> <p>User four is present.</p> <p>User five is present.</p>

R8	Assigned to User one as it was not present. Assigned to User two as it was not present. Assigned to User three as it was not present. Assigned to User four as it was not present. Assigned to User five as it was not present. User one is not present. User two is not present. User three is not present. User four is not present. User five is not present.	All user slots in use. try again later, User one is present. User two is present. User three is present. User four is present. User five is present.
R9	Assigned to User one as it was not present. Assigned to User two as it was not present. Assigned to User three as it was not present. User one is present. User two is not present. User three is present. User four is present. User five is present.	Assigned to User two as it was not present. User one is present. User two is present. User three is present. User four is not present. User five is present.
Histogram	not present = [6, 9, 5, 8, 7]	not present = [2, 0, 1, 3, 0]
	present = [4, 1, 5, 2, 3]	present = [8, 10, 9, 7, 10]

In table 4.2 showed the statistical state of primary user appearance in case of multiple primary users and it showed two action of primary user present and not present. It showed the improvement of PU detection depending on the SNR reads for each primary users as available channel can used by secondary users to increase bandwidth.

Table 4.2: Case study of the number present and not present of PUs.

User	Action	With hybrid	Without hybrid
Primary User 1	Not present	6	2
	Present	4	8
Primary User 2	Not present	9	0
	Present	1	10
Primary User 3	Not present	5	1
	Present	5	9
Primary User 4	Not present	8	3
	Present	2	7
Primary User 5	Not present	7	0
	Present	3	10

Figure 4.6 showed how many primary users are appear or not as this model showed the primary user behavior detection. It explained the Hybrid approach and the histogram showed how many channels are idle and busy. The results showed high available primary user idle channels and few reads for present primary user as busy channel so secondary users can use these channel and increase spectrum bandwidth and this is the main contribution to combined CNN deep learning and linear cooperative spectrum sensing as the Hybrid approach.

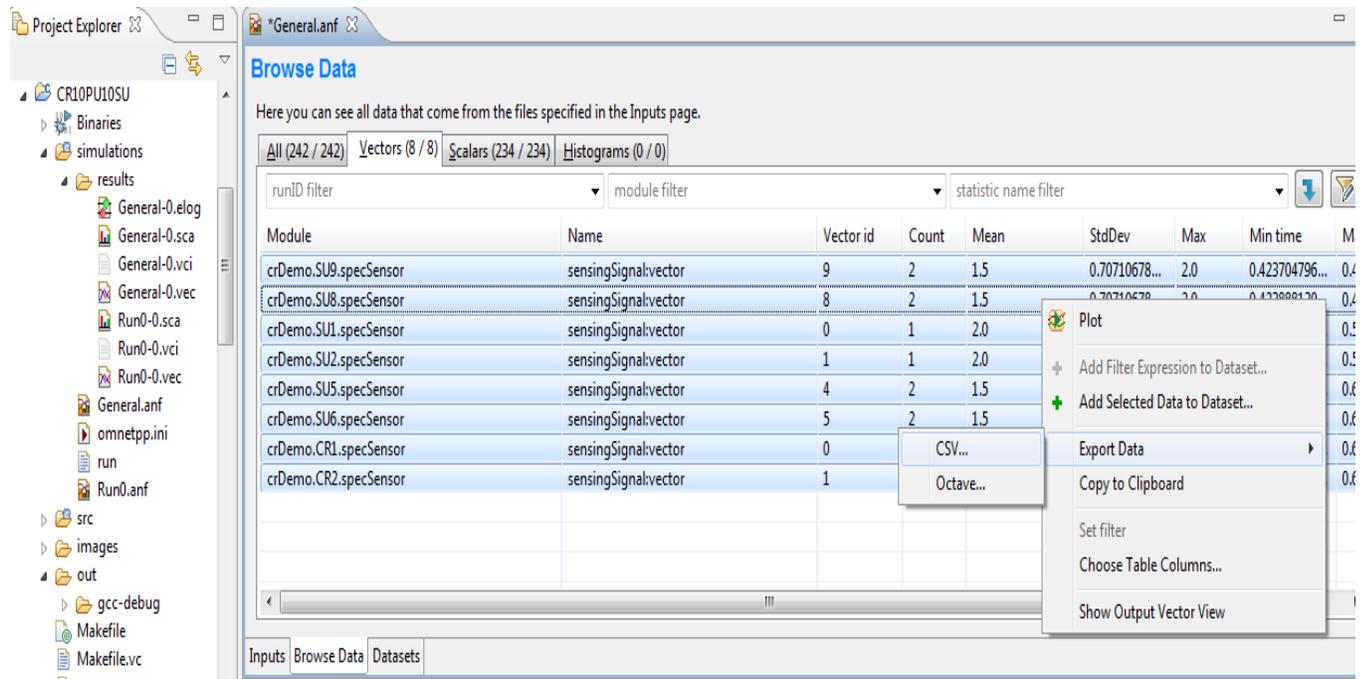


Figure 4.7: Export sensing signals to CSV dataset.

