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Information Technologies

DETECTION OF CARDIAC ARRHYTHMIAS IN ELECTROCARDIOGRAMS USING DEEP LEARNING

Amenah Alwan Salman AL_HAYALI

Master`s Thesis

Supervisor

Asst. Prof. Dr. Abdullahi Abdu IBRAHIM

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The thesis titled DETECTION OF CARDIAC ARRHYTHMIAS IN ELECTROCARDIOGRAMS USING DEEP LEARNING prepared by AMENAH ALWAN SALMAN AL_HAYALI and submitted on 00 /12/2022 has been **accepted unanimously** for the degree of Master of Science in Information Technologies

____
Asst. Prof. Dr. Abdullahi Abdu IBRAHIM

Supervisor

Thesis Defense Jury Members:

Asst. Prof. Dr. Abdullahi Abdu IBRAHIM	Faculty of Engineering and Architecture, Altinbas University	___________________
Asst. Prof. Dr. Name SURNAME	Faculty of Engineering and Architecture, Altinbas University	___________________
Asst. Prof. Dr. Name SURNAME	Faculty of, University	___________________

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Amenah Alwan Salman AL_HAYALI

Signature

DEDICATION

I dedicate my dissertation work to my family and many friends. A special feeling of gratitude to my loving parents, whose words of encouragement and push for tenacity ring in my ears.

PREFACE

I might want to thank my administrator: Asst. Prof. Dr. Abdullahi Abdu IBRAHIM Please let me express my profound feeling of appreciation and gratefulness to both of you for the information: direction and unrestricted help you have given me. I want you to enjoy all that life has to offer and further achievements and accomplishments throughout your life.

ABSTRACT

DETECTION OF CARDIAC ARRHYTHMIAS IN ELECTROCARDIOGRAMS USING DEEP LEARNING

Al_hayali, Amenah

M.Sc., Information Technologies, Altınbaş University,

Supervisor: Asst. Prof. Dr. Abdullahi Abdu IBRAHIM

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Medical diagnostic support systems based on automatic learning algorithms, called machine learning, represent a form of artificial intelligence (AI) that improves the performance, quality and speed of health care. Improvements in embedded machine learning applications have led to the design of many medical monitoring devices. The latter are equipped with biological signal sensors to measure the activity of the target organ of a subject. The essential objective of these devices is to record, save and analyze the acquired signals to establish an appropriate diagnosis and/or identify the signs of pathological symptoms. The work of this paper falls within this context and has the main objective of implementing new strategies for the analysis and diagnosis of Electrocardiogram (ECG) signals, focused on the detection of episodes of cardiac arrhythmia.

Keywords: UAV, ML, DL, ANN

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1. INTRODUCTION

1.1 BACKGROUND

In this first chapter, the work developed in this project is presented, in a summarized way. Initially, a framework of the theme related to the project is made, as well as the description of the problem that motivates its development, and the objectives to be achieved with it. This is followed by a description of the expected results, a small section where a brief analysis of the value of the project will be carried out, as well as the approach taken for its development. Finally, a brief presentation of the chapters that are part of this document is made. The area of health is one of the most important in society, motivating constant research, so that new types of treatments are achieved, or existing ones are improved. More and more technology has been applied in the health area, reflecting in this way in constant improvements. One of the areas of health that has benefited most from this is the area of diagnostic medicine, which has achieved frequent improvements both from the point of view of patients and professionals in the area. These improvements refer to greater simplification, greater speed and safety in the preparation of exams, procedures and generation of results [1]. In addition, there has been a great improvement in the accuracy of diagnoses, reducing the possibilities of errors and also providing a better selection of the treatment to be adopted in a given pathology. The Electrocardiogram allows us to record and measure our heart rhythm. If performed during the time the arrhythmia appears, it may be sufficient to make the diagnosis, however, in numerous situations, arrhythmias can occur sporadically and episodically. In these cases, the ECG may prove to be insufficient to make the diagnosis, therefore, it is necessary to carry out a series of tests, such as: Holter (24: hour ECG), echocardiogram, stress test, laboratory tests, among others. In this work, these concepts will be approached several times, given their importance for the topic in question. [1].

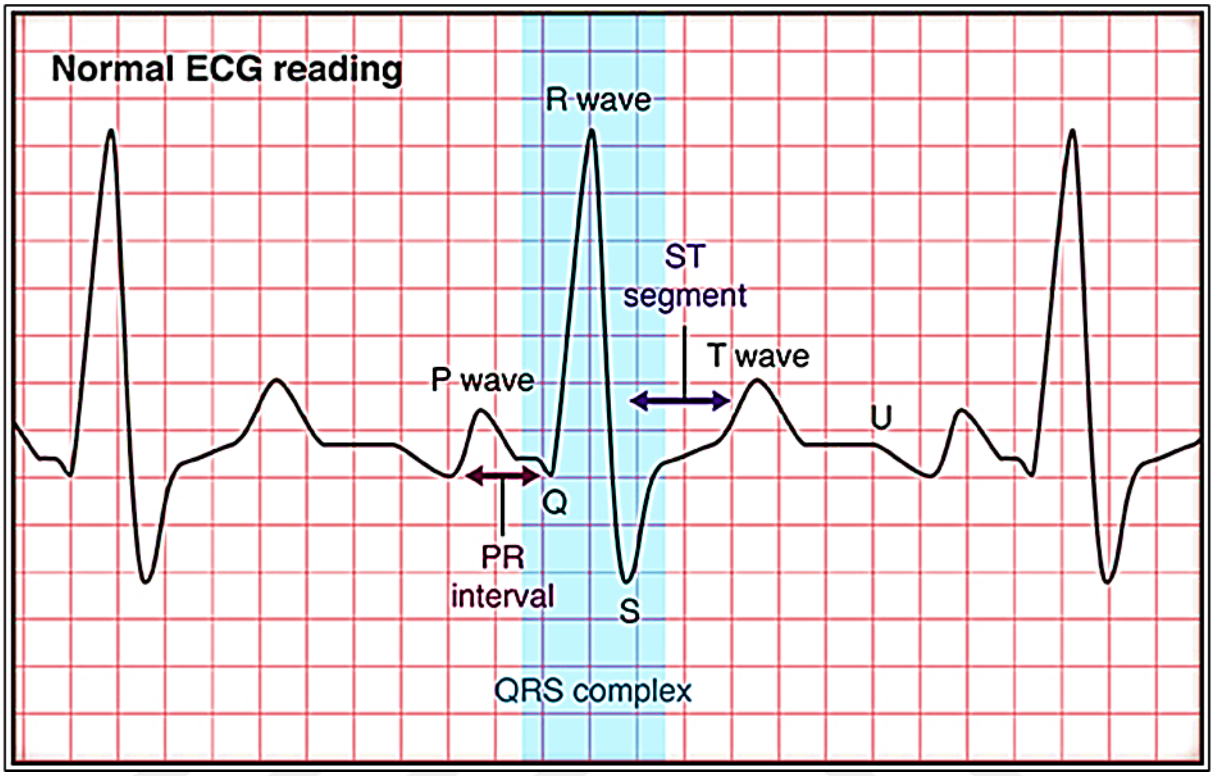


Figure1.1: Cardiac Arrest in Electrocardiogram (ECG) [3]

An electrocardiogram (ECG) is a recording of the electrical activity of the heart. It is one of the most used means to analyze and monitor the state of the heart since it can contain important indicators on the nature of diseases that can affect the heart. But since the ECG recording is a nonstationary signal, this indication may occur randomly over time. In this case, the symptoms of the disease may not occur all the time but appear at certain irregular intervals during the day. Therefore, for effective diagnostics, the study of the ECG signal should be carried out for several hours. Thus, the volume of data being enormous, the study is monotonous and long. Consequently, computer: assisted analysis and interpretation of ECG signals becomes necessary both to prepare the work of the cardiologist when analyzing long recordings, and to ensure continuous monitoring of patients; This is a privileged field of biomedical informatics applications. Various research works concerning the automatic classification of ECG signals have been proposed in the literature in recent years. In particular, the connectionist methods are the one that have proven to be the most effective and have had the most success [2,3]

1.2 PROBLEM STATEMENT

Cardiovascular disease (CVD) is one of the most pressing health concerns. CVD is the leading cause of death worldwide. According to the World Health Organization (WHO), CVD causes 17.9 million deaths worldwide each year, or 31% of all deaths [10], CVD is the second cause of death after cancer, with around 150,000 deaths per year and 400 deaths per day. Myocardial infarction, also called heart attack, is the deadliest form of CVD in the world. It causes 18,000 deaths per year, or 10% of total mortality [11]. In this thesis, we are interested in CVD, and more specifically in one of its main causes, namely cardiac arrhythmias. Arrhythmia is an abnormality of cardiac conduction that can be accompanied by various often fatal complications. An arrhythmia can occur when the electrical impulses that coordinate the heartbeat no longer work properly, causing the heartbeat to speed up, slow down, or become irregular [12–14]. In the elderly, atrial fibrillation (AF) is the most common form of arrhythmia [12, 13].

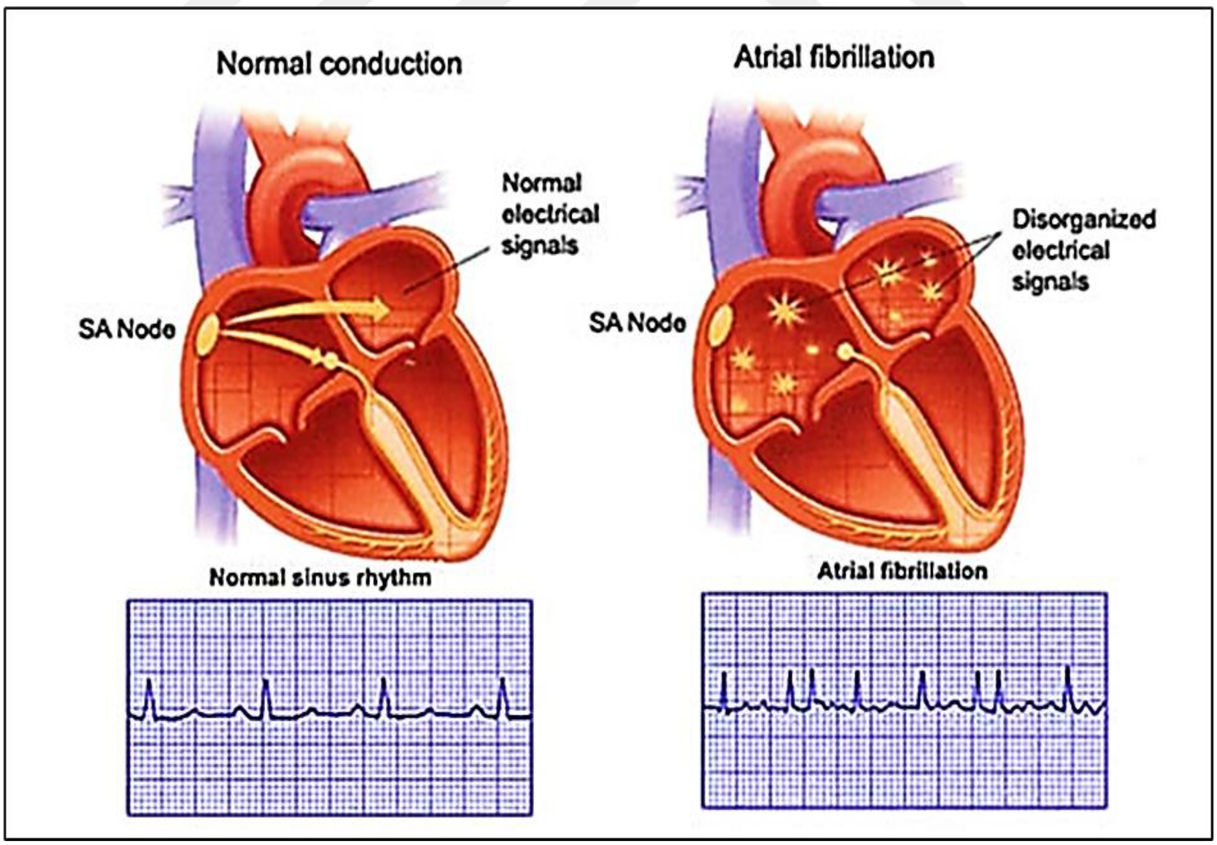


Figure 1.2: Atrial Fibrillation (AF) A Common Cardiovascular Disease (CVD) Shown in an ECG.

The diagnosis of AF is a delicate task because of its silent clinical forms and the paroxysmal form of AF [12]. Current recommendations are to use a 24:48 hour Holter electrocardiogram (ECG) to detect the presence of paroxysmal AF when it is suspected, but the recognition rate remains low [15]. In cardiology, ECG is a common practice for the detection of many forms of arrhythmias due to its noninvasive and inexpensive nature. Conventional diagnosis of arrhythmia consists of examining the ECG tracing, including its intervals and waves, generated by the various heart tissues, and checking its morphological conduction. The main morphological characteristics used to identify arrhythmias are the absence of P waves, the irregularity of the R: R intervals, or the waveform of the ECG tracing. Conventional analytical methods for the diagnosis of arrhythmia by visual inspection of Holter ECG recordings are costly in terms of time and money. In addition, the presence of permanent ectopic beats, motion artifacts, and noise superimposed on ECG waveforms significantly complicate the interpretation and identification of signs associated with cardiac arrhythmias. Given these constraints and the enormous time invested in manual analyzes of Holter ECG signals, doctors have favored the use of automated systems to help diagnose arrhythmia. These systems are designed to facilitate arrhythmia diagnosis, overcome decision: making difficulties and reduce evaluation time.

1.3 MOTIVATION

The main motivation of this work is based on the analysis of data obtained by electrocardiograms (ECG). These tests contribute to the study of heart diseases, as they record information about the heart's functioning through the electrical activity of each beat. An arrhythmia is a disturbance of the heart rhythm. It is usually not possible to perceive the heartbeat of our heart, however, it is possible to feel small rhythm irregularities. As a rule, these cases are not a sign of heart disease, however if their frequency increases or if they appear accompanied by other symptoms (dizziness, fainting, tiredness, chest pain, shortness of breath), they may be manifestations of arrhythmias. more severe

Academic research and industry rely on technological advances to develop computer tools in cardiology to meet the constraints of medical practice. Many research works have focused on proposing methods to distinguish healthy subjects (normal) from subjects with AF (abnormal).

All these methods are based on the electrocardiogram (i.e., the signal of the ECG), then the distinction is based on the choice of the morphological characteristics of the tracing. The majority focuses on the analysis of the ECG waveform, especially the P and R waves. The appearance of the P wave is a better characteristic than that of the R wave. However, the determination the exact P wave is very complicated due to its low amplitude, or even its complete absence. Indeed, the implementation of a diagnostic system based on the P wave in low power electronic devices is not realistic. For these reasons, analysis based on the R wave — or the study of R:R intervals — attracts more interest than the absence of the P wave or the combination of the two characteristics. Indeed, the R:R interval is a key factor for the diagnosis of cardiac irregularities and contains valuable information for establishing a rapid and efficient diagnosis of AF. Nevertheless, the presence of ectopic beats in healthy subjects greatly increases rhythm variability and mimics the behavior of an abnormal rhythm, but the latter remains consistent, which is not the case with arrhythmia. Studies using heart rate variability to distinguish normal from abnormal subjects reach their limits in the presence of ectopic beats. Therefore, statistical analysis (variability study) cannot distinguish these two forms (normal and abnormal) with sufficient precision. This constitutes our main challenge: developed a diagnostic tool capable of distinguishing a normal sinus rhythm (NSR) in the presence of ectopic beats from an AF rhythm [23].

1.4 CONTRIBUTION & OBJECTIVES

1.4.1 Objectives

Medical diagnostic support systems based on automatic learning algorithms, called machine learning, represent a form of artificial intelligence (AI) that improves the performance, quality, and speed of health care. Improvements in embedded machine learning applications have led to the design of many medical monitoring devices. The latter are equipped with biological signal sensors to measure the activity of the target organ of a subject. The essential objective of these devices is to record, save and analyze the acquired signals to establish an appropriate diagnosis and/or identify the signs of pathological symptoms. The work of my thesis falls within this context and has the main objective of implementing new strategies for the analysis and diagnosis of Electrocardiogram (ECG) signals, focused on the detection of episodes of cardiac arrhythmia.

1.4.2 Contribution

In this study, and with the aim of obtaining an efficient classification system, we propose a hybrid neuronal structure, combining two stages:

i. The first stage consists of a Kohonen map [7] with unsupervised learning, which performs a reclassification task.

ii. The second stage is a supervised learning MLP (Multi-layer Perceptron) network which is responsible for the final classification [1 3].

1.5 THESIS ORGANIZATION

The thesis is structured as follows: Section 2 is where we review some of the previous work and implementation on smart grids. Section 3 is where we give a background about all the components. Section 4 is where we explain our model in details and implementation of that model in details, Section 5 is where we simulate our model and record the results obtained. Section 6 is where we conclude our work and put a future scope into perspective.

2. STATE OF THE ART

2.1 INTRODUCTION

A shorter 'low: flow' time, during which the patient remains in cardiac arrest, yet CCPR is done, has been shown in earlier studies, including this one, to be a predictor of a favorable outcome in ECPR patients. [3:6]. Cardiopulmonary resuscitation (CCPR) produces only 25–30% of normal cardiac output when chest compressions are used, and this 'low: flow' state lasts longer, increasing the risk of irreversible multiorgan failure, including hypoxic brain injury, as well as the likelihood of achieving adequate coronary perfusion pressure and resuming spontaneous circulation following the procedure. There is inadequate evidence to determine whether patients may benefit most from early cardiopulmonary resuscitation (ECPR) over traditional cardiopulmonary resuscitation (CCPR). A recent systematic review and meta: analysis of ECPR patients treated outside of the hospital revealed that the existence of a low: flow time and a shockable rhythm resulted in improved results [8].

2.2 RELATED WORKS

The first, by Koziakova et al. To test whether noble gases have any protective effects on the brain, an in vitro model of hypoxic: ischemic damage to the rat hippocampus was utilized. 37 Recently, it has been proposed that noble gases such as krypton, neon, and helium, as well as other noble gases, might be used as neuroprotective agents after any kind of brain injury, including cardiac arrest. To test this notion, the researchers employed a rat hippocampus cell culture model and subjected the cells to anoxia and glucose deprivation in order to assess the effects of two distinct neuroprotective medicines on the brain. Given the in vitro nature of the study, these results are consistent with previous studies about the neuroprotective effects of these noble gases, albeit it is still difficult to assess their therapeutic value.

The second study by Manning et al. To explore noncompressible bleeding in the thorax, we developed a traumatic arrest model in pigs with selective aortic arch perfusion. 38 While earlier traumatic arrest studies have shown that HBOC:201 may enhance ROSC rates, the goal of this experiment was to compare the efficacy of HBOC:201 selective aortic arch perfusion to that of fresh whole blood perfusion in this context. 38,39 Three key aims were to compare HBOC:201 to fresh whole blood effectiveness, to accomplish ECLS conversion, and to cure systemic derangements by selective aortic: arch perfusion. Due in part to the ease with which HBOC:201 can be kept and transported, the rate at which ROSC could be acquired using blood or HBOC:201 was comparable, even in a systolic animal. Transfer to extracorporeal support was expected to be equally achievable.

Despite the HBOC:201 group's higher recovery rate, both groups had comparable physiologic derangements because of the ischemia reperfusion damage, with pulmonary hypertension being more prevalent in the HBOC:201 group. While it is feasible to achieve ROSC with HBOC:201, the risk of pulmonary hypertension and the difficulty of providing this therapy may preclude its widespread usage until more trials are completed and reperfusion damage is avoided more frequently with this treatment.

