Republic of Iraq
Ministry of Higher Education and Scientific Research
University of Babylon
College of Information Technology
Department of Information Networks

"Identification Modulation Types using Cognitive Radio Network based on Deep Neural Network"

A Thesis

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 Master in Information Technology-Information Networks.

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2022 A.D. **1443 A.H**

بِسْمِ اللَّهِ الرحمن الرَّحِيمِ

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Acknowledgement

In the name of **Almighty Allah**, Most Gracious, Most Merciful. At first, Praise be to Him and thanks to God and the satisfaction of parents and conciliation only from Almighty Allah greatest praise is to **Allah** for His assistance in facing the difficulty that I have met in my study, and for His help to achieve my aims, also for His great graces and boons all the time.

I would like to express my deepest thanks to my supervisor **Prof. Dr. Sattar B. Sadkhan** for his valuable advice, motivation, guidance, and fruitful discussions throughout the preparation of this thesis.

I would like to extend my respect and deepest gratitude to the College of Information Technology and the presidency of University of Babylon

Sincere appreciation and love to my father, my mother, my wife, my children (Zaid, Amir, Fadhl and Karrar) and my brothers and sisters as well as all my close friends for providing me with optimism, pure emotion, great hope, encouragement and support at every step in my life in This thesis.

Finally, Sincere thanks and appreciation to all friends, colleagues and loved ones

Abstract

Automatic Modulation Recognition (AMR) is the core of the (Software Defined Radio) SDR system. , It used in a variety of fields, including military, civilian, and cognitive radio (CR) applications, and played a key role in telecommunications. the use of deep learning (DL) to detect and classify radio frequency (RF) signals is becoming increasingly popular. the reason is that the DL approach is useful because it identifies signals with no complete protocol information, it can detect and /or classify waveforms that are not connected to a connection, such as radar signals. the proposed AlexNet system is part of the Deep Neural Networks (DNNs) that were used to distinguish modulation signals generated in Radio ML2016.10a and the goal is to create better accuracy than any other system in use now by accurately distinguishing between these modulation signals. the same Radio ML2016.10a it was used for Introducing a framework by creating a dataset with GNU Not Unix (GNU) Radio that simulates flaws in a true wireless channel, and uses 11 different modulation, eight of which are digital and three are analog. Besides to AlexNet, three other models were used, namely Convolutional Long-Short Neural Network (CLDNN), Gated Recurrent Units (GRU), and Residual Network (ResNet). Google colab simulation has been used to implement the proposed system. Compared to other proposed models, AlexNet is a classification of deep learning networks used to increase network accuracy.

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Certificate of Participation

IEEE

is hereby granted to

Naseer Abdulameer Mousa and Sattar B. Sadkhan

For presenting the paper entitled

Identification of Digitally Modulated Signal Used in Cognitive Radio Network - Survey

In the 1st BABYLON INTERNATIONAL CONFERENCE ON INFORMATION TECHNOLOGY AND SCIENCE (BICITS'21) which was held on March 28-29, 2021 in Babil, Iraq by College of Information Technology-University of Babylon and technically sponsored by IEEE of IEEE Iraq Section.

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12/May/2022

LETTER OF ACCEPTANCE

(Identification the Modulation Type in Cognitive Radio Network Based on Alexnet Architecture)

Naseer Mousa

it has been accepted for presentation in the "**5th International Iraqi Conference on Engineering Technology and its Applications (5th IICETA 2022)**". The final decision of publication in IEEE explore is subject terms and conditions of Conference Scientific Committee and IEEE.

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5th International Iraqi Conference on Engineering Technology and its Applications (5th IICETA 2022)

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Abbreviation	Definition
16-QAM	16- Quadrature Amplitude Modulation
64-QAM	64- Quadrature Amplitude Modulation
8-PSK	8- ary phase-shift keying
ALRT	Average probability Ratio Tests
AMC	Automatic Modulation Classification
AMR	Automatic Modulation Recognition
ANFIS	Adaptive Neural Fuzzy Inference System
ANNs	Artificial Neural Networks
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase Shift keying
BWFM	Bandwidth Frequency Modulation
CEC	Cognitive Experimental Channel
CLDNN	Convolutional Long Short Term Deep Neural Network
CNN	Convolutional Neural Network
CPFSK	Continuous Phase Frequency-Shift Keying
CR	Cognitive Radio
CRN	Cognitive Radio Network
CSI	Channel State Information
CWT	Continuous Wavelet Transform
DCN	Densely Connected Network
DFT	Discrete Fourier Transform
DNN	Deep Neural Network
DSB-AM	Double-Sideband Amplitude Modulation
DT	Decision Theory

DWT	Discrete Wavelet Transform
FB	Feature-Based
FE	Feature Extraction
FFT	Fast Fourier Transform
FN	false negative
FP	false positive
GFSK	Gaussian Frequency-Shift Keying
GLRT	Generalized Probability Ratio Tests
GRU	Gated Recurrent Unit
HF	High Frequency
HOC	High Order Cumulates
HOM	High Order Moments
HOS	High Order Statistical
HTP	High True Positive
ITL	Information Theoretic Learning
KNN	K-Nearest Neighbors
LB	Likelihood-Based
LFP	Low False Positive
LSTM	Long Short-Term Memory
ML	Maximum Likelihood
OSA	Opportunistic Spectrum Access
PaC	Parameter-Controlled
PAM	Pulse Amplitude Modulation
PDA	Personal Digital Assistant
PSD	Power Spectral Density
PU	Primary User

QPSK	Quadrature phase-shift keying
ReLU	Rectified-linear-unit
RF	Radio Frequency
RNN	Recurrent Neural Network
ResNet	Residual Network
SDR	Software Define Radio
SNR	Signal-to-Noise Ratio
SR	Software Radio
SS	Spectrum Sensing
SSB-AM	Single-sideband Amplitude Modulation
SU	Secondary User
SVM	Support Vector Machine
TN	true negative
TP	true positive
UHF	Ultra High Frequency
VHF	Very High Frequency

Chapter One

General Introduction

1.1 Introduction

The identification of Digital modulation signals is required in a wide range of applications, including wireless communication and military applications. This technique is most commonly used in military electronic surveillance and reconnaissance, where identifying the type of alteration is critical for gathering intelligence and ensuring national security by identifying a potential threat that can be hidden or eliminated. Software Defined Radio (SDR) and smart receivers both strongly rely on it. Modern radio systems may alter their settings and modulation types on the fly, depending on the transmission channel's quality. Not only can the created modulation identification process be used to analyze High Frequency (HF) signals, but it can also analyze radio communication signals from higher RF bands, such as Very High Frequency (VHF) or Ultra High Frequency (UHF). There are several of military and civilian mobile radios operating in such ranges. For services with a low data rate and limited coverage, cognitive radio might be a useful way of communication [1].

These devices could configure themselves in any Radio Frequency (RF) environment by changing the modulation scheme, frequency, power, coding, and so on, using in-built software. As a result, they might be used even in areas where communications infrastructure is damaged or not completely operational. Cognitive Radios (CR) would also be capable of overcoming a hostile party's frequency jamming. As a result, it's ideal for military applications. In this situation, cognitive radio might detect the jamming and automatically adjust its broadcast characteristics to connect with the intended receiver. The difficulty is in designing cognitive radio systems that can detect spectrum gaps at very low signal-to-noise ratios and dynamically change multiple transmission settings to enhance system performance [2].

By altering the modulation schemes while keeping a constant Bit Error Rate (BER), the transmitter can readily adjust itself to the current channel circumstances. In order to do this, the receiver and transmitter must work together in order to estimate the channel [3].

One of its strategies is artificial intelligence. These are some of the most often used strategies for recognizing signals. Actually, it causes CR to learn, change, make judgments, and alter transmission power and other parameters in real time in response to changes in the external environment for network transmission or performance improvement. The signal identification information is critical in the detection of digital modulation. Because basic information such as symbol rate, mode, and other parameters are unknown for CR, it is important to extract wave attributes in a highly non-standard manner. It has to synchronize and show the type of change [4].

As a result, with CR systems, the design of a broad cognitive receiver must be able to determine the modulation waveform's many features. According to the published studies, there are several key difficulties to consider when building a system for automatic identification of digital signal type (modulation), which, if properly handled, recognizes will become more robust and efficient. The classification technique is has to be addressed. The application of several supervised classifiers in modulation categorization has not gotten the attention it deserves, according to a literature study, despite its considerable potential. Another challenge is selecting the feature set [5]. At the moment, automatic modulation recognition methods comprise decision theory and algorithms for recognizing patterns [6].

Artificial Neural Networks (ANNs) based on a recurring pattern recognition technology, is particularly well suited to signal classification and can be considered the most efficient method. The basic ANN algorithm has been proposed in this work.

The method works by extracting the signal's instantaneous amplitude, phase, and frequency from the original signal, determining the distinctive parameters statistically or visually, and ultimately creating the decision threshold using the training sample set. For instance, Features extracted manually from signals (such as QAM and QPSK) are entered into the ANN system, to distinguish between these signals [7].

1.2 Literature Review

In [8 / 2009], Authors in this work presented categorize modulation approaches, and generalized modulation identification algorithm. The proportion of proper modulation is shown to be high in this study. With 200 ensembles, identification is more than 97.8%. When the SNR is less than 5 dB, symbols appear**.**

In [9 / 2012], authors present the automated modulation categorization (AMC) of communication signals. In Information Theoretic Learning (ITL), the correlation coefficient is a novel approach for automated classification that is based on a measure of similarity that is produced from the data (ITL). The performance of the classifier is assessed in terms of classification hit-rates in AWGN noisy circumstances, with SNR ranging from 5 to 15 dB in the input signal. Simulated classification hit rates for binary modulations are 83 percent for 5 decibels.

In [10 / 2015], researchers achieves an identification rate of about 100% for modulated signals (2FSK, 4FSK, 8FSK, 2PSK, 4PSK, 5dB, noise-free), while the output is the Maxnet unit. The system has a high recognition rate when Adaptive Neural Fuzzy Inference System (ANFIS) devices are used.

In [11 / 2017] , authors of this research recommended that three independent training data inputs were employed for the categorization of digital modulation schemes when using a deep learning network to achieve this classification. It is clear from the comparison of the three different training inputs that deep networks can be used for modulation candidate identification in transmitted signals, and it is also clear that the notion of bypassing the distinct feature computation module in the future is a viable one.

In [12 / 2017] , Author's used Convolutional neural network (CNN) is utilized to complete the classification task. They transmit the raw modulated signals to CNN for network training after converting them into pictures with a grid-like architecture. For performance comparison, two existing techniques are used: cumulant and support vector machine (SVM) based categorization algorithms. The proposed CNN-based modulation classification strategy provides equivalent classification accuracy without requiring manual feature selection, according to simulation findings.

In [13 / 2017], the authors focused on the DL and aim to use it to solve communication issues. They present a new data transformation algorithm to improve communication signal modulation classification accuracy, and they demonstrate that the signal modulation classification accuracy can reach 88 percent.

In [14 / 2017], in this paper, the authors present convolutional neural network (CNN) architecture. They found out that it recognized modulation types with 75% accuracy, and began tuning the CNN architecture and coming up with a new design. The accuracy is about 83.8 percent when the Signal-to-Noise Ratio (SNR) is high. Next, they created structures based on newly proposed concepts of one of the two forms of densely connected network (DenseNet) and ResNet is used. 83.5 percent and 86.6 percent, respectively, are the percentages. Convolutional neural networks are also presented. As its name suggests, a long-range convolutional deep neural network (CLDNN) is a long-range deep neural network. Achieve up to 88.5 percent accuracy with a high SNR.

In [15/ 2019], Authors will explore a framework for extracting time-frequency features from signals automatically. Features can be used to perform modulation classification using a deep learning network. The accuracy can be up to 90%.

In [16/ 2019], Authors present an AMR method based on a convolutional neural network (CNN) for considering PO in the OFDM system. To obtain high classification accuracy, the proposed method is employed to eliminate the PO. When comparing the suggested method to conventional methods, experiment results are supplied.

In [17/ 2020], Author's Using the AlexNet convolutional neural network, offers a modulation recognition approach for 5th-generation (5G) signal modulation. Aiming at the challenge of signal modulation recognition in non-cooperative conditions, which requirements significant a priori signal information and a sophisticated artificial feature selection, The simulations results showed that with a (SNR) 15 dB, the average recognition accuracy signals is up to 90%.

In [18/ 2020], Authors propose a Deep Learning-based modulation classification approach for non-Gaussian environments. AlexNet was used to classify signal modulation types. In non-Gaussian noise, the suggested technique successfully suppresses the sharp pulse and improves modulation detection accuracy. The simulated results appear the proposed method's validity. When SNR is equivalent to 6dB, classification accuracy reaches above 85 percent.

In [19 / 2020], authors in this paper study the CLDNN which is DNN architecture. The suggested design benefits from the complementarity of RNNs and CNNs in comparison to pure Long Short-Term Memory (LSTM) and Convolutional Neural Network CNN guideline models. At high SNRs, identification accuracy rose from 80% to 91.8 percent.

In Table (1.1) we illustrate the status, Extracted feature, Identified modulation type, the simulation used of previous researchers.

Table (1.1) Previous literature for methods used to modulation identification

Ref. No	Extracted feature	Type of classifier	Identified the modulation type	The simulation used
[8]	Statistical feature	WT	QPSK, GMSK, FSK, QAM	MATLAB
[9]	Statistical feature	ITL	BPSK, BFSK, OOK	MATLAB
[10]	Time Domain Features, Statistical Features, Zero-Crossing	ANFIS	FSK, ASK, BPSK,QPSK, QAM, CPFSK	MATLAB
[11]	AUTO	DNN	BPSK, QAM, 16QAM, 64QAM	MATLAB
[12]	AUTO	CNN	QPSK,8PSK, 16QAM, 64QAM	Python
[13]	AUTO	AlexNet, GoogLeNet	BPSK, 4ASK, QPSK, OQPSK, 8PSK, 16QAM, 32QAM, 64QAM	Python
[14]	AUTO	DNN	RadioML2016.10b (BPSK, QPSK, 8PSK,	Python

			QAM16, QAM64, BFSK, CPFSK, PAM4, WBFM, and AM-DSB)	
[15]	AUTO	CNN	(BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, PAM4, GFSK, CPFSK, B-FM, DSB-AM, SSB-AM)	MATLAB
[16]	AUTO	AlexNet	BPSK, QPSK, 16QAM, 64QAM, and 256QAM	Python
[17]	AUTO	CNN	BPSK, QPSK, 8-PSK, (16QAM)	Python
[18]	AUTO	AlexNet	8PSK, QPSK, OQPSK, 16QAM and 64QAM	MATLAB
[19]	AUTO	CLDNN	RadioML2016.10b (BPSK, QPSK, 8PSK, QAM16, QAM64,BFSK, CPFSK, and PAM4, WBFM, and AM-DSB)	Python

In the past, Traditional methods of classification modulation were commonly used, but due to several issues, including computational complexity and accuracy results; researchers have begun to turn to DL.

DL provides the ability to handle large amounts of data, such as (RadioML2016.10a), which contains a huge amount of data. (DL) automatically distinguishes between these signals, without the need to extract the features manually, this facilitates the classification methods.

1.3 Problem Statement

i- The topic of modulation recognition is difficult for many reasons, including the crowded spectrum and the variety of waveforms that may be found in any particular frequency band.

ii-The time required to extract features manually is too long to train a machine learning method, and the consequent computational complexity, versus the huge data sets required to train a deep learning network.

iii- How to present this signal to the receive, there are unexpected challenges, i.e. signals not previously recognized, how to deal with them, how the signals interfere with each other.

1.3 The Aim of the Study

The work objectives for the thesis are displayed in the next steps.

i- The main objective of this thesis is to classify (some) different modulation digital and analog used in modern wireless communication networks, such as Software Defined Radios (SDRs) or Cognitive Radio Networks (CRNs).

ii- The main task of classification (identifying, or distinguishing)11 modulation signals (digital and analog) 3 analog and 8 digital in a Radio Machine Learning (RML 2016.10a) on the basis of the Alexnet model.

iii- Obtaining high accuracy for results when comparing with literature previous works.

1.5 Thesis Outline

This thesis also comprises four chapters besides the first, which are as follows:

Chapter Two: This chapter focuses Identification for digitally modulation signals (characteristic, Advantages and challenges of AMR), the cognitive radio. Also, it shows feature extractions. Furthermore, a still open problem and common simulation tools used in this environment.

Chapter Three: This chapter presents the proposed system and illustrates the practical stages of the system and explains the proposed algorithms system.

Chapter Four: This chapter describes the results and evaluates proposed system.

Chapter Five: This chapter shows the results' conclusion. Also, it describes future works suggestions.

Chapter Two

Automatic Digital Modulation

2.1 Identification for Digitally Modulation Signals

Digitally Modulation Signals is critical to know the modulation in order to analyze any form of communication signal. Adaptive digital modulation identification techniques are becoming increasingly important in a wide range of communication systems, including several applications for software-defined and cognitive radios in military communications, as well as military communication systems. Electronic warfare, threat analysis, spectrum monitoring, communication jammers, and adaptive communications. One of the fundamental enablers of next-generation communications is adaptive modulation. With the intending to enhance junction conditioning performance [22].

For maximum spectrum efficiency and transmission dependability, channel state should be considered when deciding the best modulation scheme. Demodulation is used to recover the received signal's modulation type and categorize adaptive digital modulation recognition systems. It is possible to use adaptive digital modulation identification techniques to figure out the modulation pattern of a received signal that is not known. The receiver has no prior knowledge of the transmitter modulation system [23].

The estimation of any receive modulation scheme, followed by demodulation with the corresponding technique, are methods for determining adaptive digital modulation. Pre-Adaptive digital demodulation techniques are used to select the demodulator for the modulation system, resulting in an SDR with several demodulators. This makes it multifunctional and compact to execute on a re-programmable device [24].

Complex techniques like as AMR, referred to as automatic modulation classification in some studies, were included in some research [25], Traditional receivers become rendered inefficient because of the inefficiency of both the transmitter and the receiver. To enhance transmission efficiency, smart receivers that can blindly extract modulation information might reduce information or complementary modulation patterns [26].

The Cognitive Radio must be able to detect reliably the RF spectrum even if you have no prior information on the characteristics of the incoming signal. Encoder types and modulation might also be key characteristics to be designed carefully in order to raise the CR's level of awareness in relation to its environment [27].

A piece of prior information cannot be used since there is no prior knowledge. In the case of an unknown modulation model, AMR refers to a procedure that lets the receiver identify the modulation model from the received signal. AMR has a major impact on both cooperative and antagonistic communication. There are several ways to communicate information in a co-operative manner, including sharing your own information and repeating the information of other people. There are two types of non-cooperative communications: those that are mutually exclusive and those that are mutually exclusive. feature extraction and classification, followed by pre-processing, are the first three steps in the process[28].

a. Preprocessing

Stable and clear signal samples can only be obtained by proper preprocessing which includes a variety of tasks:

i. Centering and adjusting for alignment and variance because of propagation.
ii. The following feature extract block is fed from extracting clean signal segments.
iii. Estimating the carrier to noise ratio, carrier frequency, and other relevant parameters.

b. Feature Extraction

Signal features are present in both spectral and vector time distances, and both classifier and feature extraction adapt to different Signal-to-Noise Ratio (SNR) signals. The Hilbert transform is applied when the incoming signal is generated from real data samples and the goal is to get the complex envelope and the simultaneous analytical phase.

c. Feature Pattern Classification

If the transmitter and receiver are both error-free, it is supposed that the channels are identical. AMR may be divided down into two categories[29]:

i. Maximum Likelihood (ML) which derived from the received signal statistics.
ii. Using various Pattern Recognition algorithms to identify the signal's properties.

an ideal AMR should meet the following criteria:

i. Short observation intervals are required to achieve High True Positive (HTP) and Low False Positive (LFP) classification probabilities.
ii. Use diverse modulation schemes and varied channel conditions to detect signals.
iii. Embedded systems, real-time operation, and minimal computational cost are all desirable requirements.

Two stages are required to perform AMC [30]:

i. feature extraction using signal pre-processing
ii. Selective signal properties.