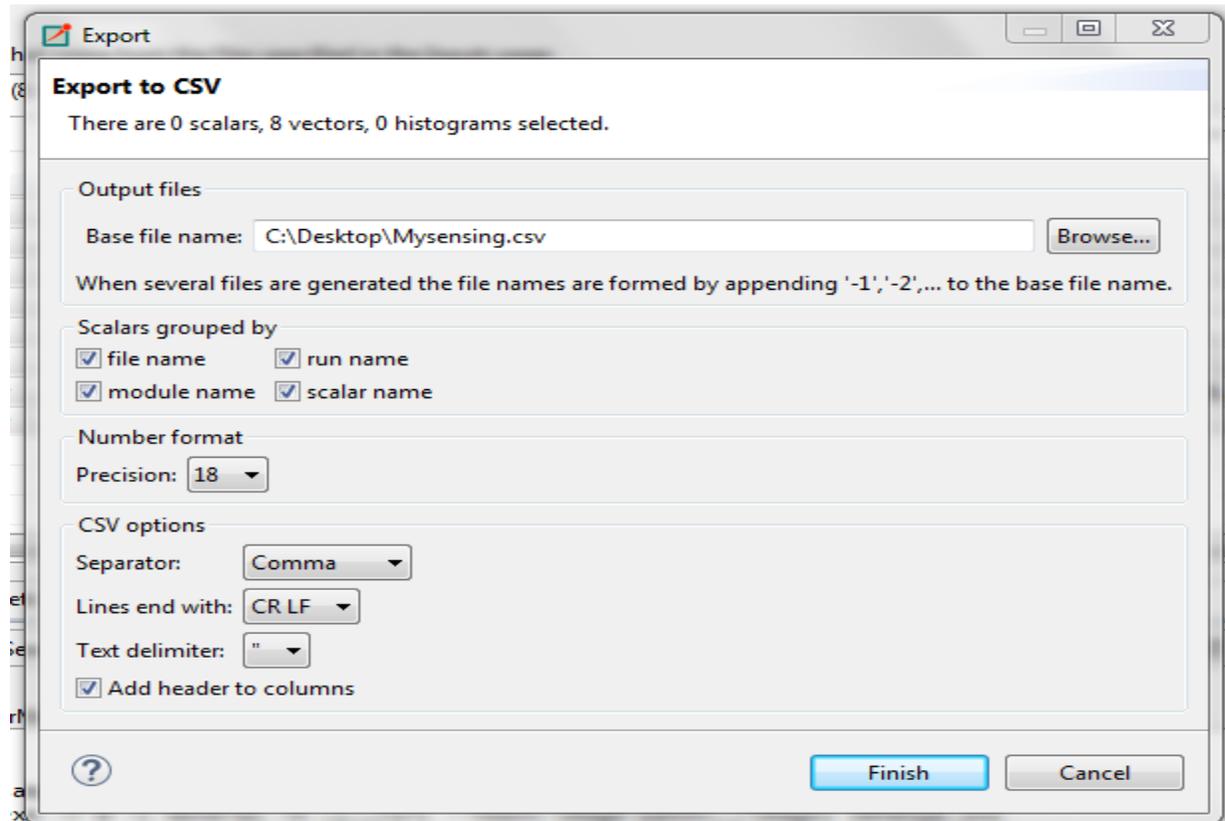


Figure 4.8 : Export sensing results into CSV dataset.

Figure 4.9 showed the CSV dataset open and how the spectrum sensing during specific period of simulation for some of nodes in the network.

time,crDemo.SU6.spe	time,crDemo.CR1.spe	time,crDemo.CR2.spe	time,crDemo.SU9.spe	time,crDemo.SU2.spe
0.60299670371,1	0.548863502304,2	0.549046835637,2	0.423704796788,1	0.549046835637,2
0.640233333333,2	0.60005,2	0.600283333333,1	0.44005,2	
	0.6001,1			
	0.64005,2			
	0.6401,1			
	0.64015,2			

Figure 4.9: CSV dataset of sensing signals for cognitive secondary users.

The proposed system case studies are showed as follow:

4.3.1 The first case study of 5 SUs and 20 PUs

The first case study applied with 5 secondary users and 20 primary users to implement spectrum sensing approach in cognitive radio network, the simulated environment is OMNET++ and programming language is C++, the required library is INET++ and connected layers and modules for overall connection layers, interfaces and links as it showed in Figure 4.10.

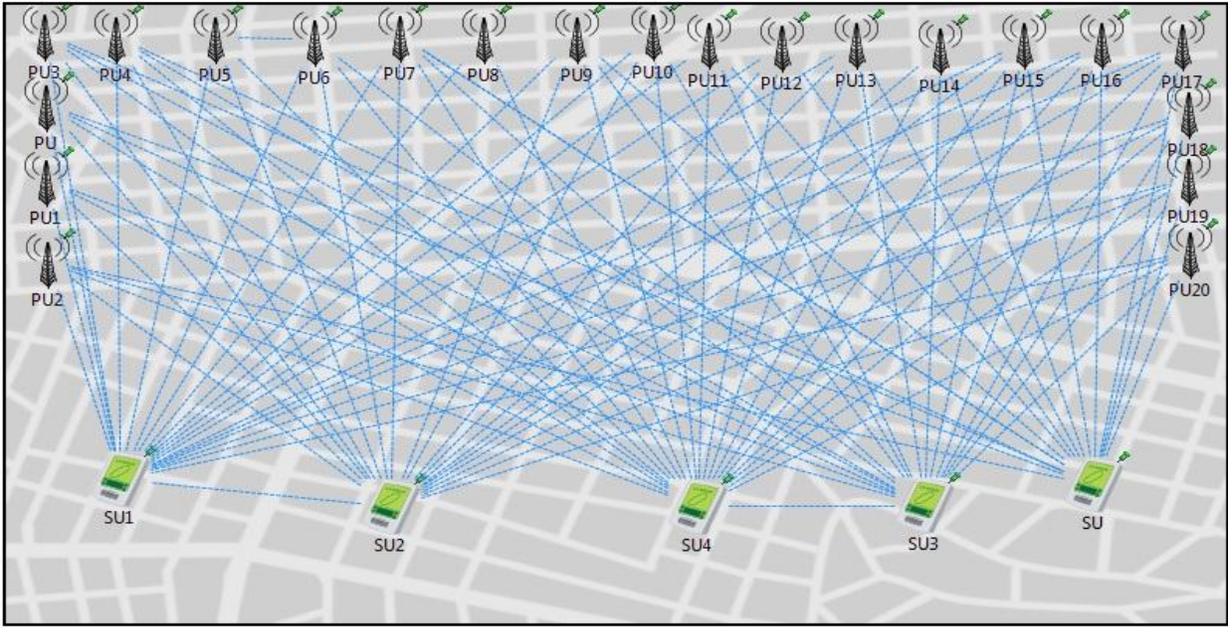


Figure 4.10: The first case study with 5 SUs and 20 PUs.

The used simulation details in OMNET ++ which are explained in chapter 2 section 2.15 which is applied as follow in table 4.3:

Simulation Time is: 10 minutes = 600 seconds. Numbers of sensing signals are generated from each CR nodes and each node generate as sender and receiver nodes. It showed the state of 5 SU and 20 PU.

Table 4.3: 5 Secondary Users and 20 Primary Users

Node Type	Active SU Nodes	No. of Sensing signal	No. of Data signal
Sender	SU 1	2317	151
	SU 2	2486	149
Receiver	SU 3	2201	148
	SU 4	1367	72
	SU 5	994	70

The used sensing signal in byte as 32 Bytes, and the used data signals in byte as 64 Bytes and throughput of data signals showed in Table 4.4. No. of Sensing signal is calculated by multiplication number of sensing signals with size of sensing signal packet (32 bytes), and No. of Data signal is calculated by

multiplication number of data signals with size of each data packet(64 bytes). In addition, throughput value is calculated by the total size of transmit data signals in byte is divided by the required simulation time as 10 minutes (600 seconds).

Table 4.4: Total size of data and sensing signals and total throughput.

