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Dedication

In the name of Allah, the Most Gracious, the Most Merciful. Peace and blessings be upon the most honorable of messengers, Muhammad, may God bless him and grant him peace. I express gratitude to the Almighty for His divine grace, which has facilitated the accomplishment of this modest endeavor.
This work is dedicated to my esteemed parents for their unwavering support in my pursuit of achievements and in navigating challenges.
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Daoud

Dedication

The praise is to Allah, the Lord of all worlds, and blessings and peace be upon the noblest of messengers. I thank and praise Allah for His guidance in my humble endeavor.
I dedicate this humble work to my dear parents, who have been a supportive pillar in achieving numerous accomplishments, both academic and otherwise.
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Mohammed

مـلـخـص

لقد حقق التعلم العميق نجاحاً مذهلاً في العديد من المجالات، بما في ذلك الرؤية الحاسوبية والتعرف على الكلام ومعالجة اللغات الطبيعية، لأنه أداة قوية، وتكمن قوة التعلم العميق في قدرته على التعلم من كميات هائلة من البيانات. ومع ذلك، يُعزى الكثير من هذا النجاح إلى نماذج التعلم الخاضعة للإشراف، مما يعني أن نماذج التعلم العميق تعتمد بشكل كبير على البيانات المصنفة. غالبًا ما تستغرق عملية تصنيف البيانات يدويًا وقتًا طويلاً وتتطلب خبرة في المجال، مما يجعلها تحديًا كبيرًا في نشر حلول التعلم العميق. وقد تم تطوير العديد من الحلول لمواجهة التحدي المتمثل في وجود كمية كبيرة من البيانات غير المصنفة، مثل التعلم الخاضع للإشراف الذاتي والتعلم شبه الخاضع للإشراف وغيرها. في هذا العمل، نهدف إلى استكشاف وتطبيق مفهوم التعلّم شبه الخاضع للإشراف، وهو نهج تعلّم آلي يستخدم كلاً من البيانات المصنفة وغير المصنفة، لأداء مهمة تصنيف الإشارات اللاسلكية. يعد تصنيف الإشارات اللاسلكية أمرًا بالغ الأهمية لمختلف تطبيقات الاتصالات اللاسلكية، ولكنه يتطلب حجمًا كبيرًا من البيانات المصنفة. يقدم التعلّم شبه الخاضع للإشراف حلاً واعداً من خلال تمكين إنشاء مصنفات فعالة من حيث البيانات يمكنها التعلم من مجموعة أصغر من البيانات المصنفة مع كمية أكبر من البيانات غير المصنفة.

كلمات مفتاحية: الشبكات العصبية التلافيفية ,(CNN) بيانات غير مصنفة, التعلم العميق ,(DL) التعلم شبه الخاضع للإشراف, تصنيف التحوير, تصنيف الإشارات الراديوية.

Abstract

Deep learning has been incredibly successful in many areas, including computer vision, speech recognition, and natural language processing, because it is such a powerful tool, and the power of deep learning lies in its ability to learn from vast amounts of data. However, much of this success has been attributed to supervised learning models, which means that deep learning models rely heavily on labeled data. The process of labeling data manually is often time-consuming and requires domain expertise, making it a significant challenge in the deployment of deep learning solutions. Many solutions have been developed to address the challenge of large amount of unlabeled data, such as self-supervised learning and semi-supervised learning and others. In this work, we aim to explore and implement the concept of semi-supervised learning, a machine learning approach that uses both labeled and unlabeled data, to perform the task of radio signal classification. Classifying radio signals is crucial for various wireless communication applications, but it requires a large volume of labeled data. Semi-supervised learning offers a promising solution by enabling the creation of data-efficient classifiers that can learn from a smaller set of labeled data combined with a larger amount of unlabeled data.

Keywords: Convolutional Neural Networks (CNN), unlabeled data, Deep Learning (DL), Semi-supervised learning, Modulation Classification, Radio Signal classification.

Résumé

L'apprentissage profond a connu un succès incroyable dans de nombreux domaines, notamment la vision artificielle, la reconnaissance vocale et le traitement du langage naturel, parce qu'il s'agit d'un outil puissant, et que la puissance de l'apprentissage profond réside dans sa capacité à apprendre à partir de grandes quantités de données. Cependant, une grande partie de ce succès a été attribuée aux modèles d'apprentissage supervisé, ce qui signifie que les modèles d'apprentissage profond reposent fortement sur des données étiquetées. Le processus d'étiquetage manuel des données prend souvent beaucoup de temps et nécessite une expertise dans le domaine, ce qui en fait un défi important pour le déploiement de solutions d'apprentissage profond. De nombreuses solutions ont été développées pour relever le défi d'une grande quantité de données non étiquetées, telles que l'apprentissage auto-supervisé et l'apprentissage semi-supervisé, entre autres. Dans ce travail, nous visons à explorer et à implémenter le concept d'apprentissage semi-supervisé, une approche d'apprentissage automatique qui utilise à la fois des données étiquetées et non étiquetées, pour effectuer la tâche de classification des signaux radio. La classification des signaux radio est cruciale pour diverses applications de communication sans fil, mais elle nécessite un grand volume de données étiquetées. L'apprentissage semi-supervisé offre une solution prometteuse en permettant la création de classificateurs efficaces en termes de données, capables d'apprendre à partir d'un ensemble plus restreint de données étiquetées combinées à une plus grande quantité de données non étiquetées.

Mots clés: Réseaux neuronaux convolutifs (CNN), données non étiquetées, apprentissage profond (DL), apprentissage semi-supervisé, classification de la modulation, classification des signaux radio.

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Introduction

Classification of radio signals is fundamental to many applications due to the tremendous advances in wireless communication technology. Despite its considerable complexity, the process of automatically detecting and classifying wireless communication signals is of great importance. This is an essential operation for spectrum learning and sharing, enabling more effective use of the spectrum.

The signal classification is a complex and challenging process, involving the determination of the modulation type to which it belongs, this is considered a multi-class classification problem, where the number of classes equals the number of signal types in the dataset, the factor that has made the field of wireless communications more complex and challenging is the increasing number and complexity of different signal types, additionally, accurately configuring the signal modulation mode in conditions of low Signal-to-Noise Ratio (SNR) has become a challenging issue.

Previously, signal classification relied on traditional methods, primarily through manual feature extraction. However, it was later evident that these approaches did not yield precise and accurate classification, leading to the adoption of more efficient methods.

Over the past decade, the advancement of artificial intelligence and deep learning techniques has expanded their use in a variety of fields. These include, among others, image and speech recognition, natural language processing, and wireless transmission.

Deep learning's power comes from its capacity to learn from large amounts of data. Yet, these achievements are largely due to supervised learning, which means that deep learning is highly dependent upon labeled data.

Manual annotation of data is time-consuming and often requires domain expertise, which makes it a significant challenge for implementing deep learning solutions.

To address the challenge of large amounts of unlabeled data, several solutions have been developed, including self-supervised learning and semi-supervised learning.

In the present work, our goal is to explore and implement the concept of semi-supervised learning, which is a machine learning approach that uses both labeled and unlabeled data, in order to perform the task of radio signal classification.

Classification of radio signals is crucial for several wireless communication applications, but requires a large amount of labeled data. Semi-supervised learning offers a promising solution, allowing the creation of data-efficient classifiers able to learn from a smaller amount of labeled data combined with a larger amount of unlabeled data.

Our thesis consists of three chapters:

- **In the first chapter,** We present some generalities and preliminary knowledge about signals, radio, as well as concepts in deep learning and its architecture.
- **In the second chapter,** We represent the state of the art semi-supervised learning.
- **In the third and final chapter,** We do experiments and discuss the results.

Chapter 1

Generalities and preliminary knowledge

1.1 Introduction to signals

Signals are omnipresent, enveloping us from all directions, constituting a significant realm of knowledge applied across nearly every facet of contemporary life. Digital signals particularly stand as the cornerstone of communication technology in this era, permeating mobile phones, televisions, and the myriad electronic devices surrounding us. Within communication systems, radio technology enables the transmission of diverse signal types, thereby streamlining the communication process and facilitating information exchange.
The signals are the physical representation of the information it carries from its source to its destination. It serves as a conduit for information, embodying the measurable manifestation of a quantity (such as current, voltage, force, temperature, pressure, etc Cottet (2017). Its physical nature can vary greatly, including acoustic, electronic, optical, and other forms Jutten (2009).

1.1.1 Electromagnetic spectrum power data transmission

The electromagnetic spectrum refers to a structured arrangement of electromagnetic waves based on their wavelength or frequency.

- **Radio waves**
  For instance, are generated by the acceleration of charges in conducting wires and typically span from a few hertz to 10^9 hertz in frequency.
  They exhibit properties like reflection and diffraction. Radio waves find applications in various communication systems such as radio, television, and cellular phones, particularly in transmitting voice signals within the ultra-high-frequency range.

- **Microwaves**
  Microwaves are generated by specialized vacuum tubes like klystrons, magnetrons, and Gunn diodes. Their frequency spans from 10^9 Hz to 10^{11} Hz. Microwaves exhibit characteristics such as reflection and polarization. They find application in radar systems for aircraft navigation and vehicle speed determination, microwave ovens for cooking, and long-range wireless communication via satellites.Weinstein (1988)
  Figure 1.1 representing the electromagnetic spectrum

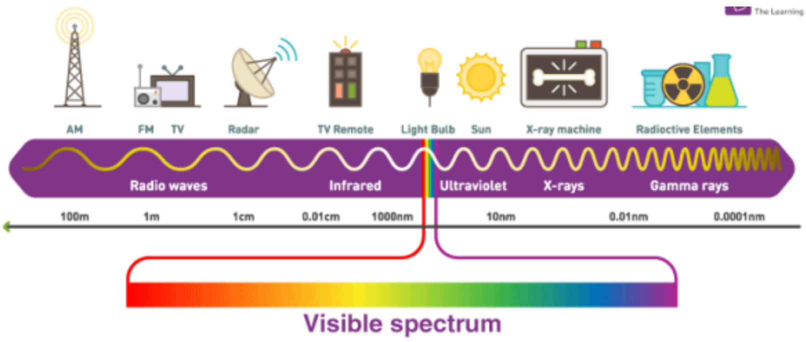

Figure 1.1: Electromagnetic spectrum AYAD & MESSLEM (2022)

1.1.2 Transmitting Signal (Electromagnetic)

Electromagnetic in nature, it likely includes turn around attractive field lines. Concurring to Maxwell, the active vitality of this development accurately compares to electromagnetic vitality, the presence and esteem of which tests have freely uncovered, and which hypothesis disseminates in a decided way over diverse parts of space.Lorentz (1892)

1.1.3 Frequency of signal

Frequency refers to the quantity of cycles executed by a wave within a single second, and its Unit is Hz (Hertz). The frequency signal is given by:

$$F = \frac{1}{T} \quad Carlson\ (2002) \tag{1.1}$$

Where F called the frequency of the signal and T called period of the signal.Carlson (2002)
The figure 1.2 represents the frequency and its period for the signal

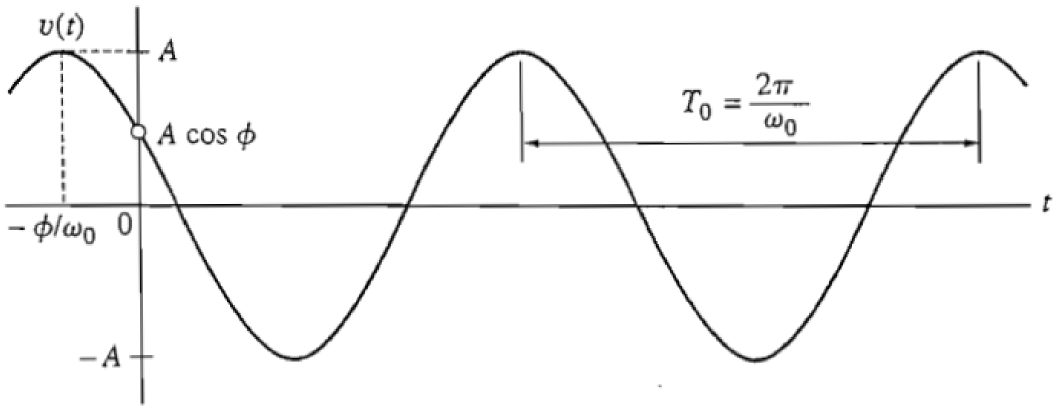

Figure 1.2: Sinusoidal waveform $V(t) = A\cos(\omega t + \phi)$ Carlson (2002)

1.1.4 Amplitude of signal

The amplitude is represented by the (A) symbol shown in Figure 1.2. It is called discrete frequency spectrum or line spectrum.Hsu (2011). Is defined as the difference between the maximum (+ amplitude) and minimum (− amplitude) values, Therefore, for a symmetrical signal, this peak-to-peak amplitude equals twice the amplitude, Giovanni et al. (2021).

1.1.5 Phase of signal

The phase of the signal is represented by the (ϕ) symbol shown in Figure 1.2 , is derived by calculating the arctangent of the ratio of the imaginary signal component to the real signal component, performed voxel by voxel. The resulting values of f range between $-\pi$ and π. Vegh et al. (2016)

1.1.6 Signal power to noise

Noise, in its most basic definition in electronics, refers to an undesirable disturbance in an electrical signal Kogan (1996). In signal processing, noise typically signifies unwanted (and often unknown) alterations that a signal may undergo during capture, storage, transmission, processing, or conversion.Tuzlukov (2010)
The signal-to-noise ratio is the ratio between the powers of the signal, PS, and the noise, PB Jutten (2009) :

$$SNR = \frac{P_S}{P_B} \tag{1.2}$$

or , in dB

$$SNR_{dB} = 10 \log \left(\frac{P_s}{P_B} \right) \tag{1.3}$$

(SNR) measures the quality of the signal. It's an objective measure. However, in many cases, especially those involving human intervention in the processing chain, this measure may not be very meaningful.