The third basic science In an investigation of the potential intra:arrest therapeutics cyclosporin and methylprednisolone for limiting the severity of post:arrest myocardial dysfunction, it was discovered that the intervention arm swine had higher mean arterial pressure and thus lower cardiac output, but no improvement in post:arrest myocardial dysfunction. Earlier Phase III studies using just cyclosporin had equivalent results. As indicated in the RE research by Gazmuri et al., blocking Sodium: Hydrogen Exchanger Isoform:1 (NHE:1) may be a possible therapeutic target for delaying cardiac cell death. Even though this target has been studied in clinical trials funded by pharmaceutical companies only in the context of myocardial infarction and coronary bypass grafting, the potential cardioprotective benefits of disrupting cytosolic and mitochondrial calcium accumulation are compelling enough to warrant further investigation. Conclusions and predictions (PRO) Five of the highest: scoring publications in the area of Prognosis and Outcomes were included. In the unexpected and critical context of a resource: intensive event such as cardiac arrest, neurologic outcome prediction remains a high priority for research.

The fourth study According to Jentzer and his team, patients who went to the cardiac critical care unit were more likely to have a heart attack in the hospital if they had a higher classification level under the Society for Cardiovascular Angiography and Intervention standards. They did a very detailed review and meta: analysis of 23 studies to find that people over 60, males, people who had active cancer, and people who had chronic renal disease were the main risk factors for death in people who had been in the hospital for cardiac arrest. 44 Patients who had endotracheal intubation also had a lower survival rate, but more research is needed to confirm this because of the different types of studies that were included, the risk of confounding factors, and the retrospective design of the study.

The UN10 Rule, first presented in 1999, is another strategy for estimating the fatality rate after a cardiac arrest in the hospital. 45 Patek and colleagues retrospectively examined over 95,000 patients to establish the predictive value of this criterion for mortality using the AHA Get with the Guidelines Registry. Despite the simplicity and ease of implementation of the three: component strategy, this group determined that the almost 6% false: positive rate, along with the reality that many patients lived with great neurologic outcomes, was insufficient to justify its widespread adoption.

The level of procalcitonin in your body is linked to how severe sepsis: related systemic inflammation in your body is, according to a study this year. Procalcitonin levels measured in the first 48 hours of hospitalization were linked to a higher risk of death and a worse prognosis for the brain, say Shin and his coauthors. It was done by Lopez Soto et al., who did a systematic review and meta: analysis of 44 studies about how important post: arrest imaging is in predicting how people will do after they're arrested. Anoxic damage on MRI and CT scans has been shown to be a good predictor of poor neurologic outcomes.

After cardiac arrest, neuroimaging using CT or MRI may be another useful predictive tool for the neurologic prognosis of patients; nevertheless, there are still information gaps in this sector regarding standard imaging acquisition durations and methods for calculating hypoxic: brain damage load.

3. ECG AND MACHINE LEARNING

Cardiology is a branch of medicine that deals with disorders of the heart as well as certain parts of the circulatory system. The field includes the medical diagnosis and treatment of congenital heart defects, coronary heart disease, heart failure, valvular heart disease, and electrophysiology. The ECG (Electrocardiogram) is one of the most important tools in the field. Cardiologists must study ECGs to make life: saving decisions about their patients. This makes automated ECG analysis an excellent tool for cardiology.

3.1 ANATOMY OF THE HEART

3.1.1 Presentation

The heart is a hollow, muscular organ like a pump, which ensures the circulation of blood in the veins and arteries. Its shape is like an inverted cone (its base up and to the right and its apex down and to the left). The heart is in the mediastinum, it is the median part of the rib cage bounded by the two lungs, the sternum, and the vertebral column. It is a little to the left of the center of the thorax. The heart weighs about 300 grams in adult men, 250 grams in women. It is capable of propelling, at rest, 4 to 5 liters of blood per minute. The heart is a muscular pump subdivided into four cavities: two atria and two ventricles allowing blood to be propelled to all the cells of the human body. [2].

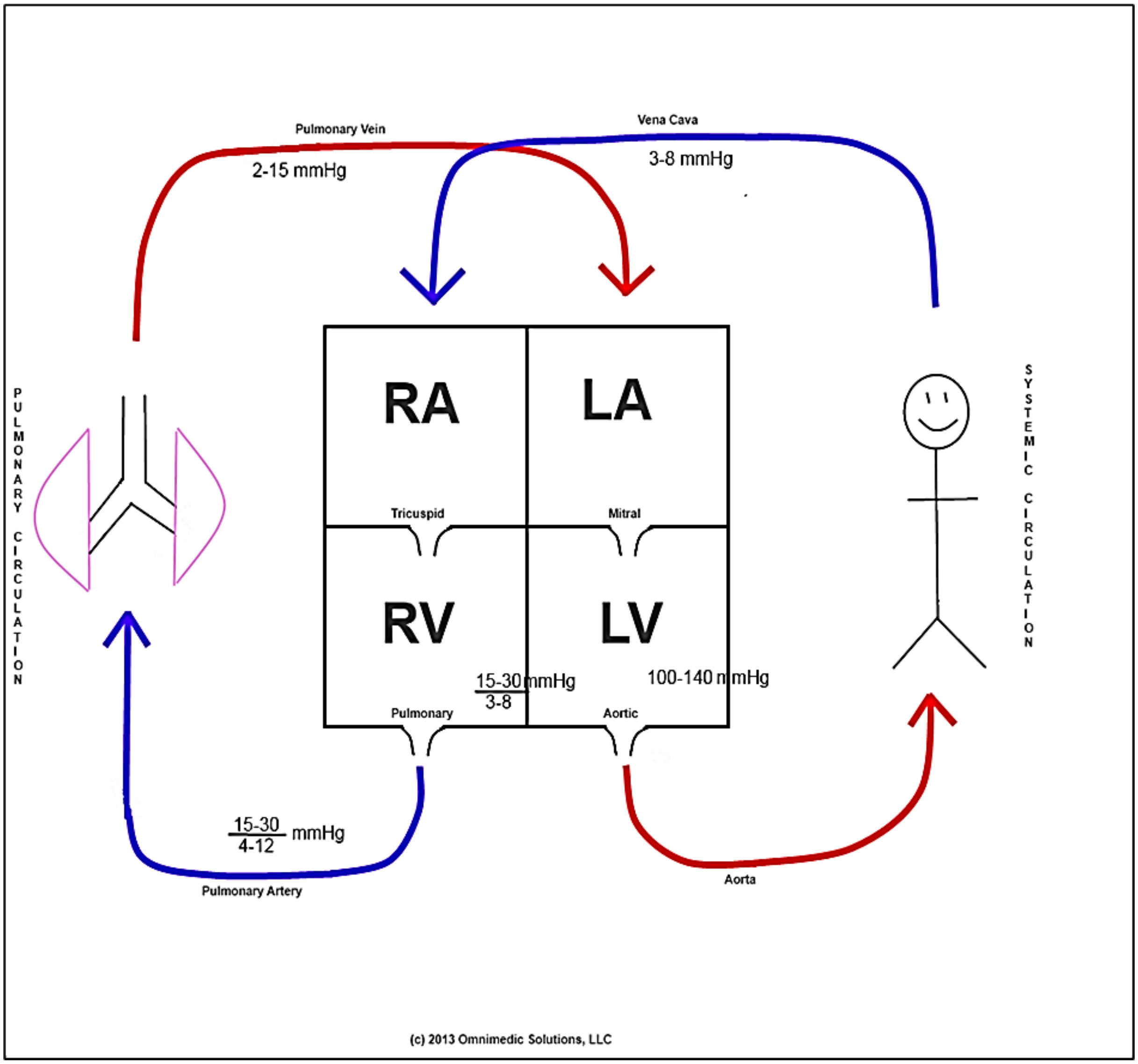


Figure 3.1: General Diagram of The Heart.

3.1.2 Functioning of the heart

To move blood through the body, the heart contracts and expands. This pumping action is well illustrated by the alternating clenching and loosening of a fist. With each beat, the heart pumps blood into the arteries. This is what creates the pulse [3].

a. First, the right atrium fills with oxygen: depleted blood from the body (muscles, organs, brain, and even the heart). When the atrium is full, it contracts. On contraction, the tricuspid valve connecting the right atrium and the right ventricle opens. Blood then enters the right ventricle.

b. When the right ventricle is full, it in turn contracts to push blood into the lungs through the pulmonary valve.

c. The lungs replace carbon dioxide in the blood with oxygen. The blood, now oxygenated, is expelled to the left atrium.

d. When the left atrium contracts, the mitral valve connecting it to the left ventricle opens. Thus, the blood enters this ventricle.

e. The left ventricle pushes oxygenated blood through the aortic valve to the aorta, which supplies the rest of the body with the heart.

f. Oxygen:rich blood circulates throughout the body. Finally, the veins bring the oxygen:poor blood back to the right atrium, which fills with it, and the cycle begins again.

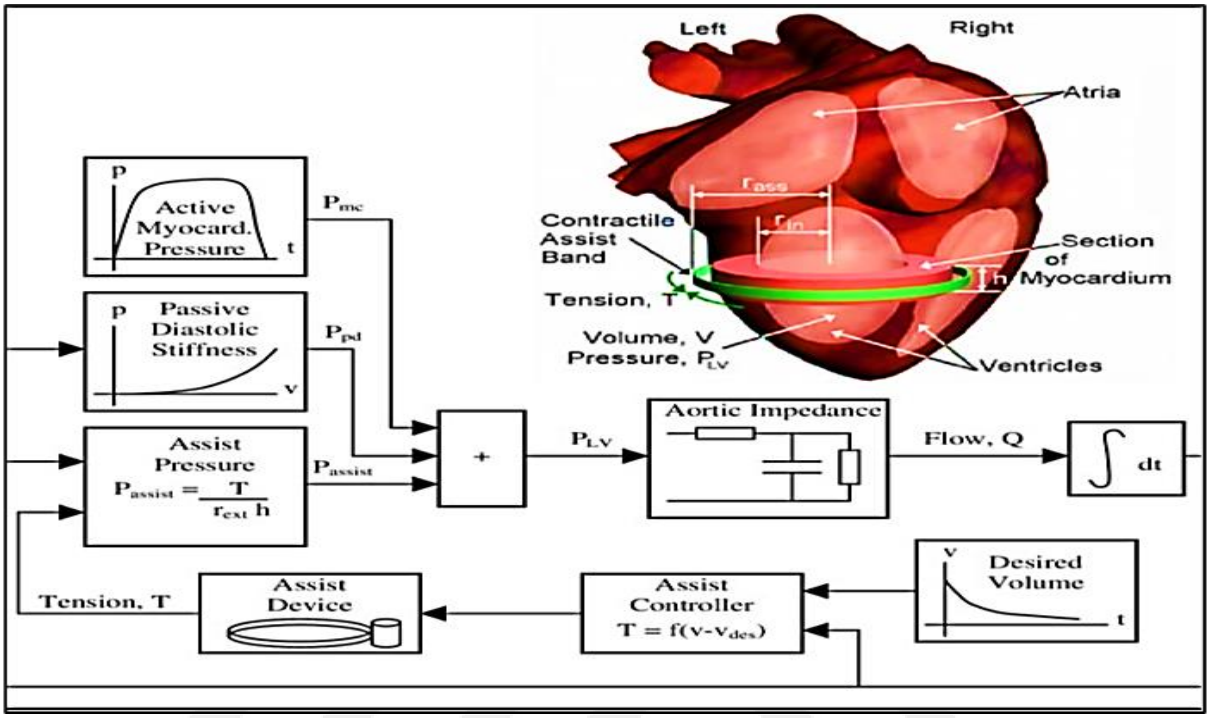


Figure 3.2: Blood Circulation in The Heart

3.2 ELECTROCARDIOGRAPHY

3.2.1 Electrocardiograph

An electrocardiograph is a device that measures and records the electrical activity that passes through the heart:

a. The tracing of this recording is called an electrocardiogram (often noted as ECG).

b. This device was invented by Willem Einthoven in 1895 (Nobel Prize in 1924).

c. The electrocardiogram is today the most common examination to study the functioning of the heart and to detect cardiac disorders.

3.2.2 Electrocardiogram

An electrocardiogram (ECG) is a test that studies the functioning of the heart by measuring its electrical activity. With each heartbeat, an electrical impulse (or "wave") passes through the heart. This wave causes the heart muscle to contract so that it expels blood from the heart. An ECG therefore represents a measurement tool and records the electrical activity of the heart [4]. A doctor can determine whether the electrical activity thus observed is normal or irregular. Why have an electrocardiogram? The ECG is an essential examination in cardiology. It may be prescribed in many situations:

i. During a medical check: up before surgery.

ii. When a patient complains of palpitations or chest pain.

iii. In an emergency (cardiac arrest, suspicion of myocardial infarction).

iv. To detect arrhythmias (heart rhythm disorders)

v. When taking certain medications that can affect the functioning of the heart.

vi. To monitor heart activity in case of known heart disease.

vii. In all these situations, the electrocardiogram is abnormal.

How to prepare for an electrocardiogram?

No preparation is required before the exam:

i. There is no need to fast.

ii. No product is injected either before or during the examination.

iii. If the patient is taking medication, it is not necessary to interrupt the treatment, but the patient must absolutely tell the doctor all the medication taken. Indeed, certain drugs can modify the tracing of the electrocardiogram.

iv. However, it is recommended that you refrain from smoking.

ECG procedure:

The examination can be carried out at the cardiologist's office, at the hospital and sometimes even at home. To carry out the electrocardiogram, the doctor applies to the skin about ten small electrodes (small metal discs glued to the skin using patches) arranged at the level of the arms, legs and chest. For better adhesion of the electrodes, it may be necessary to shave some areas of the skin. Then the examination proceeds as follows depending on the type of ECG:•The recording of the resting electrocardiogram lasts between 5 and 10 minutes:

a. It is important during the recording not to speak, to remain calm and relaxed, to avoid disturbing the plot.

b. The doctor can ask the patient to hold their breath at certain times during the recording.

i. The continuous electrocardiogram during an effort lasts between 10 and 30 minutes:

a The intensity of the effort required of the patient is increased in stages.

b The examination lasts until the patient reports the onset of fatigue to the doctor.

c The patient should not speak during the recording except to report any abnormal symptoms.

d The recording is followed by a recovery period during which the patient remains under the supervision of the doctor.

ii The Holter: ECG lasts at least 24 hours:

a A small portable ECG recording device is connected to the electrodes and accompanies the patient in his daily activities.

b The patient should note the times when he experiences particular symptoms to facilitate the interpretation of the results of the examination.

3.2.3 ECG Signal Waves

The ECG signal is represented by letters of alphabet "P, Q, R, S and T", they correspond to the electrical activation of the various parts of the heart which is formed by several waves, the signal represents the morphology and the amplitude of these waves but the duration changes according to the ECG leads used:

a. P wave: This is the first detectable wave, representing atrial depolarization. It is a small positive (or negative) deviation before the QRS complex, which spreads from the SA node and is conducted into all the cells of the atrium by intermediate junctions which connect these cells.

b. The QRS complex: It is a set of positive and negative deflections which correspond to the contraction of the ventricles. For a normal case, it has a duration of less than 0.12 seconds, and its variable amplitude is between 5 and 20 mV.

c. The Q wave: Is the first downward or “negative” initial deviation.

d. The R wave: Is then the next deflection upwards (provided it crosses the isoelectric line and becomes "positive").

e. The S wave: Then is the next deflection down, provided it crosses the isoelectric line to briefly go negative before returning to the isoelectric baseline.

f. The T wave: It corresponds to the repolarization of the ventricles. The normal T wave has a lower amplitude than the QRS complex [5].

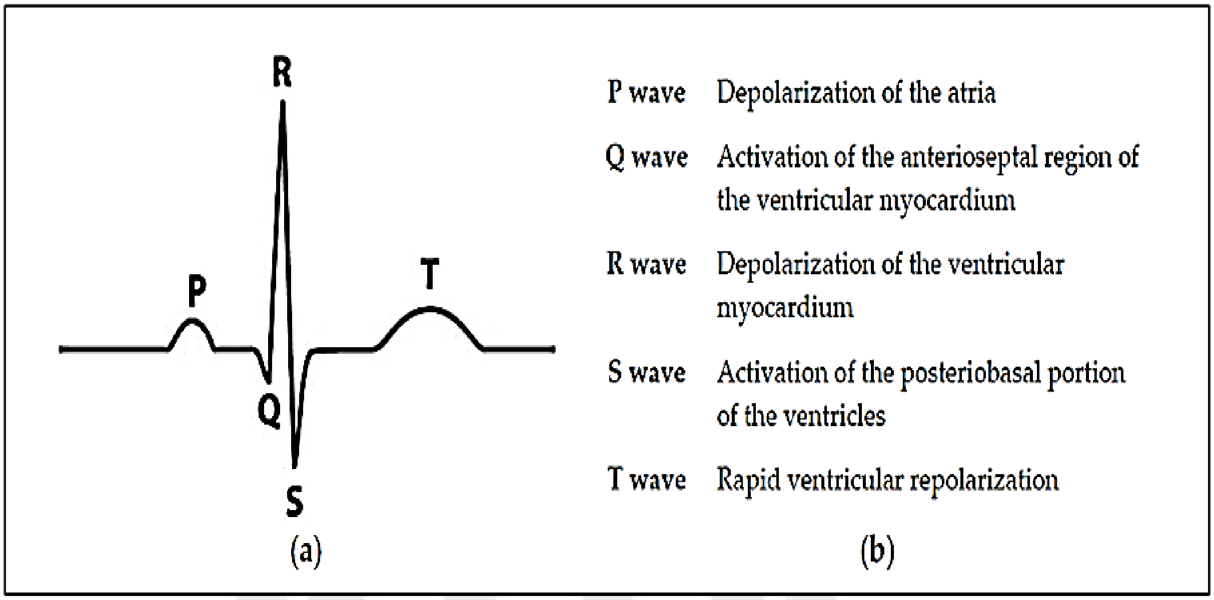


Figure 3.3: ECG Signal Waves.

3.2.4 Segments and Intervals That Characterize a Normal ECG:

In addition to the different waves which are the basic parameters for a good characterization of an ECG signal, there are several intervals and segments which carry very useful information on the conduction velocity of the electrical impulse in the different parts of the heart. The most important intervals and segments are:

g. RR interval: The RR interval corresponds to the delay between two depolarizations of the ventricles. It is this interval that is used to calculate the heart rate.

h. PR segment:(Pause of the AV node) The PR segment corresponds to the delay between the end of the depolarization of the atria and the beginning of that of the ventricles. This is the time during which the depolarization wave is blocked at the AV node [6].

i. PR interval:(atrioventricular conduction time) The PR interval corresponds to the propagation time of the depolarization wave from the sinus node to the ventricular myocardial cells.

j. QT interval:(duration of ventricular systole) This interval corresponds to the ventricular systole time, which goes from the beginning of the excitation of the ventricles until the end of their relaxation.

k. ST segment:(duration of complete stimulation of the ventricles) The ST segment corresponds to the phase during which the ventricular cells are all depolarized, the segment is then isoelectric.