Node Type	No. of Sensing signal	Total size in Byte	No. of Data signal	Total size in Byte	Total Throughput Bps
Sender	2317	74144	151	9664	16.10667
	2486	79552	149	9536	15.89333
Receiver	2201	70432	148	9472	15.78667
	1367	43744	72	4608	7.68
	994	31808	70	4480	7.466667

Packet loss ratio data signals are the remained number of (sent packets – received packets). While the Handover is showed how much time system collect the channel from primary user. Figure 4.111 showed how secondary user SU1, SU2, SU3, SU4, and CR1, CR2 make handover on free or idle channel and determined the busy channel to make handoff as a count value for each channel idle acquisition.

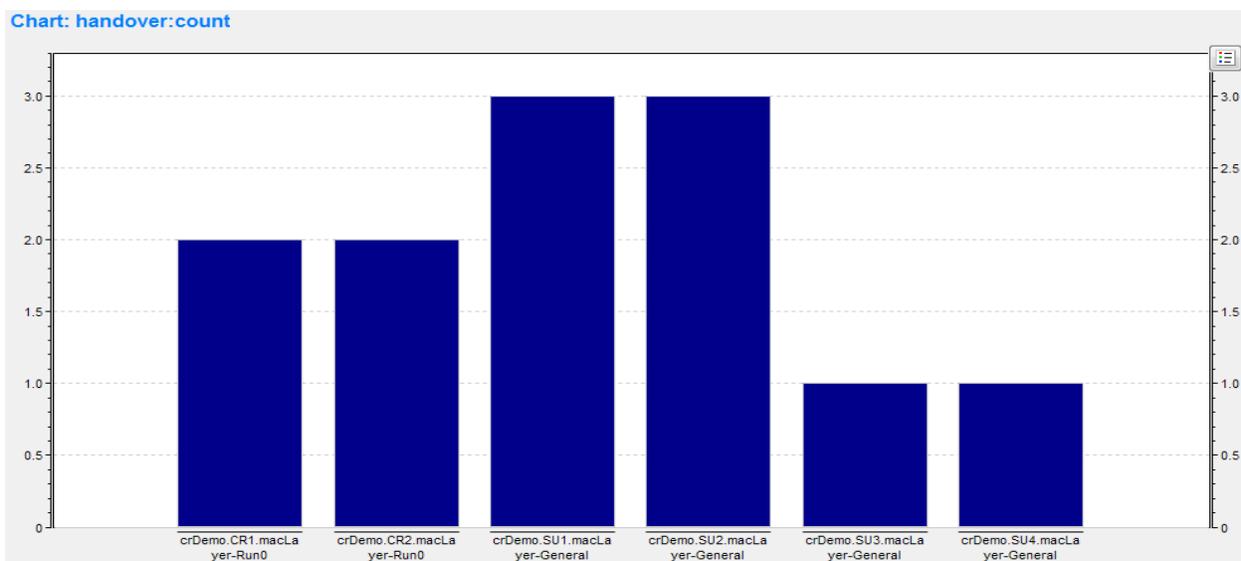


Figure 4.11 : Handoff and Handover channel acquisition.

Table 4.5 showed the packet loss ratio data signals and handover channel allocation.

Table 4.5: loss signal and handover of 5 Secondary Users and 20 Primary Users

No. of Data signal		No. of packet loss ratio data signals	Handover
Sender	Receiver		
SU 1	SU 3	3	4
SU 2	SU 4	7	6
SU 2	SU 5		8

4.3.2 The second case study of 10 SUs and 20 PUs

It implemented with 20 secondary users and 20 primary users to explain the cognitive radio network architecture with spectrum sensing approach, it showed in Figure 4.12.



Figure 4.12: The second case study of 10 SUs and 20 PUs.

It based on the increased number of secondary users which required more channels for signals transmission. Table 4.6 showed the number of sensing and

data signals for each cognitive radio node. Each secondary user has at least two primary users channel through idle transmission when overall nodes are connected and ready to send and received packets .

Table 4.6: Network Evaluation with 10 Secondary Users and 20 Primary Users

Node Type	Active SU Nodes	No. of Sensing signal	No. of Data signal
Sender	SU 1	627	45
	SU 2	638	47
	SU 3	626	46
	SU 4	657	48
	SU 5	649	48
Receiver	SU 6	615	44
	SU 7	621	44
	SU 8	639	41
	SU 9	643	41
	SU 10	758	47

Table 4.7 showed the number of sensing signals is decreased due to the increased number of secondary users compared with first case study as in this case each node required more time to build system and required delayed from each node after get access to the channel and transmit the packets. The throughput value is calculated based on the total number of successful packets arrived through time units.

Table 4.7: Total size of data and sensing signals and total throughput.

Node Type	No. of Sensing signal	Total size in Byte	No. of Data signal	Total size in Byte	Total Throughput Bps
Sender	627	20064	45	2880	4.8
	638	20416	47	3008	5.013333
	626	20032	46	2944	4.906667
	657	21024	48	3072	5.12
	649	20768	48	3072	5.12

Receiver	615	19680	44	2816	4.693333
	621	19872	44	2816	4.693333
	639	20448	41	2624	4.373333
	643	20576	41	2624	4.373333
	758	24256	47	3008	5.013333

Table 4.8 showed number of lost packets is increased compared with the first case study due to the increased number of nodes and high data traffic generated from all users and it make channel is more overloaded so the packet loss ratio data signals is increased

Table 4.8: loss signal and handover of 10 Secondary Users and 20 Primary Users.

No. of Data signal		No. of packet loss ratio data signals	Handover
Sender	Receiver		
SU 1	SU 6	1	2
SU 2	SU 7	3	3
SU 3	SU 8	2	2
SU 4	SU 9	7	4
SU 5	SU 10	1	2

4.3.3 The third case study of 30 SUs and 20 PUs

It applied with 30 secondary users and 20 primary user in cognitive radio environment to simulate spectrum sensing approach. The applied number of secondary users required more than available channel to use for transmission signals and in this case number of channels is less than secondary users so there will be high traffic and overloading when there are different nodes need the channel and make handover to the channel acquisition. The used topology showed in Figure 4.13.