1.1.7 Signal Processing

The tools of signal theory and signal processing apply to numerous domains whenever a sensor measures a physical quantity carrying information, which is often disturbed (by noise or the measurement system) and needs to be processed to extract useful information from it. Signal processing methods enable the development of safer, more reliable, and faster approaches to analyze and transmit signals. In the field of communications, spread spectrum, GSM, etc., serve as representative examples. Jutten (2009),we mention some of the operations on the electrical signal:

1.1.7.1 Analog digital converters ADC

Analog to digital conversion consists of transformers Analog signals are transmitted according to time and amplitude to form discrete time signals (sampling) and en amplitude (quantification). Distribution will generally be carried out in three stages differences: sampling , the blocking and the quantification.Traoré (2006)
Convert analog messages to digital messages. Therefore he led a Sampling and quantizing signals carrying analog messages. This is not ADC of course, this is of no use if the message is already in digital form.ADDOU & ALLAM (2022)
The figure 1.3 shows how a ADC converter works

1.1.7.2 Periodic signal sampling

Sampling a continuous signal involves taking samples of the signal to obtain a discrete signal, which is a sequence of numbers representing the original signal. This process is carried out to store, transmit, or process the signal. Sampling plays a crucial role in analog-to-digital conversion operations, such as in sound or image digitization devices.Legrand & Commons (n.d.)
The sambling process is shown in the following figure 1.4

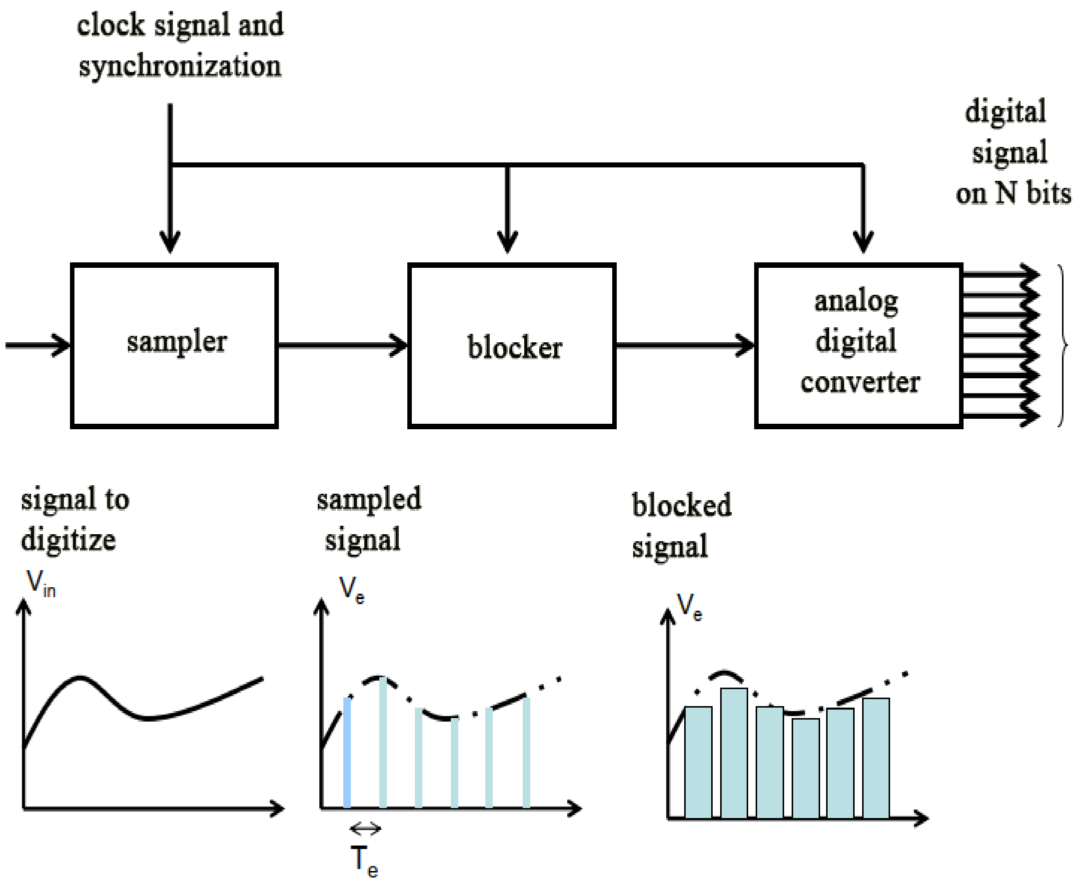

Figure 1.3: Functional diagram of an Analog-to-Digital Converter.Traoré (2006)

1.1.7.3 Signal Quantization

Quantification involves approximating each value of the signal $a_x(t)$ by an integer multiple of a specified quantity denoted as q, known as the "quantization step." If q remains constant regardless of the signal's amplitude, the quantization is referred to as uniform. The quantized signal $q_x(t)$ differs from the original signal $a_x(t)$ by an error term e(t), which can be expressed as:

$$a_x(t) = q_x(t) + e(t) \quad \textit{Dumartin}\ (2004) \tag{1.4}$$

This error term is denoted as e(t). is referred to as quantization noise. Dumartin (2004)

The quantification process is shown in the following figure 1.5

1.1.7.4 The Fourier transform

We are interested in a function x of the variable t. This function can take complex values and depends on a variable t, which could potentially be a vector variable, we will mainly focus on the case of a scalar variable, and it will often be convenient to consider t as time, with the function then representing the temporal evolution of a signal.

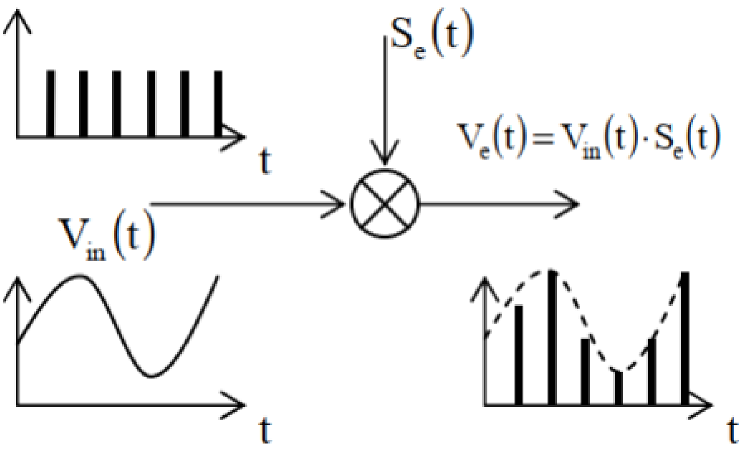

Figure 1.4: Principle of sampling.Traoré (2006)

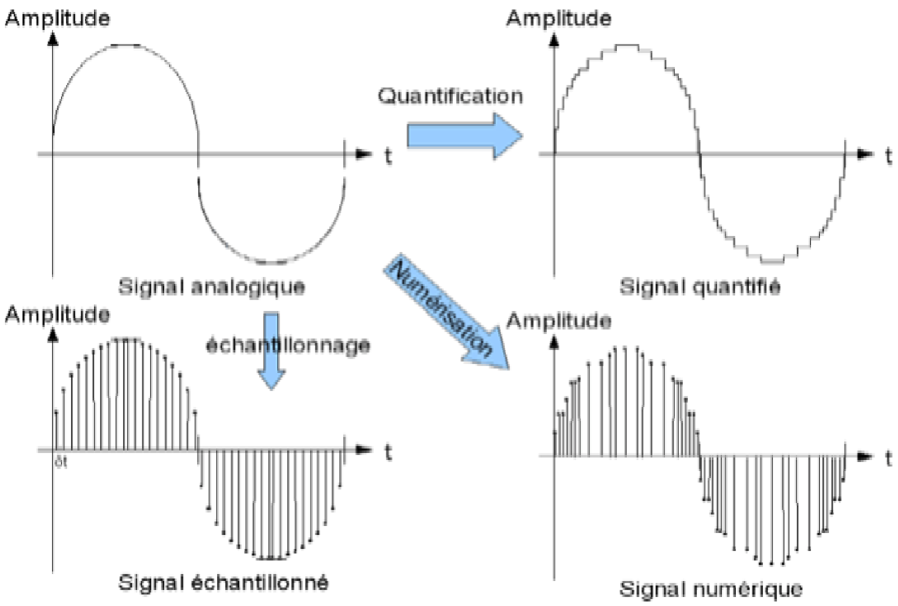

Figure 1.5: Explanatory diagram on quantification.Meziane & Zahir (2018)

However, note that t does not necessarily represent time, and we can study the behavior of signals with respect to spatial variables, concentration, etc.

Any non-periodic function x(t) can be decomposed into a Fourier integral form as follows:

$$x(t) = \int_{-\infty}^{\infty} X(f)e^{j2\pi ft}\,df \quad \textit{Baudoin \&Bercher}\ (1998) \tag{1.5}$$

or

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}\,dt \quad \textit{Baudoin \&Bercher}\ (1998) \tag{1.6}$$

We say that x(t) and its Fourier transform X(f) form a Fourier transform pair, denoted by:

$$x(t) \longleftrightarrow X(f) \qquad \textit{Baudoin \&Bercher}\ (1998) \tag{1.7}$$

Baudoin & Bercher (1998)

1.1.7.5 In-phase and quadrature components (IQ)

In digital communications, modulation is often expressed in terms of I/Q components (Inphase/Quadrature). The I/Q formulation is written as:

$$x(t) = I(t)\cos[\omega ct] + Q(t)\sin[\omega ct] \quad \textit{Janicot}\ (2002) \tag{1.8}$$

The I/Q diagram is a rectangular representation of the graph in polar coordinates. On a polar diagram, the I axis aligns with the 0 phase line, and the Q axis is perpendicular to it. The projection of the signal vector onto the I axis gives the I component, and the projection onto the Q axis gives the Q component.
A trajectory diagram represents the variations of the Q component of the signal against its I component over time. The constellation diagram depicts the coordinates of points. Janicot (2002)
The figure 1.6 IQ modulator and de-modulator block diagram.

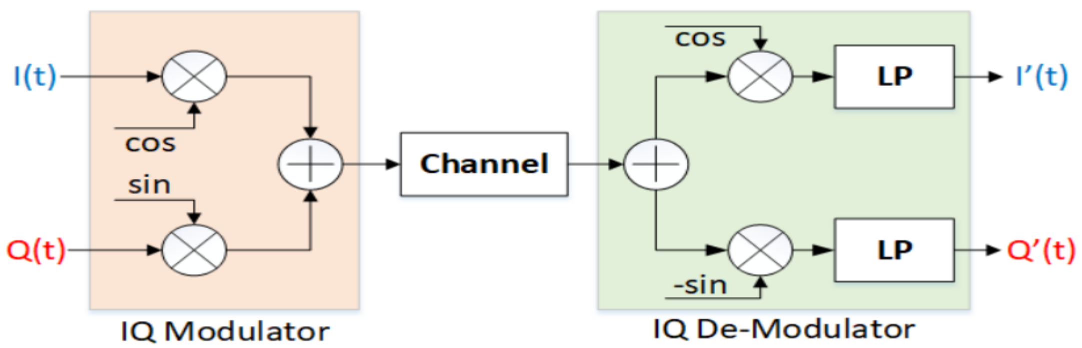

Figure 1.6: IQ modulator and de-modulator block diagram..B. Wang et al. (2018)

1.1.8 Modulation of signal

Modulation involves converting a known signal into the signal intended for transmission. The signal intended for transmission is referred to as the information signal. When we modulate a signal, it is called:

- **Carrier** : the known signal
- **Modulating signal** :the information signal
- **Modulated signal** : he resulting signal from transforming the carrier by the modulating signal

Refers to a procedure that alters the frequency range within a signal.
Signals sharing identical frequency ranges can be distinguished.
Modulation aids in managing noise and attenuation, which are contingent on the physical medium Agbo & Sadiku (2017),Modulation stands as a fundamental signal-processing technique essential for transmitting an information-carrying signal across a communication channel, whether in digital or analog communication settings. It involves altering a parameter of a carrier wave in alignment with the information-containing (message) signal.Haykin & Moher (1989)
There are two types of modulation as shown in the figure 1.7

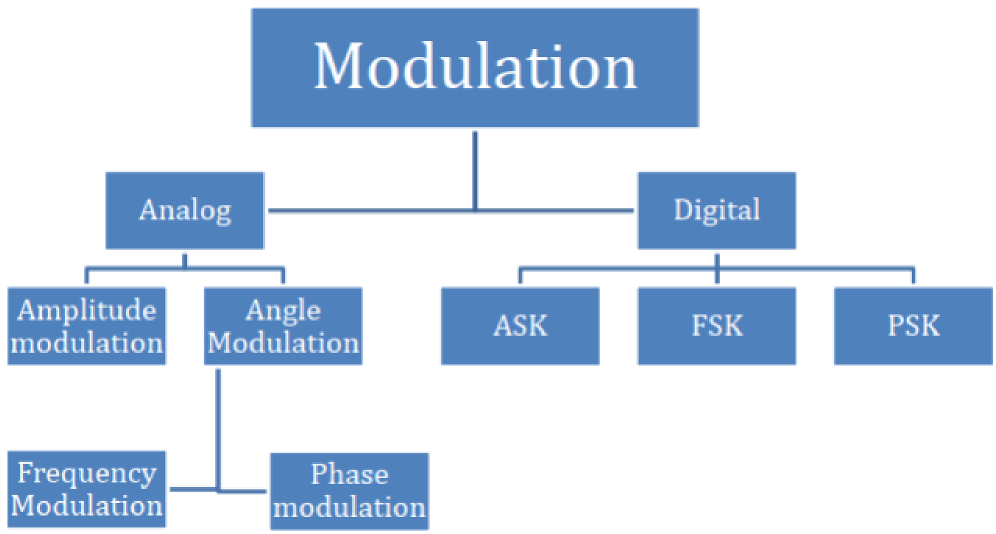

Figure 1.7: Classification of Modulation Phuntsho & Bhooshan (2015)

1.1.8.1 Analog modulation

An analog signal changes continuously over time. It can be either periodic or non-periodic. When an analog signal is regular, it's termed periodic. This means the signal showcases a fundamental pattern: a segment of the curve repeats at consistent time intervals.

- **Period (T)** Represent the duration of a change in seconds (s). The period can be understood as the duration between two "peaks" of the curve.

- **The frequency (F)** of a periodic signal corresponds to the number of repetitions of the fundamental pattern of that signal within one second. The frequency f is the inverse of the period T.Ambardar et al. (1995)

We mention two types of this modulation

- **AM Modulation**
  The signal undergoes modulation through a carrier signal denoted as:

$$C(t) = A\cos(2\pi f t) \quad \textit{Agbo \&Sadiku } (2017) \tag{1.9}$$

  Where the carrier frequency is represented by f. This process involves multiplying the source signal by the carrier signal, resulting in the transmitted modulation signal, denoted as S(t) according to equation (1.2).

$$S(t) = X(t)A\cos(2\pi f t) \quad \textit{Agbo \&Sadiku } (2017) \tag{1.10}$$

  X(t) : the source signal is analogue.Agbo & Sadiku (2017)
  Types: M-SSB, AM-DSB...
  The figure 1.8 shows AM modulation process

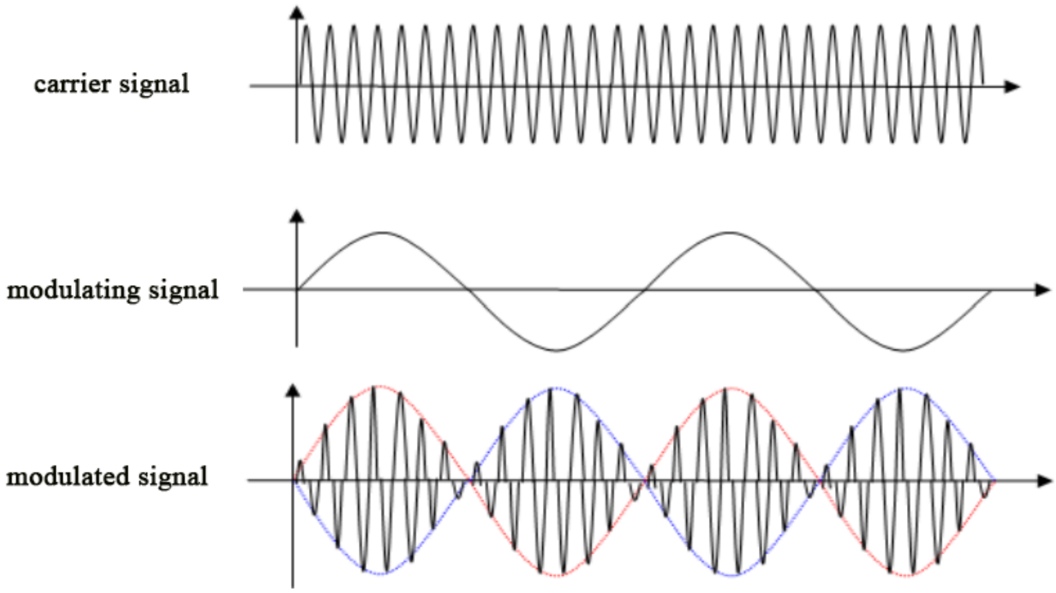

Figure 1.8: AM modulation.Krioui et al. (2019)

- **FM Modulation**
  Frequency modulation is a technique used to convey information through radio waves or wired channels. It finds application in UHF/VHF radio transmission (FM radio) and radio transmission via microwave links. Nowadays, it's progressively being replaced by digital transmission methods.KHALFALLAOUI (2021)
  Types: WBFM...