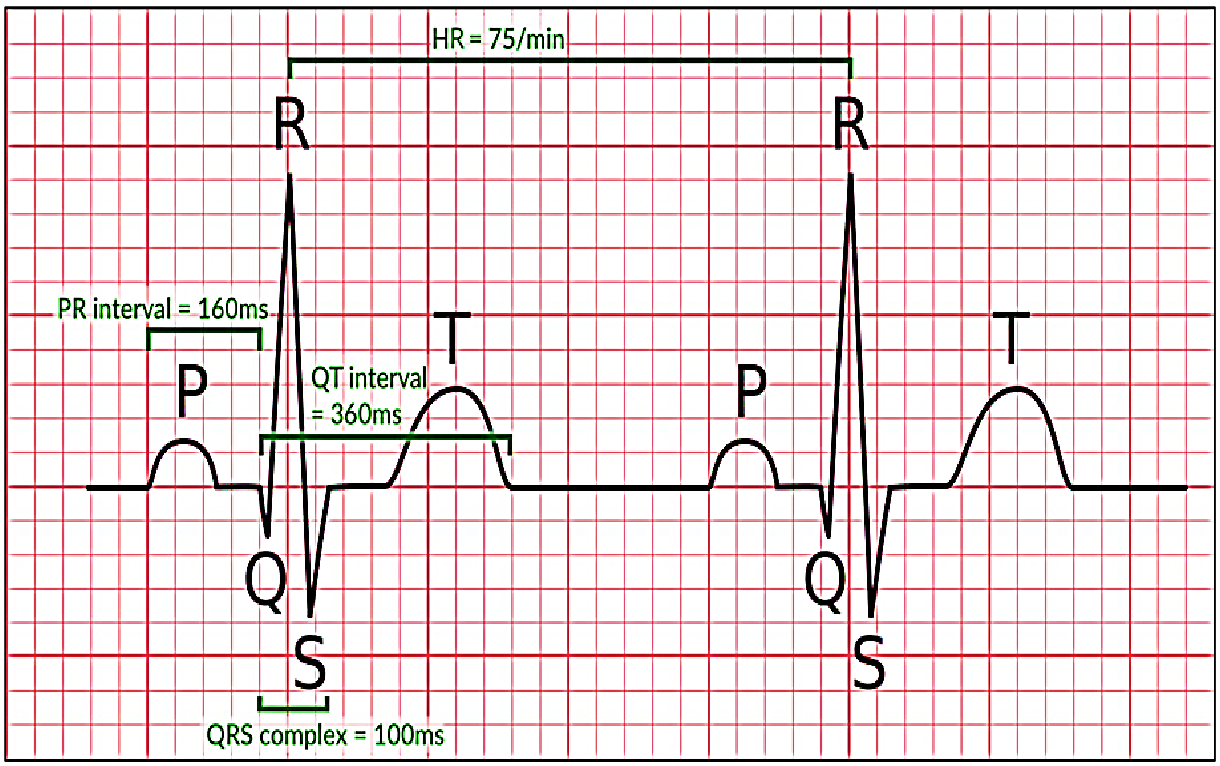


Figure 3.4: Segments and Intervals of a Normal ECG.

3.2.5 Different Cardiac Pathologies

Our objective in this part is not to precisely analyze the origins of cardiac pathologies and their consequences on cardiac functioning nor to describe the treatments that these pathologies require, but simply to relate certain abnormal observations of the ECG tracing with these pathologies. . Among the most common diseases are those that affect heart rhythm and are called cardiac arrhythmias. But before talking about arrhythmias, it is interesting to know the characteristics of the normal rhythm also called sinus rhythm.

a. Sinus Rhythm: Sinus rhythm is the normal heart rhythm. It corresponds to a physiological activation of the atria, then of the ventricles, from the sinus node. Its rhythm is between 60 to 80 beats per minute with a regular interval between normal beats.

b. Cardiac arrhythmias: Arrhythmia is an abnormality that affects the heart rate normal. Several types of arrhythmias do not present any health problems; however, they can cause a variety of bothersome symptoms, such as dizziness or chest pain. Other, more dangerous forms of arrhythmias affect the blood supply and therefore require medical attention.

In our project, we will use 4 types of arrhythmias:

i. Premature ventricular contraction (PVC): Are abnormal heartbeats

ailments that come from the ventricles of the heart. They are caused by electrical irritability of the heart muscle in the ventricles and disrupt the normal rhythm of the heart, causing the chest to rock or skip a beat. Premature ventricular contractions are very common and are likely to appear in the elderly, people with high blood pressure and people with heart disease.

ii. Premature atrial contraction (APC): Is a premature depolarization pre:

nant originating at any point in the atria, usually but not constantly spread to the ventricles. The morphology of the extra systolic P wave is different from that of the sinus P wave and depends on the location of the ectopic atrial focus.

iii. Right bundle branch block (RBB): When there is right bundle branch block, the ventricle

right is not directly activated by electrical impulses traveling through the right branch of the bundle of His. The left ventricle, on the other hand, is normally activated by the left branch. These electrical impulses then progress through the myocardium, from the left ventricle to the right ventricle, finally activating the latter. The prevalence of right bundle branch block increases with age.

iv. Beating the rhythm (Paced Beat: PAB): Is generally the manifestation of a malfunction

tion of the heart muscle. It can appear at any age, but it is frequently the consequence of a myocardial infarction. It is manifested by the desynchronization of beats which leads to a decrease in blood pumping [7].

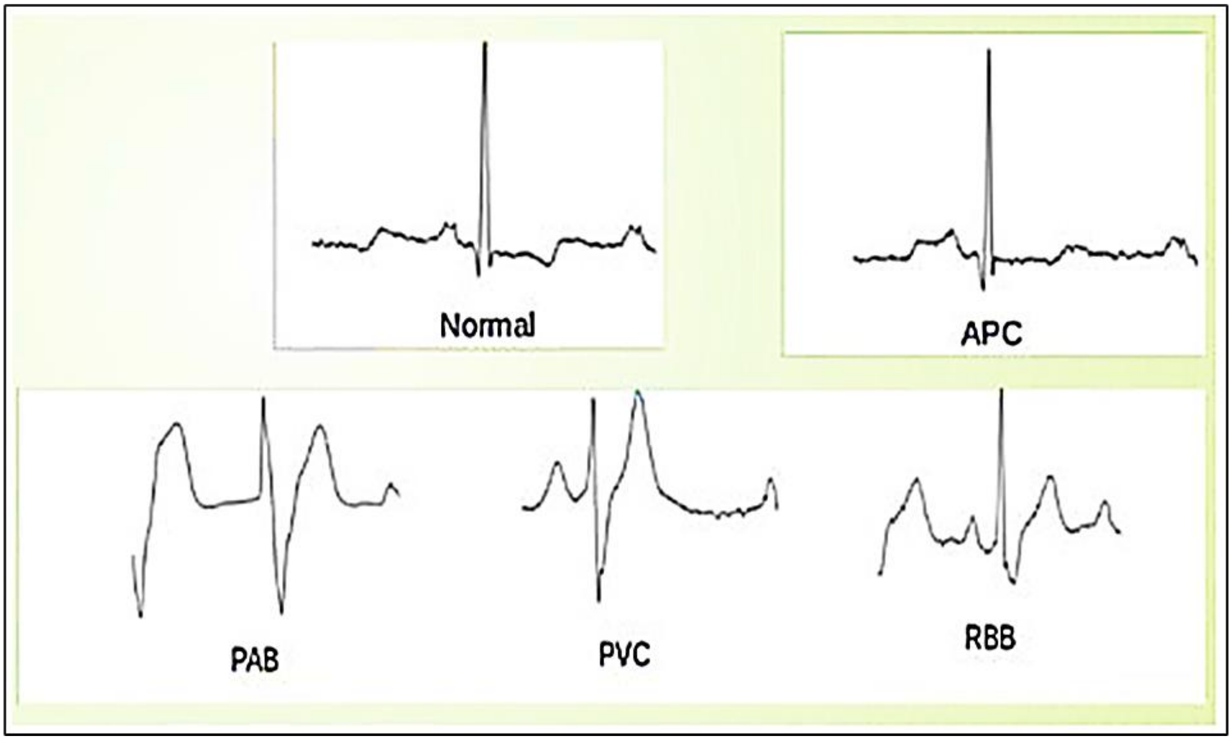


Figure 3.5: Types of ECG Results (1 Normal, 4 Abnormal).

3.3 MACHINE LEARNING

3.3.1 Definition

Machine learning is a subfield of artificial intelligence, which gives a system the ability to understand through its algorithms. It is based on the idea of learning algorithms from data and making predictions with this data and by this computer learn to solve specific tasks, without the need to program them. The objective of Machine Learning is recognized structures in data that are often too difficult to detect or measure manually. From these structures, we can seek to classify individuals and objects, to predict the value of a variable at a certain horizon, to explain the appearance or not of a characteristic.

3.3.2 Different Types of Learning

A. Supervised Learning

Supervised learning is certainly the most widespread form of machine learning. It consists in training the program on examples whose category is known (it is to this knowledge that it owes the name “supervised”). The program has a database with known classes. Its purpose will be to store one or more value(s) assigned to it in the defined classes. The algorithm will classify the new values assigned by the user. Whatever the value, it will be assigned to one of the existing classes by the algorithm. Since this algorithm was not developed to create new classes, it is very useful for targeted classification tasks.

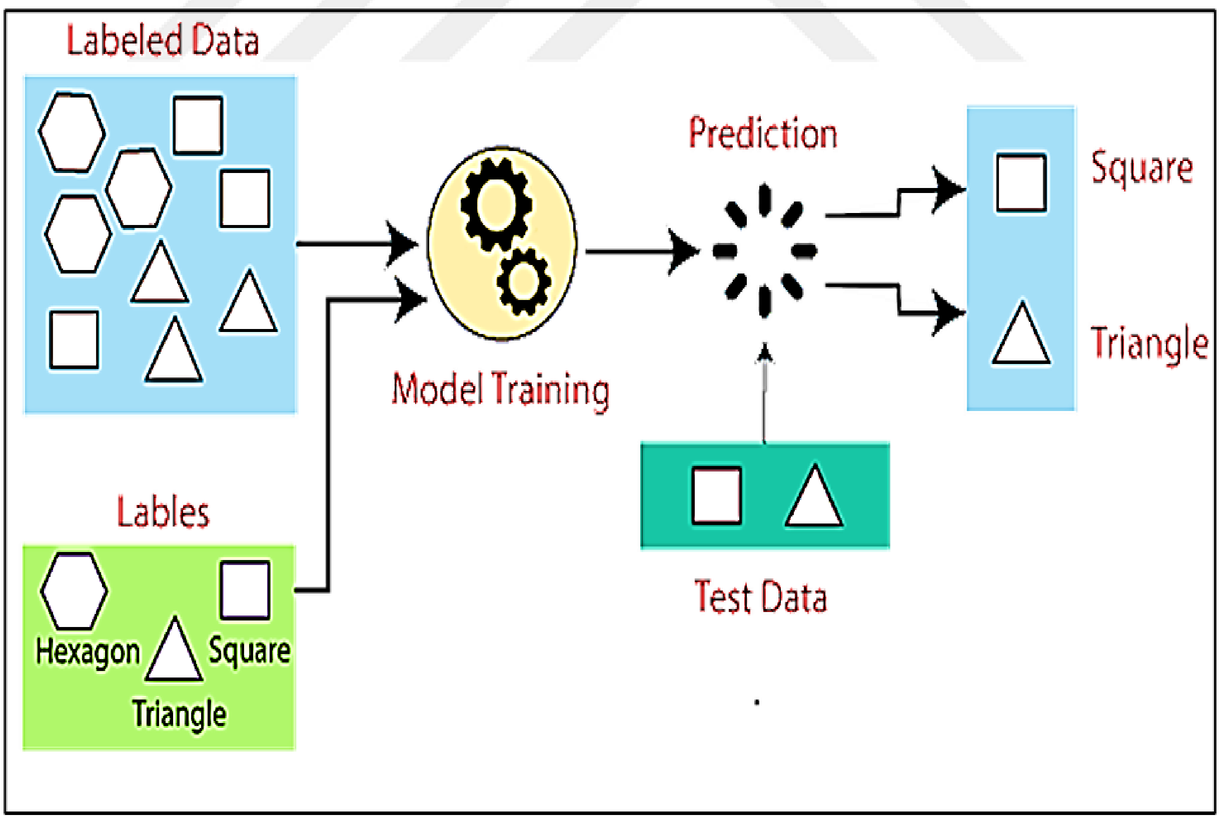


Figure 3.6: Supervised Learning

B. Unsupervised learning:

In this case, the program only receives values and must create the classes in which to assign them. It will therefore "decide" itself the number of classes to create and then store the data in each class. These algorithms are used when we do not have a sample available [8].

(Note that this method can be used to build up a sample and then use supervised learning to classify new data).

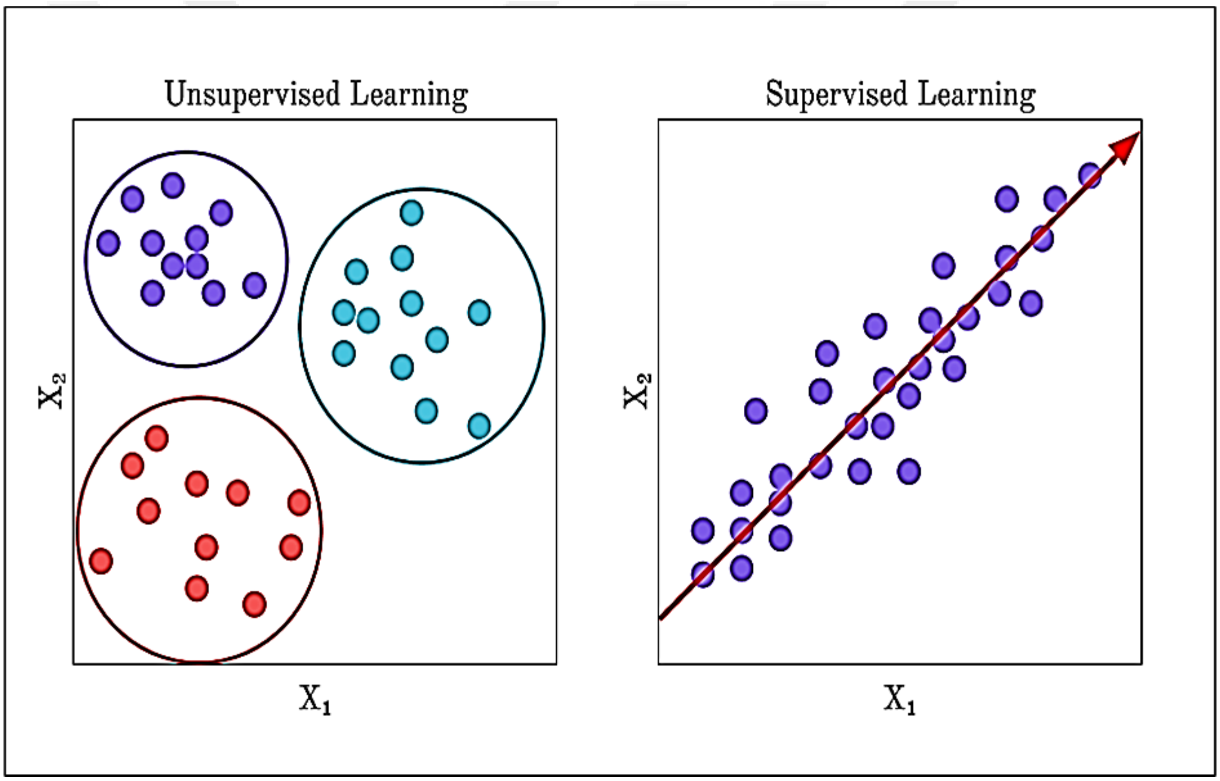


Figure 3.7: Unsupervised Learning

C. Reinforcement learning:

This last type of machine learning is driven by reinforcement. That is, the machine can learn based on different trial and error given in different contexts. Whether or not you know the results from the start, the machine still doesn't know the best decisions to make to get the right results.

In this case, the algorithm alone associates the success patterns. And it is their repetition that allows the algorithm to constantly obtain exact and infallible results.

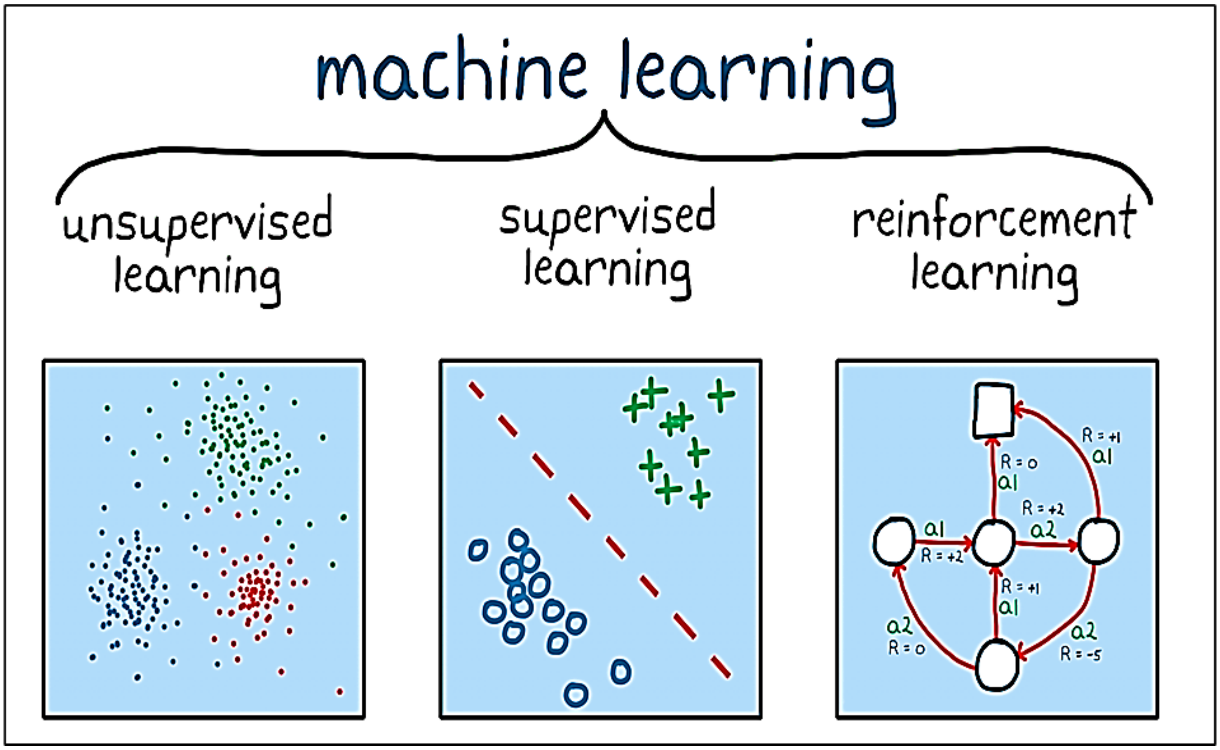


Figure 3.8: Reinforcement Learning

3.3.3 Application Areas of Machine Learning

a Automating: Machine learning, which operates completely autonomously in any domain without any human intervention. For example, robots perform essential process steps in manufacturing plants.

b Finance industry: Machine learning is gaining popularity in the industry

c financial. Banks mainly use ML to find patterns in data but also to prevent fraud.

d Government organization: Government uses ML to manage public security e oblique and public services. Take the example of China with massive facial recognition. The government uses artificial intelligence to prevent jaywalkers.

f The healthcare industry: Healthcare was one of the first industries to use learning

g automatic stage with image detection.

h Transport: In the transportation industry, data is analyzed to identify patterns and trends. Thus, routes are more efficient and potential problems can be predicted to increase profitability. Data analysis and machine learning models are used as valuable tools by delivery companies, public transport, and other transport companies.

3.3.4 Machine Learning Algorithms

i. Logistic regression

Logistic regression is a supervised learning classification algorithm used to predict the probability of a target variable. The nature of the target or dependent variable is dichotomous, which means that there would only be two possible classes. Simply put, the dependent variable is binary in nature, with the data being coded as either 1 (means success/yes) or 0 (means failure/no) [9].

