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Dedicated

first, All praise is due to Allah, by his honor and his majesty, deeds of virtue are accomplished.

I dedicated this work

To my dear father, who raised me and supported me throughout my academic career and my life.Thanks for providing my needs and paving the way for me to study and get a diploma.

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Abstract

Radio signal classification is a modulation recognition that are used by a wide collection of applications in radio communications and electromagnetic spectrum management. It is the process of deciding, based on observations of the received signal, what modulation is being used at the transmitter. Significant progress has been made in this area using Deep Learning (DL). In recent years, DL has shown success in solving radio signal classification problems. There are two important types of Neural Networks (NN) in DL, Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Long Short-Term Memory (LSTM) is one of the most popular RNN architectures that perform well in classifying signals. The aim of this work is to determine the appropriate NN model architecture that achieves good performance and high accuracy of modulation classification of the signals. Thus, in this document we tried two different approaches.
The first one uses CNN, while in the second we combine CNN with LSTM in order to perform classification. The dataset DeepSig:RadioML2016, is used for the performance analysis. Experiment results shows that the use of the second approach of LSTM-CNN achieved better performance compared to the first one that use only CNN.

Keywords: Radio Signal classification, Deep Learning (DL), Neural Networks (NN), Modulation Classification, Convolutional Neural Networks (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM).

ملخص

تصنيف الاشارات الراديوية هو التعرف على التضمين الذي تستخدمه مجموعة واسعة من التطبيقات في الاتصالات الراديوية وإدارة الطيف الكهرومغناطيسي. إنها عملية تحديد، بناءً على ملاحظات الإشارة المستقبلة، ما هو التضمين المستخدم في المرسل. تم إحراز تقدم كبير في هذا المجال باستخدام التعلم العميق. في السنوات الأخيرة، أظهر التعلم العميق نجاحا في حل مشاكل تصنيف الإشارات الراديوية .
هناك نوعان مهمان من الشبكات العصبية في التعلم العميق، الشبكات العصبية التلافقية والشبكات العصبية المتكررة. تعد الذاكرة طويلة المدى واحدة من أكثر معماريات الشبكات العصبية المتكررة شيوعا والتي تؤدي أداء جيدًا في تصنيف الإشارات. الهدف من هذا العمل هو تحديد بنية نموذج الشبكة العصبية المناسبة التي تحقق أداء جيدًا ودقة عالية لتصنيف تضمين الإشارات. وهكذا، في هذه الوثيقة جربنا طريقتين مختلفتين. الأول يستخدم الشبكات العصبية التلافقية ، بينما في الثانية نجمع بين الشبكات العصبية التلافقية و الذاكرة طويلة المدى من أجل إجراء التصنيف. تستخدم مجموعة البيانات : DeepSig RadioML2016 لتحليل الأداء. تظهر نتائج التجربة أن استخدام النهج الثاني الذي يجمع بين الشبكات العصبية التلافقية والذاكرة طويلة المدى حقق أداء أفضل مقارنةً بالنهج الأول الذي يستخدم الشبكات العصبية التلافقية فقط .

الكلمات المفتاحية: تصنيف إشارات الراديو، التعلم العميق ، الشبكات العصبية ، تصنيف التضمين ، الشبكات العصبية التلافقية ، الشبكة العصبية المتكررة ، الذاكرة طويلة المدى.

Résumé

La classification des signaux radio est une procédure de reconnaissance de la modulation qui est utilisée par une large collection d'applications dans les radiocommunications et la gestion du spectre électromagnétique. C'est le processus qui consiste à décider, à partir d'observations du signal reçu, quelle modulation est utilisée par l'émetteur. Des progrès significatifs ont été réalisés dans ce domaine grâce à l'apprentissage profond (AP). Ces dernières années, le AP s'est révélé efficace pour résoudre les problèmes de classification des signaux radio. Il existe deux types importants de réseaux neuronaux (RN) en AP, les réseaux neuronaux convolutifs (RNC) et les réseaux neuronaux récurrents (RNR). Le réseau récurrent à mémoire court et long terme (MCLT) est l'une des architectures RNR les plus populaires, qui donne de bons résultats pour la classification des signaux. L'objectif de ce travail est de déterminer l'architecture appropriée du modèle RNR qui permet d'obtenir de bonnes performances et une grande précision dans la classification de la modulation des signaux. Ainsi, dans ce document, nous avons essayé deux approches différentes. La première utilise le RNC, tandis que dans la seconde nous avons combiné le RNC avec le MCLT afin d'effectuer une classification. Le jeu de données DeepSig:RadioML2016, est utilisé pour l'analyse des performances. Les résultats des expérimentations montrent que l'utilisation de la seconde approche MCLT-RNC permet d'obtenir de meilleures performances par rapport à la première approche qui utilise uniquement le RNC.

Mots-clés: Classification des signaux radio , Apprentissage Profond (AP), Réseau de Neurones (RN), Réseau de Neurones Convolutive (RNC), Réseau de Neurones Récurrent (RNR), Mémoire court et long terme (MCLT)

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INTRODUCTION

With the rapid growth of wireless communication technology, the classification of radio signals has become extremely important in various applications. Rapid wireless signal recognition and classification have become an important process for accurate learning and reliable spectrum sharing to improve spectrum utilization efficiency.
Classification of these signals includes recognition of their modulation type, And therefore, This is a modulation classification problem, which includes how to determine the type of modulation to which the signal belongs. This is a multi-category classification issue with the number of categories equal to the number of modulation types in the signal collection. Which made the wireless communication environment more complex is that signals with different types of modulation have become more diverse and complex. In addition precisely setting the signal modulation mode under low SNR has became a difficult problem. In the past years, when recognizing the modulation of signals, the methods used included traditional methods based on extracting features manually, but it turns out that these methods do not give a classification with good efficiency and high accuracy. Which made resorting to the application of other methods.
In recent years, with the development of deep learning, and it has been widely used in the fields of image recognition, speech recognition, natural language processing, and wireless communication, deep learning has been used to solve the problem of radio signal classification, and has achieved better in terms of rating and outperformed traditional methods. It has opened a lot of doors to many applications in this field.

In this thesis, we present DL models for classifying radio signals, Which include Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), as we train them using the RML2016.10a dataset and compare and discuss their performances.

Our thesis consists of three chapters:

- **In the first chapter**, we present the concepts and basics of signals, radio, in addition to the concepts of deep learning, in which we state its contents, principles and architectures.
- **In the second chapter**, we represent the state of the art of radio signal classification, covering several concepts such as automatic modulation classification, modulation recognition, tradiotional methods, and finally coming to DL models.
- **In the third and final chapter**, we present the implementation of two different models for signal classification including a brief explanation of the software, hardware and the dataset used for the experiment and finally, a discussion of the results reported by each model.

CHAPTER 1

RADIO-SIGNAL GENERALITIES AND DEEP LEARNING

1.1 Introduction

The Signals are everywhere, they surround us on all sides. Signals are a major field of knowledge that finds applications in almost all aspects of modern life. As a digital signals are considered the backbone of communication technology in this era, as they are found in mobile phones, telephones, televisions and all the electronic devices or systems that surround you. In communication system, the radio Enable to transmit signals of different types, making facilitates communication process and information exchange.

Recently, the so-called deep learning has gained wide attention and shown good performance of different tasks in different fields.

In this chapter, we present a brief overview of some of the main aspects related to signals. We begin by discussing the basic concepts related to signals that include their properties, types, modulation, representation, and then we will discuss some concepts related to the field of radio. In the last part, we introduce some basic concepts and techniques related to the field of deep learning.

1.2 What is Signal?

You can't see it, but there are signals everywhere we are, the signal could be audio video, speech, image, sonar, radar, etc.[1]. In signal processing, signal it is a function that transfer information about the behavior of a system or the characteristics of some phenomena [2] . It is an electronic function. A typical example in the field of electronics and telecommunications the signal takes the form of voltage and current that carry information. Thus, communication theory refers to the study of signal contents. It can take the shape of an electromagnetic wave or a sound wave [3].

A signal can also be defined as any physical quantity that bearing some information. Typically the information bearing by the signal is a function of some independent variable, such as, time. The actual value of a signal at any point in time is called its amplitude. These signals are Typically plotted as an amplitude versus time graph. This graph is called the signal waveform. A sign can be a function of one or more independent variables [4]. The general and theoretical definition that we can accept for an electronic signal is: A signal is the physical representation of information passing through a system from source to receiver [5]. The information in the signal often refers to another physical phenomenon or the result of calculations (or measurements): usually, the signal varies constantly because the information is in motion or undergoes slow or rapid changes or perturbations.

The signals are usually supplied by a sensor, and the transducer converts the original form of the signal into a waveform expressed as current (I), voltage (V), or electromagnetic waveform. For example, the microphone converts the audio signal into a voltage waveform, and the amplifier does the opposite [2].

1.3 Characteristics of Signal

The signal is determined by its characteristics. Describes the nature of the signal. These characteristics include periodic signals and are represented in:

Amplitude Is the strength or height of the signal's waveform, measured in volts or amperes. It is the maximum value, positive or negative, that the waveform can reach. The amplitude of the signal varies over time.

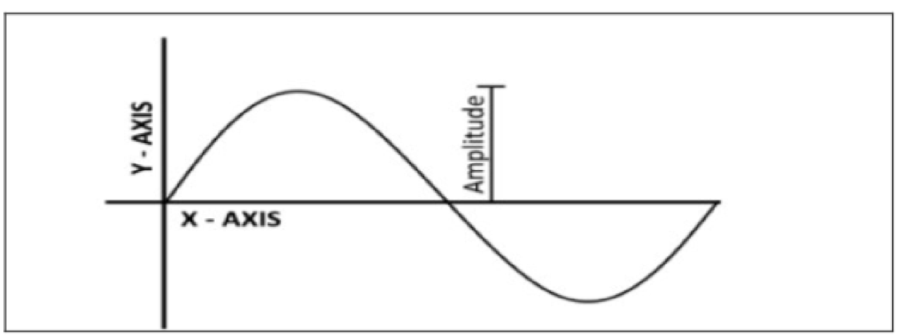


Figure 1.1: Amplitude of signal

Frequency Is the rate of repetitions of a signal's waveform in a second. Periodic signals repeat their cycle after some time, and its standard unit of frequency is Hertz, (Hz).Frequency is the reciprocal of the time period, ($F = 1/T$).

Time Period The time period of a signal is the time in which it completes its one full cycle. The unit of time is the second and is denoted by the letter "T". And it is the inverse of frequency. I.e. ($T = 1/F$).

Figure 1.2 shows a sine wave of time period 10 sec will complete its one full cycle in 10 seconds.

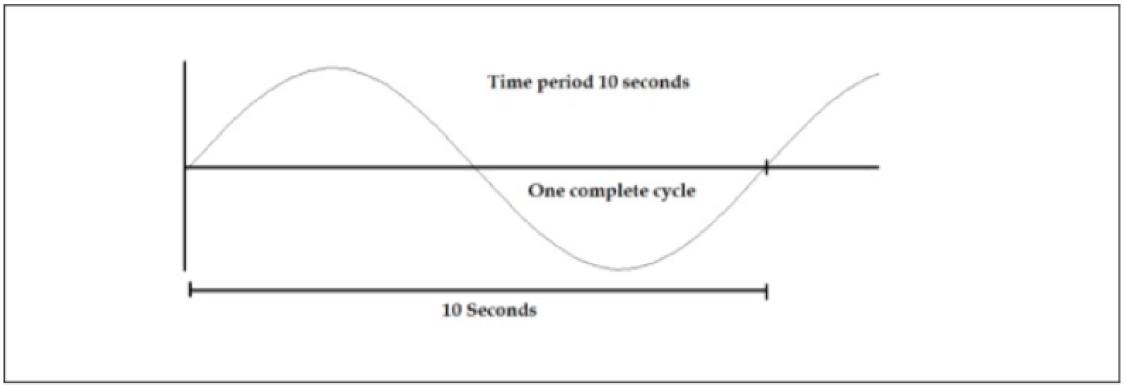


Figure 1.2: Time period of a signal

Phase Is a definition of the position of a point in time (instant) on a waveform cycle. A complete cycle is defined as 360 degrees of phase. The phase can be expressed as transformation or displacement between or among waves having the same frequency.

Figure 1.3 shows example of a 45 degree phase shift. The signal has not changed, the signal remains the same but its origin is shifted by 45 degrees.

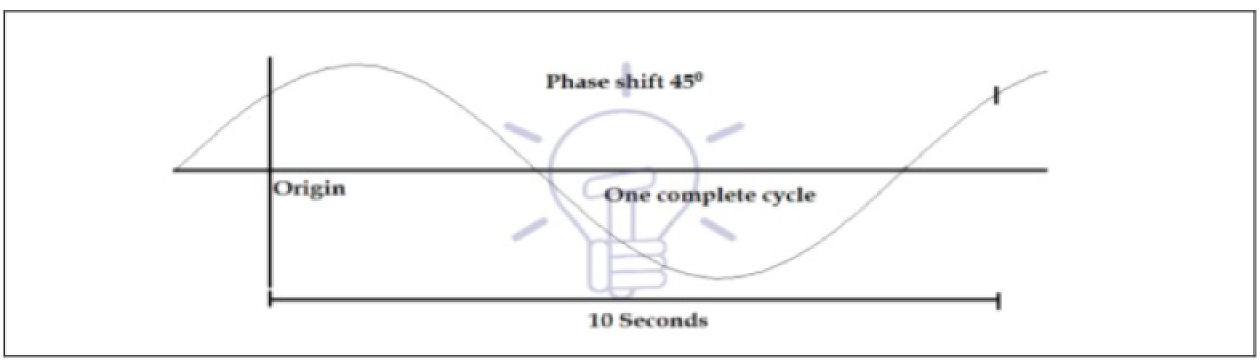


Figure 1.3: Phase of signal

1.4 The Different Types of Signals

1.4.1 Analog Signal

Analog signal is a continuous signal in which a time-varying quantity (for example voltage, pressure,...) represents another time-based variable, in other words, one variable is an analog of the other. An analog signal is always represented by a continuous sine wave as shown Figure 1.4, we describe the behavior of the wave according to the amplitude, duration, frequency and phase of the wave, on the other hand, since the analog signal is not noise-resistant, it suffers from distortion and thus reduces the transmission quality. Analog signals are commonly used to represent electrical signals such as audio recording, reproduction, direct amplification devices, and radio signals. It is also ideally suited for audio and video transmission as it has a much higher density and thus provides more accurate information, It also requires much less bandwidth than digital audio and maintains the original sound quality.

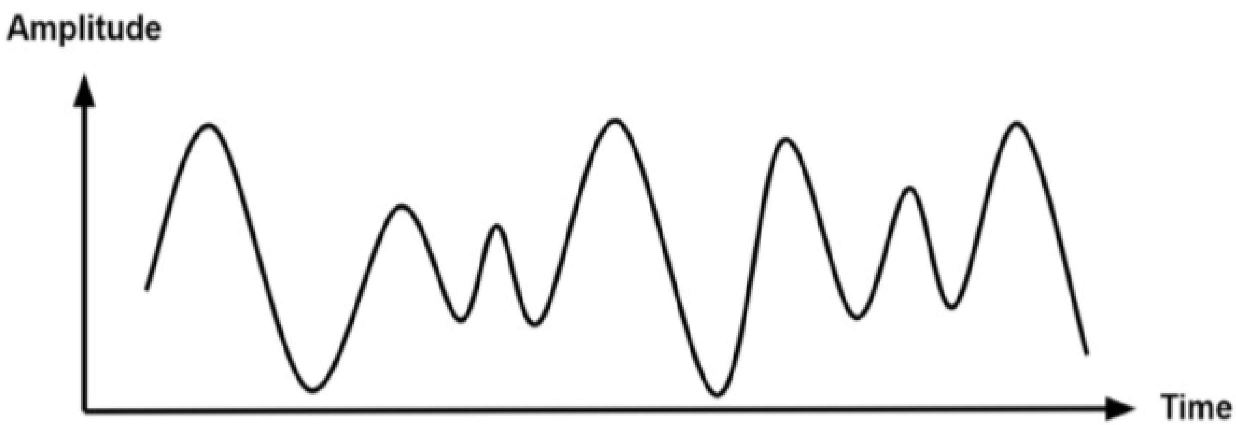


Figure 1.4: Analog Signal

1.4.2 Digital Signal

A digital signal is a signal that represents data as a series of discrete values. At any given time, it can take only one value out of a finite set of possible values. It is represented by a square wave, as shown in Figure 1.5 The digital signal carries data in binary form (0S and 1S) because it refers to the bits. These signals may be decomposed into sine waves, known as harmonics. Each simple wave has a different amplitude, frequency, and phase. A digital signal is described with a bit rate and a bit interval, where the bit interval represents the amount of time needed to transmit only one bit, while the bit rate represents the bit interval frequency. Digital signals are more noise- resistant, rarely subject to interference, so the transmission of these waves is easier and more reliable.

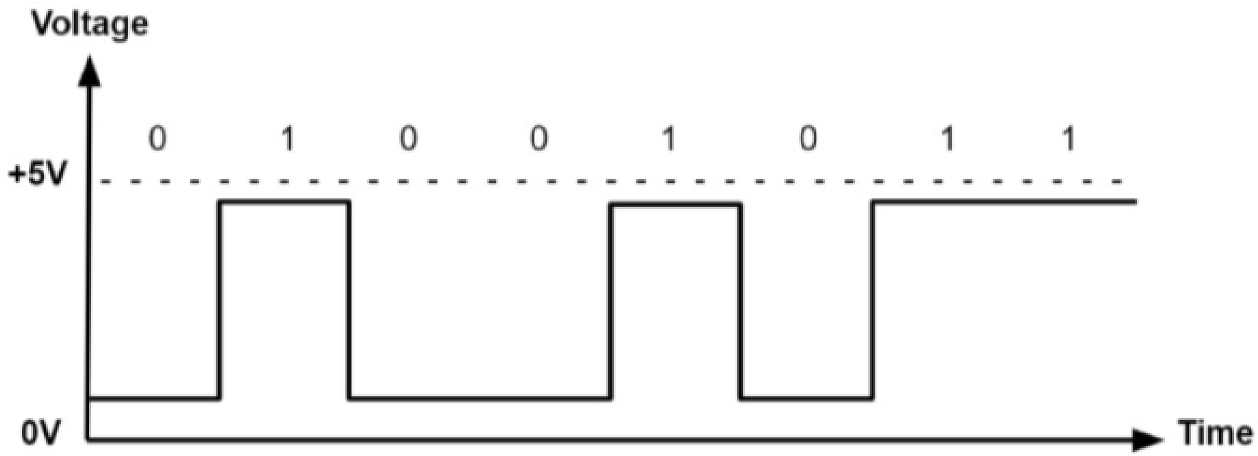


Figure 1.5: Digital Signal

1.5 Analog to Digital Conversion

Analog-to-digital conversion is present and all around us, in all kinds of electrical equipment, it is an electronic process in which a constantly changing analog signal (such as sound collected by a microphone) is taken and converted into a multilevel signal (digital) a series of values. Analog is a continuous sine waveform that cannot be read by a computer, which necessitates the need for conversion. By converting the analog signal, data can be amplified, added or taken from the original signal, to be stored and processed by a digital computer or DSP(Digital Signal Processing). An electronic device A/D or ADC (analog to digital converter) is used to perform this conversion as shown in Figure1.6.

In order to convert them into digital signals, we should perform the following two operations:

- First, the signal must be sampled (the time axis must be discretized or quantized),We call this operation **Sampling.**
- The second operation is to transform the sample values (the list of numbers obtained) so that each resulting number belongs to a separate alphabet. We call this process **quantization.**

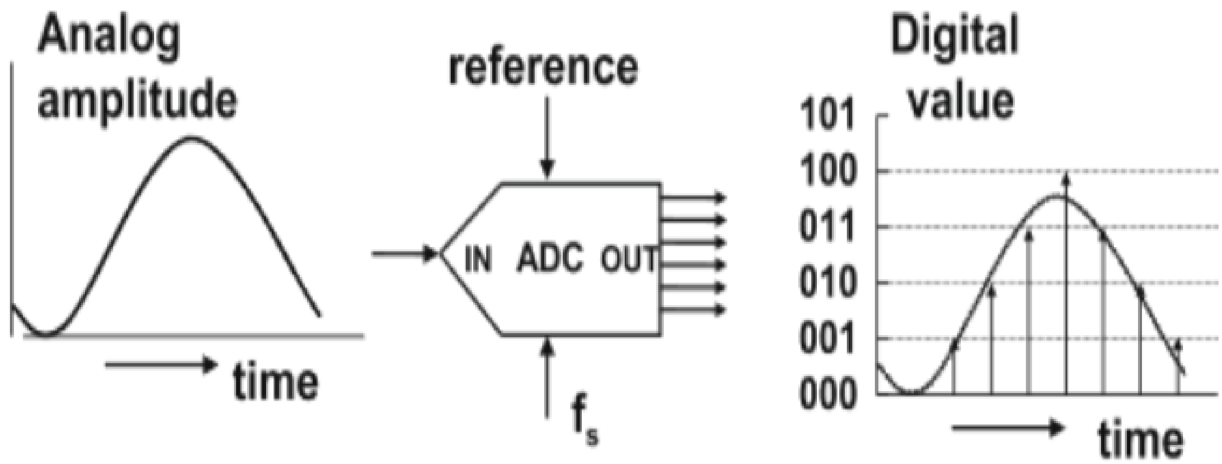


Figure 1.6: Functions of the analog-to-digital converter: sampling, quantizing, and linking to a reference [6]

1.5.1 Sampling

Sampling is the process of obtaining discrete time samples from an analog signal. In other words, If the analog time signals are sampled, we refer to this collection of numbers that may take on an infinite number of values within a specific range, a discrete time or sampled system. As shown in Figure1.7. When the sample values are restricted to belong to a discrete set, the system becomes digital[7]. Sampling means reading and measuring the value of the input signal at specified intervals, the well known Nyquist- Shannon sampling theorem states A signal may be accurately reconstructed from its samples if the sampling frequency is larger than twice the highest frequency component of the signal. The Nyquist frequency is half of a discrete signal processing system [3].

The most important factor in sampling is the rate at which the analog signal is sampled, The sampling rate or sampling frequency determines the number of samples taken from a continuous signal per second (or other unit) to create a discrete or digital signal. The higher the sampling rate, and the higher the frequency that can be accurately represented in the digital domain. The quest for more sample rate and larget accuracy is an ongoing driving force in analog-to-digital conversion research [7].

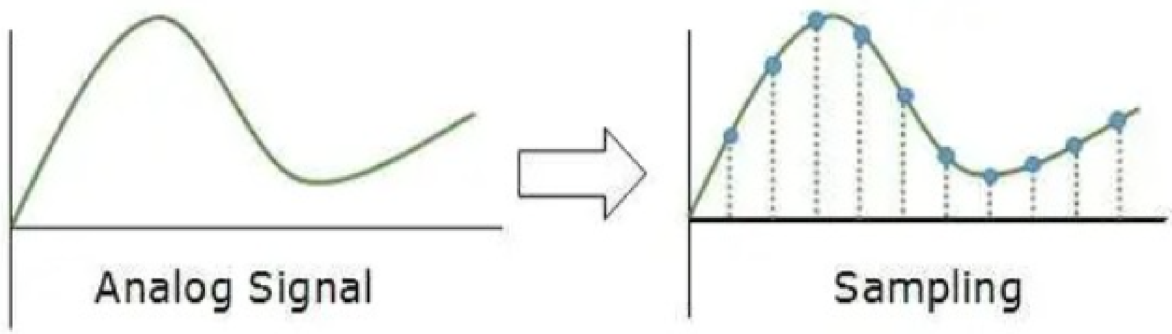


Figure 1.7: Sampling of Analog Signal

Suppose $X_a(t)$ be an analog signal as a function of time t. If we take a sample X_a with a sampling period T_s, The digital result of this process is $X[n] = X_a(nT_s)$,for all integer values n. The sampling frequency or sampling rate F is defined as the inverse of the sampling period, $F = 1/T_s$, and its unit is Hz. Figure1.8 shows some sampling processes of a sinusoidal signal. From here, analog or continuous-time signals will be expressed by parenthesis, such as $X(t)$, but digital or discrete-time signals will be expressed by square brackets, such as $X[n]$.

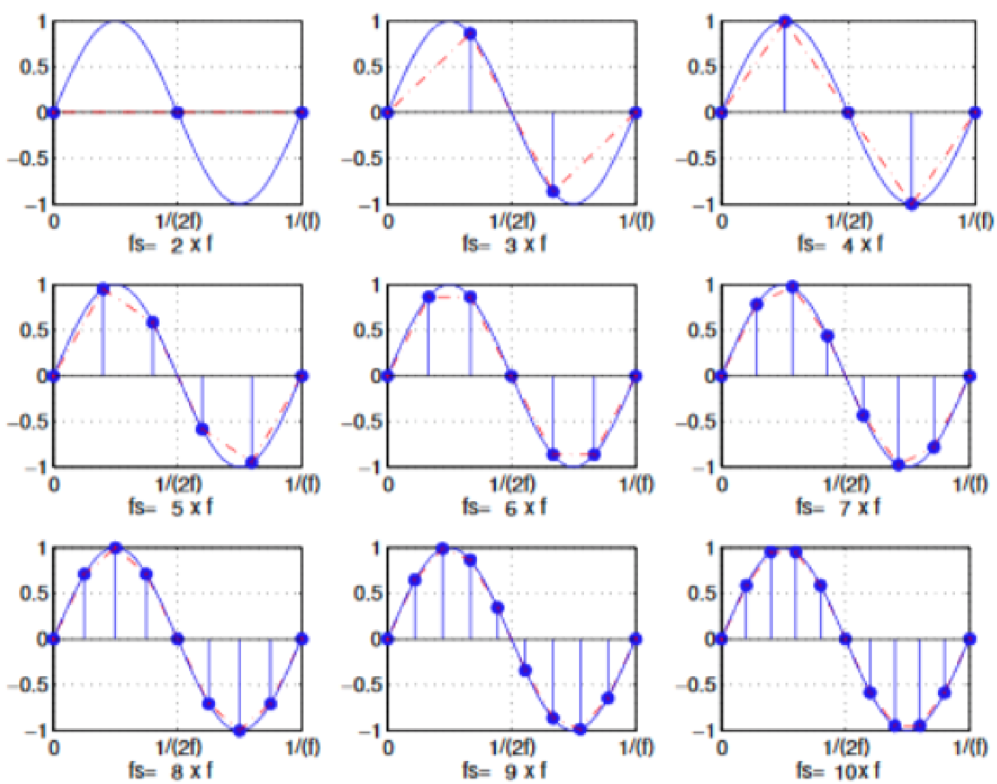


Figure 1.8: Sampling a sinusoidal signal at different sampling rates; f=Signal Frequency fs=Sampling Frequency – The Sampling Rate starts at 2f and goes up to 10f [8]

1.5.2 Quantization

After sampling, the acquired values of the signal must be transformed into a discrete collection of values. This process is called quantization. Quantization of a signal basically means to discretize a signal with a specific number of quantization levels, as shown in Figure1.9, in other words, converting a continuous-amplitude sample into a discrete-time signal. The discrete amplitudes of the quantized output are referred to as representation levels or reconstruction levels. The spacing between two consecutive representation levels is referred to as a quantum or step-size [9].