- The figure 1.9 shows FM modulation process

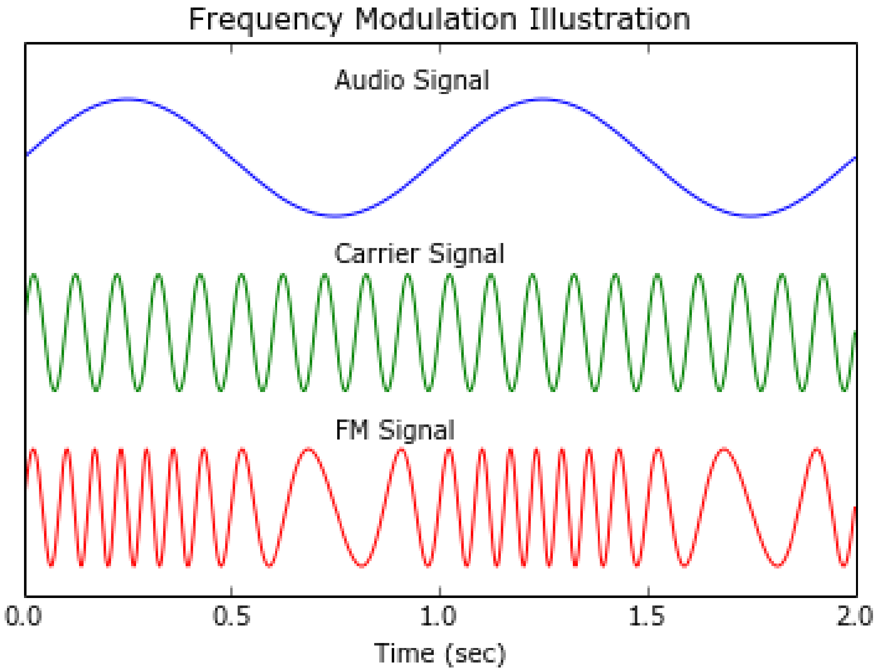

Figure 1.9: FM modulation process.Swiston (n.d.)

1.1.8.2 Digital modulation

Digital modulation refers to the method of imprinting a digital symbol onto a signal that's suitable for transmission. When it comes to short-distance transmissions, baseband modulation, often referred to as line coding, is typically employed. This involves using a series of digital symbols to generate a square pulse waveform with specific characteristics. These features are designed to represent each symbol distinctly, using variations in pulse amplitude, pulse width, and pulse position, ensuring their clear recovery upon reception.Xiong (2006)
Modulation stands as the means of transmitting information through a medium. In the context of digital communication, digital modulation signifies the movement of a digital bit stream from the transmitter to the receiver(s) through the analog information channel, which serves as the medium. In the process of modulation, the informational signal alters one or multiple aspects of a carrier signal. Typically, this carrier signal is a sine wave characterized by its amplitude, frequency, and phase. The modulation techniques vary based on which specific carrier parameter is being adjustedTarniceriu et al. (2007), resulting in three fundamental types of modulation:

- **Amplitude Shift Keying (ASK)**
  ASK stands out as the most basic modulation technique, involving the modulation of digital information by varying the amplitude of the carrier,In ASK, the amplitude of the carrier signal is adjusted to one of two values, corresponding to the logical level in the message signal at a particular moment. A high amplitude signifies logical level 1, while a low amplitude signifies logical

level 0.CHACHOUA & BENSAHA (2021)

$$s(t) = A \cdot \cos\left(2\pi f_c t + 2\pi \Delta f \int_0^t u(\tau) d\tau\right) \quad CHACHOUA \ \&BENSAHA \ (2021) \tag{1.11}$$

Types: PAM4...

- **Frequency Shift Keying (FSK)**
  Frequency-shift keying (FSK) is a frequency modulation technique where digital information is transmitted through distinct changes in the carrier signal's frequencyKennedy & Davis (1992). In this method, binary digital information (0 and 1) is represented by a signal with constant amplitude, with the frequency altering for each state. In its simplest form, FSK assigns one frequency to represent a 1 (a mark) and another frequency to represent a 0 (a space). These frequencies fall within the transmission channel's bandwidth William Buchanan BSc (Hons) (2000).
  Types: GFSK, CPFSK...

- **Phase Shift Keying (PSK)**
  Is a digital communication scheme that transmits data through modification or modulation. The phase of the reference signal (carrier). Each digital modulation scheme uses a limited number of different signals to represent digital data. phase shift keying A limited number of stages are used, each assigned a unique binary number pattern. Usually each stage Encode the same number of bits. Each bit pattern is represented by a corresponding phase.Phuntsho & Bhooshan (2015)
  Types: PSK, QPSK, 8PSK,...
  The figure 1.10 shows how the three basic modulatation work

- **Quadrature Amplitude Modulation (QAM)**
  ASK is also combined with PSK to create hybrid systems such as Quadrature Amplitude modulation (QAM), where both amplitude and phase are present change at the same time.Jahagirdar & Ukey (2010)
  Types: QAM16, QAM64...

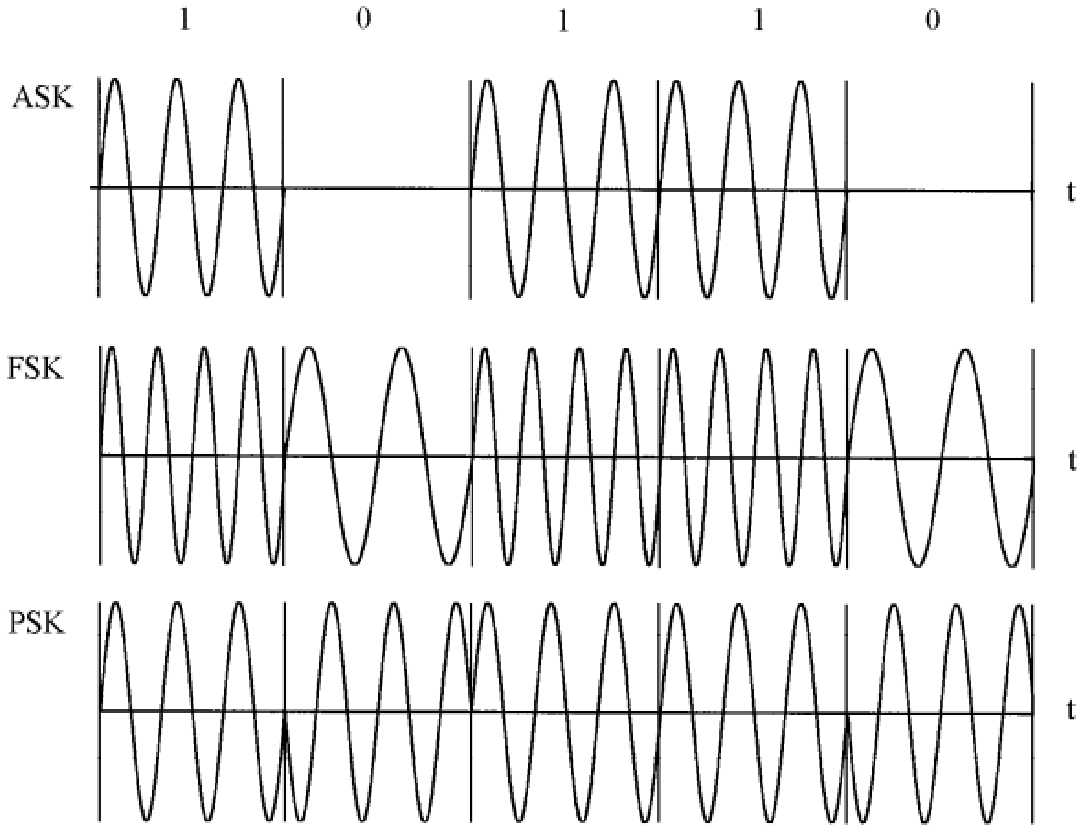

Figure 1.10: Three basic bandpass modulation schemes.Xiong (2006)

1.1.9 Communication process

The primary goal of a communication system is to facilitate the exchange of information between two entities. Put differently, its purpose is to transmit information from one location to another. The essential elements of this system include the source of information, transmitter, channel, receiver, and user of information, as shown in figure 1.11

- **Source of information**
  Audio/voice communication : involves information presented in the form of audible sound waves, such as what we typically hear on the radio. Voice communication is widely prevalent globally. However, due to the recent emergence of mobile applications, data transmission has surpassed voice communication.
  Data : This form of information is generated by computers and exists in digital format, typically represented in binary as 0s and 1s. This type of information exhibits burstiness, where it is transmitted in bursts with intervals of silence. Data lacks inherent meaning until it is interpreted. For instance, 1234.56 is considered data, whereas the statement "Joe owes me "1234.56" represents information derived from interpreting that data.
  Video : refers to the electronic depiction of still or dynamic images. In a televised broadcast, the video constitutes the visual content, while the audio corresponds to the audible component. Agbo & Sadiku (2017)

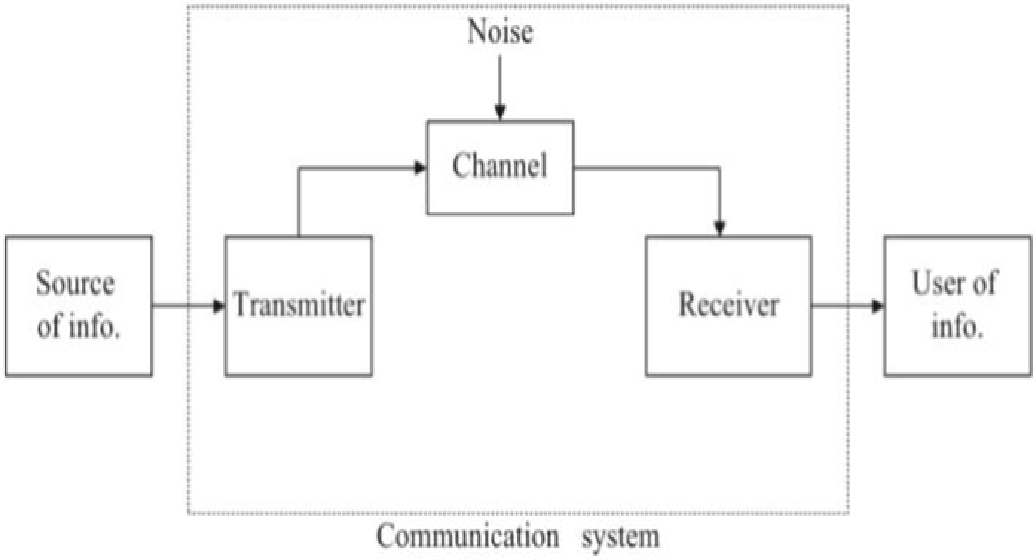

Figure 1.11: Components of a communication system.Agbo & Sadiku (2017)

- **Transmitter(Modulation) :** Modulation involves converting a known signal into the signal intended for transmission. The signal intended for transmission is referred to as the information signal. Agbo & Sadiku (2017)
- **Noise :** (return 1.1.6 Signal power to noise, page6).
- **The user of information :** That is the final destination of the signal. Once the signal has been transmitted, received, and processed, it is up to the user to interpret and use it. Communication engineers have a high degree of control over the design and operation of the transmitter and receiver, but they have less influence over the source of the information, the transmission channel, or the user's actions.Agbo & Sadiku (2017)
- **Channel :** A channel serves as the route for the flow of an electrical signal, A channel can be seen as the medium through which information propagates. Channels can be categorized based on the medium that they utilize, such as wire or wireless. Examples of wire channels include twisted pairs employed in telephone lines, coaxial cables in computer networks, waveguides, and optical fibers. Wireless channels encompass mediums like vacuum, atmosphere/air, and sea.
  Channels can also be characterized by their transmission mode, with three types highlighted in Figure 1.2: simplex, half duplex, and full duplex.
  Simplex : Communication flows in one direction only, One can transmit but not receive or receive but not transmit. like a radio broadcast or a TV signal.
  Half-duplex : Communication can go in both directions, but not at the same time. Think of a walkie-talkie; you have to press a button to talk, and then release it to listen.
  Full-duplex : Communication can occur in both directions simultaneously, like a phone call or a computer network. You can talk and listen at the same time.Agbo & Sadiku (2017)
  The channel operation methods are shown in the figure 1.12

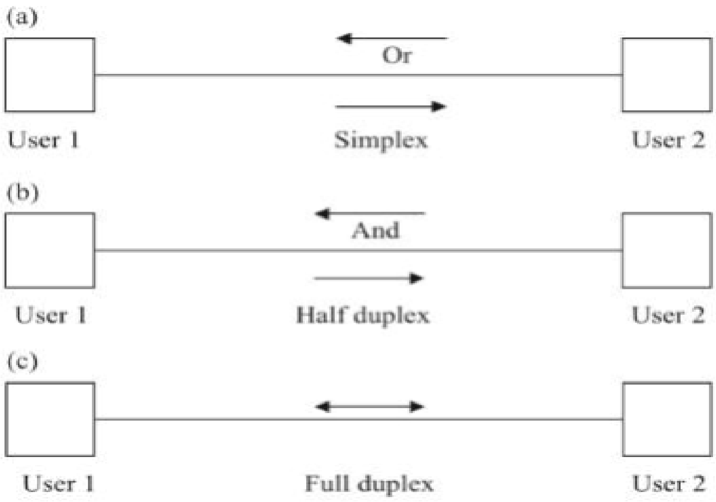

Figure 1.12: Modes of channel operation.Agbo & Sadiku (2017)

1.2 Automatic modulation classification

Serves as the transitional phase within a radio monitoring system or cognitive radio, occurring between signal detection and demodulation, there are two main categories of AMC algorithms: those based on likelihood (LB) and those based on features (FB).
Both categories evaluate the received signal against a selection of potential modulation options.Weber et al. (2015).
The process preceding signal demodulation in the physical layer is presently drawing increased interest from signal processing and communication communities. Essentially, AMC is focused on identifying the modulation type of an incoming signal at the receiver, often presenting itself as a multi-class decision-making challenge within the realm of artificial intelligence (AI). Huynh-The et al. (2021).
The figure 1.13 shows the architecture of feature-based AMC method.

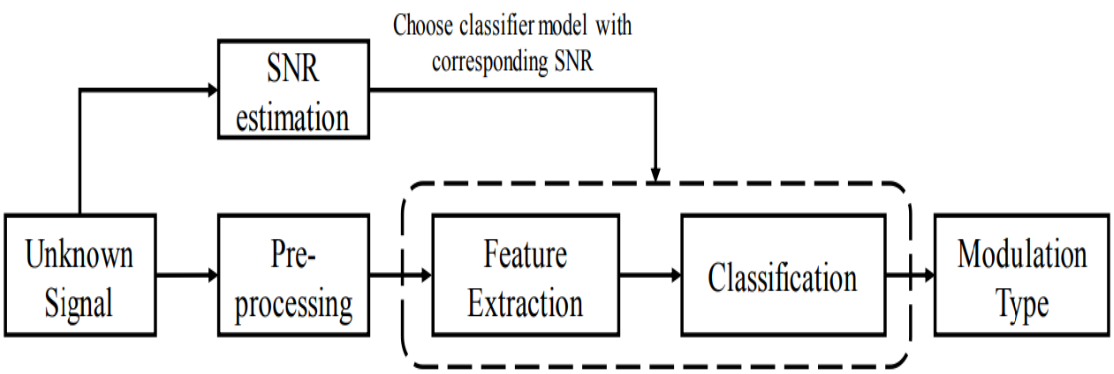

Figure 1.13: The architecture of feature-based AMC method.Y. Wang et al. (2020)

1.3 General definitions of artificial intelligence

- **Introduction**
  Artificial Intelligence is a field within computer science that focuses on creating systems capable of learning, adapting, reasoning, and interacting with their environment in ways that resemble human capabilities. It's considered one of the most advanced fields in the modern era, finding applications in various areas such as robotics, image recognition, speech recognition, machine learning, deep learning, and many others.