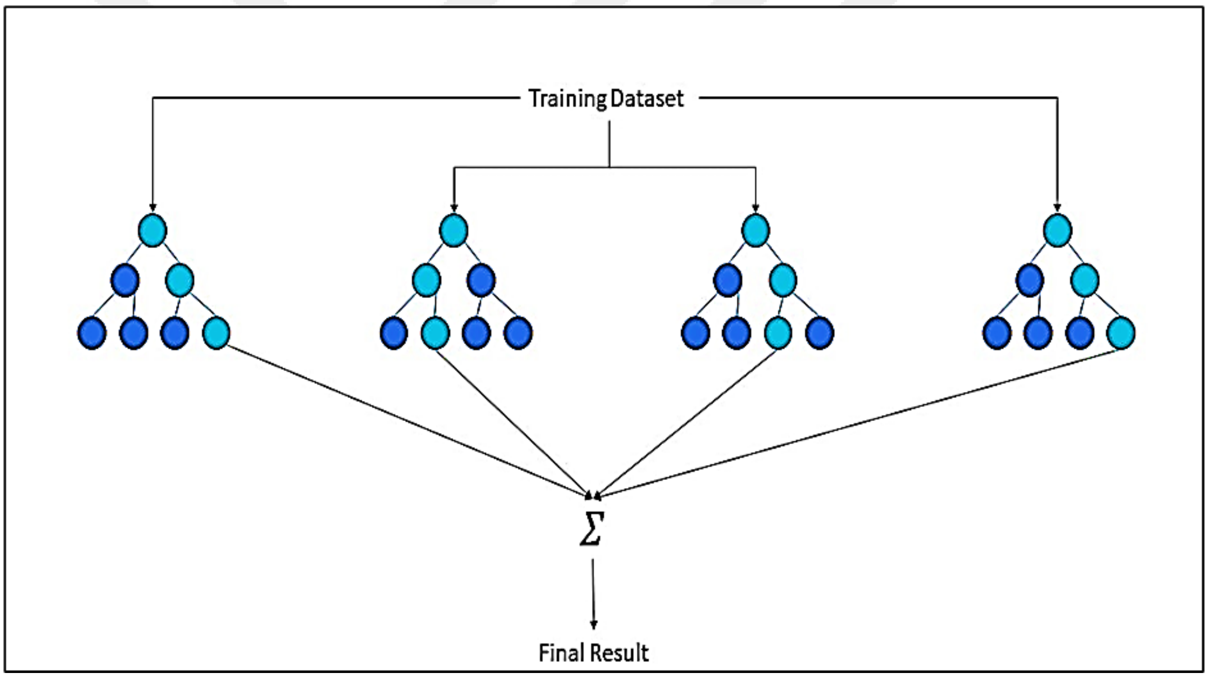
Mathematically, a logistic regression model predicts P(Y) as a function of X. It is one of the simplest ML algorithms which can be used for various classification problems such as spam detection, disease detection, etc...

Generally, logistic regression means binary logistic regression having binary target variables, but there can be two other categories of target variables which can be predicted by it.

ii. Random Forest:

Random forest is a supervised learning algorithm. It can be used for both classification and regression. It is also the most flexible and easy to use algorithm. A forest is made up of trees. It is said that the more trees there are, the more robust the forest.

Random forests build decision trees on randomly selected data samples, get predictions from each tree, and select the best solution by voting. It also provides a fairly good indicator of feature importance [10].



iii. Support Vector Machines (SVM):

SVMs are powerful supervised machine learning algorithms that are used for both classification and regression. But generally, they are used in classification problems. In the 1960s, SVMs were first introduced, but they were further refined in 1990 [11].

3.4 DEEP LEARNING

3.4.1 Definition

Deep Learning or deep learning is a subfield of machine learning (and a sub: subfield of AI in general) where the machine can learn on its own, unlike programming where it is satisfied with executing predetermined rules to the letter. Like machine learning, deep learning also contains supervised, unsupervised, and reinforcement learning.

3.4.2 Applications of Deep Learning

i. Facial Recognition: Eyes, nose, mouth, just as many features

that a DL algorithm will learn to detect on a photo. It will first be a question of giving a certain number of images to the algorithm, then with training, the algorithm will be able to detect a face on an image.

ii. Automatic natural language processing:

Its goal is to extract the meaning of words, or even sentences, to analyze feelings. The algorithm will for example understand what is said in a Google review, or will communicate with people via chatbots. The automatic reading and analysis of texts is also one of the fields of application of DL with Topic Modeling: such text addresses such subject.

iii. Autonomous cars: Companies that build such types of support services

driving, as well as self: driving cars such as Google, must teach a computer to master certain essential parts of driving using digital sensor systems instead of the human mind. To do this, companies usually start by training algorithms using large amounts of data. You can imagine how a child learns through constant experimentation and replication. These new services could provide unexpected business models for companies.

taken.

iv. Voice search and voice: activated assistants:

DL's most popular are voice search and voice: activated smart assistants. With major tech giants already making significant investments in this area, voice: activated assistants can be found on almost every smartphone. Apple's Siri has been on the market since October 2011. Google Today's voice: activated assistant for Android was launched less than a year after Siri. The newest voice: activated smart assistant is Microsoft Cortana.

v. Image recognition: Another popular area of DL is recognizing

image session. Its purpose is to recognize and identify people and objects in images, as well as to understand content and context. Image recognition is already used in several industries such as gaming, social media, retail, tourism, etc. This task requires the classification of objects in a photo among a set of previously known objects. A more complex variant of this task, called object detection, involves specifically identifying one or more objects in the photo scene and drawing a frame around them.

vi. Detection of brain cancer: A team of French researchers noted that it was

difficult to detect invasive brain cancer cells during surgery, in part due to the effects of lighting in operating rooms. They found that using neural networks in conjunction with Raman spectroscopy during operations allowed them to detect cancer cells more easily and reduce residual cancer after surgery.

vii. Sentiment analysis of the text: Many applications have comments or feedback: based review systems built into their apps. Research into natural language processing and recurrent neural networks have come a long way, and now it's entirely possible to deploy these models to your application's text to extract higher: level information. This can be very useful for assessing sentimental polarity in comment sections or for extracting meaningful topics using named entity recognition patterns

viii. Marketing Research: In addition to researching new features that may to improve your application, DL can also be useful in the background. Market segmentation, marketing campaign analysis and many more can be improved using regression models and DL classification. It will really help you a lot if you have a large amount of data. Otherwise, you're probably better off using traditional machine learning algorithms for these tasks rather than DL [13].

3.4.3 The Neural Network

Practically, all DL algorithms are neural networks [14]. Neural networks, also called ANNs, are information processing models that simulate the functioning of a biological nervous system. It's like how the brain handles information at the functioning level. The Xi are numerical values that represent either the input data or the output values of other neurons. The weights Wi are numerical values which represent either the power value of the inputs, or the power value of the connections between the neurons. There are operations that take place at the level of the artificial neuron. The artificial neuron will do a product between the weight (w) and the input value (x), then add a bias (b), the result is passed to an activation function (f) which will add some nonlinearity. Activation functions: After the neuron has performed the product between its inputs and its weights, it also applies a nonlinearity to this result. This nonlinear function is called the activation function. The activation function is an essential component of the neural network. What this function has decided is whether the neuron is activated or not. It calculates the weighted sum of the inputs and adds the bias. It is a nonlinear transformation of the input value. After the transformation, this output is sent to the next layer. Nonlinearity is so important in neural networks, without the activation function, a neural network just became a linear model.

A. The Sigmoid function: This function is one of the most used. He is bounded

between 0 and 1, and it can be interpreted stochastically as the probability that the neuron will fire, and it is usually called the logistic function or the logistic sigmoid.

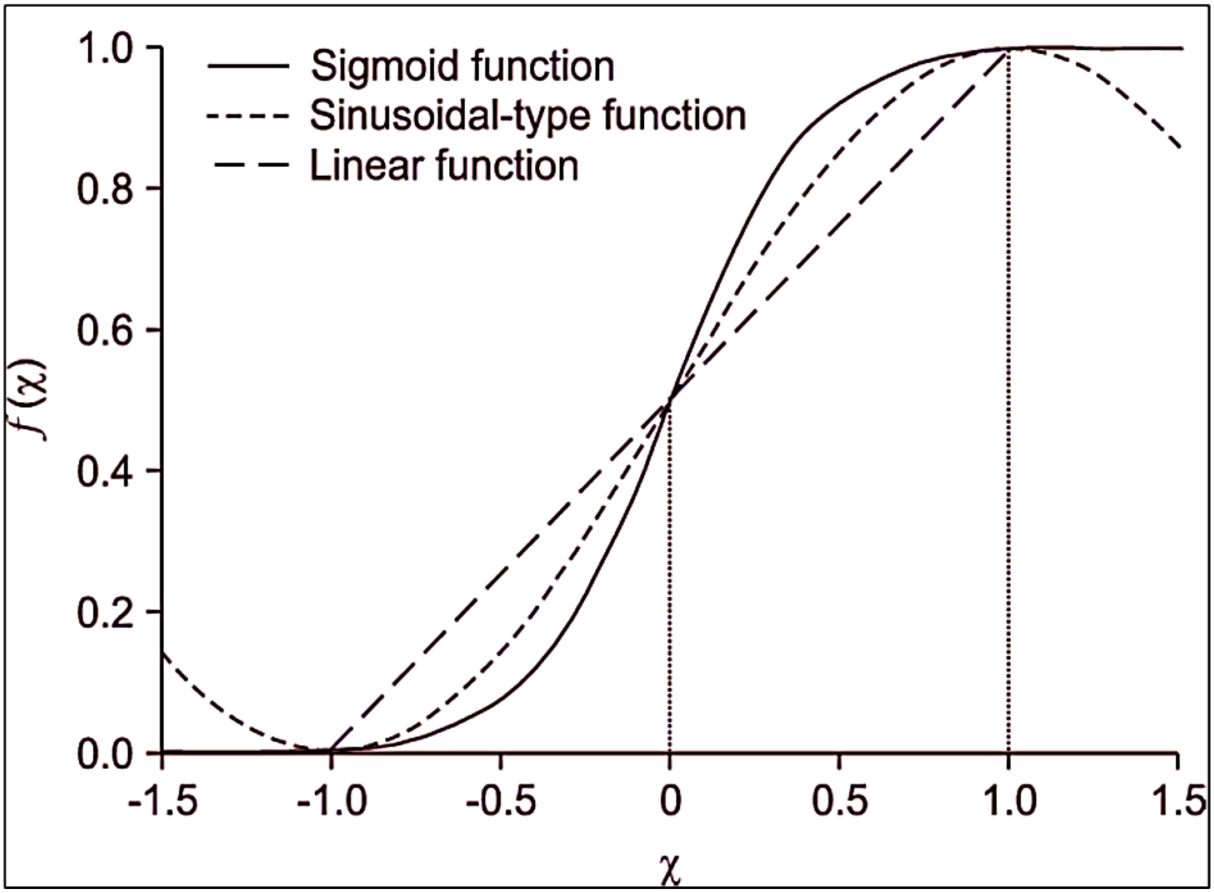


Figure 3.9: Graphic Representation of The Sigmoid Function.

B. The ReLu function: The RELU function is probably the closest to its biological counterpart [15]. This function has recently become the choice of many tasks (notably in computer vision) [16]. As in the formula above, this function returns0 if the input z is less than 0 and returns z itself if it is greater than 0.

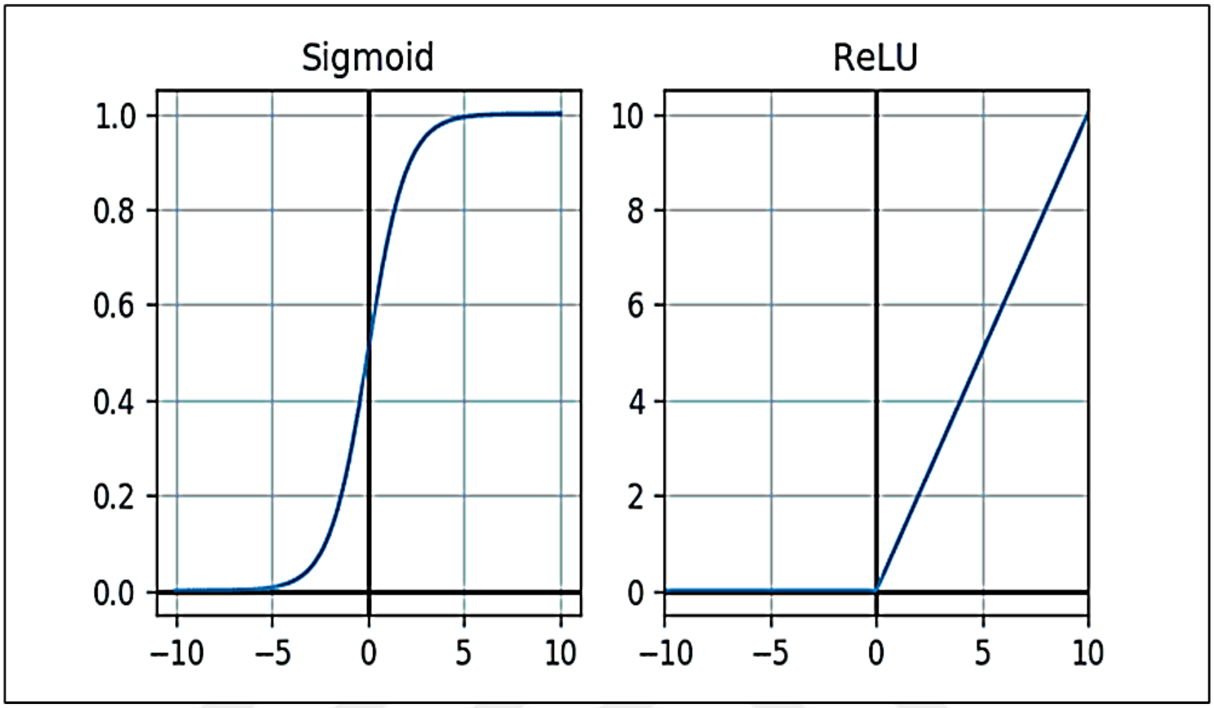


Figure 3.10: Graphic Representation of The RelU Function.

C. The SoftMax function: SoftMax regression (synonyms: Multinomial logistics, Classified:

maximum entropy cator, or simply multiclass logistic regression) is a generalization of logistic regression that we can use for multiclass classification [17]. Unlike other types of functions, the output of a neuron in a layer using the SoftMax function depends on the outputs of all other neurons in its layer. This is because it requires the sum of all outputs to be 1.

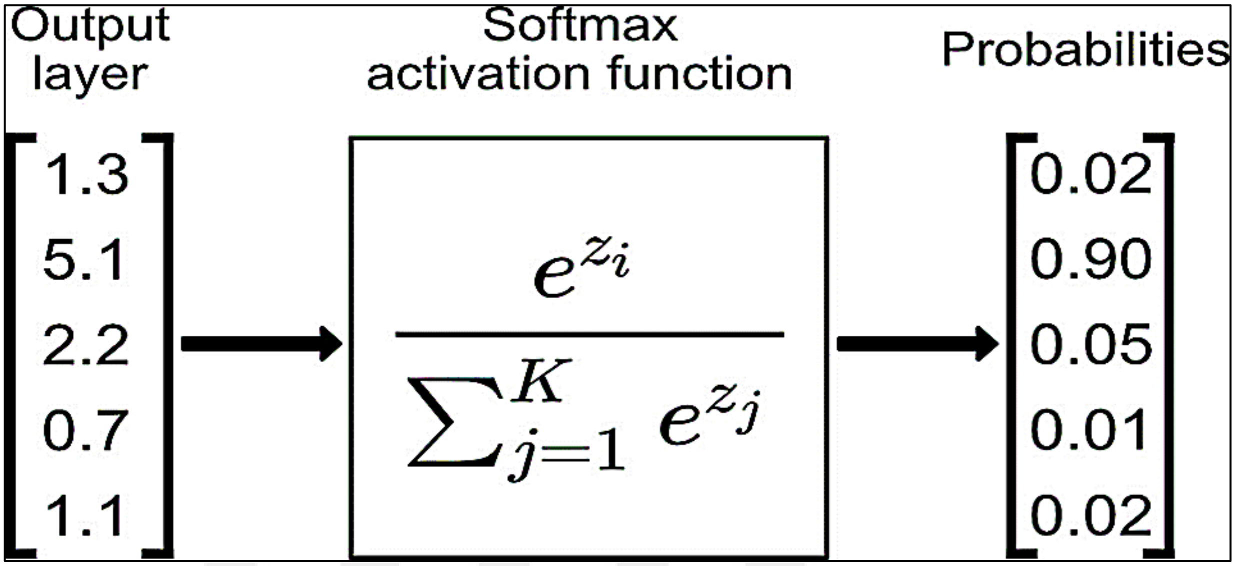


Figure 3.11: Graphic Representation of The SoftMax Function.

3.4.4 Types of Neural Networks

There are different types of neural networks. We can thus cite:

A. Convolutional Neural Networks:

Convolutional Neural Networks (CNN) are a type of specialized neural network for data processing having a grid: like topology. Examples include time series type data, which can be thought of as a 1D grid by taking samples at regular time intervals, and image type data, which can be thought of as a 2D grid of

pixels. Convolutional networks have had considerable success in practical applications. CNN is a sequence of layers, and each layer transforms one activation volume into another by a differentiable function [18]. The three main types of layers to build this type of network are: convolutional layer, pooling layer, and fully connected layer. The convolutional layer: This is the most important layer and the heart of the constituent elements. tutorials of the convolutional network, and it is also the one that performs the heaviest calculations The pooling layer: It is common practice to periodically insert a Pooling layer into this type of architecture. Its function is to gradually reduce the spatial size of the representation to reduce the number of parameters and calculations in the network, and therefore also to control overfitting. The fully connected layer This layer is always the last layer of a neural network, it is entirely connected to all the output neurons (hence the term fully connected: fully: connected).

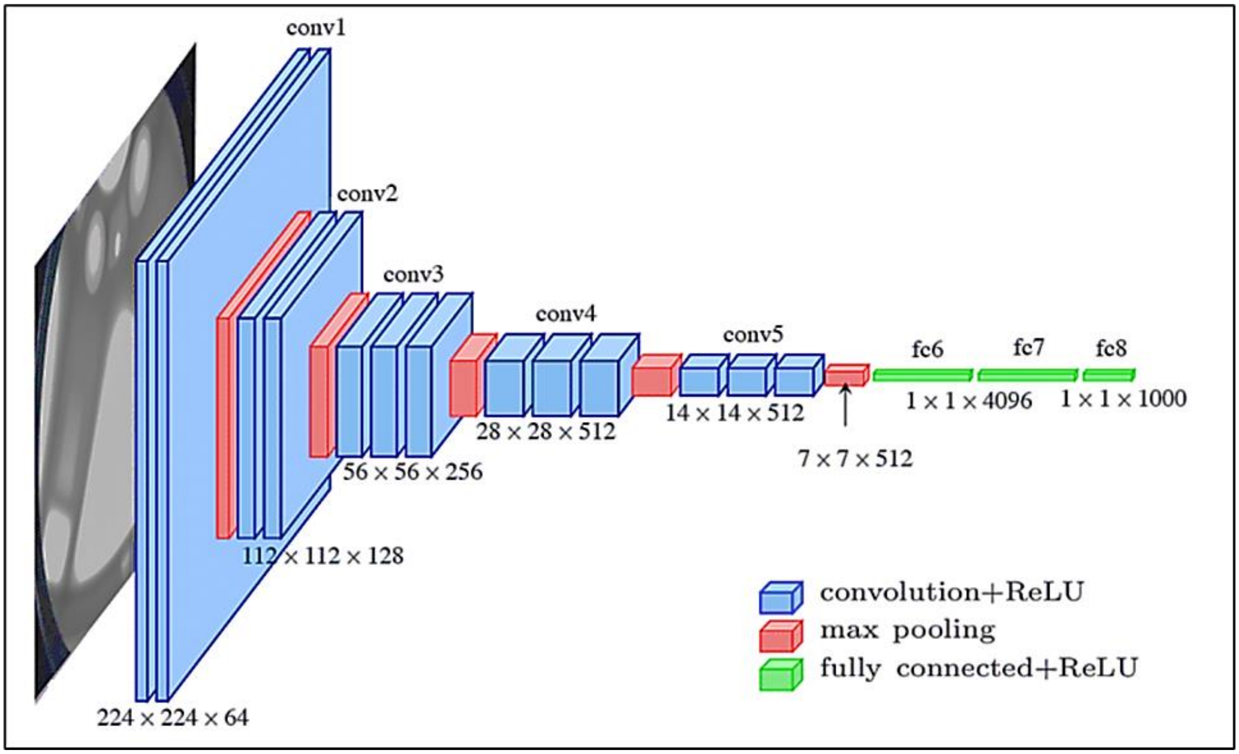


Figure 3.12: Architecture of The CNN Model.