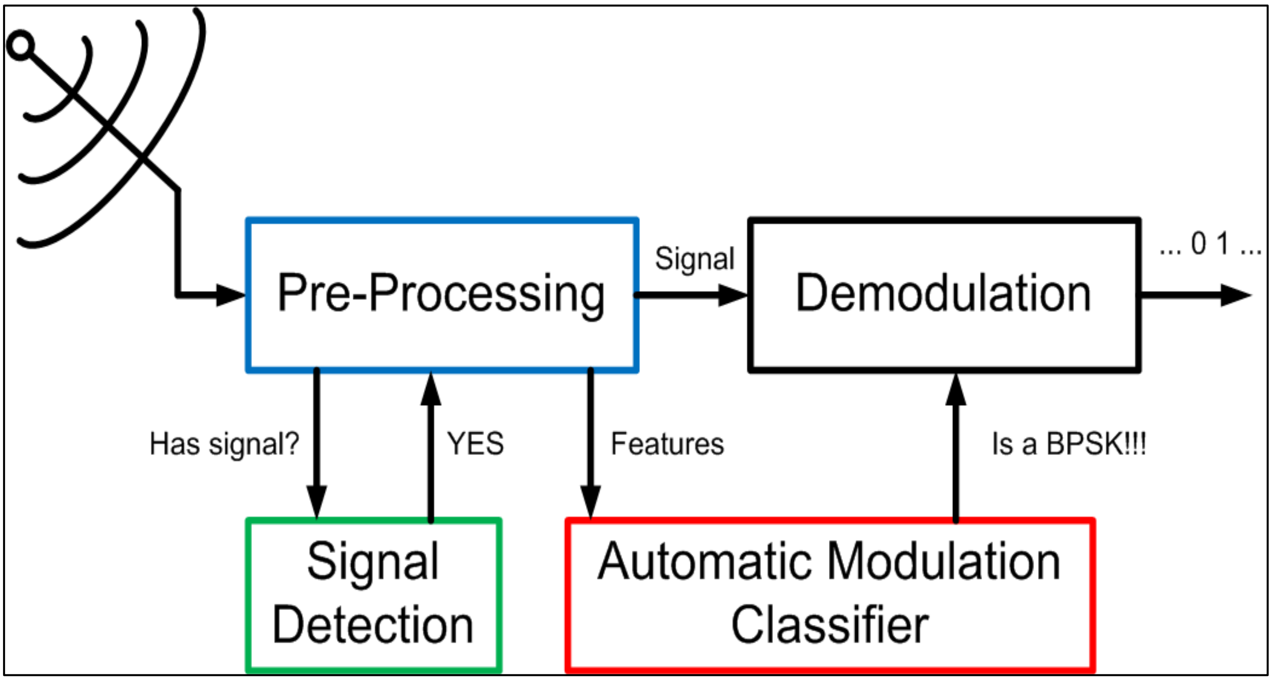


Fig. (2.1) demonstrates steps work in receive signal

Carriers and symbol periods, signal intensity, noise reduction and channel equalization might be approximated during preprocessing. For example, signal feature extraction is a frequent pre-processing approach for AMC. it needs a lot of computing power, which makes their use in real-world applications costly or perhaps impractical for systems built with today's available technology Figure (2.1) demonstrates how these steps work together in receive signal. In the past, a AMR method was divided into following approaches:

i. likelihood-based method (LB)
ii. Feature-Based method (FB)

2.1.1 Likelihood-Based Method (LB)

According to an assumption of a uniform prior, probabilistic and hypothesis arguments used in LB algorithms to deal with the modulation recognition problem, assuming that received signals (such as channel information and noise variation) are statistically likely. This is the best approach. Prior knowledge of probability functions and certain assumptions are employed in the decision theory approach to arrive at probabilistic answers. Pattern recognition, on the other hand, is based on the extraction of certain fundamental aspects of the signal, which are referred to as features.

The goal of the LB algorithms is to reduce the likelihood of misclassification and get the best possible result. Although that the LB techniques provide the best result, they have many drawbacks. Analysis challenges need computing complexity for the execution of these ideas [31].

The example below shows how (Likelihood) works when using Modulation Signals (QAM16, QPSK, 8PSK, PAM4) to choose the least likely

QAM 16	**QPSK**	**8PSK**	**8PSK**	**QPSK**	**8PSK**	**8PSK**	**QPSK**	**PAM4**	**PAM4**	**QPSK**

Solution:

According to the table above,

Step 1: Number of repeat for Modulation signal (QPSK and 8PSK) is (4) case.

Step 2: Number of repeat Modulation signal (PAM4) is (2).

Step 3: Number of repeat Modulation signal (QAM16) is 1.

The least likely to catch the modulation signal is the one that occurs the least number of times, so (QAM16) the least likely to be picked up.

2.1.2 Feature-Based Method (FB)

Both subsystems are used by the feature-based method: feature extraction and pattern classifications. FB approaches categorize the incoming signals based on derived characteristics termed key features extraction .In addition to classifications like blind clustering, neural networks, or support vector machines that are practically impervious to imperfect conditions like model mismatches or completely blind cases, some of these features can be derived from instantaneous information, such as higher order statistics, spectrum features like cumulates or wavelets, and so forth. Although this method yields a less-than-optimal answer, it reduces the computing burden.

Feature-based classifiers are more accurate than PR classifiers, but they need previous knowledge of signal waveform features, which is not workable. PR classifiers are simpler to develop and do not rely on a specific signal to work. ALRT and GLRT (average and generalized probability ratio tests) are used to evaluate received signal probability functions with various modulation functions. PR classifiers must select the specific modulation. Cumulates are the best feature and classification accuracy even under vanishing situations for PR classifiers that employ high-level statistics (HoS) or cumulative materials [32].

Data from the received signal's constellation points, as far as we know, have only been utilized as training data input seldom. It's not just the difficulty of implementation that makes ML-based recognition difficult; it also relies significantly on the entire Channel State Information (CSI) database.

Under time-varying fading effects, there are two new obstacles for adaptive recognitions which are, adaptive modulation scheme would be determined based on time-correlated fading circumstances, which interact. there are no longer any time-varying modulation candidates, as a result of this [15,17]. Furthermore, classification tools include the SVM, which is a strong and novel one. Statistical learning theory is its mathematical base. However, However, SVMs have a key problem because they must be trained offline before they can become particularly precise [33].

2.2 Cognitive Radio

Cognitive radio is a type of Software Radio (SR) that has additional capabilities and functions, such as environmental sensing, learning (learning from the result got), and decision making, that allow it to achieve the desired dynamic performance. At the software level, Cognitive Radio allows high-level applications to run in order to emulate a personal digital assistant (PDA). Software-specific radios and their practical equivalents should be investigated, Software-defined radios (SDR) and cognitive radios have many new and exciting benefits for radio users.

It is a natural platform on which new cognitive features can be built. The rest of this section summarizes of software radios and SDR [34]. SR is a transceiver in which communication operations will executed as programs running on an appropriate processor. As a result, SR includes all layers of the communication system protocol stack. Software can be changed for sender/receiver algorithms to meet multiple transmission criteria based on the same hardware. The device has equipped with a wide band antenna that allows it to operate over many bands.

As a result, a software radio is extremely malleable and versatile, meeting the spirit of the cognitive radio standards. In an ideal SR, the antenna output has directly sampled and converted to digital domain, and then the whole base band signal processing will be done in the digital domain. Because digitizing the wide-band antenna output directly would cause in the digitization of an unwanted large bandwidth packed with many separate signals of little relevance, software radio is more of a theoretical concept. This isn't acceptable from a technological or business standpoint.

The received signals will be sampled after an appropriate band selection filter to decrease sampling and digitization complexity in a software-defined radio (SDR), which is a realistic form of an SR. The difference between an SDR and a normal receiver is the SDR's configurability capability, which allows broadcast settings to be changed through a control bus.

A parameter-controlled (PaC) SDR is one of such arrangement. using cognitive radio technology as the foundation for next-generation wireless networks has led to introducing of new ideas, definitions, and measurements. In order to make the topics in the next parts simpler to absorb and digest, will examine some of the major ideas and terminologies offered by cognitive radio technology in the following sub-sections [35].

The intelligent management system and reconfigurable radios are the major components of the CRS system shown in Figure (2.2).

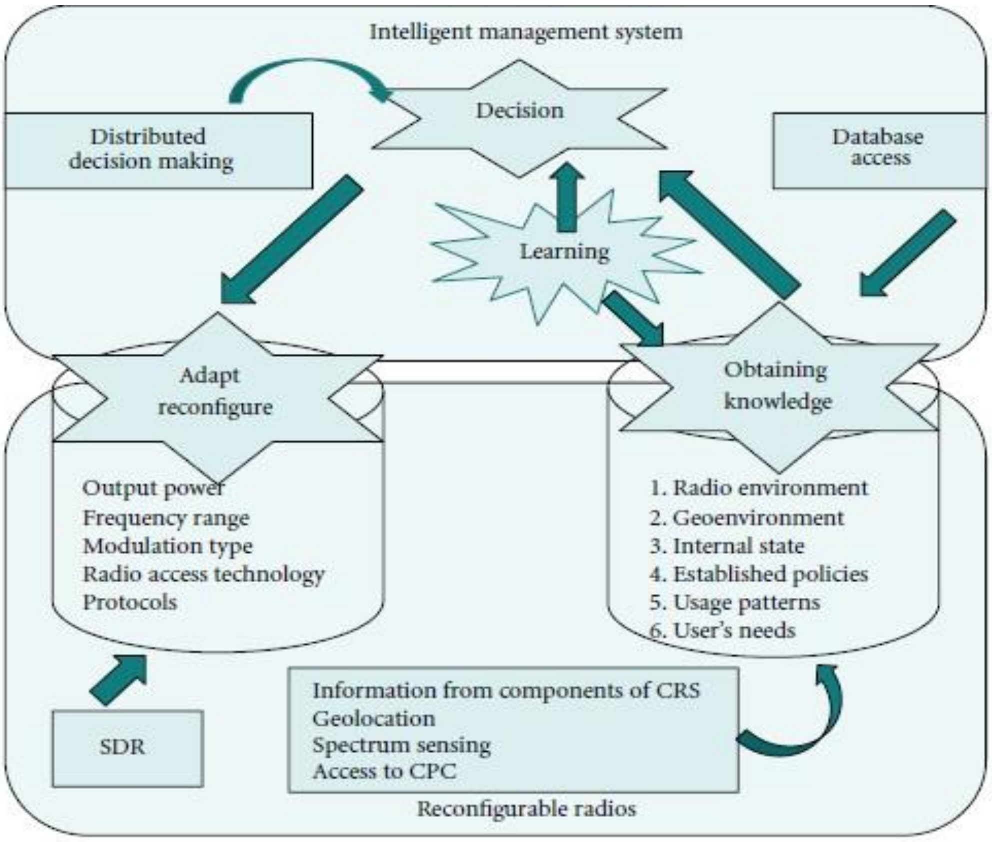


Fig. (2-2) cognitive radio concept.

The knowledge used by the CRS includes knowledge about the geographical environment, operational radio, usage patterns, internal conditions, and user needs. This knowledge is obtained from obtaining information from the CRS component, accessing the cognitive experimental channel (CEC), spectrum sensing, accessing the database and geolocation[36].

There are several of challenges, including decision making. the first challenge is where and how to decide, e.g. (decision on spectrum availability, access channel selection strategy, sensing, or how to improve radio performance). it shows whether the cognitive process should carry out in a centralized or distributed manner. This aspect is more important not only for cognitive networks but also for cognitive radios because decision-making can be affected by the cooperation among themselves as well as with other devices.

The second challenge is the learning process. An important aspect is whether supervised learning or not. The application of any method in CRS is to avoid wrong choices before a decision is made, particularly in the process of independent or unsupervised learning. Also, concretely defining the learning process of its goals and contributions to CRS [37].

2.3 Parameters used for Identification

Pattern recognition (PR), and feature extraction (FE) are two of the most common ways to distinguish between objects in categorization (physical, structural, and mathematical) [37] Signs different based on their structural and physical properties, such as their color and fragrance.

In order to increase classification accuracy, choose features that are most relevant. Because of the limited processing resources and memory available, it is vital to extract features that can be recovered quickly, are invariant to certain irrelevant changes, are not prone to noise, and can differentiate between different objects.

Because the features extracted for classification will be used by classifiers, the optimal feature must offer information that makes the duty of the classifiers as simple as workable, Because of this, samples from the same class must be comparable in feature values, whereas examples from other classes must differ in feature values[38].

Below, we will review some specifications of the features used in previous researches:

i. Implementation-friendly spectral characteristics. The increased noise, influences.
ii. Additive white Gaussian noise (AWGN) and multipath channels have a high impedance, and high-level statistics are more sensitive

to differentiating between different modulation schemes, including M-PSK and M-QAM[39].

iii. Features are difficult to discern between a broad variety of modulation schemes while using Cyclostationary because of its high complexity and poor signal-to-noise ratio (SNR).

iv. M-QAM is recognized by its constellation properties. However, the method's susceptibility to noise and high SNR need to recognize higher-order modulation were its major drawbacks.

v. M-FSK modulation schemes can be easily distinguished using FFT characteristics, even at low SNRs [40].

vi. The wavelet feature demands a numerous of samples and is best suited for differentiating modulation schemes at high SNRs[41].

vii. Higher-order statistical moments are used to create the HOC equation (HOMs).

viii. Because cyclostationarity does not need prior knowledge of carrier phase, carrier frequency, or time offsets, it is extensively used in blind AMC methods[42].

To improve categorization, a feature displays periodic robust cyclic frequency for highlights the features, they can be divided into the following categories:

a. Transform Features [43].
   i. Discrete Fourier Transform (DFT).
   ii. Fast Fourier Transform (FFT).

b. Spectral Features or time domain features As in some researches
   i. The maximum number of power spectral density (PSD).
   ii. Nonlinear components of instantaneous phase ap's instantaneous phase deviations.

iii. In the nonweak signal segment, standard deviation of the absolute val ue of the normalized centered instantaneous amplitude _a.

iv. the nonlinear component of the direct instantaneous phase's centered nonlinear component's standard deviation _dp.

v. Normalized instantaneous amplitude of signal segment aa's normalized center instantaneous amplitude.

vi. Normalized center instantaneous frequency of signal segment af's standard deviation.

vii. An increase in the normalized center instantaneous amplitude (_a 42) at the same time.

viii. An instantaneous frequency _f 42's kurtosis in the normalized center frequency [44].

c. Statistical features

Can be divided as the following:

A. Higher order statistical (HOS).
   i. Higher Order Moments (HOMs).
   ii. Higher order comulants (HOCs)

B. cyclostationary analysis.

C. WT may be divided into the following categories:
   i. Continuous Wavelet Transform (CWT)
   ii. Discrete Wavelet Transform (DWT)[45].

d. Zero-crossing intervals.
   i. Temporal feature.

e. Constellation Shape Features [46].

The traits used to distinguish modulation types have been extracted from previous research, and are effective methods. Features should be carefully selected based on factors including high discrimination sensitivity and inversely different SNRs with low computational complexity. The researcher extracts the features from the modification types and then inserts them into the classifier. The goal is to obtain high accuracy. The following figure shows the types of features commonly used in discrimination.

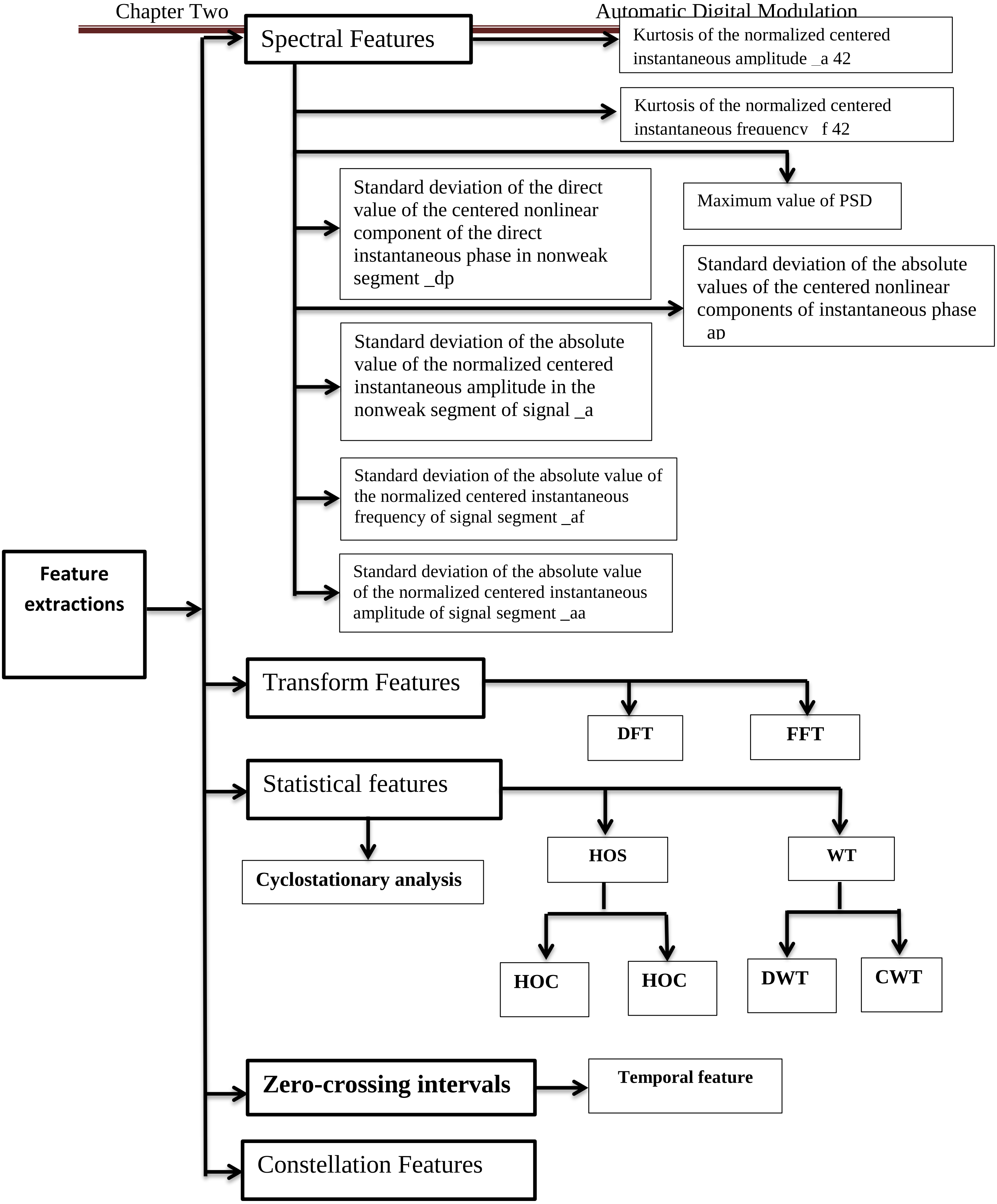


Fig. (2-3) Types of features commonly use

2.4 Types of Classifiers

In AMR, selecting a classifier type follows feature extraction [47]. Artificial Neural Networks (ANN), Decision Trees (DT), K-Nearest Neighbors (KNN), and Support Vector Machines (SVM) were integrated using artificial intelligence methods for classification. The supervised machine learning algorithm applicable to both SVM and ANN, while the block classifier is an unsupervised algorithm. Optimization strategies were used by researchers to identify the most important or dominant traits of the retrieved traits in order to increase classification accuracy. In addition to these previously mentioned classifiers, in recent years an important group of classifiers has appeared in the field of modulation, which have been well received by many researchers, such as (DNN), and they are good in this field for their active role in distinguishing modulation signals. In the next part, you will find more information about each classifier.

2.4.1 Deep Neural Network (DNN)

A DNN is a neural network (NN) that contains multiple input and output layers [48]. There are many neural networks, but they share the same components: neurons, functions, weights, biases, the difference is that DNN is more layered than NN. Because they work similarly to human brains they can be trained like other machine learning algorithms. (DNN) When using feature merging from lower layers, complex nonlinear relationships can be presented .DNN have some basic structures, such as CNN, RNN, etc. As shown in Figure (2.4), which was used in the thesis.