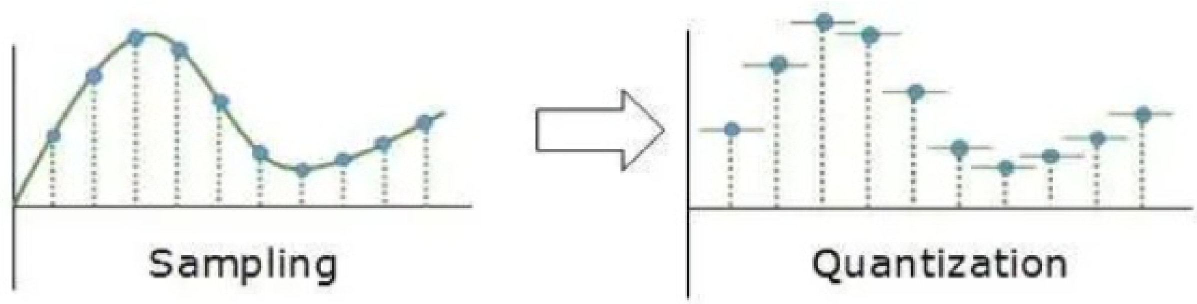


Figure 1.9: Quantization of sampled analog signal

1.6 Fourier Transform

The Fourier transform is named after the French mathematician Joseph Fourier, is usually applied to time functions that we call signals, as it is considered the basis of all sign theorems. The Fourier transform can be thought of as the transformation of a signal in one domain (typically time or space) into another domain, the frequency domain. Fourier transforms applications, also known as Fourier analysis or harmonic analysis, enable helpful decomposition of a signal into fundamental or "primitive" components, supply shortcuts to the computation of complex sums and integrals, and frequently reveal hidden structure in data[10].

The basic principle underlying Fourier transformation is that any signal can be decomposed into a sum of simple sinusoidal functions represent amplitude coefficients. In other words, no matter how complex a signal is, may be represented by a sum of sinusoids. The resultant function is referred to as a Fourier series [11].

In the mathematical sense, the Fourier transform is the transformation of a mathematical function from a time function $X(t)$ to a frequency function $X(\omega)$.The Fourier transform of a function is defined to be:

$$X(\omega) = \int_{-\infty}^{+\infty} X(t)e^{-j\omega t}dt \tag{1.1}$$

1.7 Methods of Signal Analysis

To analyse a signal, it must be represented, the signal representations are unique, The signal is either analog or digital, **time domain or frequency domain.**

1.7.1 Time Domain

Time domain refers to describing the signal in terms of time, so that we represent the signal and discuss it in terms of its ordered values. It also describes the changes of the signal over time. When we want to sample the signals, we will sample them in the time domain so that it gives a representation of time. The time domain is the analyze of mathematical functions and physical signals in relation to time. In the time domain, the signal or function's value is known for all real numbers in the case of continuous-time, or at different discrete instants in the case of discrete-time. An oscilloscope is an instrument that is widely used to view real-world signals in the time domain. A time- domain graph show how a signal changes in time [12].

Time domain analysis provides information on the behavior of a signal over a certain time period. And the analysis employs a unit of time, such as seconds or one of its multiples (minutes or hours), as a unit of measurement. The s(t) time-domain representation also provides information about the signal's actual presence, its start and finish timings, intensity, and temporal evolution, as well as how the signal energy is distributed along the t axis [13].

1.7.2 Frequency Domain

The frequency-domain refers to the analysis mathematical function or signals with respect to frequency, Put simply, a frequency-domain graph depicts how much of the signal contained within each given frequency band over a range of frequencies. A frequency-domain representation can also contain information on the phase shift that must be applied to each sinusoid in order to recombine the frequency components and recover the original time signal [12].

The purpose of signal processing in the frequency domain is the analyze of signal properties. The frequency spectrum may be examined to determine which frequencies are present in the input signal and which are missing. The analysis of signals in the frequency domain is also known as spectrum analysis [3]. The frequency domain is actually the mathematical result of the **Fourier transform** of the time domain signal, any waveform can be decomposed into the sum of multiple sine waves. So that each sine wave has its own frequency and amplitude. So any wave signal has its own set of frequency and amplitude. The drawn waveform is represented by a spectrogram Describing the frequency structure of the signal and the relationship between frequency and amplitude of the frequency signal. The final spectrum contains all sine frequencies.

Figure1.10 shows the relationship between the time domain and frequency domain plot of sine wave.

In 1.10(a), a three-dimensional graph for adding sine waves, the three axes represent time, amplitude and frequency. Time and amplitude axes cross the time domain, The third axis (frequency) helps us to clearly distinguish between sine waves, which add up to give us the complex waveform. When we look at this three-dimensional graph along the frequency axis, we obtain the width depicted in 1.10(b).This is the time do main view of the sine waves. The original wave shape is obtained by adding them together at each moment of time.
In 1.10(c), we have the axes of amplitude versus frequency. This is called the frequency domain. Each sine wave that we separate from the input is shown as a vertical line. So that its height represents its amplitude and its position represents its frequency. The representation of the frequency domain of our signal is called the signal spectrum. Each sine wave in the spectrum is referred to as the component of the total signal.

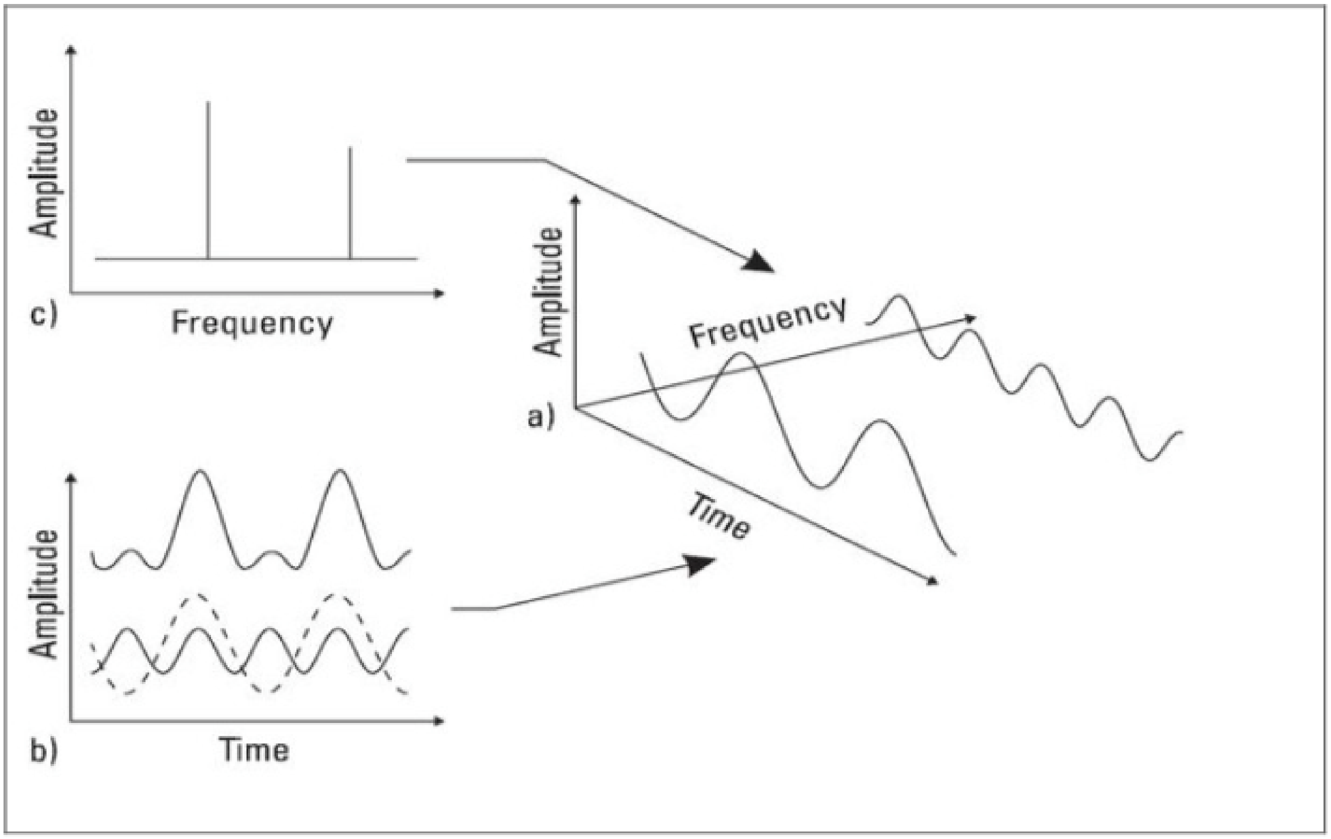


Figure 1.10: a) A three-dimensional graph three coordinates showing time, frequency b) Time domain, c) Frequency domain

1.8 Signal Noise

1.8.1 Noise

Noise, in its most fundamental sense, In electronics, noise is defined as an undesirable disruption in an electrical signal [14]. In signal processing, Noise generally indicates unwanted (and, in most cases, unknown) modifications that a signal may experience during capture, storage, transmission, processing, or conversion [15].

Noise or interference is also considered an unwanted electrical signal, which can distort or interfere with the original (or desired) signal. Noise can be transitory (ephemeral) or constant. Transient noises that are unpredictable may occur. Noise can be achieve from inside system (internal noise) or from outside origin (external noise),and can be the result of various factors anywhere, Noise may arise in certain types of signals for different fields and often has specific features such as

noise (audio, Video, image, radio,...etc). Noise reduction is the process of removing noise from a signal, reduction algorithms include altering signals to a greater or lesser degree. The local signal-and- noise orthogonalization algorithm can be utilized to avoid changes to the signals [16].When the noise properties are known and distinct from the signal, a noise reduction filter can be employed. noise can also be minimized by averaging the signal over time.
The Figure1.11 shows Combination of Signal and noise.

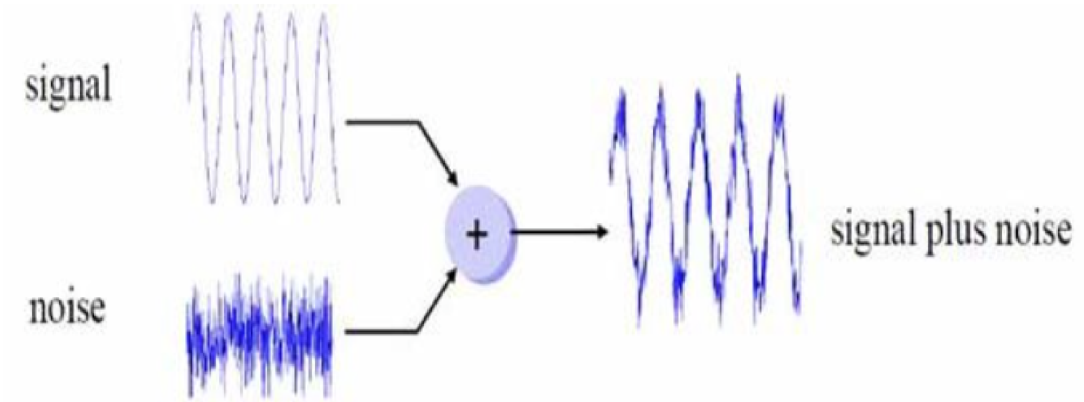


Figure 1.11: Noise Combination Signal

1.8.2 Measures of Noise in Signal

The signal-to-noise ratio plays an important role in any measurement, as measures how much noise is in a signal. It can also be applied to any form of a signal, to determine the clarity or strength of electrical signals. Its importance also relates to signaling applications.
The Signal-to-noise ratio often abbreviated(SNR or S/N),is a measurement parameter used in science and engineering that compares the level of a desired signal with the level of background noise. SNR defines the ratio between the signal power and the noise power. SNR is measured in decibels (dB). It is easier to identify, eliminate and isolate the source of noise if the SNR value is greater. An original signal cannot be separated from the unwanted noise if the SNR value is zero [17]. Signal to noise ratio (SNR) as in Equation:

$$SNR = 10 \log(S/N) dB \tag{1.2}$$

Where the symbol **S** represents signal power, and the symbol **N** is the noise power. An SNR value greater than 0 dB implies that there is more signal than noise. SNR is frequently used figuratively to refer out the ratio of relevant information to incorrect or irrelevant data in an exchange or a conversation [17].

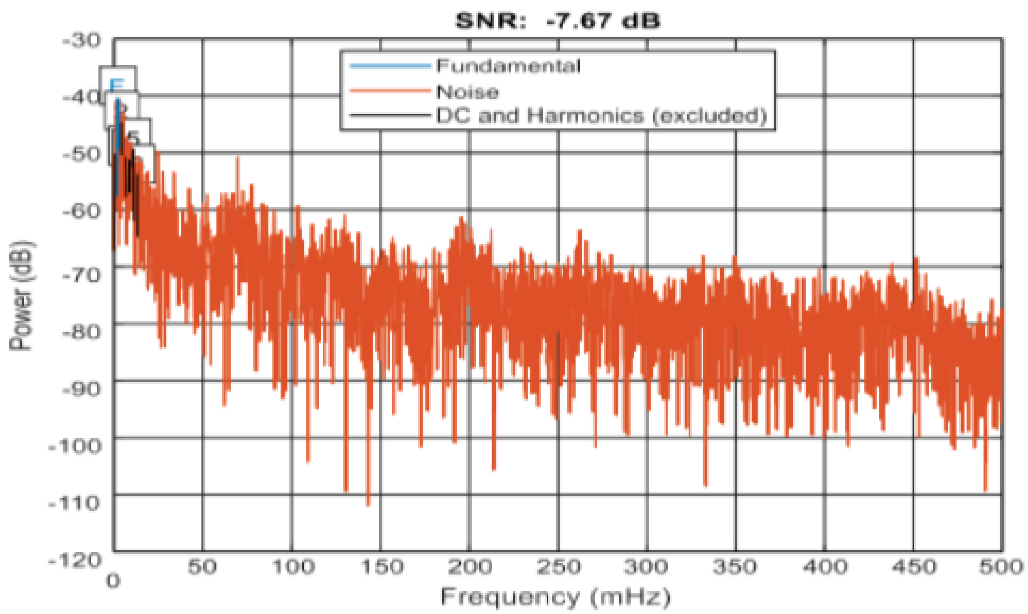


Figure 1.12: Signal-to-Noise Ratio (SNR) [9]

1.9 Modulation

Modulation is one of the fundamental branches of electronics science that is widely used in communication systems. It includes the basic characteristics of a signal for transmission from one location to another.

Communication stands for transferring of information from source to destination through some medium. It is necessary to strengthen the signal to travel long distance. This process of strengthen the signal is called **Modulation**. The strengthening of signal is done by varying one of characteristics of carrier signal such as amplitude or frequency or phase according to the instantaneous amplitude of the baseband signal/modulating signal [18]. Modulation can be also defined is the process of superimposing a low frequency message over a high-frequency carrier signal to make it suitable for long-distance transmission.

1.9.1 Signal Modulation

It is the transmission of a signal carrying a message over a long distance with the help of a high-frequency signal, such that it does not change the original properties of the message signal and in order to create a reliable communication.

The message signal's properties when it is altered, the message contained in it also changes and it is important to take care of the message signal. Furthermore, the high-frequency signal may travel a greater distance without being impacted by outside disturbances, because it gets help from the high-frequency signal which is known as the carrier to transmit the signal. These high-frequency signals are utilized as a carrier signal to convey the message signal.

1.9.2 Types of Signals in the Modulation Process

The three sorts of signals in the modulation process are as follows:

- **Message or Modulating Signal:** A message signal is a signal that contains a message to be conveyed. It is a baseband signal, which must go through the modulation process in order to be transmitted. As a result, it is also known as the modulating signal.
- **Carrier Signal:** This is a high-frequency signal with specific amplitude, frequency, and phase values, but it does not contain information. It is an empty signal called a carrier signal. It is only used to transmit the signal to the receiver part by following the modification procedure.
- **Modulated signal:** The resulting signal received after the modulation process is performed is called the modulated signal. This signal is a combination of the modulation signal and the carrier signal.

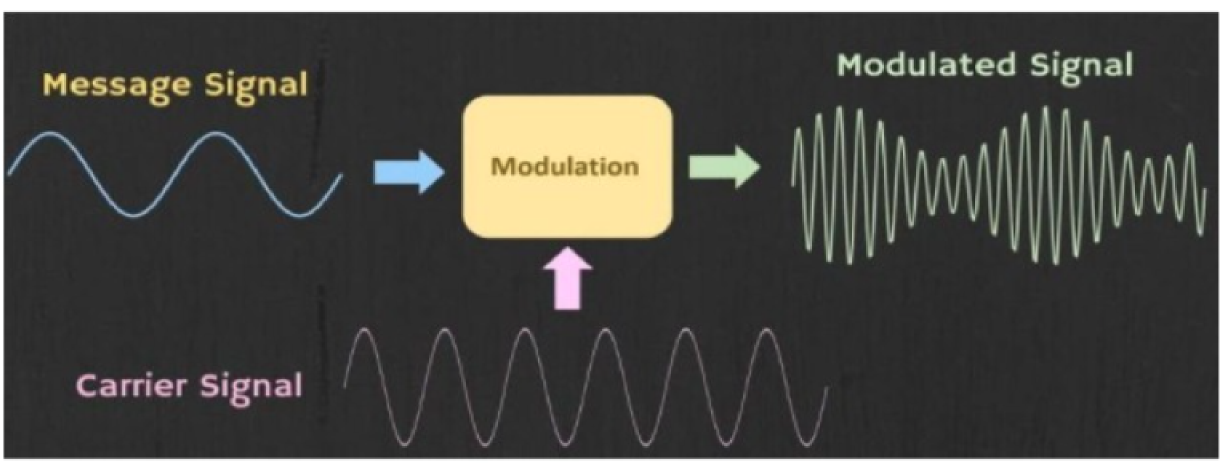


Figure 1.13: Signal in the Modulation Process

1.10 Types of Modulation

Basically, the modulation follows two types, based on the nature of message signal (analog and digital):

- **Analog Modulation**
- **Digital Modulation**

Figure 1.14 Show Scheme Classification Types of Analog and Digital Modulation Techniques

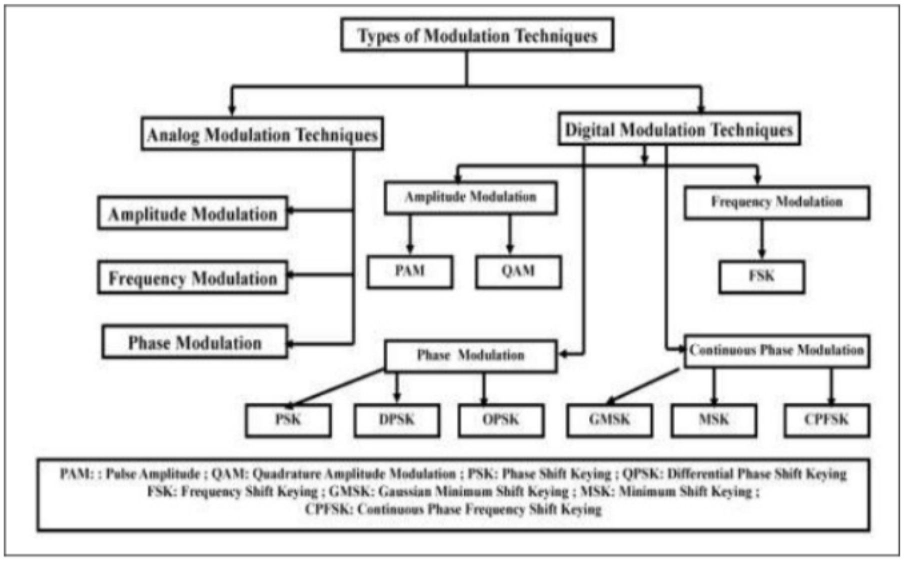


Figure 1.14: Schema of Types for Analog and Digital Modulation[18]

1.10.1 Analog Modulation

In analog modulation, An analog signal (sinusoidal signal) is used as a carrier signal to modulate the message signal or data signal. In accordance with the signal, some characteristic of the carrier wave (amplitude, phase, or frequency) is modulated; the characteristic can take values constantly within a range. Since the carrier wave is sinusoidal[19].

a. Amplitude Modulation (AM)

In amplitude modulation, the amplitude of a carrier is change linearly with the message signal. The carrier is much higher in frequency than the baseband message signal [20]. While other parameters such as frequency and phase stay constant. The spectrum of the modulated signal consists of a lower frequency band, a higher frequency band, and carrier

frequency components. This type of mod requires more bandwidth and power. Filtering is tricky with this modulation.
Among the most common analog modulation techniques are:

➢ Double-sideband modulation (DSB).

- Double-sideband modulation with carrier (DSB-WC) (used on the AM radio broadcasting band).
- Double-sideband suppressed-carrier transmission (DSB-SC).
- Double-sideband suppressed-carrier modulation (DSB-DC).

➢ Single-sideband modulation(SSB, or SSB-AM).

- Single-sideband modulation with carrier (SSB-WC).
- Single-sideband modulation suppressed carrier modulation (SSB-SC).

b. Frequency Modulation (FM)

In frequency modulation, the frequency instead than the amplitude of the carrier wave is made to vary in proportion to the changing amplitude of the modulating signal [21].While the carrier amplitude is kept constant. Because radio wave frequency is less susceptible to noise than the amplitude, FM was initially introduced to minimize noise and enhance radio reception quality. To achieve this, FM radio signals transmits more bandwidth than AM signals.

c. Phase Modulation (PM)

In phase modulation (PM), the phase of the carrier changes in accordance , while the amplitude of the message signal, while the amplitude of the carrier does not change. PM is closely related to FM. In fact, FM is derived from the rate of change phase of the carrier frequency [22].When the phase of the signal changes, then it influences the frequency. because of this, this modulation is also come under the frequency modulation. In general, phase modulation is utilized to transmit waves.

d. Pulse Amplitude Modulation (PAM)

It is a type of analog pulse modulation. In modulated signal (PAM), the width and location of pulses remain fixed, while the amplitude of pulses differs proportionately to the amplitude of analog useful signal. The Carrier signal originates from a clock [23]. In PAM, The message signal is sampled at regular periodic or temporal intervals, and Each sample is made proportionate to the size of the message signal.

Figure1.15 show difference between AM, FM & PM.

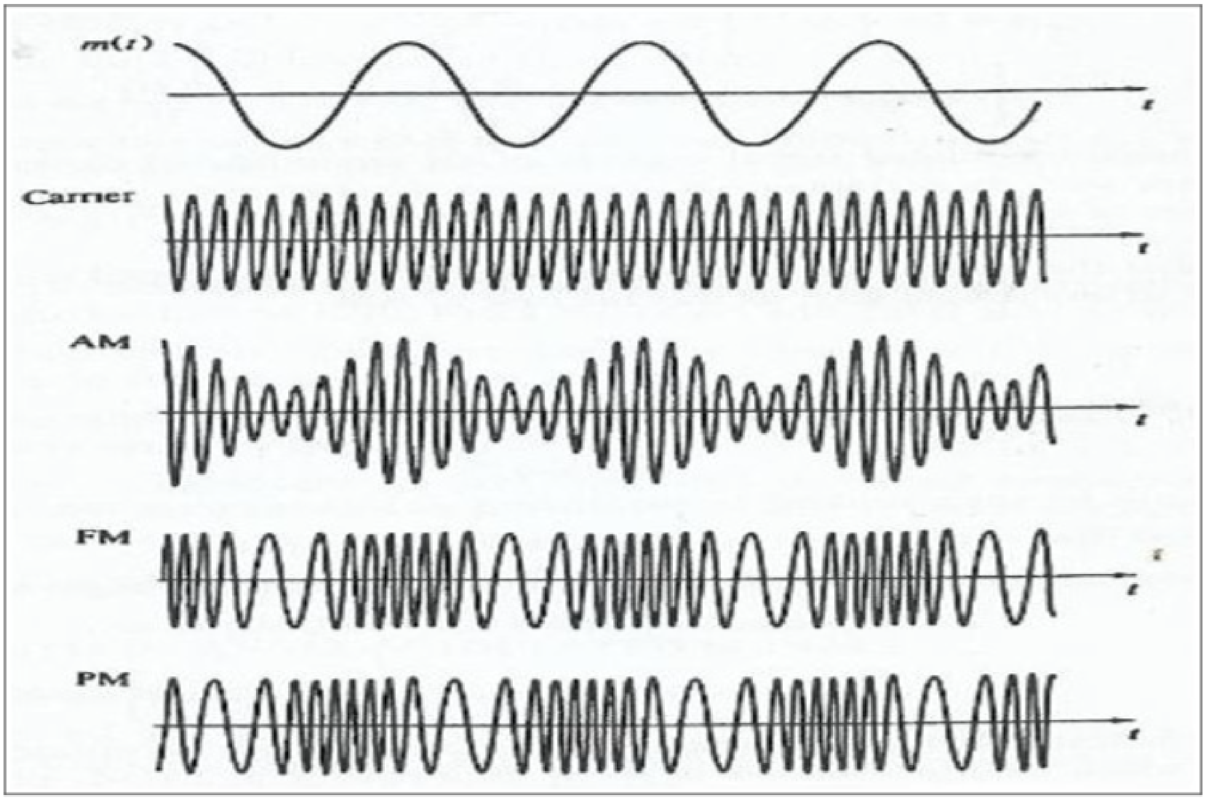


Figure 1.15: Basic Analog Modulation technique representation

1.10.2 Digital Modulation

In digital modulation, the message signal is transformed from analog to digital and then modulated using a carrier. The carrier is switched on and off to conduct pulses, which modulate the signal, comparable to analog-digital modulation. The kind of digital modulation, is determined by the amplitude, frequency, and phase oscillation of the carrier. Digital modulation techniques are becoming more significant in modern wireless systems. Digital systems outperform analog systems in terms of better spectrum efficiency, have better noise ability, and fade rejection, and require lower transmit power. Furthermore, error correction and encryption can be easy to implement in digital systems [24].

a. Amplitude Shift Key (ASK)

Amplitude-shift keying (ASK) is the most simple modulation technique, in which digital information is modulated across the amplitude of the carrier, analogous to amplitude

modulation for analog modulation [25]. ASK can be considered a digital representation of analog amplitude modulation. Using ASK, The amplitude of the carrier signal is set to one of two values that correspond to the logical level in the message signal at a given time. High amplitude indicates logical level 1 and low amplitude indicates logical level 0.
Some Other Forms of ASK:

- On-Off Keying (OOK)

b. Frequency Shift Keying (FSK)

FSK is a frequency modulation scheme in which digital information is sent by discrete frequency changes of a carrier signal[26]. In this method, the binary digital information 0 and 1 is represented by a signal of constant amplitude and the frequency is changed for each state. FSK, in the most basic case, represents a 1 (a mark) by one frequency and a 0 (a space) by another. These frequencies lie within the bandwidth of the transmission channel [27].
Some Other Forms of FSK:

- Binary Frequency Shift Keying (BFSK).
- Gaussian frequency-shift keying (GFSK).

c. Phase Shift Keying (PSK)

In phase-shift keying (PSK), the phase of the carrier alters in discrete levels in accordance with the input digital signal [22]. PSK is the process of transmitting data by modulating the phase change of a carrier signal, the frequency and amplitude of the carrier remain the same so that only the phase changes. Specifically, the phase changes at the point where the binary value 1 changes to Binary 0 or 0 to 1. Thus, binary number 1 may be transmitted as a zero degree phase shift, while binary 0 may be transmitted as a180 degree phase shift.
Some Other Forms of PSK:

- Binary Phase-Shift Keying (BPSK).
- Quadrature Phase-Shift Keying (QPSK).
- Offset-Quadrature-Phase-Shift-Keying (O-QPSK).
- 8 Point-Phase-Shift-Keying (8PSK).
- 16 Point-Phase-Shift-Keying (16 PSK).