B. Recurrent neural networks:

Recurrent Neural Networks (RNN) is a type of neural network in which the output of the previous layer is fed as the input of the current layer. In traditional neural networks, all inputs and outputs are independent of each other, but in cases like when it is necessary to predict the next word in a sentence, the previous words are needed and hence it is necessary to remember previous words. This is how RNN came into existence, which solved this problem with the help of a hidden layer. RNNs are called recurrent because they perform the same task for each element of a sequence, with the output dependent on previous computations. This is what a typical RNN looks like:

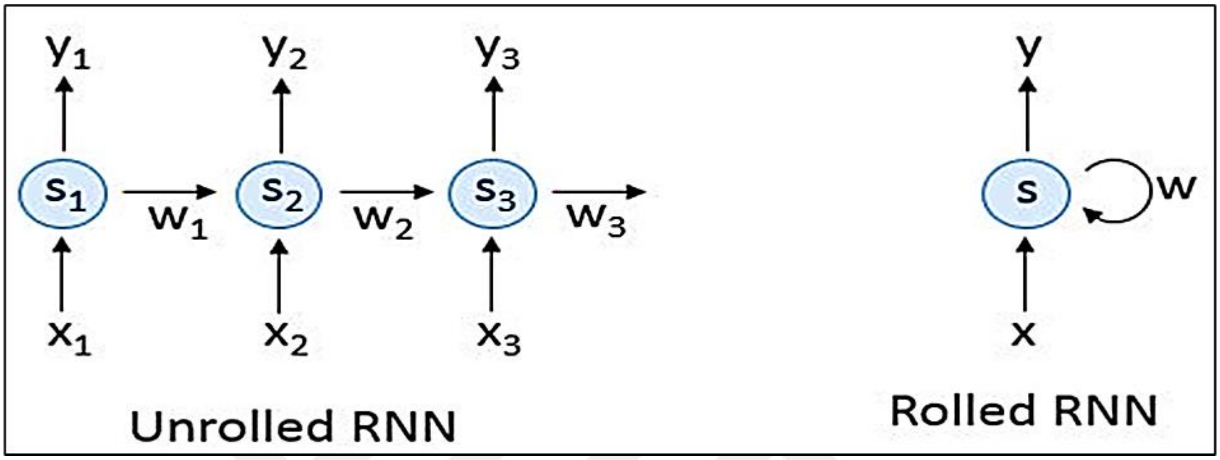


Figure 3.13: (Left) An RNN (Right) Its Unrolled Version.

The diagram above shows an unrolled RNN. By scrolling, we simply mean that we are showing the network for the complete sequence. For example, if the sequence we are interested in is a 3: word sentence, the network would be unrolled into a 3:layer neural network, one layer for each word. RNNs have difficulty learning long: term dependencies and interactions between words that are far apart [19]. This is problematic because the meaning of a sentence is often determined by words that are not very close. In this precise case if the activation function is a tan or a sigmoid then we will have the problem of the disappearance of the gradient. It is for this reason that we turn to the ReLu activation function which does not suffer from this problem, but there is an even more widely used solution is the use of Long Short-term Memory (LSTM) architectures or Gated Recurrent Unit (GRU):

C. RNN LSTM (Long Short:Term Memory):

Commonly referred to simply as Long Short Term Memory (LSTM) networks are a special type of RNN. The Recurrent Neural Networks presented in the previous section can learn arbitrary sequence update rules in theory. In practice, however, these patterns usually quickly forget the past [20] . It's called the vanishing gradient problem and that's why they invented LSTM. The

LSTM cell is an adaptation of the recurrent layer that allows older signals from deep layers to travel to the present cell. In an LSTM network, three gates are present:

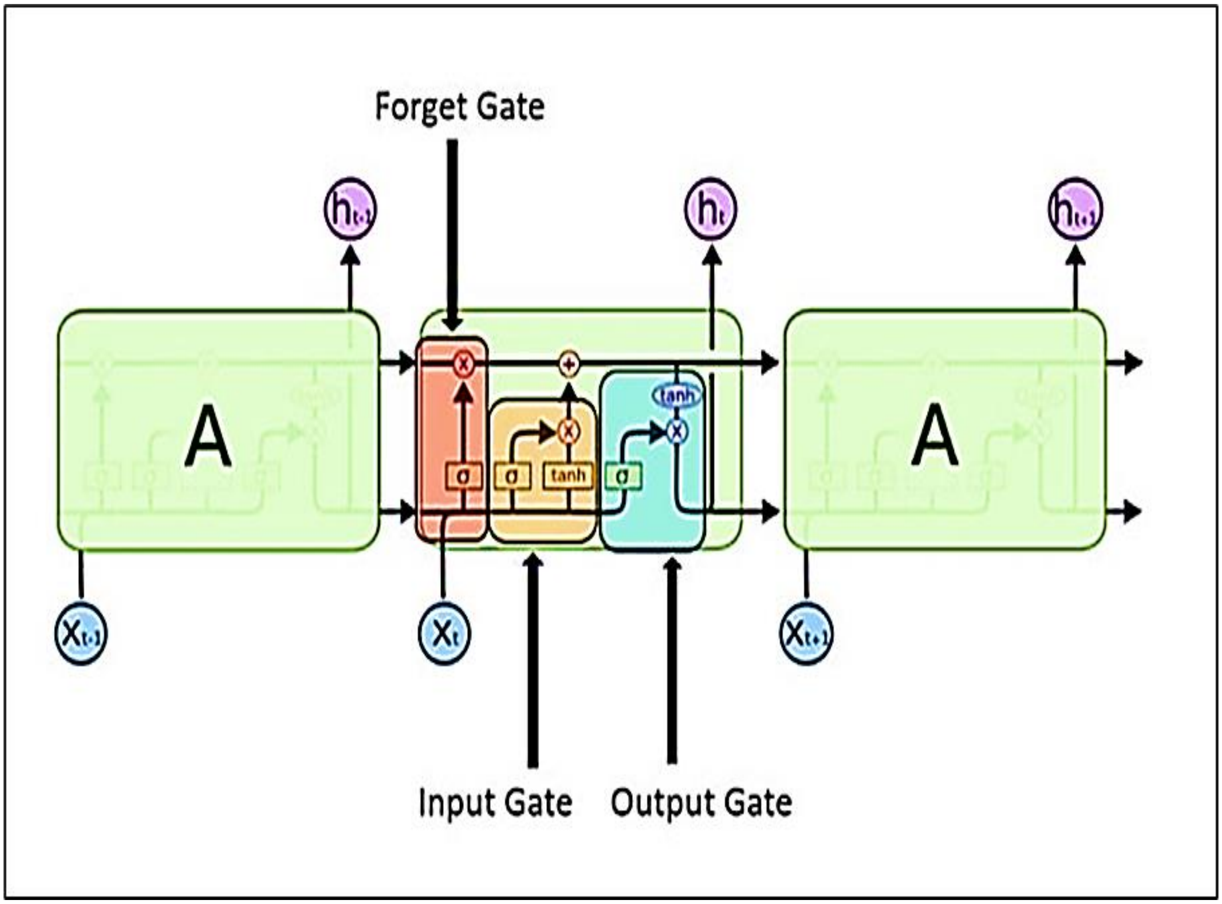


Figure 3.14: LSTM With Its Gates.

I. Forget gate: This gate decides what information should be kept. it is decided by the sigmoid function: it looks at the previous state (ht:1) and the input (Xt), if the output of the sigmoid is close to 0, it means that we must forget the information and if it is close to 1 then it must be memorized for the rest.

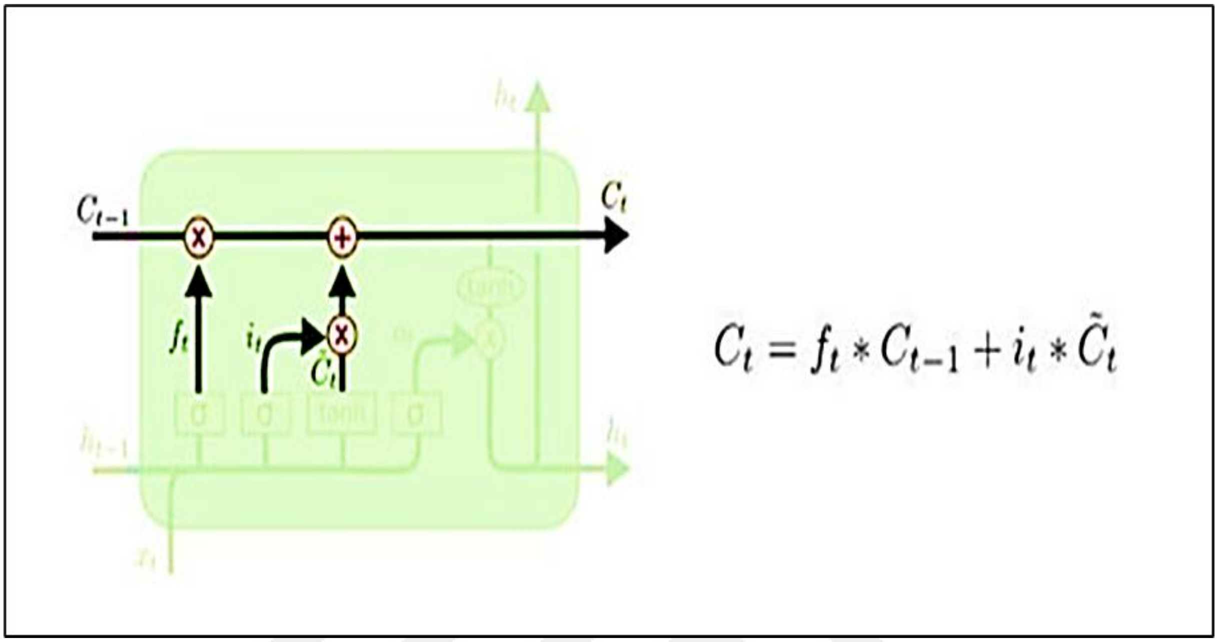


Figure 3.15: The Forgetting Gate.

II. Input gate: This gate decides whether the input should modify the contents of the cell. The sigmoid function decides which values to pass through 0 and 1, and the tanh function gives weight to the values that are passed by deciding their level of importance ranging from :1 to 1.

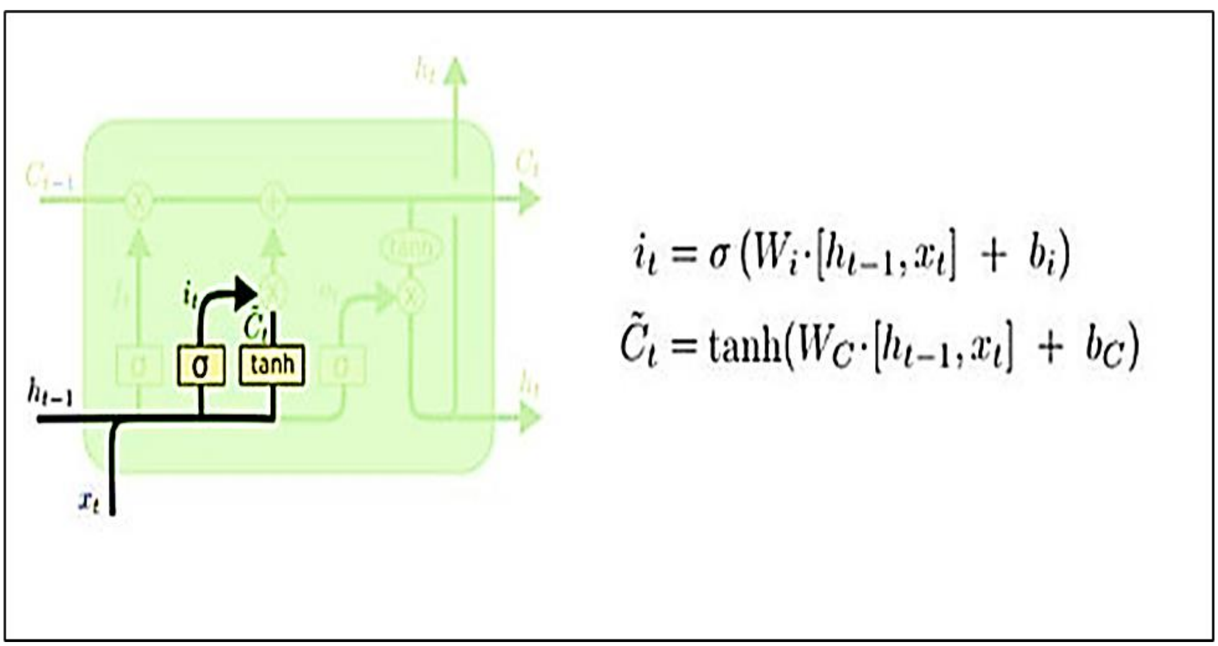


Figure 3.16: The Front Door.

III. Output gate: This gate determines whether a cell can send a value to other cells or not. Indeed, when its value is close to zero, the cell does not provide any information at the output. This gate decides which part of the current cell arrives at the output.

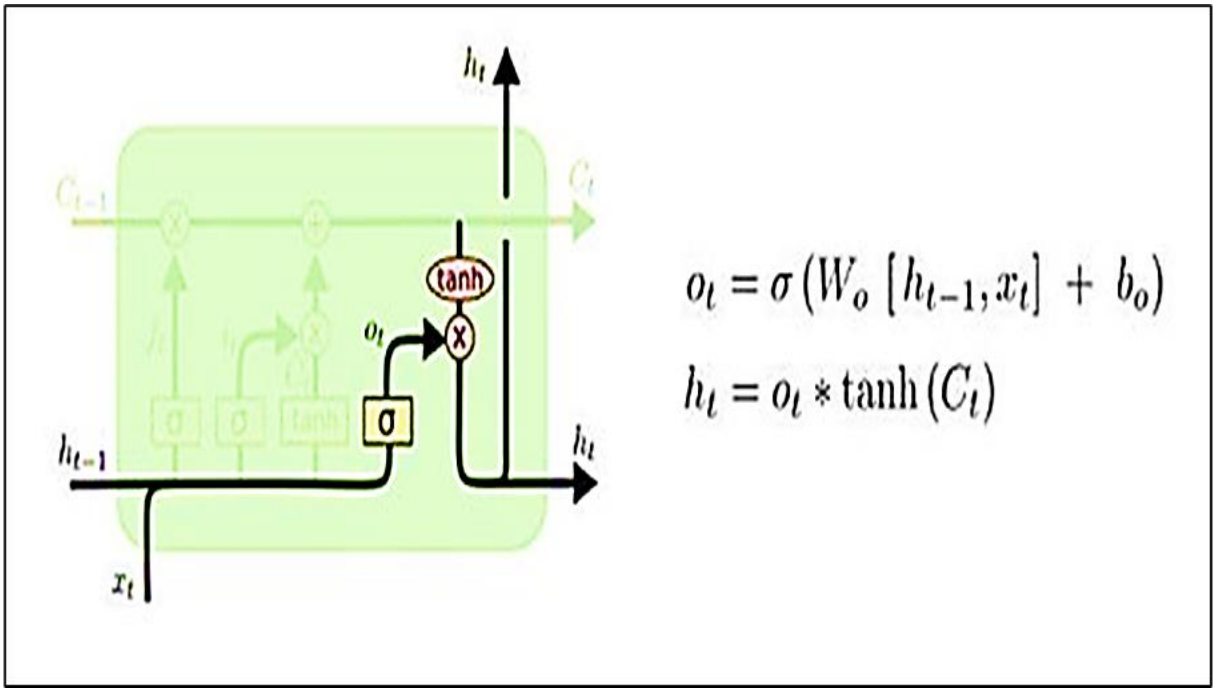


Figure 3.17: The Exit Door.

D. RNN GRU (Gated Recurrent Unit)

RNN GRU is another type of recurrent neural networks [21], aims to solve the gradient vanishing problem that comes with a standard recurrent neural network. GRU is a modification of the hidden RNN layer that allows better capture of long: range connections.

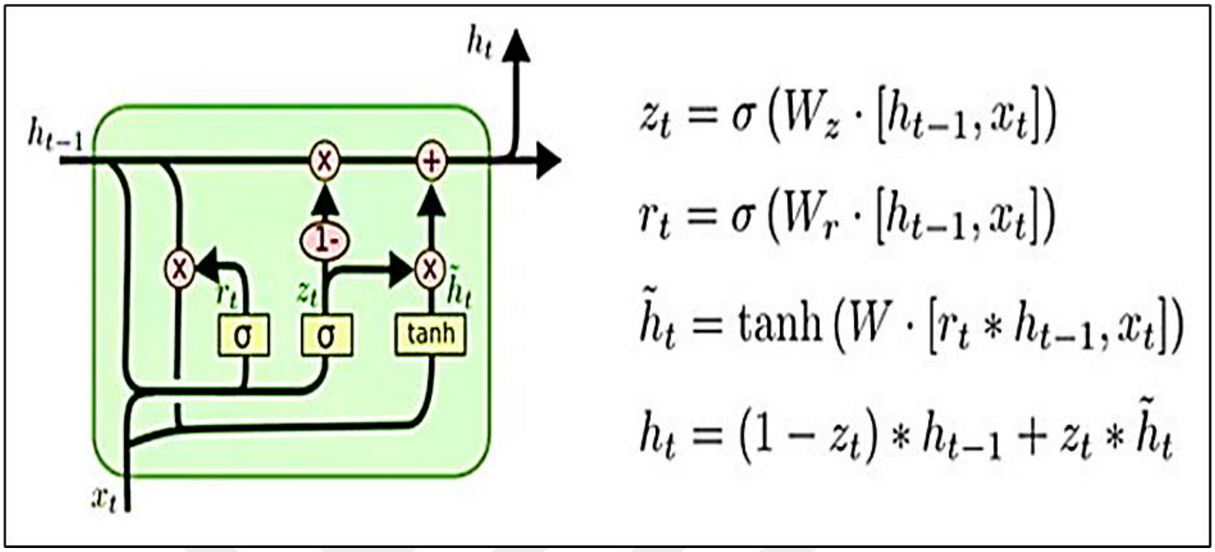


Figure 3.18: GRU Cell.

GRU is like LSTM, but its structure is simplified. Like LSTM, to solve the problem of vanishing gradient of a standard RNN, GRU uses, so called, update gate and reset gate. Basically, these are two vectors that decide what information should be passed to the output. The neural networks mentioned are not all the networks that exist, an excellent resource that summarizes perhaps all the architectures is in [22]. The following figure shows a representation of their work:

3.4.5 Deep Learning

The learning process in Deep Learning amounts to training the neural network using iterative optimizers, which only drive the cost function to a very low value [23]. We can use different algorithms to perform the learning, but the most used algorithm is the iterative gradient descent optimization algorithm which is the most used method almost on all neural networks with its different models.

The learning process comes back to the optimization problem where it is a question of minimizing or maximizing a function f(x). This function is called the objective function, the authors in [23] also called it the cost function, the loss function and the error function. During training, the algorithm attempts to identify the global minimum without falling into the local minimum trap. The following diagram produced by the authors in [23] is an illustration of this concept:

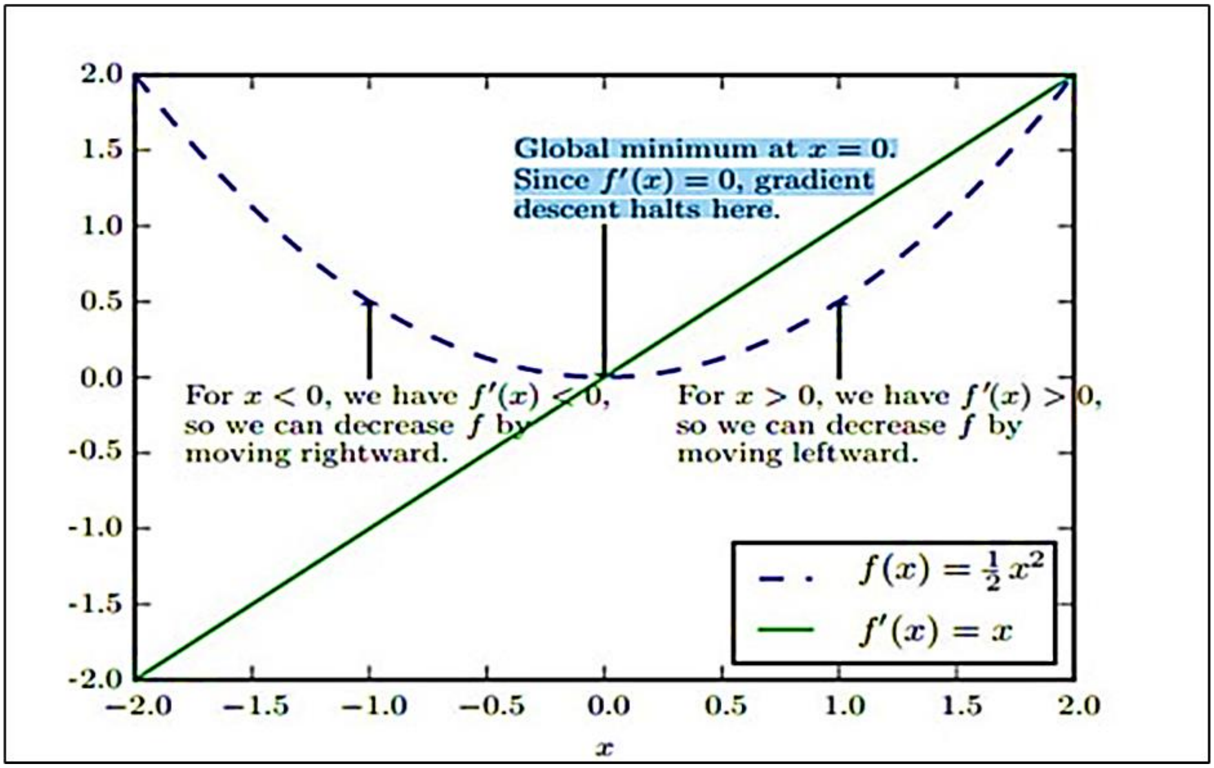


Figure 3.19: An illustration of the optimum search process [23].