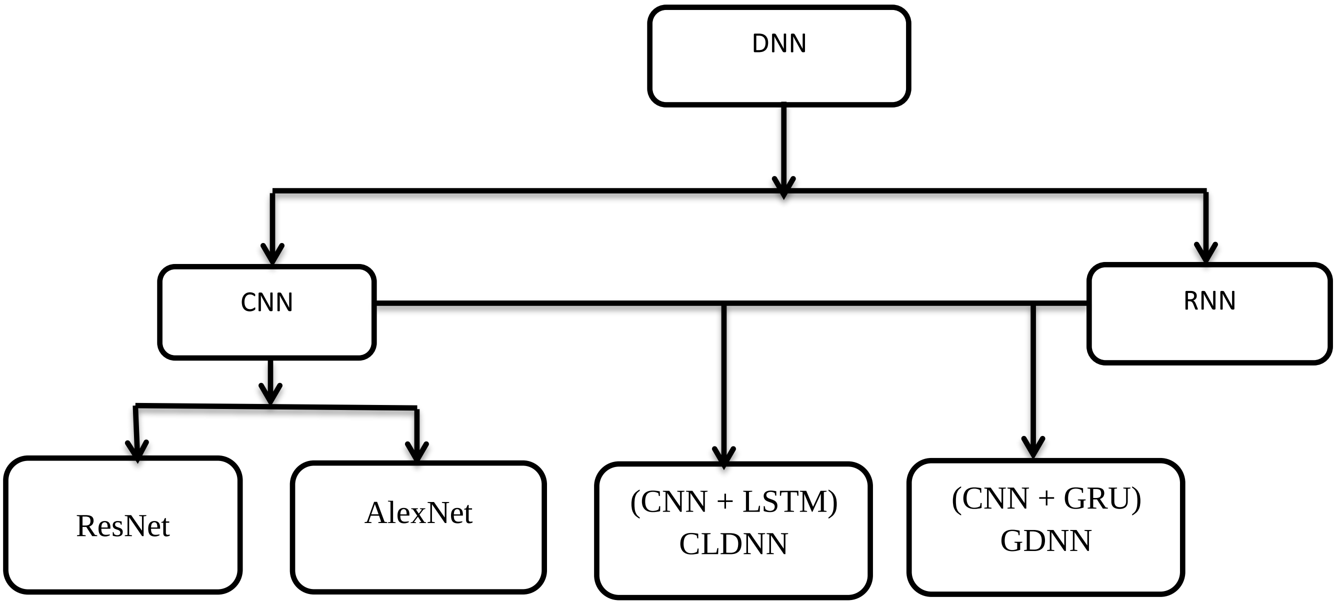


Fig. (2.4). types of the DNN classifiers

a) Convolutional Long- Short Term Deep Neural Network Architecture (CLDNN)

Recently, there are alternative types of neural network architectures with which further improvements to DNN have been obtained, including (LSTM) and (CNN) [49]. The performance of variable signal recognition is thought to be improving by combining CNN and LSTM networks into a unified framework. Its proposed model is a few CNN layers that feed into the input features, and the goal is to reduce spectral variance. Specifically, pass the output of the CNN layer to the LSTM layers. will refer to a CLDNN architecture with these additional connections as a multi-scale CLDNN. The proposed CLDNN architecture in this work uses the same configuration as the CNN model, except that the convolution and max layer has been replaced by the LSTM layer, and the goal is to get better results.

Because they are limited in modeling capabilities when stand-alone. It is possible to predict the outputs in an easy and simplified manner. According to this paper, the third and maximum convolution layers of CNNs have been replaced by the LSTM layer in the proposed CLDNN model in order to provide a fair comparison.

Three LSTM layers have been proposed [50]: a front layer (referred to as FWLSTM), a back layer (referred to as BWLSTM), and a bidirectional layer (referred to as BWLSTM) (referred to as BLSTM). As a result, the layers hidden in the foreground are associated with the next time period, and the layers in the background floor are associated with the previous layer. The back and front layers are combined into a bidirectional layer, which propagates data from the past as well as the future. After the final convolution layer, the output is resampled into a series of vectors and each vector represents the extracted feature for the corresponding time step in the LSTM layer. For FWLSTM and BWLSTM, 256 hidden nodes are used, and the output of the last time step is sent to the fully connected layer. The final output from both forward and backward directions is combined by BLSTM and sent to the next layer.

For the proposed CLDNN model, the LSTM layer only sends the output of the last time step to the fully connected layer for classification, which summarizes all the information about the previous time steps. In identification tasks, the memory properties inherent in the CLDNN lead to temporal correlations in the input signal, which can be exploited to identify patterns**.**

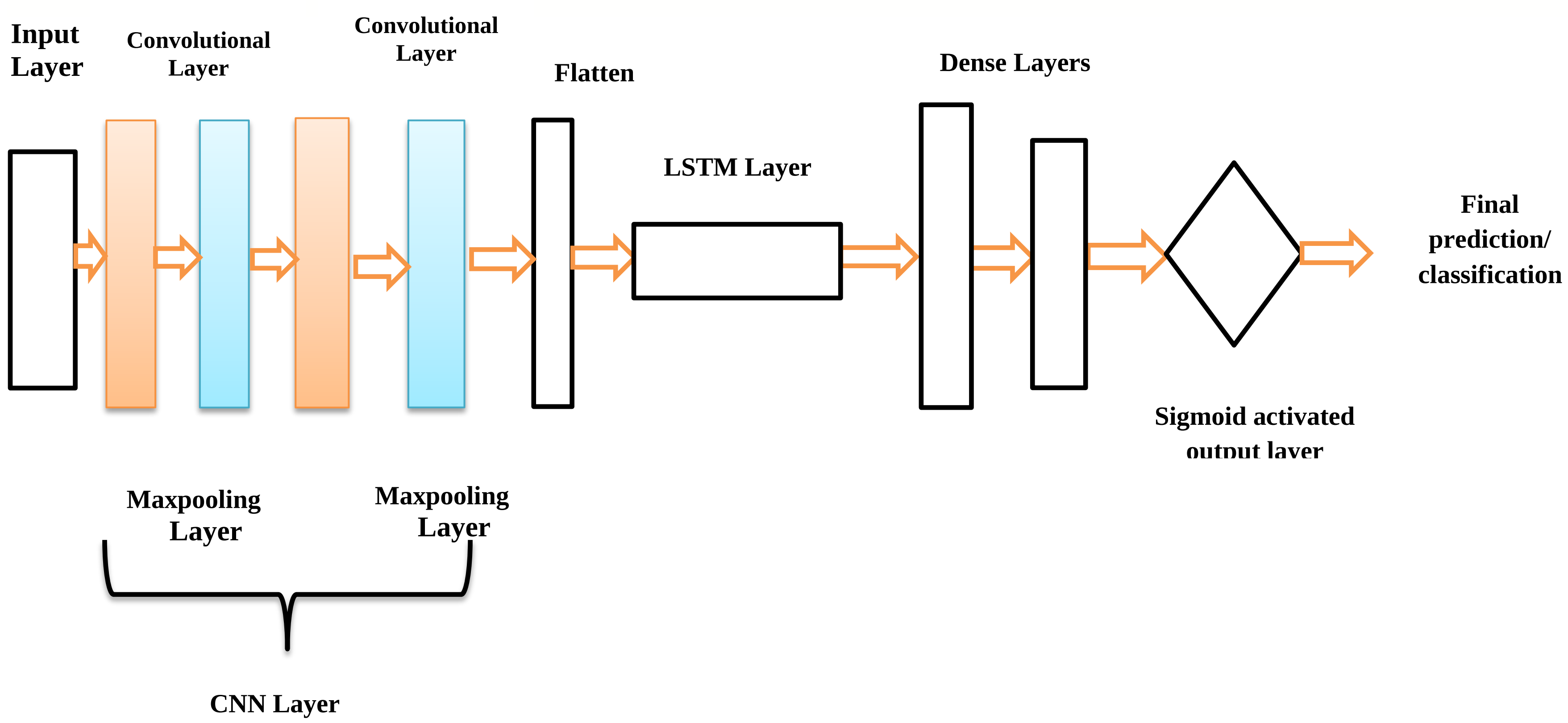


Fig. (2.5) the general diagram of the (CLDNN) architecture

b) AlexNets(2012) architecture

AlexNets was developed in 2012 by by Alex Krizhevsky and his colleagues.it is one of the newer CNN architectures, and is considered a simple model. It has a contribution huge to computer vision with its large and deep architecture. It can be skillfully improved and trained. When compared to other profound and complex CNN architectures (GoogLeNet, VGG, etc).

Through which it is possible to classify quickly and get satisfactory results [51]. A new paradigm in computer vision was established when this network revealed for the first time that characteristics learned via experimentation may overrule those created deliberatel. However, the properties of the current pre-trained AlexNet architecture are restricted, because of the multi-domain property of semantic scenes defined with native objects, so the AlexNet architecture must be pre-trained optimized, to obtain a good classification performance. Large and complicated datasets (RML) can aid in the development of a well-trained AlexNet architecture, and well-trained network parameters are critical for the initialization of the subsequent classification framework. As a result, the pre-training process aids the AlexNet architecture in successfully completing the signal categorization task.

The Alexnet includes eight layers , each with its own set of parameters that may be learned. The model comprises of five layers, each of which uses Relu activation, with the exception of the output layer, which uses a combination of max pooling and three fully connected layers Figure (2.6) shows the general architecture of AlexNets model.

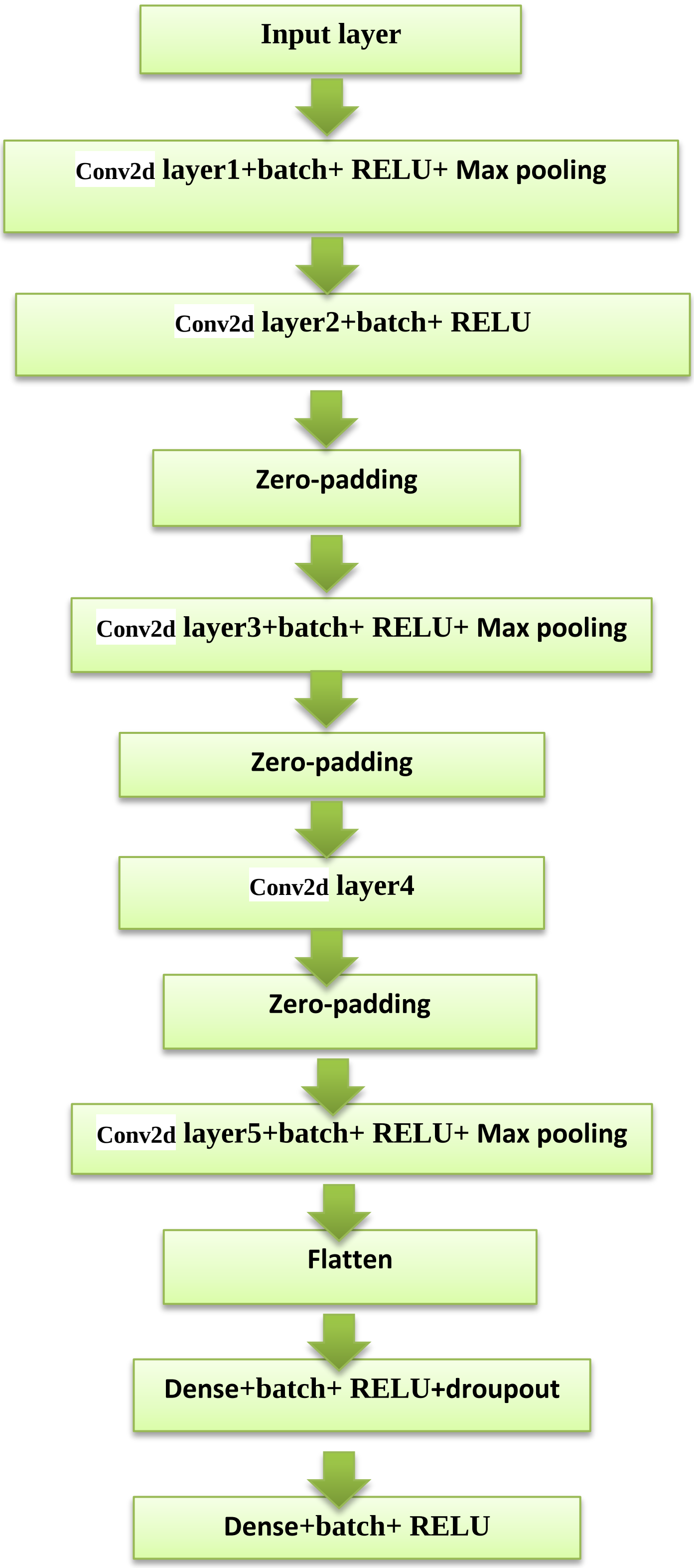


Fig. (2.6) the architecture for Alexnet model

c) Residual Network(2015) architecture (ResNet)

Residual Network was developed in 2015 by Kaiming He et al. Used to distinguish between different modulation signals greatly use very deep models. But the working team of this architecture found that it did not get good accuracy when the depth was increased significantly, and the reason was because of the problem of deterioration. So they developed it, which may help solve the problem. Also, in order to balance the computation between the internal model networks, carefully re-adjust the size of the layers Figure (2.7) shows the proposed structure of the ResNet model [52].

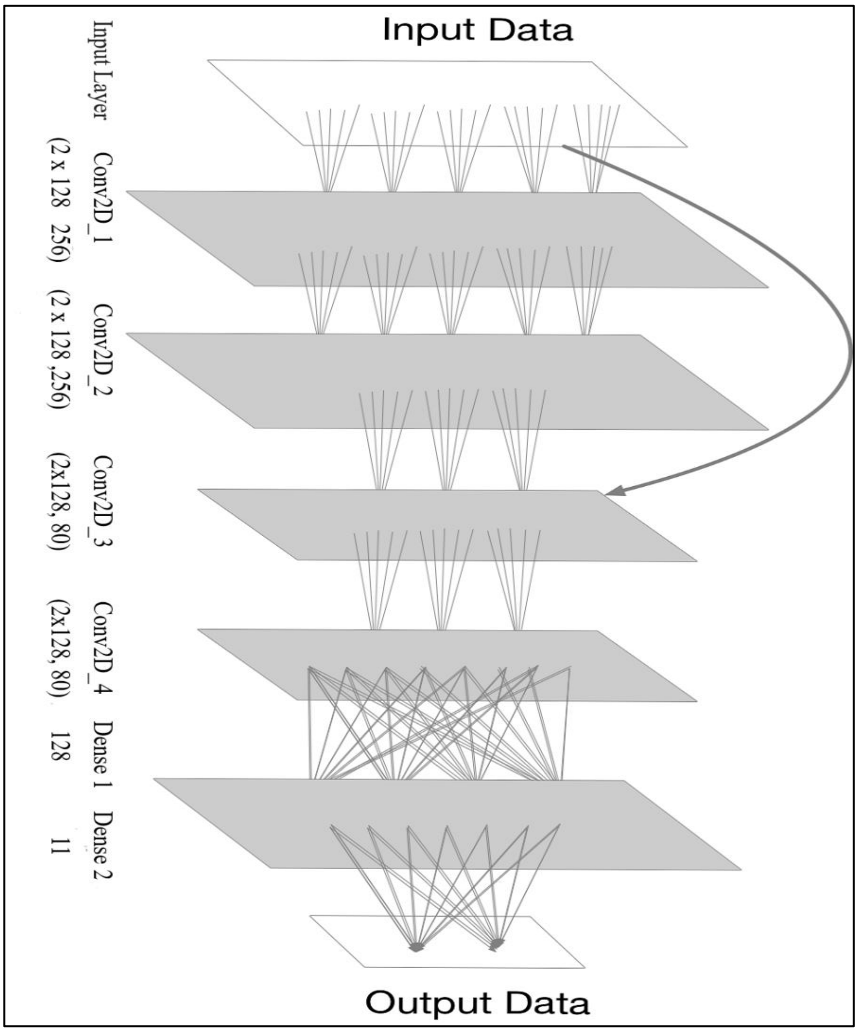


Fig. (2-7) the proposed architecture for ResNet's model

d) The Gated Recurrent Unit- Convolutional Neural Network GRU-CNN (GDNN) Architecture (2014):

The Convolutional Deep Neural Network architecture (2014) (CNN + GRU = GDNN) is a combination of CNN and GRU. GRU in recurrent neural networks, presented by K. Cho et al. 2014 is one of the core algorithms of Recurrent Neural Network (RNN) that saves its input due to internal memory, which makes it well suited for machine learning problems.

A gated recurring module is a variant of the RNN design that uses a gated process to control and manage the flow of information between cells in neural networks. The GRU makes it easy to capture dependencies from large sequential data without excluding information from the previous part of the data series. These gates control what information must be disposed of or retained at each step. Although RNNs are very powerful, they have the problem of short-term memory. For a long data series, RNN has trouble transferring data from the previous steps to the later steps. Therefore, if a paragraph of the text is processed to complete the predictions, there is a possibility that the RNN will leave out important information from the start. Since RNN is prone to gradient fading problems where gradients are used to update the weights of neural systems. Thus, in RNN, if the previous level gets the lowest gradient, it stops learning. Since these layers do not learn, the RNN can fail to remember what was tested in a long data chain and thus encounter short-term memory. GRU also uses gates like LSTM, but there are only two gates in GRU which are update gates and reset gates [53]. In the figure (2.8), the general scheme of the hybrid algorithm is shown

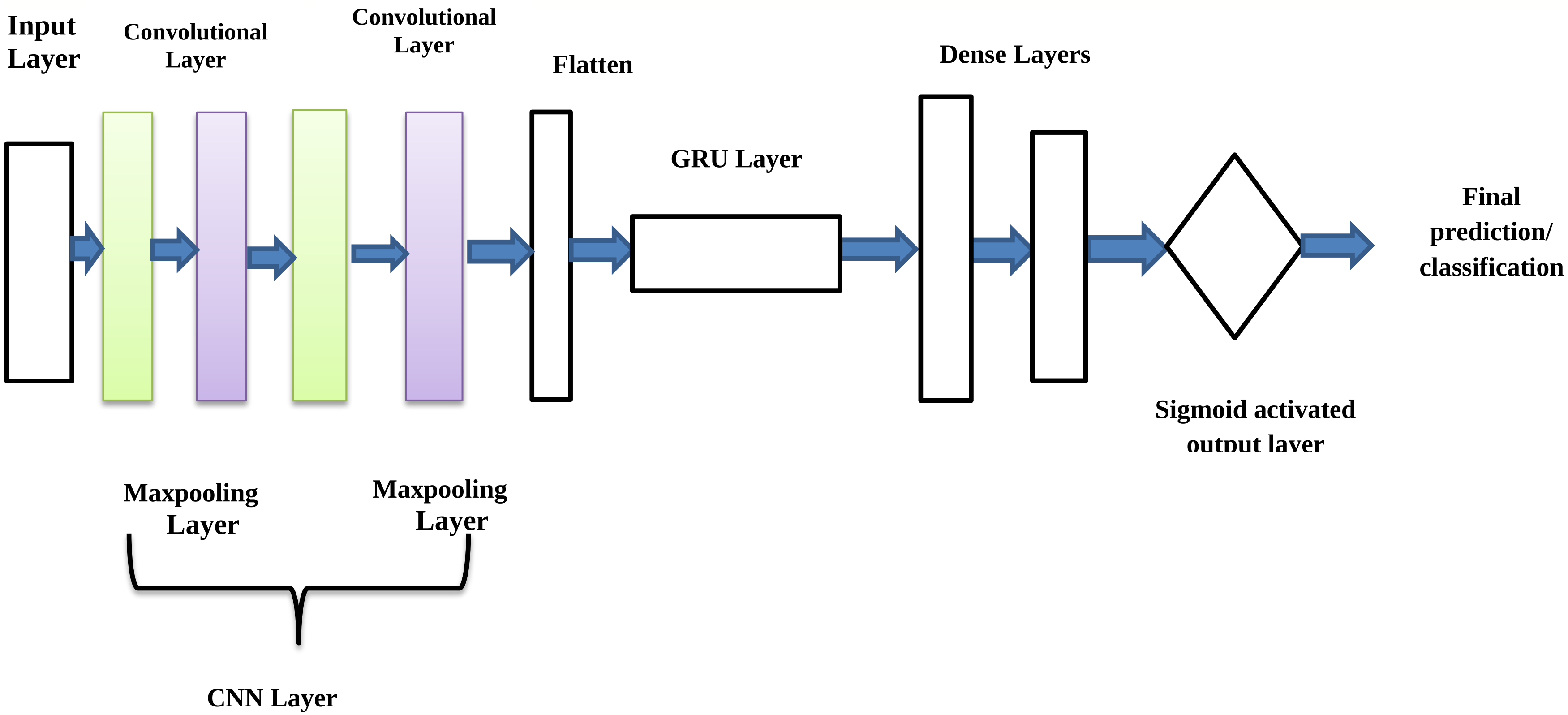


Fig. (2.8) the general diagram of the (GDNN) architecture

2.4.2 Artificial Neural Network (ANN)

An ANN classifier is a popular method for analyzing data (AMR). These grids are aimed to help you identify trends. It's important to note that these networks establish numerical patterns that must be translated into all real-world data, such as pictures, sound or time series. ANNs are used to categorize and identify objects.