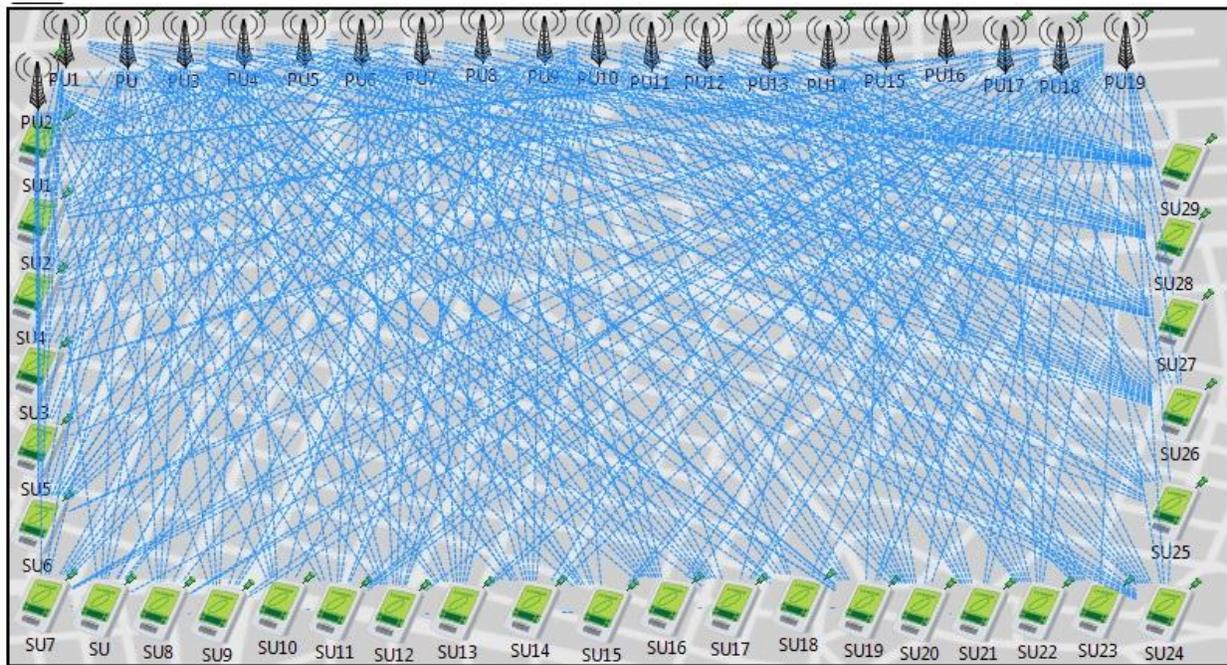


Figure 4.13: The third case study of 30 SUs, and 20 PUs.

Table 4.9 showed the network evaluation of the third case study. The sensing signals is decreased and number of data signals also decreased due to each active node required more time for getting channel and transmit data so it effected on the network performance in general, it is important to determine number of active secondary users and then determined number of required channel for these active nodes.

Table 4.9: Network Evaluation with 30 Secondary Users and 20 Primary Users

Node Type	Active SU Nodes	No. of Sensing signal	No. of Data signal
	SU 1	81	6
	SU 2	82	9
	SU 3	71	7
	SU 4	88	7
	SU 5	82	9
	SU 6	70	7
	SU 7	76	8

Sender	SU 8	63	10
	SU 9	84	8
	SU 10	83	6
	SU 11	89	6
	SU 12	60	9
	SU 13	87	8
	SU 14	89	5
	SU 15	77	6
Receiver	SU 16	60	4
	SU 17	80	7
	SU 18	68	6
	SU 19	74	4
	SU 20	76	7
	SU 21	67	5
	SU 22	68	3
	SU 23	77	8
	SU 24	65	5
	SU 25	89	6
	SU 26	77	6
	SU 27	84	7
	SU 28	88	8
	SU 29	67	5
	SU 30	86	6

Table 4.10 showed the size of each data signals and spectrum sensing signals and the number of these signals are decreased due to the increased number of active nodes which required channel idle to transmit their data.

Table 4.10: Total size of data and sensing signals and total throughput.

Node Type	No. of Sensing signal	Total size in Byte	No. of Data signal	Total size in Byte	Total Throughput Bps
Sender	81	2592	6	384	0.64
	82	2624	9	576	0.96
	71	2272	7	384	0.746667
	88	2816	7	448	0.746667
	82	2624	9	576	0.96
	70	2240	7	448	0.746667
	76	2432	8	512	0.853333
	63	2016	10	640	1.066667
	84	2688	8	512	0.853333
	83	2656	6	384	0.64
	89	2848	6	192	0.64
	60	1920	9	576	0.96
	87	2784	8	512	0.853333
	89	2848	5	320	0.533333
	77	2464	6	384	0.64
Receiver	60	1920	4	256	0.426667
	80	2560	7	448	0.746667
	68	2176	6	448	0.64
	74	2368	4	256	0.426667
	76	2432	7	448	0.746667
	67	2144	5	320	0.533333
	68	2176	3	384	0.32
	77	2464	8	512	0.96
	65	2080	5	320	0.64
	89	2848	6	384	0.746667
	77	2464	6	384	0.96
	84	2688	7	448	0.746667

	88	2816	8	512	0.853333
	67	2144	5	320	1.066667
	86	2752	6	384	0.853333

Table 4.11 showed the number of packet loss ratio and it is increased due to the overloading and increased number of busy channel and increased number of secondary which effected on the network performance in general.

Table 4.11: loss signal and handover of 30 Secondary Users and 20 Primary Users

No. of Data signal		No. of packet loss ratio data signals	Handover
Sender	Receiver		
SU 1	SU 16	2	1
SU 2	SU 17	2	1
SU 3	SU 18	1	1
SU 4	SU 19	3	0
SU 5	SU 20	2	1
SU 6	SU 21	2	0
SU 7	SU 22	2	0
SU 8	SU 23	2	1
SU 9	SU 24	3	1
SU 10	SU 25	0	1
SU 11	SU 26	3	1
SU 12	SU 27	2	0
SU 13	SU 28	0	0
SU 14	SU 29	0	0
SU 15	SU 30	0	1

4.3.4 The fourth case study of 10 SUs and 5 PUs

It simulated with 10 secondary users and 5 primary users, each secondary user have a few number of primary users channel and it showed in Figure 4.14.