A. Variants of Gradient Descent:

There are three main types of variants of the gradient descent algorithm. The main difference between them is the amount of data we use when calculating the gradient for each learning step. Optimization algorithms that use the entire training set are called deterministic gradient methods or batch gradient descent, because they are methods where all the training examples are processed simultaneously in a large batch, while the term "batch" to describe a group of examples. Optimization algorithms that use only one example at a time are sometimes called stochastic or online gradient descent methods. Most algorithms used for deep learning fall somewhere in between, using more than one but less than all the training examples. They are called the stochastic minibatch or minibatch gradient descent methods.

4. PROPOSED METHODOLOGY

In this chapter, the design of the solution will be presented, starting with an analysis of the data set that will be used in its development. Next, the approach considered to solve the presented problem will be presented. Still in this chapter, it is possible to visualize the implementation of the proposed solution that contains the details about each of the procedures carried out to solve the problem.

4.1 DATASET

For the development of this project, a dataset available in a contest will be used. These data were recorded using the Alive Cor device and donated to this challenge. The recordings were made by people who purchased the single: channel ECG device from this entity, Alive Cor the dataset comprises a total of 12,186 ECG recordings, of which 8,528 would be used for training purposes and 3,658 for testing. However, the recordings corresponding to the test set are not available to the public, for the purpose of scoring the participants during the challenge period. Thus, only the recordings provided for training the classification models will be used in this project. These recordings have an interval of 9 to 61 seconds in length, approximately, having been made from 2 electrodes, one in each hand at 300Hz

Table 4.1 shows the details of the training dataset, and these recordings were classified into four categories (normal rhythm, RECALL, other rhythm, and recordings with noise). The number of existing records by category is exposed, together with some metrics related to their length of time, such as the average and median of the length of time of a recording, the standard deviation and the maximum and minimum lengths existing in each one of the categories. It is also important to mention that the classification of these ECG data was performed manually by a team of specialists, and a series of revisions were carried out. However, an accuracy rate of 100% of their classification is not guaranteed.

Table 4.1: Training Dataset Details

Category	Records		Time Lengths			
		Average	Standard Deviation	Maximum	Median	Minimum
Normal	5076	31.9	10.0	61.0	30	9.0
RECALL	758	31.6	12.5	60.0	30	10.0
Other	2415	34.1	11.8	60.9	30	9.1
with noise	279	27.1	9.0	60	30	10.2
Total	8528	32.5	10.9	61	30	9.0

The data related to the ECG recordings are stored in .mat files, which are accompanied by a .hea file, which contains information about the signal characteristics. Figure 4.1 shows examples of the ECG signal waveforms, with a duration of 20 seconds, for the four categories.

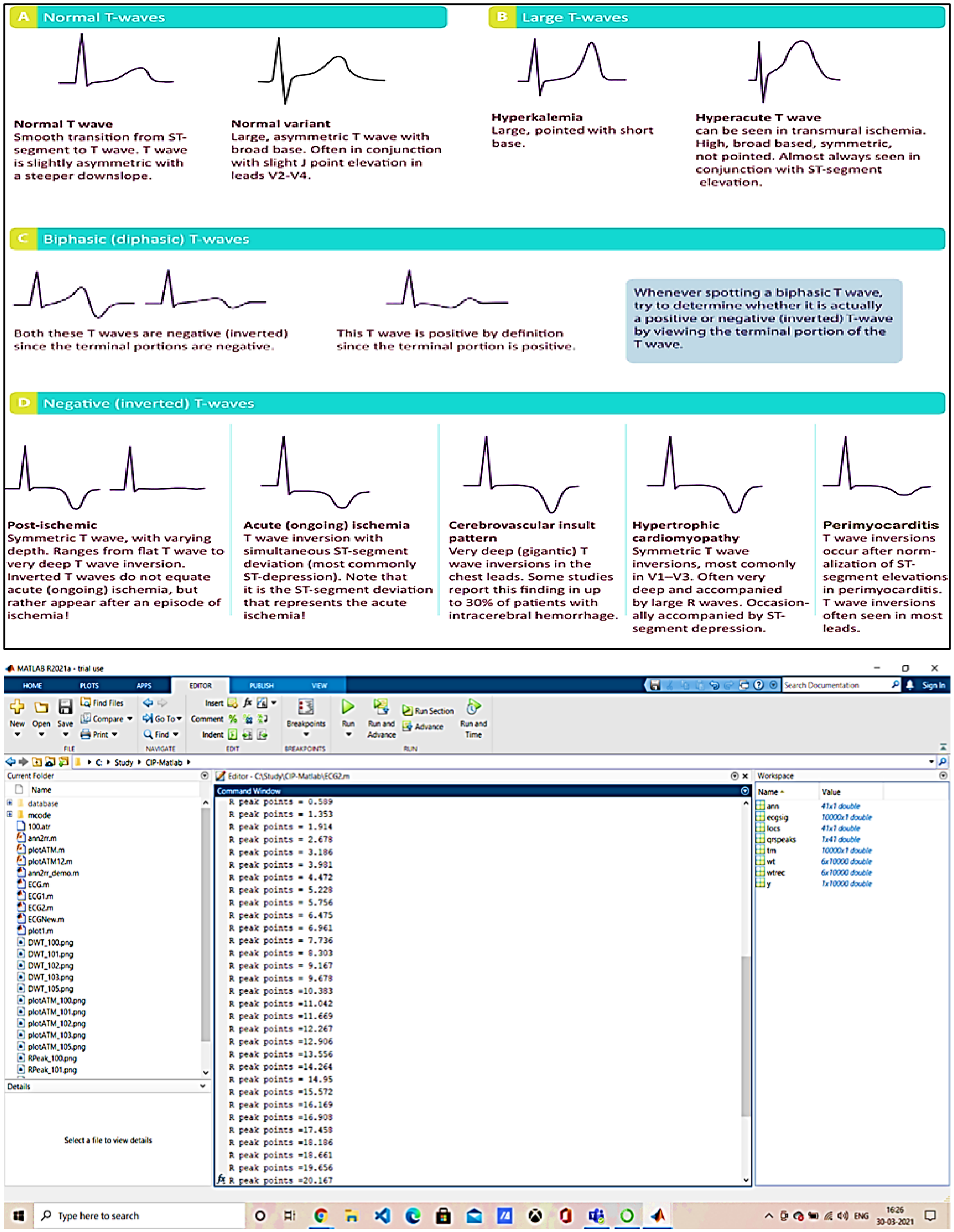


Figure 4.1: Examples of ECG Waveforms

4.2 APPROACH

To solve the problem presented, two approaches of possible methodologies are exposed, for the analysis and classification of ECG signals.

In the first approach, represented in Figure 4.2, the most common methodology is displayed, consisting of the following steps:

a. Signal Acquisition: the signal is acquired, and at this point it may be necessary to carry out some pre-processing of the data, such as applying filters to reduce possible noise, for example.

b. Attribute Extraction: extraction of attributes from the dataset and consequent creation of a new dataset, composed of the extracted attributes.

c. Classification: use classification algorithms, such as Random Forests or SVM (section 3.1.5).

d. Evaluation– obtain the results of the classification of ECG signals, and evaluate these results, according to some evaluation measures, such as those listed in section 3.1.9.

In the second approach, a deep learning methodology is presented, using convolutional neural networks (or CNN).As in approach 1, it has the signal acquisition stage, where it may be necessary to carry out some pre-processing of the data as well as the evaluation stage, where the results of the classification of the signals are obtained, evaluating them afterwards.

CNN's attribute detection layer implicitly learns from training data, thus avoiding explicit attribute extraction and classification. That is, using CNN it is possible to directly map the input signal to obtain the results As previously mentioned, the second approach represents the methodology that will be followed to develop the resolution of the problem, using ML library to create the CNNs.

4.2.1 Development Process

Figure 4.2 shows the activity diagram that generally represents the solution development process.

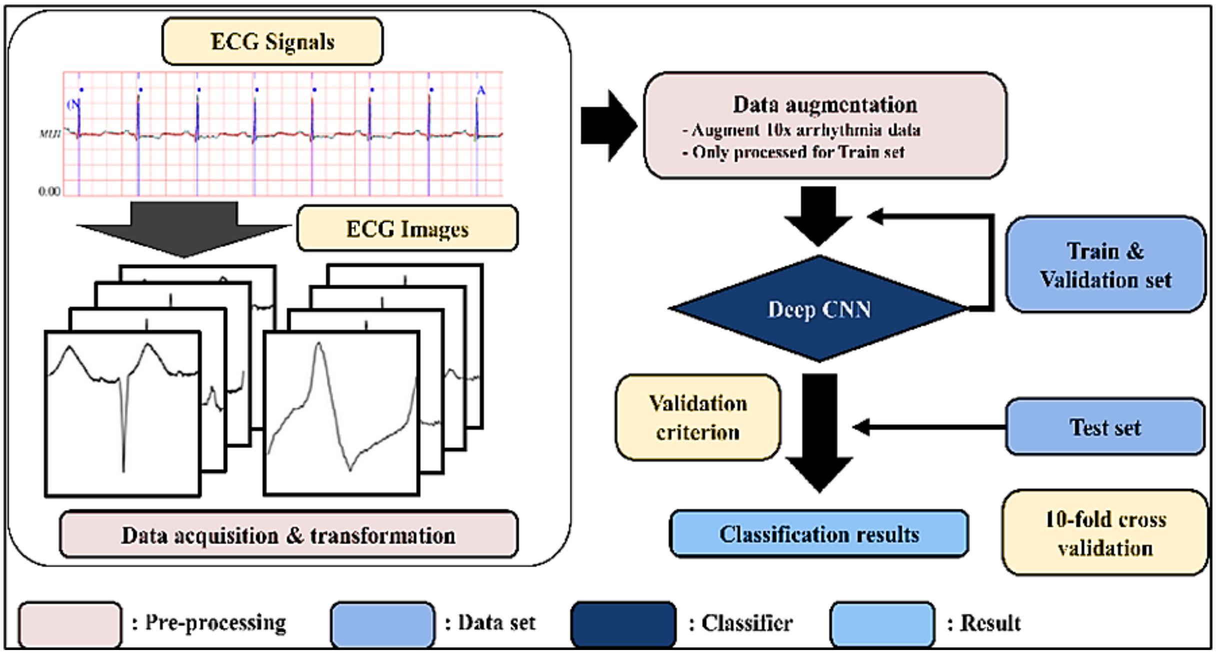


Figure 4.2: Representation of The Proposed Method

The development process begins with the transformation of the dataset, which is available in .mat format, into images since the proposed work tools do not work directly with this type of formatting. Subsequently, the architecture and the necessary parameters of the CNN neural network are defined, to treat the ECG data, previously converted to images, using ML library and MATLAB. With the neural network built, tests are now performed on it, with the images obtained previously. These tests will be carried out by applying the 10:fold cross: validation method to the image dataset. This method consists of dividing the input dataset into 10 subsets of the same size (9 training sets and one testing set) and building 10 sub models. Sequentially, a subset will be evaluated using the classification algorithm trained on the other 9 subsets, and the test set used will be different in each iteration, not being also present in the training data of that iteration. In this way, each subset of the complete dataset will be predicted once. The average hit rate of these 10 iterations will be calculated as the ranking result. The same applies to the other classification measures. The cross: validation technique can help to avoid the problem of over: fitting. Finally, it is necessary to carry out an analysis and evaluation of the results obtained by this classification model.

4.3 IMPLEMENTATION

In this subchapter, the procedures carried out, sequentially, for the implementation of the previously suggested design will be presented and detailed. During the implementation phase, different approaches were followed, both in the pre-processing of the data and in the definition of the model's architecture, always with the objective of improving the results. In the technical description of the implementation, these approaches will be presented, in general, and more detail will be given on the final model implemented.

4.3.1 Pre-Processing

As mentioned in section 4.1 of this document, the datasets used to carry out this project were made available in a competition As was also mentioned, only 8,528 records were available for the development of this project, since the remaining 3,658 records were deprived of the contest, for the purpose of validation of results. These records are stored in .mat files, and there is also a "REFERENCEv3.csv" file, also provided by the competition, along with the records, where the mapping of the records with the respective associated classes is. Two dimensional CNN requires images as input data. Therefore, in the first stage, the pre-processing stage, the data sets (ECG signals) were transformed into images. Two approaches were followed, whose result (the generated images) proved to be quite different between them. Both solutions were implemented using the MATLAB language, also using external libraries, which will be presented in the description of the approaches.

In the first approach, external libraries NumPy and SciPy were used to manipulate data (ECG signals) and record them in images, respectively. The execution of this solution included all records (8528 records), transforming them into .bmp images. As mentioned in section 4.1 of this document, the records are not all the same size, having a range of approximately 9 to 61 seconds in length. For each 1:second segment, approximately 300 signals are covered, thus making up an interval of 2,700 to 18,300 signals between the various records. In this transformation, each signal originates a pixel in the image, which is differentiated by color depending on its value (using byte scale). This way, looking at this image, it is possible to verify that it is an arduous task, or even impossible for the human being, to identify the category that this ECG record belongs to just by observing the image, contrary to what happens with the images in Figure 24, which are much more readable. At the beginning of the training process, still part of the preprocessing, the algorithm opens the .bmp images, reads them and extracts a part (96x96 bytes), creating new images of 96x96 resolution, with the extracted part. These new images are then added to a list of images that will later be used to feed the neural network; The second approach arose from the need to improve the results of the model that used the images conceived in the Transformation of Datasets into Images : Approach 1. Since they were images with variable resolutions and with a large discrepancy between height and width, only a part of each image was used by the neural network. In this way, the risk of using an uninteresting part of the image, given its category, was great. The main objective would be, therefore, to look for an alternative way of representing the signals in an image, and preferably that these were used in their entirety by the network.

After a study on the subject, and implementation of some tests, an alternative was found, quite viable. External libraries Matplotlib were used to create graphs from arrays of values (signals) and OpenCV to create . png image files with the graphs. As, in ECG signals, colors are of no importance, the conversion to grayscale images was carried out, as had also been done in the first approach. The resolution of these images could be configured in this case, having been defined the resolution 512x512. In this way, 8528 two:dimensional images were obtained, with the same resolution, corresponding to the available ECG records.

In Figure 4.3, the image corresponding to the same example (A00001) of Figure 4.3 is shown.

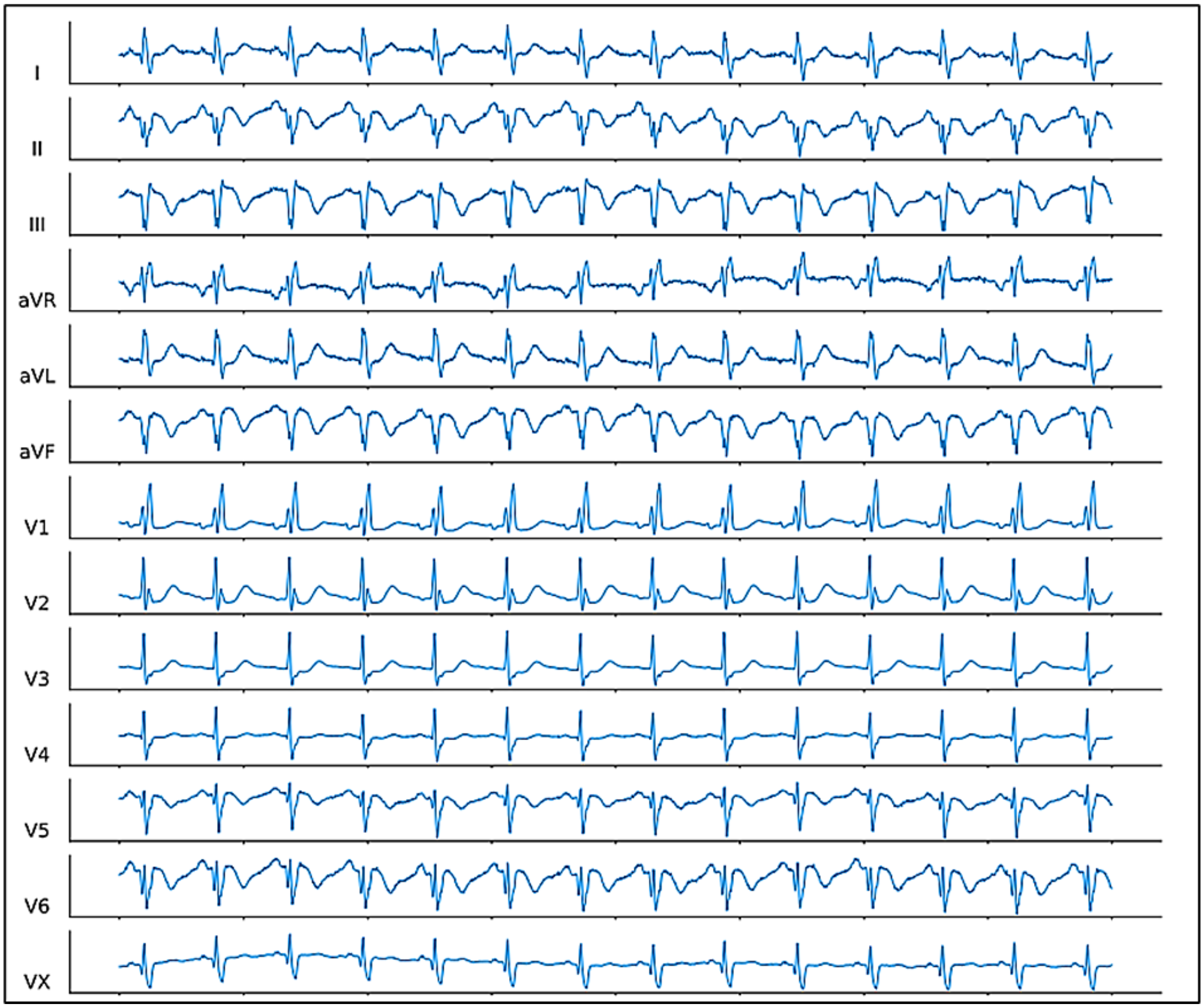


Figure 4.3: Approach 2: Record A00001 Converted to Image A00001.Png

Contrary to what happens with the images generated in the first approach, the images resulting from this second approach are much more readable to the human being, even allowing, in some cases, to identify the category associated with the ECG record, through image analysis.

Second when transforming one: dimensional ECG signals into two: dimensional ECG images, noise filtering and attribute (or feature) extraction are no longer necessary, which is very important, as some of the ECG beats are sometimes ignored in these steps. In addition, training data can be enlarged by enlarging the ECG images, which results in a higher classification hit rate. Data augmentation is difficult to apply to one: dimensional signals, as distortion of the one: dimensional ECG signal can degrade the performance of the classifier.

