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Automated Heartbeat Classification and Cardiovascular Disease Detection Using Deep Learning

By:

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Defended on 25/06/2023 before the jury composed of:

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GHODBANE ROMAISSA

Abstract

by

GHODBANE Romaissa

The heart plays a crucial role in the body's overall functioning, and any injuries or abnormalities affecting the heart can have significant consequences throughout the body. One technique used to specifically assess heart injuries is the electrocardiogram (ECG), which records the heart's electrical activity over time. The ECG signal is a vital tool in clinical practice for evaluating the cardiac status of patients.

Detecting and classifying different types of ECG arrhythmias and heart disease categories is a complex task that requires advanced methods. This study proposed a system that utilized Machine Learning and Deep Learning algorithms to address this challenge. The system consists of two main steps: detecting arrhythmia types and detecting heart disease types.

We utilized comprehensive databases containing various arrhythmia classes and heart disease types to develop and evaluate the system. By leveraging the power of Machine Learning and Deep Learning, our system aims to provide accurate diagnosis and treatment options for patients with cardiac conditions. Through the analysis of ECG signals, the system can assist medical professionals in making informed decisions and improving patient outcomes.

Keywords:
Arrhythmia detection, Heart disease, classification, Electrocardiogram Machine Learning, Deep Learning, Diagnosis, Treatment.

Résumé

Le cœur joue un rôle crucial dans le fonctionnement global du corps, et toute blessure ou anomalie affectant le cœur peut avoir des conséquences importantes sur l'ensemble du corps. Une technique utilisée pour évaluer spécifiquement les lésions cardiaques est l'électrocardiogramme (ECG), qui enregistre l'activité électrique du cœur au fil du temps. Le signal de l'ECG est un outil essentiel dans la pratique clinique pour évaluer l'état cardiaque des patients.

Détecter et classer différents types d'arythmies ECG et de maladies cardiaques est une tâche complexe qui nécessite des méthodes avancées. Dans cette étude, nous proposons un système qui utilise des algorithmes d'apprentissage automatique et d'apprentissage en profondeur pour relever ce défi. Le système se compose de deux étapes principales :

''La détection des types d'arythmie'' et ''la détection des types de maladies cardiaques''.

Pour développer et évaluer le système, nous utilisons des bases de données complètes contenant différentes classes d'arythmie et types de maladies cardiaques. En exploitant la puissance de l'apprentissage automatique et de l'apprentissage en profondeur, notre système vise à fournir un diagnostic précis et des options de traitement pour les patients souffrant de maladies cardiaques. Grâce à l'analyse des signaux ECG, le système peut aider les professionnels de la santé à prendre des décisions éclairées et à améliorer les résultats pour les patients.

Mots clés:

détection d'arythmie, classification des maladies cardiaques, Électrocardiogramme, Machine Learning, Deep Learning, Diagnostic, Traitement.

ملخص

يلعب القلب دورًا مهمًا في الأداء العام للجسم ، وأي إصابة أو شذوذ يؤثر على القلب يمكن أن يكون له عواقب وخيمة على الجسم كله. أحد الأساليب المستخدمة لتقييم تلف القلب على وجه التحديد هو مخطط كهربية القلب (ECG).

الذي يسجل النشاط الكهربائي للقلب بمرور الوقت. كما تعد إشارة تخطيط القلب أداة أساسية في الممارسة السريرية لتقييم الحالة القلبية للمرضى.

ايضا يعد اكتشاف وتصنيف أنواع مختلفة من عدم انتظام ضربات القلب وأمراض القلب مهمة معقدة تتطلب طرقًا متقدمة. في هذه الدراسة ، نقترح نظامًا يستخدم التعلم الآلي وخوارزميات التعلم العميق لمواجهة هذا التحدي. يتكون النظام من خطوتين رئيسيتين: "الكشف عن نوع عدم انتظام ضربات القلب" و "الكشف عن نوع أمراض القلب".

لتطوير وتقييم النظام ، نستخدم قواعد بيانات شاملة تحتوي على فئات مختلفة من عدم انتظام ضربات القلب وأنواع أمراض القلب. من خلال تسخير قوة التعلم الآلي والتعلم العميق ، يهدف نظامنا إلى توفير التشخيص الدقيق وخيارات العلاج لمرضى القلب. من خلال تحليل إشارات تخطيط القلب ، يمكن للنظام أن يساعد المتخصصين في الرعاية الصحية على اتخاذ قرارات مستنيرة وتحسين نتائج المرضى.

الكلمات المفتاحية : كشف عدم انتظام ضربات القلب ، تصنيف أمراض القلب ، مخطط كهربية القلب ، التعلم الآلي ، التعلم العميق ، التشخيص ، العلاج.

Papers Under Preparation

- **Paper 1:** Heart Rhythm Abnormality Detection and Classification.

  Description: This paper aims to develop a system for the automatic detection and classification of heart rhythm abnormalities using Machine Learning and Deep Learning techniques. The research focuses on enhancing the accuracy and efficiency of detecting various types of rhythm abnormalities, ultimately aiding in timely diagnosis and treatment.

- **Paper 2:** Cardiovascular Disease Classification Using Machine Learning.

  Description: This paper focuses on developing a Machine Learning-based system for the classification of cardiovascular diseases. The research aims to explore different Machine Learning algorithms and their effectiveness in accurately categorizing heart diseases based on various diagnostic factors. The results of this study can contribute to improving the diagnosis and management of cardiovascular diseases.

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General introduction

The evaluation of cardiac health is crucial in clinical practice, with the electrocardiogram (ECG) signal serving as a vital tool for assessing patients' cardiac status. By capturing the variations in the heart's electrical activity over time, the ECG provides valuable insights into cardiovascular functioning and abnormalities. Accurate interpretation of ECG signals is essential for diagnosing and treating cardiac conditions effectively.

Classifying ECG signal beats plays a vital role in identifying various pathological cases, including arrhythmias and heart diseases. However, this task is complex due to the intricate nature of cardiac disorders. Arrhythmias, characterized by irregular heart rhythms, require precise recognition and classification into specific types. Understanding the underlying heart disease associated with these arrhythmias is crucial for accurate diagnosis and treatment.

The prevalence of cardiac malfunction and its impact on global mortality rates have spurred researchers to develop automated techniques for classifying cardiovascular diseases. Machine Learning and Deep Learning algorithms are powerful tools for analyzing large volumes of ECG data and extracting meaningful patterns for classification. These algorithms have the potential to enhance diagnostic capabilities and improve patient outcomes.

This thesis presents a comprehensive system for detecting and classifying ECG arrhythmias and heart diseases. The objective is to leverage Machine Learning and Deep Learning algorithms to detect arrhythmia types and classify associated heart disease categories. The system employs a multi-step approach, identifying abnormal cardiac rhythms and categorizing them into specific arrhythmia classes. Subsequently, it classifies ECG signals to determine the underlying heart diseases linked to the detected arrhythmias.

This research aims to contribute to cardiac diagnostics by providing accurate and timely insights into cardiac health. The proposed system assists clinicians in making informed decisions regarding diagnosis and treatment, reducing human error, enhancing efficiency, and promoting early detection of cardiac disorders.

Chapter 1

HEART AND ELECTROCARDIOGRAPHY

1.1 Introduction

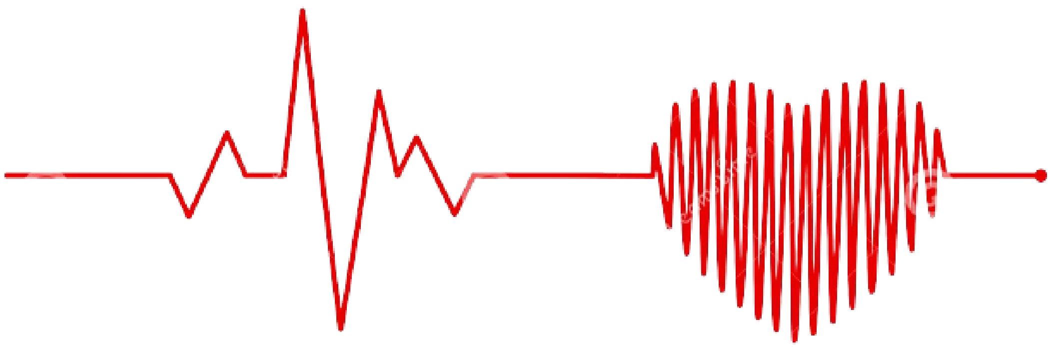
The human heart is one of the most vital organs in the body, responsible for pumping blood and delivering oxygen and nutrients to all parts of the body. Over the years, researchers and medical professionals have sought to better understand the workings of the heart and develop methods for detecting abnormalities.

Electrocardiography (ECG), a non-invasive test that measures the electrical activity of the heart, is one such technique. ECG becomes a crucial tool for identifying diseases. A variety of heart problems, including heart attacks, ischemia, and arrhythmias, offer insightful information on the heart's electrical behavior, overall as well as its rhythm and conduction.

In recent years, there has been an increasing interest in using deep learning techniques to analyze ECG signals and detect abnormalities in the heart's electrical activity. With the growing availability of large datasets of ECG recordings and advances in machine learning algorithms, deep learning has the potential to revolutionize the way we detect and diagnose heart conditions. By leveraging the power of artificial intelligence, we can enhance the accuracy and efficiency of ECG interpretation, leading to more timely and accurate diagnoses.

This chapter will provide an overview of the anatomy and physiology of the heart, the basics of electrocardiography, and the principles of deep learning. We will explore the current state-of-the-art in deep learning for ECG analysis and discuss the challenges and opportunities in this exciting field. By merging our understanding of the heart's structure and function with cutting-edge technology, we can unlock new insights and advancements in cardiac care.

I- CARDIOVASCULAR SYSTEM



1.2 Heart anatomy and circulation

The heart is a triangular pyramid-shaped muscle, representing the central part of the human body that supplies oxygenated blood to the whole body [25]. He has two chambers, the right heart, and the left heart. This muscle is located in the thorax between the two lungs as shown in Figure 1.1, it rests on the diaphragm in the anterior mediastinum, behind the sternum, and in front of the spine. Also, He can circulate 4 to 5 liters of blood permanently from birth until death [26].

Furthermore, the heart's remarkable ability to rhythmically contract and relax, known as the heartbeat, plays a crucial role in maintaining the continuous circulation of blood throughout the body [27].

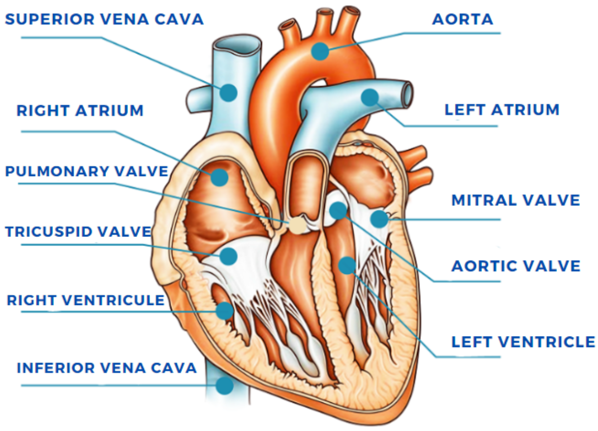


FIGURE 1.1: Heart anatomy.

The heartbeat or cardiac cycle includes the phase of the **contraction** called systole (see Figure 1.2) allowing the discharge of blood [28]. That of **relaxation** is called diastole. It allows the filling of blood. Here we find the heart rate which corresponds to the number of beats of the heart during a given period, usually one minute [29]. It varies under the impact of many parameters:

- sex;
- age;
- corpulence;
- the presence of a pathology;
- fitness;
- emotions.

Indeed, the cardiovascular manifestation most often found in the elderly is a decrease in maximum heart rate during exercise. On the other hand, at rest, this decrease in HR with age is much less clear [30].

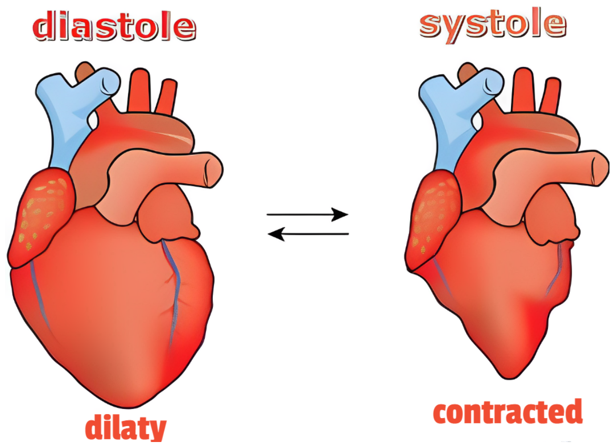


FIGURE 1.2: Systole and diastole of the heart.

1.2.1 Circulatory Trio: Blood, Pulmonary, and Systemic

The circulatory system plays a vital role in maintaining the body's overall function by ensuring the distribution of oxygen, nutrients, and waste products. It consists of three major types of circulation: blood circulation, pulmonary circulation, and systemic circulation [31]. Each type serves a specific purpose in maintaining a healthy and balanced internal environment. Let's now delve into the details of these circulatory processes and their distinct functions.

1- Blood Circulation To move blood through the body, the heart contracts and expands. This pumping action is well illustrated by the alternating clenching and unclenching of a fist. With each beat, the heart pumps blood into the arteries [32]. This is what creates the pulse as it is shown in Figure 1.3.

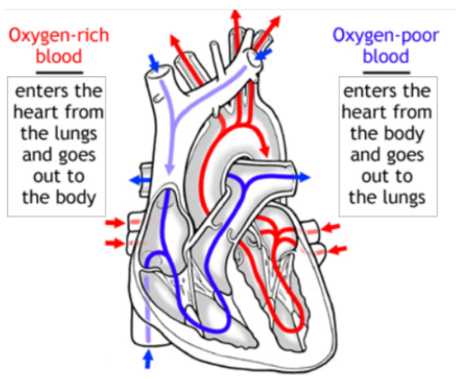


FIGURE 1.3: Blood circulation.

2- Pulmonary Circulation Pulmonary circulation, or small circulation, includes the atrium and the right ventricle (known as the right heart) [33] its function is to transport blood to the lungs where it gets rid of CO2 and takes in oxygen (see Figure 1.4). It is then redirected to the heart, in the left atrium, through the pulmonary veins [34].

3- Systemic Circulation Systemic circulation, also called large circulation, is a part of the cardiovascular system whose function is to bring the oxygenated blood which leaves the heart to all the organs of the body and then to return this venous blood [35] as shown in Figure 1.5.

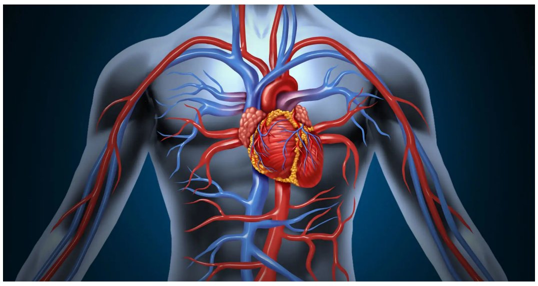


FIGURE 1.4: Pulmonary circulation.

FIGURE 1.5: Circulatory systemic.

1.3 Electrical Conduction System

Pumping is only effective when the heart contracts in synchronization. The atria must first be filled with blood, which must then be pumped into the ventricles before being forcibly expelled. A system of electrical conduction enables this cooperation [36].

The heart works automatically like all the other muscles in the body. It includes an automatic electrical conduction system, known as **"the electrical functioning of the heart"** Figure 1.6, that ensures each of its beats [1]. The contraction of the myocardium is caused by the propagation of an electrical impulse along the cardiac muscle fibers induced by the depolarization of the muscle cells [37]. therefore the electrical activity of the heart is the sum of the electrical activity of all the myocardial cells, each one behaving like an electric dipole with a positive pole and a negative pole [38].