Figure 1.16 show difference between ASK, FSK & PSK.

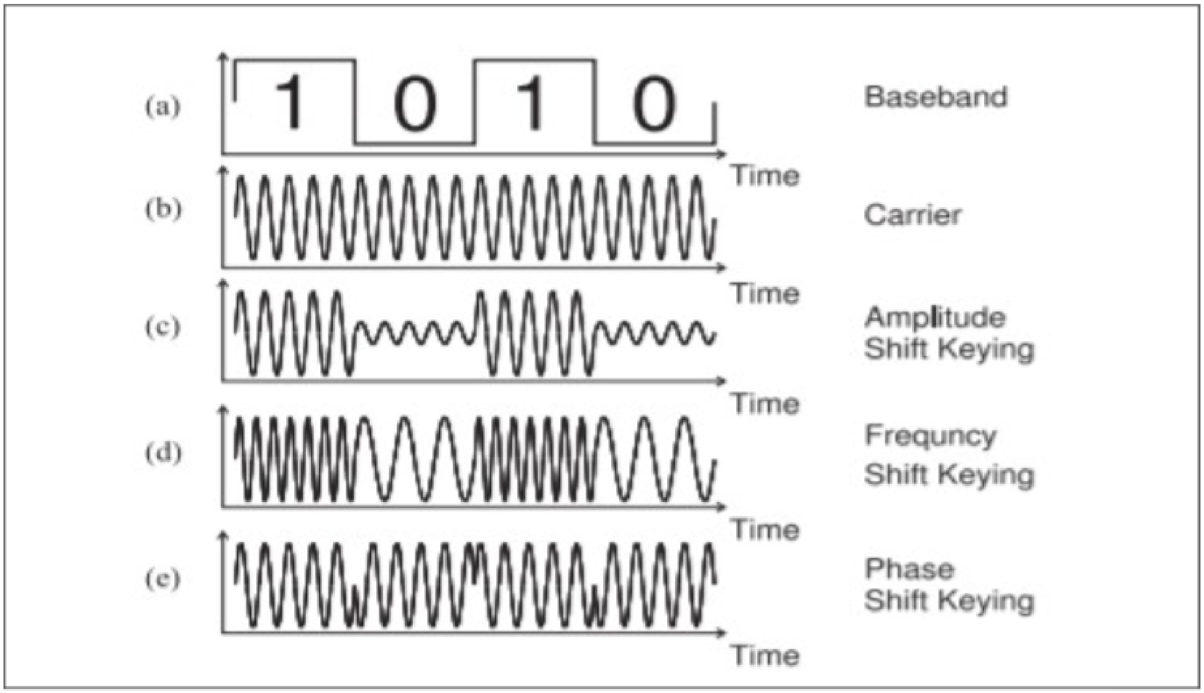


Figure 1.16: Basic Digital Modulation technique representation

d. Continuous-Phase Frequency-Shift keying (CPFSK)

Is can be considered as a traditional frequency shift keyed (FSK) signal that is restricted to preserve continuous phase at its symbol time boundaries. This constraint provides important advantages in terms of error rate performance as well as signal spectrum containment [28]. Some Other Forms of PSK:

- Gaussian Minimum Shift Keying (GMSK)

e. Quadrature Amplitude Modulation (QAM)

QAM modulation is defined as a combination of phase and amplitude modulation of a carrier in a single channel. One advantage of combining different modulation methods is to increase the number of available symbols. rising the number of available symbols is a standard way to rising the bit rate because rising the number of symbols increases the number of bits per symbol. QAM is a modulation technology that increases the data rates within the same bandwidth. The technique entails sending multiple bits for each time interval of the carrier symbol. The term "symbol" refers to a some unique combination of phase and amplitude [29].

QAM is considered the format of modulation that collect between two carriers, where whose amplitudes are separately modulated with the same optical frequency and whose phases are 90° apart. These are known as in-phase carriers (I) and quadrature-phase carriers (Q) [30]. In mathematical terms, One of the carrier signals can be represented by a sine wave (i.e. sin omega t), while the other can be represented by a cosine wave (i.e. cos \ omega t).
Figure1.17 show Waveform of the QAM.

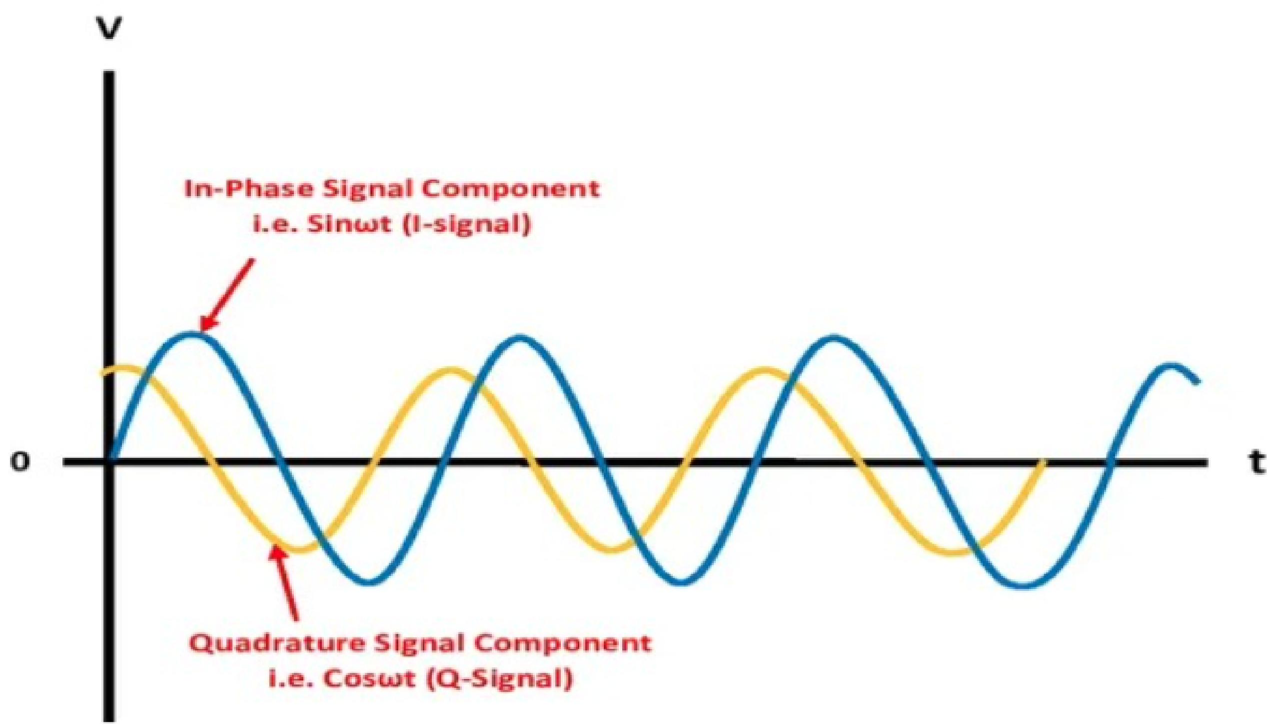


Figure 1.17: In-Phase Signal and Quadrature Signal Component

In digital QAM schemes, Different points can be utilized to specify the phase and amplitude values. This is referred to as a constellation diagram. As a result, a constellation diagram represents the set of possible message points.

The collection of values or symbols in QAM may be appropriate represented on a signal constellation diagram (Figure1.18). It is a graph of the I and Q amplitudes where I on the horizontal axis and Q on the vertical axis. Each point in Figure1.18 is a symbol, because it represents a combination of the amplitude and phase of the I and Q waves. In each symbol period, only one of the "points" is sent. Since data in digital communications is often in binary form and has two states, 0 or 1, the number of constellation points in the grid is typically a power of two, i.e. 2, 4, 8, 16, 32..., the most popular QAM formats are 16-QAM (24), 32-QAM (25), 64-QAM (26), 128-QAM (27), and 256-QAM (256). (28).

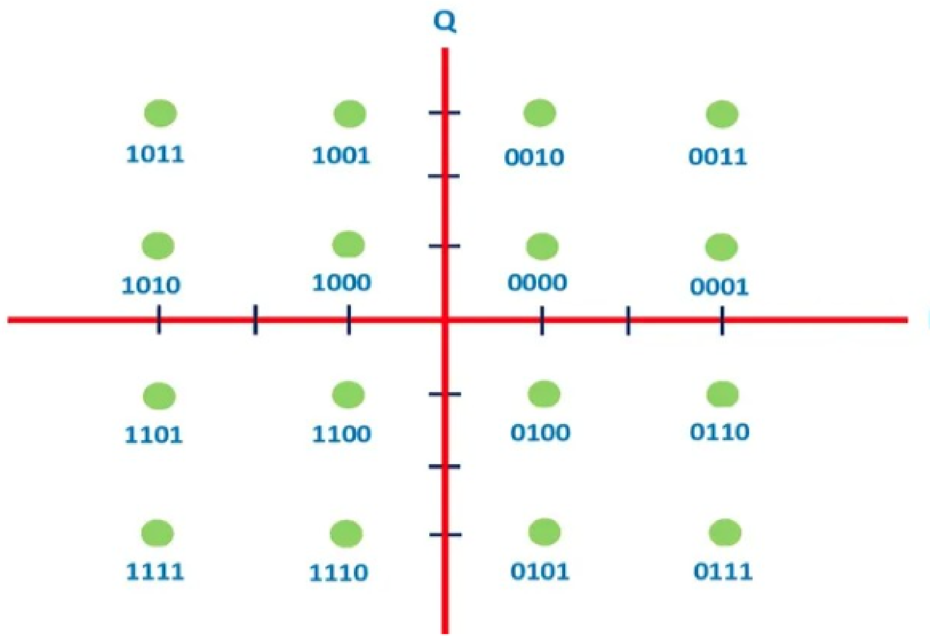


Figure 1.18: Constellation diagram for 16-QAM

1.11 Radio Wave

1.11.1 Brief History

Scottish physicist James Clerk Maxwell predicted the existence of radio waves, where he published equations, Through these equations discovered in **1864-1865** the existence of electromagnetic waves [31]. And it was confirmed in **1888** by the German physicist Heinrich Hertz, who proved the existence of radio waves [32]. In his laboratory, Heinrich Hertz tested Maxwell's theories on the production and reception of radio waves. Hertz was the first to send and receive controlled radio waves. In his honor, the unit of frequency of an electromagnetic wave with one cycle per second, Hz, is named on his name. Shortly after Hertz's research, It was left to the Italian inventor Guglielmo Marconi to turn Hertz's discovery of radio into a commercially viable technology. In **1895**, Italian inventor Guglielmo Marconi succeeded in transmitting radio signals over distances of several kilometers (Hertz had only managed a few meters) [33], was the first to demonstrate the practical use of radio waves for communication, and developed practical radio transmitters and receivers. The **1920**s saw the next major leap in the development of radio wave technology. Marconi's company began broadcasting programs every day, and soon the BBC was founded. Technology continued to advance. By the **1930**s, the vast majority of privately owned radios were superheterodyne walkie-talkies, greatly improving radio performance. Radio was the main electronic medium for news, entertainment, and sports before the advent of television, dubbed the "Golden Age of Radio".

1.11.2 Definition

Radio wave, a wave from the part of the electromagnetic spectrum at lower frequencies than microwaves. Radio waves have wavelengths ranging from thousands of meters to 30 cm. These frequencies Suit to frequencies as low as 3 Hz and as high as 1 GHz. Radio-wave communications signals transfer in through the air, reflect off of clouds or layers of the ionosphere or are transferred by satellites in orbit [34]. Like all electromagnetic waves, radio waves can travel long distances through different types of media and through a vacuum, They also have the ability to travel at a high speed parallel to the speed of light, because of this, radio waves play an important role in all types of communication technologies. Radio waves are produced by charged particles that are accelerated, such as time-varying electric currents [35]. Artificially produced radio waves are utilized in fixed and mobile radio communication, broadcasting, radar and navigation systems, communications satellites, computer networks, and a variety of other applications [36].
show the electromagnetic spectrum, showing the major categories of electromagnetic waves: Among them is the radio wave.

1.11.3 Types of Radio Waves

a. AM Radio Waves

AM radio waves are used to transmit commercial radio transmissions with frequencies ranging from 540 to 1600 kHz. AM is an acronym for amplitude modulation, which is the method used to put information onto these waves. A carrier wave with the radio station's fundamental frequency (for example, 1530 kHz) is varied or modulated in amplitude by an audio signal. The resultant wave has a fixed frequency but a variable amplitude.

b. FM Radio Waves

FM radio waves are also used for commercial radio transmission, However, the frequency range is 88 to 108 MHz. FM is an abbreviation for frequency modulation, which is yet another method of carrying information. In this situation, The radio station's basic frequency carrier (possibly 105.1MHz) is modulated in frequency by the audio signal. producing a wave with a fixed amplitude but variable frequency.

Figure1.19 show band Frequencies of AM and FM

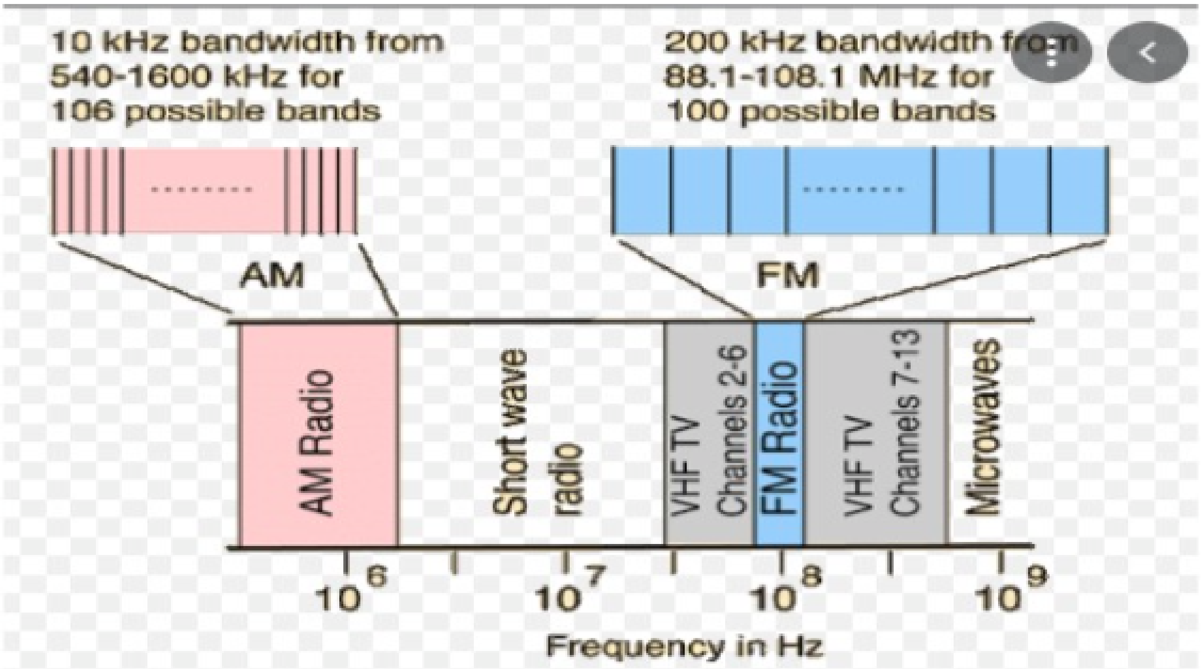


Figure 1.19: Frequencies of AM and FM

1.12 Radio Frequency

Radio frequency (RF) technology, often known as wireless technology, is the exploitation of the phenomena of electromagnetic waves in that part of the spectrum between 3 KHz and 300 GHz [37]. As well as the alternating currents that bearing radio signals. This is the frequency band that is utilized for the transmission of communications and broadcasting. Although RF refers to the rate of oscillation of the waves, However, we consider it synonymous with the term "radio", or simply wireless communication. Radio frequency is generated by oscillating current a certain number of times and then radiating it off a conductor known as an antenna.

Radio frequency is utilized in many fields, but in the background of information and communications technology, it refers to the frequency band at which wireless telecommunications signals are sent and broadcast. The frequency band is divided into various sections, that are assigned to various technology industries. This is referred to as the radio spectrum.
Figure1.20 show Commercially exploited radio-frequency spectrum bands

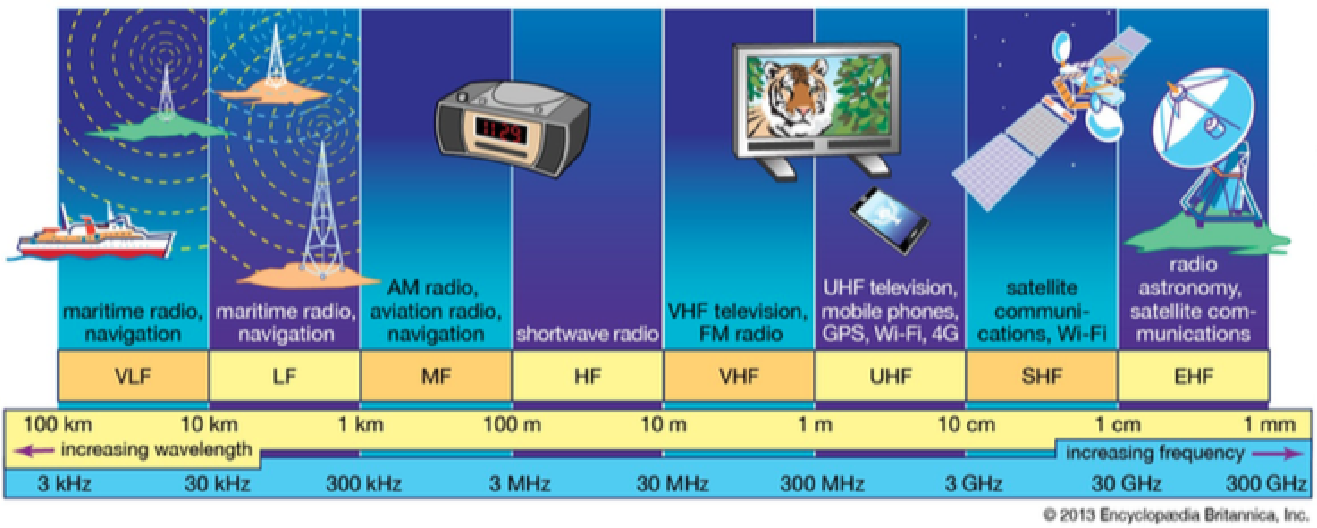


Figure 1.20: RF Spectrum and Frequency Bands

1.13 Signal Representation

1.13.1 Quadrature Signals

Quadrature signals, also known as IQ signals, IQ data, or IQ samples, are often utilized in radio frequency (RF) applications. They form the foundation for complex RF signal modulation and demodulation, both in hardware and in software, as well as **complex signal** analysis [38]. Quadrature signal formats, also known as complex signals, are utilized in a wide range of digital signal processing (DSP) applications, where require Many DSP applications the processing I/Q data. **I/Q data** is a different way of describing a signal's magnitude and phase data. It is the data we use to process signals received over the air, obtained by sampling complex signals. Two signals where the phase is 90 degrees apart are called **"in quadrature"**.The signal that is **"in-phase"** or "reference signal" is referred to as **"I"**, and the signal that is 90 degrees displaced (the signal in **quadrature**) is referred to as **"Q"**.

1.13.2 Quadrature Sampling

In digital systems, several methods can be used to detect the amplitude and phase of RF signals. The primary reference in digital signal processing (DSP) is the local **sampling rate**, and is therefore highly dependent on I and Q signals for processing.

A sinusoidal wave can be expressed in equation:

$$V(t) = A \times \sin(2\pi f t + \Phi) \tag{1.3}$$

Where: **A** is the Peak Voltage, **f** is the frequency, **t** is the time, Φ is the phase shift

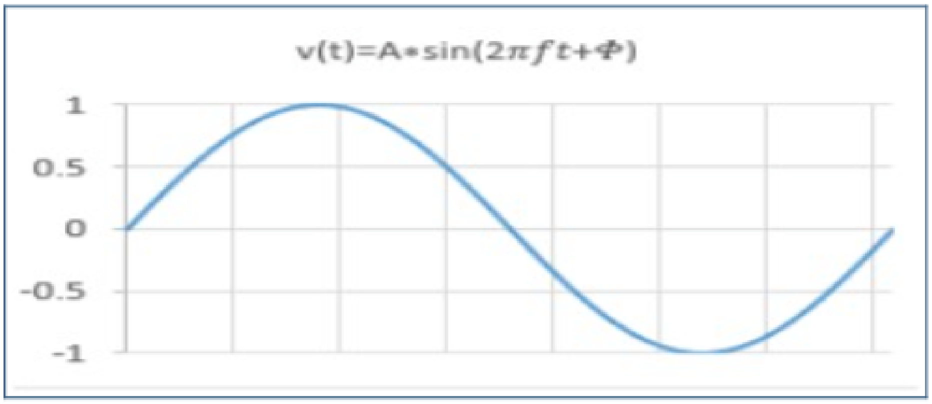


Figure 1.21: sinusoidal wave V(t)

Accordingly, the signal **I** is a **cosine** waveform, and the signal **Q** is a **sine** waveform. On the other hand, the sine wave is shifted (without any additional phase) by 90° relative to the cosine wave. Cosine wave and sine wave are quadratic waveforms.
The amplitude of the In-phase signal I:

$$I \times \cos(2\pi f t) \tag{1.4}$$

The amplitude the quadrature signal (Q):

$$Q \times \sin(2\pi f t) \tag{1.5}$$

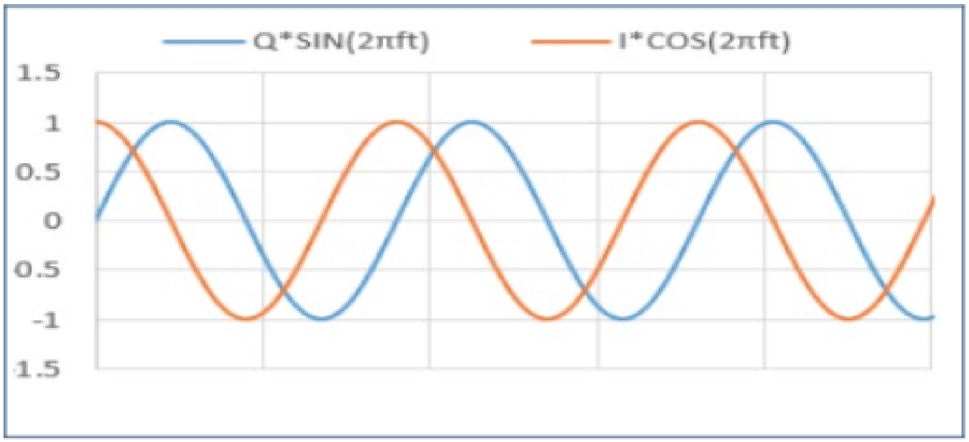


Figure 1.22: I and Q sinusoidal wave

When we add cos() and sin(), we get another sine wave of different phase and amplitude, The 'advantage' of this behavior is that we can control the phase and amplitude of the resulting sine wave by adjusting the amplitudes I and Q:

$$I \times \cos(2\pi f t) + Q \times \sin(2\pi f t) \tag{1.6}$$

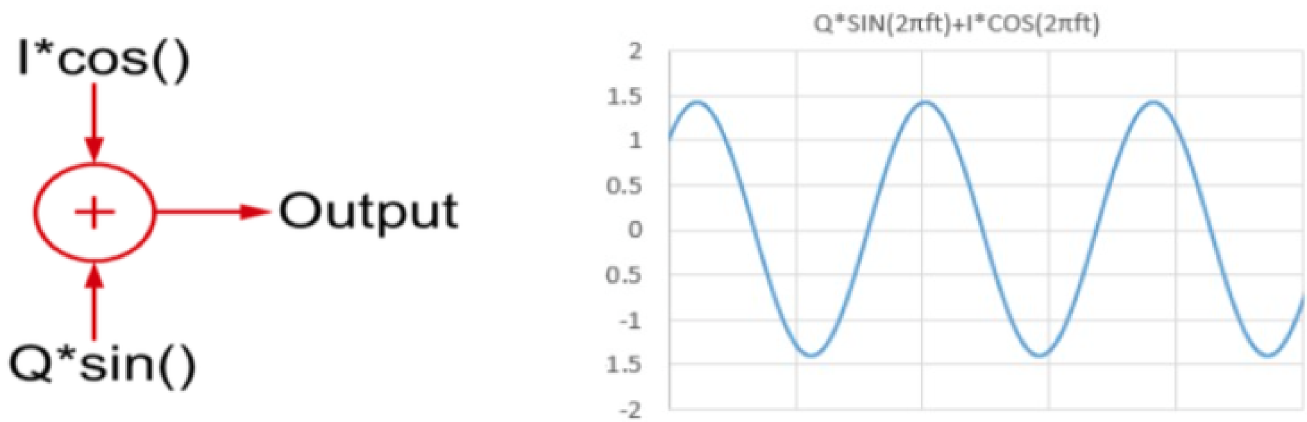


Figure 1.23: I and Q signals and a sinusoidal signal

"Nyquist frequency is twice highest frequency, not twice bandwidth of signal. For example: common frequency used in analog signal processing is 455 kHz. To sample in digital processing, requires 910 kS/s. But bandwidth is only 10 kHz. With I & Q, sampling requires only 20 kS/s " [39].