At the beginning of the training process, still part of the pre:processing, the algorithm runs over the previously generated images (512x512), and resizes them to a smaller size, with a resolution of 128x128. These new images are added to a list of images that are stored in memory, being later submitted to the neural network, which will use them to carry out its learning process This

4.3.2 Data Balancing

The distribution of the dataset, comprising a total of 8528 ECG recordings, across the four categories (normal rhythm, RECALL, other rhythm, and noisy data) is largely unbalanced (unbalanced), as can be seen in section 4.1, and in more detail in Table 18. Most of the records belong to the normal rhythm class (about 60%), 9% are records of patients with arrhythmias (RECALL), 28% records with other rhythms, and the remaining 3% are records with noise.

One of the techniques presented is the Dataset Augmentation technique, which would be useful to increase the records of classes that have fewer examples, as is the case of records with noisy rhythm and with RECALL. However, it was not possible to implement this technique, since, due to hardware limitations, it would not be possible to perform a network training with all available records in the implemented model. The increase in registers of the classes with fewer examples proved to be unnecessary, as they would end up not being used in their entirety anyway.

On the other hand, the dataset resizing strategy was used, also described in section 3.1.3.4, being a strategy framed in the data balancing techniques.

A parameter “records_per_class” was defined in the model, which must be passed in the execution of the model, defining the number of records of each class that must be taken into account in the training of the network, and ignoring the others. This parameter is used in the phase of obtaining the images that will be part of the CNN input, not allowing a number of records per class to be higher than the same. For example, when setting the parameter to the value 100, the model will be executed with a maximum of 400 training records, which correspond to 100 examples of each of the four classes. This measure was used to determine the possibility of distinguishing the classes in an equilibrium scenario. Although this is a different problem from the original, it allows us to assess the extent to which a lack of results is due to class imbalance.

In this way, it is possible to guarantee that the data is 100% balanced, with the same number of records for each class.

4.3.3 Selection of Images by Segments

the records (of the dataset) are not all the same size, there are records with an interval of 9 to 61 seconds in length, approximately. However, the images were all generated at the same size, 512x512 resolution. An image that corresponds to a 60: second recording has twice as much information (signals) as an image that corresponds to a 30: second recording, however, both images will have the same resolution. It is possible to foresee that the image related to the 60: second recording will be more distorted than that of the 30: second recording.

In Figure 4.4, three images are displayed, which correspond to three records with different lengths of time (10, 30 and 60 seconds).

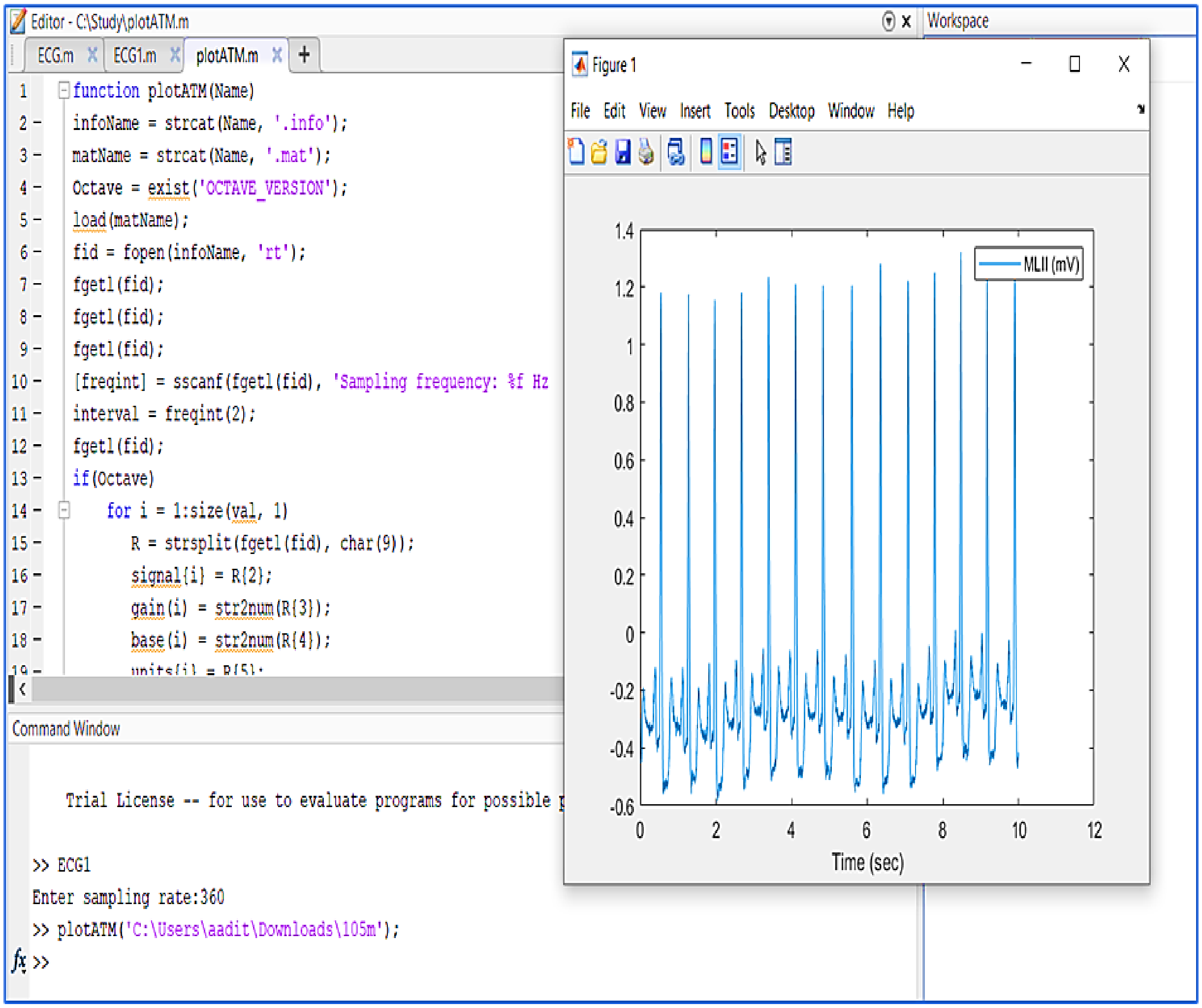


Figure 4.4: Records with Different Time Intervals

As you can see, the first image (corresponding to register A00592) is much sharper than the second (register A00001), which in turn is sharper than the third image (register A00003). This is due to the lengths of time that the registers have, and consequently the number of signals that each register has.A study was then carried out on the existing records, to obtain statistics on their lengths of time, as can be seen in Table 4.2.

Table 4.2: Record Statistics (Time Lengths)

Segments (Time Lengths)	Number of Records	Percentage
10s ~ 19s	616	7.22%
19s ~ 29s	351	4.12%
30s	5977	70.09%
31s ~ 39s	450	5.27%
40s ~ 49s	161	1.89%
50s ~ 59s	125	1.47%
60s	809	9.49%
> 60s	39	0.45%
Total	8528	100%

With these metrics, it was possible to extract relevant information to solve the problem of supplying the network with images referring to records with different lengths of time.

An image selection method was defined by segments, that is, during the selection phase of the images that will be part of the CNN input, only images from the same segment (same lengths of time) will be able to enter. Looking at the number of records of each segment, in Table 4.2, it is possible to verify that most of the records (about 70%) correspond to 30:second recordings. This segment of records proves to be a great dataset for training the network.

4.3.4 Splitting Images by Segments

Using the segmental image selection technique and after some experiments carried out on the models using this pre-processing technique, the idea arose of implementing a method that would divide the images into small time windows. (10s being defined as the time window).

The implementation of this pre-processing action can offer great advantages to the arrhythmia detection process, such as:

a. Equity In Data: the learning process of a model is fed only with images with the same time window.

b. Quality In the Data: the learning process of a model is fed with clearer images, which may lead to a greater ability to extract attributes by the algorithm.

c. Data: Augmentation: This technique of dividing images into segments is also part of the data: augmentation technique Using this technique, a recording of 30 seconds generates 3 images (of 10 seconds).

In Figure 4.5, an example of this image division by segments is presented. The original image (which corresponds to register A00001) appears with the original time length of 30 seconds. Below, 3 images appear, which are the result of the application of this technique, which correspond to the 10: second segments of that same record.

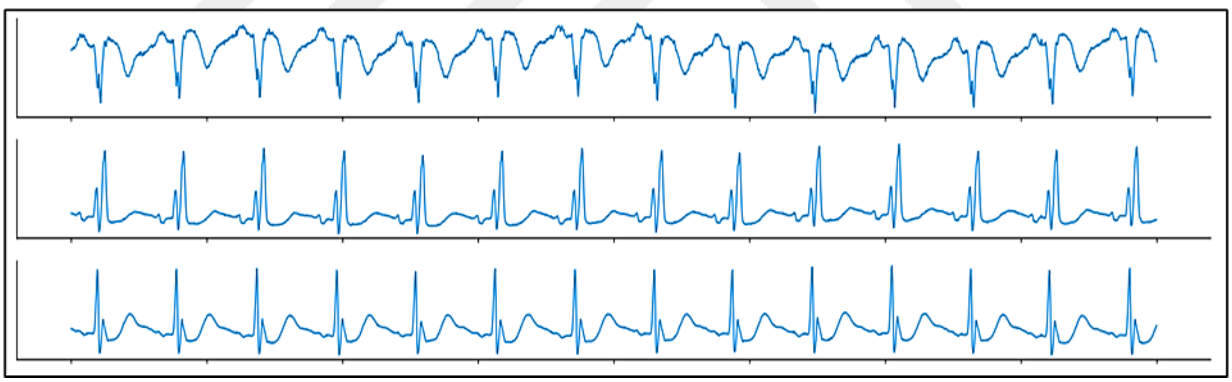


Figure 4.5: Image Division Into 10: Second Segments

The application of this pre-processing technique not only brings advantages, but also possible disadvantages. One of them is the possibility of information loss, which can be important for the classification of a record in a certain class. For example, a 30 second ECG recording may be classified as "Atrial Fibrillation", as the heart rhythm is irregular from 10 to 30 seconds, however, the first 10 seconds the rhythm appears to be normal. In the model learning process, this image, referring to the first 10 seconds of the recording, will be indicated as an example with "Atrial Fibrillation".

4.3.5 Model Architecture

In section 4.2, the initial approaches of the methodologies that were studied for the development of this project were presented, having selected the second approach, which used the deep learning methodology, through CNN.

As in the pre-processing phase, two approaches were followed in the implementation of the model, both using the same methodology (deep learning, using CNN), using ML library as an implementation framework in aid of the MATLAB language.

In each of these approaches, two models were implemented, with the same architecture. The first model is adapted to the problem described in this document, for multiclass classification (4 classes). The second model is adapted to a binary classification problem, that is, a problem of two classes only (with arrhythmia (RECALL) and without arrhythmia (normal rhythm, another rhythm and rhythm with noise together)). The decision to create this alternative in each approach arose to simplify the model learning process (from 4 to 2 classes), and in this way to improve the results of cardiac arrhythmia detection, and this is the problem that this work intends to help resolve.

It is important to mention that already known architectures were not used, such as AlexNet, as Alex Krizhevsky did in one of his projects The model architectures were designed and implemented from scratch, taking into account the existing dataset, as well as the hardware resources available for the execution of the model training. In this section, the procedures performed will be described, as well as the technical specifications of the architectures of the implemented models, in the different approaches. The first approach in the implementation of the neural network took into account the set of images generated in approach 1 (.bmp) of the pre:processing, at this point, when the model training process starts, it already has the list of generated images (96x96) from the original images (which have sizes from 2700x1 to 18,300x1)

Figure 4.5 shows the general architecture of the CNN model implemented in this first approach.

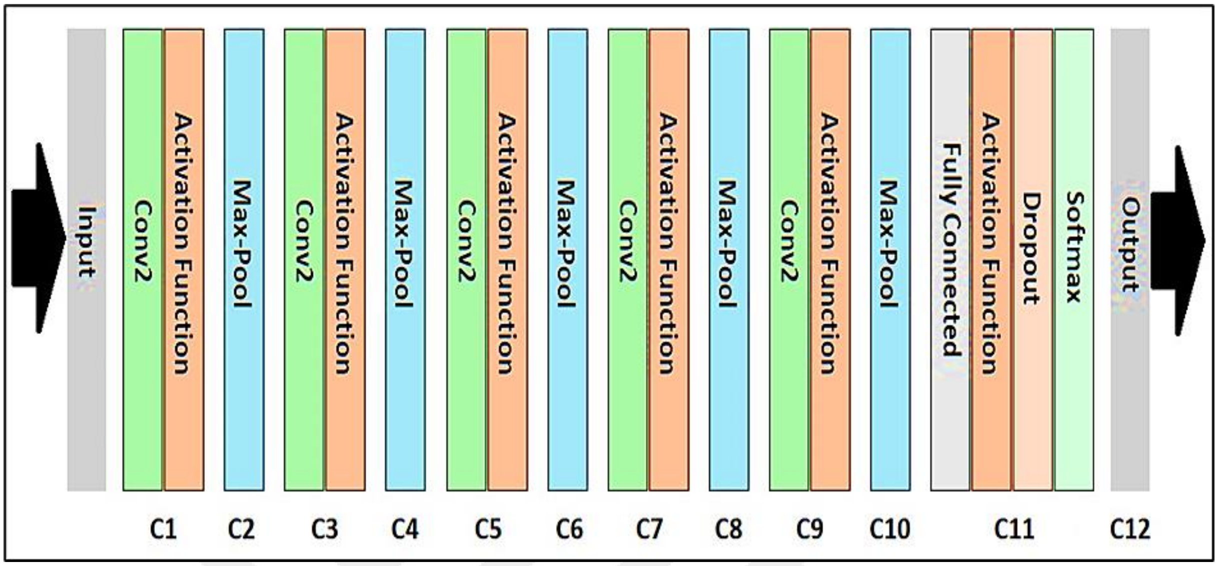


Figure 4.5: Architecture of The Neural Network

The neural network architecture is composed of 12 layers: 5 convolutional layers (C1, C3, C5, C7 and C9), where the activation function is always performed after convolution. After each convolutional layer, a pooling layer (max:pooling) follows, making a total of 5 layers as well (C2, C4, C6, C8 and C10).The penultimate layer (C11) is fully connected, being responsible for classifying the features obtained after the convolutional layers. This classification is followed by the dropout, which helps to avoid over:fitting the training data, and is then submitted to the softmax algorithm, which is responsible for producing the distribution over the various classes. It is also important to mention that the neural network uses an optimization function (training function) in order to update the parameters of the neural network and thus minimize the loss rate.

As can be seen in Figure 4.5, it is not defined which activation function is being used in the model. This is because it is not statically defined in the model, being parameterizable in the execution phase of the same. That is, when starting the execution of the model training, the activation function to be used is passed as an argument, and the model is prepared to receive one of the four functions described in section 3.1.7 (tanh, relu, sigmoid or softplus).

The same is true for the optimization function, which is an argument also submitted when the model is run. The model is also only prepared for the optimization functions described in section 3.1.8 (Gradient Descent or Adam).

Table 4.3 describes the detailed architecture of the CNN model, which is represented in Figure 4.5.

Table 4.3: Detailed Architecture of The Neural Network: Approach 1

Layer	Type	Kernel Size	Stride	kernel	Input Size
C1	Conv2D	5 x 5	1	32	96 x 96 x 1
C2	Max Pool	2 x 2	two		96 x 96 x 32
C3	Conv2D	5 x 5	1	64	48 x 48 x 32
C4	Max Pool	2 x 2	two		48 x 48 x 64
C5	Conv2D	5 x 5	1	128	24x24x128
C6	Max Pool	2 x 2	two		24x24x128
C7	Conv2D	5 x 5	1	256	12 x 12 x 256
C8	Max Pool	2 x 2	two		12 x 12 x 256
C9	Conv2D	5 x 5	1	512	6 x 6 x 512
C10	Max Pool	2 x 2	two		6 x 6 x 512
C11	Full: Connected			1024	3 x 3 x 1024
C12	output			4 / 2*	1024

* 4 for the 4:class model, and 2 for the binary model.

Briefly, the convolutional layers use 5x5 filters (Kernel Size) to calculate the features (Kernel represents the number of features), with a stride of 1 pixel, while in the max:pooling layers, the filter used in the pooling operation has a size 2x2, with a stride of 2 pixels.the implementation of the second approach arose from the need to improve the results presented by the first approach implemented. For this, new images were generated (with 512x512 resolution), preprocessed, as explained in that section, and a new neural network implemented, which will be described in this section.

At this point, when the model training process starts, it already has the list of images resized (112x112) from the original images (512x512).

Figure 4.6 shows the general architecture of the CNN model implemented in this first approach.

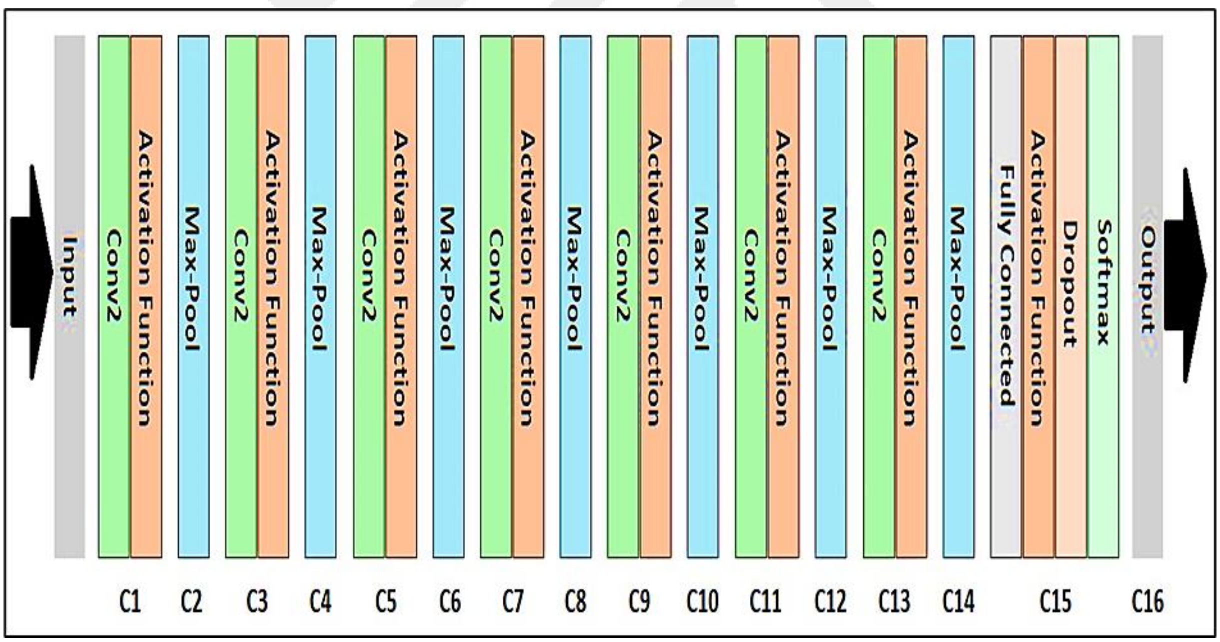


Figure 4.6: Architecture of The Neural Network

The penultimate layer (C15) is fully connected, being responsible for classifying the features obtained after the convolutional layers. This classification is followed by the dropout, being then submitted to the SoftMax algorithm, responsible for producing the distribution over the various classes. The neural network also uses an optimization function, in order to update the parameters of the neural network and thus minimize the loss rate.

As in the first approach, the activation and optimization functions are not statically defined in the model, they are submitted as parameters at the beginning of the model's learning execution. The model is prepared to receive one of the four activation functions described in section 3.1.7 (tanh, relu, sigmoid or softplus) as well as one of the optimization functions described in section 3.1.8 (Gradient Descent or Adam).

* 4 for the 4:class model, and 2 for the binary model.