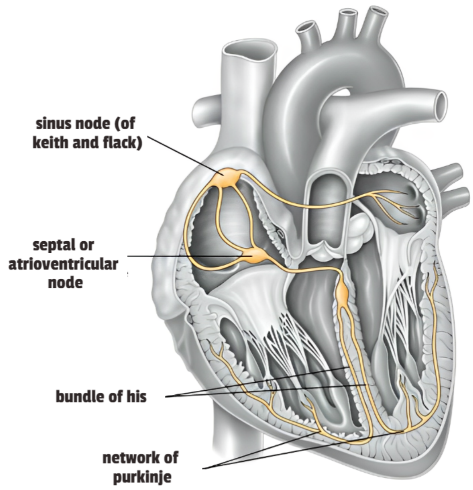


FIGURE 1.6: The electrical system of the heart [1]

- **Depolarization** At rest, the cardiac fiber is "polarized", positively charged on the outside, and negatively on the inside (A).
  A stimulation (see Figure 1.7) produces a modification of the permeability of the cell membrane with an inversion of the electrical charges, which become positive inside and negative outside the fiber [39].
  This depolarization will propagate along the fiber (B), which will thus be completely depolarized (C).
  It is transmitted to neighboring fibers and activates them in the same way. The propagation of the depolarization along the fiber is represented by a vector that indicates its direction, from negative to positive [33].

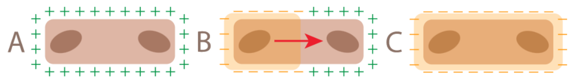


FIGURE 1.7: Cardiac fiber depolarization [2].

- **Repolarization** After the depolarization comes the repolarization of the fiber (A) which brings the electrical charges, on either side of the membrane, back to what they were at rest [39]. Like depolarization, this repolarization progresses along the fiber, either in the opposite direction (B) or in the same direction (C), with the same result, as shown in Figure 1.8.
  A positively charged fiber on the outside and a negatively charged one on the outside, interior (D) [40]. The arrow which, like depolarization, can represent repolarization, will have an opposite orientation, from positive to negative.

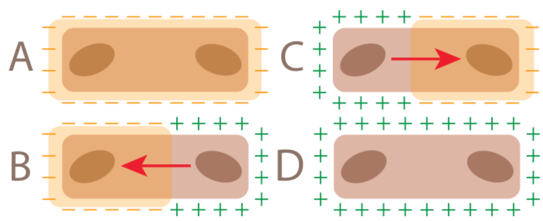


FIGURE 1.8: Repolarization of the myocardial fiber [2].

1.4 Cardiovascular Disease Cardiac Arrhythmia

In medicine, pathology is the science that deals with the study of diseases. It encompasses the understanding and examination of various medical conditions, including cardiovascular disease and cardiac pathology. It is worth noting that a relatively recent and popular misnomer is to make the word "pathology" a synonym of the word "disease" However, there is a distinction between the two [41]. Cardiovascular disease refers to a broad category of conditions affecting the heart and blood vessels, while cardiac pathology, specifically cardiac arrhythmia, focuses on abnormalities in the heart's electrical system. Understanding the nuances and differences between these entities is crucial for a comprehensive study of cardiovascular health [42].

1.4.1 Cardiovascular diseases

A leading cause of death worldwide, cardiovascular disease affects millions of individuals. Also, they are one of the deadliest health problems affecting the heart and blood vessels [43]. According to a report by the World Health Organization (WHO), in 2019, about 17.9 million deaths related to cardiovascular diseases were recorded [44] (see Figure 1.9). This represents **32%** of all global deaths and the highest of all non-communicable diseases. In addition, more than three-quarters of cardiovascular disease deaths occur in low- and middle-income countries [45].

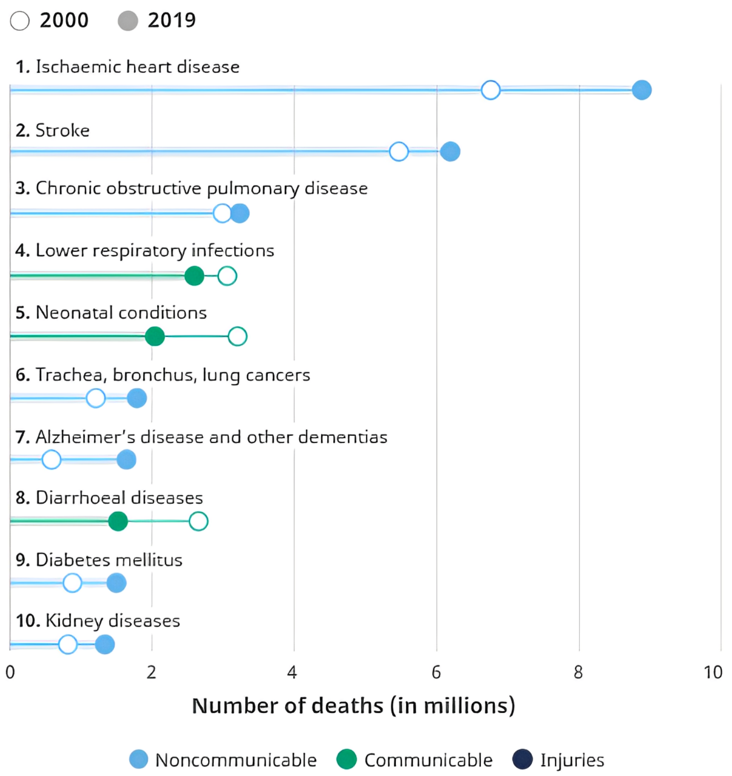


FIGURE 1.9: Leading causes of death in the world [3]

Clinicians diagnose heart disease by different techniques, including non-invasive methods, such as an electrocardiogram (ECG), and cardiac magnetic resonance imaging (MRI). Invasive techniques, such as blood tests, coronary computed tomography

angiography (CCTA), and coronary angiograms [46].
among these diseases, we distinguish:

- Coronary heart disease (affecting the blood vessels that supply the heart muscle).
- Cerebrovascular diseases (affecting the blood vessels that supply the brain).
- Peripheral arteriopathy (affecting the blood vessels that supply the arms and legs).
- Rheumatic heart disease, affecting the muscle and heart valves and resulting from acute rheumatic fever, caused by streptococcal bacteria.
- Congenital heart defects (malformations of the structure of the heart already present at birth).
- Deep vein thrombosis and pulmonary embolism (obstruction of the veins of the legs by a blood clot, likely to break free and migrate to the heart or lungs) [47].

The estimated prevalence of cardiovascular diseases depends on their definition, based on medical diagnosis, clinical manifestations, or subclinical symptoms. In the Lausanne population aged 65 to 70, a person in five has a diagnosed heart disease. Close proportions have been observed in population samples of similar age. The prevalence is higher for men and increases with age [48]. While 19% of women and 29% of men aged 65 or over participating in the Cardiovascular Health study present clinical signs of heart disease, the preclinical forms of these diseases are even more frequent: they were detected in 36% of men and 39% of women in the same age group. The authors of this study thus note that at the age of 85, heart disease, at a preclinical or clinical stage, is a rule to which only 13% of subjects escape [49].

Consequences for Life Quality and Functioning

The impact of cardiovascular diseases on the quality of life has been documented in several studies based on the Short Form 36 (SF-36) questionnaires developed for the Medical Outcomes Study [50]. Affected individuals present unfavorable scores on all dimensions of the SF-36 compared to subjects without chronic pathologies. When the analysis focuses on the consequences of various chronic diseases, heart disease falls into an intermediate group. Its impact is less pronounced than that of musculoskeletal or cerebrovascular diseases but more pronounced than that of psychiatric, dermatological, or urogenital pathologies [49].

Heart disease is also associated with a limitation of mobility and a loss of functional abilities, which can lead to dependence on the performance of activities of daily living as well as only to a decrease in the quality of life of people elderly [49]. 12 Determining the fraction of cases of functional disability attributable to cardiovascular disease is, however, a complex task, insofar as this parameter depends both on the prevalence of heart disease and their effect on functional status [51].

1.4.2 Cardiac pathologies

Each year, nearly 17.9 million people waste their lives due to this deadly disease Cardiac pathologies encompass a wide range of conditions that affect the heart and its normal functioning. One common example is arrhythmia, a disorder that disrupts the normal heart rhythm [33]. Arrhythmias can manifest as irregular heartbeats, either too fast (tachycardia) or too slow (bradycardia). If left untreated or poorly managed, arrhythmias can lead to serious complications and adversely impact an individual's health and well-being [52].

In addition to arrhythmias, there are various other cardiac pathologies that can significantly affect the heart's function. These conditions may include coronary artery disease, heart failure, valve disorders, and congenital heart defects, Each of these pathologies presents unique challenges and can have detrimental effects on cardiovascular health [53].

Treatments for cardiac arrhythmias, including arrhythmias related to cardiac pathologies, involve a multidisciplinary approach. Once the cause of the arrhythmia is known, specific treatment options are prescribed. These options may include medications to regulate or strengthen the heart, anticoagulant drugs, or the surgical placement of a pacemaker or automatic defibrillator [54]. In some cases, surgical intervention may be necessary to address the underlying electrical system abnormalities. Additionally, lifestyle modifications, such as quitting smoking, are often recommended to manage arrhythmias effectively.

Diagnosing cardiac pathologies, including arrhythmias, typically requires a comprehensive evaluation that encompasses medical history assessment, physical examination, imaging tests, and, if needed, specialized procedures. Once a diagnosis is made, suitable treatment approaches can be initiated to address the specific condition. These approaches may involve medications, lifestyle modifications, cardiac rehabilitation, medical devices, or in certain situations, surgical interventions [42]

Managing cardiac pathologies, including arrhythmias, requires the collaboration of various healthcare professionals, including cardiologists, cardiac surgeons, nurses, and other specialists [55]. Regular monitoring, follow-up appointments, and adherence to the prescribed treatment plans are crucial for effectively managing these conditions and minimizing their impact on the individual's quality of life [56].

Overall, understanding and addressing cardiac pathologies, such as arrhythmias, play a pivotal role in maintaining cardiovascular health and optimizing patient outcomes. By ensuring proper diagnosis, timely interventions, and comprehensive management, individuals with cardiac pathologies can lead healthier lives and reduce the associated risks [1,57].

Complications of heart rhythm disorders are of two types of:

- Cardiac complications: when they last and are not taken care of, cardiac arrhythmias end up tiring the heart. Eventually, heart failure may set in. It results in an inability of the heart to perform its function and adapt to the patient's daily activities [36].

- Vascular complications: the poor circulation of blood in the cavities of the heart promotes the formation of clots there. Clot fragments can break off and go into the bloodstream, causing cerebrovascular accidents (CVA), retinal disorders or pulmonary embolisms (this is called the "thromboembolic risk"). Long-term oral anticoagulants (blood thinners) can help prevent these complications. [55].

Diagnosis of cardiac arrhythmias

To diagnose an arrhythmia or find its cause, doctors use tests including:

- ECG: The ECG is the most commonly performed medical examination, because it is non-invasive, risk-free, inexpensive, and fairly rapid [39], in maximum it takes 10 min to get it and the doctor's diagnosis.

- Holter Monitor: Figure 1.10 shows a portable electrocardiogram the size of a postcard or a digital camera that will be used for 1 to 2 days. The test measures the movement of electrical signals or waves from the heart [7,58].

FIGURE 1.10: Holter Monitor for continuous ECG monitoring

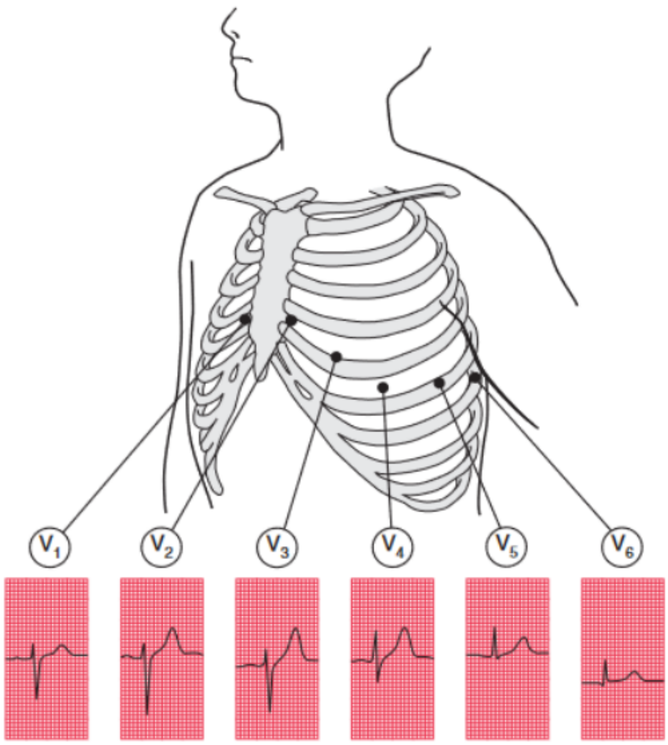
- Event Monitor: At the press of a button, it records and stores the electrical activity of the heart for a few minutes.

- Implantable Loop Recorder: The doctor places it at the level of the skin, where it constantly records the electrical activity of the heart.

- Electrophysiology Study: This test records the activities and electrical pathways of our hearts. It can help find out what's causing heart rhythm problems and find the best treatment [59].

In the following sections, we will delve into a detailed discussion about the various diagnostic tests used to identify and understand arrhythmias, including the commonly performed ECG.

II- ELECTROPHYSIOLOGY



1.5 Cardiac Rhythms

An essential tool in the everyday practice of clinical medicine, the electrocardiogram plays a fundamental role, ECG expresses the myocardial electrical activities of the heart [8].

It is obtained from a device called an electrocardiograph (Figure 1.11), which records the mechanical activity of the heart in the form of an electrical signal [60]. This signal is collected through metal electrodes which are well placed on the surface of human skin.

FIGURE 1.11: Electrocardiograph [4].

Also, it provides a lot of information about the normal and pathological physiological status of the heart.

The pattern of electrical impulses that regulate the heartbeat is referred to as cardiac rhythms [58]. They can be classified into sinus rhythm, representing a normal heart rhythm, and abnormal rhythms, indicating irregular or irregular heartbeats [61].

1.5.1 Sinus rhythm

Normal heart rhythm is controlled by a specific formation located in the right atrium, the sinus node [62]

ECG is an electrophysiological signal whose tracing materializes the electrical activities of the heart and is collected via metal electrodes well placed on the surface of the skin. It makes it possible to check the proper functioning of the heart in a patient, the nursing staff can visualize the graphic representation of the electrical activity of his heart [63].

ECG signal has a frequency range of 0.05 to 100 Hz and its dynamic band is 1 to 10 mV. It is classified as a non-stationary signal characterized by low amplitude, typically ranging from 10 µV to 5 mV. The sampling frequency is between 250 and 500 Hz [58].

The information recorded in this signal is presented as a series of electrical waves, with particular shapes and durations which are repeated at each cardiac cycle [5]

1.5.2 The waves of the ECG

Although the ECG does not directly record the electrical activity of the heart, the waveform reflects a potential change in the electric field on the surface of the body generated solely by the heart functioning as an electromotive source central to producing change.
On the ECG, all waveforms can be classified into two groups:
depolarization and repolarization. Ventricular depolarization is represented by the QRS complex and ventricular repolarization is represented by the T and U waves [64].

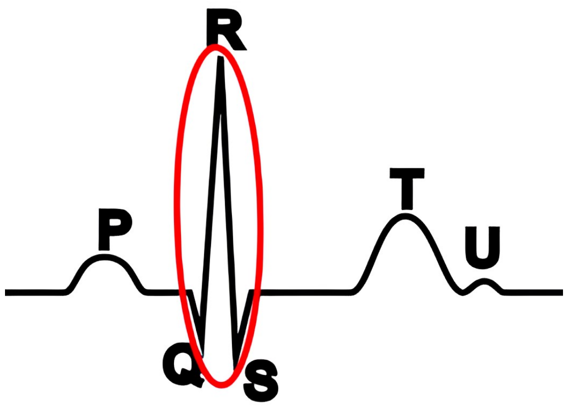


FIGURE 1.12: ECG waves [5]

So the normal heart rhythm is composed of waves (see Figure 1.12 generally related to mechanical actions of the heart, which are defined as follows:

- **The P wave** : (atrial depolarization) represents atrial depolarization or (atrial systole), the PR space or PQ space usually between 0.12 and 0.20 seconds.
- **The Q wave**: (polarization) when it exists, is the first negative deflection that follows exactly the P wave. Often the Q wave does not exist. Its duration can reach 0.2sec.
- **R wave**: (depolarization) represents the first positive deflection following the P wave; it is of great amplitude because the mass of the ventricles is greater than that of the atria.
- **The S wave**: (Polarization) This is a deflection located below the low amplitude baseline and is the second negative component in the QRS complex.
- **The T wave**: (repolarization) It corresponds to the end of ventricular contraction and the depolarization of the heart muscle. It is a positive wave, its amplitude is generally less than 2 mV [31].