- **Artificial Intelligence**
  In 1956, artificial intelligence (AI) was defined as 'the science and engineering of creating intelligent machines'McCarthy (2007). AI involves the development of intelligent machines capable of solving various problems using natural language processing, neural networks, and machine learning Mondal (2020). It is revolutionizing numerous fields, including medicine, psychology, science, and public policy Y. Xu et al. (2021).Su et al. (2023)

- **Machine Learning**
  Scientists often try to build mathematical models that connect observable data (inputs) to other related variables (outputs). These models allow us to predict outputs based on measured inputs. However, many real-world phenomena are too complex for simple models. Machine learning comes to the rescue by automatically building complex models that analyze data and maximize performance. This process of automatically building models is called "training," and the data used for training is called "training data." Trained models can provide insights into how inputs are related to outputs and can be used to make predictions for new, unseen data. Baştanlar & Özuysal (2014)

  The diagram 1.14 represents Machine learning algorithms learning concepts and classes

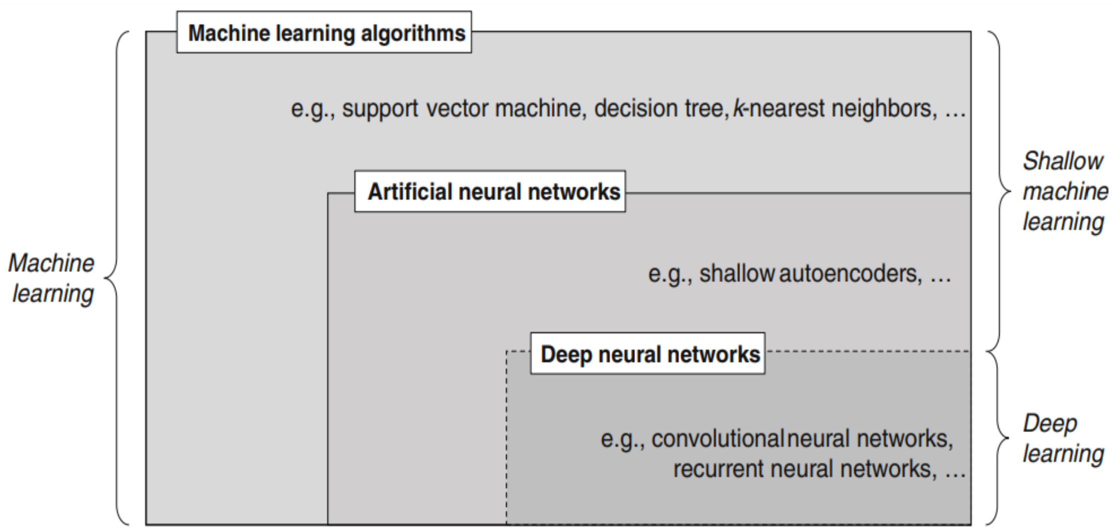

Figure 1.14: diagram of machine Machine learning algorithms learning concepts and classe.Janiesch et al. (2021)

There are many methods in machine learning, including:

- Supervised Learning.
- Unsupervised Learning.
- Semi-Supervised Learning.
- Self-Supervised Learning.
- Reinforcement Learning. Baştanlar & Özuysal (2014)

- **Deep Learning**
  An integral component of the larger machine learning family, distinguished by the unique arrangement of neural networks structured in numerous layers, mimicking the human learning process and enhancing the capacity to tackle intricate problems. Iterative in nature, deep learning networks disseminate information, autonomously refining their features using gradient-based optimization techniques and backpropagation.Chassagnon et al. (2020)

  - **Neural Networks**
    Neural networks are a group of algorithms designed to achieve this goal Discover potential relationships in your data set A process that mimics the functions of the human brain. exist In this sense, a neural network refers to a system of neurons, Organic or man-made in nature. Neural networks can Adapt to changing inputs; so that the network produces the best Get possible results without redesigning the output standard. The concept of neural networks has its roots Artificial intelligence is rapidly spreading around the world Development of trading systems. Mahesh (2020).
    The figure 1.15 shows a Perceptron which is the elementary unit of a neural network.

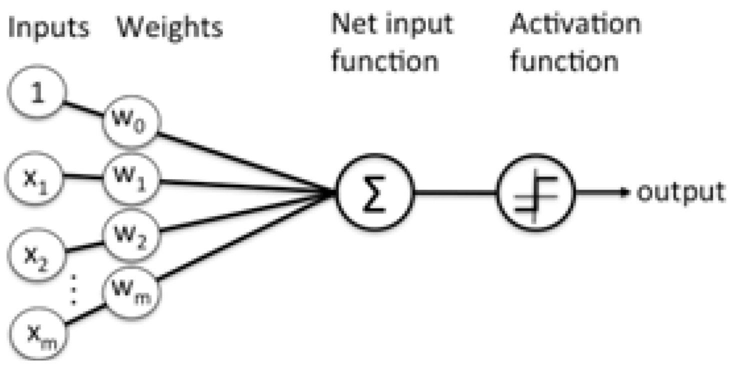

Figure 1.15: Perceptron : the basic unit of a neural network. Mahesh (2020)

  - **Deep Learning Models**
    Since their inception, numerous deep learning models have emerged, with notable ones like Deep Belief Network (DBN), Autoencoder (AE), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) Du et al. (2016), Attention models and Transformers. Vaswani et al. (2017).

1.3.1 CNN architecture

Convolutional neural networks are currently the most effective models for classifying images, Referred to by the acronym CNN. They consist of two distinct parts. At the input, an image is provided in the form of a pixel matrix. For a grayscale image, it has two dimensions. Color is represented by a third dimension, with a depth of 3 to capture the fundamental colors [Red, Green, Blue].Boughaba et al. (2017)
Convolutive part aims to extract unique features from each image by compressing them to reduce their initial size. In essence, the input image undergoes a sequence of filters, thereby generating new images known as convolutional feature maps. Eventually, these obtained convolutional maps are concatenated into a feature vector called the CNN code.Boughaba et al. (2017)
The other part, for classification, takes the CNN code from the convolutive section as input. It consists of fully connected layers known as a multilayer perceptron (MLP). This section's role is to amalgamate the CNN code's features in order to classify the image. Boughaba et al. (2017). CNN has layers similar to convolutional layers, Pooling layers (max, min and average), ReLU layers and fully connected layers. Convolutional layers have kernels (filters) Each core has width, depth and height. This layer Generate feature maps as a result of computing scalars Product between kernel and local image area.Akhtar & Feng (2022). A CNN architecture is formed by a set of independent processing layers:

- **Convolution Layer**
  The convolutional layer is the most important unit CNN,convolves the input using convolution kernels. It acts as a filter and is then activated by a non-linear filter The activation function is as follows:

  $$a_{i,j} = f\left(\sum_{m=1}^{M}\sum_{n=1}^{N} w_{m,n} \cdot x_{i+m,j+n} + b\right) \quad \textit{Xia etal.}\ (2020) \tag{1.12}$$

  where $a_{i,j}$ is the corresponding activation, $w_{m,n}$ represents m×n weight matrix of convolution kernel, represented by $x_{i+m,j+n}$ Activation of upper layer neurons connected to neurons (i,j), b is the bias value, f is the nonlinear function.Xia et al. (2020)

- **Pooling Layer**
  After obtaining the feature map, pooling (subsampling) needs to be added. A layer in a CNN that is immediately adjacent to a convolutional layer. The role of the pooling layer is to shrink the data The spatial dimensions of the collapsed feature. Due to dimensionality reduction, computers The power consumption required to process data is reduced.
  There are two forms of pooling: maximum pooling and average pooling.Bhatt et al. (2021) The figure 1.16 shows pooling layer how it work.

- **Normalization layer**
  is also called The Rectified Linear Unit (ReLU) process sets all negatives of the filtered image The value is 0. When applied to all filtered images. The equation 1.13 shows the ReLU activation function:

  $$f(x) = max(0, x) \quad \textit{Gupta etal.}\ (2022) \tag{1.13}$$

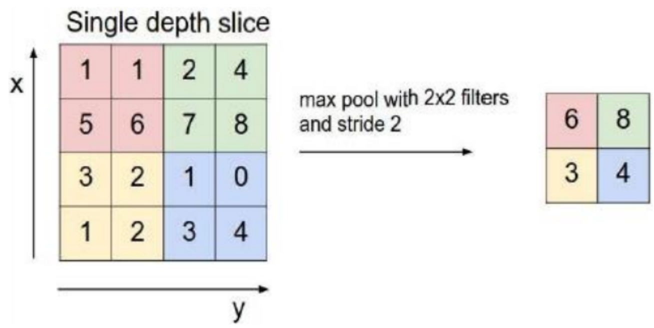

Figure 1.16: Pooling layer of a CNN.Süßle (2021)

- **Fully Connected Layer**
  Often called a classifier, it is the final layer of a CNN design. All values at this level play a role in determining classification. Each middle layer votes On dummy "hidden" classes, causing multiple fully connected layers to be overwritten on top of each other. Additionally, each new layer of the neural network improves decision-making This enables the network to learn increasingly complex feature combinations.Gupta et al. (2022)

  The figure 1.17 shows how the CNN model works.

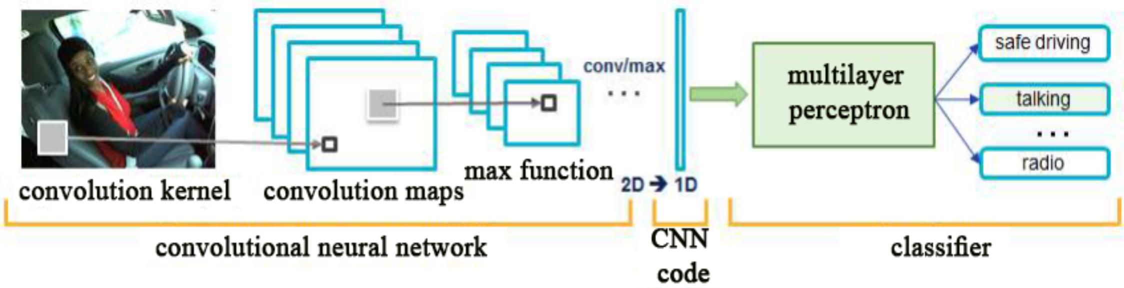

Figure 1.17: Convolutional neural networks.Boughaba et al. (2017)

1.3.2 Long Short Term Memory LSTM

Long short-term memory (LSTM) is a recurring phenomenon Recently popular neural networks The field of machine learning. LSTM, originally proposed by Hochreiter and Schmidhuber (1997), Subsequent variants developed since Contributions from many other researchers. Turkoglu et al. (2022);
LSTM-based method, Integrating information from pedestrian neighborhoods Incorporate into the training process and use scene context Attempts have been made to improve trajectories.
In the basic LSTM network architecture, given an input The sequence is represented by $(x_1, \ldots, x_T)$, and the output sequence yt can be obtained by iteratively calculating the equation. 1.14 and 1.15 For t = 1,...,T:

$$h_t = LSTM(h_{t-1}, x_t; W) \quad Xue\, etal.\ (2018) \tag{1.14}$$

$$y_t = W_{hy}h_t + b_y \quad Xue\, etal.\ (2018) \tag{1.15}$$

Where W terms represents different weight matrices, through b_y represents the bias vector of the output y_t, h represents Hidden state. In the cellular function LSTM(·), the hidden state Determined by the entrance door i, the forgetting door f and the exit door o and cell state c via the following equation:

$$o_t = (W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \quad Xue\ etal.\ (2018) \tag{1.16}$$

$$h_t = o_t \tanh(c_t) \quad Xue\ etal.\ (2018) \tag{1.17}$$

where W_{ab} is the weight matrix from layer a to layer b; $\sigma(\cdot)$ represents a Sigmoid activation function; each b term is preceded by a. The index is the deviation vector of the corresponding level.Xue et al. (2018).
Conventional RNNs face difficulty in maintaining connections over increasing intervals, akin to memory decay in the human brain. This issue, known as vanishing gradient, is remedied by LSTM, which employs gate mechanisms to enhance information flow between memory cells. These structures encompass input, output, and forget gates.D. Zhang et al. (2018)
The figure 1.18 represents a structure of LSTM :

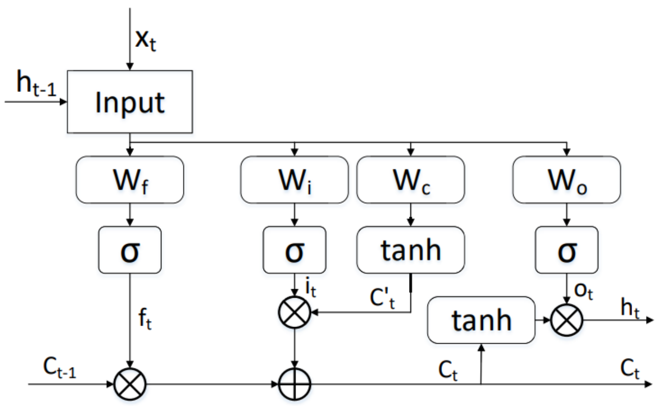

Figure 1.18: lustration of LSTM structure.Y. Ding et al. (2019)

1.3.3 Supervised Learning

In supervised learning, a collection of examples or training instances is supplied along with their corresponding correct outputs. The algorithm improves its accuracy by learning from these training sets and evaluating its output against the provided inputs. Supervised learning is alternatively referred to as learning from examples or learning from exemplars. Supervised learning tasks are classified into two main types: classification tasks, where output labels are distinct, and regression tasks, where output values are continuous. Such algorithms: Decision Tree, Naïve Bayes, Support Vector Machines, Regression Analysis,..Alzubi et al. (2018)
example: Supervised learning is applied in predicting outcomes based on past data. For instance:

- it can predict the Iris species by analyzing flower measurements
- or identify celestial objects such as galaxies, quasars
- or stars in a colored telescope image

1.3.4 Unsupervised Learning

The unsupervised learning method focuses on identifying inherent patterns within data to extract rules from them. This approach is suitable when the data's categories are unknown, and the training data lacks labels. Unsupervised learning is considered a statistical approach, addressing the challenge of uncovering concealed structures within unlabeled data.Alzubi et al. (2018)
Such algorithms: K-Means Clustering...
example:
Imagine a machine (or living organism) that receives a series of inputs x^1,x^2, x^3,..., which x^t represents the sensory input at time t. This input, commonly referred to as the data, may include information like an image on the retina, pixels from a camera, or a sound waveform. It could also encompass less evident sensory data, such as the words in a news story or the items listed in a supermarket shopping basket.Ghahramani (2003)
We show a representation of image Supervised Learning vs Unsupervised Learning in figure 1.19

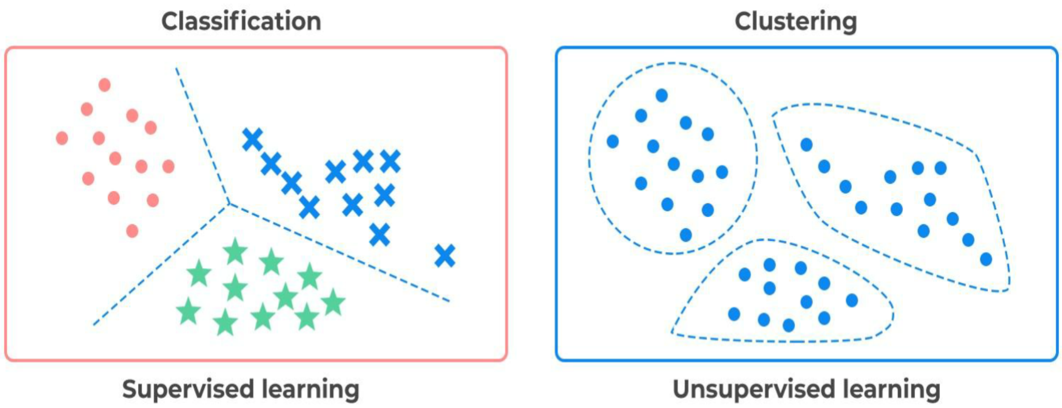

Figure 1.19: Supervised Learning vs Unsupervised Learning.ARK (n.d.)