I and Q permit distinction of positive and negative frequencies:

$$\text{If:} \quad H(f) = a + jb \tag{1.7}$$

$$\text{Then:} \quad H(-f) = a - jb \tag{1.8}$$

1.13.3 Quadrature as Complex Number

The IQ convention is an alternative method of representing magnitude and phase, which leads us to complex numbers and the capacity to represent them on a complex plane. “A quadrature signal is a two-dimensional signal whose value at some instant in time can be specified by a single complex number having two parts, what we call the real part and the imaginary part “[40]. Sinusoidal signals can be represented as time-varying complex numbers, namely amplitude, and phase (Polar coordinates). where I and Q are the In-phase and Quadrature components of a signal.

- I and Q (rectangular coordinates).
- I = In phase (real).
- Q = Quadrature (imaginary). The time domain waveform $x(t)$ of a complex signal is given by:

$$X(t) = xi(t) + jxq(t) \tag{1.9}$$

As seen in the graph in figure1.24 the I and Q projections of the polar coordinate sinusoidal wave are on the x- and y-axes, respectively.

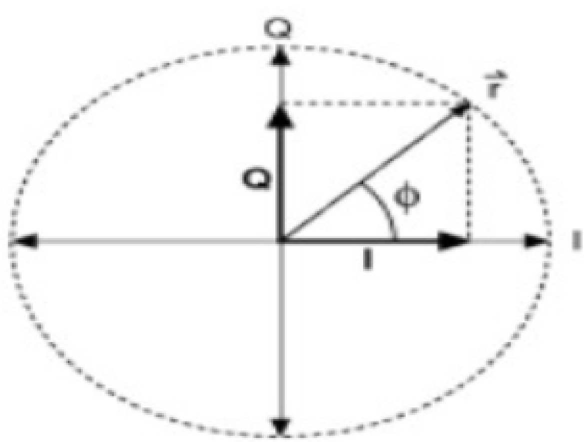


Figure 1.24: Polar representation of sine wave

Figure1.24 shows the frequency of the sine wave as the rate of rotation of the vector r traveling around the circle.

The magnitude (M) is given by:

$$M = \left(I(t)^2 + Q(t)^2\right)^{\frac{1}{2}} \tag{1.10}$$

The phase φ is given by:

$$\varphi = \tan^{-1}(Q/l) \tag{1.11}$$

Although magnitude and phase data appear to be more intuitive, I and Q data are the best option for RF waveforms due to hardware design considerations. .The RF signal may be generated using any type of modulation by utilizing the proper baseband signals I (t) and Q (t) (which in role vary the amplitude of the cosine and sine waves that are collected together)

I & Q values might be generated by a DAC (digital – to – analog – converter) and modulated to be transmitter to RF system.

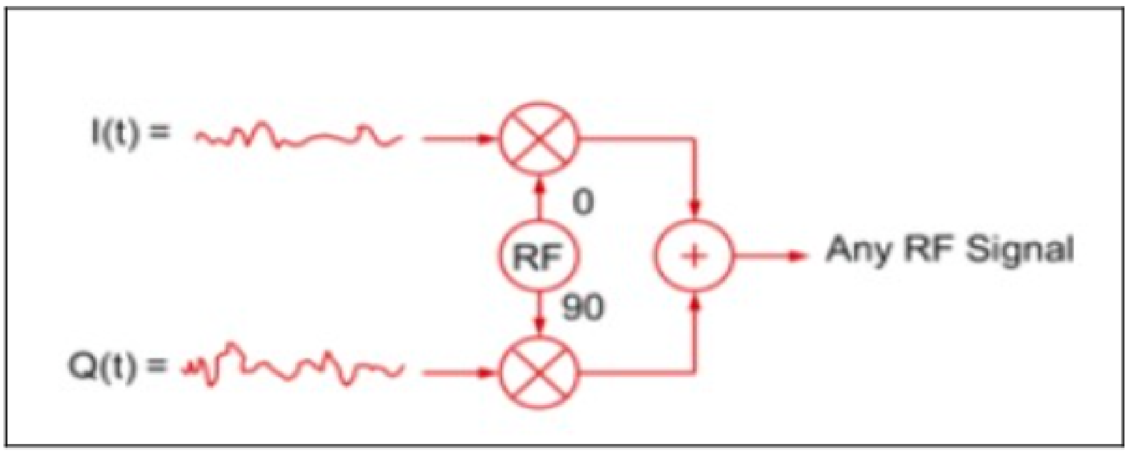


Figure 1.25: block diagram of I/Q modulator

The same process is used to demodulate an RF signal. By Mixing an RF signal with LO (local oscillator) signals in quadrature, I (t) and Q (t) baseband signals may be generated.

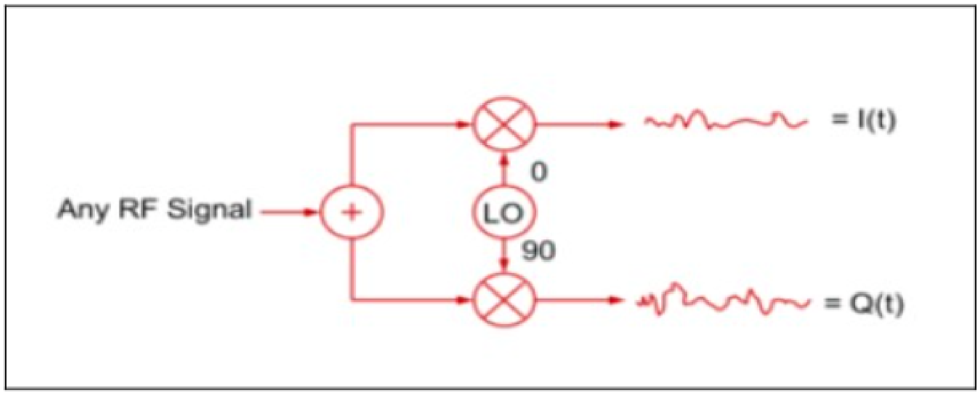


Figure 1.26: block diagram of I/Q demodulator

AM Modulation in IQ

In amplitude modulation (AM), the amplitude of the modulating signal m(t) modifies the amplitude of the carrier signal. In the following equation, A represents the carrier amplitude and M represents the modulation amplitude [41].

$$y(t) = (A \cdot \cos(2\pi ft)) \cdot (1 + (M/A \cdot m(t))) \tag{1.12}$$

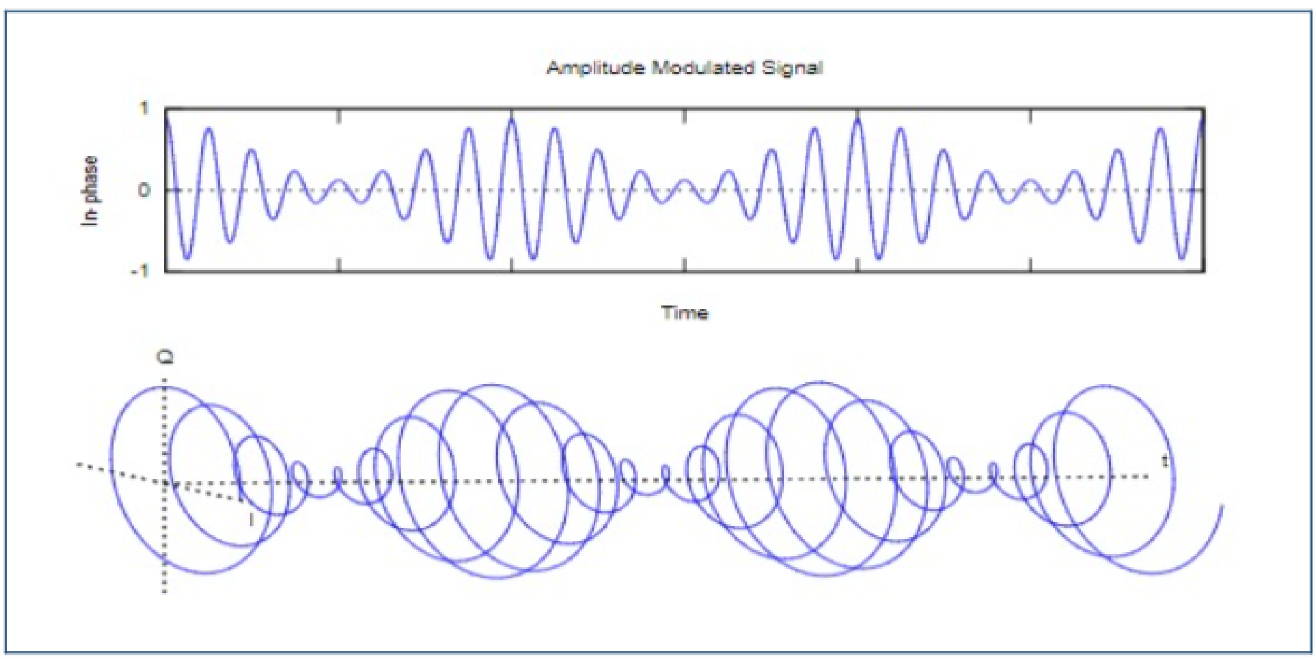


Figure 1.27: AM Modulation in I/Q data

FM Modulation in IQ

In frequency modulation (FM), the amplitude of the modulating signal m(t) modifies the frequency of the carrier signal. The actual modulation makes use of a constant k based on m(t) characteristics and a signal $\psi(t)$ that is an invertible acceptable transform on m(t) [41].

$$y(t) = \cos(2\pi jct + (k\dot{\psi}(t))) \tag{1.13}$$

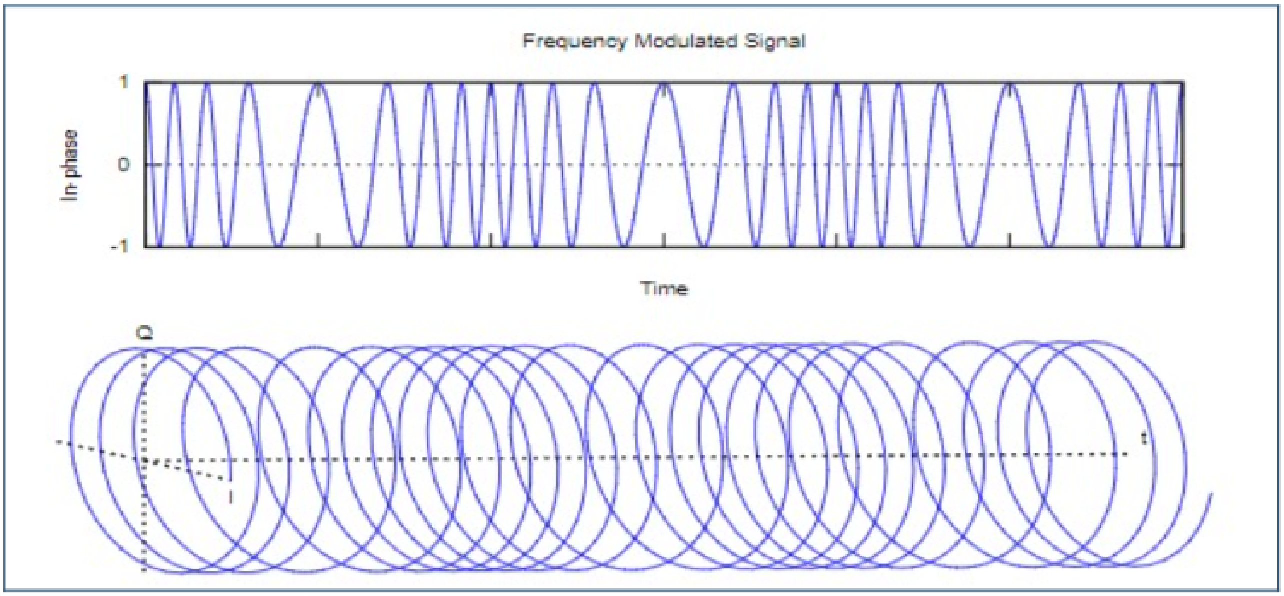


Figure 1.28: FM Modulation in I/Q data

Spectrogram

A Spectrogram is a detailed view representing the signal strength over time at various frequencies present in a particular waveform, able to represent time, frequency, and amplitude all on one graph. Is created by stacking a series of spectra together in time and compressing the amplitude axis into a greyscale 'contour map.' The final graph shows time on the horizontal axis, frequency on the vertical axis, and the signal's amplitude at each given time and frequency as a grey level. Black is traditionally used to indicate the highest level of energy, whereas white is used to indicate the lowest level of energy. [42] Spectrograms can be two-dimensional or three-dimensional graphs with a fourth color variable [43] also can visually display broadband, electrical, or intermittent noise in audio, allowing you to quickly determine the source of the problem. Because of the high degree of detail[44].

1.14 Neural Network

"A neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the inter unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training "[45].

1.14.1 Biological Neuron

These are cells located in the cerebral cortex, where the dendrites receive electrical signals as weight inputs. As shown in figure1.29, The input is utilized to calculate the output signal by the cell body. Once again, the output signal arrives at a specified value, it passes via the axon. The wire connects to other neurons utilization the synaptic tip.

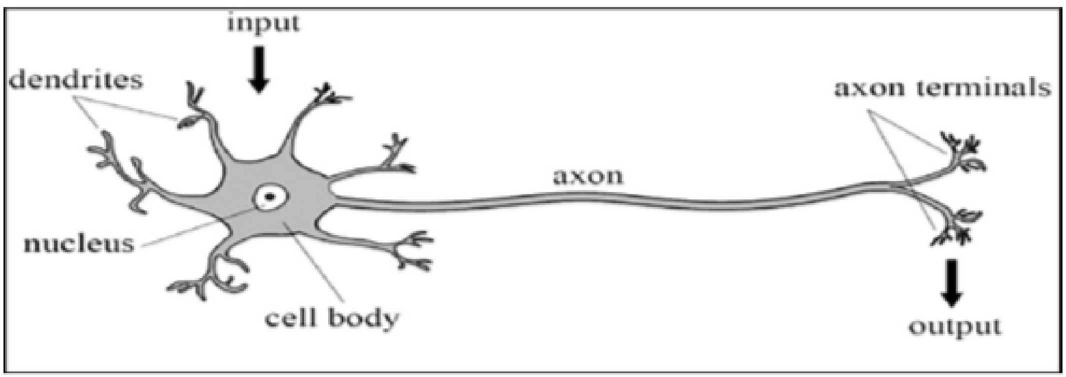


Figure 1.29: Biological Neuron Structure

1.14.2 Artificial Neural Network

Artificial Neural Network is a model based on units called neurons or perceptrons. An artificial neural network is a collection of connected input and output units, each with its own weight.. During the learning phase, the network learns by adjusting the weights in order to anticipate the right class label of the input tuples [46]:

- Inputs connections is a vector (X_i) with weights (W_i) each input is multiplied by its weight.
- Pre-activation function is a summation function that sums weights after multiplies each of input by their own associated weight plus the bais $\sum_{1}^{n} X_i W_i + b$
- Activation function transforms the pre-activation f(x).

- Output is responsible for producing the final result.

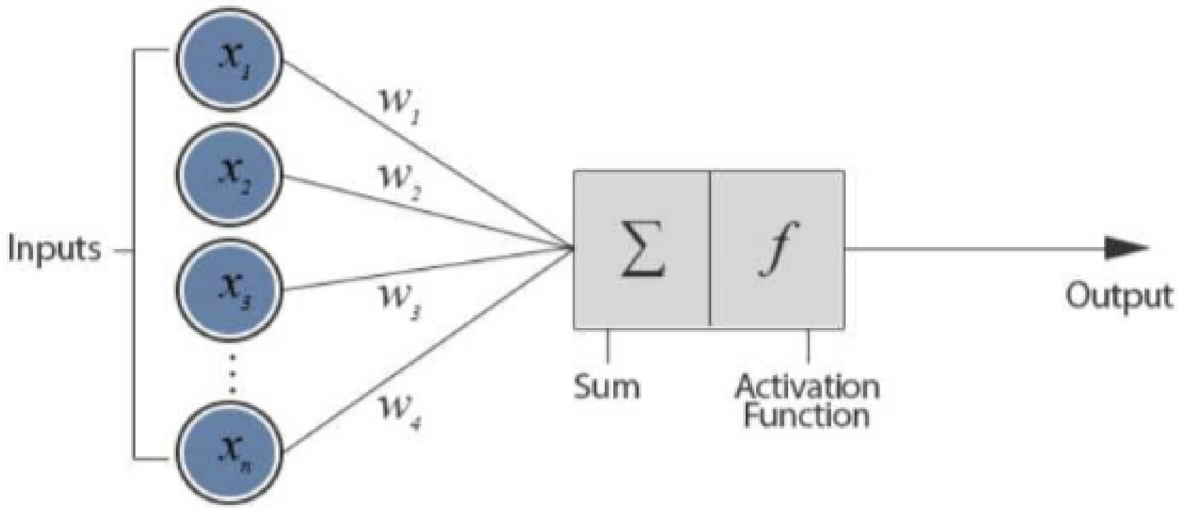


Figure 1.30: Artificial Neuron Structure

1.15 Activation Functions

An activation function decides whether a neuron should be activated or not. The role of the Activation Function is to derive output from a set of input values fed to a layer, is chosen according to the problem and outputs [46], we will list some of the most common activation functions:

a. Sigmoid: is helpful in performing computations that should be interpreted as probabilities and transforms the values between the range 0 and 1. The Sigmoid function is defined mathematically by equation(1.14) and figure1.31 represents its plot:

$$f(z) = \frac{1}{1+e^{-z}} \tag{1.14}$$

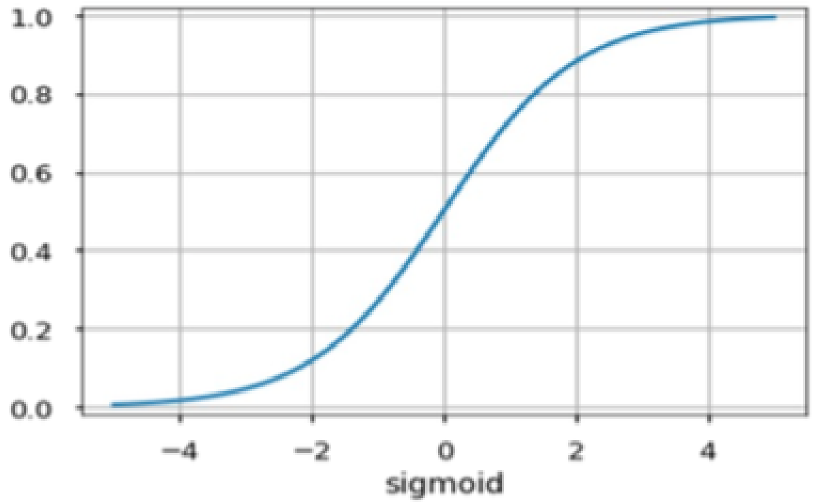


Figure 1.31: The Sigmoid Function Plot

b. Hyperbolic Tangent (Tanh): is very similar to the sigmoid activation function, The only difference is that it is symmetric around the origin, its output value is in the range $[-1, 1]$. Tanh is defined mathematically by equation(1.15) and figure1.32 represents its plot:

$$f(z) = \frac{1 - e^{-2z}}{1 + e^{-2z}} \tag{1.15}$$

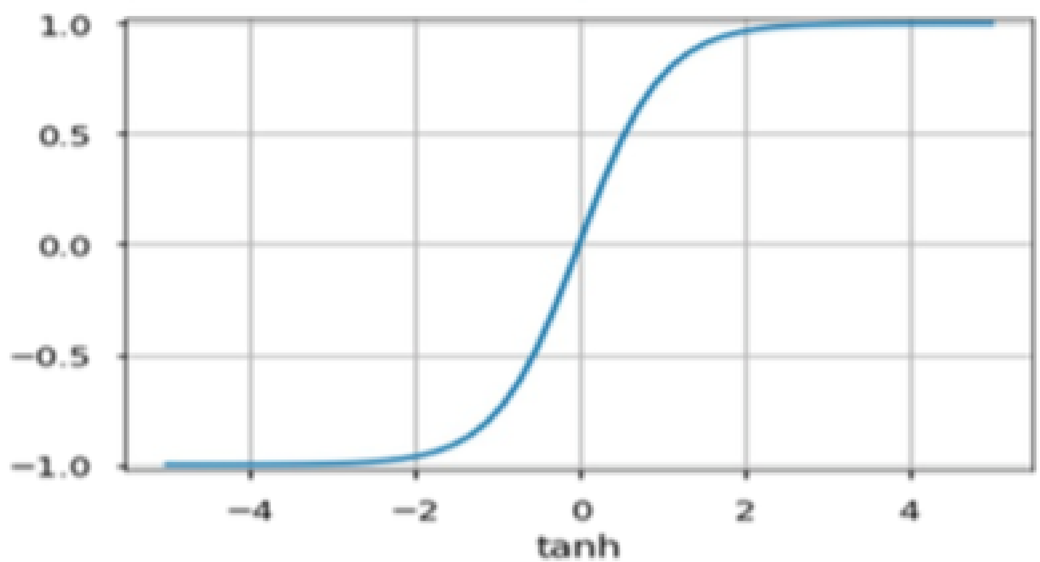


Figure 1.32: The Tanh Function Plot

c. Rectified Linear Unit (ReLU): 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. ReLU is defined mathematically by equation(1.16) and figure1.33 represents its plot:

$$f(z) = \max(0, z) \tag{1.16}$$

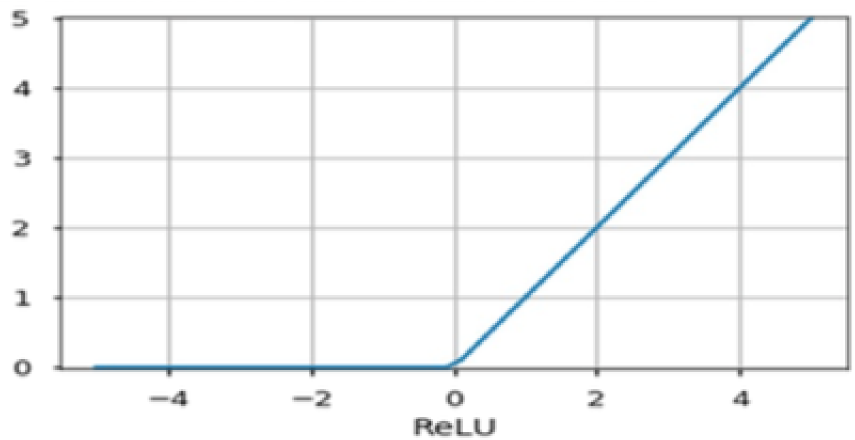


Figure 1.33: The ReLu Function Plot

d. Softmax: used for multiclass classification problems, its gives output value in the range $[0, 1]$. The Softmax function is defined by equation(1.17):

$$f(z) = \frac{e^{zj}}{\sum_{k=i}^{k} e^{zk}} \quad \text{for } i = 1, \cdots, k \tag{1.17}$$

1.16 Deep Neural Networks

A deep neural network (DNN) is a type of stacked neural network, which is made up of multiple layers [47]. A deep neural network as show Figure1.34 is a bio-inspired algorithm. Graphically shown as a series of layers, where each layer is a vertical collection of nodes. When fed raw input data, each node corresponds to a processing unit that employs a linear function followed by a non-linear activation function. This application will convert the data representation at each layer, give rise to a statistical model that will assist us in doing the classification/detection task later on. The output is a sequence of probabilistic nodes, each of which corresponds to the likelihood of categorizing the input in a certain class.

DNNs can extract high-level features from raw sensory data after using statistical learning over a large amount of data to obtain an effective representation of an input space. This is different from earlier approaches that use hand-crafted features or rules designed by experts, There are a lot of layers that help them be more effective [48].
Figure1.34 represents an 'N' layered Deep Neural Network.

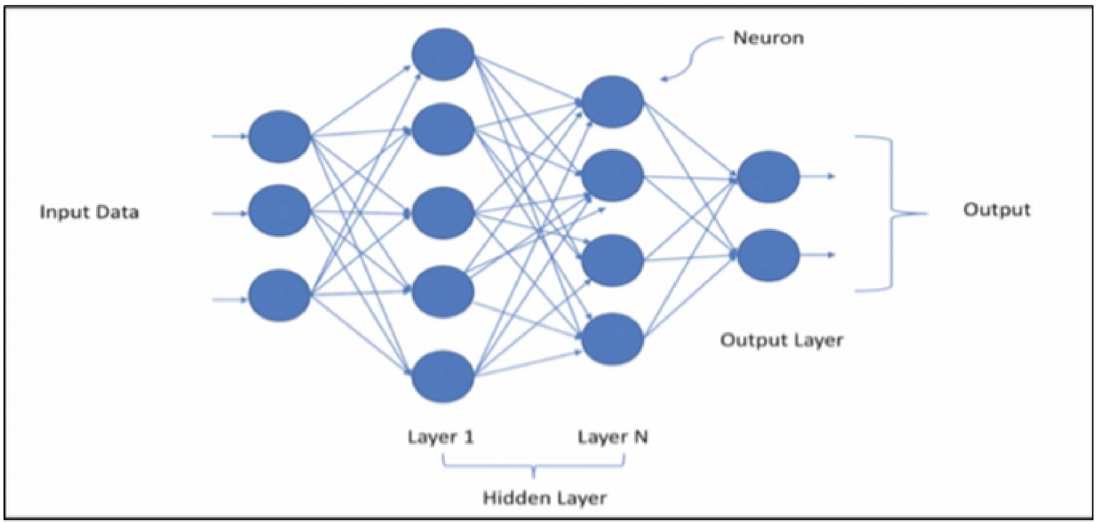


Figure 1.34: A Deep Neural Network

1.17 Convolutional Neural Network

Convolutional Neural Network (CNN), also called ConvNet, is a particular type of feed-forward neural network. CNN's are models that are most frequently used for image processing and computer vision. They are designed in such a way to imitate the structure of the animal visual cortex [49]. It is designed to work with grid-structured inputs, that have strong spatial dependencies in local regions of the grid [50]. This type of network relies on a linear arithmetic process, is the convolution, from here the name convolutional neural network. The primary benefit of CNN compared over its predecessors is that it automatically determines the relevant features without the need for human intervention [51]. The most important feature that distinguishes them from neural networks is the convolutional layer, which extracts features. In CNN first stage, there are many stages are the convolution and pooling layers. In the final stage, there are the Fully-Connected layer and the Classification layer. Following these multiple consecutive trainable layers, the Deep

Learning structure proceeds with a training layer. CNN gives an output to Verification with veritable/correct results. This comparison gives an error rate which is that the difference between generated output and targeted result. CNN can utilize different input files such as images, audio videos, or other signals.
Figure 1.35 shows the structure of a CNN.