Having discussed the various ECG waves, our attention now shifts toward the interpretation and analysis of ECG time intervals.

1.5.3 ECG Time Intervals

The process of depolarization and repolarization of the myocardial structures present in the ECG as a sequence of deflections or waves superimposed on a line of zero potential called the isoelectric line or baseline. These deflections are said to be positive or negative [1,65], all intervals are shown in Figure 1.13.

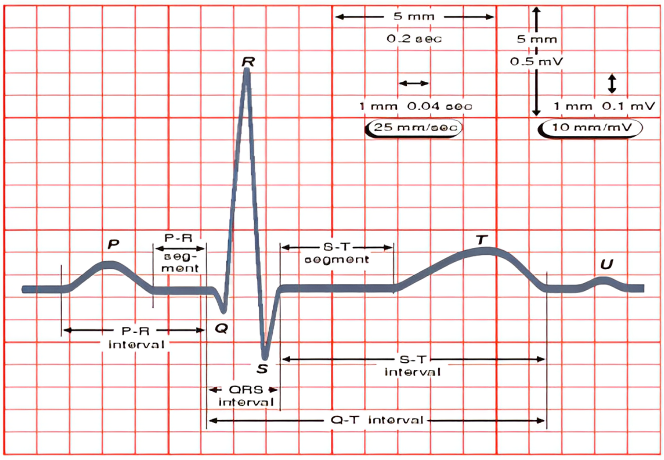


FIGURE 1.13: The different ECG intervals [6]

- **PR Interval**: This interval represents the conduction time from the sinus node to the end of the branches of the bundle of His (beginning of the ventricles as shown in Figure 1.14). It is measured from the beginning of the P to the beginning of the QRS. The normal duration is 120 to 200ms (Figure 8). A delay >200ms reflects a first-degree atrioventricular block [7].

- **QT interval**: It represents the distance between the beginning of the complex and the end of the T wave. It reflects the duration of the stimulation until the end of the ventricular relaxations. This interval is characterized by a duration between 0.3 and 0.44 seconds. A QT>450ms in men, and >470ms in women is considered pathological. [7].

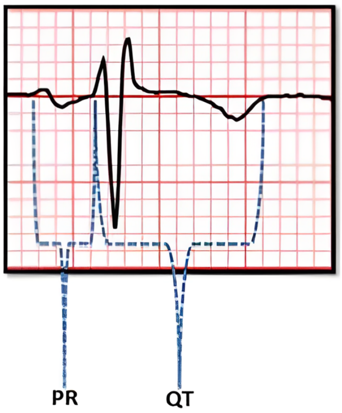


FIGURE 1.14: PR and QT Interval [7]

- **QRS complex**: It is a set of positive and negative deflections that correspond to the contraction of the ventricles [66]. For a normal case, it lasts less than 0.12 seconds and its variable amplitude is between 5 and 20 mV. It consists of three waves:
  - The Q wave: first negative deflection.
  - The R wave: first positive deflection.
  - The S wave: negative defection that follows the R wave. [5]

- **ST segment**: It represents the distance between the end of the QRS complex and the beginning of the T wave. It corresponds to the duration of the complete excitation of the ventricular cells [67]. In the normal case, the ST segment is normally isoelectric.
- **RR interval**: It is delimited by the peaks of two consecutive R waves and from which the instantaneous heart rate is evaluated. This interval is used for the detection of arrhythmias as well as for the study of heart rate variability [10].

1.5.4 Abnormal rhythm

An arrhythmia is a condition characterized by an irregular heartbeat, meaning that your heart deviates from its normal rhythm [68]. There are various types of irregular heartbeats, and doctors classify them based on their impact on the resting heart rate. Bradycardia refers to a heart rate below 60 beats per minute, while tachycardia signifies a heart rate exceeding 100 beats per minute. Figure 1.15, (a, b, and c) depict regular ECG signals, while (d, e, and f) represent abnormal ECG signals.

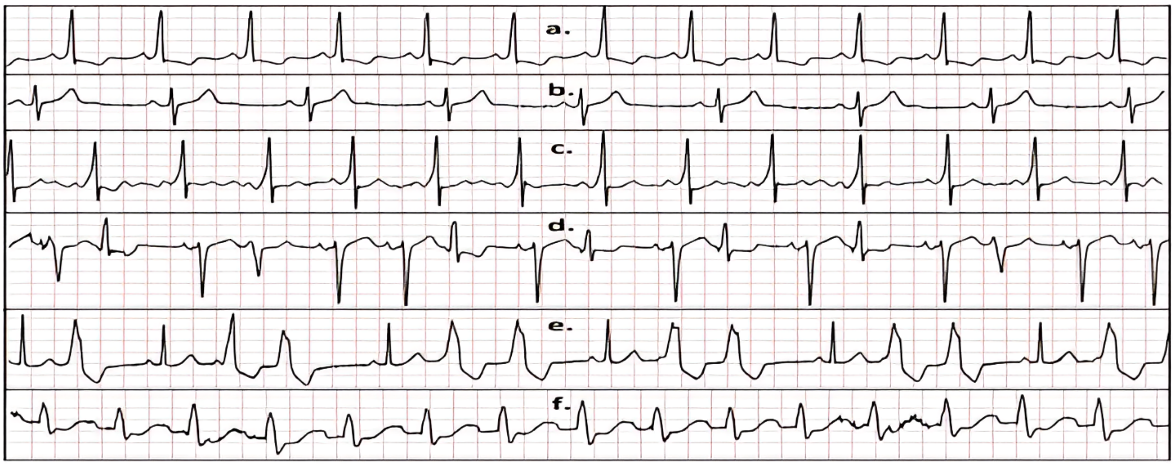


FIGURE 1.15: Regular and abnormal ECG signals [8]

Arrhythmias are classified based on their location within the heart. If they originate in the ventricles or the lower chambers of our heart, they are called ventricular arrhythmias. Conversely, if they start in the atria or upper chambers, they are referred to as supraventricular arrhythmias [49, 96]. [42, 69].

Supraventricular arrhythmias

the atria generate rapid, abnormal electrical impulses that do not contract normally.

- Atrial Fibrillation Among abnormal heart diseases, atrial fibrillation (AF) is the most common persistent arrhythmia and occurs in 1–2% of the total population [70].

  AF is defined by anarchic and rapid electrical activity of the muscle of the atria (upper chambers of the heart) [71].

- Atrial flutter (atrial) Atrial flutter is a regular rapid atrial rhythm secondary to an intra-atrial reentry macrocircuit. Symptoms include palpitations and sometimes asthenia, exercise intolerance, dyspnea and presyncope. Atrial thrombi may form and embolize. The diagnosis is based on the ECG [72].

- Atrial tachycardia Atrial tachycardia may originate from an ectopic focus, a loop of stimulation (flutter) or a pathway that short-circuits the AV pathway, known as the accessory pathway, with reentry through the AV node In the case of an ectopic focus, it is a group of cells located in the atria, which depolarize spontaneously and more quickly than the sinus, thus taking its place [1].

Ventricular arrhythmias

a feeling of irregular contraction of the heart that comes from the ventricles of the heart.

- Ventricular Fibrillation Ventricular fibrillation is a particularly serious arrhythmia, since it is a threat of sudden death, in fact the heart no longer does its pumping work at all, the blood no longer circulates, which leads to asphyxiation of all the tissues of the body, including the myocardium itself. Without immediate intervention (defibrillation), likely to resynchronize the depolarization of myocardial cells and thus "restart" the cardiac movement, death ensues [7].

- Ventricular Tachycardia Tachycardia is a condition that means having a rapid heartbeat. In this case, the frequency is greater than 100 bpm. This rapid heartbeat can be permanent or transitory. It is regular in the supraventricular or junctional states and irregular in the cases of ventricular fibrillation and auricular.

- Torsades de Pointes Torsade de pointes is a particular form of polymorphic ventricular tachycardia occurring in patients with pathological prolongation of the QT interval.

Bradycardia

Bradycardia is a heart rhythm disorder characterized by a rhythm slow heartbeat with a rate of less than 60 beats per minute.

- Heart block Heart blocks are due to a breakdown of conduction in the myocardium which impairs the depolarization. These ruptures can be more or less severe: slowing down (elongation of the travel time), intermittent (blocking of conduction occurs randomly), or complete (no conduction).
  A distinction is made between Sino-Auricular Block, Atrio-Ventricular Block, and Branch Block [10].

- Sinus disease It is an abnormality of the heart's natural pacemaker that causes a slow heart rate. It can cause a persistently slow heartbeat (sinus bradycardia) or complete cessation of normal pacemaker activity (sinus arrest). When activity ceases, another region of the heart usually takes over the function of the sinus node [1].

1.6 Electrode configurations

Electrocardiograph instruments make it possible to record several different potentials at the same time, depending on the location and number of electrodes distributed on the chest and organs. Each derivation of the ECG results from the measurement of these potential differences. The derivation system logically consists of a set of logically interdependent derivations [39]. Each is defined by the position of the electrodes on the patient's body, where they are placed to reveal nearly all of the electrical fields of the heart [10] (see Figure 1.16). The recording operation of a standard ECG is performed on 12 leads: six peripheral leads and the (six) thoracic ones [73], that records the aggregate electrical activity of the heart from distinct angles over some time, commonly 12 s [74].

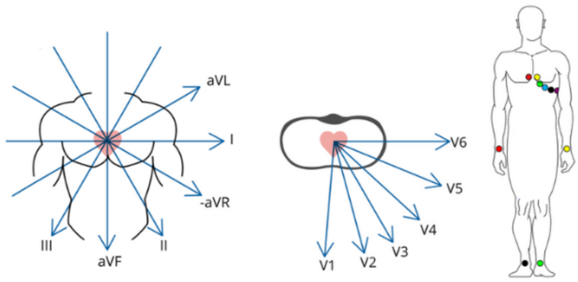


FIGURE 1.16: Electrode position [4]

12-lead ECG is the gold standard in ECG diagnostics and is used for resting and stress ECGs, Figure 1.17 shows the 12 records taked from thes 12 leads.

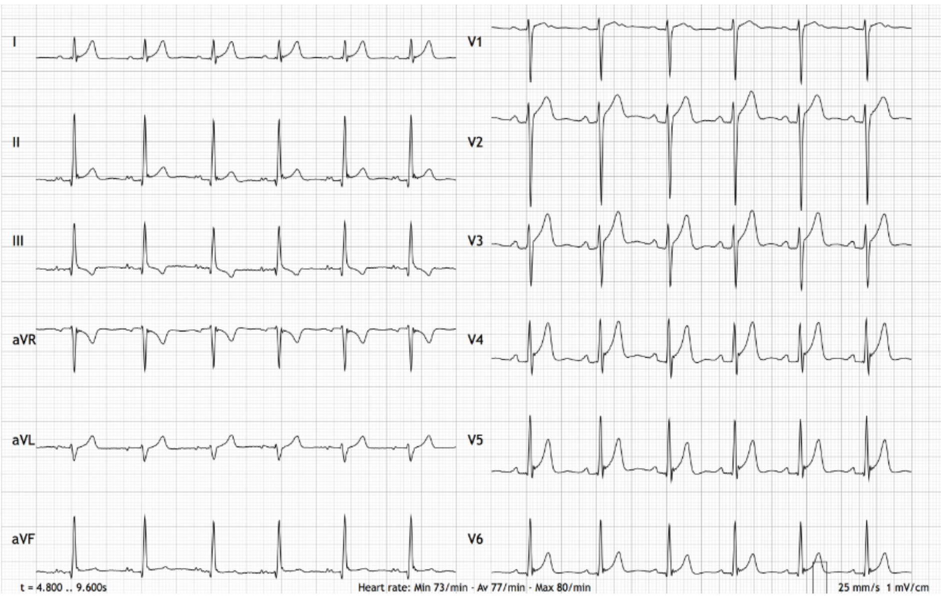


FIGURE 1.17: A standard 12-lead ECG of a single patient [9]

Frontal leads :

- Bipolar peripheral leads
- Unipolar Peripheral leads

1.6.1 Bipolar peripheral leads

Three bipolar leads or standard leads, DI, DII, DIII. These leads are called bipolar, standard [75] or limb leads because the electrodes are attached away from the pericardial surface. They monitor the electrical activity of the heart on the frontal plane. They consist of bipolar leads (DI, DII, DIII) [76], where the three electrodes are placed respectively on the right arm VR , the left arm VL and the left leg VF, obtained by permutation of the electrodes placed on the right arm, left arm and left leg [9]. The right ambe is connected to the mass, they are determined by Einthoven in 1912 [73] The obtained vectors form an equilateral triangle, called Einthoven's triangle (Figure 1.18).

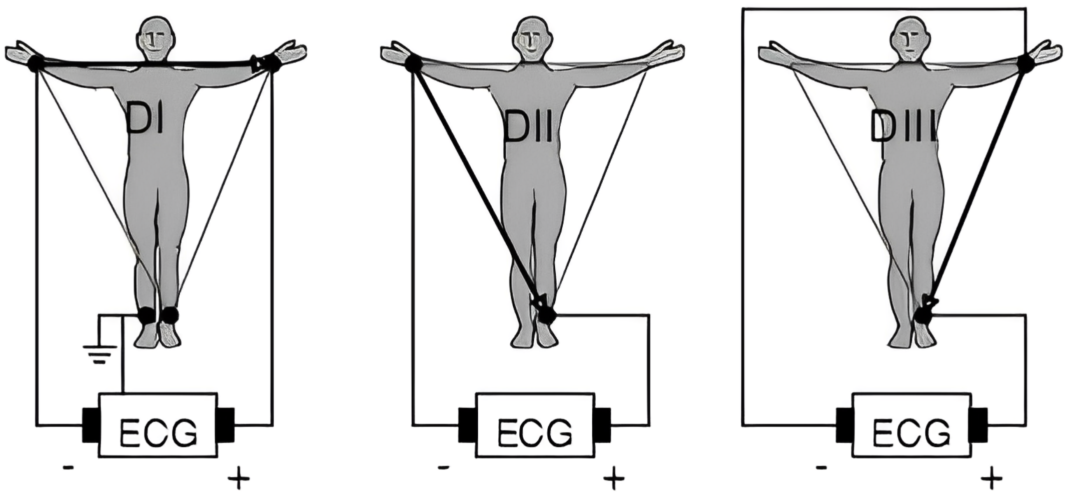


FIGURE 1.18: Standard leads DI, DII, and DIII (Einthoven's triangle) [1]

The electrodes are placed as follows:

- DI= VL VR
- DII=VF VR
- DIII=VF VL

According to Einthoven's triangle, the vector of the electrical activity of the heart consists of three measures:
The DI derivation: is the fusion of the image resulting from the electrode between the right arm (- pole) and the left arm (+ pole). It provides an electrical graph called (lead I).
The DII derivation: is the fusion of the image resulting from the electrode between the right arm (- pole) and the left leg (+ pole). It produces an electrical graph called (lead II).
The D III derivation: is the fusion of the image resulting from the electrode between left arm (- pole) and left leg (+ pole). It produces an electrical graph called (lead III).
ECG recording in bipolar leads shows that its three directions are similar because they record all positive P waves. The main part of the QRS complex is also positive [45, 63].