Advantages of ANNs are improved accuracy, lower computing complexity, and a greater classification rate. Using a high number of input features and any tiny data set that demands a considerable training period for the calculation are useless with this method [54].

Machine learning and learning are facilitated by artificial neural networks, which are activated by the central nervous system. It is common for ANNs to include several levels (such as an input layer, an output layer, and many of layers in between). Each layer has several of nodes, or neurons, that resemble the human brain's processing methods. Weights are used to connect nodes in the previous layer to each other in the following layer. The prior presence of training data can distinguish between unsupervised neural networks and supervised neural networks for learning purposes [40, 55]. Weights are responsible for correlating inputs with outputs.

The artificial neural network collects the data stream into several training sets in unsupervised networks. While there are certain drawbacks to using artificial neural networks, they are regarded as the best classifiers when compared to alternative options.

2.4.3 Decision Tree (DT)

DT is an unsupervised learning classifier that employs a tree-like model to determine actions and the ramifications that may result from them (i.e. modification scheme type).

With the except for leaf nodes, DT classifiers are binary classifiers, which means that each node contains two sub-nodes. The decision-making process begins at the root node and proceeds to the leaf node in order to determine the precise modulation format. When not enough training features are employed, the DTC classification accuracy decreases with increasing tree depth (number of leaves). As an AMR classifier, DT makes consecutive decisions based on predetermined thresholds that distinguish between different modifications and different orders. At each step, the choice is dependent on the preceding stage's decision (testing), which is based on preset threshold values that primarily impact total performance.

Multi-class problems are no problem for the DT algorithm. During the DT, a specific characteristic will be evaluated at each stage.

By adding new branches to the tree, each subsequent change results in a new resolution. As a result, DT is a simpler option with comparable results to PR. The design and optimization phases of the DT process, on the other hand, are time demanding [56].

DT is rated as

1-Fine Tree Classifier (FTC).

2-Medium Tree Classifier (MTC).

3-Coarse Tree Classifier (CTC).

2.4.4 Support Vector Machine (SVM)

The SVM is a which is a machine learning technique used for classification. Low signal-to-noise ratio (SNR) SVMs are able to resolve redundant structures. As previously mentioned, non-linear feature mapping is accomplished in SVMs by employing kernel functions. These include the radial basis function, multilayered cognition, and polynomial functions. Multi-layer classification is a common usage for SVMs, particularly with classification. Structural risk reduction is the foundation of SVM.

A quadratic convex programming problem with linear constraints could be turned into its ultimate solution. You don't have to worry about the "local minimum". For high-dimensional data, the linear SVM may be easily extended to the non-linear SVM by inserting the kernel function. The techniques used for such cases are either.

First, SVMs are used to classify the first class from the rest of the classes and then re used to classify the second class from the remainder. This process continues until all of the classes have been classified.

Second, Multiple Class Support Vector Machine (MSVM): higher dimensional space used. According to some research, the SVM classifier faces many challenges, including computationally expensive costs, computational complexity, etc. [32, 57].

2.4.5 K-Nearest Neighbors (KNN)

Simple and non-parametric, the KNN classifier does not require knowledge of the distribution of data. "Training" and "Testing" are two of his most important concepts; they are used interchangeably in the context of their work. It has computed how far the test sample is from a class in a training sample that is being tested. Besides to the fact that the method is computationally intensive, the nonparametric learner, and the laziest learner, KNN has several of other drawbacks [58].

2.5 GNU Not Unix (GNU) Radio

Initially, it was a branch of spectra project, but in 2004, it was fully redone. It is no longer necessary to have any spectra code. As of today, GNU Radio is a GNU package3. GNU Radio is a set of open source tools for building software radios that do their entire signal processing in software. Hardware may be changed to perform many tasks at the same time, enabling it to be tailored to the specific needs of each application[62].

Flexible radio systems that are multi-service, multi-standard, multi-band, and software-configurable and re-programmable are the goals of GNU radio, a novel technology. In the future, software systems will be used in a wide range of applications because of their adaptability and flexibility. Signal processing blocks may perform a wide range of functions in GNU Radio. When appropriate, processor floating-point extensions are used to implement the specified performance-critical signal processing path in C++. GNU Radio apps are often written in the Python programming language.

As a result, the developer may design real-time, high-throughput radio systems in a user-friendly, rapid-development environment. System designers like it because of its flexibility and capacity to operate in a variety of modes. If the program provided with control blocks that are possible, GNU Radio applications might be extended to control and monitoring systems as well[63].

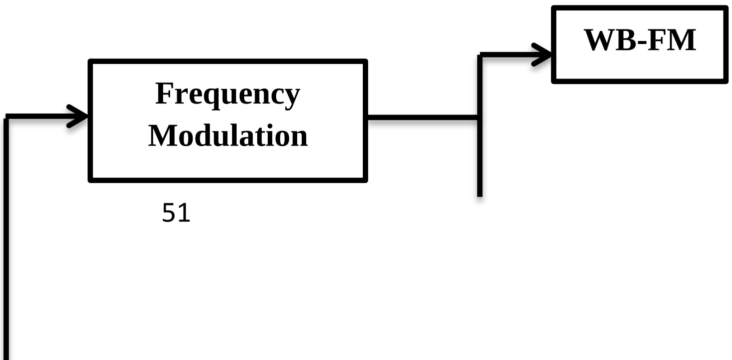
2.6 Signal Modulation

Analog and digital signal modulation types and modulations fall into two categories [59]: analog and digital. A graphic depicting many types of modulations, as well as sub-types of analog and digital modulations, can be found. As shown in Figure (2.9).

2.6.1 Analog Modulation Techniques

Analog modulation systems are divided into two categories:

Amplitude Modulation (AM) and Frequency Modulation (FM), each of which has a wide range of Sub-classes.



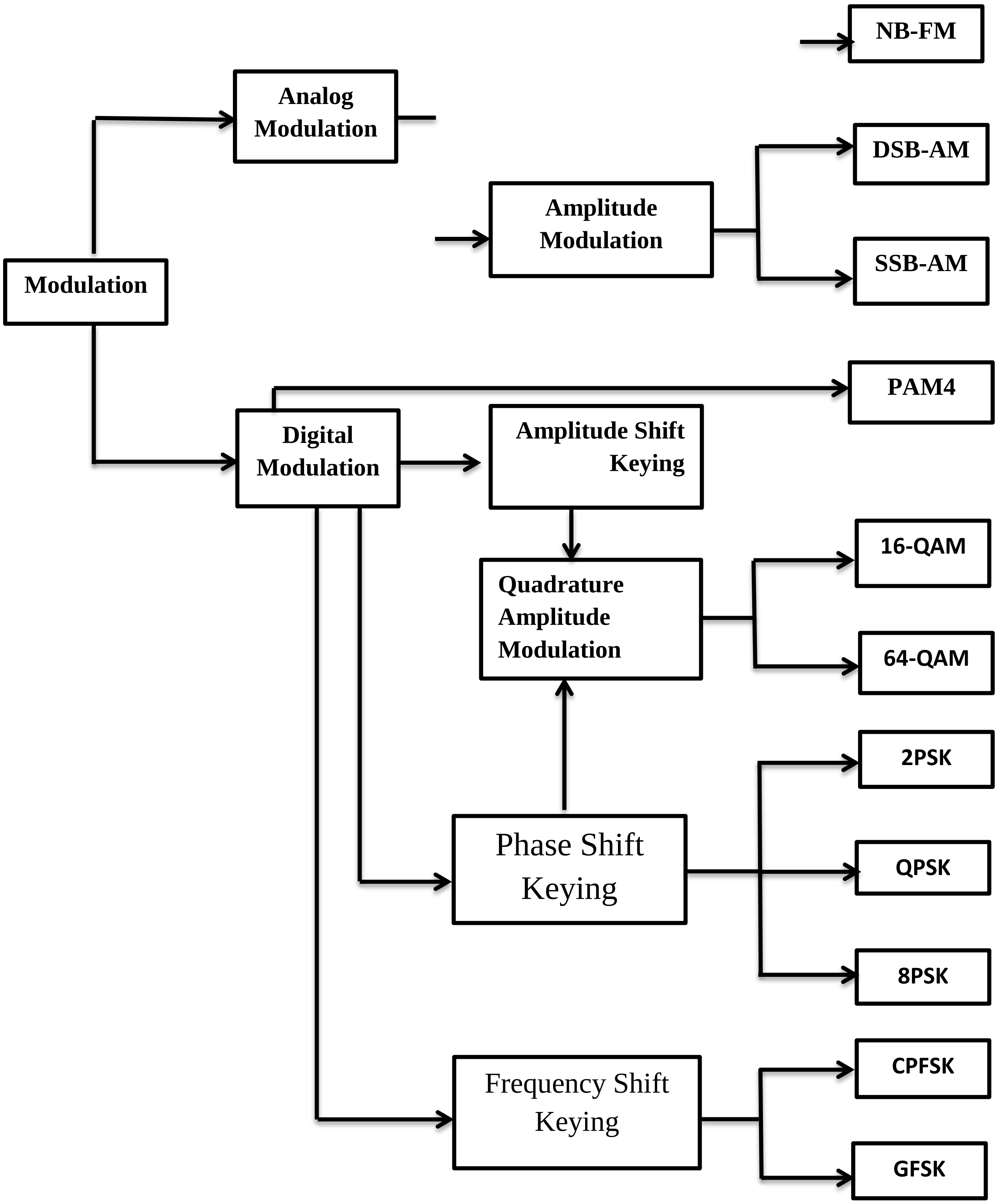


Fig. (2.9) the diagram Signal Modulation

The main drawt ıunicating across long channels is that once noise is introduced anywhere along the channel, it persists until the end.

Because analog modulation[64] systems (AM and FM) are highly susceptible to noise at the receiver end, When a digital signal is modulated and transmitted, however, the received signal is significantly less sensitive to the receiver. Amplitude modulated signals require nonlinear amplifiers because they generate spurious out-of-band spectral components that are difficult to filter out.

Amplitude modulation Signals are divided into linear and non-linear. AMS requires non-linear amplifiers because they generate spurious out-of-band spectral components that are difficult to filter. Figure (2.10) shows Classification of Analog Modulation Signals.

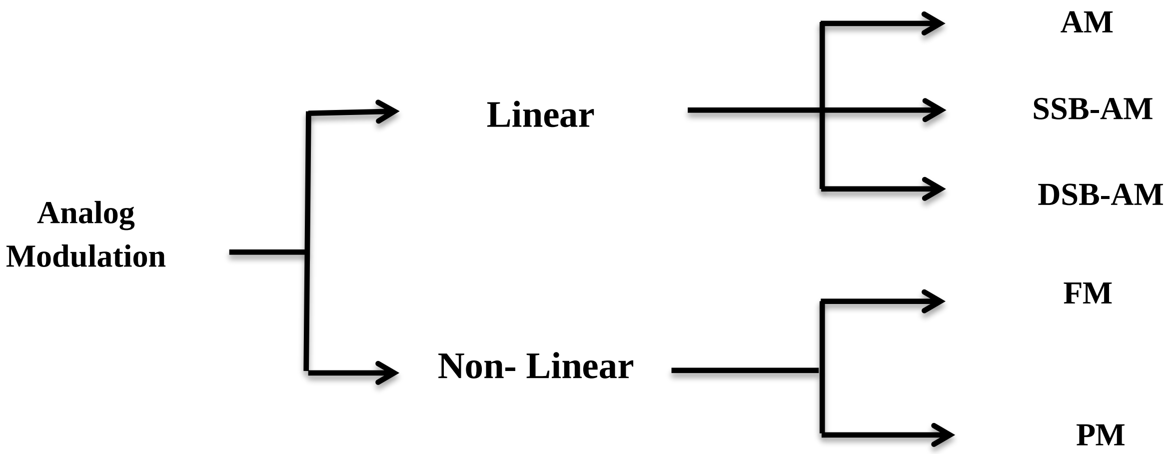


Fig. (2.10) Classification of Analog Modulation Signals

1. Frequency Modulation (FM)

Frequency modulation is altering the wave's instantaneous frequency in order to encode data on it (FM). FM technology is widely used in computer, telecommunications, and signal processing. Here is a diagram of the signal's waveform.

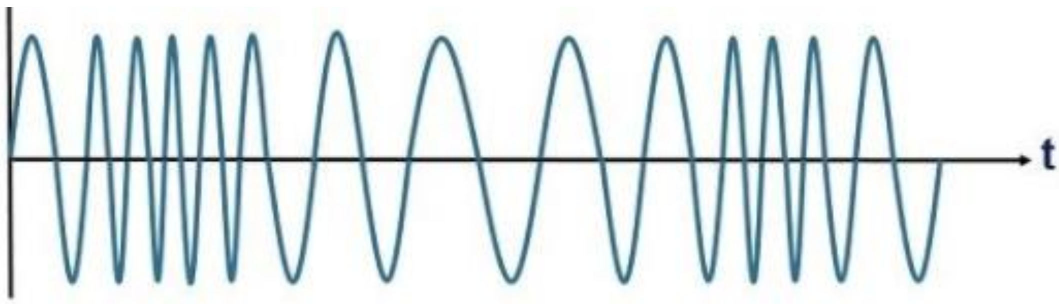


Fig. (2.11) FM signal shape

While keeping the same amplitude and phase as the modulating signal, Frequency Modulation modulates its carrier wave frequency in response to the modulating signal's current amplitude. Data or information might be sent across short distances by altering the carrier wave frequency[65].

2. Double-sideband Amplitude Modulation (DSB-AM)

Double-sideband suppressed-carrier amplitude modulation (DSB-SC) uses just two symmetrical sidebands with no carrier band. to make the most of the sideband power in an ultrasonic application, this technique was devised. For the HF2LI and the UHFLI Lock-in Amplifiers, the MOD option provides a straightforward means of generating DSB-SC modulation.

One of Zurich Instruments' most notable features is the ability to make directly synthesize and demodulate the sidebands of an audio signal using just the frequency of the carrier and its modulation. It supplied carrier frequency and modulation but not the sideband frequencies, which should be observed (the distance between carrier and sideband). This has far-reaching consequences:

i. You may simply sweep the modulation frequency for Bode displays, for e xample.

ii. The phase relationship between the two sidebands is always known. Because they were generated by the same oscillator.

iii. A PLL, for example, may adjust the carrier and modulation frequencies while maintaining constant phase relationships [66].

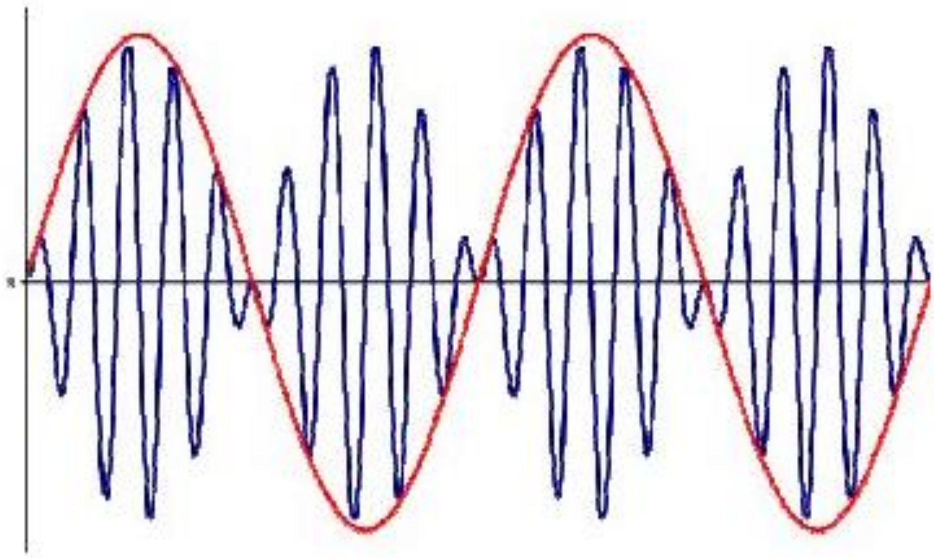


Fig. (2.12) Carrier amplitude modulated signal with two suppressed sidebands

3. Single Side-band Amplitude Modulation (SSB-AM)

The predominant modulation style used for analogue speech transmission for two-way radio communication on the HF region of the radio spectrum is single sideband modulation, or SSB. When compared to other modes, it is the most efficient in terms of spectrum and power, hence it has been the most popular option for many years. Although various versions of digital voice transmission are now in use, it is doubtful that single sideband will be phased out as the primary format on these channels for many years [67].

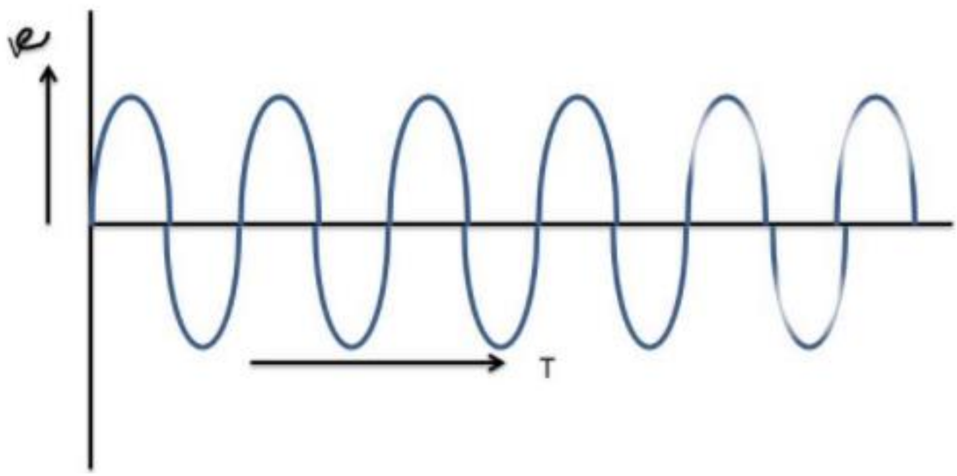


Fig. (2-13) SSB-AM signal shape

2.6.2 Digital Modulation Techniques

Digital Modulation can be defined as the process of encoding a digital signal that contains information about the amplitude, phase and frequency of the carrier signal. In general, modulation technology encodes several bits into one code.

After converting an analog signal to digital by sampling, multiple types of digital modulation schemes may be created by varying different parameters of the carrier signal, such as amplitude variation for BASK, frequency variation for BFSK, and phase variation for BPSK, for example. A combinational change of this parameter, i.e. a combinational variation of amplitude and Phase Shift Keying, is occasionally used to develop the hybrid modulation approach (APSK). Depending on the signal and the application, many different digital modulation methods are available and may be devised [68].