1.3.5 Semi-Supervised Learning

Semi-supervised learning is a type of machine learning that falls somewhere between unsupervised and supervised learning. It involves extending either unsupervised or supervised learning to include additional information typical of the other learning paradigm. Semi-supervised learning includes two main settings, semi-supervised classification, and constrained clustering.Zhu & Goldberg (2022)
Semi-supervised classification, also known as classification with labeled and unlabeled data, extends the supervised classification problem, where the training data consists of both labeled and unlabeled instances. The goal here is to train a classifier from both the labeled and unlabeled data, such that it is better than the supervised classifier trained on the labeled data alone.Zhu & Goldberg (2022)
Constrained clustering, on the other hand, extends unsupervised clustering and involves training data consisting of unlabeled instances, as well as some ”supervised information” about the clusters. This may include constraints such as ”must-link” and cannot-link” constraints, as well as size constraints. The goal of constrained

clustering is to obtain better clustering than the clustering from unlabeled data alone.Zhu & Goldberg (2022)
In a supervised learning framework, we are provided with a set of (l):
$x_1, \ldots, x_l \in X$
with corresponding labels
$y_1, \ldots, y_l \in Y$
Additionally, we are given (u):
independently identically distributed examples
Unlabeled examples.
$x_l + 1, \ldots, x_l + u \in$ X Learning (2006)

Such algorithms:

- Self-training.
- Mixture models.
- Semi-supervised SVM.
- Generative adversarial networks(Audio and video ‘manipulation, Data creation.
- Self-trained Naive Bayes classifier(Natural language processing).

Example:

- Using in Tracking visual objects in the field of computer vision(In order to handle rapid appearance changes). Zeisl et al. (2010)
- Processing documents and contemporary genetic studies. Bair (2013)

The figure 1.20 shows how Semi-supervised Learning

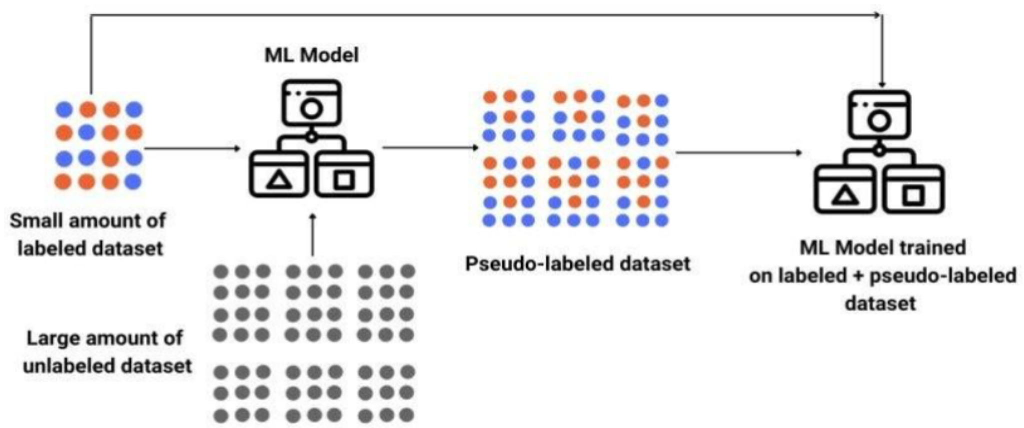

Figure 1.20: Semi-supervised Learning how it work. Dubey (n.d.)

1.3.6 Reinforcement learning

Reinforcement learning is a field of machine learning Handle how software agents should act an environment in which an idea can be maximized Cumulative rewards. Reinforcement learning is one of the three Basic paradigms of machine learning and supervised learning and unsupervised learning. The figure 1.21 shows Reinforcement learning, and how it works.Mahesh (2020)

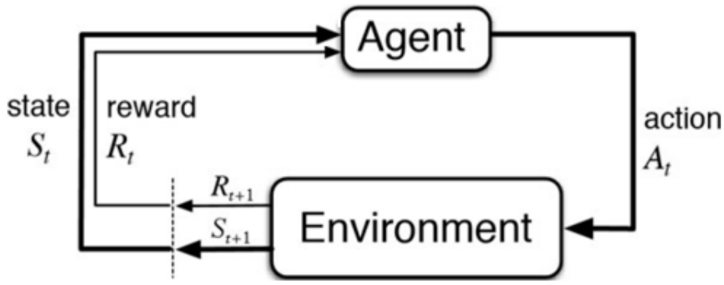

Figure 1.21: Reinforcement learning.Mahesh (2020)

1.3.7 Self-Supervised Learning

The effectiveness of deep learning often demands substantial volumes of expensive annotated data. To address this constraint, self-supervised learning (SSL) has emerged, seeking to mitigate the reliance on labeled data by formulating domain-specific pretext tasks using unlabeled data. Jin et al. (2020)
Self-supervised learning techniques have incorporated a combination of generative and contrastive approaches, effectively harnessing unlabeled data to acquire meaningful representations. Jaiswal et al. (2020). While modern self-supervised methods are recognized as cutting-edge technology in semi-supervised learning.Hendrycks et al. (2019).

We show an example of image recognition in the figure 1.22.

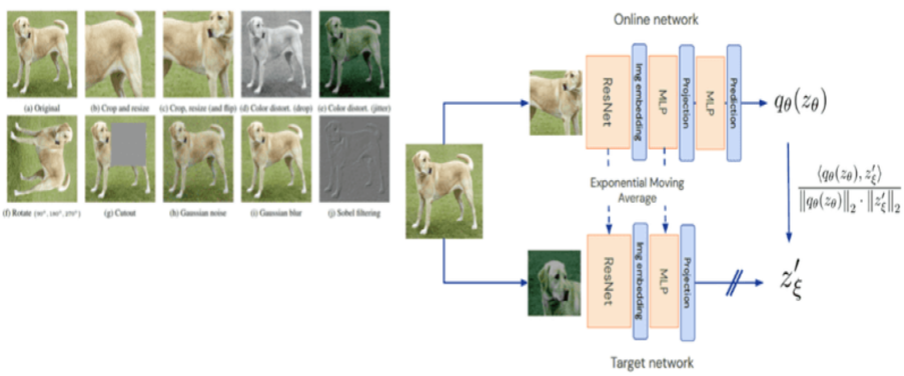

Figure 1.22: Self Supervised Learning how it work. Jain (n.d.).

Self-supervised learning, a technique for learning features without manual annotations, has been successfully applied to semi-supervised learning in time series classification.Jawed et al. (2020) The self-training algorithm, a classic approach in semi-supervised learning, has been theoretically analyzed and shown to benefit from sample rejection, regularization, and class margin.Oymak & Gulcu (2020)presents a simple yet effective semi-supervised algorithm based on self-supervised learning for image classification. Lastly, Triguero et al. (2015) provides a comprehensive survey of self-labeled techniques for semi-supervised classification, with a focus on their performance in transductive and inductive classification.

1.3.8 Comparison between Semi-Supervised Learning and some machine learning methods

We review the most important differences between Semi-Supervised Learning and Supervised, Unsupervised Learning in table 1.1 :

Table 1.1: Comparison of machine learning types.H. Ding et al. (2023)

Items	**Supervised learning**	**Semi-supervised learning**	**Unsupervised learning**
Input type	Labelled data	A mixture of labelled and unlabelled data	Unlabelled data
Accuracy	High	Mid	Low
Complexity of the algorithm	Low	Mid	High
Types of algorithm	Regression and classification	Regression, classification, clustering, and association	Clustering and association

1.4 Conclusion

The chapter mentioned the main concepts in the field of signals and the electromagnetic spectrum, as well as the basics and concepts related to artificial intelligence and machine learning, with deep learning that proves its choice in solving the radio signal classification problem.
The next chapter will be devoted to the state of the art in the field of classification of radio signals.

Chapter 2

Related Work

2.1 Modulation Classification

In the domain of Modulation classification, a series of studies have investigated the application of deep learning for radio signal classification. These studies have collectively demonstrated the potential of deep learning, particularly in real-time and embedded systems.

A work by Tandia, M. F., & Hutomo, I. S. (2020) titled :"Enhanced Low SNR Radio Signal Classification using Deep Learning", made a significant contribution to the field of radio signal classification. Their research focused on the application of deep learning for signal classification, particularly in conditions of low Signal-to-Noise Ratio (SNR). The authors noted that traditional signal classification methods required the decomposition of the signal using techniques such as Fourier Transform (FT), Scale-Invariant Feature Transform (SIFT), Mel Frequency Cepstral Coefficients (MFCC), or other handcrafting methods using statistical modulation features. However, they observed that deep learning methods could be applied to the same problem of signal classification and showed excellent results while completely avoiding the need for difficult handcrafted feature selection. In their work, Tandia and Hutomo highlighted that while ResNet, a state- of-the-art computer vision model, was used in 2018 to classify radio communication signals, it failed to distinguish signals with low SNR conditions. They noted that ResNet only worked well on signals with high SNR conditions. In response to the limitations of existing methods, Tandia and Hutomo proposed a new state-of-the-art method to better classify radio-signal networks that works on both signals with low noise (High SNR) and signals with high noise (Low SNR) 2.1. Their method even works using only RAW signals without the need for preprocessing or denoising the noisy signal. Tandia & Hutomo (2020).

An in-depth study was conducted by O'Shea, Roy, and Clancy (2018) on the performance of deep learning-based radio signal classification for radio communications signals. Their work makes a significant contribution to the field of radio signal classification using deep learning. The authors considered a rigorous baseline method using higher order moments and strong boosted gradient tree classification. They compared the performance between these two approaches across a range of configurations and channel impairments. They also considered the effects of car-

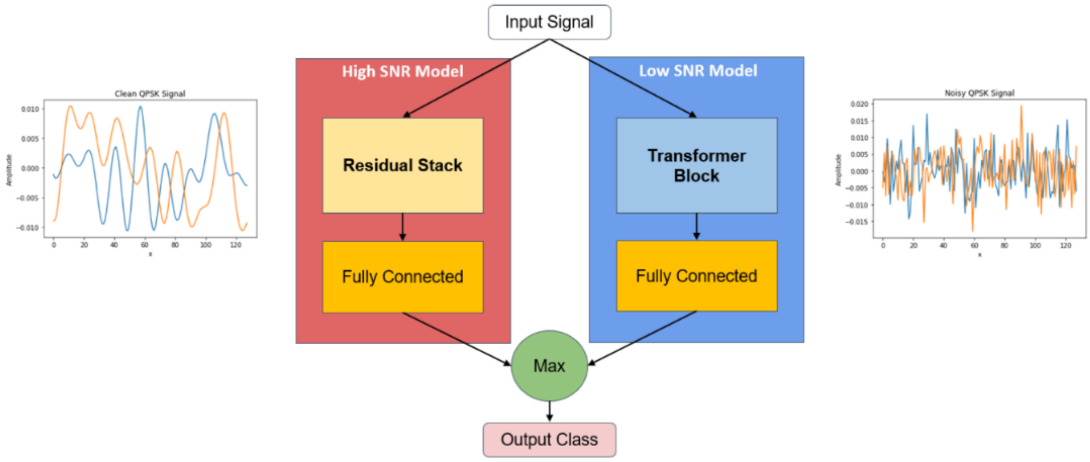

Figure 2.1: Classifier Network of Signals with High and Low SNR

rier frequency offset, symbol rate, and multi-path fading in simulation. Besides their theoretical work, the authors conducted over-the-air measurements of radio classification performance in the lab using software radios. They compared the performance and training strategies for both the deep learning method and the baseline method. Finally, the authors discuss the remaining problems and design considerations for using these methods, providing useful suggestions for future research in the area O'Shea et al. (2018).

Xu and Darwaze (2020) conducted a comprehensive study on non-cooperative communications, where a receiver can automatically distinguish and classify transmitted signal formats prior to detection. Their work is a significant contribution to the field of low-cost and low-latency systems. The authors focused on the deep learning enabled blind classification of multi-carrier signals covering their orthogonal and non-orthogonal varieties. They defined two signal groups, in which Type-I includes signals with large feature diversity while Type-II has strong feature similarity. They evaluated time-domain and frequency-domain convolutional neural network (CNN) models in simulation with wireless channel/hardware impairments. Simulation results revealed that the time-domain neural network training is more efficient than its frequency-domain counterpart in terms of classification accuracy and computational complexity. In addition, the time-domain CNN models can classify Type-I signals with high accuracy but reduced performance in Type-II signals because of their high signal feature similarity. Experimental systems were designed and tested, using software defined radio (SDR) devices, operated for different signal formats to form full wireless communication links with line-of- sight and non-line-of-sight scenarios. Testing, using four different time-domain CNN models, showed the pre-trained CNN models to have limited efficiency and utility due to the mismatch between the analytical/simulation and practical/real-world environments. Transfer learning, which is an approach to fine-tune learnt signal features, was applied based on measured over-the-air time-domain signal samples. Experimental results indicated that transfer learning based CNN can efficiently distinguish different signal formats in both line-of-sight and non-line-of-sight scenarios with great accuracy improvement relative to the non-transfer-learning approaches T. Xu & Darwazeh (2020).

2.2 Semi-Supervised Learning

X. Zhu and Goldberg's (2009) work, "Introduction to Semi-Supervised Learning", provides a comprehensive overview of semi-supervised learning, a learning paradigm that deals with both labeled and unlabeled data. This paradigm is of great interest in machine learning and data mining due to its potential to use readily available unlabeled data to improve supervised learning tasks when labeled data is scarce or expensive. The authors present popular semi-supervised learning models, including self-training, mixture models, co-training and multiview learning, graph-based methods, and semi-supervised support vector machines. For each model, they discuss its basic mathematical formulation. They emphasize the assumptions made by each model and provide counterexamples when appropriate to demonstrate the limitations of the different models. The authors compare semi-supervised learning with traditional learning paradigms, namely unsupervised learning (e.g., clustering, outlier detection) where all the data is unlabeled, and supervised learning (e.g., classification, regression) where all the data is labeled. They discuss how combining labeled and unlabeled data may change the learning behavior and how algorithms can be designed to take advantage of such a combination. Semi- supervised learning also shows potential as a quantitative tool to understand human category learning, where most of the input is self-evidently unlabeled. This aspect of their work could be particularly relevant if a research involves understanding or mimicking human learning processes. The authors conclude the book with a computational learning theoretic perspective on semi-supervised learning and a brief discussion of open questions in the field. This provides valuable insights for future research in this area Zhu & Goldberg (2022).