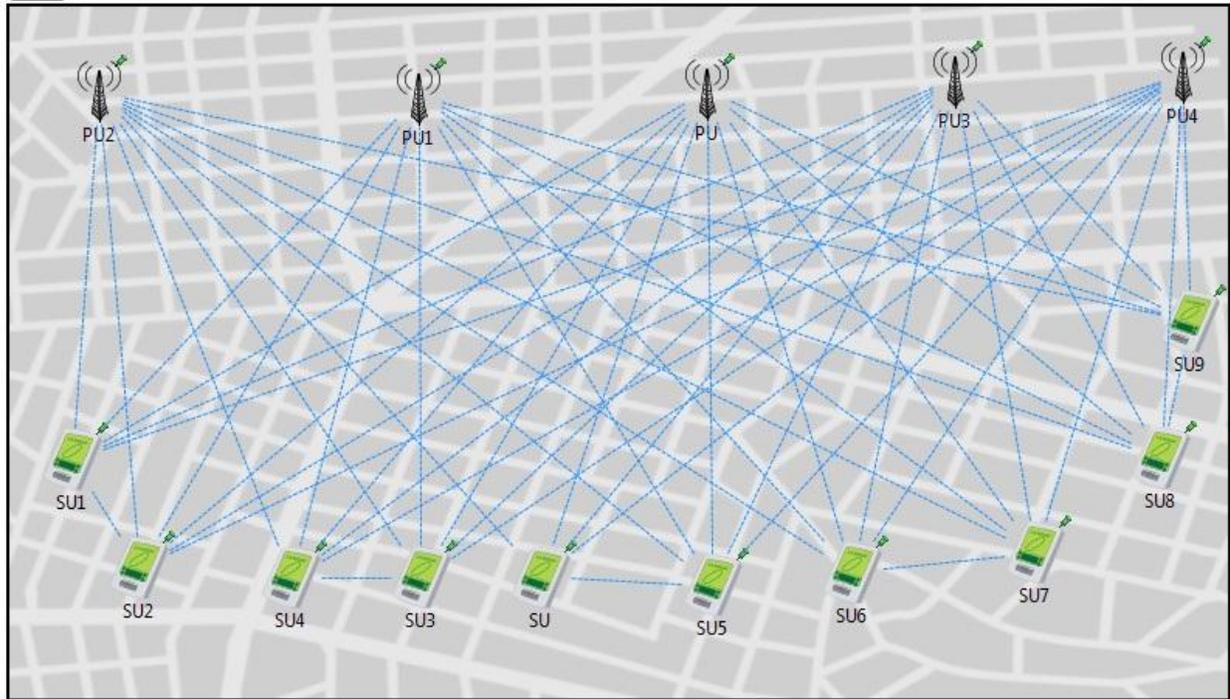


Figure 4.14: The fourth case study of 10 secondary users and 5 primary users

Table 4.12 showed the increased number of sensing and data signals due to the increased number of free (idle) channels to use by secondary users in state of overall users required to send their data.

Table 4.12: Network Evaluation with 10 Secondary Users and 5 Primary Users

Node Type	Active SU Nodes	No. of Sensing signal	No. of Data signal
Sender	SU 1	221	24
	SU 2	232	20
	SU 3	223	20
	SU 4	254	23
	SU 5	245	27
	SU 6	215	20
	SU 7	221	18

Receiver	SU 8	239	15
	SU 9	243	20
	SU 10	258	25

Table 4.13 showed the calculation of total sensing and data packets size in Byte with throughput measurement for successful signals. The total number of packets is increased due to the increased number of primary users (PU) as free channels to Hanover and transmit throughout.

Table 4.13: Total size of data and sensing signals and total throughput.

Node Type	No. of Sensing signal	Total size in Byte	No. of Data signal	Total size in Byte	Total Throughput Bps
Sender	221	7072	24	1536	2.56
	232	7424	20	1280	2.133333
	223	7136	20	1280	2.133333
	254	8128	23	1472	2.453333
	245	7840	27	1728	2.88
Receiver	215	6880	20	1280	2.133333
	221	7072	18	1152	1.92
	239	7648	15	960	1.6
	243	7776	20	1280	2.133333
	258	8256	25	1600	2.666667

Table 4.14 showed number of packet loss and handover for each active nodes in the proposed environment and it showed with increased number of channel the lost ratio is decreased due to the dropped and discarded packet and delay is decreased which effect positively on the network.

Table 4.14: loss signal and handover of 10 Secondary Users and 5 Primary Users

No. of Data signal		No. of packet loss ratio data signals	Handover
Sender	Receiver		
SU 1	SU 6	4	2
SU 2	SU 7	2	3
SU 3	SU 8	5	2
SU 4	SU 9	3	4
SU 5	SU 10	2	2

4.3.5 The fifth case study of 10 SUs and 10 PUs

The fifth case study is based on 10 secondary users and 10 primary users to simulate the proposed spectrum sensing approach in cognitive radio network. Figure 4.15 showed the proposed fifth topology.

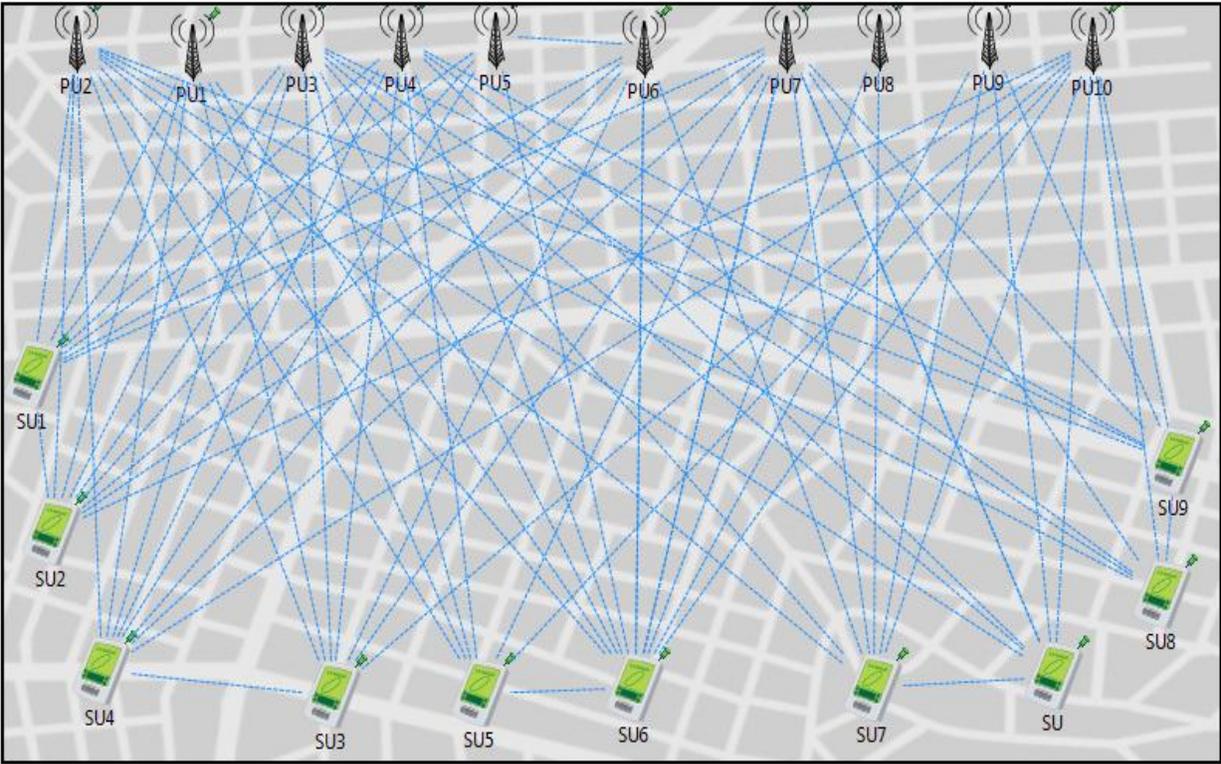


Figure 4.15 : The fifth case study of 10 SUs, and 10 PUs topology.