1. 2Phase Shift Key (2PSK)

Phase-shift keying, often known[69] as PSK, is a digital modulation technique. With of modulation including periodic signal properties such as phase, this procedure is referred to as "keying." Discrete phase shifts in the carrier wave are used to carry the data. The number of revisions is a function of chance and is based on a factor of two used to distinguish between several forms of PSK modulation, such as BPSK and its DBPSK variation, and QPSK and its DQPSK variant, among others.

2. Quadrature Phase Shift Key (QPSK)

Four phase shift values of –45°, –135°, +45°, or ++135° have been[70] used in QPSK modulation (Quaternary Phase Shift Keying), which is expressed as two bits in binary code: 00, 01, 11, or 10.The graphic depicts a constellation diagram for QPSK modulation with four points. Two bits are used to encode each constellation point.

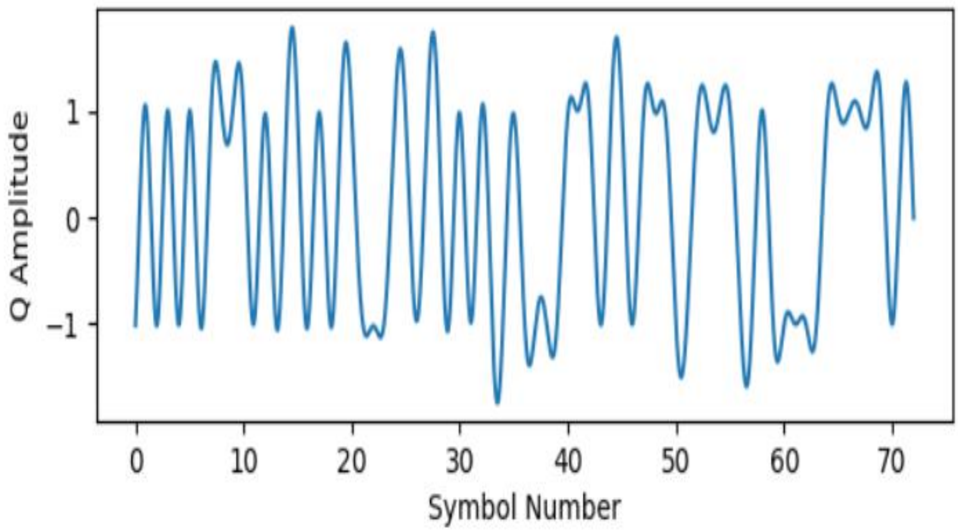


Fig. (2-14) QPSK signal shape

3. 8Phase Shift Key (8PSK)

This is an eight-state modulation method [71]in which the carrier can be in any of the eight states. Each state can thus represent three bits, ranging from 000 to 111. EDGE use this modulation approach (Enhanced Data rates for Global Evolution).

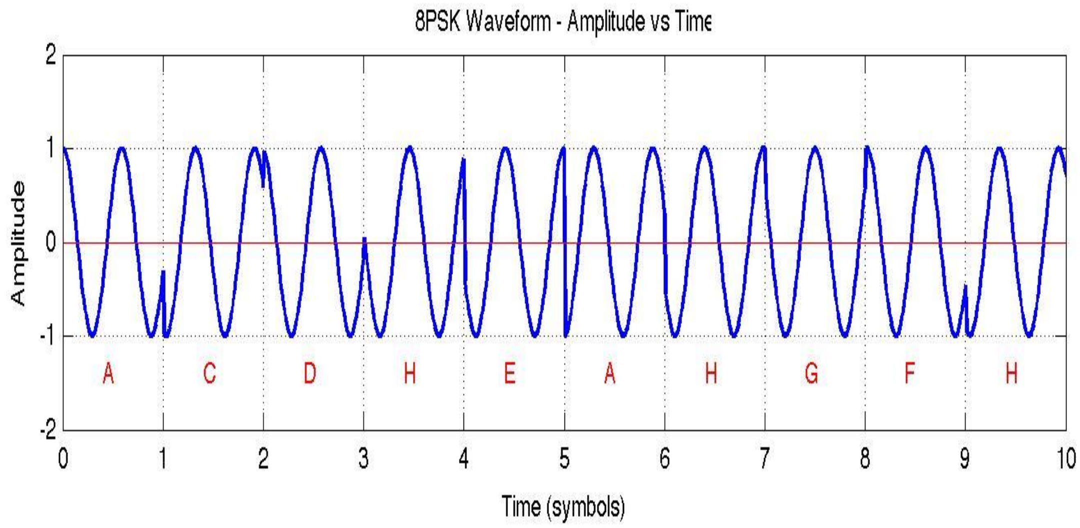


Fig. (2-15) 8PSK signal shape

4. Continuous-Phase Frequency-Shift Keying (CPFSK)

Because of its narrow spectrum [72]and ability to increase receiver sensitivity with differential detection, continuous-phase frequency-shift keying (CPFSK) is a potential modulation scheme. Two MZMs are embedded in each arm of a primary modulator to create a CPFSK modulator.

5. Gaussian Frequency-Shift Keying (GFSK)

Frequency shift keying (FSK) using a Gaussian filter [73] before modulation is called Gaussian frequency-shift keying. This limits the spectral bandwidth and out-of-band spectrum, in order to fulfill the criteria for adjacent-channel power rejection.

Fig. (2.16) GFSK shape

6. Quadrature Amplitude Modulation (QAM)

Dual-carrier QAM (Quadrature Amplitude Modulation) employs two carriers that are 90 degrees out of phase regarding to one another to create a signal that may be manipulated or combined. It is derived from the fact that they have a phase difference of 90 degrees that the phrase quadrature is used. The "I" signal refers to the in-phase or "I" signal, whereas the "Q" signal refers to the quadrature or "Q" signal. the entire signal formed by mixing both I and Q carriers contains both amplitude and phase shifts. The presence of both amplitude and phase variations allows it to be categorized as an amplitude and phase modulation combination.

A power of two, i.e. 2, 4, 8, 16, 32, is used to represent the number of constellation points in a grid since digital data is commonly in binary form, with two states of 0 and 1. Most common QAM forms include 16-QAM, 32-QAM, 64-QAM, and 128-QAM. 256 QAM is the least common.

i. The carrier signal will be modulated into one of sixteen potential phase and amplitude states in 16 QAM.
ii. A total of 64 QAM in 64 QAM, the carrier signal might be modulated into any of 64 distinct phase and amplitude states [74].

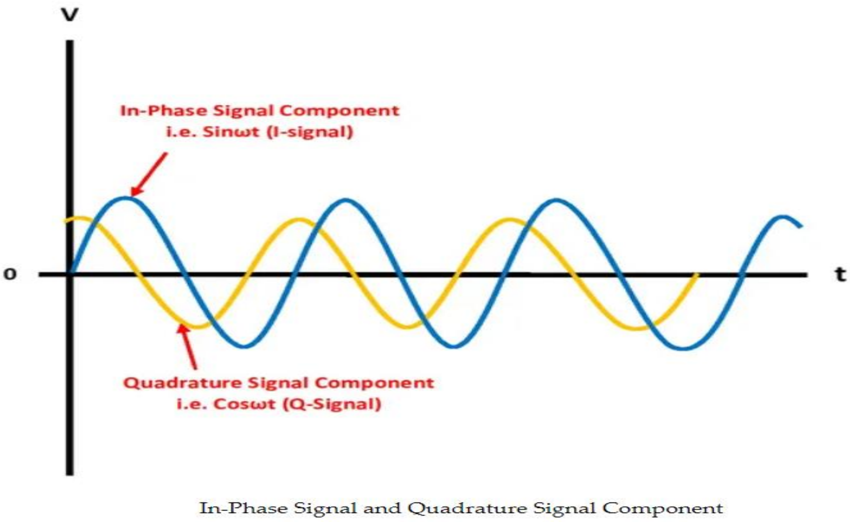


Fig. (2.17) QAM signal

7. Pulse Amplitude Modulation4-level (PAM4)

The Pulse Amplitude Modulation 4-level (PAM4) signal modulation format is a multilevel signal modulation format that is used to transfer signals. double bits of logic information can be represented by each signal level. Image 3 shows the three eyes generated utilizing four voltage levels for the PAM 4 eye (00, 01, 11, 10). Eye height is likewise essential in this case, as A covers all three eyes' heights. Larger eye apertures imply a higher signal quality[75].

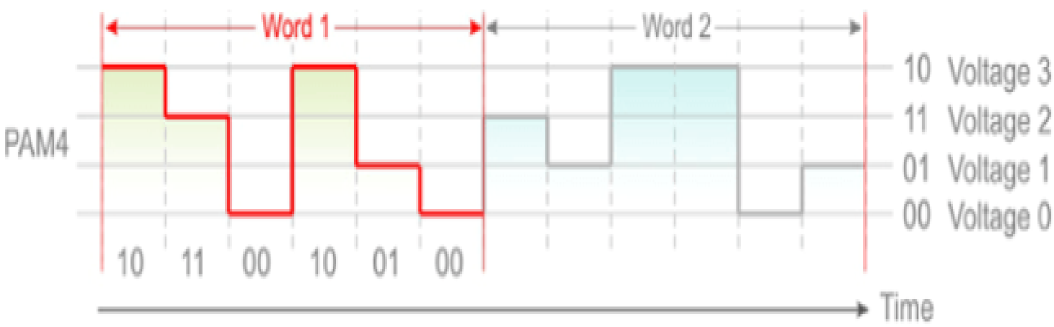


Fig. (2.18) PAM4 Signal

Chapter Three

A Proposed Architecture System

3.1 Introduction

AMR technologies are very important. When it presents, signal analysis and processing can be performed, and modulation can be defined as the process of converting data into radio signals by adding additional information to the electronics. The carrier signal is a signal of constant height, fixed waveform, amplitude and frequency. Modulation technique. The process of converting data into electrical signals optimized for transmission, which are categorized into digital and analog.

Learning algorithms are at the heart of Deep Learning. Basically deep learning is comprised of a network of deep connections Deep networks are just neural networks with numerous hidden layers, which is what they are. In this type of learning deep network is an advantage, it is having multiple hidden layers, which undergo a keen process to get desired output. Increasing the network structure's breadth improves classification performance. The training and validation phases of DL are often separated by a step. If you have a large amount of data, training a deep network is a lengthy and difficult process that requires a lot of computing power. It just takes a few moments for the validation step to finish, in which a data instance is used to check whether or not the trained network can recognize it. The trained network is employed in the actual deployment of the communication system, and this is analogous to the validation step.

DL in general has played a vital role in classifying the signals, especially when the signals are relatively large for example. This contains a wide range of digital and analog signals. DL has the ability to discriminate between such big data, and in recent years, researchers' efforts have focused on classifying signals in these multiple ways, which shown efficiency at work. In this chapter, four models of deep learning modification classification algorithms (AlexNet ,ResNet, CNN-GRU and CLDNN) are based.

3.2 Data Set

In this thesis, a dataset called (RML 201610A) was used that was created in GNU Radio, and contains 11 types of digital and analog modulation. Eight digital signals (CPFSK, PAM4, GFSK, BPSK, QPSK, 8PSK, QAM16, and QAM64) and three analog signals (AM-DSB, AM-SSB, and WBFM) were used.

Table (3.1) no. of modulation used in Dataset of thesis

SNR	The value of samples per signal	Repetition for each one the modulation	No. of modulation in SNR	Repetition of the Modulation in one SNR
0dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
2 dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
4 dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
6 dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
8 dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
10 dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
12 dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
14 dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
16 dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
18 dB	(2 X 128)	1000	11 modulation	11 X 1000 = 11000
	110000 Modulation Repetition in SNR (0 ~ 18) dB			

The data (RML 201610A) contains a huge dataset with different SNRs ranging from (-20~18) dB for even numbers equal to 20 SNR values, each SNR contains 11 modulations mentioned earlier, one modulation is repeated 1000 times, each modulation consists of (128×2) model, the total signal in (RML 201610A) becomes 220,000 signals, for not taking advantage of SNR with negative values are excluded by thesis and only the positive part equals 10 SNR values from (0 ~ 18) dB, which is equivalent to 110000 signals, the table shows below are the details.

3.3 Simulation type

In this thesis, algorithms were implemented for the purpose of classification using a simulation program (Colaboratory Google). It is an extension of the Python programming language, chosen for several reasons.

Including that the code is more concise and readable; Colab can contain many functions in a free and open source file or module that supports data recovery. (Colab) is a project that allows programming without the need for high-spec computers, and its advantages are that there is no need to download libraries such as Keras that support Tensorflow and Matplotlib.

It is a framework based on Python, which makes Keras easy to debug and is an important library when using a DL because it supports all models of neural networks (Fully Connected, Convolutional and Maxpooling). These models can also be combined to build a more complex model, deep learning is sometimes criticized for requiring a great deal of computational power, but in our case the network is compact and the data set is modest. Due to the complexity of many radio systems, training and compilation time are critical issues.

The compilation time with the general Keras model turned out to be much faster than most other models, the reason being to work smoothly with the Graphic Processor Unit (GPU), the benefit of the GPU is to reduce the training time. Figure (3.1a) shows the use case of the GPU during training time. While Figure (3.1b) shows the case when the GPU is not being used, the time difference can be observed.

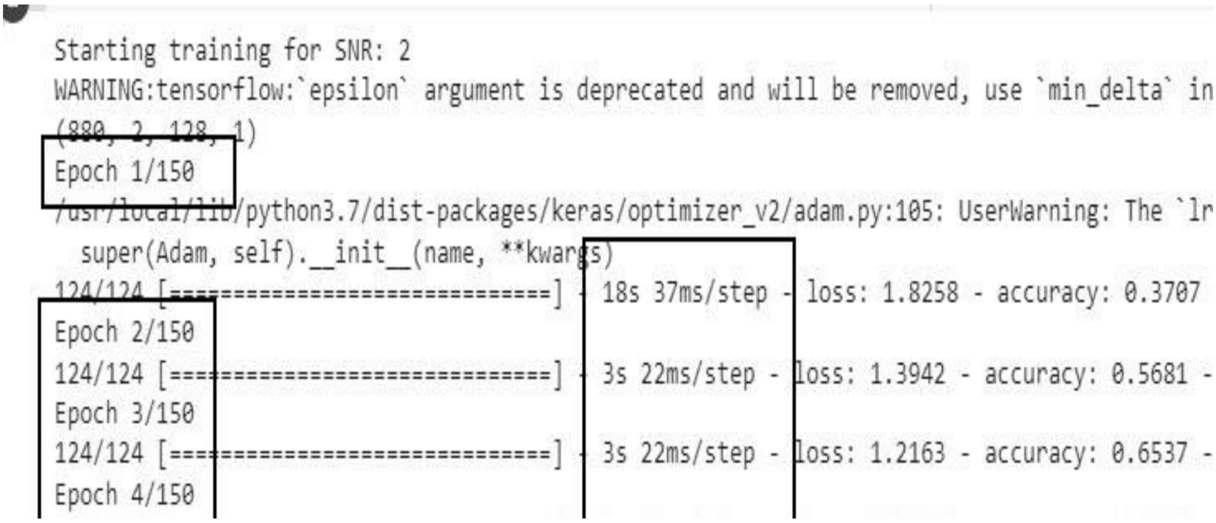


Fig. (3.1 a) using GPU during training time.

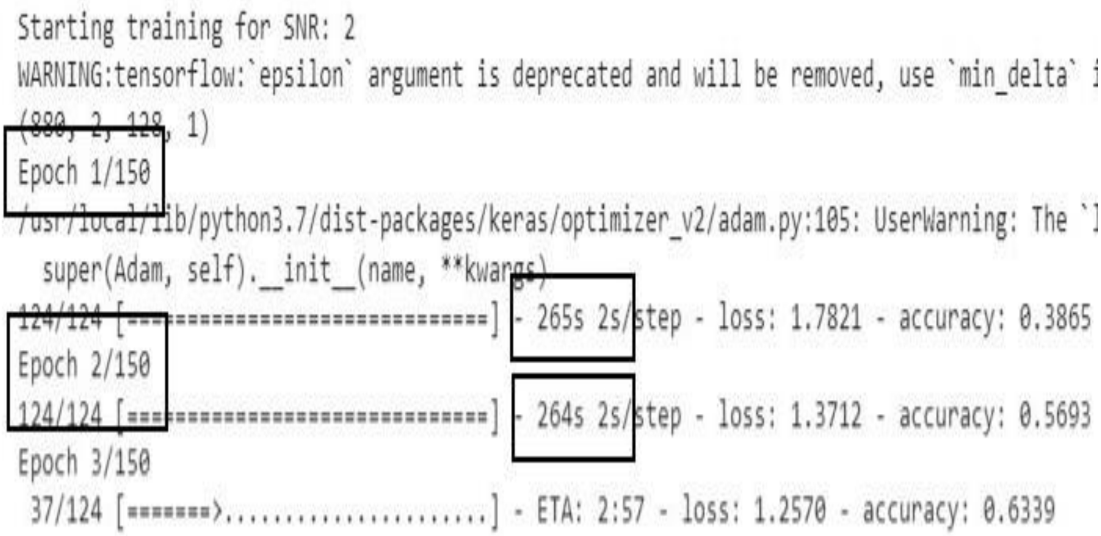


Fig. (3.1b) without using GPU during training time.

Figure (3.1a) shows that the period of one epoch is equal to 18 seconds and 37 milliseconds when using the GPU, whereas Figure (3.1b) shows that the period of one epoch is approximately 4 minutes and 25 seconds when not using the GPU and this difference is significant, so it is necessary to use the GPU to work.

Finally, Colab requires a normal internet connection to perform the required tasks, and generally displays the results using the Matplotlib library. In order to assess the overall effectiveness of each model, we calculate the overall accuracy, check the loss plots during training, and then build a confusion matrix.

3.4 Proposed Method

The method adopted for prediction using deep learning techniques which includes (DNN) and (RNN) derived using flowchart. Though it is necessary to first comprehend the business demand and acquire data in the real world before supplying data in this module.

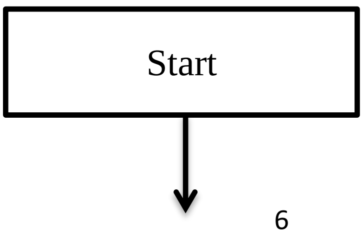
Requirements data to perform the analysis and build a model. The steps involved in building a data model are explained by creating a diagram. The steps involved in building the data model for (AlexNet) Figure shows (3.2) proposed system layout.

a) **Initializing libraries**

To implement the project, download the following libraries:

i. Keras: It is used to implement all neural networks running on both CPUs and GPUs and is an open source library.

ii. Matplotlib: A Python visualization tool used to display graphics and results.