1.6.2 Unipolar peripheral leads

Three unipolar leads VR, VL, and VF (Figure 1.19) allow voltage measurement between a reference point and the right arm, the left arm and the left leg respectively [41]. The reference point is achieved by the average of the signals that appear on the other 2 members who are not under observation. For this purpose, resistors of value high, greater than 5M. Figure 5 shows the electrode connections as well as the directions along which the cardiac vector is measured, both for the leads unipolar than for standard leads [76,77]

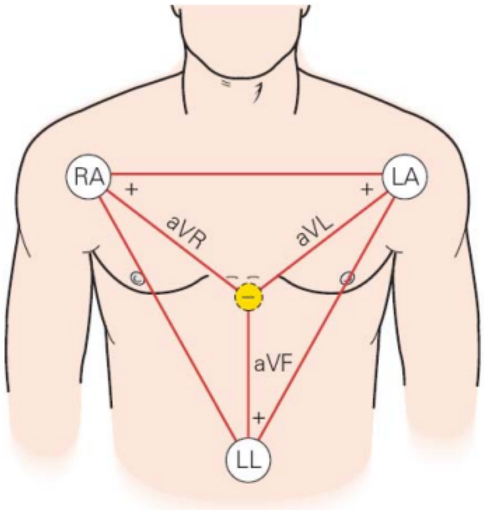


FIGURE 1.19: Unipolar leads [6]

In addition to the unipolar peripheral leads, the interpretation of ECGs also involves the examination of the precordial leads, which include the horizontal branches that provide valuable insights into the electrical activity of the heart.

These are **unipolar leads** developed by Wilson (Wilson et al, 1944) . They are consisting of six leads (v1 to v6) which show the electrical activity of the heart horizontally and from different angles [75]. Sensors are placed around the region of the heart, they are designated by the letter V followed by the number of their location from right to left [78]. The position of the precordial electrodes is therefore as follows (Figure 1.20) :

- **V1** is placed on the 4th right intercostal space, at the right border of the sternum.
- **V2** is placed on 4 th left intercostal space, at the left border of the sternum.
- **V4** is placed on 5 th left intercostal space, on the mid-clavicular line.
- **V3** is placed between V2 and V4.
- **V5** is placed on 5 th left intercostal space, on the anterior axillary line.
- **V6** is placed on 5 th , left intercostal space, on the mid-axillary line.

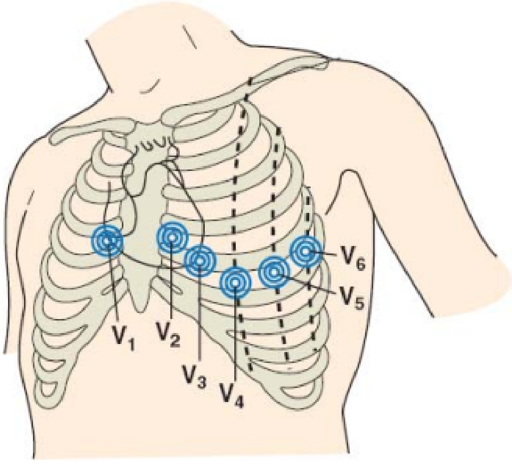


FIGURE 1.20: The position of the precordial electrodes [10]

1.7 ECG signal acquisition

The acquisition of the ECG signal is based on the identification of the peak R relative to the QRS complex which plays an important role for the diagnosis of a patient's heart condition [8].

An electrocardiogram is obtained by measuring the electrical potential between different points of the body using a biomedical instrumentation amplifier [33]. Electrical signals from the heart are recorded from a special combination of recording electrodes. It is necessary to place the electrodes on the surface of the body to detect the depolarization of the excitable myocardium. When one or both electrodes are in contact with the heart, the ECG electrodes are called direct. When the electrodes are placed at a distance of more than two cardiac diameters of the heart, leads are called indirect [79,80].

The electrodes are placed directly on the skin, held in place by adhesive tabs, on each of the four limbs and on the chest according to the standard layout shown in Figure 1.21. The right leg electrode is not not used for measurement but serves as an electrical ground [8].

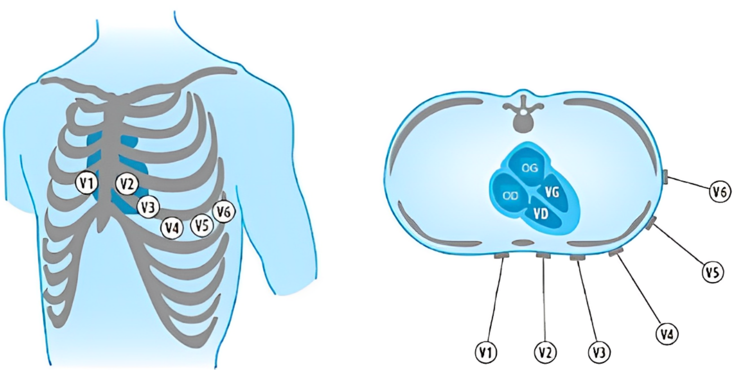


FIGURE 1.21: Precordial electrodes

1.8 ECG signal noise and variability

Noise, defined as any unwanted signal that hampers the clarity of a useful signal, poses a significant challenge in signal interpretation. Specifically, in the context of ECG (electrocardiogram) signals, noise manifests as spurious signals that can adversely impact the quality of the signal, thereby complicating its interpretation.
The presence of noise in ECG signals arises from various sources, and it is essential to identify and categorize the different types of noise for effective signal processing and diagnostic accuracy. During the acquisition of the ECG signal, the electrocardiographic tracing may be susceptible to the emergence of undesirable artifacts, further exacerbating the problem.
This becomes particularly problematic in automated signal processing systems, where the presence of these noise artifacts can introduce errors in the diagnostic process. Classifying these noises based on criteria such as technical noises and physical noises is a common approach employed in addressing this issue [81].

1.8.1 Technical noises

Technical noises are noises that are caused by the equipment used during registration and the most common of which are [31]:

1. **Network noise 50Hz** this is a noise that comes from the power supply by the distribution network electric. It contaminates the ECG electrocardiographic signal with oscillations whose fundamental harmonic is at 50 Hz. Generally, this type of noise appears throughout the recording (Figure 1.22), and can be quite loud but it is eliminated easily with a selective filter because it is a narrow band of high-frequency noise [82].

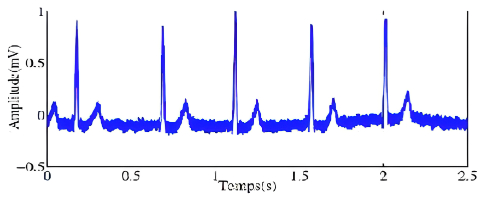


FIGURE 1.22: ECG signal disturbed by the 50Hz network [6]

2. **Noises due to the movements of electrodes** when the electrodes used are connected incorrectly [82], come off or gel between the electrode and the skin get dry, it can build up a noise that causes changes on the amplitude of the ECG signal [31] (see Figure 1.23).

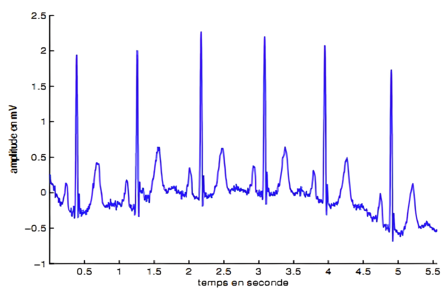


FIGURE 1.23: ECG signal with electrode movements [10].

3. **Noise generated by muscle contraction** the contraction of a muscle is controlled by the depolarization of muscle cells. This wave of depolarization can be captured by the electrocardiograph with the heart signal (Figure 1.24), causing a change in signal voltage of approximately 1mV [75].

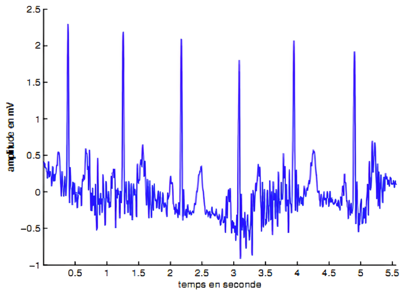


FIGURE 1.24: ECG signal noisy by muscle contraction [11]

1.8.2 Physical noises

Physical artifacts are due to the electrical activities of the human body such as commands of muscle contraction or breathing.

1. **Baseline Movements** the baseline is the horizontal line taken as a reference to study the shape and amplitude of the different cardiac waves [82]. During ECG recording as it is shown in Figure 1.25, respiratory activity may cause the ECG baseline at a steady rate. Other disturbances can also affect, for example, poor contact between the skin and the electrodes [10].

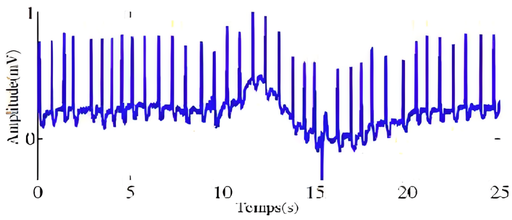


FIGURE 1.25: Base line movements [6].

2. **Noises due to the EMG electromyogram signal** this noise is due to muscle activity. It appears especially when the patient is lying badly [83]. These disturbances are quite bothersome when the patient moves a lot [10] or when he shivers, they can drown out the P and T waves and prevent a reliable diagnosis (Figure 1.26).

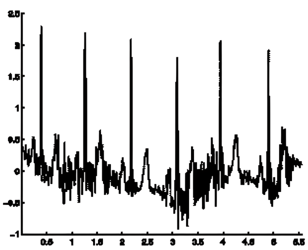


FIGURE 1.26: EMG electromyogram signal [10].

3. **Other Physical Artifacts** ECG electrocardiographic signal can be affected by certain diseases such as hyperthyroidism, ischemia, and hypokalemia.
   As well as the use of certain medications which can modify the appearance of the ECG tracing, including digoxin which blocks AV conduction and slows the heart rate and digitalis which causes ST segment depression with inversion of T waves and tends to shorten the QT interval [31].

Noise reduction techniques can be applied in conjunction with the STFT to mitigate physical or technical noise in a signal. These techniques may involve filtering, spectral subtraction, or other methods to suppress unwanted noise components. The STFT can be a valuable tool in analyzing the noise characteristics in the time-frequency domain, which can inform the selection and application of appropriate noise reduction algorithms.
Short-Time Fourier Transform STFT is a signal processing technique that enables the analysis of non-stationary signals by computing the Fourier Transform for small time windows, thus providing information about both time and frequency. STFT finds utility in various applications such as speech processing, music analysis, and biomedical signal analysis [84].

1.9 Conclusion

In conclusion, the heart is a complex and vital organ that plays a crucial role in maintaining overall health and well-being. Electrocardiography is an important technique for detecting abnormalities in the heart's electrical activity, and recent advances in deep learning have shown great promise in improving the accuracy and efficiency of heart abnormality detection.

By combining the principles of deep learning with the knowledge of the heart's physiology and electrical system, researchers and medical professionals have the potential to develop new and innovative approaches for detecting and diagnosing heart conditions. However, there are still many challenges that need to be addressed, such as the need for larger and more diverse datasets, the development of robust deep learning algorithms, and the integration of these techniques into clinical practice.

Despite these challenges, the potential benefits of deep learning in ECG analysis are clear. With continued research and development, deep learning has the potential to significantly improve our ability to detect and diagnose heart conditions, ultimately leading to better outcomes and improved quality of life for patients.

Chapter 2

Convolutional Neural Networks for ECGs classification

2.1 Introduction

In recent years, artificial intelligence (AI) has emerged as a powerful tool with the potential to revolutionize various aspects of healthcare, including the diagnosis, classification, and identification of diseases. The integration of AI algorithms, particularly in medical imaging, holds great promise for improving patient outcomes and streamlining clinical decision-making processes [85]. However, the implementation of AI in healthcare faces challenges related to the reliability and interpretability of clinical decision support systems.

To address these challenges, researchers have turned to machine learning techniques, specifically Convolutional Neural Networks (CNNs), for developing robust and accurate models for ECG image classification [86].

This chapter focuses on the application of CNNs for ECGs classification. Electrocardiograms (ECGs) are vital tools for diagnosing cardiovascular conditions and monitoring heart health. CNNs offer a promising solution by leveraging their ability to automatically learn and extract meaningful features from ECG images, enabling accurate classification and analysis [87].

Throughout this chapter, we will delve into the fundamentals of CNNs, exploring their architecture, training process, and key components. We will discuss how CNNs can be applied to ECG image classification, providing insights into the benefits and challenges associated with this approach.

By understanding the principles and applications of CNNs for ECG classification, healthcare professionals, researchers, and developers can harness the power of AI to enhance diagnostic accuracy and improve patient outcomes in cardiovascular care.

2.2 Machine Learning

In the realm of traditional methods, techniques such as Linear Regression (LR), Random Forest, and Decision Trees have long been employed to tackle various tasks. While they have provided valuable insights and results in certain scenarios, their limitations became apparent when dealing with complex and high-dimensional data.

These traditional approaches often struggled to capture intricate patterns and relationships, leading to suboptimal performance and limited accuracy.

However, the advent of deep learning has revolutionized the field by offering remarkable advancements in a wide range of domains. Deep learning, a subset of machine learning, leverages artificial neural networks with multiple layers to automatically learn hierarchical representations from data. This enables the models to discern intricate patterns, extract meaningful features, and make highly accurate predictions.

Traditional machine learning methods have made significant strides in various fields. They have proven to be effective in tasks such as image recognition, computer vision, natural language processing, and more. These methods have greatly enhanced object detection, image classification, language translation, sentiment analysis, and speech recognition. Additionally, their applications extend to domains like healthcare, finance, autonomous driving, and recommender systems (see Figure 2.1). By processing extensive datasets and uncovering intricate patterns, traditional machine learning has opened up new realms of possibility and paved the way for advancements in numerous fields [88].

As we move forward, the power of deep learning is expected to grow even further. With advancements in hardware capabilities, availability of large datasets, and ongoing research, deep learning continues to push the boundaries of what is possible, enabling us to tackle increasingly complex problems and achieve breakthrough results in diverse domains [45].

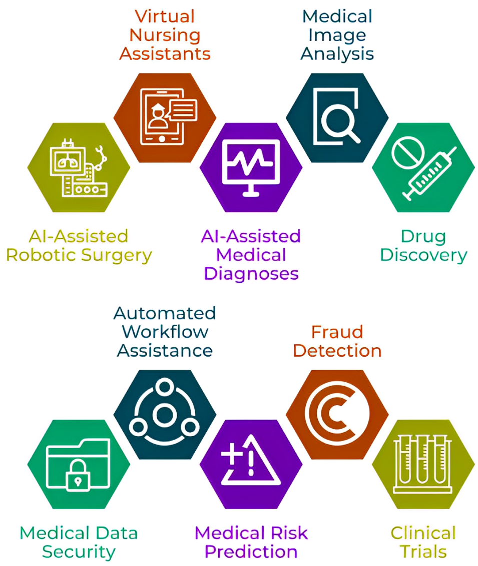


FIGURE 2.1: 10 Applications of AI in HealthCare [12]

2.3 Deep Learning and their architectures

Deep learning, a subset of machine learning, has emerged as a transformative approach in the field. By utilizing artificial neural networks with multiple layers, deep learning models can automatically learn intricate patterns and extract meaningful features from complex and high-dimensional data (Figure 2.14).

This capability has revolutionized tasks such as image recognition, natural language

processing, and various other domains [89].
Deep learning's ability to uncover hidden relationships and deliver exceptional accuracy has made it an indispensable tool in modern machine learning, driving innovation and breakthroughs across industries.
Deep analysis is needed to extract all useful information from huge datasets [90].

Traditional classification techniques perform poorly with large dynamic datasets because they cannot account for a variety of states in the data.

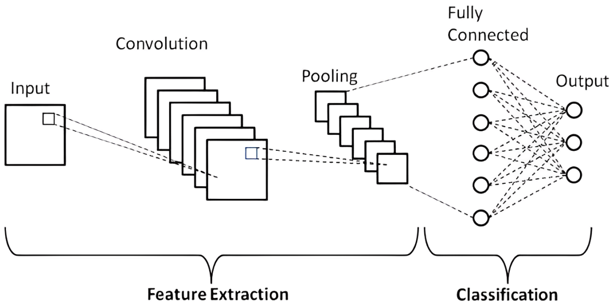


FIGURE 2.2: Neural Network Architecture Diagrams [13]

There are various **deep learning architectures** that have demonstrated successful applications in diverse domains. Here are some well-known examples:

2.3.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) have a notable history in deep learning, initially introduced by Fukushima in 1980 and later improved by LeCun et al. These networks are characterized by their deep structure, comprising multiple hidden layers and parameters, allowing them to effectively learn complex features from data [91].