Table 4.15 showed the network evaluation for active node of 10 primary users and 10 secondary users and it presented that the decrease number of primary users channel as idle is effected on number of sensing and transmitted signals.

Table 4.15: Network Evaluation with 10 Secondary Users and 10 Primary Users

Node Type	Active SU Nodes	No. of Sensing signal	No. of Data signal
Sender	SU 1	321	27
	SU 2	333	25
	SU 3	324	27
	SU 4	355	26
	SU 5	349	29
Receiver	SU 6	318	22
	SU 7	324	24
	SU 8	333	23
	SU 9	342	25
	SU 10	357	27

Table 4.16 showed the total size of each sensing and data signals of transmitter and receiver, with increased number of secondary users and decreased channel allocation as free to transmit the number of sensing and data is decreased.

Table 4.16: Total size of data and sensing signals and total throughput.

Node Type	No. of Sensing signal	Total size in Byte	No. of Data signal	Total size in Byte	Total Throughput Bps
Sender	321	10272	27	1728	2.88
	333	10656	25	1536	2.666667
	324	10368	27	1472	2.88
	355	11360	26	1664	2.773333
	349	11168	29	1728	3.093333
Receiver	318	10176	22	1408	2.346667
	324	10368	24	1600	2.56

	333	10656	23	1728	2.453333
	342	10944	25	1600	2.666667
	357	11424	27	1856	2.88

Table 4.17 showed the packet loss ratio is effected when number of primary users is decreased so each user can get few number of handover of channel acquisition.

Table 4.17: loss signal and handover of 10 Secondary Users and 10 Primary Users

No. of Data signal		No. of packet loss ratio data signals	Handover
Sender	Receiver		
SU 1	SU 6	5	2
SU 2	SU 7	1	2
SU 3	SU 8	4	2
SU 4	SU 9	1	3
SU 5	SU 10	2	2

4.3.6 The sixth case study of 10 SUs and 15 PUs

It simulated with 10 secondary users and 15 primary users as it showed in Figure 4.16.



Figure 4.16 : The fifth case study of 10 SUs, and 15 PUs topology.

Table 4.18 showed the number of sensing signals and data signals is increased compared with the state of 10 SU, and 10 PUs above due to the increased available channel as free to use by secondary users for channel transmission and sensing .

Table 4.18: Network Evaluation with 10 Secondary Users and 15 Primary Users

Node Type	Active SU Nodes	No. of Sensing signal	No. of Data signal
Sender	SU 1	428	34
	SU 2	435	35
	SU 3	429	33
	SU 4	456	35
	SU 5	440	36
Receiver	SU 6	412	34
	SU 7	426	34
	SU 8	421	30
	SU 9	433	32
	SU 10	438	34

Table 4.19 showed the signals is increased with increased number of idle channel and also throughput value is effected positively, which effected on the network performance.

Table 4.19: Total size of data and sensing signals and total throughput.

Node Type	No. of Sensing signal	Total size in Byte	No. of Data signal	Total size in Byte	Total Throughput Bps
Sender	428	1088	34	2176	3.626667
	435	1120	35	2240	3.733333
	429	1056	33	2112	3.52
	456	1120	35	2240	3.733333
	440	1152	36	2304	3.84
Receiver	412	1024	34	2176	3.626667
	426	992	34	2176	3.626667

	421	960	30	1920	3.2
	433	1024	32	2048	3.413333
	438	1088	34	2176	3.626667

Table 4.20 showed the number of packets loss ratio is decreased due to the increased number of free channel of primary user which effected on the Handover mechanism of secondary users and it provide better channel allocation compared with the decreased number of primary users.

Table 4.20: loss signal and handover of 10 Secondary Users and 15 Primary Users

No. of Data signal		No. of packet loss ratio data signals	Handover
Sender	Receiver		
SU 1	SU 6	0	3
SU 2	SU 7	1	3
SU 3	SU 8	3	3
SU 4	SU 9	3	4
SU 5	SU 10	2	3

4.4 Discussion and System Comparison

Figure 4.17 showed the proposed system compared with different case studies as with increased number of secondary user and decreased number of PU the throughput is decreased due to the required time to pass packet from sender to receiver which effect on the number of total packets between them, loss signals increased due to the idle free channel effected on the receiver behavior to get accepted to the incoming packets from the sender, and total handover increased due to the increased number of PU element which represented as open free channel used by the cognitive radio nodes to transmit their signals.