A paper of Zeisl et al. (2010) introduces an online semi-supervised learning algorithm that integrates both approaches into a unified framework, aiming to achieve more robust results compared to their applications. Furthermore, a unified loss function is introduced, leveraging both labeled and unlabeled samples concurrently, enhancing the tracker's adaptability in contrast to earlier online semi-supervised methods. Experimental results demonstrate that by incorporating the semi-supervised multiple-instance approach and employing robust learning techniques, the proposed method surpasses state-of-the-art approaches across various benchmark tracking videos Zeisl et al. (2010).

The work by Thomas N. Kipf and Max Welling titled "Semi-Supervised Classification With Graph Convolutional Networks", presented a scalable approach for semi-supervised learning on graph-structured data. This work is based on an efficient variant of convolutional neural networks which operate directly on graphs, making a significant contribution to the field of semi-supervised learning. The authors motivated the choice of their convolutional architecture via a localized first-order approximation of spectral graph convolutions. Their model scales linearly in the number of graph edges and learns hidden layer representations that encode both local graph structure and features of nodes. In a number of experiments on citation networks and on a knowledge graph dataset, Kipf and Welling demonstrated that their approach outperforms related methods by a significant margin. This indicates the effectiveness of their approach in practical applications Kipf & Welling (2016).

Augustus Odena in (2016) in his work, presented a novel approach for semi-supervised learning using Generative Adversarial Networks (SGANs). That work is a significant contribution to the field of semi-supervised learning and generative models. The author extended GANs to the semi-supervised context by forcing the discriminator network to output class labels. A generative model G and a discriminator D were trained on a dataset with inputs belonging to one of N classes. At training time, D was made to predict which of N+1 classes the input belongs to, where an extra class was added to correspond to the outputs of G. The experiments conducted by the authors on the MNIST dataset to compare the performance of SGANs and regular GANs. They trained an SGAN using the actual labels of MNIST dataset and with only the labels REAL and FAKE, and found that the results from the SGAN were much clearer than those from the regular GAN. This observation has held true across a variety of initializations and network architectures. It was demonstrated that this method can be used to create a more data efficient classifier and that it allows to generate higher quality samples than a regular GAN, which illustrates the effectiveness of the approach in practical applications Odena (2016).

Another interesting paper of “Sohn, K., Berthelot, D., Carlini, N., Zhang, Z., Zhang, H., Raffel” (2020) titled “FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence”. The authors presented a new algorithm, FixMatch, that simplifies semi-supervised learning by combining two common methods: consistency regularization and pseudo-labeling. Their work represents a significant addition to the semi-supervised learning field. FixMatch first generates pseudo-labels using the model’s predictions on weakly-augmented unlabeled images. For a given image, the pseudo-label is only retained if the model produces a high-confidence prediction. The model is then trained to predict the pseudo-label when fed a strongly augmented version of the same image 2.2. Despite its simplicity, FixMatch achieves state-of-the-art performance across a variety of standard semi-supervised learning benchmarks, including 94.93% accuracy on CIFAR-10 with 250 labels and 88.61% accuracy with 40 – just 4 labels per class. The authors also carried out an extensive ablation study to tease apart the experimental factors that are most important to FixMatch’s success Sohn et al. (2020).

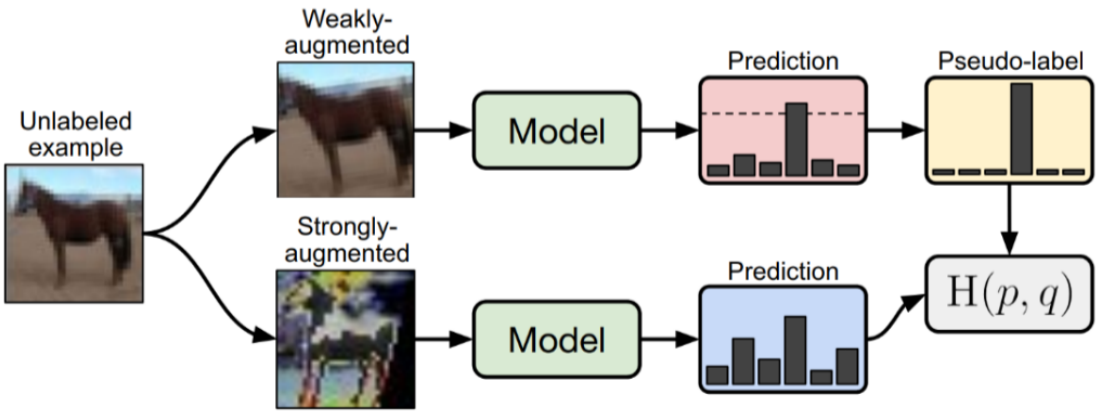

Figure 2.2: Diagram of FixMatch, the proposed semi-supervised learning algorithm.

In the work presented by Ya Tu, Yun Lin, Jin Wang, and Jeong-Uk Kim, titled “Semi-Supervised Learning with Generative Adversarial Networks on Digital Signal Modulation Classification”, a results of an exploratory study on the potential of Deep Learning to solve signal modulation recognition problems, especially in the context of automatic modulation classification in cognitive radio networks. The work is a significant contribution to the field of semi-supervised learning and signal modulation classification. The authors acknowledged the complexity of DL models and their propensity for overfitting, especially given the need for large amounts of high-quality labeled training data, which may not always be readily available or affordable. The authors suggested using semi-supervised learning as a technique to efficiently use unlabeled data to reduce overfitting as a solution to this issue. More precisely, they proved that Generative Adversarial Networks are useful in creating a classifier that is more data-efficient by extending them to the semi-supervised learning setting Tu et al. (2018).

The work of Min Ma, Shanrong Liu, Shufei Wang, and Shengnan Shi (2024) titled “Refined Semi-Supervised Modulation Classification: Integrating Consistency Regularization and Pseudo-Labeling Techniques” presented a novel semi- supervised approach for Automatic Modulation Classification, a crucial aspect of wireless communication that involves identifying the modulation scheme of received signals 2.3. Their work is a significant contribution to the field of semi-supervised learning and signal processing. Recognizing the challenge of performing accurate signal processing without prior information and the dependency of deep learning’s effectiveness on the availability of labeled samples, the authors introduced a method that combines consistency regularization and pseudo-labeling. This method leverages the inherent data distribution of unlabeled data to supplement the limited labeled data. Their approach involves a dual- component objective function for model training: one part focuses on the loss from labeled data, while the other addresses the regularized loss for unlabeled data, enhanced through two distinct levels of data augmentation. The authors demonstrated that their method outperforms established benchmark algorithms such as decision trees (DTs), support vector machines (SVMs), pi-models, and virtual adversarial training (VAT). It exhibits a marked improvement in the recognition accuracy, particularly when the proportion of labeled samples is as low as 1–4 M. Ma et al. (2024).

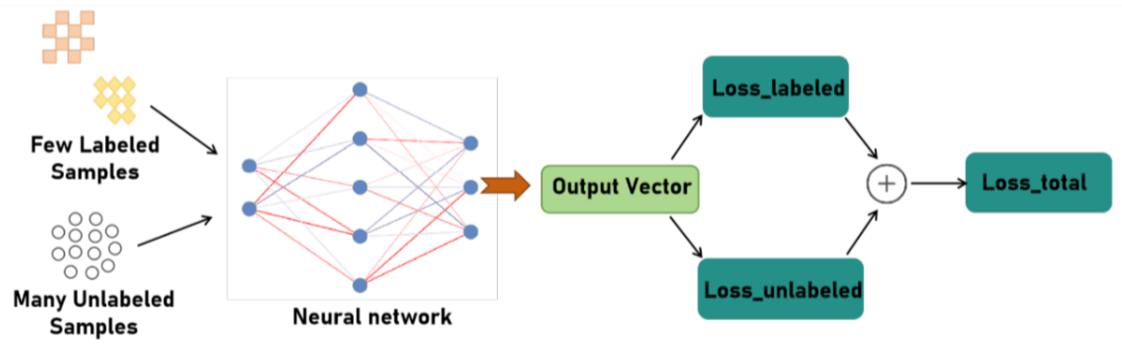

Figure 2.3: A semi-supervised learning framework for signal recognition.

The paper ”Self-Contrastive Learning based Semi-Supervised Radio Modulation Classification” by Dongxin Liu, Peng Wang, Tianshi Wang, and T. Abdelzaher (2021) makes progress in the fields of semi-supervised learning and signal processing by presenting a novel semi-supervised learning framework specifically designed for automatic modulation classification. The framework strategically utilizes unlabeled signal data and incorporates a self-supervised contrastive learning pre-training step. This approach allows the framework to achieve improved performance with smaller amounts of labeled data, effectively reducing the labeling workload associated with deep learning. The performance of this semi- supervised framework was assessed on a publicly available dataset. The evaluation results revealed that the semi- supervised approach surpasses the performance of supervised frameworks. It significantly enhances its capacity to train deep neural networks for automatic modulation classification by leveraging unlabeled data D. Liu et al. (2021).

The paper : “Augmented Semi-supervised Learning for CNN Based Automatic Modulation Classification” by Hu Liu, Zhechen Zhu, proposes a semi-supervised learning strategy for a modulation classifier based on convolutional neural networks (CNNs), with the goal of reducing the number of labeled signals needed while preserving good classification performance. The traditional semi-supervised learning framework has been modified by a number of approaches, which has increased modulation classification performance. The results show that the suggested approach performs much better than a similarly labeled signal-limited classifier, reaching accuracy values that are comparable to a fully supervised classifier with a large number of labeled signals H. Liu & Zhu (2022).

2.3 Conclusion

This chapter is dedicated to the state-of-the-art in Semi-Supervised Automatic Modulation Classification, where we delved into a selection of research papers that highlight Automatic Modulation Classification, Semi-Supervised Learning, and the intersection of the two. A lot of work has been done in this domain, but we have selected some of it to present in this chapter to find out what's going on in the field and to keep up with the latest developments. The next chapter is devoted to practical implementations.

Chapter 3

Experiment/ Implementation

3.1 Introduction

The role of automatic modulation classification (AMC) is crucial in modern wireless communication systems, as it enables efficient spectrum utilization, signal detection, and interference mitigation. While traditional supervised learning approaches for AMC have achieved significant success by training classifiers on labeled datasets to accurately identify modulation schemes across various operating conditions, the reliance on annotated data poses challenges especially in scenarios where obtaining large labeled datasets is impractical or cost-prohibitive.

In response to these challenges, semi-supervised learning (SSL) techniques have emerged as promising alternatives. SSL leverages both labeled and unlabeled data during model training. By utilizing the abundant unlabeled data available in real-world scenarios, SSL aims to enhance the generalization, adaptability, and robustness of modulation classifiers. This chapter delves into the application of SSL methods for AMC, with a specific focus on using the RML2016.10a[1] dataset as a benchmark for evaluation.

3.2 Datasets details

A dataset produced through the utilization of GNU Radio for synthetic generation, This dataset was initially unveiled during the 6th Annual GNU Radio Conference O'shea & West (2016).

The input data dimension of 2×128, 2×128 and 2×1024, respectively. The RML2016.10a dataset comprises 220,000 modulated signals, representing 11 frequently employed modulation schemes. We split the datasets into labeled, unlabeled, and test sets using a 0.2:0.5:0.3 ratio per class, randomly selecting samples. The loss function employed is categorical cross-entropy F. Zhang et al. (2021).

[1]https://www.deepsig.ai/datasets/

This dataset comprises 220,000 signals across signal-to-noise ratios ranging from -20 to 18 decibels, encompassing 11 modulation categories including 8 digital and 3 analog types H. Ma et al. (2020) :

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

We present some examples of signals in the form of graphical images, and on the opposite side in the form of spectral images, and the figure 3.1 represents these signals.

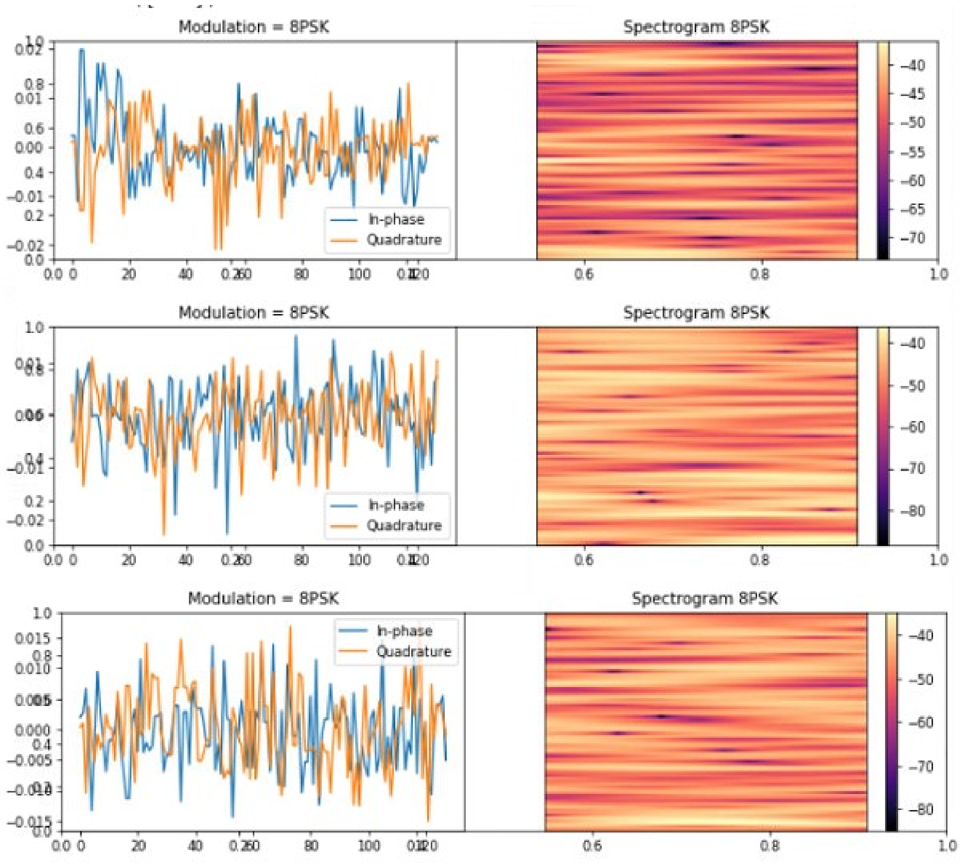

Figure 3.1: Some examples of representations of signals

3.3 Environment

- **Python**

  Python is merely one of numerous programming languages available. Similar to the diversity found in human languages, the realm of computer languages encompasses various options, including Java, it's a robust and graceful programming language, characterized by its simplicity in readability and comprehension. It encompasses many features shared by numerous other languages, making it valuable for practical applications. Additionally, it's freely available software Python (2021),it was created in 1991 by Guido van Rossumt and is used for: web development,software development, gui mathematics Van Rossum & Drake (2009).

- **PyTorch** PyTorch, an open-source machine learning framework, derives its foundation from the Torch library and is chiefly advanced by Facebook's AI Research lab. It furnishes a versatile, effective, and user-friendly environment tailored for constructing and refining AI models, with a special focus on machine learning and deep learning domains. Embraced across academia and industry, PyTorch stands out for its user-friendly syntax, dynamic computation graph, and robust framework for constructing neural networks Jalolov (2023).

- **keras**

  Keras represents a Python-based, high-level neural network interface capable of operating atop TensorFlow and various underlying frameworks, Keras is capable of processing diverse neural network elements, including dense layers, convolutional layers, recurrent layers, dropout layers, and their respective modifications, the code dynamically manages resources like the Central Processing Unit (CPU) and Graphics Processing Unit (GPU), optimizing their utilization Chicho & Sallow (2021).