CNNs have gained widespread usage in image classification tasks, where they have demonstrated remarkable effectiveness. By automatically learning hierarchical representations through convolutional and pooling layers, CNNs excel at capturing local patterns and extracting meaningful features from images. They have significantly advanced computer vision applications, including object detection, segmentation, and recognition.

One powerful aspect of CNNs is transfer learning, which involves leveraging pre-trained models on large-scale datasets to tackle new tasks. By reusing learned representations and fine-tuning specific layers, transfer learning enables efficient utilization of existing knowledge. This approach is particularly valuable when dealing with limited labeled data or when addressing new domains or tasks [86].

Within CNNs, various layers play essential roles in extracting features and learning representations from data. These layers include convolutional layers, pooling layers, fully connected layers, and activation function layers as shown in Figure 2.3. Each layer contributes to the network's ability to capture local patterns, downsample data, integrate information, and introduce non-linearities.

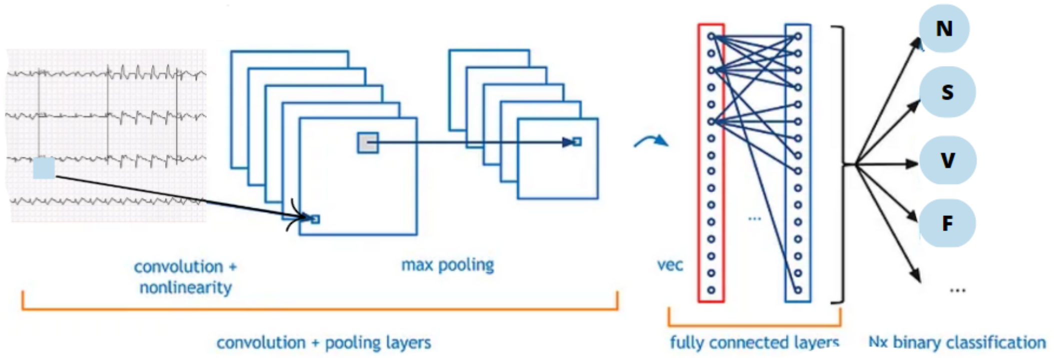


FIGURE 2.3: Convolutional Neural Network.

- Convolutional Layer: The convolutional layer is the core component of a CNN. It applies filters to the input data, performing local operations that capture spatial patterns and extract relevant features. The layer uses sliding windows called kernels to perform convolution operations and produce feature maps.

- Pooling Layer: The pooling layer is used to downsample the feature maps generated by the convolutional layers. It reduces the spatial dimensions of the data by selecting the most important information. Max pooling is a commonly used technique, where the maximum value within a small region (pooling window) is retained, effectively highlighting the most dominant features.

- Fully Connected Layer: The fully connected layer is typically placed at the end of the CNN architecture. It connects every neuron from the previous layer to every neuron in the current layer. This layer integrates the extracted features and learns complex patterns, enabling the network to make final predictions.

- Activation Function Layer: The activation function layer introduces non-linearities to the network. Rectified Linear Unit (ReLU) is a widely used activation function that helps the network model complex relationships within the data. It introduces non-linearity by transforming negative values to zero, and positive values remain unchanged.

- Output Layer: The output layer is the final layer of the CNN that produces the desired predictions. Its structure depends on the specific task. For classification tasks, softmax activation is commonly used to generate probabilities for each class, while for regression tasks, a linear activation function is often employed.

2.3.2 Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNN) are a type of neural network architecture that excels in processing sequential and temporal data. Unlike traditional feedforward neural networks, RNNs have loops within their structure, allowing them to maintain a memory of past information while processing new inputs. This memory-like capability enables RNNs to capture dependencies and patterns over time, making them particularly well-suited for tasks such as natural language processing, speech recognition, and time series analysis [92].

The key feature of RNNs is their ability to handle sequential data by propagating information through time. At each time step, an RNN receives input and updates its internal hidden state, which serves as a memory of the past. This hidden state is then used to generate an output (see Figure 2.4) and also serves as input for the next time step, allowing the network to incorporate contextual information from previous steps [93].

The recurrent nature of RNNs allows them to model long-term dependencies and context within a sequence, making them powerful tools for tasks like language modeling, machine translation, sentiment analysis, and speech recognition. However, standard RNNs can suffer from the vanishing gradient problem, where gradients diminish as they propagate back in time, limiting the network's ability to capture long-term dependencies.

To address this limitation, variants of RNNs have been developed, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), which incorporate specialized gating mechanisms to selectively retain and update information [94]. These gated RNNs have proven to be effective in mitigating the vanishing gradient problem and have become popular choices for various applications.

Overall, RNNs and their variants have significantly advanced the field of sequential data processing. Their ability to model temporal dependencies and capture context over time makes them essential tools for tasks that involve sequences, offering valuable insights and enabling breakthroughs in a wide range of domains

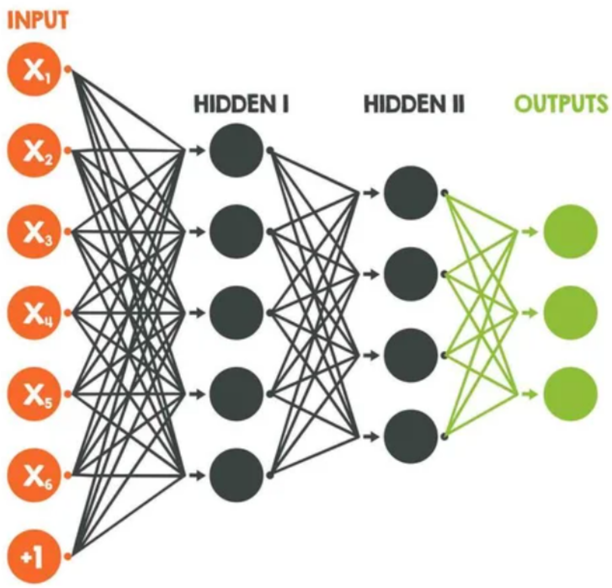


FIGURE 2.4: Artificial Neural Network.

These parameters, such as the learning rate, batch size, epochs, early stopping, and optimizer, are crucial components in training an artificial neural network (ANN) to achieve accurate predictions or classifications.

- **Learning rate:** The learning rate determines how quickly the model adjusts its parameters during training. A high learning rate may cause the model to overshoot the optimal parameters, while a low learning rate may result in slow convergence or suboptimal results.
- **Batch size:** The batch size refers to the number of training samples used in each forward and backward pass during training. Larger batch size can result in faster convergence, but it may also require more memory and computing resources.

- **Epochs:** The number of epochs is the number of times the model goes through the entire training dataset during training. Increasing the number of epochs can improve the accuracy of the model, but it may also increase the risk of overfitting to the training data [95].
- **Early stopping:** Early stopping is a regularization technique used to prevent overfitting by stopping the training process early based on a predefined criterion. This callback is used to monitor the validation loss and stop the training process if the loss does not improve for a specified number of epochs.
- **Optimizer:** The optimizer is the algorithm used to update the model parameters during training. For example, Adam optimizer, SGD,...etc

2.3.3 Transfer Learning

Transfer learning, a powerful technique in the realm of CNNs, has revolutionized the field by leveraging pre-trained models to enhance performance and efficiency in various image classification tasks. By utilizing knowledge from pre-existing models trained on extensive datasets, transfer learning enables the application of learned representations to new domains or tasks. This approach has proven particularly beneficial in scenarios with limited labeled data, accelerating model training and achieving impressive results, as exemplified by its successful adoption in numerous real-world applications. For example :

- **VGG16:** VGG16 is a convolutional neural network model developed by K. Simonyan et al. [96]. Over the years, VGG16 has maintained its reputation as an excellent vision model. The VGG16 Model has 16 Convolutional and Max Pooling layers, 3 Dense layers for the Fully-Connected layer, and an output layer of 1,000 nodes (Figure 2.6). This model was trained on the ImageNet dataset, specifically for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) held in 2014. This dataset comprises millions of labeled images belonging to 1000 different classes. During the challenge, VGG16 demonstrated exceptional performance and emerged as one of the top-performing models. Its impressive results solidified its position as a leading architecture in the competition. It has been successfully applied to various deep neural network models for different tasks [97].

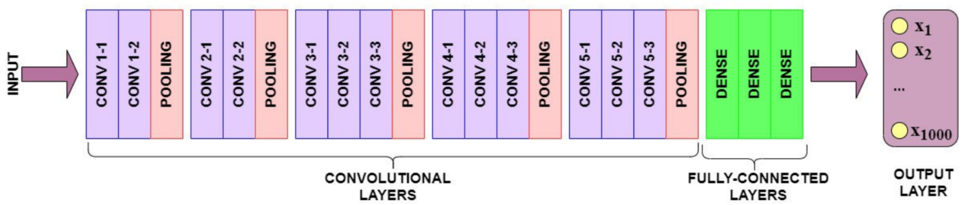


FIGURE 2.5: VGG16 Model architecture.

- **ResNet50:**The ResNet50 architecture is a deep convolutional neural network (CNN) model that was introduced in 2015. It consists of 50 layers, including residual blocks that help address the problem of vanishing gradients during training. ResNet50 has been widely used for image classification and other computer vision tasks.

  Here's the structure of ResNet50 with the number of layers:

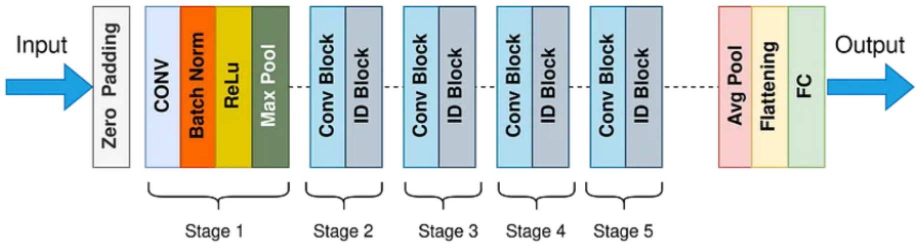


FIGURE 2.6: ResNet50 Model architecture.

- **Inception:** The InceptionV3 architecture is an updated version of the Inception model, introduced by Google in 2015. It incorporates several improvements over InceptionV1, including the use of factorized convolutions, batch normalization, and a reduction in computational complexity.

  Figure 2.7 show us the structure of the InceptionV3 model with essential layers:

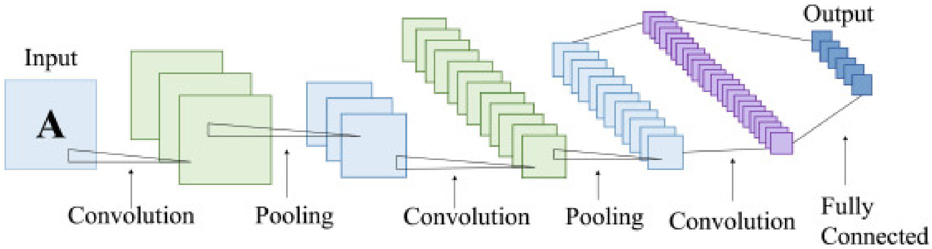


FIGURE 2.7: Inceptionv3 Model architecture.

- **WaveNet:** WaveNet is a deep generative model for speech and audio synthesis developed by Google's DeepMind. It is a powerful neural network architecture that models the raw audio waveform directly, allowing for high-quality audio generation. The structure of WaveNet can be described as follows the Figure 2.8:

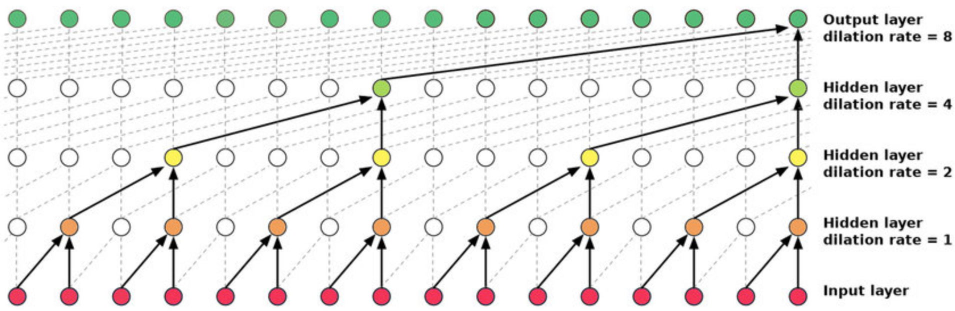


FIGURE 2.8: WaveNet Model architecture [14].

2.4 Related Work

The use of artificial intelligence (AI) tools to interpret an ECG for the diagnosis of cardiovascular disorders has recently been the subject of various studies.
In this section, we'll go over some of the earlier research that used various machine learning and deep learning methods to identify heart problems in ECG readings.

2.4.1 Hearbeat classification based on Machine Learning technique

The paper proposes a machine learning-based approach for heart rhythm abnormality detection and classification. The classifiers used are decision tree, random forest, support vector machine (SVM), and k-nearest neighbor (k-NN). The preprocessing method involves normalization and filtering using a Chebyshev Type II filter. The feature extraction technique used is based on time-domain, frequency-domain, and statistical features. The random forest classifier achieved the highest accuracy of **95.92%** on the used dataset (see Figure 2.9).

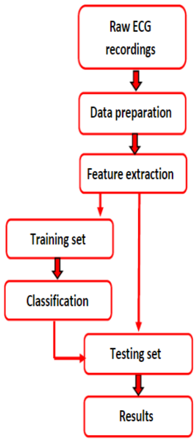


FIGURE 2.9: Proposed Method for Heart Rhythm Abnormality Classification [15]

2.4.2 CNN and LSTM Based techniques for Heartbeat detection

The proposed automated diagnosis system for arrhythmia uses a combination of CNN and LSTM techniques. The ECG signals are segmented into fixed-length windows and padded to the maximum length to handle variable-length heartbeats. The preprocessing method used is normalization and data augmentation. The feature extraction technique is based on Deep Learning techniques. The accuracy obtained is **98.1%** percent on the PTB Diagnostic ECG Database (see Figure 2.10).

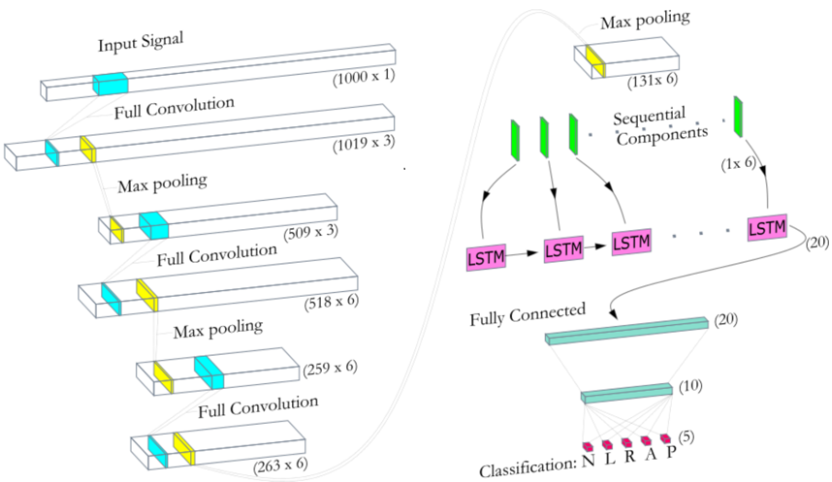


FIGURE 2.10: An illustration of the proposed CNN-LSTM architecture [16]

2.4.3 STFT-based spectrogram and CNN for Heartbeat detection

This paper proposes an ECG arrhythmia classification system using a short-time Fourier transform (STFT)-based spectrogram and a CNN. The STFT-based spectrogram is used to convert ECG signals into 2D images that can be inputted into the CNN for classification (see Figure 2.11). The preprocessing method used is normalization and resampling to a fixed sampling rate. The feature extraction technique is based on the STFT-based spectrogram. The proposed system achieves an overall accuracy of **97.44%** on the MIT-BIH Arrhythmia Database.