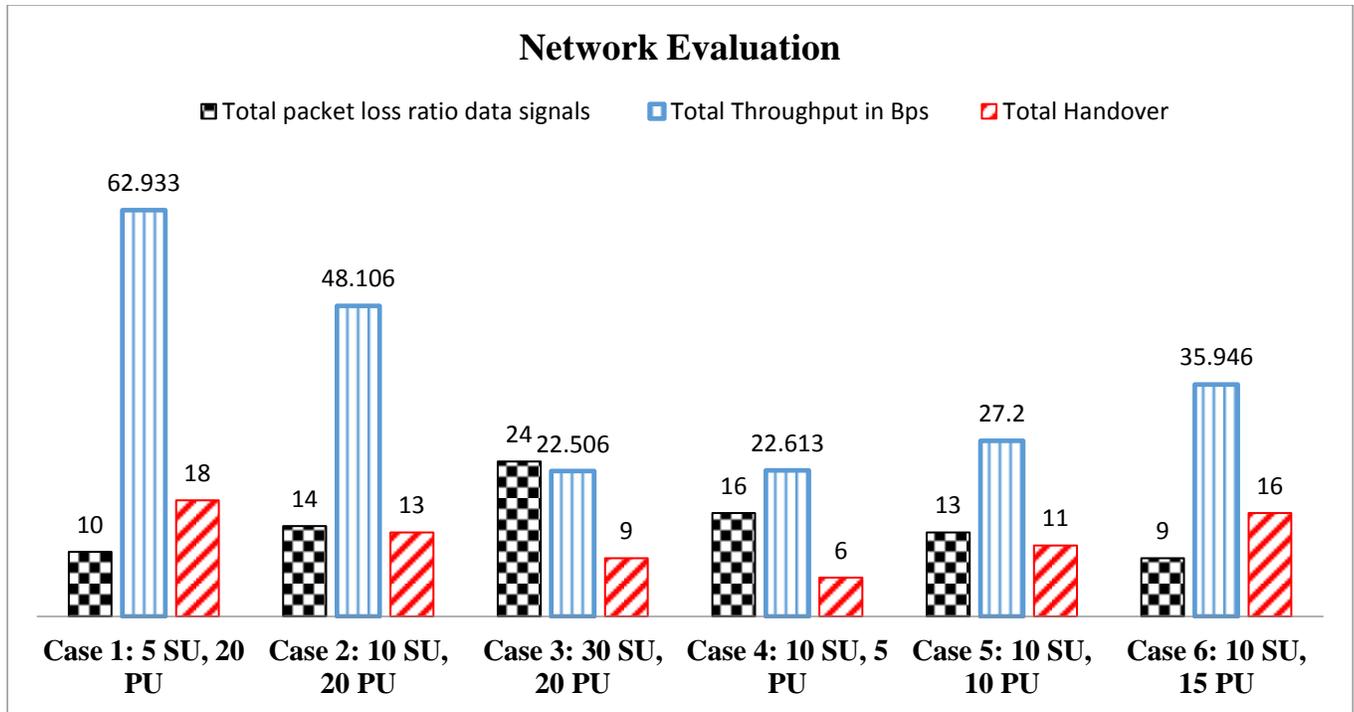


Figure 4.17: Network simulation evaluation with overall case studies.

Table 4.21 showed the system comparison with other related works in case of implementation CNN Deep learning algorithm with the same used dataset as dataset 1 (RML 2016.10b class), and dataset 2 as 2016.04C.multisnr.tar.

Table 4.21: The proposed system compared with other related with other related works

Dataset	Author	Multiple Data Sets	Work with Big Data?	Proposed Method	Accuracy	Detection Rate
Dataset 1 (RML 2016.10b class)	Kumar , 2018 [8]	No	Yes	CNN	80%	/
Dataset 1 (RML 2016.10b class)	Dong , 2017 [6]	No	Yes	CNN	/	70%
Dataset 1 (RML 2016.10b class)	Thomas 2021 [7]	No	Yes	Mod-LRCNN	93%	/
Dataset 2 (2016.04C.multisnr.ta)	Timothy 2016 [5]	No	No	CNN	87.4%	/
Dataset 1 Dataset 2	Proposed System	Yes	Yes	CNN + Cooperation	94%	79%

Figure 4.18 showed the accuracy calculation for each dataset with the proposed CNN deep learning algorithm and the accuracy of BPSK, CPFSK, and PAM4 modulation type is 94% in the used dataset. In addition, Recall and F-score is calculated for overall classes. The best Recall value is 98% of BPSK and GFSK, and best F-score value is 98% of BPSK, and CPFSK modulation classes.

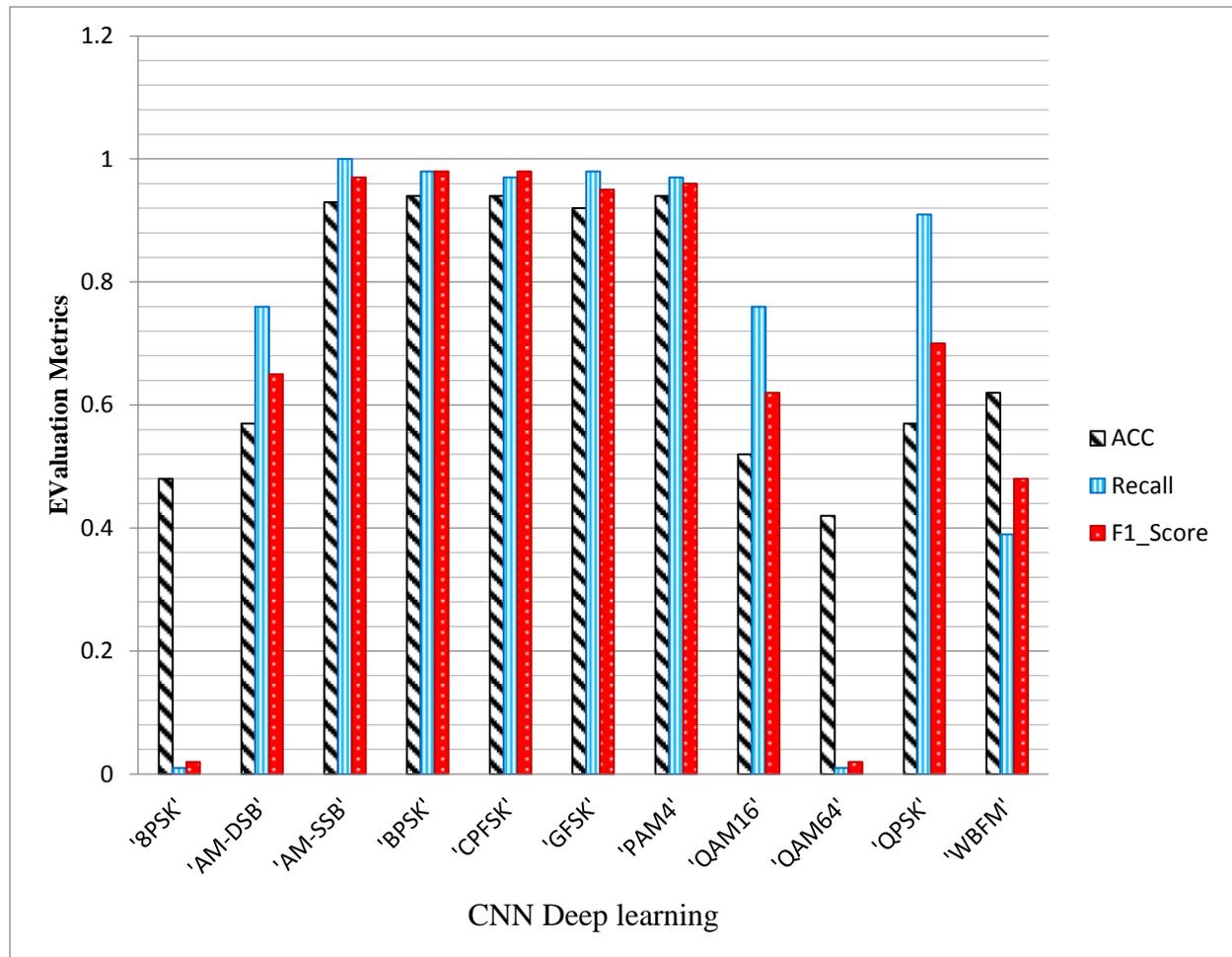


Figure 4.18: The proposed results of CNN Deep approach.