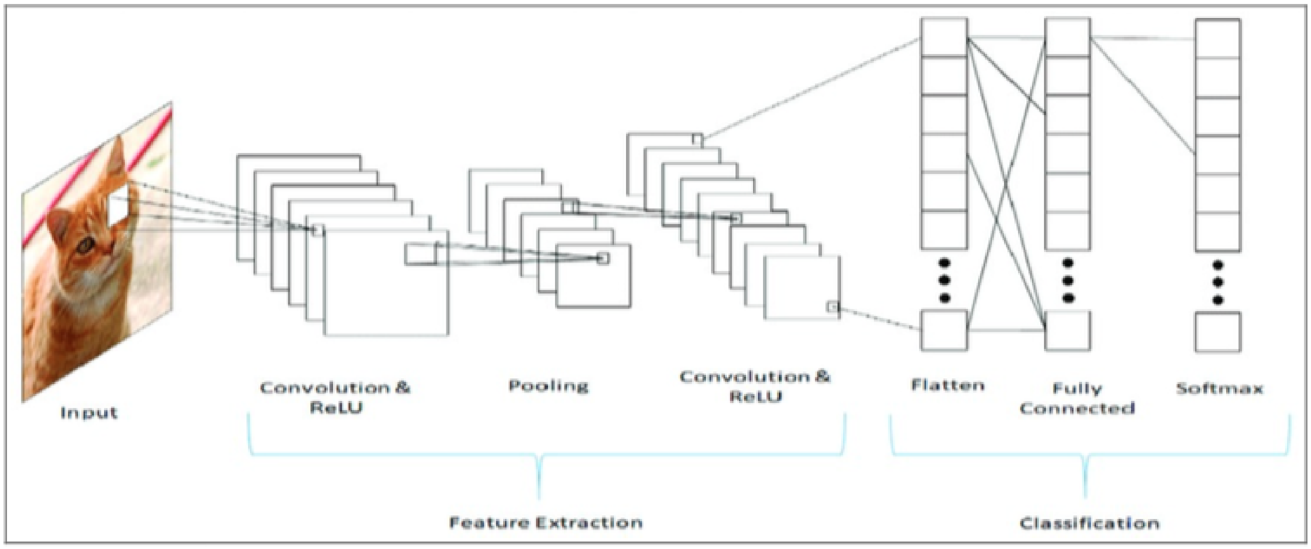


Figure 1.35: Convolutional Neural Network [52]

1.17.1 Convolution Neural Networks Layers

a. **Convolutional Layer:** The convolutional layer is the most important component. This layer's role is to analyze the images supplied as input and detect the existence of a set of features. so that the convolutional layer grab the input and applies a filter to each position, when outputting this layer we get a set of feature maps. This convolution process creates feature maps where each individual feature map is a convoluted result of different individual feature detector which is shown in Figure 1.36. Rectified linear unit (ReLu) activation function is then applied to increase the non linearity in the resulting feature maps in order to distinguish adjacent pixels of the maps more accurately [53].

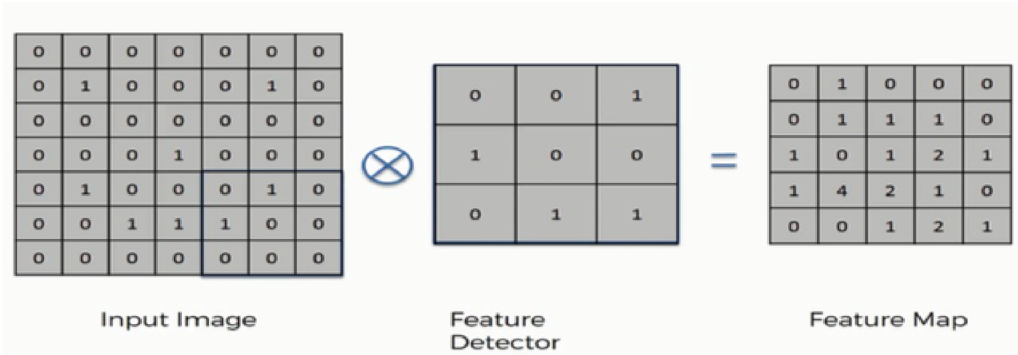


Figure 1.36: Convolution operation

b. Pooling Layer: The Pooling layer is in charge of reducing the spatial size of the Convolved Feature. This is done to reduce the computational power necessary to process the data by reducing the dimensions. Furthermore, it aids in the extraction of the most dominating and useful features. Different types of pooling exist as shown in Figure 1.37:

- Max pooling: Takes the maximum value among all values in the collection window and it is the most common type.
- Average pooling: Takes the average of values in the collection window

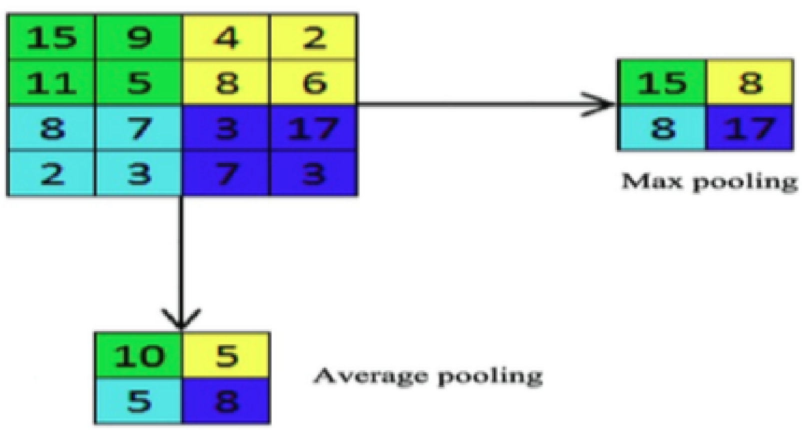


Figure 1.37: Pooling Types

c. Flattening Layer: This layer converts the input size from shape (width, height, depth) to a one-dimensional array. This is done in order to take use of all layer information and be prepared to connect to the artificial neural network show in Figure 1.38 :

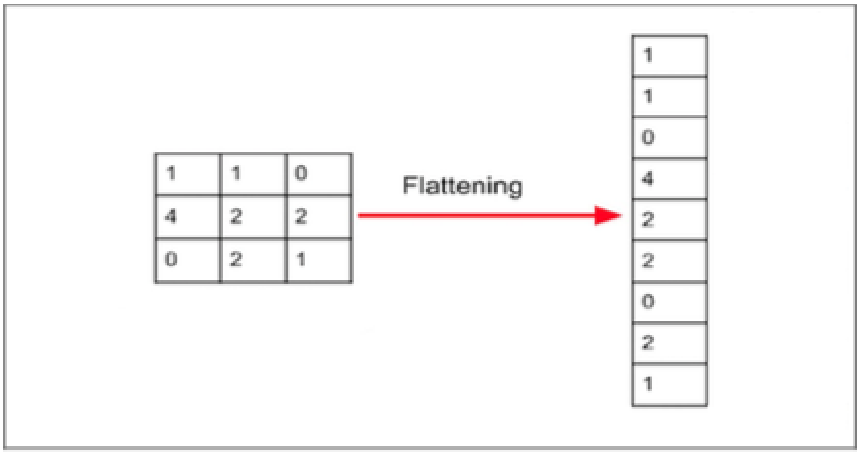


Figure 1.38: Flattening

d. Fully Connected layer: Once the features were extracted, the final features are passed through a dense neural network, which is assumed to categorize the pictures into the proper class and give the output probabilities based on the training process as shown in Figure 1.39. The fully connected layer employs the non-linear Softmax function To categorize its outputs.

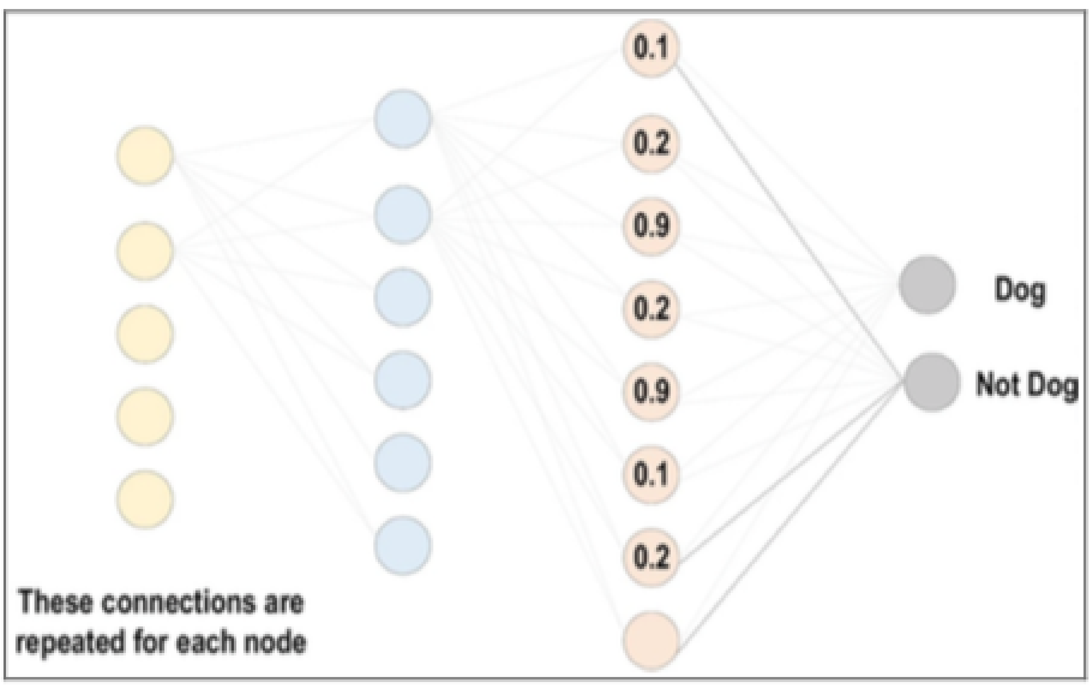


Figure 1.39: Fully Connected Layer

1.17.2 CNN Architectures

1. **LeNet-5:** The LeNet-5 is the first CNN architecture designed. It is one of the first successful applications of CNNs. It was created by Yann LeCun in 1998 for the Classification of numbers and determination of handwritten numbers in the numbered checks as 32 * 32 pixel input image., and it was trained on the MNIST dataset [54]. More convolutional layers contribute to the usage of the LeNet-5 for high-resolution pictures. Figure 1.40 illustrates the basic design of the LeNet-5 architecture. It consists of 7 layers, does not comprise an input, Each of them has trainable parameters. Three convolutional layers, two pooling, and two fully linked layers. Each layer contains a set of the feature map, which is a characteristic of each of the Feature Map inputs extracted by a convolution filter, and then each feature map there are many neurons. The output layer is made up of 10 neurons with radial basis activation functions.

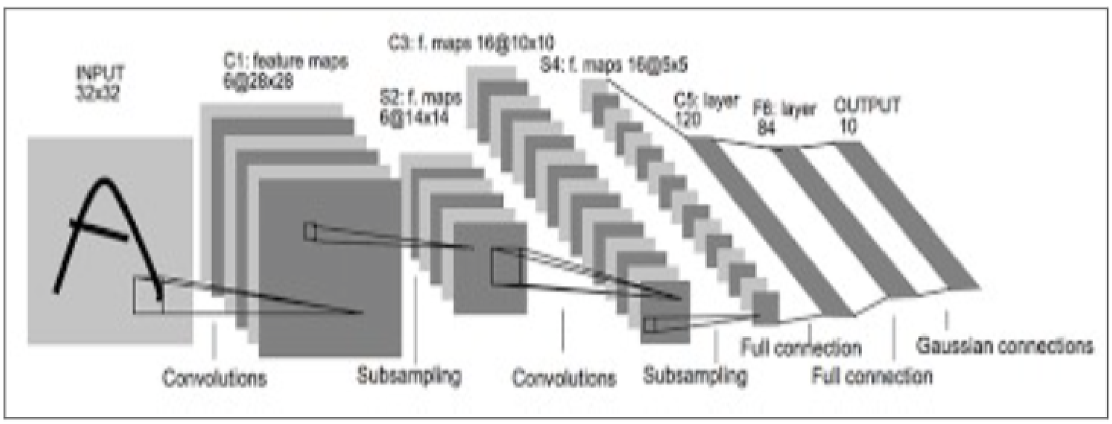


Figure 1.40: The Architecture of The LeNet-5 CNN

2. **AlexNet:** It is one of the first works aimed at generalizing convolutional neural networks in computer vision. AlexNet [55] was presented into the ImageNet ILSVRC challenge in 2012 and outperformed the other handcrafted models substantially. In comparison to LeNet, this network was deeper (60 million parameters) and larger (5 convolutional layers, 3 max-pooling , and 3 fully-connected layers). And therefore, improved the CNN learning ability by raising its depth and implementing many parameter optimization strategies. Figure 1.41 illustrates the basic design of the AlexNet architecture.
   A modified version of AlexNet called ZFNet[56] was developed by Matthew Zeiler and Rob Fergus. It is the same as AlexNet with Few number variable hyperparameters (number of feature maps, kernel size, stride, etc.), where the size of its middle convolutional layers have been expanded. Additionally, the stride and filter size of its first layer have been reduced.

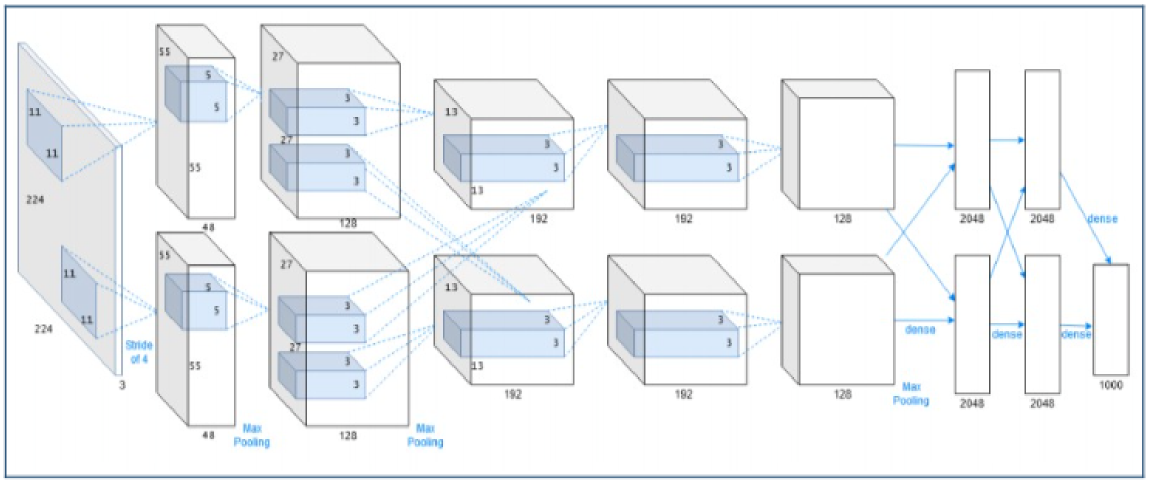


Figure 1.41: The Architecture of The AlexNet CNN [57]

3. VGG: VGG Net was introduced by Simonyan and Zisserman in 2014. The VGG Net, also known as the VGG-16, contains about 16 convolutional layers. It has a very uniform architecture, which is one of its advantages. similar to AlexNet, The VGG contains also just 3×3 convolutions. In comparison to AlexnNet, VGG employs a plethora of filters. This CNN is trained during a two- to three-week period. Weights implementations often use as a basis for developing their own feature extraction, While these are some of VGG Net's positive aspects that make it easier and more beneficial to use,Some elements such as its parameters add complexity . VGG Net has about 138 million parameters, This might get complicated and difficult for certain users. Figure 1.42 shows architecture.

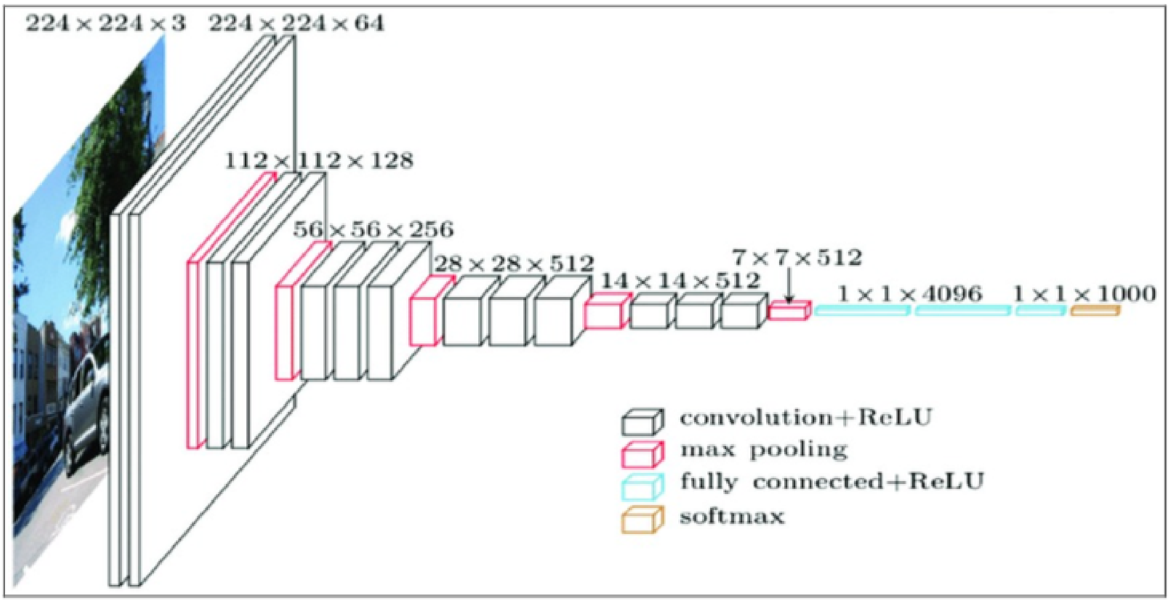


Figure 1.42: The Architecture of The VGG-16 CNN

4. **ResNet:** ResNet was developed in 2015 by Kaiming He et al. It is a cutting-edge model, having won the ILSVRC 2015 in image classification, detection, and localization, as well as the Microsoft Common Objects in Context (MS COCO) 2015 detection and segmentation. Kaiming desired to solve the vanishing gradient problem. He developed ultra-deep networks to achieve this [58]. Adding more layers creates the problem of gradients Vanishing/Exploding, ResNets beat this challenge by entering Skip/Shortcut Connection inside what is known as a residual block. the approach behind this network so instead of layers learning the underlying mapping, we permit the network to suitability the residual mapping. wherefore, Instead of saying $H(x)$, initial mapping, let the network fit, $F(x) := H(x) - x$ which produces $H(x) := F(x) + x$. These skip connections permitted the implementation of extremely deep networks with no vanishing gradients. The depth of the network reached 152 layers, and as a result, an error rate of 5.71% was obtained from the top 5 which is much better compared to some other architectures. Figure 1.43 shows the architecture of a residual block, whereas Figure 1.44 shows the 34 layer ResNet along with the regular 34 plain networks and the VGG-19 network.

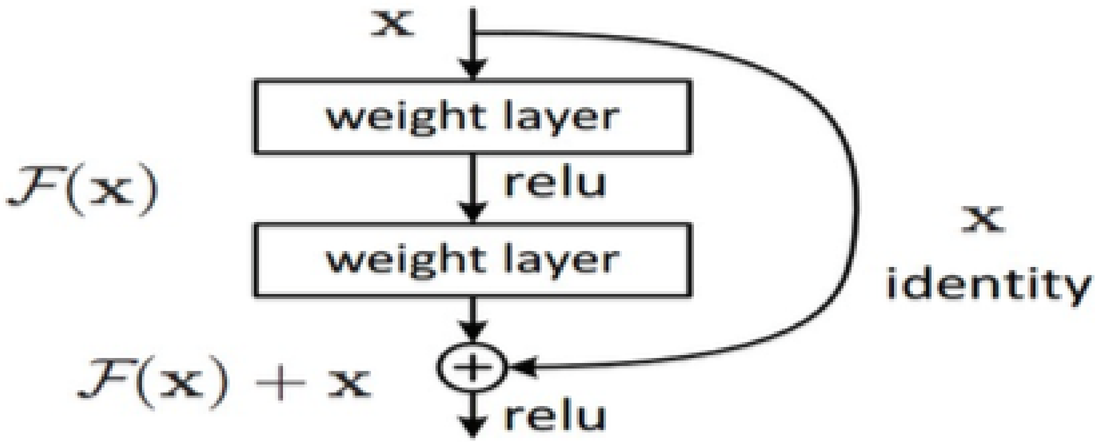


Figure 1.43: Residual Block

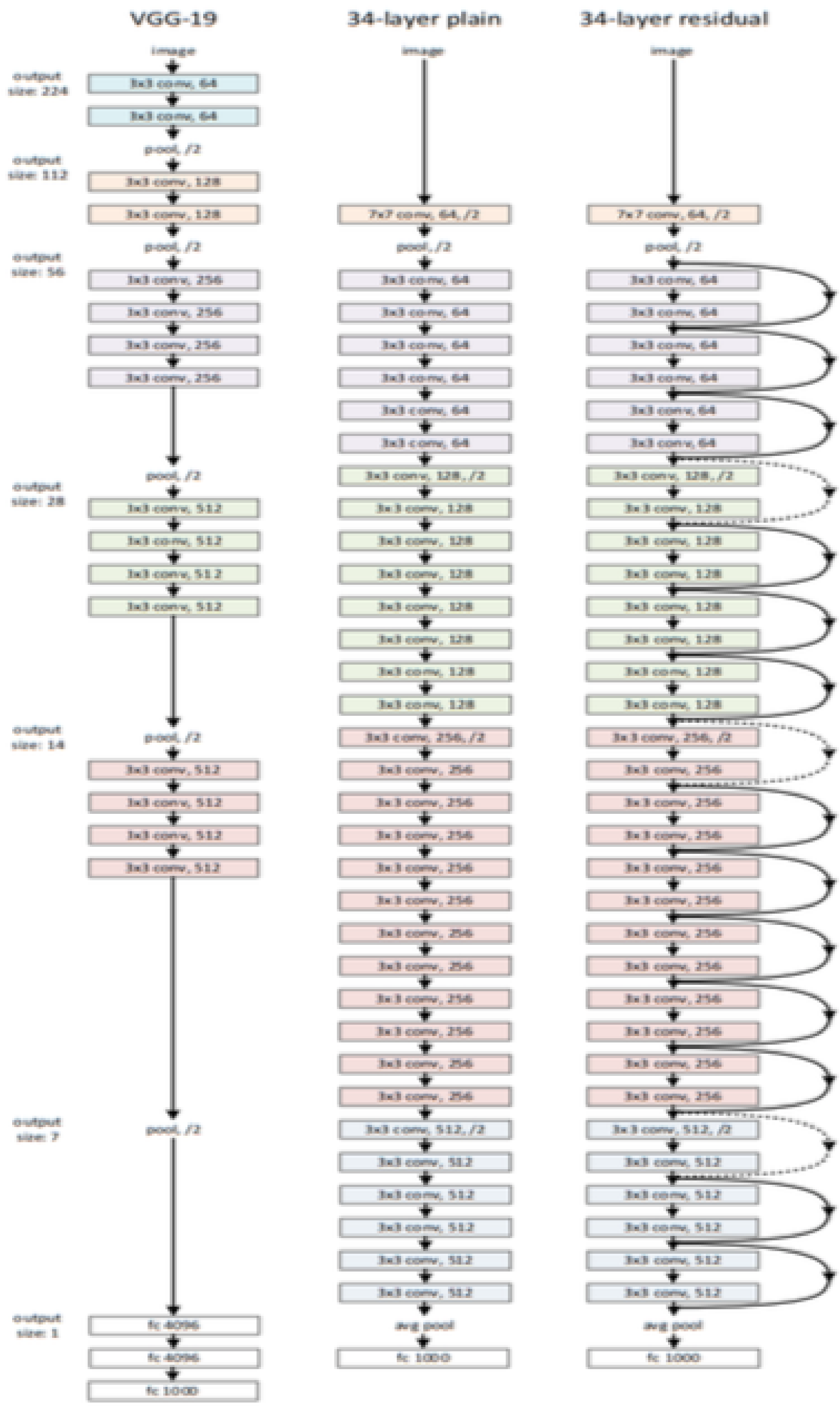


Figure 1.44: PART-1 of ResNet (right), Pure Network (middle), VGG-19 (left)

1.18 Recurrent Neural Network

The first RNN network, Hopfield nets developed by John Hopfield was proposed in 1982 [59]. it is class of neural networks that are naturally suited to processing time- series data and other sequential data [60]. It is widely used to solve a wide range of complex problems, including, machine translation, speech recognition, automatic image annotation, and inventory forecasting. RNN is distinguished by its unique architecture that differs from the rest of the networks, where its peculiarity is that its output depends not only on the current input, but also on the previous output. In fact, RNN neurons can retain memory information about previous values belonging to a sequence, Which makes it possible to predict the next value in the sequence.

For example, a person who reads a text, reads the words one by one, But consider the meaning of the preceding words, on which the comprehension of the present word is predicated, It is this sequence that causes it possible to give meaning to the whole sentence. This is a typical case of Recurrent Neural Networks (RNNs).

RNNs are called recurrent because they perform the same task for each element of the sequence, and the output is based on previous calculations. the most fundamental component of an RNN is the recurrent neuron. as each time step, the neuron receives a standard input in addition to the output from the previous time step.

1.18.1 How RNN Works?

RNN takes vector X_t as input and creates vector Y_t as output, as shown in Figure1.45. Nevertheless, this vector produced as output is not only affected by the input we present in real-time but also on the input history that is fed before. Every time, when the step is to know the RNN, class updates internal state. The single hidden vector h being present can be concluded as the simplest case [61]. The mechanism illustrated in figure 1.45 permits the network to function in a variety of ways different, depending on the size of the input sequence we present it, and the size of we expect output sequence.