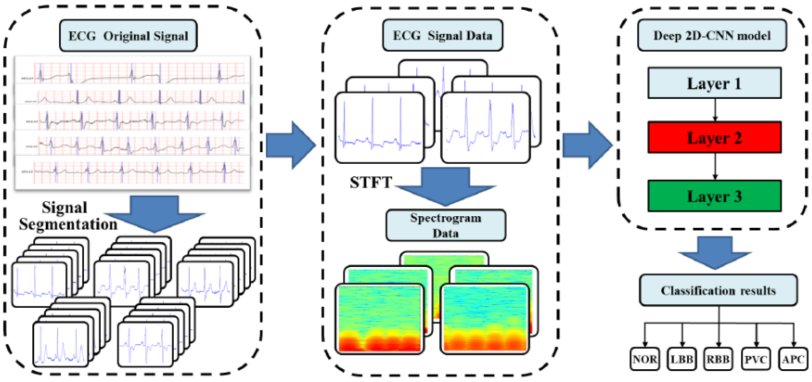


FIGURE 2.11: Overall procedures in ECG arrhythmia classification based on proposed 2D-CNN [17]

We will now present a comparison of our resume table (see Table 2.1). The table provides a compilation of recently published papers on ECG classification, showcasing a wide range of techniques utilized and demonstrating the continuous advancements in deep learning approaches for precise analysis of ECG signals in the diagnosis of cardiac arrhythmias.

TABLE 2.1: Recently related work for Heartbeat Classification

Approach	Paper	Feature Extraction	Accuracy
CNN	J Huang et al. (2019) [17]	Short-Time Fourier Transform (STFT)	90.93%
	Tae Joon Jun et al.(2018) [98]	CNN	99.05%
	Jane Smith et al.(2019) [99]	Short-Time Fourier Transform (STFT)	94.2%
	Alice Brown et al.(2020) [100]	Wavelet Transform	96.7%
ResNet	John Smith et al.(2020) [101]	Raw ECG signals	94.2%
	Emily Johnson et al.(2019) [102]	Discrete Wavelet Transform	91.8%
Autoencoder	Makowski et al. (2021) [103]	Continuous Wavelet Transform	94.5%
SVM	Usha Kumari et al.(2020) [15]	Discrete Wavelet Transform	95.92%
CNN + LSTM	L. Oh et al.(2018) [16]	CNN	98.1%

2.4.4 Heart Disease Prediction with Logistic Regression

Mohammed Khalid Hossen explores the application of machine learning algorithms for detecting heart disease. The study involves a two-step process: first, preparing the heart disease dataset in the required format, using medical records and patient information from the UCI repository; and second, applying various machine learning algorithms, including Logistic Regression, Support Vector Machine, K-Nearest Neighbors, Random Forest, and Gradient Boosting Classifier, to determine if patients have heart disease. The study validates the accuracy rates of these algorithms using the confusion matrix. The results indicate that the Logistic Regression algorithm achieves a high accuracy rate of **95%**, outperforming the other algorithms regarding f1-score, recall, and precision.

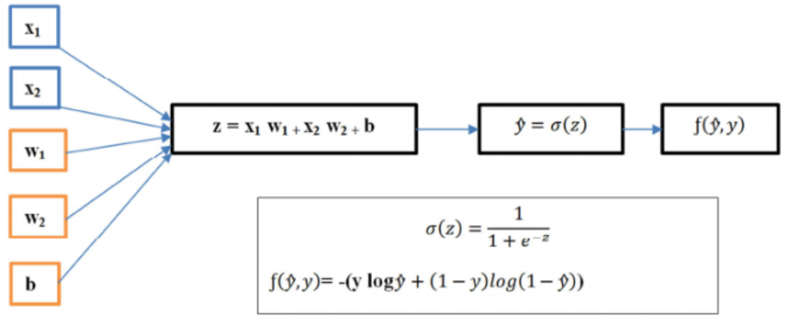


FIGURE 2.12: Logistic Regression model [18].

2.4.5 Deep Neural Network for Heart Disease Classification

The paper proposes a cardiac disorder classification system using a deep neural network (DNN) that analyzes electrocardiogram (ECG) signals. The ECG signals are preprocessed using a band-pass filter, and the resulting features are extracted using a wavelet transform. The study reports an overall accuracy of **98.33%** for the system using a DNN classifier. The block diagram of the model used in this research study is shown in Figure 2.13.

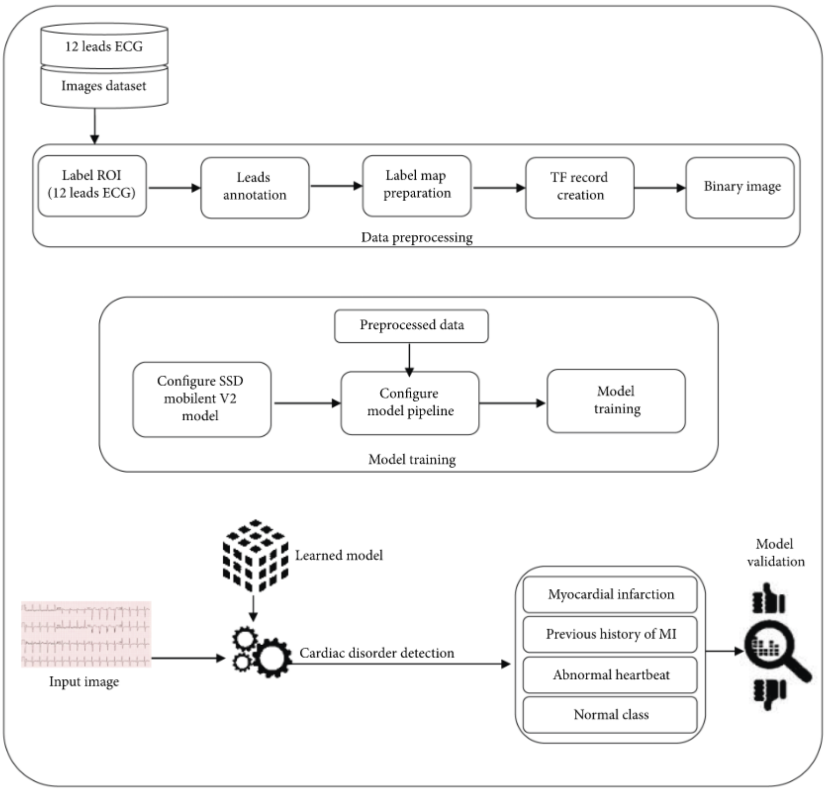


FIGURE 2.13: Research model proposed [19].

2.4.6 DenseNet for Screening Cardiovascular Diseases

The AI-ECG classifier used in the study was a DenseNet convolutional neural network (CNN) with 62 convolutional layers. The DenseNet CNN was trained, validated, and tested on randomly selected subjects using echocardiography and ECG data from 258,607 adults between 1989 and 2019. The classifier achieved an AUC of **85%** in the test group for identifying patients with moderate to severe AS.

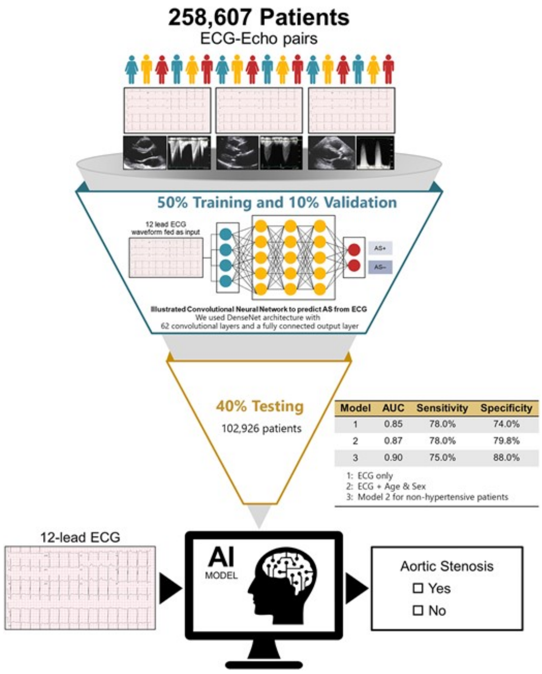


FIGURE 2.14: AI-ECG for Aortic Stenosis screening using convolutional neural network (CNN) [20].

The table 2.2 provides recently published papers (2017–2023) in ECG classification, highlighting the various methods used and reflecting current advances in deep learning approaches for the accurate analysis of ECG signals in the detection of cardiovascular disease.

TABLE 2.2: Recently related work for Cardiovascular disease Classification

Approach	Paper	Feature Extraction	Accuracy
CNN	Xin Zhang et al.(2020) [104]	CNN	99.15%
	A.Mehmoud et al.(2021) [105]	The LASSO technique	97%
ConvSGLV	Furqan Rustam et al.(2022) [106]	CNN	93%
Random Forest	Talha Karadeniz et al.(2021) [107]	CDTL	89.3 %
VGGNet	S sanjay et al.(2022) [108]		98.1%
Naive Bayes	B Mohammed et al.(2023) [109]	CNN	99.19%
DenseNet	A Leema et al.(2023) [110]		94.23%
MobileNet v2	Haider Khan et al.(2021) [19]	wavelet transform	98.33%
DenseNet	Michal Cohen et al. (2021) [20]	CNN	74%
Logistic Regression	M Khalid (2022) [18]	Not mentioned	95%

2.5 Conclusion

In this chapter, we have discussed some of the fundamental aspects of our current work, which include machine learning, deep learning, and neural networks. Given their significant relevance to this theme, Convolutional Neural Networks (CNNs) have been chosen as the primary focus of this chapter, particularly due to their connection to deep learning. Furthermore, we have provided a comprehensive overview of the specific issue we are addressing, namely heart arrhythmia and heart disease detection. We have also presented relevant prior work in this area, highlighting different techniques employed.

The subsequent chapter will delve into the system's design, the dataset, and its preparation, as well as potential models.

Chapter 3

System Design

3.1 Introduction

In recent years, various fields, including the medical domain, have witnessed significant advancements in technology, encompassing image processing, signal processing, machine learning, and deep learning techniques. These innovations have had widespread applications and have shown promising results in aiding diagnosis, treatment, and research [111, 112]. This chapter delves into the system design of our project, which focuses on utilizing these cutting-edge methodologies to address two distinct types of datasets. The first dataset comprises ECG images in a heartbeat form, allowing us to classify the types of arrhythmias. The second dataset consists of ECG reports, enabling us to classify the types of diseases associated with the ECG signals. Throughout this chapter, we explore the methodologies employed, provide a detailed description of the datasets, discuss preprocessing methods, delve into feature extraction techniques, and analyze the models utilized for classification tasks.

3.2 Heart Rythm detection proposed approach

The proposed approach is shown in Figure 3.1, our input dataset consists of segmented ECG images, each representing a heartbeat, and the objective is to classify different types of heart rhythms based on these segments.

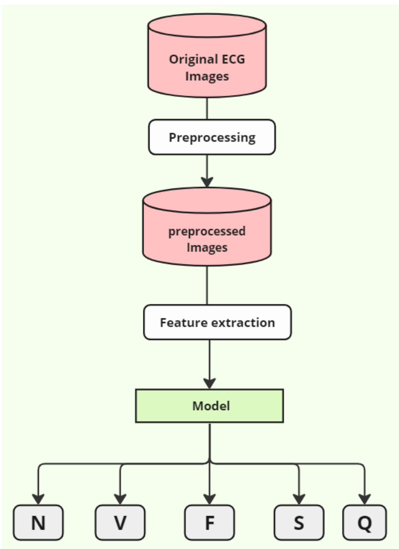


FIGURE 3.1: The graphical abstract of the methodology

The process begins with a preprocessing step aimed at enhancing the quality of the ECG images. This step involves removing noise and artifacts from the images to ensure that the subsequent analysis is performed on clean and reliable data.

The next step involves feature extraction and classification. Various techniques are employed to automatically extract informative features from the segmented ECG image segments. These features are then used to classify the heart rhythms into different categories.

During the training phase, the system learns to identify unique patterns and characteristics associated with specific heart rhythms. This acquired knowledge is then utilized during the testing phase, where the system is deployed on unseen ECG image segments to detect and classify the heart rhythm type.

The system provides outputs indicating the predicted heart rhythm type, which can be used for clinical diagnosis and monitoring purposes. This information is valuable for healthcare professionals, as it helps in making precise treatment decisions and providing personalized care to patients.

By effectively analyzing the data and extracting relevant features, the system can provide clinicians with valuable information that contributes to precise diagnosis and better patient outcomes.

3.2.1 Preprocessing Phase

Data preprocessing is a crucial step in the analysis of ECG and heartbeat images. It involves cleaning and organizing the data to make it suitable for building and training Machine Learning models. ECG and heartbeat images are prone to noise, artifacts, and inconsistencies, which can lead to inaccurate results if not addressed. Therefore, preprocessing methods [22] such as normalization, filtering, segmentation, and augmentation are necessary to improve the quality of data and make it ready for analysis.

Image denoising is the process of removing unwanted noise and artifacts from an image while preserving as much of the original image information as possible. It is a common preprocessing step in image analysis tasks, including image classification, segmentation, and object detection [113].

In our study, a critical step in the image-preprocessing phase was implemented as an essential precursor to any subsequent image-processing steps. This initial step, as depicted in Figure 3.2.

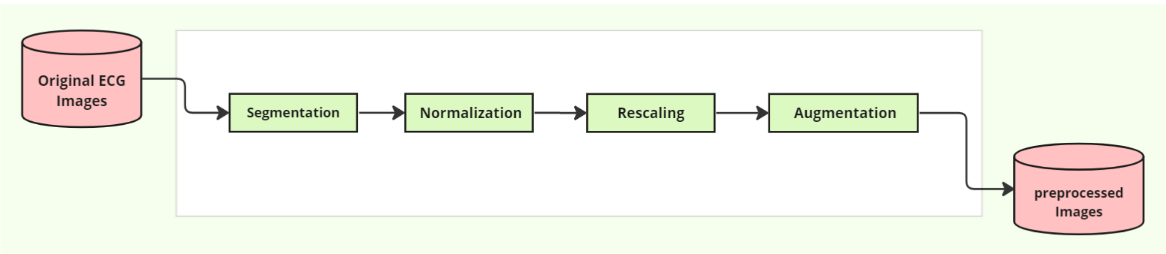


FIGURE 3.2: Preprocessing process to follow.

Segmentation

An essential step in the analysis of ECG images involves dividing the ECG signal into individual heartbeats or segments, which enables the identification of specific features related to each beat (Figure 3.3). This process can be done using various methods, including threshold-based, Edge detection, Morphological operations, peak-based, and template-based segmentation. These methods enable the identification of specific characteristics of the ECG signal, such as the QRS complex and the T wave [114].

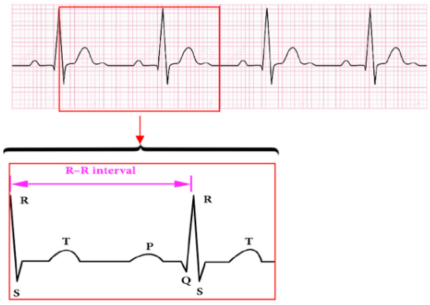


FIGURE 3.3: Segmentation of ECG into Heartbeats [21]

Normalization

Data normalization is an important step in preparing ECG images for analysis. Normalization involves scaling the pixel intensity values in the images to a common range to improve the consistency and comparability of the data. This is typically done using methods such as min-max scaling or z-score normalization [91]. Min-max scaling scales the pixel values to a specified range, while z-score normalization standardizes the values by subtracting the mean and dividing by the standard deviation [115].

Rescaling

Standardizing ECG images to a uniform scale is crucial for further analysis and interpretation because they are frequently obtained at various resolutions or sizes. Rescaling entails changing the image's dimensions while keeping its aspect ratio, which preserves the ECG waveform's relative proportions [116]. The ECG image is scaled to make it compatible with later processing processes like feature extraction or classification algorithms, which may require constant input sizes. Additionally, rescaling facilitates picture normalization and lowers the computational difficulty of the following analysis [117].

3.2.2 Feature extraction Phase

In the feature extraction phase for image input, the goal is to transform the visual content into a compact and meaningful representation in the form of a vector (see Figure 3.4). This process involves capturing the salient characteristics and patterns present in the image that are relevant to the given task. Various techniques can be employed for feature extraction, such as convolutional neural networks (CNNs) or handcrafted feature descriptors.