5.1 Conclusions

This chapter explains the proposed approach conclusions for different results and implementation for both programming language with Python and simulation environment with OMNET++, in addition to the main suggestions for future works, They can be summarized as :

1. Developing Hybrid blind spectrum sensing technique to create an embedded approach to manage primary user appearance by implementing an integrated approach based on CNN Deep learning algorithm, and Efficient Linear Cooperative Spectrum Sensing (LCSS).
2. Mitigating interference in radio spectrum of cognitive radio network by detect Primary Users signal as it present or not present and Secondary Users signals effectiveness on PU signals to get better blind spectrum sensing in CRNs.
3. Applying blind spectrum sensing model to improve spectrum sensing mechanism in cognitive radio network with blind linear cooperative approach.
4. Prediction channel signals based on SNR value of each PU element by training classifier with CNN deep learning model.
5. The network evaluation result of the first case study in OMNET++ with:
The 5 Secondary Users with 20 Primary Users , Total packet loss ratio data signals is 10, Total Throughput is 62.933 Bps, Total Handover is 18., while the 10 Secondary Users with 20 Primary Users , Total packet loss ratio data signals is 14, Total Throughput is 48.106 Bps, Total Handover is 13.Besides, the 30 Secondary Users with 20 Primary Users , Total packet loss ratio data signals is 24, Total Throughput is 22.506 Bps, Total Handover is 9.
6. The network evaluation result of the second case study in OMNET++ with:
The 10 Secondary Users with 5 Primary Users, Total packet loss ratio data signals is 16, Total Throughput is 22.613 Bps, Total Handover is 6, while the

10 Secondary Users with 10 Primary Users, Total packet loss ratio data signals is 13, Total Throughput is 27.2 Bps, Total Handover is 11. In addition, the 10 Secondary Users with 15 Primary Users , Total packet loss ratio data signals is 9, Total Throughput is 35.946 Bps, Total Handover is 16.

5.2 Suggestions for Future Works

1. Managing the accessibility of the nodes to the allocated frequency channels while maximizing spectral and sharing efficiency is the goal of the second access technique used in CR-IoT applications. This tactic may be associated with the sensor's data format, the duplication of the data (which may be disregarded or compressed), and the data needed.
2. Channel encoding for interference sensing: choose a method that works well with SUs' quality of service and doesn't get in the way of SUs' ability to identify PUs.
3. In cognitive radio frequency bands, it needs to improve path fading channel scenarios such (flat or frequency-selective fading channels) and add noise in order to compute some route space loss work, analysis, and evaluation.
4. Building an energy consumption take into consideration computation process of each node when build a cognitive radio network where it is likely to play a significant role if a cooperative method is used.

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الخلاصة

تم اقتراح تقنية الراديو الإدراكي لتحسين كفاءة الطيف من خلال جعل أجهزة الراديو المعرفية تعمل كمستخدمين ثانويين للوصول بشكل انتهازى إلى نطاقات التردد غير المستغلة. يُمكن استشعار الطيف شبكات الراديو الإدراكي من قياس بيئة التشغيل الخاصة به والتعلم منها والاطلاع عليها. تواجه شبكات الراديو الإدراكي مشكلة رئيسية هي ندرة التحسس لعرض النطاق الترددي الموجي خصوصا حالة عدم المعرفة المسبقة بالقنوات المتوفرة والذي يعرف بالتحسس الاعمى والذي يلعب استشعار الطيف الأعمى دوراً مهماً في اتصالات CRNs والذي تكون نسبة الضوضاء قليلة الى قوة الإشارة المتولدة من المستخدم الاساسي لأنه الخطوة الأولى في السماح للمستخدمين غير المرخصين (مستخدم ثانوي) بالوصول إلى القنوات المرخصة الفارغة (المستخدمون الأساسيون). يستفيد المستخدمون الثانويون في شبكة CR ، من نطاقات التردد المحجوزة للمستخدمين الرئيسيين عندما تكون النطاقات ليست قيد الاستخدام ؛ ولكن إذا احتاج المستخدم الرئيسي إلى إعادة الاتصال ، فيجب على المستخدم الثانوي التخلي عن القناة والبحث عن أخرى. في استشعار الطيف CR ، تتمثل التحديات الرئيسية في تحديد الإشارة الأولية. بيئة الانتشار المتغيرة والتداخل الناشئ عن العديد من المستخدمين الثانويين ، سيستخدم العديد من المستخدمين الأساسيين تقنيات تعديل مختلفة ، وسرعات البيانات ، ونقاط قوة الإرسال ، ويمكنهم استخدامها لبناء نظام متكامل لتعزيز استشعار الطيف في الراديو الإدراكي.

لتعزيز تقنيات استشعار الطيف في الراديو الإدراكي ، يمكن أن تستخدم الوحدات النطاقات الترددية عند عدم وجود وحدات المستخدمين الرئيسيين ، بحيث لا يتداخل المستخدمين الثانويين مع المستخدمين الرئيسيين.

يعتمد النظام المقترح على استشعار الطيف الأعمى في CRN للتنبؤ بتأثير إشارة CR على إشارة المستخدمين الرئيسيين، ويعتمد على قواعد بيانات مختلفه والمتمثلة (RML 2016.10b ، RML 2016.11b ، 2016.04C.multisnr.tar) وهو عبارة عن نظام تكييفي لقناة انتقائية من أعلى قائمة مقترحه . يحقق النظام المقترح تحسينات كبيرة في الدقة لإشارات SNR العالية أو المنخفضة وكلاهما.

أظهرت النتائج أن تقنيات الطيف المقترحة حققت أداءً عاليًا للشبكة لتكون على معرفة بإشارات المستخدم الأولية بتنبؤ عالٍ يعتمد على نموذج الشبكة العصبية العميقة لظهور المستخدمين الأساسيين حيث تم قياس الدقة بنسبة ٩٤٪. كما أشارت إلى أن الطريقة المقترحة ساهمت بشكل دقيق ومناسب كمرحلة أولية في الكشف الموثوق أو التنبؤي لإشارات المستخدمين الرئيسيين لتعزيز استخدام شبكة الطيف الإدراكي.

إضافة الى ذلك اظهرت نتائج المحاكاة ان اقل عدد الحزم المفقودة كانت ٩ حزمة في حالة الدراسة السادسة التي تحتوي على ١٠ مستخدمين ثانويين و ١٥ مستخدمين رئيسيين واعلى طاقة انتاجية للشبكة هي ٦٢.٩٣٣ بايت بالثانية واعلى استحواذ على القناة المتوفرة كان ١٨ في حالة الدراسة الاولى والتي تتضمن ٥ مستخدمين ثانويين و ٢٠ مستخدم رئيسي.



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قسم شبكات المعلومات

تقنية الاستشعار الاعمى بالاعتماد على التعلم العميق والتعاون الخطي

اطروحة مقدمة
الى مجلس كلية تكنولوجيا المعلومات - جامعة بابل و هي جزء من
متطلبات نيل درجة الدكتوراة فلسفة في تكنولوجيا المعلومات /
شبكات المعلومات

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