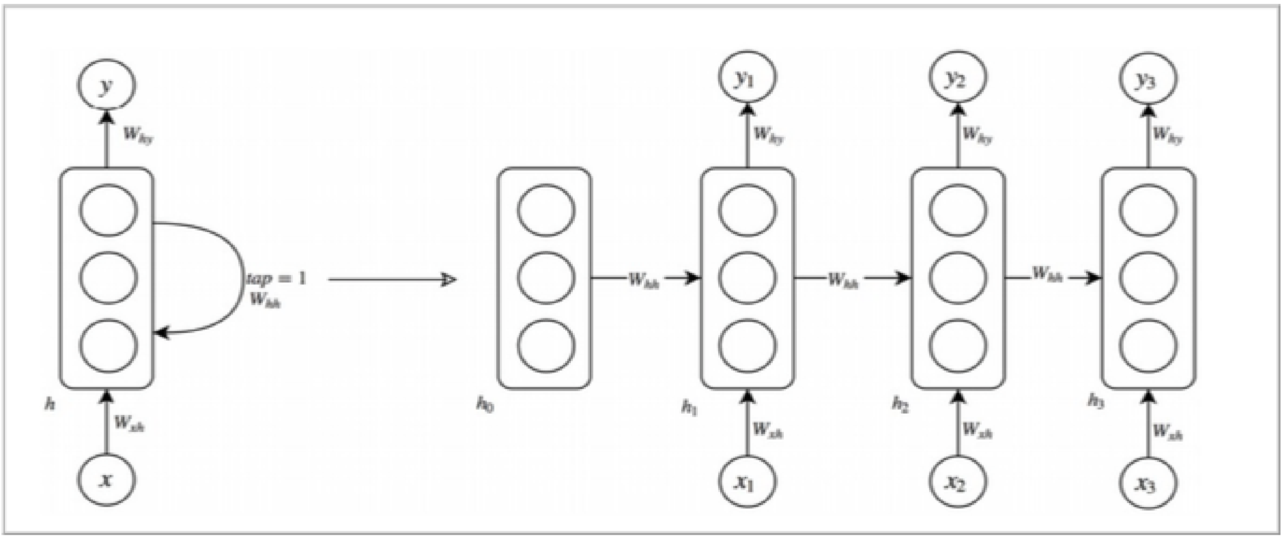


Figure 1.45: Recurrent Neural Network

In more formal, a measure recurrent neural network models the temporal dynamics of an input sequence $x = \{x_1, x_2, \cdots, x_T\}$ by calculating the hidden vector sequence $h = \{h_1, h_2, \cdots, h_T\}$ and output vector sequence $y = \{y_1, y_2, \cdots, y_T\}$ and W is weights, where W_{xh}, W_{hh}, and W_{hy} are the learned weight matrices, The formula to calculate current state t is defined :

$$h_t = f(h_{t-1}, x_t) \tag{1.18}$$

It is worth noting that we have input hidden weight w_{xh} and hidden layer hidden weight Whh, as well as the resulting hidden weight w_{yh} . Using tanh as a function, the equation became:

$$h_t \;=\; tanh(W_{hh} \cdot h_t, W_{xh} \cdot x_t) \tag{1.19}$$

The output is:

$$y_t \;=\; W_{yh} \cdot h_t \tag{1.20}$$

1.18.2 RNN Problems

In partical, RNNs are challenging to train, particularly when utilized with gradient descent to modeling long-term dependencies. This is due to two major issues: **exploding and vanishing gradients.**

- **Exploding Gradient:** referred to as a grand raise in the norm of the gradient during training, which blocks us from training the model by causing numerical instabilities and polluting the whole graph.

- **Vanishing Gradients:** When the fast exponential gradient criterion drops to zero which blocks the model from paying attention to the long-range dependencies in the sequence.

Interestingly, both result from the frequent use of W_{hh} and the prior case h_{t-1} when calculating gradients. Exploding gradient can mostly be processed by gradient norm clipping [62]. and appropriate initialization. From the other hand, mitigating vanishing The gradient problem requires more effort. once again, initialization along with regularization or using ReLU lieu of tanh can help. The most popular and effective choice is the use of gated variants of the standard RNN.

1.18.3 Long Short Term Memory (LSTM)

First proposed by Hochreiter and Schmidhuber (1997). It is a common architecture for supply RNNs a memory unit. LSTM is a type of RNN that was created to relieve some of the problems faced by traditional RNNs, Especially the Vanishing Gradient problem, where the gradients are very small or even zero when the sequences are large, thus blocks learning. The problem is solved thanks to the organization of saved and forgotten data, which is implemented by the system of "gates" provided by the LSTMs. An unlike to the conventional RNNs, the LSTM model is capable to remember information for a long period of time [63]. The LSTM consists of a memory cell and its structure is shown in Figure 1.46. A memory block consists of 3 main components: the input gate, the forget gate, and the output gate. Basically, each gate has its private responsibility. The input gate defines what information should be stored in the cell, the forget gate define which information from the previous hidden state must be passed to the network, The output gate controls the information of the new calculated hidden state that is transmitted to the output vector of the network.

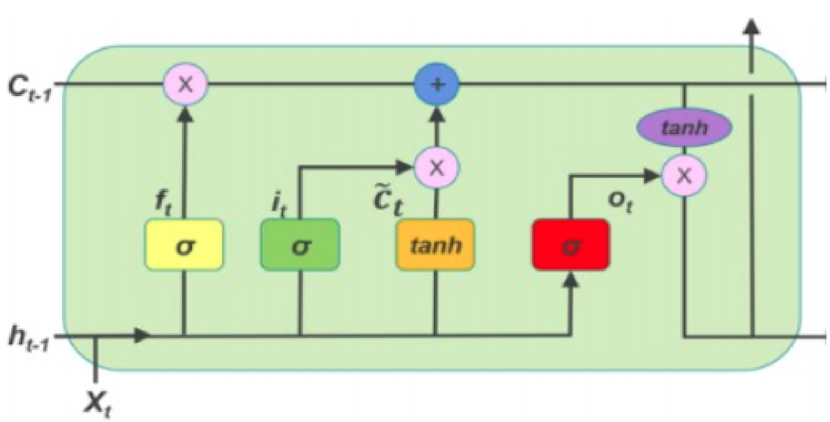


Figure 1.46: Structure of an LSTM Cell

The following formulae explain mathematically how the network layer in a memory cell is updated at each time step t. We designate x_t as the vector of the input sequence at time step t and ht as the hidden layer value of the memory cell at time step t. C_t, C_t, and $\tilde{C}_{t-1}$ we consider are the current, candidate, and prior cell states, respectively. First, the input and forget vector gates are computed as follows:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad \text{and} \quad f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{1.21}$$

Next, the current and candidate cell states are calculated:

$$\tilde{C}_t = \tan h(W_c x_t + U_c h_{t-1} + b_c) \quad \text{and} \quad C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{1.22}$$

Finally, the output gate value and the memory cell output value are computed:

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad \text{and} \quad h_t = o_t \times \tan h(C_t) \tag{1.23}$$

1.18.4 Gated Recurrent Units

Gated Recurrent Units (GRU) are improved version of standard recurrent neural network, where the forget and input gates are substitution by the zt update gate, the reset gate rt is inserted to modifyh_{t-1} , and the internal memory C_t is eliminated [64] As shown in Figure 1.47 by the following equations:

- The Update Gate z_t:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{1.24}$$

- The Reset Gate r_t:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{1.25}$$

- Hidden State $\tilde{h}_t$

$$\tilde{h}_t = tanh(W \cdot [r_t \times h_{t-1}, x_t]) \tag{1.26}$$

- The New Hidden State h_t:

$$h_t = (1 - z_t) \times h_{t-1} + z_t \times \tilde{h} \tag{1.27}$$

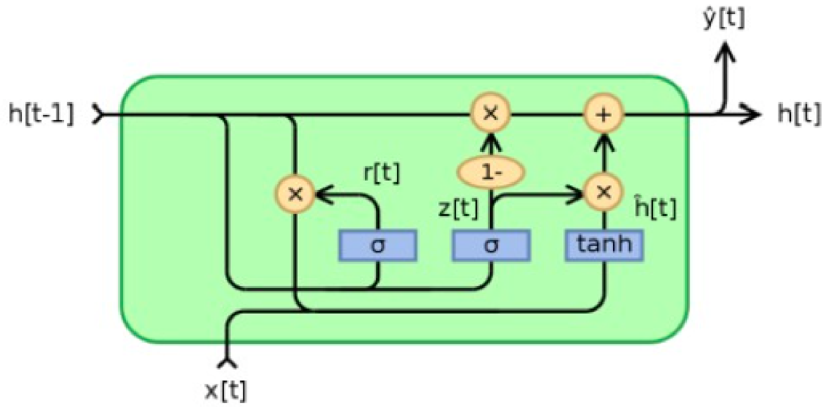


Figure 1.47: GRU structure

1.19 Regularization

Overfitting is a fundamental and unavoidable problem, which prevents us from fully generalizing the models to well fit observed data on training data, as well as the invisible data on the test set. Due to the presence of noise, the limited size of the training set, and the complexity of the classifiers, overfitting occurs [65].

In machine learning, and even more so in deep learning, Overfitting is a main problem that occurs during training. The model is an overfitting of the training data when the training error continues to decrease however the test error (or generalization error) begins to increase. At this stage, we tend to think that the model learns to distribute training data and not generalize to unseen data. In other words, We say a model is overfitting when it performs well in the training data while it misses to classify the test data. Furthermore, the model is learning the details and noise in the training data to some extent as it cannot recognize the new data, because the noise acquired from the training data does not apply to new data. As a result, the model begins to lose its capacity to generalize. To beat this problem, we use the so-called regulation techniques.

Regularization is defined as: "any modification we make to a learning algorithm that is intended to reduce its generalization error but not its training error." [66].

Regularization is a technique for decreasing variation in the validation set, And therefore, blocking the model from overfitting during training. When you do this, the model can generalize better to new examples. When training deep neural networks, there are two strategies to use as a regularize [67].

1.19.1 Dropout

Dropout is one of the most widely used and powerful organizing techniques developed by Hinton and his students at the University of Toronto in 2012. The term “dropout” refers to dropping out units (hidden and visible) in a neural network. By dropping a unit we mean tentatively eliminating it from the network, Besides all its incoming and outgoing connections, as shown in Figure1.48. The choice of which units to drop is random [68]. In other words, Dropping out a unit implies that it is momentarily erased from the network during training with all its connections. As a consequence, the units in the following layer are not reliant on any specific inputs since all inputs have an equal chance of being present.

In addition to being absent, This also causes the network to acquire uniform weight distributions, which means that no connections are biased With the training of the largest weights. Forward propagation is performed during testing using the trained uniform weights, and this may be regarded as an approximation of averaging the predictions of all the weak networks formed each time a unit is dropped during training[69].

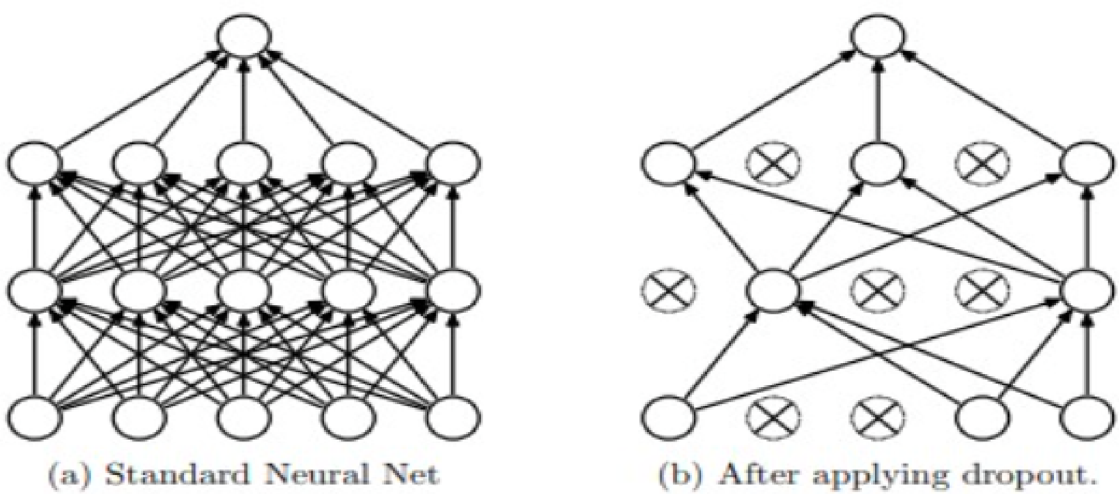


Figure 1.48: Dropout Neural Net Model. Left: standard neural network with two hidden layers. Right: An example of a thinned net generated by applying dropout to the network on the left. Crossed units have been removed [68]

.

1.19.2 Data Augmentation

Data augmentation is one of the most widely utilized pre-processing techniques for training neural networks. The term augmentation refers to an increase in the size, amount, or process of making, which summarizes the result of this technique. Based on this idea, data augmentation aims to increase the size of the existing training data set without the need to actually collecting any new data. This augmented data is obtained by a series of pre-processing conversions performed on existing data. Also, we can consider data augmentation as a strategy that concentrates, on renewal more images from the available images. And, more particularly, it is a technique that allows us to recreate an image in a different shape or dimension. Where it entails making certain modifications to the dataset images prior to training. and Includes modifications such as horizontal and vertical flipping, skew, shear, and rotate, applying noise to the image, ect (Figure 1.49). we hope subtle variations in these "extra" images should be enough to help train a more stronger model.

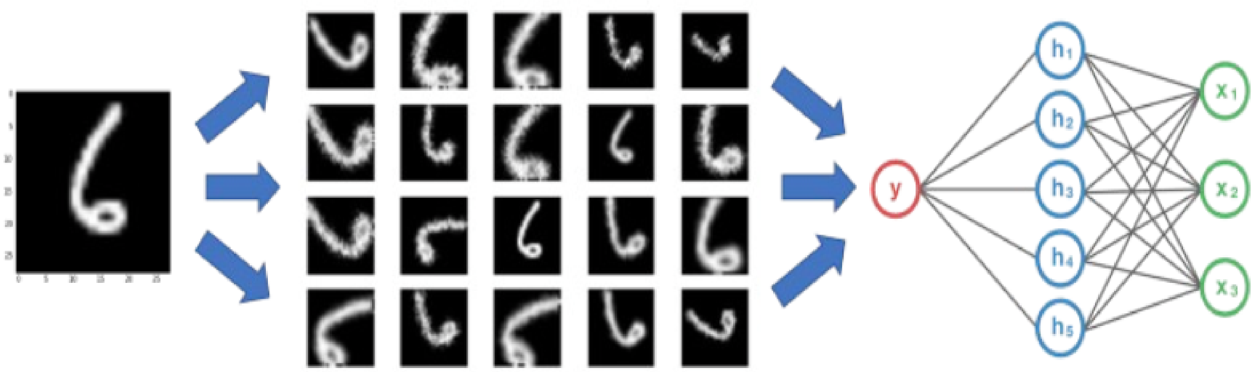


Figure 1.49: Some of the most often used image modifications for data augmentation

1.19.3 Early Stopping

Overfitting can also be caused by training the model over an extended period of time. However, it is not certain that training the model for long periods may improve the prediction. After the number of iterations is increased, the overfitting occurs after a certain level is reached, As shown in Figure 1.50, thus, the accuracy of the training set and the accuracy of the test set begin to diverge from each other, so that we see that the accuracy of the training set has improved, but the accuracy of the test set has changed, that is, it increased and then decreased. As a result, we could undoubtedly utilizing a tool that stops training when the model begins to overfit. This is known as Early Stopping. It comprises of measuring both training and test accuracy at the end of each period. The model stops in some stage, either when the training accuracy reaches a certain value, or when the test accuracy reaches a certain value, or when we find no improvement, As a result, more training is useless. If you save the model in the early stop position, you do not need to train it repeatedly to find the optimal solution.

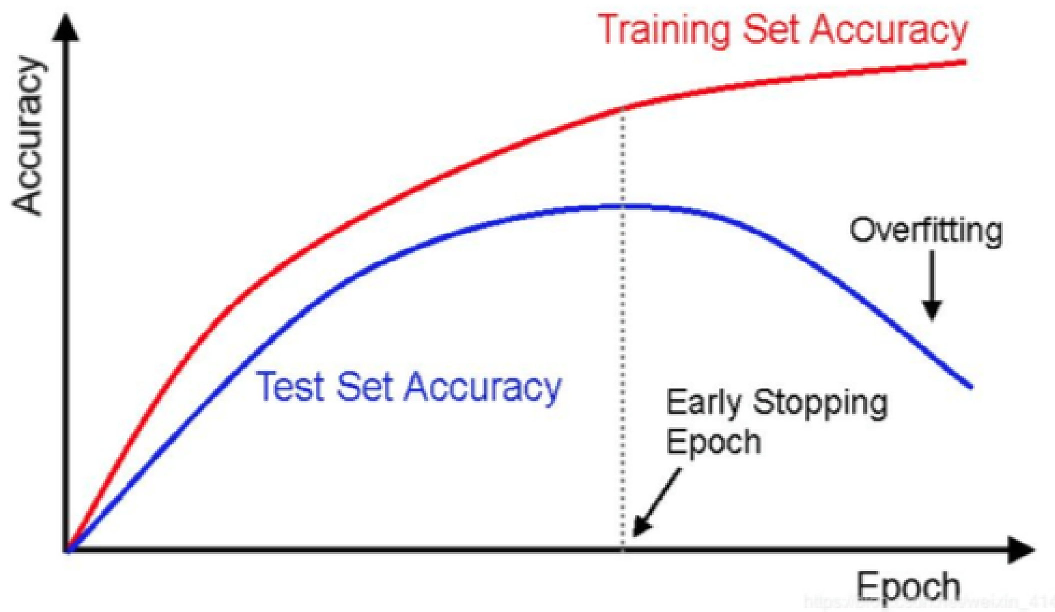


Figure 1.50: Training set error and testing set error

1.20 Transfer Learning

We need to transfer learning when there is a limited amount of target training data. or may be because the data is too little, expensive to collect and categorized, or inaccessible.

The term "learning transfer" is used to describe that humans can apply the knowledge they learn in one field to another to achieve better results. In other words, transfer learning allows knowledge learning from previous tasks to be used in target new tasks [70].

Transfer learning can be also defined as a notion that allows trained models to share their knowledge and contribute to the amelioration of the results. Where transfer learning allows the benefit of knowledge (features, weights, etc.) through before trained models for training modern models and even treating problems such as getting less data for the modern task. Jason Yosinski et al. provide a succinct explanation: "In transfer learning, we first train a base network on a base dataset and task, and then we repurpose the learned features, or transfer them, to a second target network to be trained on a target dataset and task. This process will tend to work if the features are general, meaning suitable to both base and target tasks, instead of specific to the base task" [71].

1.21 Conclusion

This chapter mentioned basic concepts of signals and concluded with deep learning that proves its choice in solving the radio signal classification problem. For additional proof, we'll see how he did it.

The next chapter will be dedicated to the main problem and present the different methods used in radio signals classification.

CHAPTER 2

RADIO SIGNAL CLASSIFICATION USING DEEP LEARNING

2.1 Introduction

Wireless communication plays an important role in the communication system, it is a routine file for modulating the transmitted signals. Being an intermediate stage between signal detection and demodulation, modulation recognition is gaining more and more attention, as it is an essential step for providing signal modulation information and thus the possibility of their classification. The traditional methods were used to identify the modulation and classification of radio signals, which relied on extracting features manually, which made the matter difficult and complex and required a cost to develop and have limited accuracy, thus making the need to resort to applying the latest DL based methods to classify radio signals.

Our interest is mainly in the radio signal classification task, so we will define them and will mention some of the tasks that fall into the classification of radio signals. We mainly focus on the modulation recognition process. Finally, we report some main state-of-the-art methods made by the DL community for classifying radio signals.

2.2 Automatic Modulation Classification

Automatic Modulation Classification (AMC) is critical in modern wireless communications [82]. It's necessary because it helps reconfigure communication and analyze the radio wave environment by determining the modulation mode inside the self-operating band [83]. AMC is a particularly challenging task in a non-cooperative environment with no prior knowledge of the incoming signal, and besides multipath propagation, frequency selectivity, and the time-varying nature of the channel [84]. AMC presents an argument step between signal detection and demodulation [85]. Its goal is to maximize classification accuracy for a wide range of modulation formats under various channel conditions, while maintaining the computational complexity acceptable [86]. Figure2.1 shows a simple block diagram of an AMC-based communication system. The AMC architecture involves two stages: signal pre-processing and a proper classification algorithm. Pre-processing tasks include noise reduction, carrier frequency estimate, symbol period estimation, equalization, and signal power assessment [87].

AMC is an important technology that has applications in various civil, military fields. In civilian applications, AMC is necessary for signal in sensing for cooperative communication and spectrum interference surveillance. For military applications, AMC offers additional benefits for the signal interception, jamming, and localization of a hostile signal in electronic warfare and surveillance.

AMC can be divided into two main categories:

- Likelihood-based (LB): The LB modulation classifier recognizes the modulation of a signal via comparing the likelihood function value of the received signal within the known modulation set [88]. It has been utilized for modulation classification in multiple channel environments with high and excellent accuracy [89].

- Feature-based (FB): The received signal's features are extracted, and the modulation of the signal may be determined either through comparing the features to threshold values or nutrition feature to pattern recognizer [90-91].

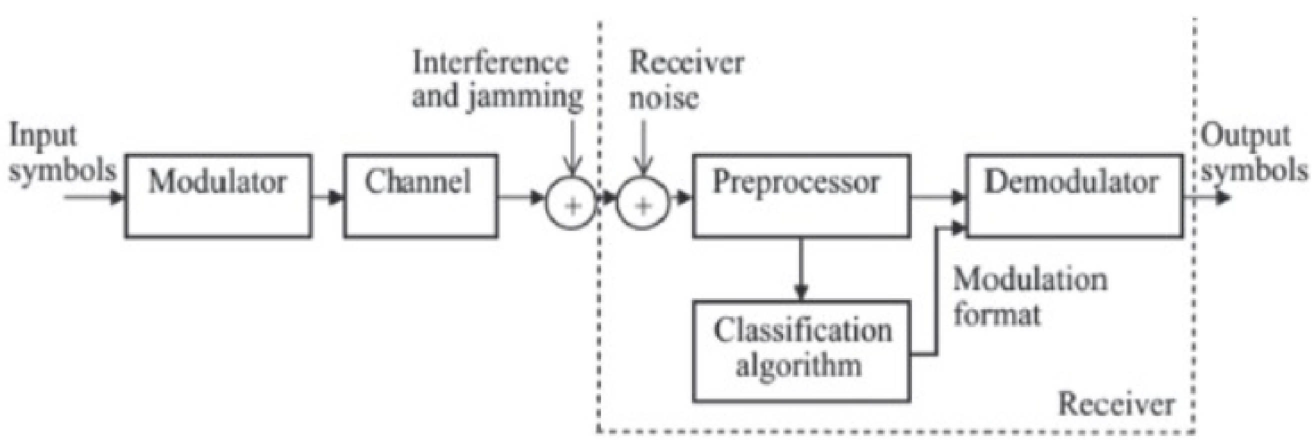


Figure 2.1: block diagram of an AMC [87]

2.3 Radio Signal Classification

Radio signals classification has become an important matter in intelligent signal processing, because of the wide usage of radio technology in numerous fields[72]. and has a very wide range of applications in wireless communications and electromagnetic spectrum management [73-74]. In electromagnetic space, there are different radio signal classification jobs according to various standards and applications, such as modulation recognition [75]. and ACARS (Aircraft Communication Addressing and Reporting System) signal classification etc [76].With the widespread use of mobile devices and the development of 5G technology [77],the demand for limited electromagnetic spectrum resources in modern society is quickly increasing, which makes radio signal management in open electromagnetic space more challenging. Improving the precision of modulation recognition can rapidly manage the effective range of electromagnetic spectrum, and guarantee the safety and reliability of communication systems [78].

Radio signal classification is an important task in signal intelligence and surveillance applications, and it has recently been adopted in applications such as cognitive radio[79], where he can detect the primary user signal by determining the radio signal in the sensing band, And therefore avert harmful interference to the primary user. In electromagnetic spectrum management [78-80], some detrimental users may send identified signals to inconvenience spectrum utilization. In these conditions, with the overlapping and cohabitation of different radio signals, if it is possible to identify each radio signal, it will assist to identify the existence of detrimental users, and then take efficient procedures to deal with the situation [81].

2.3.1 Modulation Recognition

Modulation recognition (MR) is also called modulation classification [92]. Refers to the process of automatic processing of the received signal and the determining of its modulation type [93]. In other words, indicates identifying the modulation mode of a signal after receiving it. building on observations of the received signal, what modulation is being used at the transmitter [94]. In wireless communication, there are different sources of possible radio interference in the surrounding surroundings, and each of them has different behaviors or needs. Therefore, the receiver must be able to deduce the modulation type from a received radio signal in order to be aware of the current type of communication scheme and the transmitter. This is exactly what modification recognition does [95].

After many decades of research and development, modulation recognition technology has attained several results. However, there are still numerous problems to be solved. A great number of efforts have been suggested to solve the modulations recognition problem. Via applying signal analysis and processing techniques, Where researchers were able to attain high accuracies [96]. On the other hand, O'Shea et. al [97] generated a dataset with varied modulations under different Signal-to-Noise Ratio levels. They've also suggested a number of classification techniques to solve the modulation recognition problem[98]. West et al. [99] suggested the Convolutional Long short-term Deep Neural Networks (CLDNN) that can be considered as the Latest solutions to the problem. moreover, blind recognition of the modulation format of the received signal is a considered problem in commercial systems, especially in software-defined radio (SDR), which is adapt to a variety of communication systems. The SDR system is usually reconfigured by sending supplementary information. Blind techniques can be used with an intelligent receiver, Which leads to increase transmission efficiency by decreasing overhead. appeared like applications the need to flexible intelligent communication systems.

The basic architecture of a modulation recognition system consists of three parts:

- **signal pre-processing:** Includes carrier synchronization, abnormal signal removal, noise suppression, and parameter estimation.
- **feature extraction:** It extracts the features that can characterize the modulation type.
- **signal classification:** It based on feature parameter extraction, selection and identification of appropriate decision rules and recognition classifiers

2.3.2 MR Based Deep Learning

The deep learning-based method gives more interest to the automatic extraction of features using deep neural networks. Expert features must be extracted from the input signal, and the network fully implements the features extraction process. When the modulated signal is received by the receiver, a modulation recognition system based on deep learning to identify modulated signals typically follows the following workflow: The first step is to pre-process the signal, which often contains data normalization, denoising, and fixed-length sampling. After that, The original IQ data should be dropped as input if it is an end-to-end system, and to increase improve the algorithm's performance, researchers typically analyze the IQ data further, such as extracting the signal's high order cumulants. In modern researches, The raw IQ data is substituted with the form of pictures and input into the convolutional neural network in order to fully utilize the efficient features extraction performance of the convolutional neural network in the picture. These picture formats contain constellation diagrams, eye diagrams, vector diagrams, polar features, and so on. After determining the input, a more critical step than deep learning is to construct a deep neural network that fits the input data. Most of these networks are based on convolutional and recurrent neural networks and a combination of the two. The deep neural network's output is the modulated signal's classification information [92].

Figure2.2 shows a typical framework for modulation recognition based on deep learning.