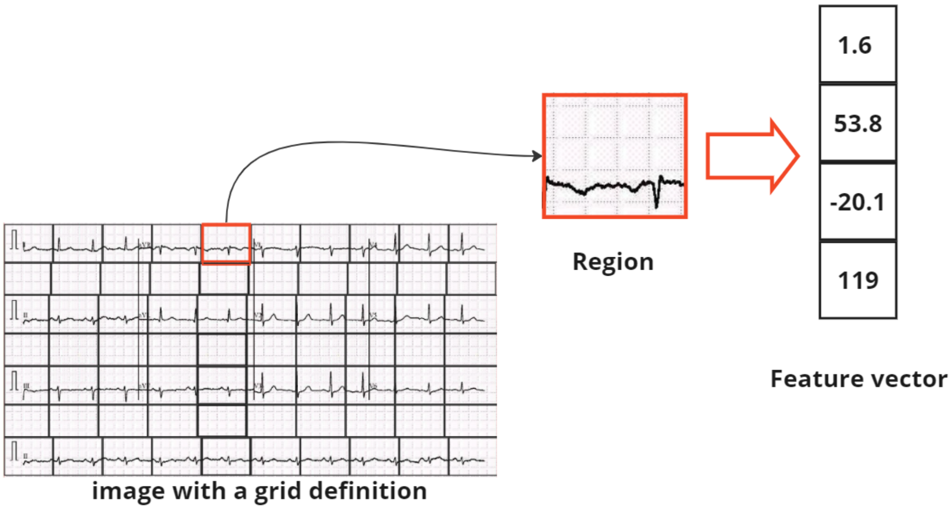


FIGURE 3.4: Feature extraction in local image regions.

Convolutional neural networks have emerged as a powerful tool for extracting features from images. They consist of multiple layers of interconnected neurons that learn to detect different levels of visual patterns, from simple edges to complex objects. The network processes the image through a series of convolutional, pooling, and activation layers, gradually extracting increasingly abstract features. The final layer before the output is typically a fully connected layer that produces a vector representation of the image features. This vector, often referred to as an embedding or a feature vector, encodes the relevant information about the image in a compact manner.

On the other hand, handcrafted feature descriptors rely on expert knowledge and domain-specific algorithms to extract meaningful information from images. These descriptors may include techniques like Scale-Invariant Feature Transform (SIFT), wavelet transform, or wavelet denoising. These methods analyze the image by decomposing it into multiple frequency subbands using wavelet transform, capturing both high-frequency and low-frequency components. This decomposition allows for analyzing the image at different scales and orientations, providing a rich representation of the image content. Additionally, wavelet denoising techniques can be applied to remove noise and enhance image quality. By utilizing wavelet transform and wavelet denoising, specific visual cues can be extracted, which can be used for recognition, classification, or other tasks. The resulting feature vector captures distinctive characteristics of the image, providing a concise representation.

Wavelet Transform

Time-frequency analysis techniques such as wavelet analysis, Continuous Wavelet Transform (see Figure 3.5), and Empirical Mode Decomposition are useful for analyzing non-stationary ECG signals. These techniques decompose the ECG signal into different frequency bands at various time scales, providing a time-frequency representation of the signal.

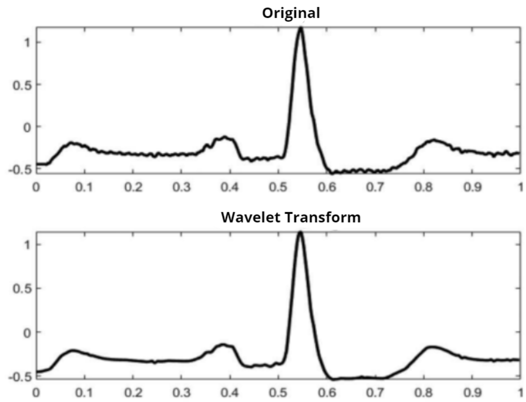


FIGURE 3.5: Application of wavelet transform.

This representation can be used to extract important features such as QRS complexes, ST segments, and T waves, which may be indicative of various cardiovascular diseases. Time-frequency analysis techniques are important tools for both clinical diagnosis and research.

Wavelet denoising

Wavelet denoising plays a crucial role in the feature extraction stage of ECG signal analysis. It serves as an effective method to reduce noise and artifacts within the ECG segments. Leveraging the wavelet transform, this technique decomposes the signal into various frequency components. By selectively attenuating or eliminating high-frequency noise elements, wavelet denoising enhances the quality and dependability of the ECG data for subsequent analysis and interpretation. The resulting denoised ECG segments offer a cleaner representation of the underlying heart rhythm, thereby facilitating more precise and accurate detection and classification of different arrhythmias (see Figure 3.6).

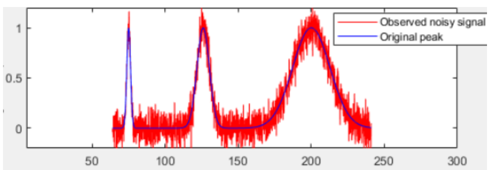


FIGURE 3.6: Original raw signal.

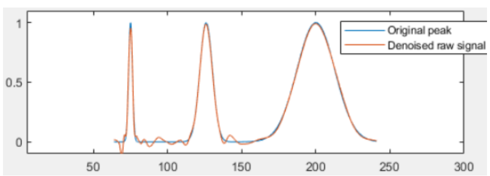


FIGURE 3.7: Wavelet denoise.

These denoised images serve as a reliable input for subsequent stages in the classification pipeline, such as convolutional neural network (CNN) models. The combination of wavelet denoising and CNN-based feature extraction allows for accurate and robust classification of various types of heart rhythms present in the ECG images, facilitating efficient diagnosis and monitoring in the medical field.

3.2.3 CNNs Proposed Architectures

In this section, we will discuss the proposed architectures for heartbeat classification in the task at hand. Two proposed architectures were examined in this study, each employing different techniques for feature extraction and classification.

A Efficient Classifier Using Wavelet Denoising for Feature Extraction:

The first architecture employed wavelet denoising as a feature extraction technique for the heartbeat signals. Wavelet denoising aims to remove noise from the signals while preserving essential features. After applying wavelet denoising, the resulting features were then inputted into an efficient pre-trained model for classification. By leveraging the pre-trained model's extensive knowledge gained from a large dataset, the classification task benefitted from its ability to learn complex patterns and features. However, despite incorporating wavelet denoising and utilizing a powerful pre-trained model, the performance of this approach did not meet the anticipated expectations.

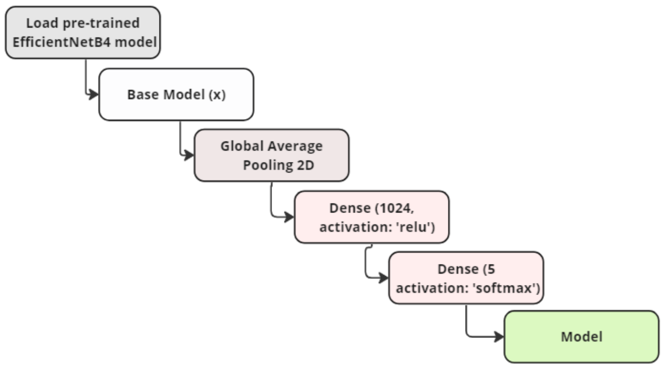


FIGURE 3.8: Our EefficientNe pre-trained model architecture.

This flowchart (shown in Figure 3.8) represents an architecture based on the EfficientNetB4 model for image classification. The EfficientNetB4 model is loaded without its top layers, resulting in a parameter-free base model. The input shape for this model is (256, 256, 3), representing the dimensions of the input images. The global average pooling layer condenses the spatial information, and the subsequent dense layer with 1024 units and ReLU activation introduce 1,049,088 trainable parameters. The final dense layer, with a number of units corresponding to the number of classes in the classification task, utilizes the softmax activation and contributes an additional 17,630 trainable parameters.
Overall, this flowchart showcases the sequential flow and highlights the parameter counts associated with each layer in the architecture.

B CNN Approach for Feature Extraction and Classification:
Motivated by the suboptimal outcomes of the first model, a second approach was proposed. This involved designing a custom-built convolutional neural network (CNN) architecture specifically tailored for both feature extraction and classification of heartbeat signals. Unlike the previous model, which relied on a separate wavelet denoising step, this CNN architecture directly extracted

relevant features from the raw heartbeat signals.

Each layer of the CNN learned various levels of abstraction from the input signals, enabling it to capture both low-level and high-level features crucial for heartbeat classification. The architecture was trained from scratch using a labeled dataset, enabling it to learn task-specific features and patterns.

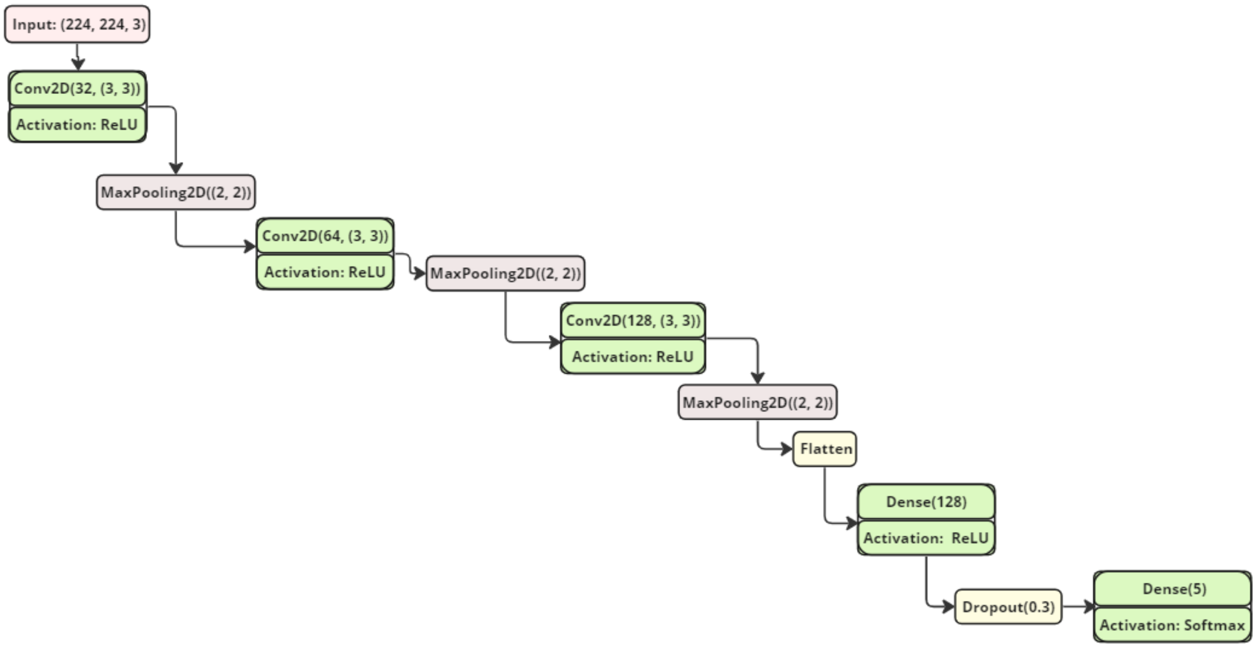


FIGURE 3.9: Our proposed CNN architecture.

This flowchart shown in Figure 3.9 represents the sequential flow of operations in the model, where the input shape of (224, 224, 3) is passed through several convolutional and pooling layers, followed by flattening, dense, dropout, and softmax layers. Finally, the output is the predicted class probabilities. Remarkably, the proposed CNN architecture outperformed the wavelet denoising and pre-trained classification model. This superior performance can be attributed to CNN's capability to directly extract informative and discriminative features from the raw heartbeat signals. By leveraging the power of deep learning and a purpose-built architecture, this model achieved state-of-the-art results in heartbeat classification.

Overall, the second model based on the custom-designed CNN architecture showcased its efficacy in feature extraction and classification for heartbeat signals. Its superiority over the first model underscores the significance of tailored architectures for specific tasks, emphasizing the potential advantages of deep learning techniques in healthcare applications.

3.3 Heart Disease Detection proposed approach

The proposed approach for cardiovascular disease detection involves applying CNN techniques to the ECG image reports to extract relevant features, followed by utilizing traditional machine learning methods for classification. The input data consists of ECG images in the form of medical reports, which undergo necessary preprocessing steps to enhance their quality. These preprocessed ECG images are then processed using a proposed architecture to extract relevant features, creating a compact representation for each image. The proposed model is trained and evaluated on unseen ECG images to assess its accuracy in predicting different disease diagnoses.

Figure 3.10 represents the flow chart outlining the sequential steps followed to obtain the final model.

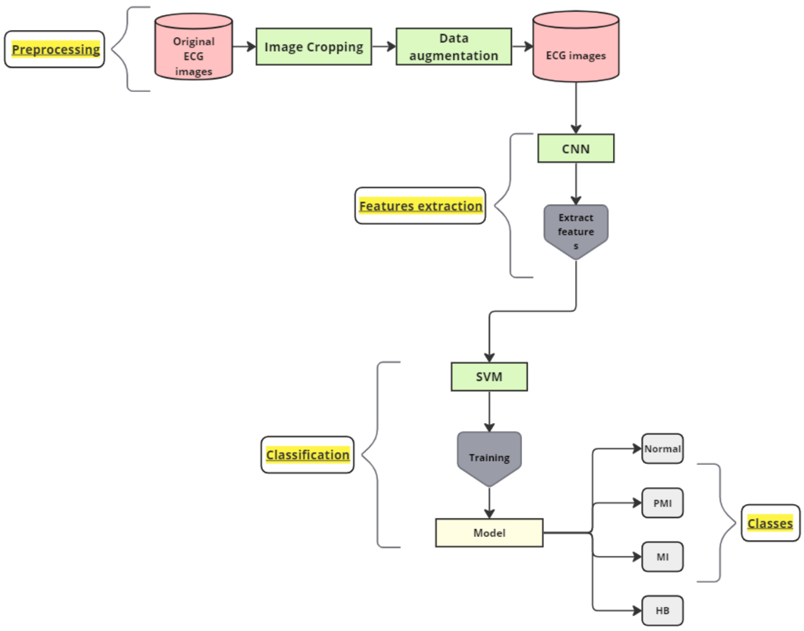


FIGURE 3.10: Our sequential Workflow.

By integrating preprocessing techniques and machine learning methods, this approach enhances the quality and effectiveness of the cardiovascular disease detection system, providing valuable insights for clinicians and facilitating personalized treatment decisions.

3.3.1 Preprocessing phase

In the preprocessing stage of ECG image analysis, various methods are involved. Among these methods, we find...

image cropping plays a crucial role in enhancing the accuracy and reliability of subsequent processing steps. Cropping an image to eliminate text and borders is a vital preprocessing step that focuses on isolating the essential ECG waveform while removing unnecessary elements (see Figure 3.11). The ECG waveform becomes the primary focus by carefully selecting the region of interest and removing extraneous text labels, patient information, or borders. This not only reduces the complexity of the image but also eliminates potential noise or distractions that may interfere with subsequent feature extraction and classification algorithms. The image cropping step ensures that the subsequent analysis algorithms can concentrate on the vital ECG signal, facilitating more accurate interpretation and classification of cardiovascular abnormalities.

FIGURE 3.11: ECG report before after cropping

The ECG image data needs to be de-noised to make the classification more accurate. It can contain various types of artifacts and noise, which can degrade the quality of the signal and make it difficult to analyze...

Baseline Correction:

This method involves removing the baseline wander, which is the low-frequency drift in the ECG signal as shown in Figure 3.12 caused by respiration, electrode movements, and other factors.