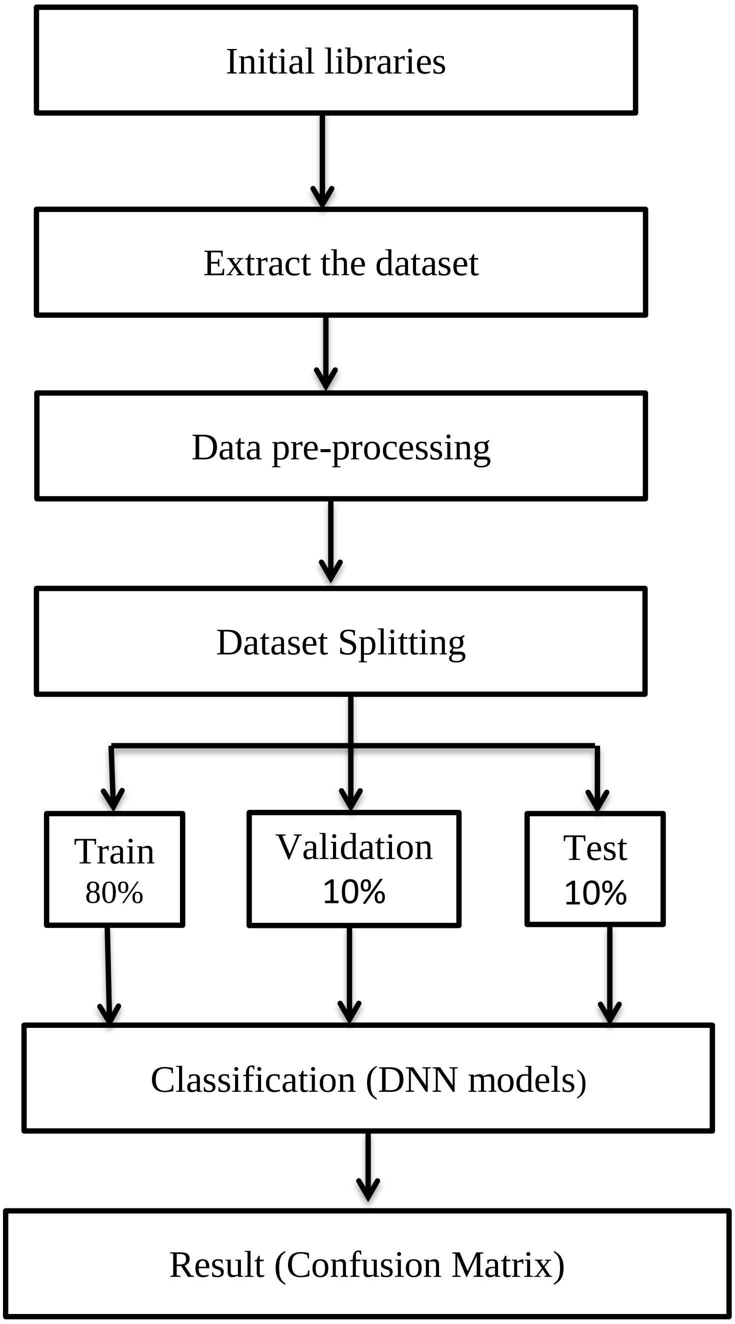


Fig. (3.2) steps of proposed method

b) **Data Set**

i. Keras deep learning library gives direct access to the dataset (RML 2016.10A) with reasonable simplicity, using its dataset module.

ii. The signals within the labeled data set are 11 digital and analog signals, encoding all the labels to binary mode and then read all the data in the file RML2016.10a_dict.pkl then add labels for each type in the array separately.

iii. Adding each SNR in an array separately (so that we have a dictionary of SNR values only).

c) **Data Segmentation**

The data will be (RML 2016.10A) into three parts where 80% of this data is for training, 10% for testing and 10% for validation of work.

d) **Training**

After initializing the data from the file (RML 2016.10A) and preparing it, the training will be in each SNR separately. We train the four models (DNN) used in the project, which contain an SNR ranging from (-18 to 20) dB.

e) **Validation:**

In this stage, the model verifies the data that was trained in the previous step (the training stage) to evaluate the performance of the network at different iterations. In other words, during training, important data such as weights and features are extracted and optimized, and also one of the important things in using validation is to avoid overfitting.

f) **Test**:

At this stage, the model analyzes the performance of the network upon completion of the training, which shows the results. It collects data from our tests for each SNR individually.

3.5 Implementation

In this thesis, four models are proposed for better classification, the (CLDNN, ResNet and AlexNet) models are part of the DNN, and the (CNN-GRU) model is part of the Recurrent Neural Network (RNN). The above models are compared for the purpose of getting a better classified. The four models were executed sequentially, as shown

3.5.1 The Gated Recurrent Unit- Convolutional Neural Network GRU-CNN (GDNN) Architecture:

In the proposed GRU-CNN model, several of single, mixed and deep machine learning models were tried across datasets with different prediction accuracy.

A unique hybrid model based on CNN-GRU. To achieve a flexible and generalized model, multi-layer GRU and CNN features are used to represent the learning sequence. As a result, the tests showed the proposed hybrid model. Remove outliers, missing or overlapping values, and duplicates from the submitted data by preprocessing it. Input data sets were normalized using a number of known procedures. Then, the data is used for training purposes. In the next step, we tested the CNN-LSTM and CNN-GRU neural networks.

The CNN-GRU results inspired us to design a hybrid model integrating CNNs with a multi-layer GRU model, and we obtained updated results. For image classification applications, CNN is optimized for two-dimensional data entry. Time series data can be analyzed using CNNs, but they only work with one-dimensional data. CNN, which excels at solving nonlinear problems, takes advantage of the idea of weight sharing. Table No. (3.2) shows the work steps for the above structure.

Table No. (3.2) shows the work steps of GRU-CCN

```
Model: "GRU-CNN"

Layers (type)                 Output Shape              Parameters
==================================================================
 conv2d_4 (Conv2D)            (Non, 2 ,128,256)          1024

 (MaxPooling2D)               (Non, 2,64,256)            0


 dropout_4 (Dropout)          (Non , 2, 64, 256)         0

 conv2d_5 (Conv2D)            (Non , 2, 64, 256)         393472

 (MaxPooling2D)               (Non , 2, 32, 256)         0


 (Dropout)                    (Non , 2, 32, 256)         0

 (Conv2D)                     (None, 2, 32, 80)          61520

 (MaxPooling2D)               (None, 2, 16, 80)          0


 (Dropout)                    (None, 2, 16, 80)          0

 (Conv2D)                     (None, 2, 16, 80)          19280

 (MaxPooling2D)               (None, 2, 8,  80)          0


 (Dropout)                    (None, 2, 8, 80)           0

 (Reshape)                    (None, 2, 640)             0

 gru (GRU)                    (None, 50)                 103800

 dropout                      (None, 50)                 0

 (Dense)                      (None, 128)                6528

 (Dropout)                    (None, 128)                0

 (Dense)                      (None, 11)                 1419
```

```
=================================================================
Total_parameters: 587,043
Trainable_parameters: 587,043
Non_trainable parameters: 0
```

3.5.2 The Convolutional Neural Network-Long Short Term Memory (CNN+LSTM) CLDNN Architecture:

The newly proposed CLDNN integrates CNN and RNN into a deep neural network, using its integration ability. The LSTM module is an RNN memory module that uses the forget gate in its memory cell to improve the gradient end problem of RNNs. Feature extraction and dimensionality reduction performed by convolutional layers with aggregation in CLDNN architectures result in significantly shorter representations of high-level features. To determine the long-term temporal correlation of the different modulation types, the shorter sequences are sequentially fed into subsequent LSTM layers.

There are 80 convolutional layers and 50 LSTM layers in the third and fourth layers, respectively. The content of the final thick layer is represented by class 10 neurons, whose lines are altered. The ReLU activation functions are used in the convolutional and LSTM layers, while the softmax is used in the final dense layer. As a result, he was not able to replicate their results and compare them with ours. Finally, a CLDNN architecture with long-term memory modules is introduced. For the most part, CLDNNs are used in audio processing tasks that involve unprocessed time domain waveforms. This system (DNN) consists of LSTM, CNN, and deep neural networks. In our architecture, four convolutional layers follow an LSTM layer with 50 compute units and two fully connected DNN layers, for a total of eight convolutional layers. CLDNN designs with different numbers of memory cells in the LSTM layer were examined to find the best one. Compared to other layer configurations, the 50-cell LSTM layer provides the highest resolution. Table No. (3.3) shows the procedures followed in their implementation.

Table (3.3): the work steps of CLDNN

Model: "CLDNN"

Type Layer	Shape Output	Parameters
Conv2D	(None, 2, 128, 256)	1024
(MaxPooling2D)	(None, 2, 64, 256)	0
dropout_21 (Dropout)	(None, 2, 64, 256)	0
conv2d_22 (Conv2D)	(None, 2, 64, 256)	393472
max_pooling2d_16 (MaxPoolin g2D)	(None, 2, 32, 256)	0
dropout_22 (Dropout)	(None, 2, 32, 256)	0
conv2d_23 (Conv2D)	(None, 2, 32, 80)	61520
max_pooling2d_17 (MaxPoolin g2D)	(None, 2, 16, 80)	0
dropout_23 (Dropout)	(None, 2, 16, 80)	0
conv2d_24 (Conv2D)	(None, 2, 16, 80)	19280
max_pooling2d_18 (MaxPoolin g2D)	(None, 2, 8, 80)	0
dropout_24 (Dropout)	(None, 2, 8, 80)	0
reshape_2 (Reshape)	(None, 2, 640)	0
lstm_1 (LSTM)	(None, 50)	138200
Dropout	(None, 50)	0
Dense	(None, 128)	6528

```
Dropout                     (None, 128)            0

 Dense                      (None, 11)             1419

=================================================================
Total parameters: 621,443
Trainable parameters: 621,443
Non_trainable parameters: 0
```

3.5.3 The Residual Network (ResNets) model:

The ResNets model is part of CNN; we implement the architecture with an increasing number of convolutional layers up to 7. Since ResNets can have variable sizes, depending on the size of each layer of the model, and the number of layers it contains, so we will illustrate the steps for this model. In Figure (3.4), we see that the seven ResNet layers consist of an input layer followed by four convolutional layers where each layer contains a dropout, followed by two dense layers 1 and 2 where the output of dense layer 1 is changed from 4096 to 128 and the density of layer 2 changes from 1000 to 11 To fit the signals used. The output of the first layer is redirected to the layer with deeper levels. Based on this design, the issue of gradient fading is mitigated to the greatest extent possible by enabling all of the few stacked layers to fit the remaining mapping. Using rudimentary CNN architectures, we observed that bigger filters near the input layer were followed by smaller filters near the output layer, resulting in a considerable increase in accuracy. The hyper parameters were chosen according to this discovery. A breakdown of the ResNet architecture's work stages is shown in Table No. (3.4).

Table (3.40 shows the work steps of the ResNet's architecture.

```
(None, 128)
```

```
(None, 11)
Model: "model_1"
________________________________________________________________________________
______________________________
 Layer (type)                   Output Shape          Parameters
Connected to
================================================================================
==============================
 input_2 (InputLayer)           [(None, 2, 128, 1)]  0            []

 conv2d_29 (Conv2D)             (None, 2, 128, 256)  1024
['input_2[0][0]']

 dropout_33 (Dropout)           (None, 2, 128, 256)  0
['conv2d_29[0][0]']

 conv2d_30 (Conv2D)             (None, 2, 128, 256)  393472
['dropout_33[0][0]']

 add_1 (Add)                    (None, 2, 128, 256)  0
['input_2[0][0]',

'conv2d_30[0][0]']

 conv2d_31 (Conv2D)             (None, 2, 128, 80)   61520
['add_1[0][0]']

 dropout_34 (Dropout)           (None, 2, 128, 80)   0
['conv2d_31[0][0]']

 conv2d_32 (Conv2D)             (None, 2, 128, 80)   19280
['dropout_34[0][0]']

 dropout_35 (Dropout)           (None, 2, 128, 80)   0
['conv2d_32[0][0]']

 flatten_3 (Flatten)            (None, 20480)        0
['dropout_35[0][0]']

 dense_14 (Dense)               (None, 128)          2621568
['flatten_3[0][0]']

 dropout_36 (Dropout)           (None, 128)          0
['dense_14[0][0]']

 dense_15 (Dense)               (None, 11)           1419
['dropout_36[0][0]']
```

3.5.4 AlexNet Models:

AlexNet consists of eight basic layers, five convolutional layers and three fully connected layers, each of which includes specific operations such as batch organization and aggregation (ReLU). The nonlinear ReLU layer technology and the dropout technology are just two examples of the practical tactics that have contributed to AlexNet's success.

ReLu is a non-linear activation function that is used in multi-layer neural networks or deep neural networks. With the ReLU activation function, large network models can be trained more quickly and with better results. the training phase can be greatly accelerated while still preventing overfitting, With the half-wave rectifier function shown in equation (1).

$$F(x) = \max(0,x) \qquad \text{..............................(2)}$$

where x = an input value

According to equation 1, the output of ReLU is the maximum value between zero and the input value. An output is equal to zero when the input value is negative and the input value when the input is positive. Thus, we can rewrite equation 1 as follows:

$$F(x) = \begin{cases} 0, \text{ if } x < 0 \\ x, \text{ if } x >= 0 \end{cases} \qquad \text{........................ (3)}$$

where x = an input value

AlexNet layers contain a layer of batch normalization by adding an additional layer to the neural network that processes inputs from the previous layer; batch normalization reduces the effect of gradient neural networks that are inherently unstable. The input values are first calibrated and standardized, and then converted using scale and change operations. Clusters of nearby neurons are summarized in the same kernel map by the pooling layers in AlexNet and as a more accurate description, the pooling layer can be thought of as a network of pooling units.

For fully linked AlexNet layers, the dropout strategy was used to limit the joint neural adaptations by reducing the number of randomly hidden neurons or neurons to zero. A neuron is lost from the network with a 0.5 percent chance during the dropout. Neurons are no longer involved in forward or reverse propagation after their prediction. For each input, the neural network architectures are given in the graphic below. Thus, the likelihood of tampering with weight gain factors is reduced.

Entering and normalizing image data into a one-dimensional array is how the normalization layer works. There are random units / neurons embedded within the thick layer. Each neuron has its own unique character. For a well-trained AlexNet, it is necessary to have a large and complex dataset (RML) and well-trained network parameters in order to start a classification framework. Thus, the AlexNet architecture is able to accomplish the signal classification function more effectively due to the pre-training method. The number of outputs in layer 8 has been reduced from the usual number 1000 to 11, which means that the number of modification types in our work is now equal to the number of outputs in layer 8. Table (3.5) shows the details of the design development process.

Table 0.5) shows the work steps for the AlexNet architecture

```
Type Layer                    Shape Output              Parameters
=================================================================
 Conv2D                           (None, 2, 128, 96)        11712
```

Batch normalization	(None, 2, 128, 96)	384
activation	(None, 2, 128, 96)	0
max_pooling2d	(None, 1, 64, 96)	0
conv2d	(None, 1, 64, 256)	614656
Batch Normalization	(None, 1, 64, 256)	1024
activation_1 (Activation)	(None, 1, 64, 256)	0
zero_padding2d (ZeroPadding 2D)	(None, 3, 66, 256)	0
conv2d_18 (Conv2D)	(None, 3, 66, 256)	590080
Batch Normalization	(None, 3, 66, 256)	1024
activation	(None, 3, 66, 256)	0
max_pooling2d	(None, 1, 33, 256)	0
zero_padding2d_1 (ZeroPaddi ng2D)	(None, 3, 35, 256)	0
conv2d_19 (Conv2D)	(None, 3, 35, 125)	288125
batch_normalization_3 (Batc hNormalization)	(None, 3, 35, 125)	500
activation_3 (Activation)	(None, 3, 35, 125)	0
zero_padding2d_2 (ZeroPaddi ng2D)	(None, 5, 37, 125)	0
conv2d_20 (Conv2D)	(None, 5, 37, 100)	112600
batch_normalization_4 (Batc hNormalization)	(None, 5, 37, 100)	400
activation_4 (Activation)	(None, 5, 37, 100)	0
max_pooling2d_14(MaxPooling2D)	(None, 2, 18, 100)	0
flatten_2 (Flatten)	(None, 3600)	0
dense_8 (Dense)	(None, 60)	216060
Batch Normalization	(None, 60)	240
Activation	(None, 60)	0
Dropout	(None, 60)	0

```
 Dense                       (None, 11)                 671

 Batch Normalization         (None, 11)                 44

 Activation                  (None, 11)                 0

=================================================================
Total params: 1,837,520
Trainable params: 1,835,712
Non-trainable params: 1,808
```

Chapter Four

Result and Discussion

4.1 Introduction

This chapter presents a simulation and discussion of the results of the proposed DNN models that were presented in the third chapter, which is based on a simulation of the four proposed structures to discuss the presented results in addition to knowing the best of them. Due to its ability to learn and extract features automatically, DNN algorithms have been used. the selection, in addition to the general classification, is made based on the facts collected.

Our rating performance is examined in the test data set to assess its performance. DL its sometimes criticized for requiring a lot of computational power, but in our case this network is compact and the data set is modest. due to the complexity of many radio systems, training and classification time are critical issues.

Simulation with Google Colaboratory for several reasons, including Colab Google is more concise and readable, can better support hash dictionary, can have many functions in a file or module, is free and open source and supports data retrieval. The results are generally displayed using the Matplotlib library. In order to assess the overall effectiveness of each model, create a confusion matrix, calculate the overall accuracy which is the most important part of the message, and check loss charts during training.

4.2 Classification Accuracy on DNN Models

As the result in figure (4.1) shows the classification accuracy for all SNRs using the classification performance of the four models (AlexNet, ResNet, CLDNN and GRU-CNN), Samples are uniformly distributed at (SNR) from -20 dB to +18 dB and varied so that we can evaluate specific subgroups of each group, negative SNR values are neglected, meaning the values from (0 to 18 dB) are used.

The results of the classifiers (AlexNet, ResNet, GRU-CNN and CLDNN) after training (91. 3%, 81%, 79.1%, 0.77%) respectively, the accuracy of the models as shown in Figure (4.1). AlexNet classifier is the best among the four selected classifiers in terms of classification accuracy.

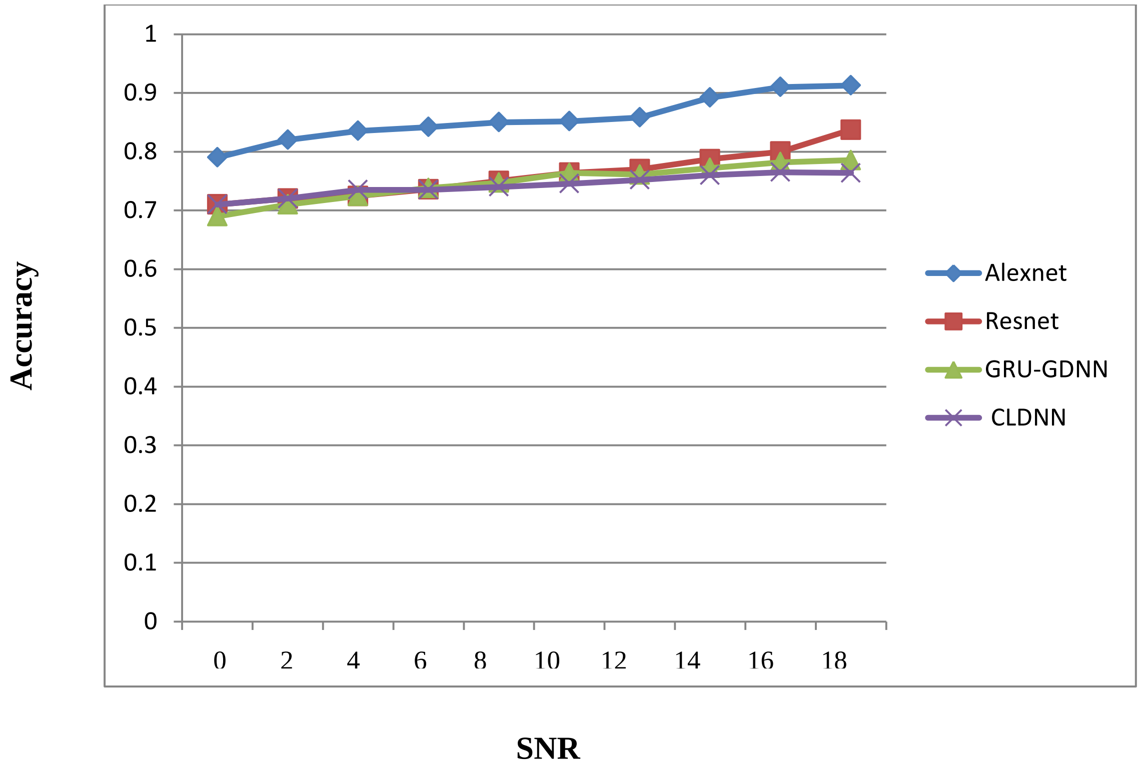


Fig. 0.1) the accuracy of DNN models

Table (4.1) demonstrates the accuracy of our research's findings, which clearly outperforms some earlier studies.

An accuracy of 91.3% was obtained for the AlexNet model, in contrast to the search results [59] that used DNN, the accuracy was 74.48%, and the results of the search [71] that used AlexNet model and got accuracy 88% which proves the strength of the proposed model.