- **Matplotlib** Matplotlib is widely recognized as a leading Python library for data visualization. Spearheaded by John Hunter and a collaborative team, it has become indispensable for researchers and scholars globally. This graphics library is an essential part of the Python data science ecosystem, seamlessly compatible with NumPy, Pandas, and other related libraries Sial et al. (2021).

- **Numpy** Numpy, an abbreviation for Numerical Python, has been fundamental in Python's numerical computing landscape for quite some time. It offers essential data structures, algorithms, and library integration crucial for a wide array of scientific tasks involving numerical data within Python McKinney (2012). This Python package is pivotal for scientific computing, introducing features such as N-dimensional array handling, element-wise operations (broadcasting), essential mathematical functions like linear algebra, and the capability to integrate C/C++/Fortran code Bressert (2012).

- **Pandas** Pandas stands as a Python module employed in handling datasets, equipped with tools for data analysis, refinement, investigation, and modification. Originating in 2008 from the efforts of Wes McKinney, it serves as a cornerstone for data analysis endeavors within the Python ecosystem H. Singh & Dhir (2019).

- **Seabron** Seaborn, a graphic visualization tool, is constructed upon Matplotlib's fundamental settings. It offers users easy access to widely used data visualization techniques, including mapping colors to variables and implementing faceting, globally. Additionally, Seaborn is well-integrated with Pandas DataFrames for streamlined data manipulation Sial et al. (2021).

- **OS** Python's OS library offers valuable tools for engaging with one's operating system, constituting part of Python's standard utility modules. It furnishes a platform-independent method for accessing operating system-specific features. Within this module, both 'os' and 'os.path' incorporate a range of functions tailored for interacting with the file system A. Singh & Singh (2020).

- **GPU** GPU acceleration is derived from extensive data parallelism, wherein numerous independent operations are executed simultaneously on multiple data elements. For instance, in graphics, a typical data-parallel operation involves applying a rotation matrix across coordinates representing object positions during view rotations. Likewise, in molecular simulations, data parallelism can be employed for the independent computation of atomic potential energies. Similarly, deep learning model training entails forward and backward passes, typically expressed as matrix transformations that lend themselves well to parallelization Pandey et al. (2022).

3.4 Network architecture

3.4.1 CNN Architecture Approach

For implement the signal modulation classification model,in our work, we utilized the entire dataset.
The Convolutional neural networks model is considered more significant in this work, as we design a CNN structure for signal modulation recognition,the table 3.4.1 illustrates the proposed CNN architecture.

Table 3.1: CNN Architecture

Layer(type)	Output Shape	Param #
Conv2d-1	[-1, 256, 2, 128]	1024
BatchNorm2d-2	[-1, 256, 2, 128]	512
Dropout-3	[-1, 256, 2, 128]	0
Conv2d-4	[-1, 128, 2, 128]	98,432
BatchNorm2d-5	[-1,128, 2, 128]	256
Dropout-6	[-1,128, 2, 128]	0
Conv2d-7	[-1,64,2,128]	24,640
BatchNorm2d-8	[-1,64,2,128]	128
Dropout-9	[-1,64,2,128]	0
Conv2d-4	[-1, 32, 2, 128]	6,176
BatchNorm2d-8	[-1,32,2,128]	64
Dropout-9	[-1,32,2,128]	0
Linear-10	[-1,256]	2,097,408
Dropout-11	[-1,256]	0
Linear-12	[-1,128]	32,896
Linear-13	[-1,64]	8,256
Linear-14	[-1,11]	715
Total params	2,270,507	
Trainable params	2,270,507	
Non-trainable params	0	
Forward/backward pass size (MB)	2.82	
Params size (MB)	8.66	
Estimated Total Size (MB)	11.48	

3.4.2 The main steps used for the SSL algorithm

- **Step 1** In the beginning, we train the labeled data with the CNN architect - training is only on the labeled data - to come up with a primary model.

  (repeat next steps until arrival condition)

- **Step 2** We defined 4 successive confidence coefficients [0.9, 0.8, 0.7, 0.6], with a loop for 4-step.
- **Step 3** In each step, we project the remaining examples of unlabeled data onto the model extracted from the previous step, And We calculate its(unlabeled data) confidence coefficient.
- **Step 4** Then we take from the unlabeled data the examples above the specified confidence coefficient and concatenate them into the labeled data.
- **Step 5** Then we retrain on the updated labeled data.
- **Step 6** Finally, we calculate the accuracy and loss for the last model.

3.5 Results

The following figures show the learning curve (Accuracy, Loss) for zero-confidence and the 4 confidence levels ([0.9, 0.8, 0.7, 0.6]) of the semi-supervised model after train 40 epochs.

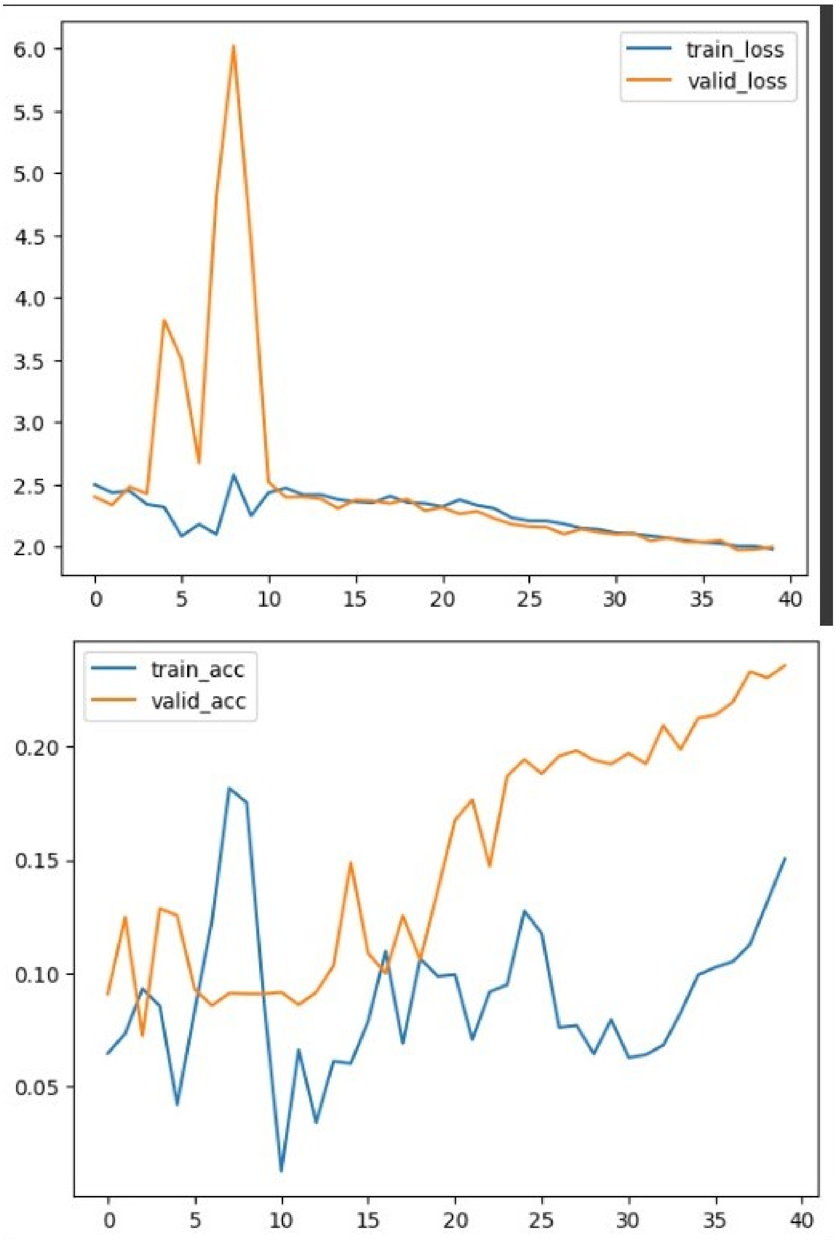

Figure 3.2: shows the learning curve of a zero-confidence semi-supervised model trained on 20% of a labeled dataset.

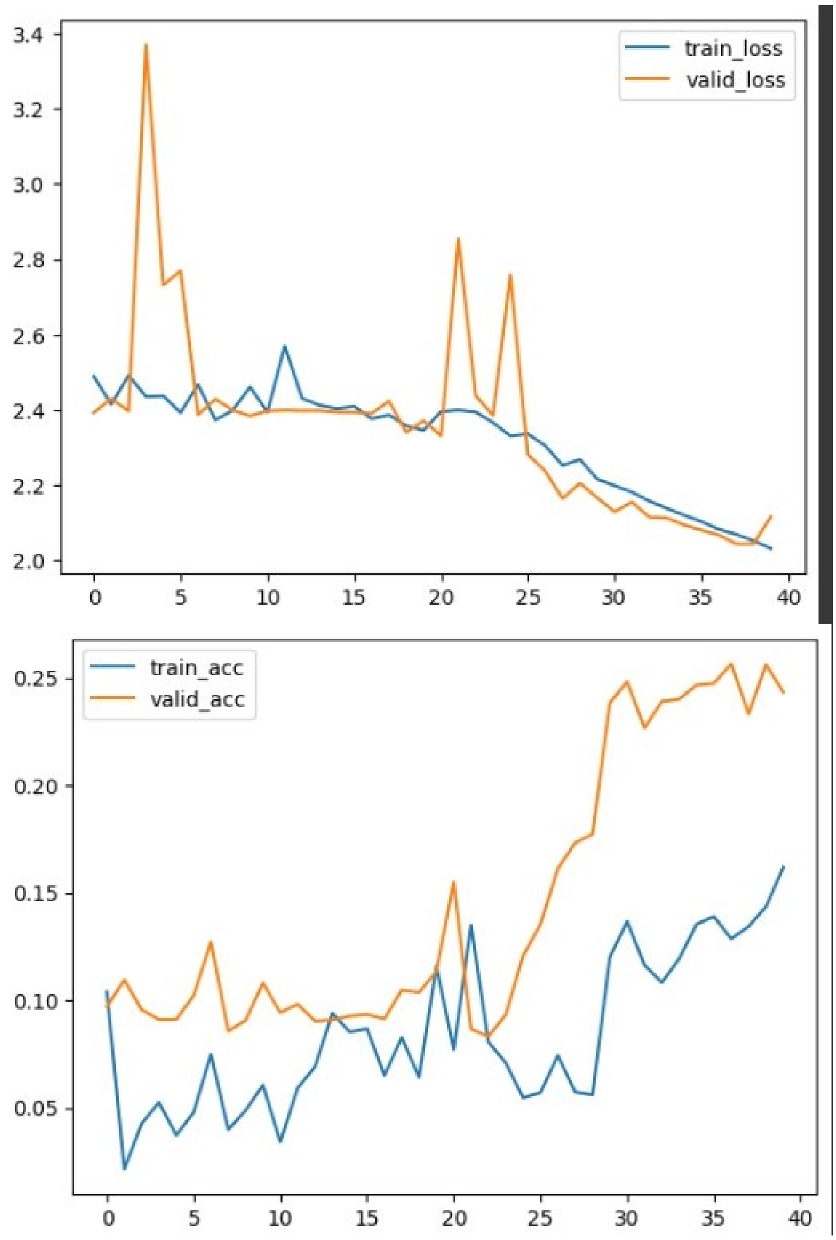

Figure 3.3: shows the learning curve of a 0.9 confidence semi-supervised model trained on the 1st update of the labeled dataset.

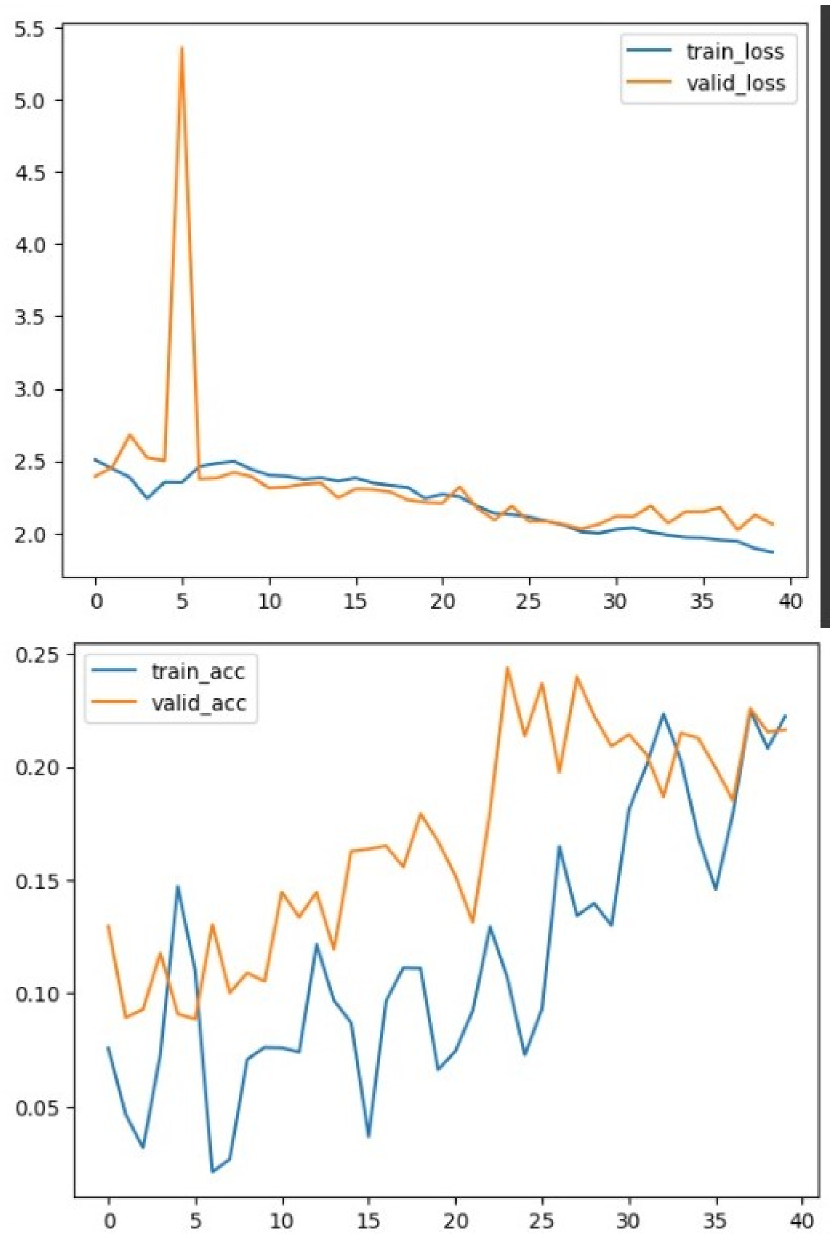

Figure 3.4: shows the learning curve of a 0.8 confidence semi-supervised model trained on the 2nd update of the labeled dataset.