As can be seen, the configurations of the neural networks referring to the two approaches are not completely different, presenting dissimilarities essentially in the number of layers, the input of data (size of the input images) and the number of characteristics that the network will extract in each image (kernel).

Figure 4.7: UI Of the Proposed Padigram

5. RESULTS OF THE SIMULATION

5.1 RESULT VALIDATION CONFIGURATION

To obtain the results of the implemented models, tests were carried out, based on the 10:fold cross: validation method. In each of the 10 possible combinations, 9 folds are used as training data and 1 as test data. The average value obtained from these 10 combinations will be considered as a result, for the different evaluation measures of the model. The validation configuration used is represented in Figure 5.1.

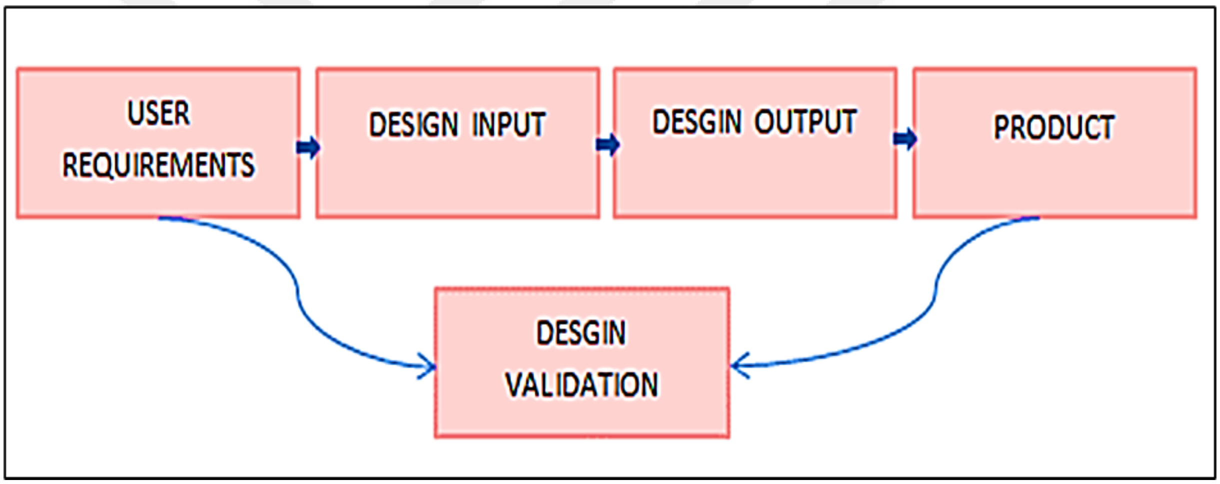


Figure 5.1: Outline of The Result Validation Configuration

To evaluate the results obtained in each of the classification models, some of the measures Fscore and Accuracy described are used.

In addition to the hit rate, the ACCURACY and F: Measure will be used as evaluation measures, and the confusion matrix will also be presented in the results of the 2:class models (binary classification). The use of the F: Measure measure will serve essentially for the purposes of comparison with the results of the contest participants since this was the evaluation measure used in the contest to define the models' scores. The ACCURACY measure will be used primarily because it is a very effective measure.

The comparison of these results, using the technique of dividing images into 10: second segments, with the results of the experiments of the other approaches, is carried out in section 0, making it possible to assess the influence of this pre-processing action. In Figure 5.2 is presented a graph that illustrates the variation of the average of the F: Measure of the 2 classes of the experiments carried out with this model, using the various activation functions (and using the Adam Optimizer training function), with the increase of the dataset size.

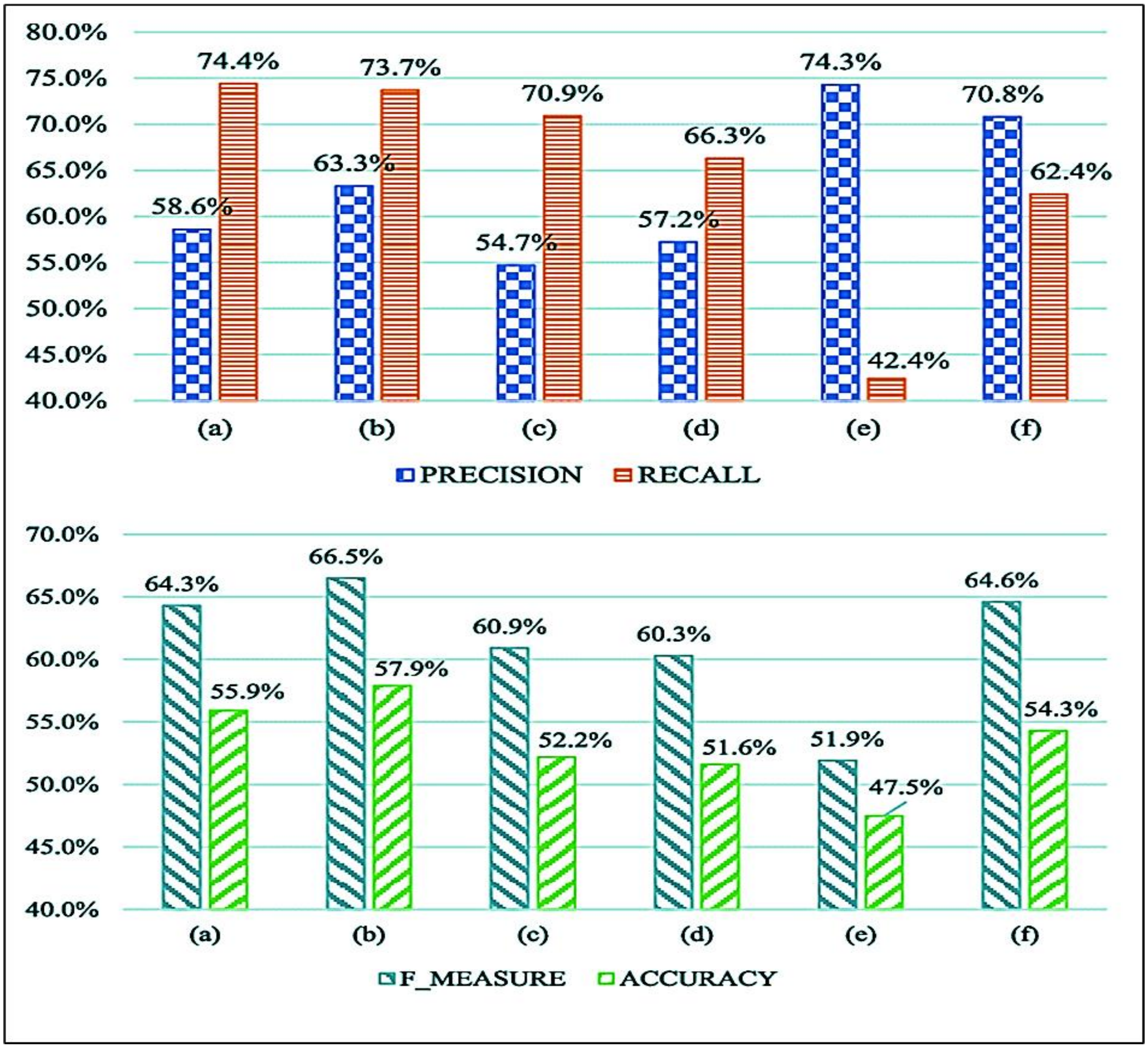


Figure 5.2: Variation of The Average of the F: Measure with Increase of The Dataset to Binary Classification (Segments Of 10 Seconds)

In Figure 5.2, the use of the activation functions Relu and Softplus in this binary model, gives rise to much better results compared to the other functions, as mentioned above. Using the Relu and Softplus functions, in addition to the results being very satisfactory, it is also visible that, throughout the experiments, with the increase in the number of input examples, the results improve several times. Contrary to what happened in the experiments carried out with the multiclass classification model (Figure 5.3).

The combination of the Tanh activation function with the Adam Optimizer training function also obtained very good results in experiments with 100, 200 and 400 training examples (above 0.80% in the various measures). However, with the increase in the number of examples, this presented a degradation in the results.

5.2 DISCUSSION OF RESULTS

In Figure5.3 and Figure 5.4 it is possible to visualize two graphs that present a summary of the best results obtained by each of the tested multiclass classification models, for the AVG evaluation measures F: Measure and F: Measure RECALL, respectively.

		PREDICTED classification				
	Classes	a	b	c	d	Total
ACTUAL classification	a	6	0	1	2	9
	b	3	9	1	1	14
	c	1	0	10	2	13
	d	1	2	1	12	16
	Total	11	11	13	17	52

Figure 5.3: Best Results For F:Measure Average : Multiclass Classification

		PREDICTED		
	Classes	Positive (1)	Negative (0)	Total
ACTUAL	Positive (1)	TP = 20	FN = 5	25
	Negative (0)	FP = 10	TN = 15	25
	Total	30	20	**50**

Figure 5.4: Best Results For F: Measure RECALL : Multiclass Classification

Analyzing Figure 5.3 and Figure 5.4, it is easy to see that, in general, the 2nd approach to the neural network architecture presents much better results than the 1st approach. In our opinion, this superiority is justified by the more complex network architecture, with more processing layers and by the set of more readable images with which this network is trained. /Tested. With the application of preprocessing techniques, image selection by 30:second segments or image division by 10:second segments in these models of the 2nd approach, it is still possible to observe a great improvement in results.

It is possible to visualize in the graph, this 2nd approach, only with the application of the data balancing technique (in red), the 2nd approach with the application of the image selection technique by 30:second segments (in orange) and finally, the 2nd approach with the application of the technique of dividing images into 10:second segments (in green).The 2nd approach, with the selection of images by 30:second segments, still proves to be the best approach to follow, achieving much better results compared to the other approaches. With the increase in the number of examples in the experiments, the results of this approach are increasingly distant (for the better) from the other approaches. This distance is not surprising, however, since, for a fixed segment length, the performance of models tends to improve as more examples are provided for training.

If we compare the results of the average of the F: Measure measure of the 4 classes with the results of the F: Measure of the RECALL class (Figure 5.4), it is possible to observe that the values of the FMeasure of this class are much higher than the values of the average. These data indicate that the models are more successful in classifying this class, that is, in detecting cardiac arrhythmias, compared to the other classes.

In Figure 5.5 and Figure 5.6, two graphs can be seen that present a summary of the best results obtained by each of the binary classification models tested, for the AVG evaluation measures F: Measure and F: Measure RECALL, respectively.

		PREDICTED classification				
	Classes	a	b	c	d	Total
ACTUAL classification	a	5	23	17	17	62
	b	10	540	21	14	585
	c	166	96	436	110	808
	d	1	2	5	87	95
	Total	182	661	479	228	**1550**

Figure 5.5: Best Results For F:Measure Average : Binary Classification

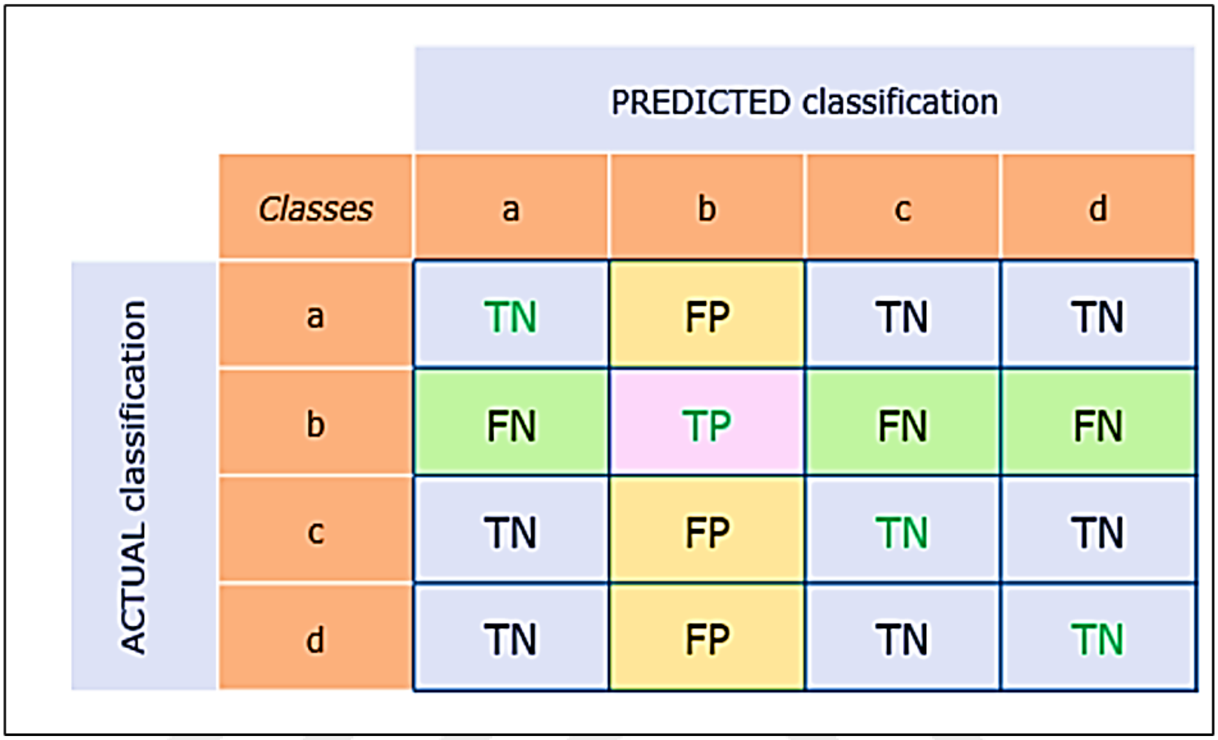


Figure 5.6: Best Results For F: Measure RECALL : Binary Classification

Figure 5.5 and Figure 5.6 show that, in the case of binary classification, the 1st approach presents slightly better results, compared to the other approaches, in the experiments with 100 and 200 examples. It obtains excellent results in these experiments, with the average F:Measure above 0.95%, and F:Measure of the class "with arrhythmia" above 96%. In experiments with larger data sets (over 200 examples) the 2nd approach proves to be superior in the success of classifying ECG records. The application of preprocessing techniques, image selection by segments or division of images by segments in these 2nd approach models, also presents improvements in the results, as in the classification multiclass. In this case, it is also important to mention that this alternative of binary classification models, despite slightly changing the problem described in this dissertation, arose to try to improve the arrhythmia detection process, since this is the main objective of this system. If we compare the graphs of Figure 5.3 with Figure 5.4 and Figure 5.5with Figure 5.6, it is possible to really notice a marked improvement in the results.

5.3 COMPARISON OF RESULTS WITH OTHER WORKS

Table 5.1 presents the results of some solutions developed by other authors to solve this problem, using the same dataset. The approaches followed by these authors can be seen in Table 5.1.The results are presented through the evaluation measure F:Measure, since this was the measure used in the contest to classify the solutions and thus define the ranking of the participants' results.

It should be noted that the results presented by these authors are the result of a test with 3,658 records, private to the tender (not available to the public), which were intended for testing Furthermore, in this work, data balancing techniques were applied, such as the selection of only a few records of each class, ignoring the others, to solve the large imbalance of the classes. When comparing the results obtained, this change to the initial problem must be considered. Therefore, due to these two conditions, these participants' results should be seen only as indicators, and cannot be directly compared with the solution developed within the scope of this dissertation.

Table 5.1: Results of Other Solutions

Authors	Classification Algorithm	Result
(Zabihi et al., 2017)	Random Forest	0.826%
(Xiong et al., 2017)	CNN	0.82%
(Zihlmann et al., 2017)	CRNN	0.82%
(Smolen, 2017)	RNN and GBM	0.81%
(Warrick et al., 2017)	CNN and LSTM	0.80%
Proposed	CNN With Segmentation	0.87%

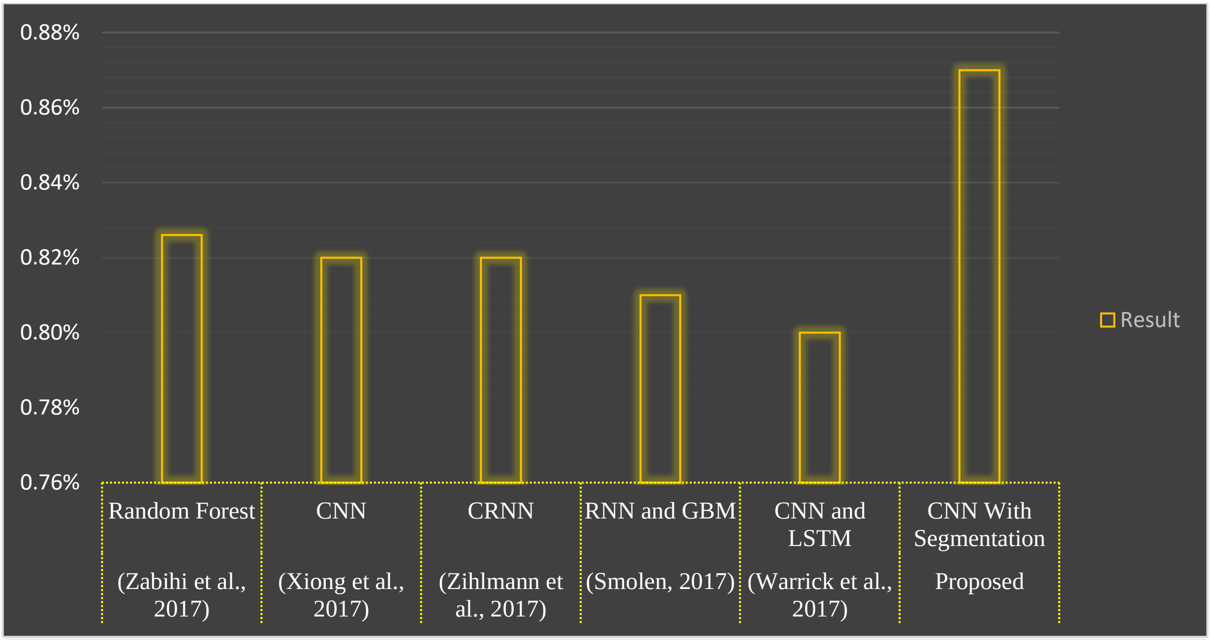


Figure 5.6: Comparison of Results with Other Works

6. CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The main objective of the work presented in this dissertation is to contribute to the development of a methodology capable of classifying signals resulting from the ECG, for the detection of cardiac arrhythmias in humans. In this way, this system can be used by health technicians, offering support in the decision on patient diagnoses, thus providing an improvement in their quality of life. In this document, a methodology was presented for the treatment of data obtained from electrocardiograms, using pre-processing techniques, and then applying and evaluating the different approaches of suggested classification models (using deep learning, more specifically Convolutional Neural Networks)The results obtained by the classification models show that the 2nd approach implemented obtains the most consistent results over the different experiments. This superiority on the part of the 2nd approach is achieved both in the multiclass model (referring to the original 4:class problem) and in the binary model (an alternative to improve arrhythmia detection results, this being the main objective). The application of the techniques of selecting images by segments or dividing images by segments in these models of the 2nd approach, still demonstrate a substantial improvement in the results. Several analyzes were carried out on the results obtained, namely with the measures of hit rate, ACCURACY and F:Measure. The best results obtained, Finally, considering all the work developed and the results obtained, we believe that this methodology could serve as a useful support for the development of systems for the detection and prediction of cardiac arrhythmias on ECG.

6.2 FUTURE WORK

With a view to continuing this work, the following points should be considered:

a. Make a better evaluation of the different parameters and configurations of the models, evaluating their possible improvements. Evaluate the variation in the number of epochs (greater than 10) and the distribution of training examples.

b. Test more data pre-processing techniques referred to in the literature. For example, the division of ECG recordings into several image segments, where each segment corresponds to an R peak of the ECG wave.

c. Improve the hardware of the machines used for the experiments, to be able to perform more complex tests, covering a larger set of data in the implemented models.

d. Optimize the implemented models, to reduce the execution time of a neural network training.

e. Extend this analysis to other types of heartbeats, to get more analysis classes.

b. Carry out more experiments, with larger and different sets of data, to consolidate the results obtained.

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