Table (4.1) comparison results with another reference

Ref.	**models**	**Accuracy**
This theses	AlexNet Model	91.3%
This theses	ResNet Model	84.18%
This theses	GRU-GDNN Model	78. 55%

This theses	CLDNN Model	76. 36 %
Ref [59]	DNN	74.48%
Ref [71]	AlexNet Model	88 %

4.3 The Confusion Matrix

Using the classification performance of the four models (Alexnet, Resent, CLDNN, and GRU-CNN), in the test data set to measure how well our classifier is performing, we train on a set of approximately 220,000 complex samples equally divided across modifications. It is divided into training examples of samples in length. Use 80% of samples for training, 10% for validation and 10% for the test. Confusion matrix results are test samples computed in Chapter 3, equal to 100 segment for each inclusion in the SNR.

The results of the accuracy are calculated according to the following equation:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \ldots\ldots\ldots (4)$$

Where:

TP - true positive.

TN - true negative.

FP - false positive.

FN - false negative.

4.3.1 Confusion Matrix of AlexNet Model:

To obtain the results, the confusion matrix for (AlexNet) is calculated using different SNR values (4 SNR, 10 SNR, 18 SNR) and the accuracy equation is used.

i. For SNR = 4 dB:

For calculate accuracy, apply the equation (4),

We can write equation (4) as follow:

Accuracy=Total correct predictions/ Sum of all predictions

Total correct predictions = diagonal matrix= 919;

Sum of all predictions = 1100,

Since there are 11 modulation signals in one SNR, each modulation signal contains 1000 segments,

The test rate is 10% of the total value

So, the value of the signal used in the test = 1000 x 10% = 100.

The sum of the signals in one SNR = 11 x 100 = 1100 the total sum used in confusion matrix for one SNR .

Accuracy= 919 / 1100

=0.8354 X 100= 83.54%   accuracy of SNR (4dB).

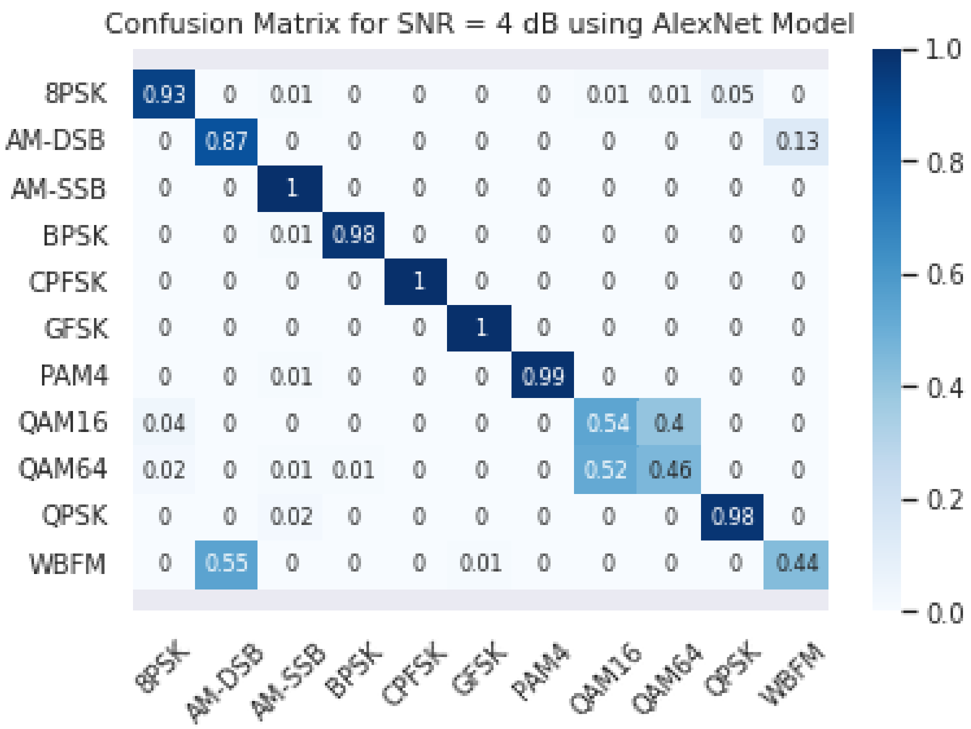


Fig. (4.2) the confusion matrix for AlexNet SNR = 4 dB

ii. For SNR=10 dB:

Accuracy=Total correct predictions/ Sum of all predictions

Total correct predictions = 839

Sum of all predictions = 1100

Accuracy= 839 / 1100

= 0.7627X 100= 76.27% accuracy of SNR (10dB).

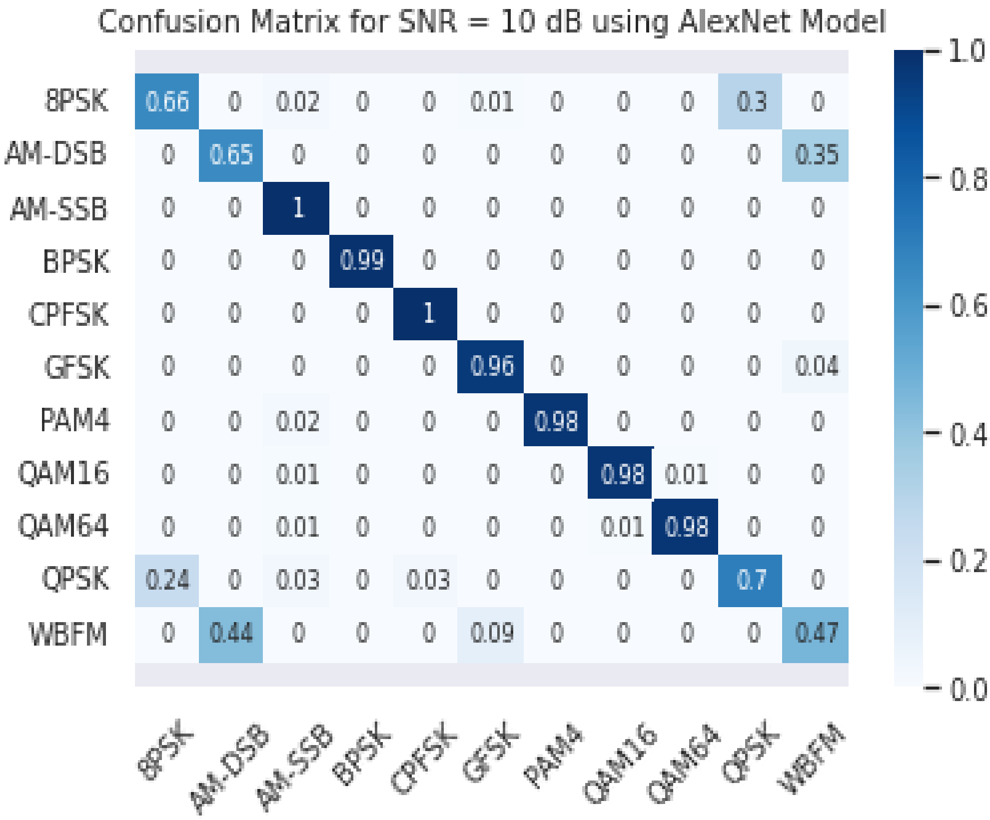


Fig. 0.3) the confusion matrix for AlexNet SNR = 10 dB

iii. For SNR =18dB:

Accuracy=Total correct predictions/ Sum of all predictions

Total correct predictions = 1004

Sum of all predictions = 1100

Accuracy= 1004/1100

= 0.9127 X 100= 91.27% accuracy of SNR (18dB).

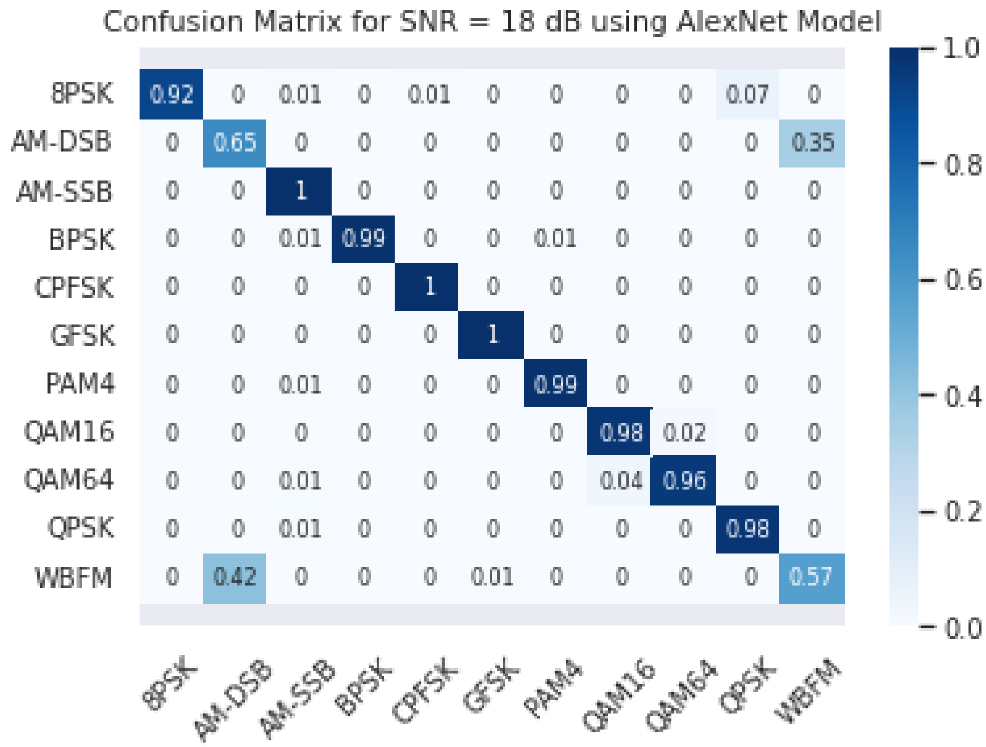


Fig. (4.4) the confusion matrix for SNR = 18 dB

4.3.2 Confusion matrix of ResNet Model:

In this part, calculating the confusion matrix for (ResNet) using the different SNR levels (4 SNR, 10 SNR, 18 SNR) and uses the accuracy equation to get the results.

i. For SNR=4dB:

Accuracy=Total correct predictions/ Sum of all predictions

Total correct predictions = 797

Sum of all predictions = 1100

Accuracy= 797/1100

= 0.7245 X 100= 72.45%   accuracy of SNR (4dB).

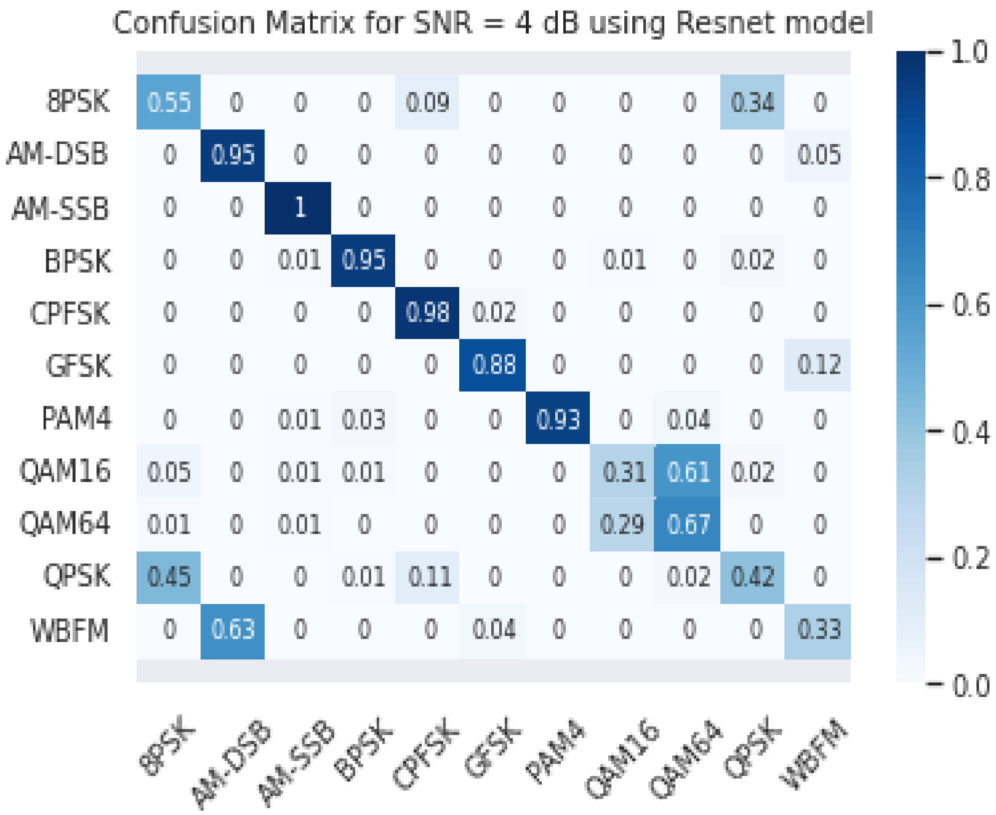


Fig. (4.5) the Confusion matrix for ResNet SNR = 4 dB

ii. For SNR=10 dB:

Accuracy=Total correct predictions/ Sum of all predictions

Total correct predictions = 840

Sum of all predictions = 1100

Accuracy= 840 /1100

= 0.7636 X 100= 76.36%   accuracy of SNR (10dB).

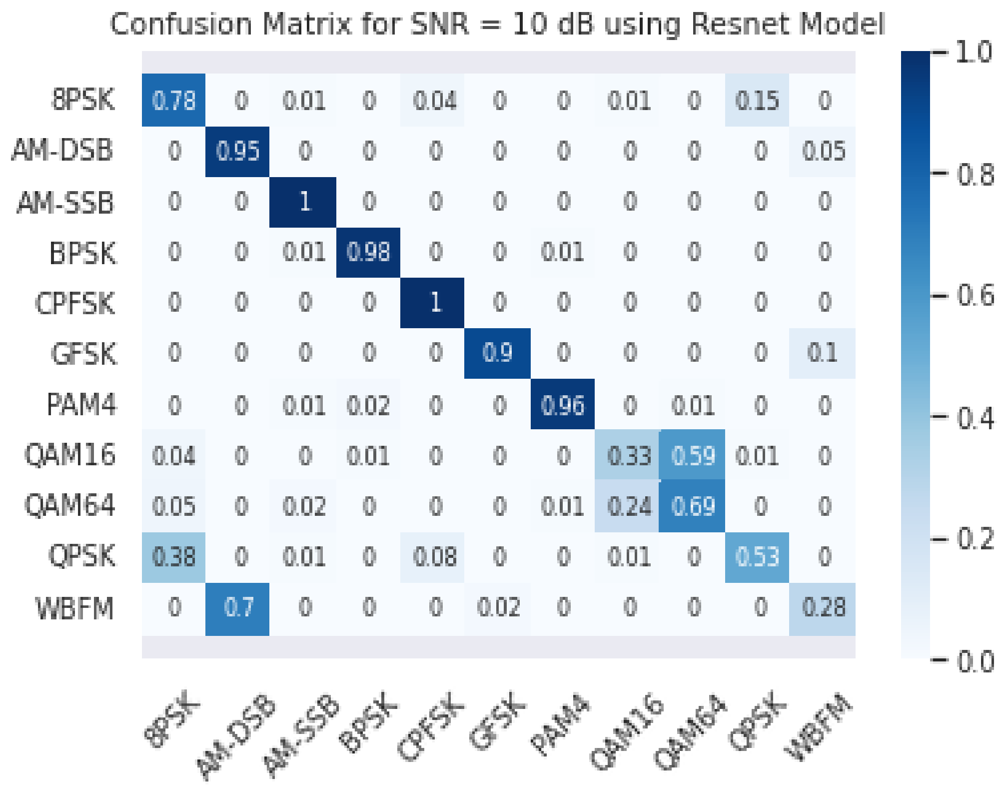


Fig. (4.6) the confusion matrix for ResNet SNR = 10 dB

iii. For SNR=18 dB:

Accuracy=Total correct predictions/ Sum of all predictions

Total correct predictions = 926

Sum of all predictions = 1100

Accuracy= 926 /1100

= 0.8418 X 100= 84.18% accuracy of SNR (18dB).

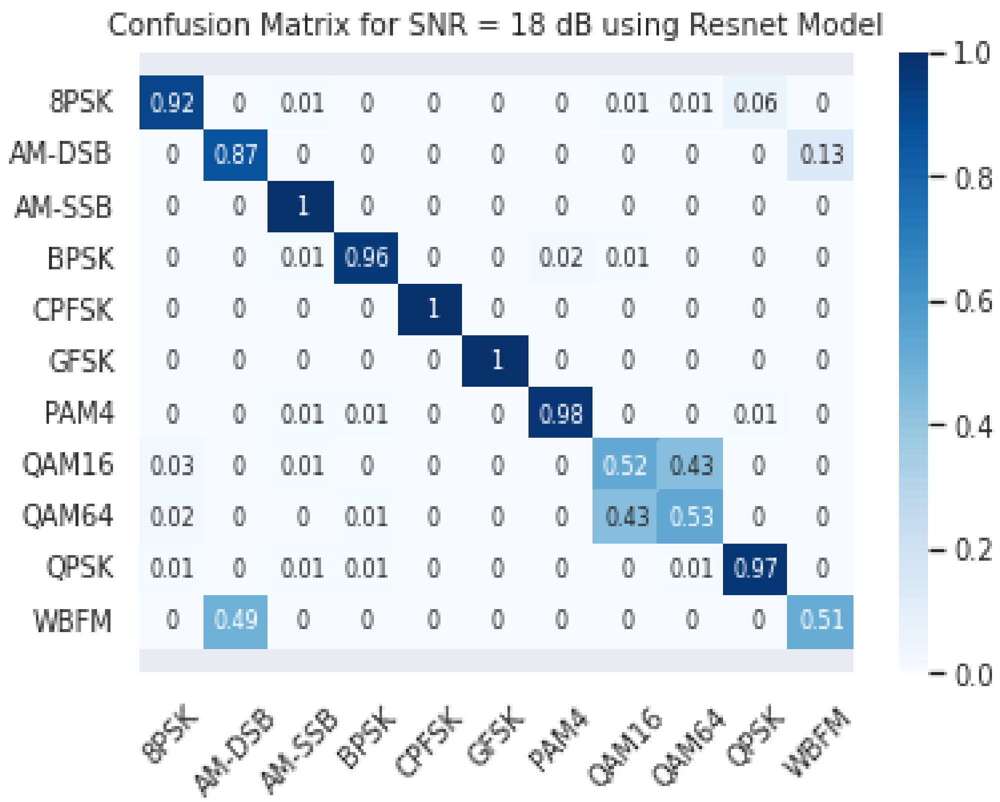


Fig. (4.7) the confusion matrix for ResNet SNR = 18 dB

4.3.3 Confusion matrix of CLDNN Model:

In this section briefly, for the confusion matrix CLDNN model a value (SNR = 18dB) will be calculated, since it is the highest accuracy value, and the accuracy equation will be used to obtain the results.