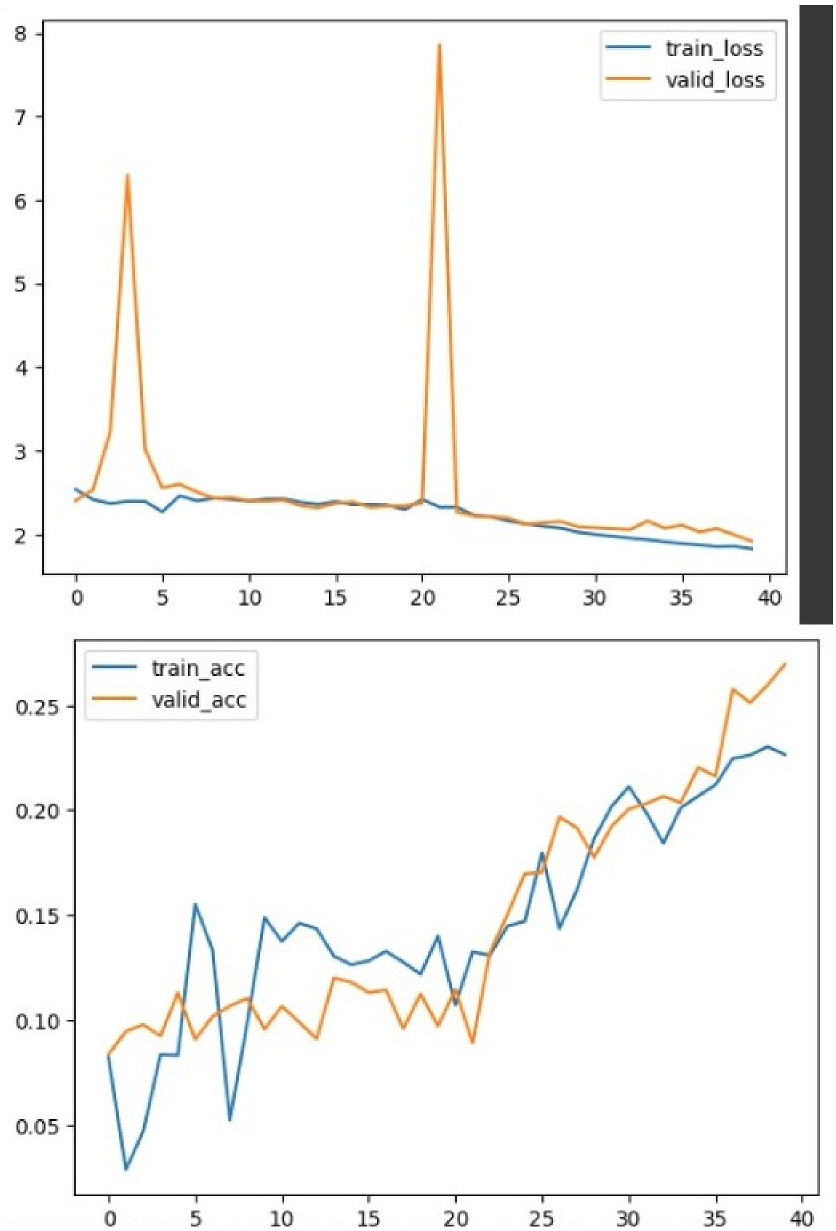

Figure 3.5: shows the learning curve of a 0.7 confidence semi-supervised model trained on the 3rd update of labeled dataset..

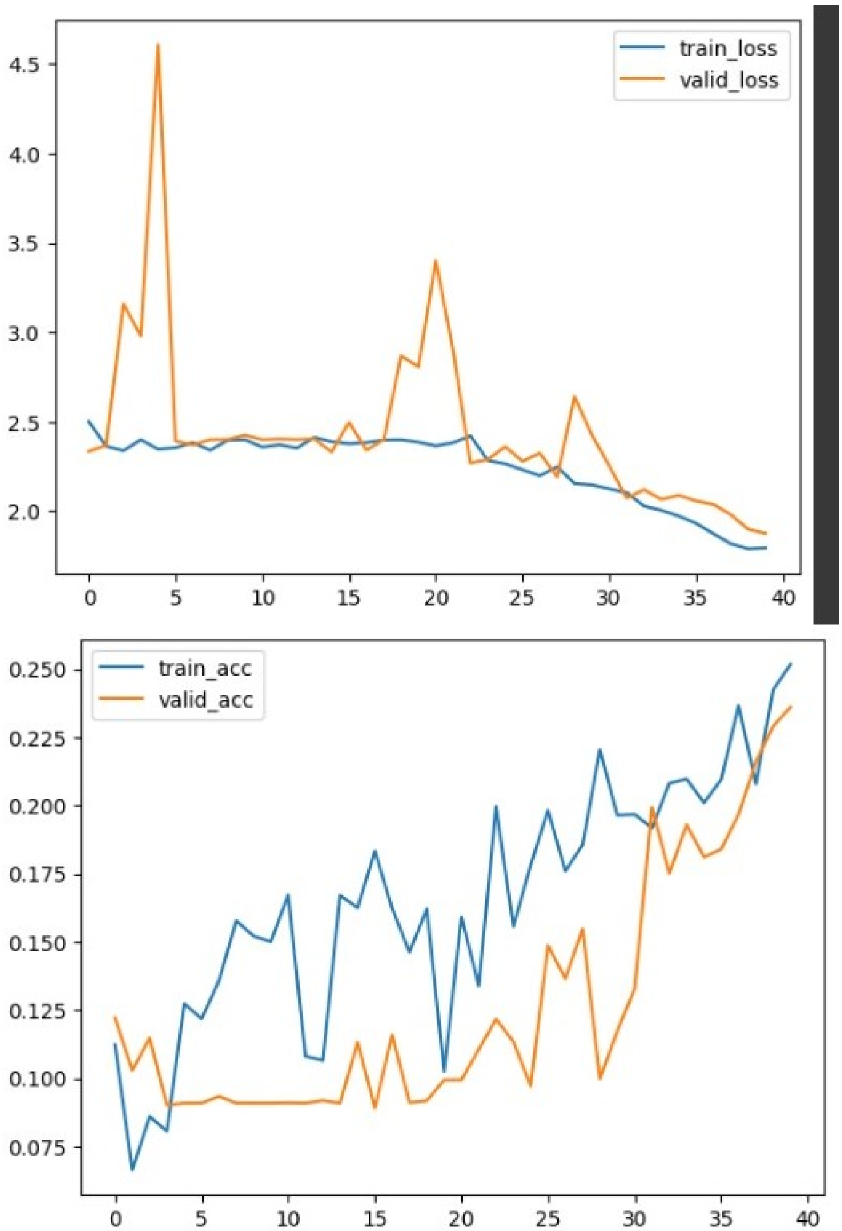

Figure 3.6: shows the learning curve of a 0.6 confidence semi-supervised model trained on the 4th update of the labeled dataset.

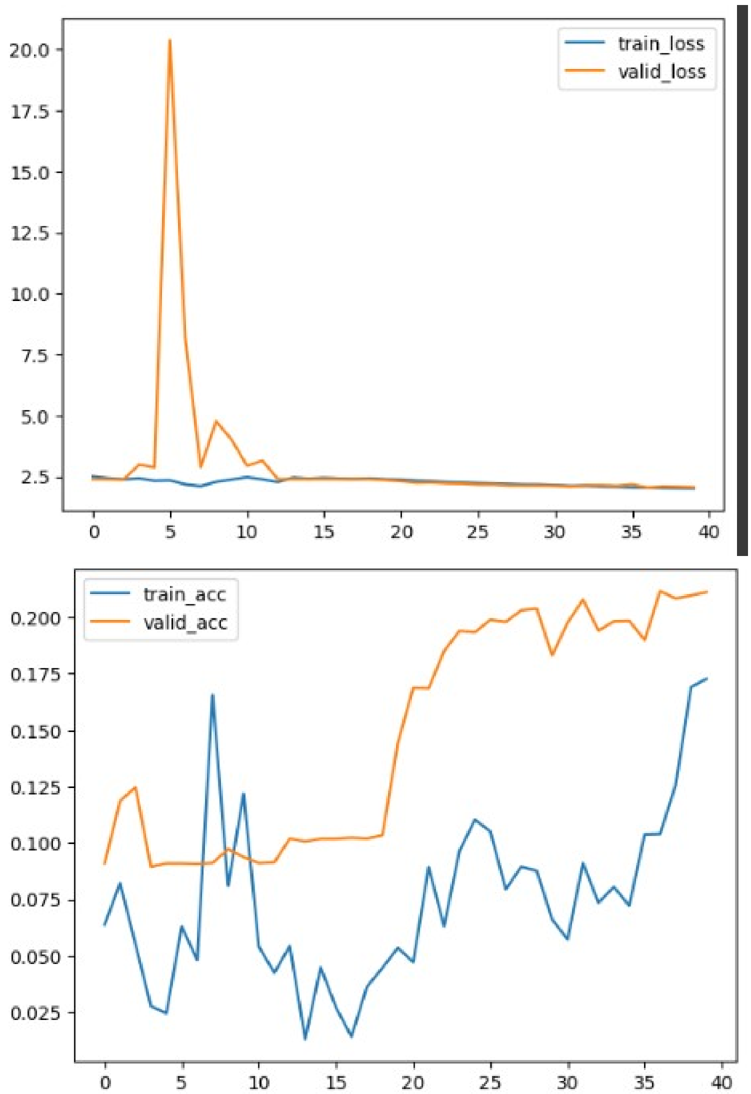

Figure 3.7: Shows the learning curve of a CNN model trained on 20% of a labeled dataset

3.5.1 Analysis of the results

In the beginning, the model's performance was weak, since it had not been trained on the entire data set, then began to improve after each training on labeled data, whose size increased each time. However, the results were still poor due to several factors:

- Initial training data (20%) were randomly divided between training and test.
- The architecture of the CNN model was not well designed.
- The model wasn't trained enough, it was trained over 40 epochs, and according to what we see on the learning curves, it's clear that the accuracy curve is still increasing, but it's interrupted at 40 epochs.

3.5.2 Comparison between the steps of the SSL and CNN

The table 3.2 is a summary of the best results (accuracy/loss) from the previous training phases. It shows a comparison between the different confidence levels of the semi-supervised models and the CNN model.

The table shows different accuracy and loss values for different training sizes, corresponding to different confidence levels.

Table 3.2: Comparison between acc and loss values using SSAMC and CNN

Confidence	Val_acc	Val_loss	Train	Added cell
0	0.2357	1.9737	44000	0
0.9	0.2564	2.0434	44646	646
0.8	0.2437	2.0210	45007	361
0.7	0.2695	1.9151	47938	2931
0.6	0.2361	1.8768	50335	2397
CNN	0.2116	2.0480	44000	/

The following figure (3.8) better interprets the data in the table (3.2) and shows the evolution of the accuracy and the loss according to the confidence level.

We can clearly see that the accuracy of the model is at its best at a confidence level equal to 0.7, which corresponds to an unlabeled training data size equal to 2931, after which it deteriorates a bit. This performance of this semi-supervised model is clearly better than the CNN model.

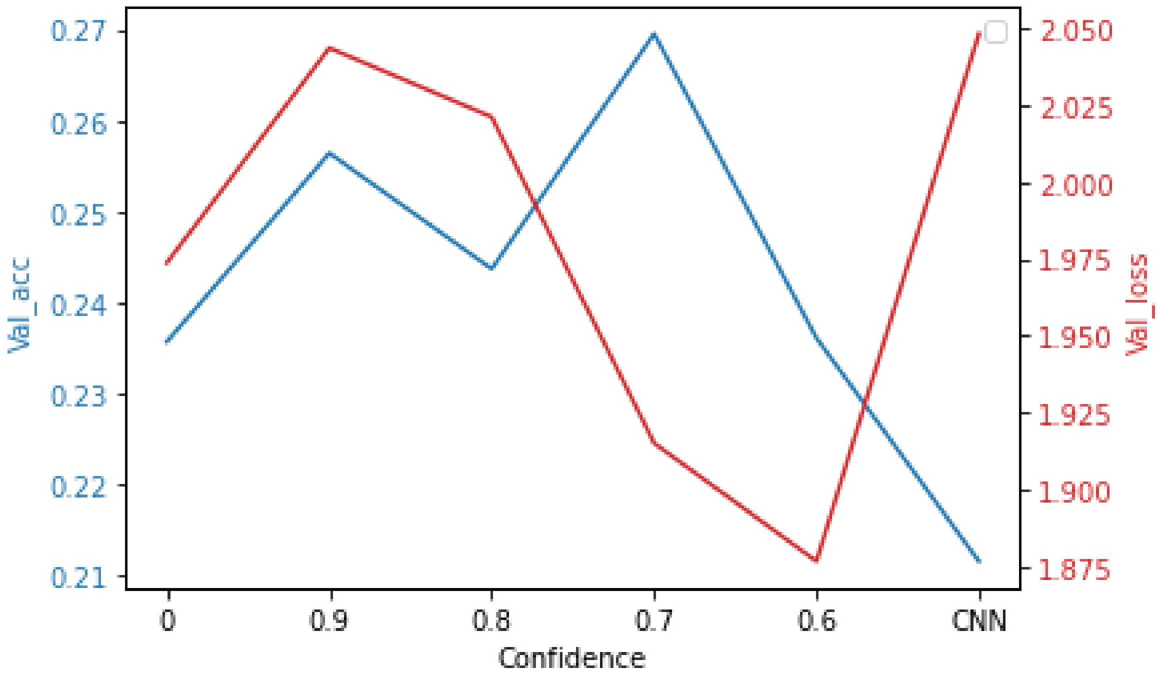

Figure 3.8: Comparison graph between the accuracies of the semi-supervised models according to the confidence levels and also with the CNN model. .

3.6 Conclusion

In this chapter, we have implemented a semi-supervised learning model. This model is designed to initially train on a small amount of labeled data. As it learns, it gradually improves its performance by incorporating additional unlabeled data. This approach uses a large amount of unlabeled data compared to labeled data.

We have also conducted a comparative study of this semi-supervised model with a traditional supervised CNN model. The comparison focuses on different confidence levels to provide a comprehensive understanding of the strengths and weaknesses of both models.

Conclusion

In this thesis we explore the implementation of semi-supervised learning to train a classifier. This classifier, designed for the task of classifying radio signals, is capable of learning from a combination of a small amount of labeled data and a larger amount of unlabeled data.

Despite the shortcomings mentioned in Section 3.5.1, the results show that the performance of this semi-supervised model significantly outperforms that of the supervised (CNN) model.

Furthermore, the goal is to study the efficiency of a semi-supervised learning model and its ability to use both labeled and unlabeled data, and we come to the conclusion that for smaller labeled datasets we prefer to use semi-supervised learning, while for larger labeled datasets we opt for supervised learning. This highlights the versatility of semi-supervised models, which are particularly useful in areas where labels are scarce and difficult to obtain.

There are many factors still need improvement. The architecture of the supervised model need to be well designed, training labeled data must be balanced, give the model enough number of epoch to get trained sufficiently and finally choose a good semi-supervised algorithm like: "semi-supervised generative Adversarial network (SGAN)" Odena (2016) or "FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence", Sohn et al. (2020).

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كلية العلوم والتكنولوجيا
قسم الرياضيات والإعلام الآلي

جامعـة غردايـــة

الرقم ....2024/ ق.ر.ا /ك.ع.ت/ج.غ

شهادة الترخيص بالإيداع

أنا الأستاذ: ....عبد الرحمان عجيلة.................................

بصفتي -مشرف- رئيس —ممتحنا [1]- والمسؤول عن تصحيح مذكرة تخرج ماستر الموسومة بـــ

.................................**Semi-Supervised Automatic Modulation Classification**............................

من انجاز الطالب(ة): ....حاج داود داود...

والطالب(ة): ....العنق محمد...

الكلية: العلوم والتكنولوجيا.
القسم: الرياضيات والاعلام الالي.
الشعبة: اعلام الي.
التخصص: الأنظمة الذكية لاستخراج المعارف.
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أشهد ان الطالب (الطلبة) قد قام (قاموا) بالتعديلات والتصحيحات المطلوبة من طرف لجنة المناقشة وان المطابقة بين النسخة الورقية والالكترونية استوفت جميع شروطها.

امضاء المسؤول عن التصحيح

مصادقة رئيس القسم

رئيس قسم الرياضيات و الإعلام الآلي
الحاج موسى ياسين

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[1] اشطب الصفة غير ملزمة