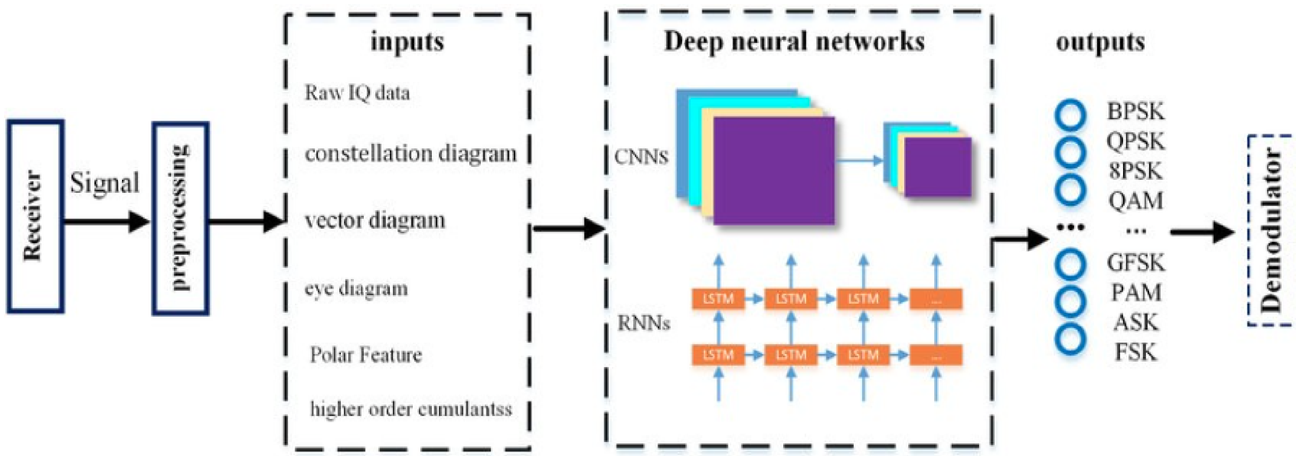


Figure 2.2: A typical framework for modulation recognition based on deep learning[92]

2.4 Radio Signal Classification State of The Art

Research on deep learning-based radio signal classification mainly focuses on three aspects: traditional methods, deep learning methods that include deep neural network models for modulation recognition, and classification of radio frequency signals with a hybrid approach. In the next subsection, we'll explain each approach and highlight some of the popular papers that followed it.

2.4.1 Traditional Methods

The first method is the traditional method, Where it is used to classify radio signals, which is a delicate process that requires handcrafted feature extraction tools. In other words, radio signal classification and modulation recognition are accomplished through the manual manufacture of feature extractors intended for specific signal types and properties.

Traditional approaches to radio signal classification depend on signal features based on probability methods, statistics, or cyclostationarity. These features must be carefully designed by expert developers, and therefore depends on their experience and knowledge of the problem structure [100]. These methods traditional are considered costly to developed and have limited accuracy. Furthermore, related variants of mod types often contain have similar features that can easily confuse classifiers [101].

The traditional modulation classification methods are mostly based on feature design [102-103]. The quality of the designed features straight identify the quality of recognition performance. nevertheless, these designed features are often linked with a specific modulation, making it challenging to discover features that are broadly applicable to a various range of modulations [104]. Expert features such as higher-order cyclic moments are used to classify modulation. They can be easily implemented in practical systems. However, hand-crafting expert features and hard-coding rules for modulation classification make Expand the range of modification types difficult challenging in non-cooperative circumstances [105]. Different statistical features of the instantaneous amplitude, phase, and frequency have been utilized to classify modulation types, such as high-order statistics (HOS) [106], and cyclostationary characteristics [107]. In addition for the classification process, the existing classifiers cover decision tree algorithms [108] and machine learning algorithms, such as support vector machine SVM [109] and artificial neural network ANN [110].

As an initial step, it is a good idea to plot the input data to look for search for features that are striking. Figure2.3 shows the time-domain input data for IQ signals generated by different modulation types that have different shape characteristics. Humans have a tough time distinguishing between signals by simply looking at them with their eyes. How can they classify types of modulation. There is no clear set of rules that can be used to differentiate all types of mod. As a result, in order to classify such signals, humans need to extract some features first. The traditional feature-extracting methods work well and provide a good classification for the signal itself. However, it still requires a lot of information to classify the signal, and therefore, it will be difficult if the information we obtained is incomplete or one of the pieces of information is missing [111].

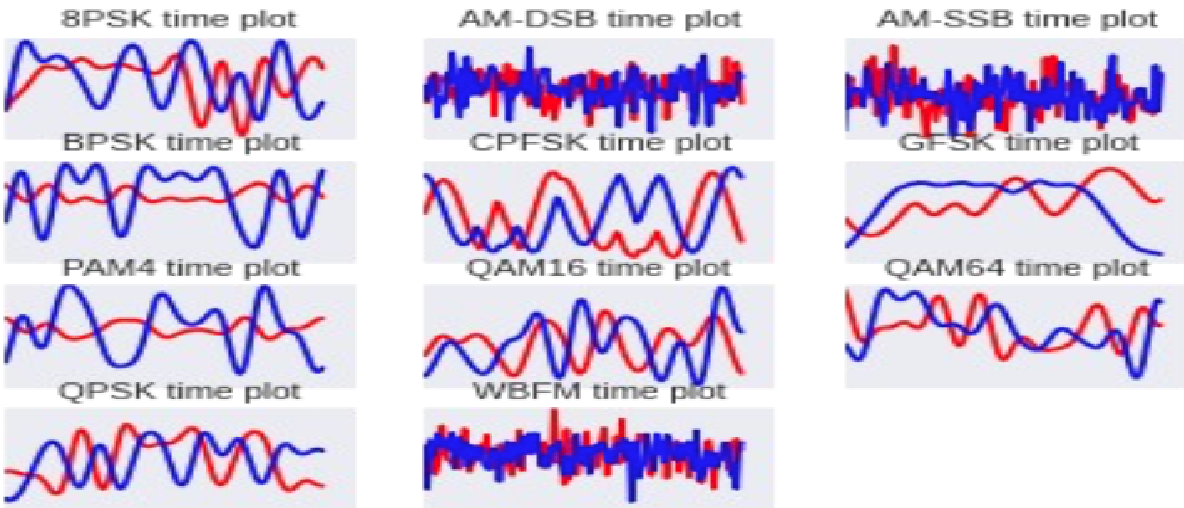


Figure 2.3: IQ time-domain signal diagram of various modulation types [112]

2.4.2 Advanced Methods Based on DL

In the past five years, We have witnessed happening a fast disruption based on optimized neural network architectures, algorithms, and optimization techniques known collectively as deep learning (DL) [113]. Where deep learning models have outperformed traditional methods, It turns out that the most recent deep learning methods may be applied to the signal classification problem and give excellent results without requiring difficult manual feature selection. As a result, deep learning has attracting wide interest and application in the classification of radio signals [76-114]. The radio signal classification method based on deep learning allows automatically learns and extracts signal features through deep neural network. without the need for a lot of manual analysis and design.

Instead of hand-crafted features, a training algorithm employs vast quantities of labelled example data to learn and extract good features from the data that are discriminative for the classification job. Which this data-driven method was initially highly effective for object categorization in image processing, it soon moved to several other applications, such as different challenges in radio communications [115].

For the function of signal classification, the neural network trains on huge amounts of raw radio signal data (e.g., IQ data samples), allowing it to discriminate between various signal classes. Neural networks, in particular, have demonstrated good performance for the job of modulation classification. [114], [117].

Figure2.4 shows the steps of the previously adopted traditional method versus the steps of the new and advanced DL methods.

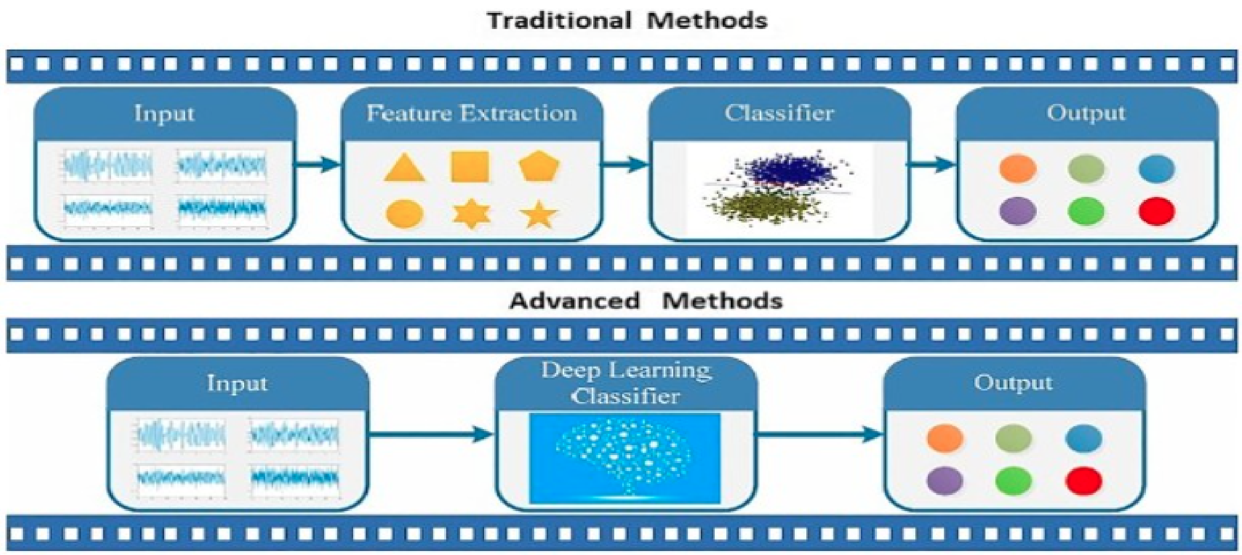


Figure 2.4: Traditional Methods VS Advanced Methods[87]

A. Deep Neural Network Models for Modulation Recognition

CNN Model

In 2016 O'Shea et al [112] proposed a convolutional neural network model for radio signal classification, they demonstrated adapting a CNN to recognize different modulation types and comparing its recognition performance to that of expert periodic moment features based methods. As well, CNN achieved a good classification, where Their experiences show that the classification accuracy of CNNs trained on time-domain data in-phase and quadrature (IQ) is significantly superior to that trained by cyclic-moment features. They also proposed a radio signal simulation data set, and It has been created using the GNU Radio Channel model and published on http://radioml.com. and And they used the data set contains 11 modulation types, including 8 digital modulation types and 3 analog modulation types. The convolutional neural network CNN model shown in Figure2.5, which contains two convolutional layers and two fully connected layers. In addition, They also built the CNN2 model by increasing the number of convolution kernels in the convolution layer. respectively. As they indicated that increasing the size of the data set will further increase the accuracy. After using 12 million data sets for training and testing, The model can reaches 87.4 % accuracy across different SNRs.

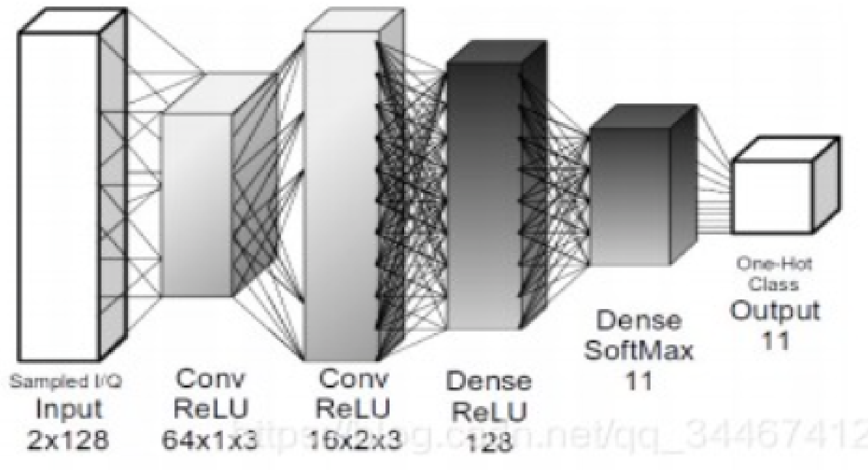


Figure 2.5: CNN Model

In 2019 Zeng et al [117] proposed a framework SCNN based on spectrum analysis for automatic modulation recognition and depends on CNN for radio signal detection. They presented a time-frequency analysis of the modulated radio signals, they converting one-dimensional radio signals into two-dimensional spectral images using the short-time discrete Fourier transform (STFT). They used spectrogram images as inputs to SCNN. They used a CNN, as shown in Figure2.6, which is a neural network with many nonlinear levels allowing it to represent a highly nonlinear classification function that maps the features of the spectrogram into modulation methods. The network output is the estimated modulation method of the input spectrogram image. They used the RadioML2016.10a dataset in [112]. They compared the proposed framework of the presented noise reduction approach, which was judged as SCNN2 with two deep learning-based methods, in terms of recognition accuracy and computational complexity. Their experiments showed that the proposed CNN architecture with spectrogram images to represent the signal achieves better discrimination accuracy than methods based on deep learning.

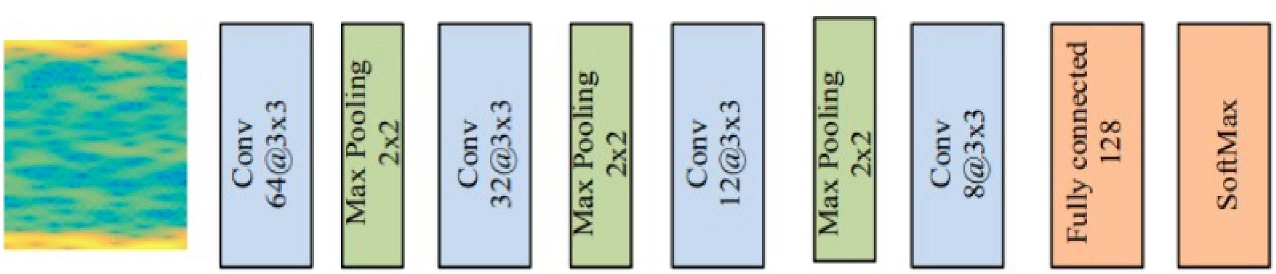


Figure 2.6: CNN model

Resnet Model

Based on prior work on using deep convolutional neural networks for radio signal classification, In 2017 O'Shea et al [114] proposed a new DL architecture using residual neural network (Resnet) by investigated the classification performance of two CNNs inspired by VGG and ResNet. the structure of which is shown in Figure2.7, and they used RadioML 2018.01 A [1] dataset where modulation consists of 24 types. in this experiment, they train the deep ResNet on a dataset of two million signals. They saw that performance steadily increases with depth in this case with diminishing returns. after training the model they note that no significant training improvement is seen from increasing the dataset from one million examples to two million examples. For comparison, they also ran the same experiment using a VGG convolutional neural network and a boosted gradient tree classifier as a baseline. in which The ResNet model showed near-perfect classification accuracy on the high SNR dataset, ultimately outperforming both the VGG architecture and baseline approach.

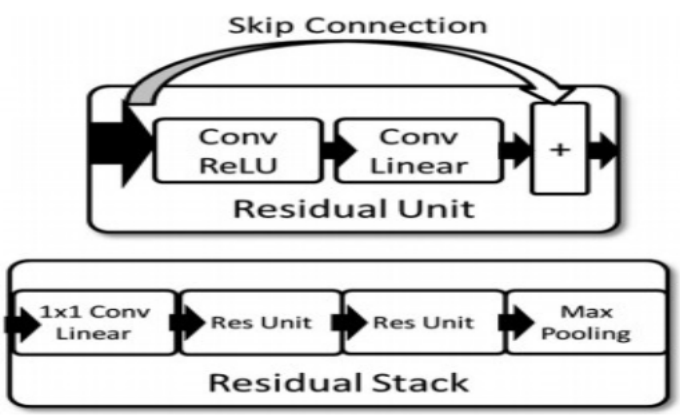


Figure 2.7: Resnet model structure diagram

LSTM Model

In 2018 Rajendran et al [118] Proposed an LSTM model for modulation classification. They used input samples in polar form the instantaneous amplitude, and the instantaneous phase of the signal as input to the long-term memory (LSTM), instead of the rectangular form utilized for all other considered models. They obtained a representation of the polar shape by calculating the amplitude and phase of the input sample I/Q at each sampling time step. They used the

[1] This dataset is available http://opendata.deepsig.io/datasets/2018.01/2018.01.OSC.0001_1024x2M.h5.tar.gz

data set presented in [112]. They used two LSTM layers, each containing 128 cells, to extract the time dependencies of the amplitude and phase characteristics of the different modulation schemes. As shown in figure2.8, where they fed the amplitude and phase of the time domain modulated signal to all cells of the LSTM model as a 2D vector, at each time step for classification. The last layer represent softmax layer that maps the classified at features to one of eleven output classes that represent modulation schemes. Their results showed that the model achieved a classification accuracy close to 90 % in conditions with a variable signal-to-noise ratio ranging from 0 dB to 20 dB.

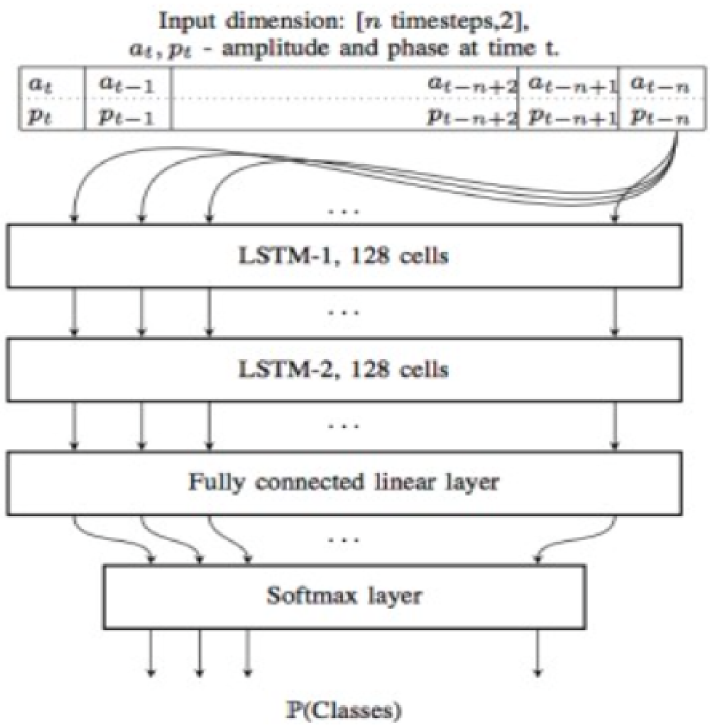


Figure 2.8: LSTM Model

Hybrid Model

Combination of CNN and LSTM and DNN (CLDNN)

In 2017, O'Shea et al[119] proposed the use of Convolutional Long Short-Term Deep Neural Network (CLDNN) model, they analyzed rating performance by comparing CNN, residual network, initial architecture, and long and short-range convolutional deep neural network (CLDNN) on the RadioML2016.10a dataset [112]. their results show that the CLDNN structure works better and consistently outperforms other network architectures when the SNRs are higher than -8dB. In addition, this type of model that uses only raw data as input has a weak classification effect on more complex modulation methods (such as 16QAM, 64QAM). They also deduced that radio modulation recognition is not limited to network depth. In 2018 X. Liu et al [120] also they developed ResNet, DenseNet, and CLDNN architectures for the modulation recognition task. Using the same data set generated in [112]. They achieved a resolution improvement of 13.5% at high SNR vs. the latest architecture presented in [112]. In the CLDNN architecture, they used four CNN convolutional layers, followed by one LSTM layer with 50 compute units and two fully connected DNN layers, as shown in Figure2.9. They got the best CLDNN architecture performance among all tested network architectures. Due to its long-term memory capacity, it achieved an accuracy of close to 88.5% at a high SNR. Where the hybrid method is considered appropriate for the causal characteristics that characterize radio signals in the time domain.

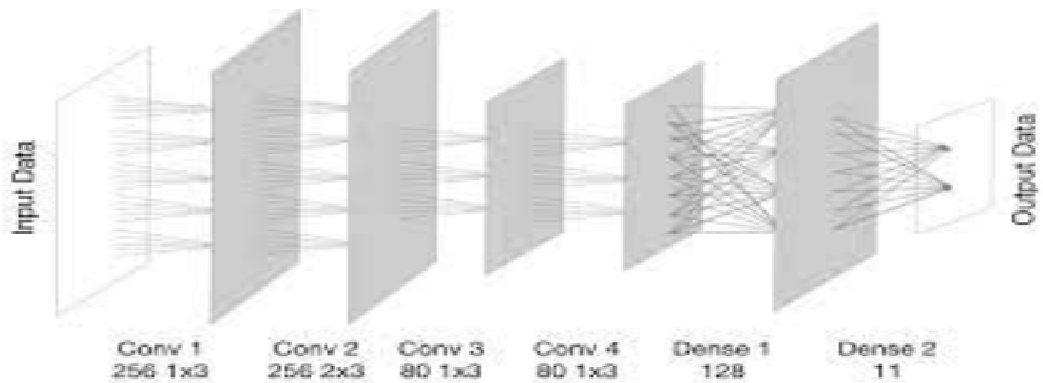


Figure 2.9: CLDNN Model

In 2019 Scholl [121] proposed using four different neural networks to classify radio signals. Rather than focusing on mod recognition, he shows out that these models learn to directly classify different transmission modes. Thus this provides further post-processing required to determine modulation modes and other signal parameters. Use a typical dataset of 18 different transmission modes that occur in the HF band, where the dataset takes into account the characteristics of the HF channel. He used networks Classical CNN, All Convolutional Net, Deep CNN, and Residual Net, as shown in Figure2.10. His experiments showed that neural networks are very powerful in classifying signals into their transmission modes even if they display very similar characteristics. Where you get the best results for Resnet network with excellent accuracy reach to of 98% when When SNR is above 5 dB. Figure 2.11 It is shown that the arrangement of the remaining eight 5-layer residual stacks of [114] is more suitable for the signal classification task.

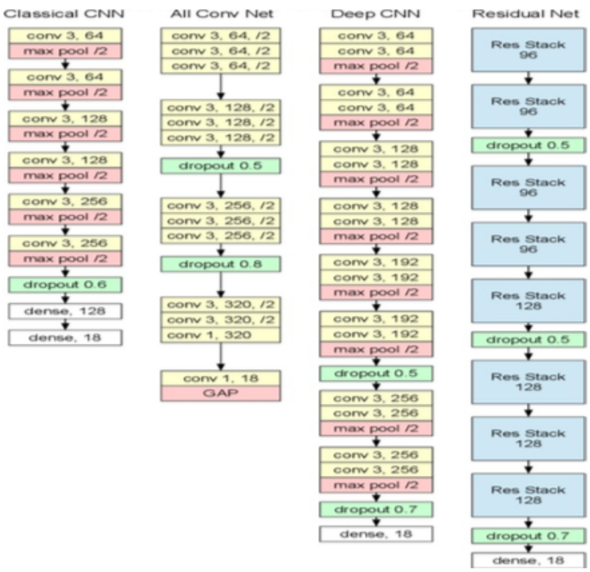


Figure 2.10: Different NN architectures

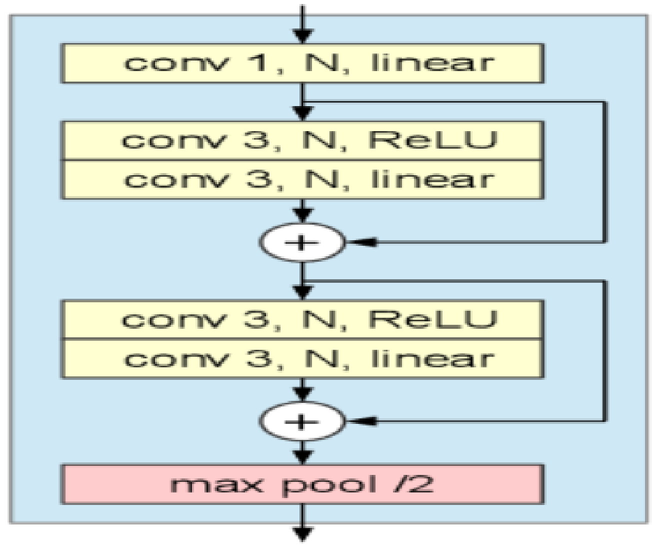


Figure 2.11: residual stack as used in Resnet

B. RF Signal Classification With Hybrid Approach

In 2019 Uppal et al [122] Proposed a model of RF signals with a hybrid approach that uses images derived from the signal constellation and spectrogram data. Their goal is to improve the speed and accuracy of classification by exploiting frequency domain information. Their idea is that this model creates IQ constellation and spectrogram images from time-domain input data and uses them as input to a convolutional neural network (CNN). their model takes spectral images and a signal constellation as input, performs similar convolutional processing on both, but with fewer layers and filters, and passes the sequential data into dense layers to classify the signal. And the images are quick to generate using FFTs. they Used the DeepSig dataset [114]. and they compared this model with Deepsigs established neural network model. Their results showed that their model works better at SNR of 6 dB and above. They also gated better accuracy and lower computational requirements.

In 2021 Elyousseph et al [123] Suggest a hybrid image that takes advantage of time and frequency domain information, and handles classification. They tested the model's ability to predict different RF signals, after different pre-processing steps. These steps focused, they used some types of signals to get enough diversity to be discernible, and they used the GNU Radio platform to add noise to the signals. Next, they used time-domain representations, using images that show the signal components in I and Q as shown in Figure 2.12. and the frequency domain, they used the PSD images and the STFT images shown in Fig2.13. However, they found that these representations are difficult to verify and weak, and do not give great accuracy. Thus, they proposed to create a three-channel hybrid image that combines the phase, quadrature, and PSD images as separate channels to form a single RGB image, as shown in Figure 2.14. Next, They implemented a CNN to test all the steps of different pre-processing for the purpose of comparison. These hybrid images achieved full resolution.