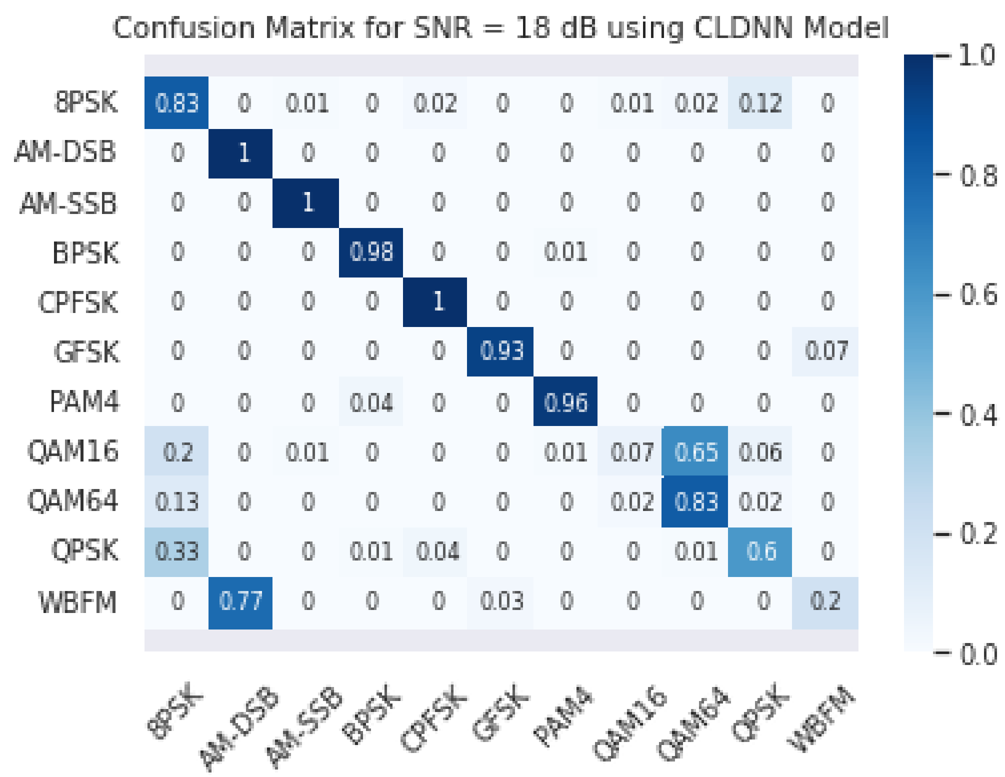


Fig. (4.8) the confusion matrix for CLDNN SNR = 18 dB

Accuracy=Total correct predictions/ Sum of all predictions

Total correct predictions = 840

Sum of all predictions = 1100

Accuracy= 840 /1100

= 0.7636 X 100= 76.36% accuracy of SNR (18dB).

4.3.4 Confusion matrix of GRU-CNN Model:

In this section briefly, the special confusion matrix GRU-CNN Model is used to calculate the value (SNR = 18dB), because it is the highest accuracy value, and the accuracy equation will be used to obtain the results.

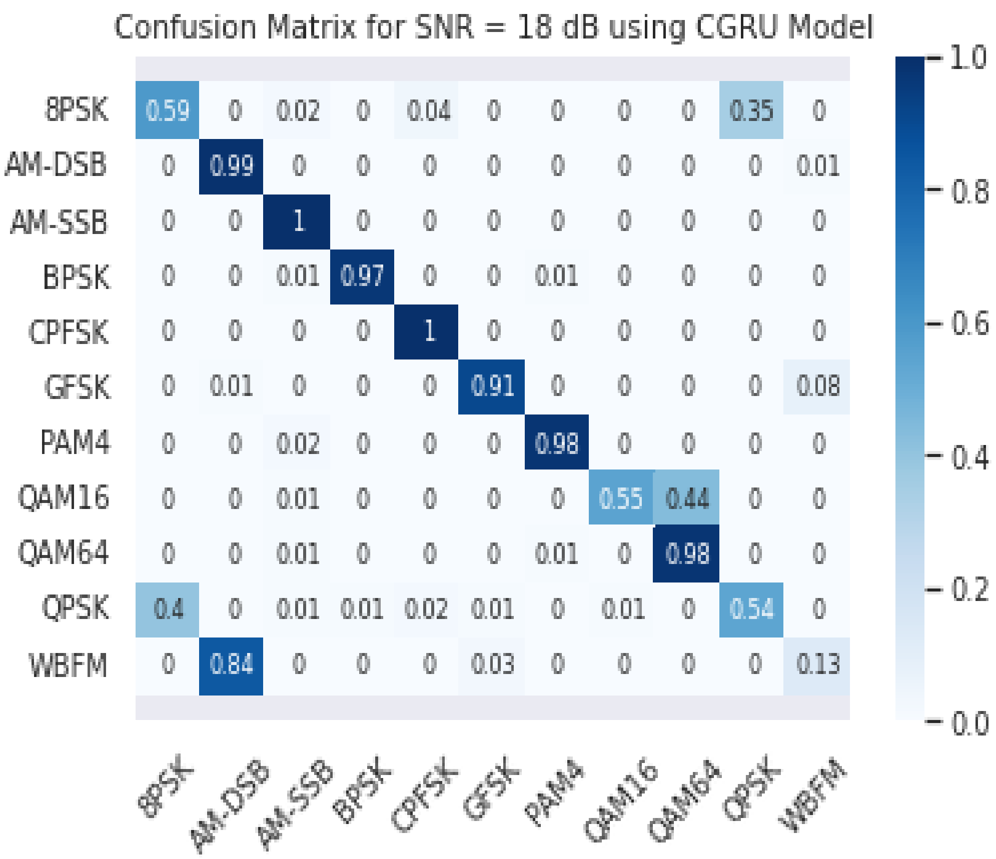


Fig. (4.9) the confusion matrix for GRU-CNN Model SNR = 18 dB

Accuracy=Total correct predictions/ Sum of all predictions

Total correct predictions = 865

Sum of all predictions = 1100

Accuracy= 865 /1100

= 0.7855 X 100= 78.55% accuracy of SNR (18dB).

4.4 The loss plots

In this section, we will review the loss-to-epoch ratio, and our data set is divided into three groups (training set 80%, validation set 10%, and testing set 10%). From the test set and training set, some embedding signals are captured and a data validation set is generated for validation purposes. The error in the training data set is called the training loss. After doing data validation over the trained network, we got some errors. This error is called missing validation. Train error and validation error decrease with increasing time period, 150 training epochs are set to avoid overfitting. With lower train loss and validation loss, train accuracy and validation increase rapidly.

4.4.1 The loss plots of AlexNet

Training loss vs AlexNet validation loss In Fig. (4.10), it was initially observed that the ratio is usually large up to point (3), but specifically, in the era (27) this ratio gradually decreased to reach (0.5)). The convergence of the curve for training loss vs. validation loss shows the correctness of the system.

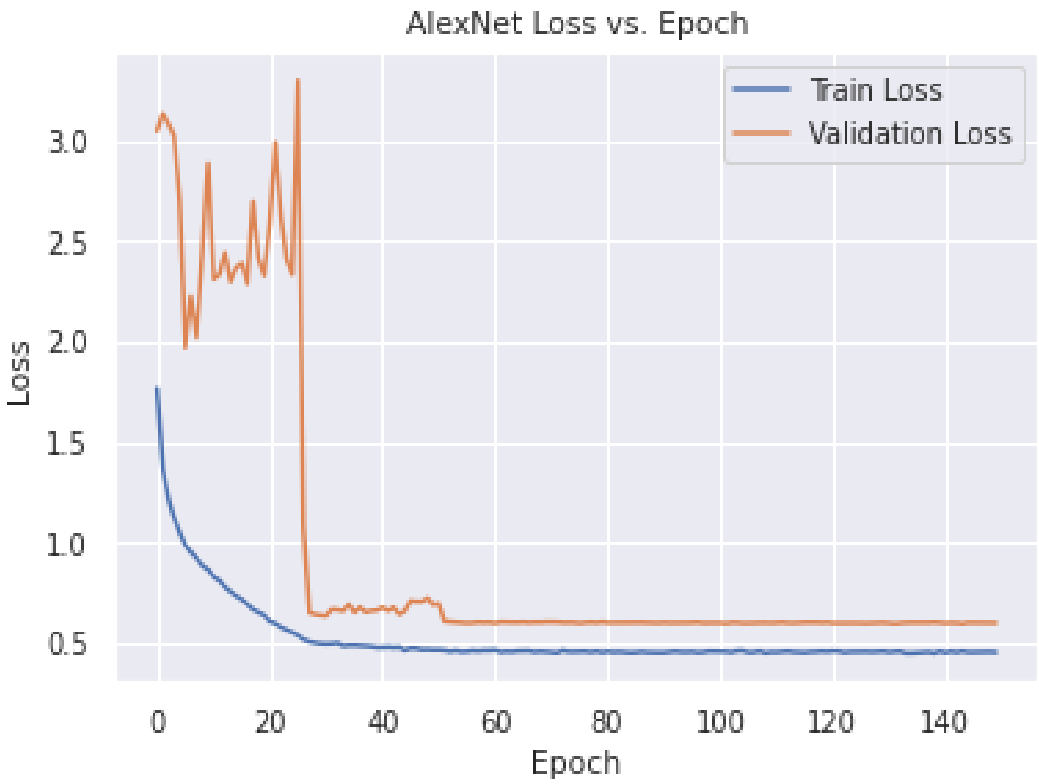


Fig. (4.10) Training loss vs validation loss of AlexNet model.

4.4.2 The loss plots of ResNet

In figure (4.11), 150 epochs were used for the purpose of gaining training versus losing validation. the goal is to accurately analyze the results. At first it was noticed that the ratio is usually large up to point 3, and gradually it began to reach (0.5).it was discovered that the ratio is usually high until point 3, and then gradually began to approach point (0.5).convergence (training loss versus validation loss) demonstrates the correctness of the system.

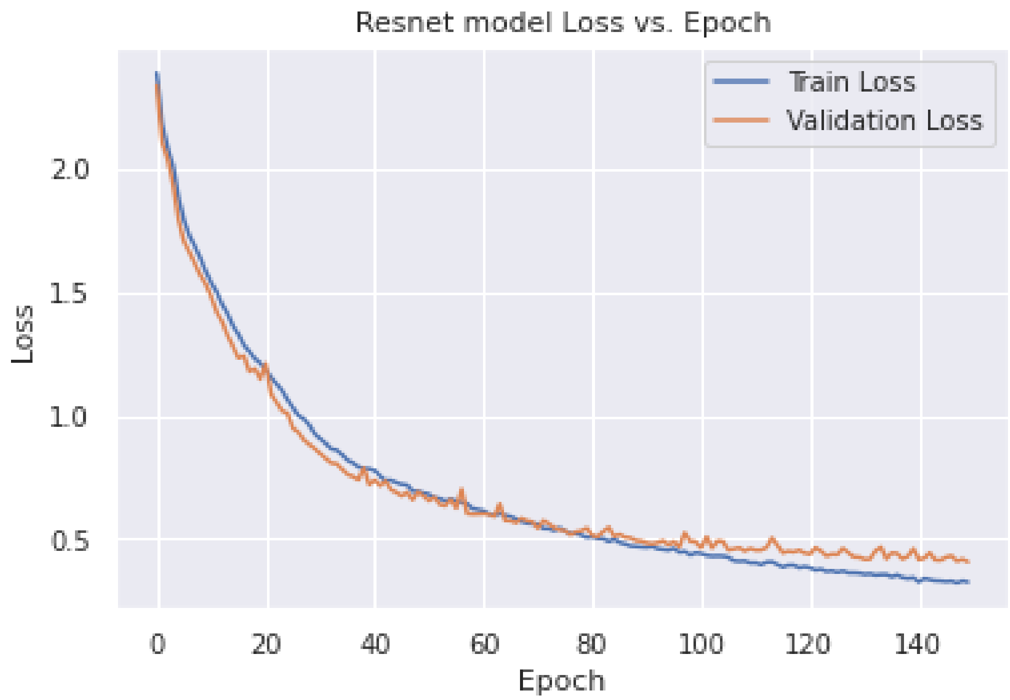


Fig. (4.11) show the loss vs Epoch of ResNet model.

4.4.3 The loss plots of CLDNN:

Using (150) epochs in Figure (4.12), for the purpose of gaining training versus losing validation. the purpose is to know the validation loss. At first it was noticed that the ratio is usually large up to point 3, and it gradually started to reach (0.5). Convergence (training loss versus validation loss) demonstrates the correctness of the system.

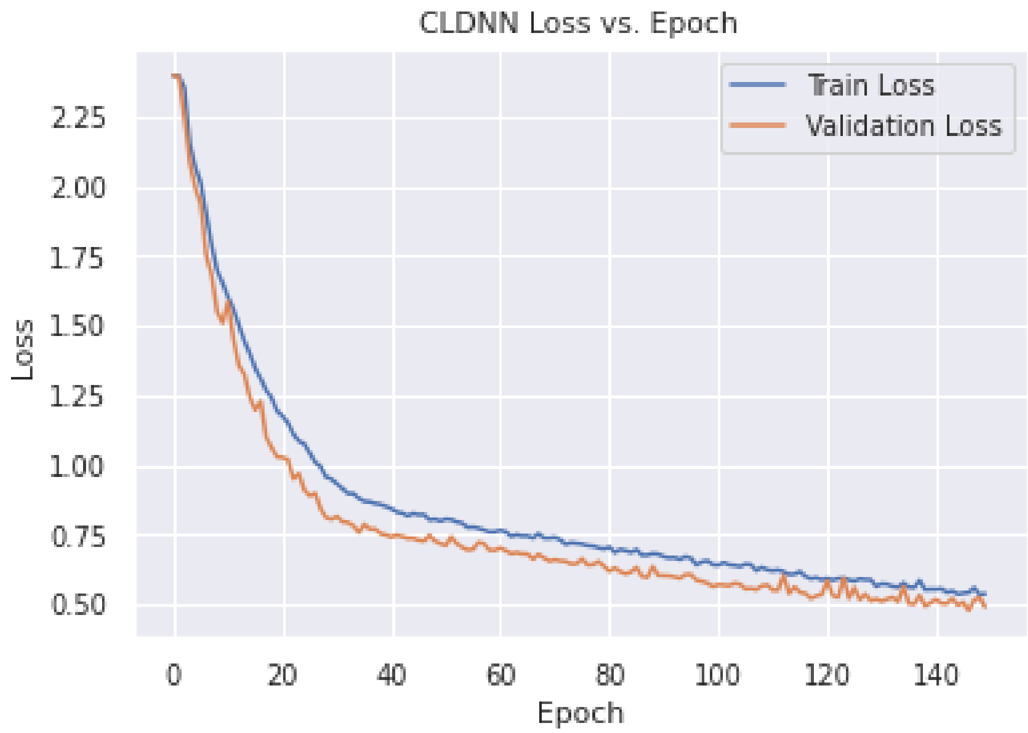


Fig. (4.12) show the loss vs Epoch of CLDNN model.

4.5 Discussion

By comparing the performance of the models (AlexNet, ResNet, GRU-CNN and CLDNN) and the classification accuracy of (91.27%, 84.18%, 78.55% and 76.36%), it is noted that the AlexNet model shows much better performance than the rest of the models.

The confusion matrix is the basis for classifying the modulation signals. The accuracy results show for the models that were used. We note that the AlexNet model shows a significantly better performance than the rest of the models, where the accuracy reached (91.3%). QAM16, QAM64) and (QPSK, 8PSK) (AM-DSB, WBFM) due to the similarities between these types.
Generally, in most confusion matrices, it is observed that modulation (QAM16 and QAM64), (AM-DSB and WBFM), (8PSK, QPSK) have an overlapping identification ratio.

The reason is that the modulations are similar in form to each other, so it is difficult to distinguish between these modulations. Figure (4.13) shows the cases of similarity modulations.

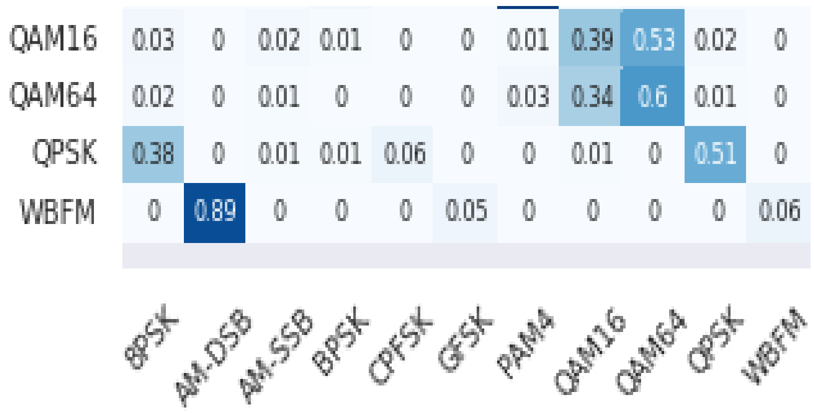


Fig. (4.13) the cases of similarity modulations

Chapter Five

Conclusion and Future work

5.1 Conclusion

Machine learning has advanced very quickly in the past 10 years and there are several main reasons for this. Algorithms have greatly improved in many ways including momentum methods for gradient regression and improvements in regularization and dropout, among others. The computational power and concurrent programming models have also been greatly improved to take full advantage of them. Deep learning may increase system identification performance, reduce signal processing stages, and offer more accurate and efficient modification recognition techniques than standard approaches. There are many networks that have been implemented to classify signal modulation in (AMR). It turns out that the extraction of signal features in the design of a deep neural network, convolutional layers and several kinds of residual layers are added. To provide the best classification model, four CNN models were introduced, and the Alexnet model was selected as the best among these models due to its higher accuracy than its peers. Accuracy (91.3%) is good. There are some types of signs that are somewhat similar to each other as in (QAM16, QAM64) which should be studied in more depth.

5.2 Future work

There is a greater degree of complexity in the communication environment, the signal frame length and limitations are generally different in real applications through the conclusion the following points show a future working method:

1. The variable-length input vector problem can be partially solved using models, but an efficient variable-length learning technique is urgently needed to fill the existing gap in signal processing. If you are dealing with a poor signal-to-noise ratio, you need to think about how to extract the useful properties.
2. There is still a need for a thorough examination of how learning algorithms can be used to successfully eliminate noise and search for deeper properties. Using the DL model in conjunction with other intelligent algorithms may yield better results in a variety of sectors.
3. There is a challenge in distinguishing between some signals such as (QAM16, QAM64) mainly because they are similar as it is difficult for the model to distinguish between these two signals and the same is the case with (QPSK, 8PSK). This topic requires focusing on these modulation groups, and investigating the similarities between their specifications in a deep way to remove confusion that occurs in the models (deep learning). We believe that one of the important things to solve this problem is to separate the data set because it plays a major role in the classification task.

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Appendix of Chapter 3

Appendix A

The case of using GPU

Appendix B

The case of without using GPU

الخلاصة

بشكل عام ، يعد التعرف على التعديل التلقائي (AMR) جوهر (SDR). تم استخدام (AMR) في مجموعة متنوعة من المجالات ، بما في ذلك تطبيقات الراديو العسكرية والمدنية والمعرفية (CR) ، ويلعب دورًا رئيسيًا في الاتصالات السلكية واللاسلكية. في السنوات الأخيرة ، تم تطبيق التعلم العميق (DL) على نطاق واسع للكشف عن إشارات التردد اللاسلكي (RF) وتصنيفها. والسبب هو أن نهج DL مفيد بشكل خاص لأنه يحدد وجود الإشارات دون الحاجة إلى معلومات بروتوكول كاملة ، علاوة على ذلك ، يمكنه اكتشاف و / أو تصنيف أشكال الموجة غير المتصلة باتصال ، مثل إشارات الرادار. يعد نظام Alexnet المقترح جزءًا من DNNs التي تم استخدامها للتمييز بين إشارات التعديل المتولدة في (Radio ML2016) والهدف هو إنشاء دقة أفضل من أي نظام آخر قيد الاستخدام الآن من خلال التمييز الدقيق بين إشارات التعديل هذه. نفس راديو ML2016 الذي تم استخدامه من أجله. تقديم إطار عمل من خلال إنشاء مجموعة بيانات باستخدام راديو GNU الذي يحاكي العيوب في قناة لاسلكية حقيقية ، ويستخدم ١١ نوعًا مختلفًا من التعديل ، ثمانية منها رقمية وثلاثة تناظرية. بالإضافة إلى Alexnet ، تم استخدام ثلاثة نماذج ، وهي CLDNN و GRU و Resnet. علاوة على ذلك ، تم تنفيذ النظام المقترح باستخدام محاكاة بايثون. مقارنة بالنماذج الأخرى المقترحة ، يعد Alexnet تصنيفًا لشبكات التعلم العميق المستخدمة لزيادة دقة الشبكة بشكل عام.

جمهورية العراق
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جامعة بابل
كلية تقنية المعلومات
قسم شبكات المعلومات

تحديد أنواع التضمين في شبكة الراديو الإدراكي القائمة على الشبكة العصبية العميقة

رسالة مقدمة

إلى مجلس كلية تكنولوجيا المعلومات في جامعة بابل والتي هي جزء من متطلبات

الحصول على درجة الماجستير في تكنولوجيا المعلومات / شبكات المعلومات

من قبل الطالب

نصير عبد الامير موسى هاشم

باشراف

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