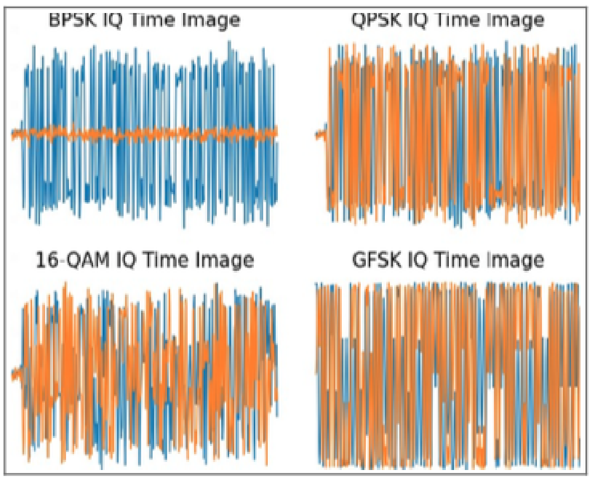


Figure 2.12: IQ time-series images

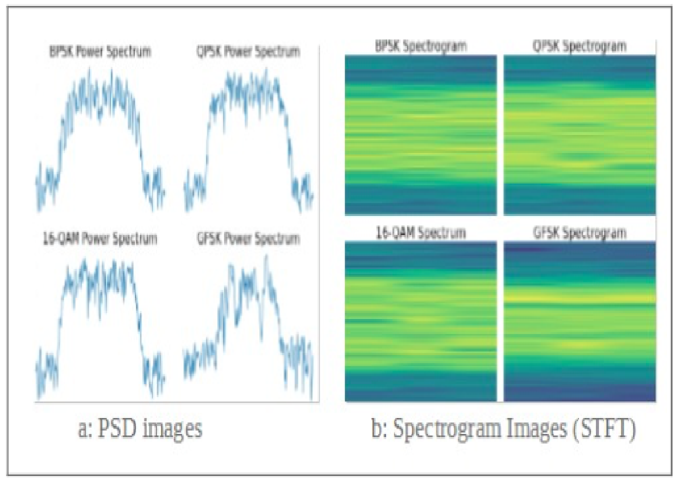


Figure 2.13: PSD and Spectrogram images in frequency domain

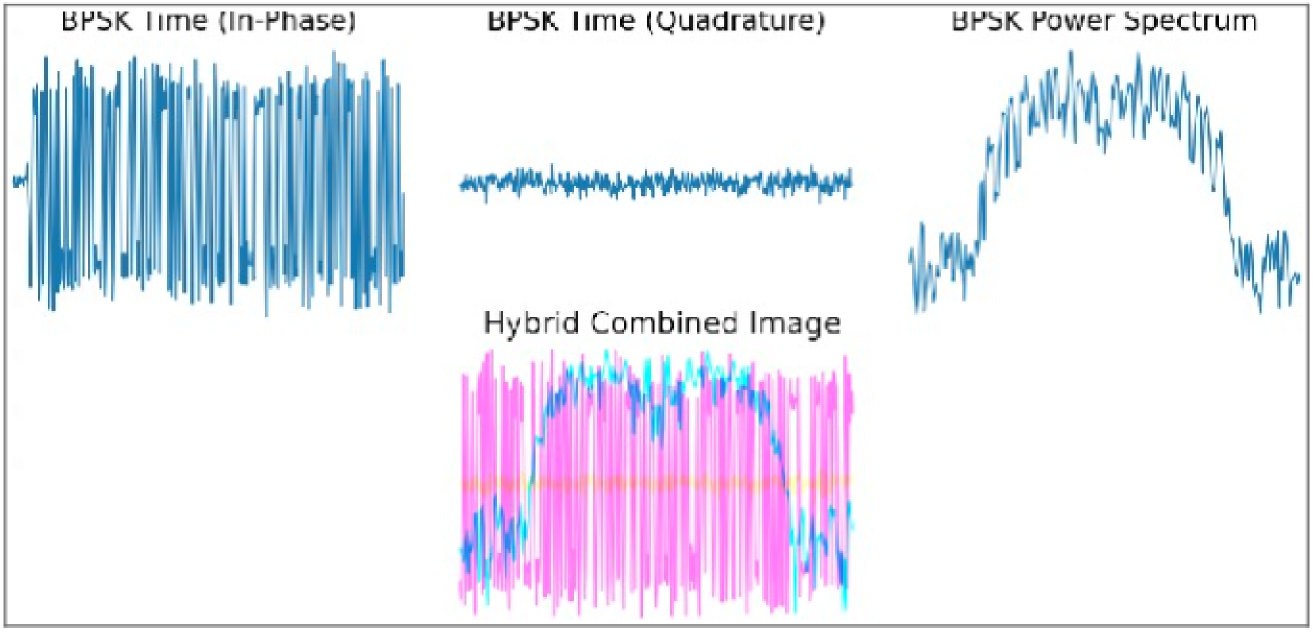


Figure 2.14: Combining the IQ and PSD images as to form one RGB image

2.5 Conclusion

In this chapter, we first provided an overview of radio signal classification starting with their definition, challenges, and drivers. Finally, we have examined and provided as many technical methods as are used to classify radio signals.

In the next chapter, we will experiment with DL-based methods for radio signal classification.

CHAPTER 3

IMPLEMENTATION

3.1 Introduction

In this chapter, we will present the implementation of two different deep learning-based models for signal modulation classification on the RML2016.10a dataset. We will discuss the two approaches and briefly explain the software, hardware, and dataset we used for the experiment.

3.2 Dataset

RadioML2016.10.a standard radio signal data set is utilized for training and testing data. which includes sampled IQ data for 11 modulations at 20 different signal-to-noise ratios (SNRs). Where GNU radio[1] was used to compile IQ signal samples. The length of each sample is 128. Each class in the dataset contains 1000 samples and is indexed by a tuple (mod, SNR). SNR ranges from -20dB to +20dB at unit steps, whereas the list of modulations contains:

- 8 digital modulations: BPSK, QPSK, 8PSK, QAM16, QAM64, GFSK, CPFSK, PAM4
- 3 analog modulations: AM-SSB, AM-DSB, WBFM.

[1] https://WWW.gnuradio.org/

3.3 Environment

3.3.1 Python

Python[2] is an interpreted, object-oriented, and high-level programming language, used for general-purpose programming. It was created by Guido van Rossum, and first released on February 20, 1991. Python is utilized in a variety of fields, including web development and software prototyping due to its simplicity and consistency, plus the access to a great number of pre-implmented libraries and frameworks to make the coding part much easier for the developer It is used by the great majority of AI and machine learning practitioners to implement their models.Python is a binary platform-independent. which can ran The same Python code on virtually all operating systems and platforms.

3.3.2 TensorFlow

TensorFlow[3] is an open source machine learning platform. Google discovered TensorFlow for the purpose of machine learning. It provides a simple approach to solve complex computations of machine learning with the help of graphs. It offers a comprehensive ecosystem of tools, libraries, and community resources that enable researchers to push the state-of-the-art in machine learning and developers to easily build and deploy ML-powered apps.

TensorFlow offers multiple levels of abstraction, Build and train models by using the high-level Keras API, which makes getting started with TensorFlow and machine learning simple.Thus, any one can get familiar with implementing complex ML model very fast.

Tensorflow can be used on different platforms meaning you get to use ML in servers, edge devices, or the web not to mention its compatibility with other programming langages
Google Brain team discovered and developed TensorFlow for internal Google use. It was released under the Apache License 2.0 in 2015.

3.3.3 keras

Keras[4] is high-level API wrapper for the low-level API. It was developed by François Chollet, a Google engineer. due to their simple interface it minimizes the number of user actions required

[2] https://www.python.org
[3] https://www.tensorflow.org
[4] https://keras.io

for common use cases.
Keras makes it easier to run new experiments,is an industry-strength framework that can scale to large clusters of GPUs or an entire TPU pod, it has the low-level flexibility to implement arbitrary research ideas while offering optional high-level convenience features to speed up experimentation cycles.

3.3.4 Google Colab

Colaboratory[5] , or 'Colab' for short, is a product from Google Research, is especially well suited to machine learning, data analysis and education. Colab can make for student, a data scientist or an AI researcher to write, run and share code, using executable documents called notebooks.In other words, it's a cloud-based Jupyter notebook[6] environment that doesn't require any installation.The best part of Google Colab is that it provides free access to heavy computing resources such as GPUs & TPUs. Google Colab is a free to use too Colab offers outstanding GPUs like the Nvidia Tesla K80, the NVIDIA Tesla P100 PCIe 16 GB and the NVIDIA Tesla T4 for the user to deploy and train ML models at ease; and the ability to connect to Google Drive for storage. As of now, these resources are completely free to anyone with a Google Account.

Colab notebooks allow to combine executable code and rich text in a single document, along with images and more ,in wihch can easily share it with co-workers or friends, allowing them to comment on your notebooks or even edit them.

Figure3.1 shows the Google Colab interface.

[5] https://colab.research.google.com/notebooks/intro.ipynb
[6] https://jupyter.org/

Figure 3.1: The interface of Google Colab.

3.3.5 GPU

using GPU (Graphics Processing Unit) that is available in Google Colab to reduce the time spent for calculating and speed up the model learning.

3.4 Network architecture

3.4.1 First: CNN Architecture Approach

In order to implement the signal modulation classification model, the first method relied on converting the I and Q signals that include some different modulation schemes into 2D spectral images, As shown Figure 3.2. In this work we removed low SNR signals and kept only those with SNR greater than -4, also we removed some modilations and kept only these modifications: ["PAM4", "CPFSK", "QAM16", "QPSK", "BPSK"].

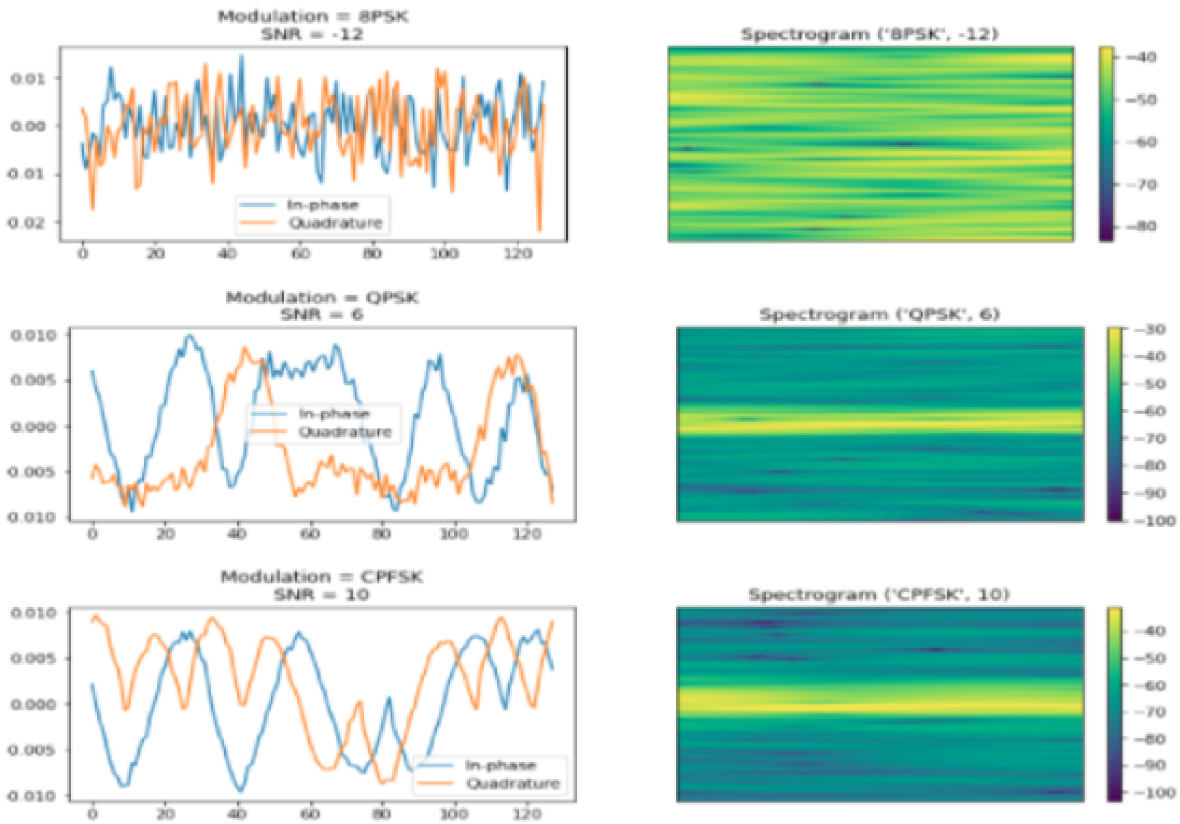


Figure 3.2: Converting IQ signal into spectrogram image

CNN is the most important element in this work. We design CNN architecture to recognize and classify modulation. Figure 3.3 shows our proposed CNN architecture. Here, the network input is the spectral images that we got. To access the network output the spectral images are fed by two consecutive convolutional layers, followed by flattening, and a fully connected layer. Each convolution layer is followed by a conv2D layer, a Batch Normalization layer, a ReLU activation layer, a maximum pooling layer, and a dropout layer. The fully connected layer contains the Dense layer, Batch Normalization layer, ReLU activation layer, and a dropout layer. And the arguments of the used layers are listed in Figure3.4. This architecture resulted in 14,971,653 parameters.

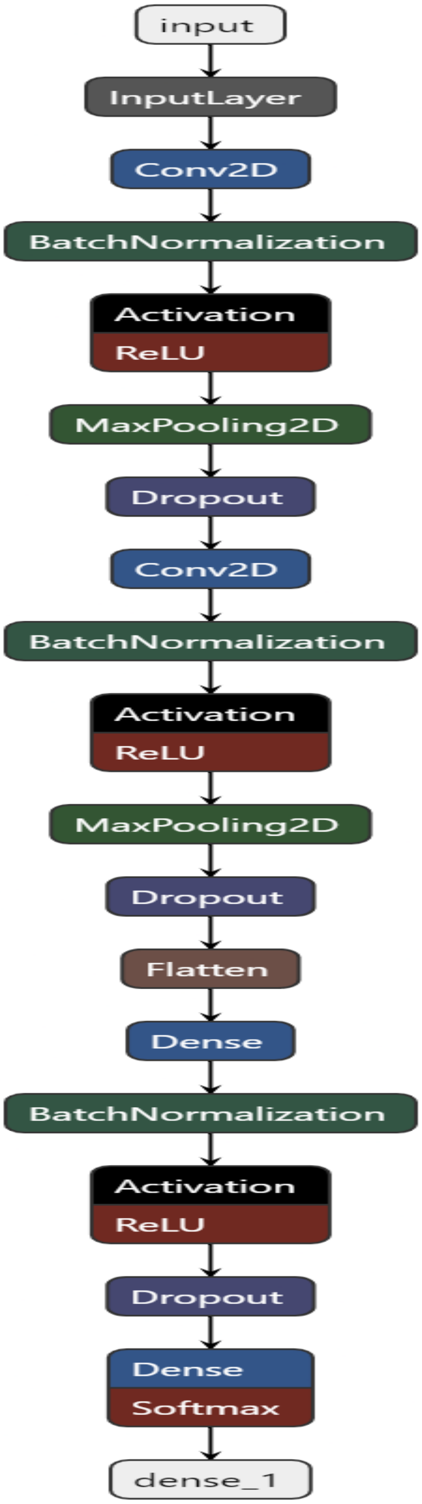


Figure 3.3: CNN architecture

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 78, 51, 32)	320
batch_normalization (BatchNo	(None, 78, 51, 32)	128
activation (Activation)	(None, 78, 51, 32)	0
max_pooling2d (MaxPooling2D)	(None, 39, 25, 32)	0
dropout (Dropout)	(None, 39, 25, 32)	0
conv2d_1 (Conv2D)	(None, 39, 25, 64)	18496
batch_normalization_1 (Batch	(None, 39, 25, 64)	256
activation_1 (Activation)	(None, 39, 25, 64)	0
max_pooling2d_1 (MaxPooling2	(None, 19, 12, 64)	0
dropout_1 (Dropout)	(None, 19, 12, 64)	0
flatten (Flatten)	(None, 14592)	0
dense (Dense)	(None, 1024)	14943232
batch_normalization_2 (Batch	(None, 1024)	4096
activation_2 (Activation)	(None, 1024)	0
dropout_2 (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 5)	5125

Total params: 14,971,653
Trainable params: 14,969,413
Non-trainable params: 2,240

Figure 3.4: CNN model summary

3.4.2 Second: CNN-LSTM Approach

In this proposed approach we combine the architectures of LSTM and CNN into a deep neural network by exploiting the complementarity advantage of CNNs, LSTMs. LSTM unit is RNN memory unit, which is responsible of optimizing the gradient ending problem in RNNs by utilizing a forget gate in its memory cell.

We trained this model based on CNN and LSTM by only using I/Q representation, Contrary to the first approach that uses spectrograms as input, The beginning of the entire network is a normal convolutional neural network layers which without the fully connected layer, is composed of Two Conv1D layers each contains 126 -124 units respectively all with a kernel-size= 3 and 64 filters and Dropout layer, Then Recurrent neural network layer (LSTM) which composed of 50 units and also Dropout layer The 11-class neurons representing the modulation schemes are the content of the last dense layer. While the convolutional layers apply ReLU activation functions, and LSTM layer utilizes a TanH activation function. the last dense layer utilizes a softmax. And the overview of the CNN-LSTM architecture can be seen in Figure3.5, and the arguments of the used layers are listed in Figure3.6.

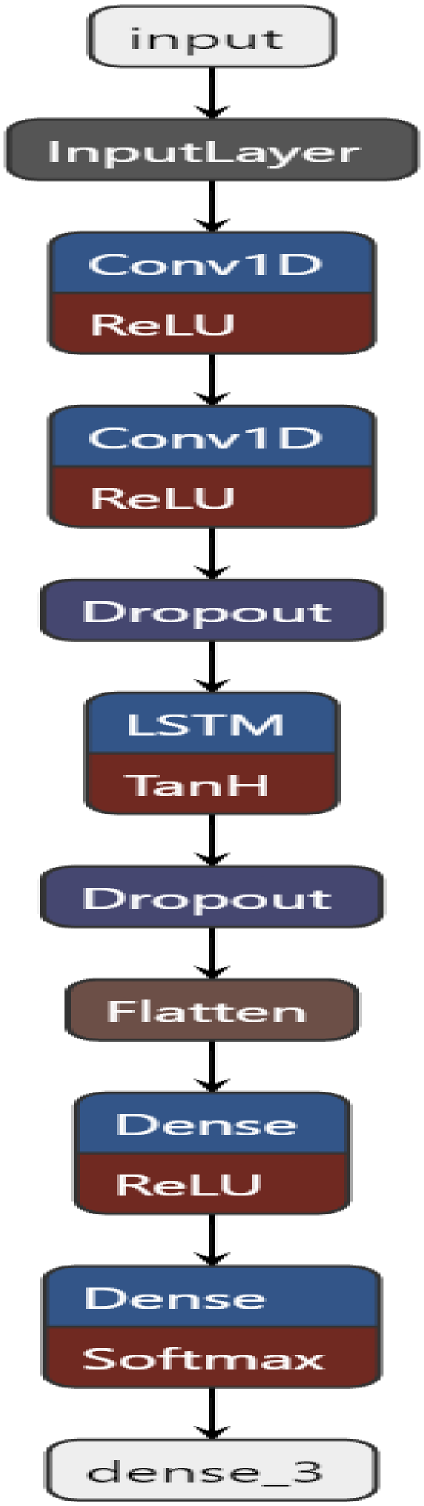


Figure 3.5: CNN-LSTM architecture

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 126, 64)	448
conv1d_1 (Conv1D)	(None, 124, 64)	12352
dropout (Dropout)	(None, 124, 64)	0
lstm (LSTM)	(None, 124, 50)	23000
dropout_1 (Dropout)	(None, 124, 50)	0
flatten (Flatten)	(None, 6200)	0
dense (Dense)	(None, 100)	620100
dense_1 (Dense)	(None, 11)	1111

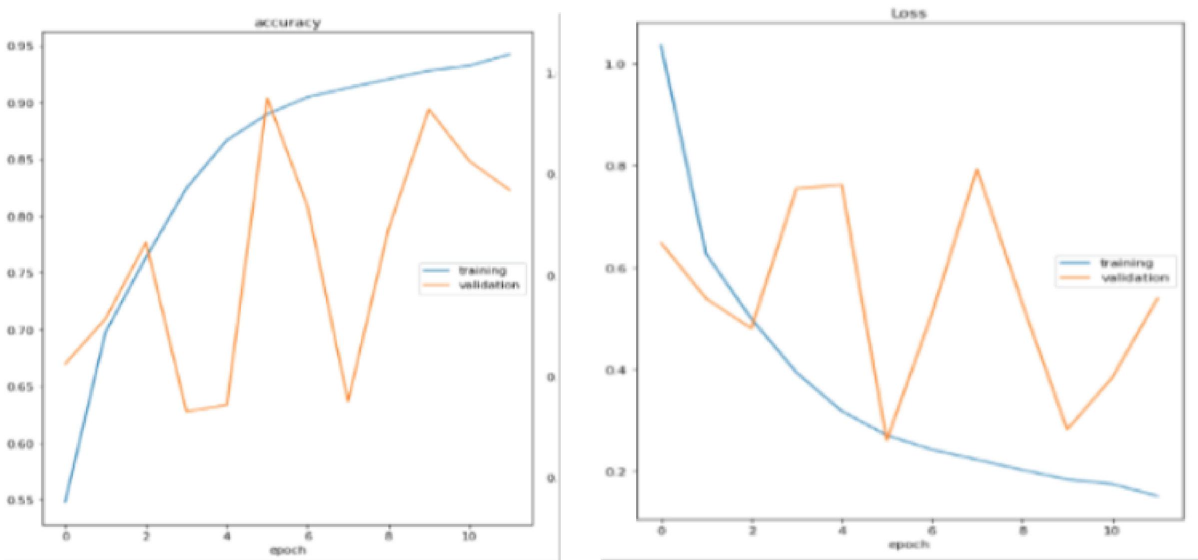
Total params: 657,011
Trainable params: 657,011
Non-trainable params: 0

Figure 3.6: CNN-LSTM model summary

3.5 Results

3.5.1 First Approach:

After training on the model CNN, we note the following observations from the accuracy and loss curves in Figures3.7, which represent the evolution of accuracy and loss outcomes. Where the accuracy of the model in the training and test group was 0.94 and 0.82, respectively. And the loss is 0.15 in training, 0.26 in test.



(a) Model accuracy (b) Model loss

Figure 3.7: Model accuracy and loss

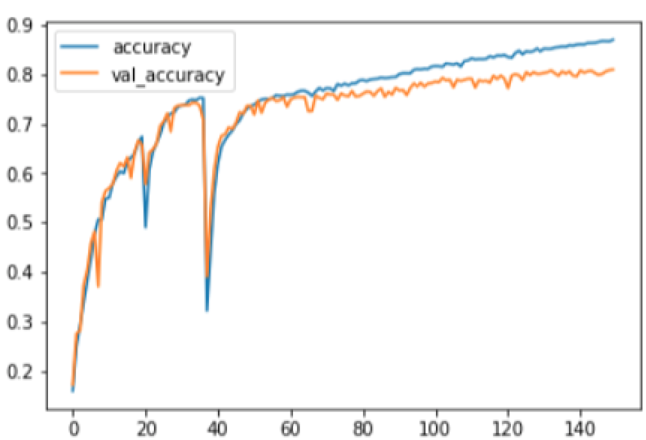
By the results obtained by our trained model, which achieved a classification accuracy of 82% in the test data set. This is considered a good result for classification.

The results of classifying our first model are shown in the form of the confusion matrix. The results are in Figure3.8 for the CNN architecture. we show the classification results of the highest SNR case in a confusion matrix, we notice confusion and misclassification in QPSK, and PAM4, and we see remaining inconsistencies are those misclassifying QAM16 as BPSK.

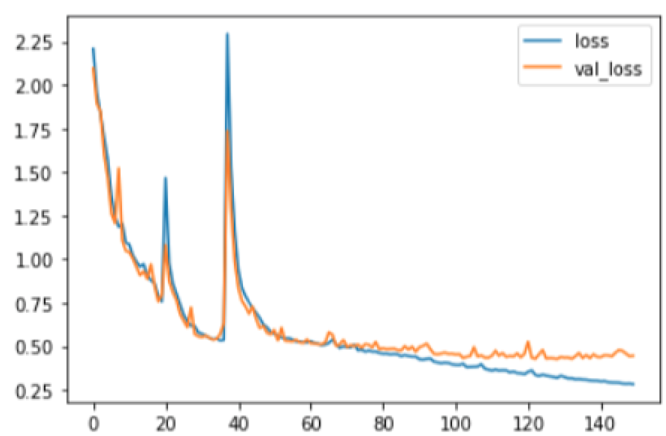
Figure 3.8: Confusion matrix f CNN classification

3.5.2 Second Approach:

After the model training, we note the following remarks from the curves of accuracy and loss in Figures3.9(a) and 3.9(b), which represent the development of accuracy and loss results, according to the epochs.Where the accuracy of the model in training and test set is 0,8587 and 0.8587, respectively. And the loss is 0.4274 in training, 0.4454 in test.



(a) Model accuracy



(b) Model loss

Figure 3.9: Model accuracy and loss

Through the results obtained by our trained model, which achieved an accuracy of 85% in the test dataset. It is considered a good result

The results of classifying our second model are shown in the form of the confusion matrix. The results are in Figure3.10 for the CNN with LSTM architecture. we notice confusion and misclassification in 8PSK for QPSK and AM-DSB for WBFM are confused, as well as for QAM16 and QPSK for 8PSK. We note inconsistencies in QAM16 and QAM64. We note that the higher the SNR, the better the modulate performance.

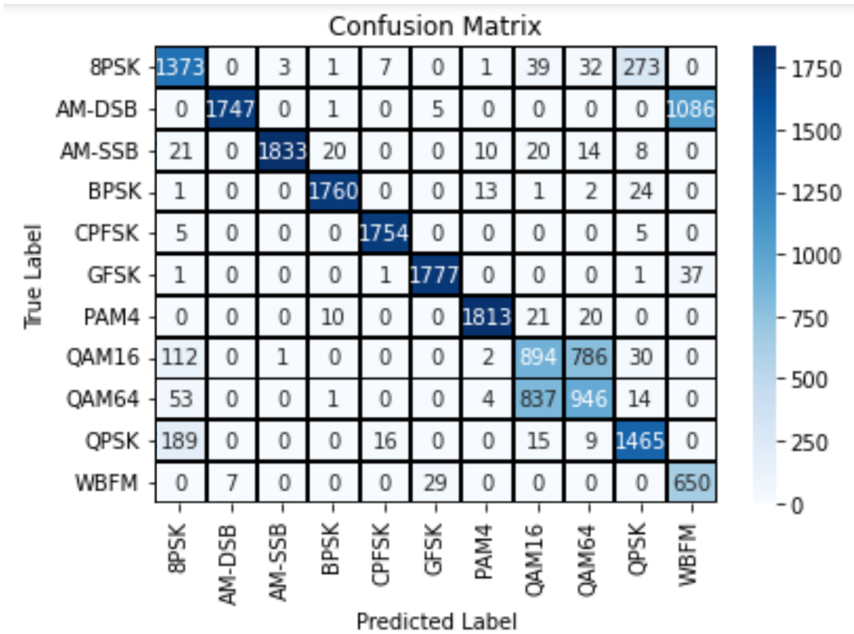


Figure 3.10: Confusion matrix for CNN-LSTM model

3.6 Conclusion

In this chapter, we implemented two DL-based models for signal modulation classification. The best results were reported by the second model (CNN with LSTM) which took advantage of the CNN's ability to extract features, in addition, capacity the LSTM to capture the temporal features. On the other hand, CNN alone struggled with the modulation classification of the data at hand.

CONCLUSION

The purpose of this study is to explore the types of neural networks that are most suitable to implement the radio signal classification model with the best possible performance. Accordingly, we have introduced the best candidate deep learning tools for the task, those being CNNs and RNNs. Moreover, we explain the classification of radio signals in detail and mention the latest methods for it.

In the first experiment, we have treated the signal as if it was an image. So we transformed the I/Q data into a spectrogram representation, then we have used CNN for a simple image classification. The second experiment involved the use of an LSTM layer along with CNN, but the input data this time are of type I/Q. The Dataset used for this study and experiments is DeepSig RadioML2016.Based on the experiments presented in the last chapter, we conclude that using CNN to extract features along with capturing temporal dependencies using LTSM perform better for modulation classification.

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