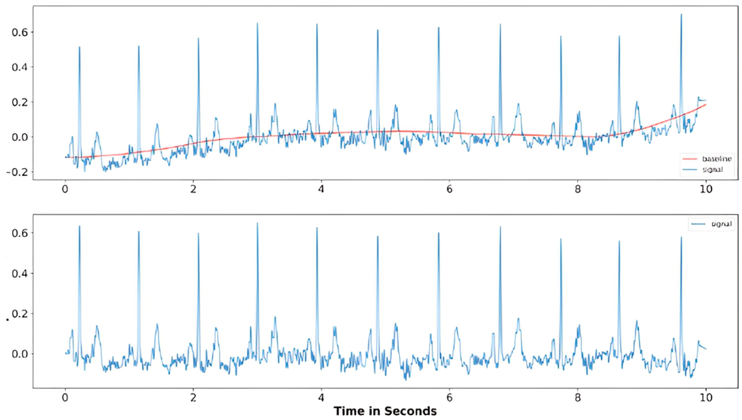


FIGURE 3.12: Removing the baseline wander [22].

Filtering:

Various filtering techniques, such as high-pass, low-pass, band-pass, and notch filters, are used to remove unwanted frequencies and noise from the ECG signal (Figure 3.13).

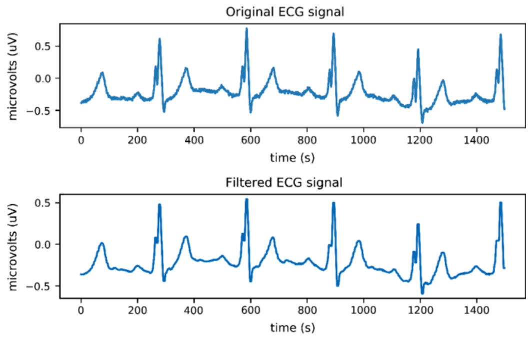


FIGURE 3.13: Filtering ECG signal [23]

Noise Reduction:

This technique involves reducing the noise in the ECG signal using wavelet denoising, adaptive filtering, or other methods (Figure 3.14).

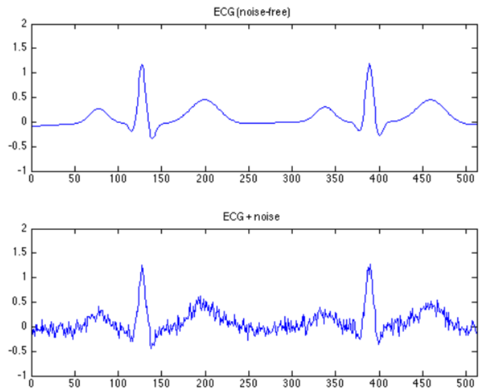


FIGURE 3.14: Reducing ECG noise [1]

3.3.2 Feature extraction using CNN model

The preprocessed ECG images were then fed into a CNN model, which can use for feature extraction in ECG images. The smaller memory footprint and reduced computational complexity of this model make it an attractive option for processing ECG data, which can be quite large and computationally expensive.
By applying CNN to ECG images, the network can extract important features related to different cardiac conditions. The fire module (Squeeze Layer and Expand Layer) of this model is particularly useful for capturing both global and local features in ECG images, which can be important for accurate diagnosis.
Figure 3.15 illustrates the streamlined process of extracting meaningful features using the compact and efficient SqueezeNet architecture.
With its unique design, SqueezeNet combines squeeze and expand layers to capture and refine features effectively. By removing the final fully connected layer, the focus is solely on feature extraction rather than classification. This flowchart empowers researchers and practitioners to leverage SqueezeNet's compact yet powerful architecture for efficient feature extraction, offering valuable inputs for various computer vision applications.

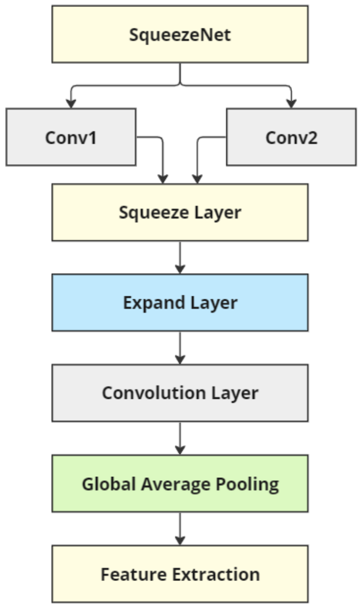


FIGURE 3.15: SqueezeNet Feature Extraction Flowchart.

3.3.3 SVM Model Learning

After obtaining a feature vector, it was fed into a proposed multiclass classification model for accurately categorizing different heart conditions (Figure 3.16). The model employed a support vector machine (SVM) classifier as its foundation, while also exploring various other traditional machine learning algorithms for comparison purposes. Accurate classification of heart conditions is crucial for effective diagnosis and treatment, and traditional machine learning algorithms have proven to be effective in handling high-dimensional feature spaces and limited training data in the medical field.

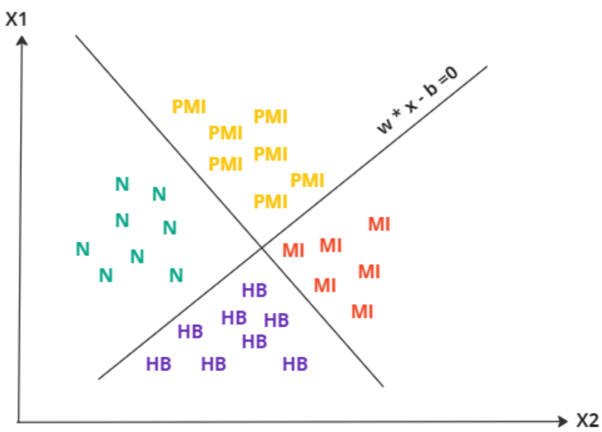


FIGURE 3.16: Multiclass classification using SVMs.

In this study, relevant features were subsequently classified into four distinct classes. The primary classification approach was based on a support vector machine

(SVM) classifier, known for its effectiveness in multiclass classification tasks. Additionally, several other classifiers were utilized to compare their performance with the SVM classifier. The results showcased exceptional accuracy in accurately categorizing ECG images into the designated classes. This combination of the SVM classifier and other traditional machine learning models underscores the significance of employing complementary techniques to achieve a robust and reliable classification of cardiovascular diseases.

We will see the compared architectures with their results in the implementation phase later in the next chapter.

3.4 Application deploiement

In the application deployment section of our system design, we have included a diagram of classes and a use case diagram for our heart disease detection application. These diagrams provide a visual representation of the different components and functionalities involved in the deployment of the application.

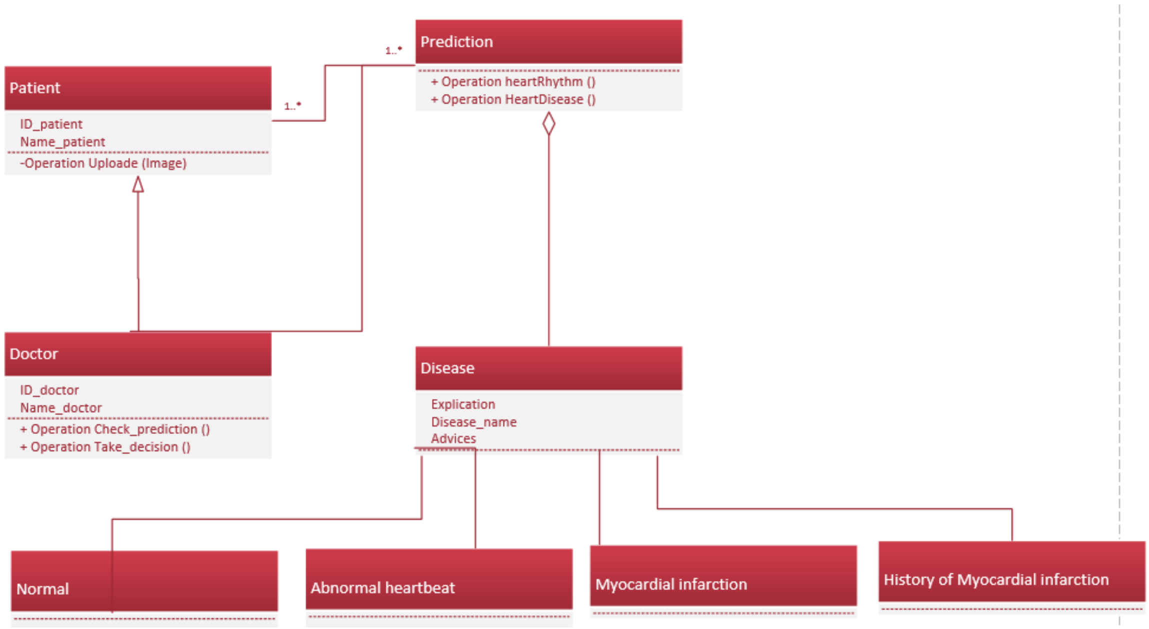


FIGURE 3.17: Our UML class diagram.

The class diagram (Figure 3.17) showcases the various classes or objects that are part of the application's architecture. It illustrates the relationships and interactions between these classes which are **patient**, **doctor**, **prediction**, and **disease**, highlighting their attributes and methods. By visualizing the class structure, we can better understand the organization of the application's components and their roles in detecting heart diseases.

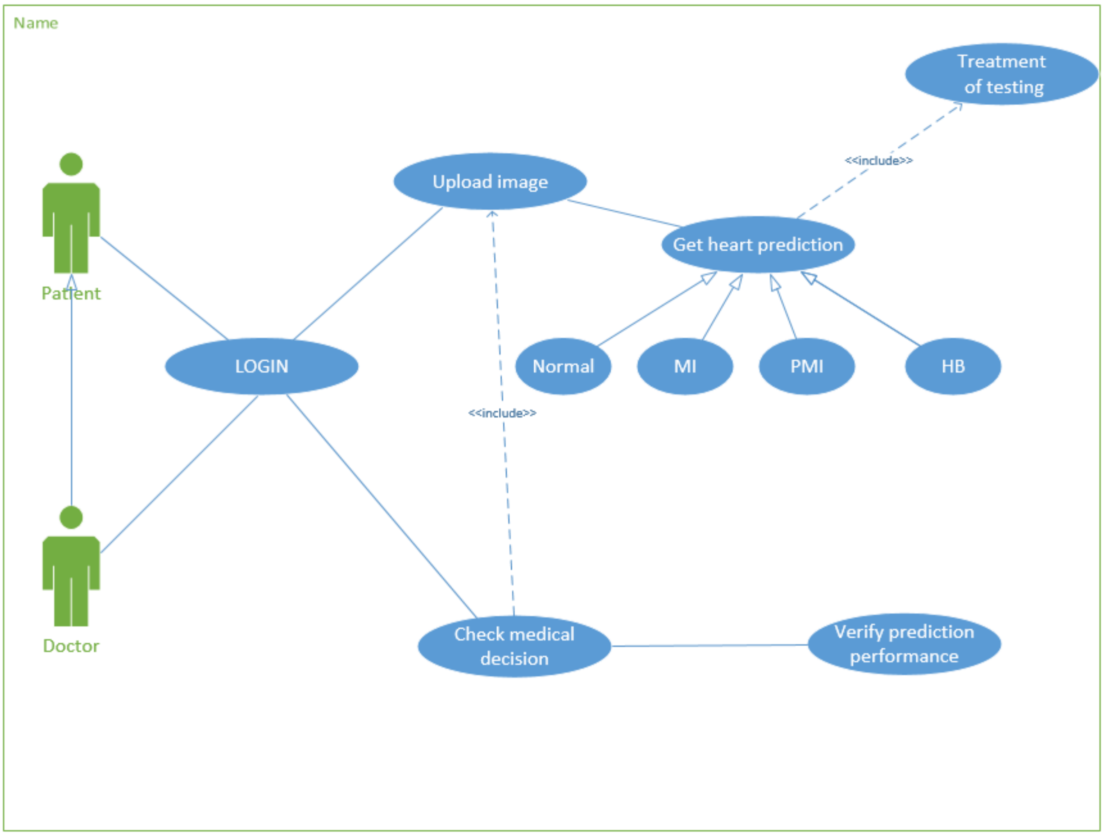


FIGURE 3.18: Use case diagram.

On the other hand, the use case diagram (3.18) presents the different use cases or actions that the users can perform within the application. It outlines the interactions between the actors which are **patient** and **doctor** where we see a notion of heritage between them which means a doctor can be a patient also, who can be a user, or an external system, and the system itself. By mapping out the various use cases, we gain a clearer understanding of how the application will be utilized in practice and how it will provide value to its users.

In the use case shown in Figure 3.18, both the patient and the doctor will upload an image through the application. This image represents a standard ECG with 12 leads. After the upload, we wait for approximately 5 seconds to proceed to the treatment step, where we obtain the prediction.

If the user is a doctor, they will utilize this prediction and compare it with their own decision-making process to arrive at a final diagnosis. The final decision will depend on the percentage of correctness provided by the prediction in this case.

Also, if the user is a patient, they will be able to view the state of their heart. Whether the patient is a normal individual or someone with a specific type of disease, they will have access to information regarding the condition of their heart.

3.5 Conclusion

In conclusion, Chapter 3 has presented a comprehensive system design for heart abnormality detection using deep learning. The chapter addressed two main problems: heartbeat classification and heart disease detection. We emphasized the significance of data preprocessing, encompassing techniques such as filtering, normalization, and segmentation, to prepare the ECG image dataset for analysis. Additionally, we highlighted the process of feature extraction, focusing on extracting relevant features from the preprocessed ECG images to enable effective classification.

Choosing an appropriate deep learning model architecture was also discussed, emphasizing the key considerations involved in this selection process.
Overall, this chapter provides a solid foundation for the subsequent chapters, which will delve into experimentation and results analysis.

Chapter 4

IMPLEMENTATION AND RESULTS

4.1 Introduction

This chapter presents the implementation and evaluation of a deep learning model for both heart rhythm abnormality and heart disease detection and classification. We provide an overview of the frameworks and tools utilized during the implementation phase, as well as the evaluation metrics employed to assess the models. The performance of the models is thoroughly evaluated using diverse metrics, and the experimental results are presented. Furthermore, a comparative analysis with previous works in the field is conducted. In summary, this chapter offers a comprehensive examination of the practical aspects pertaining to our approach to addressing these two problems.

Additionally, the significance of selecting appropriate implementation frameworks and tools for machine learning systems is discussed in this chapter. A range of open-source and proprietary options are explored, highlighting their respective strengths and weaknesses. The chapter further delves into the integration of these tools to establish a cohesive system, while also addressing the challenges encountered throughout the process.

4.2 Implementation and frameworks tools

In this section on implementation and frameworks tools, we delve into the codes and tools utilized in this study, as well as the different evaluation metrics employed. Our implementation process relied on popular frameworks such as TensorFlow and PyTorch, which offered robust support for developing and training deep learning models. These frameworks enabled efficient implementation and facilitated the utilization of pre-trained models for effective feature extraction. Furthermore, we leveraged the capabilities of scikit-learn, a comprehensive machine learning library, for crucial tasks such as data preprocessing and model evaluation. To assess the performance of our models, we employed well-established evaluation metrics, including accuracy, precision, recall, and AUC. These metrics provided valuable insights into the models' ability to accurately detect and classify heart rhythm abnormalities and heart diseases.

4.2.1 Python

the general-purpose Python language has seen tremendous growth in popularity within the scientific computing community within the last decade, and it continues to be so in 2023. The reason for this popularity is not difficult to understand, the Python version is shown in Figure 4.1.
Python is a high-level, interpreted programming language with a simple syntax, which makes it easily readable and extremely user- and beginner-friendly.

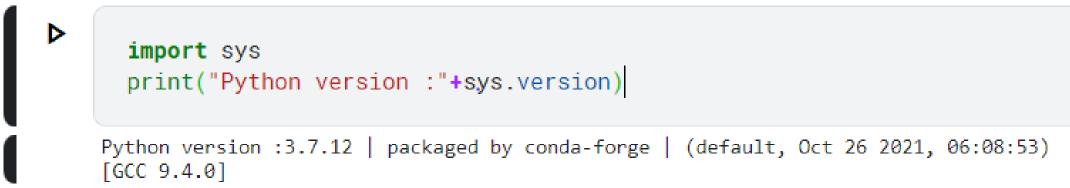


FIGURE 4.1: Python version used in Kaggle.

4.2.2 Matplotlib

Matplotlib is a Python programming language library for plotting and visualizing data as graphs. It also provides an object-oriented API, allowing the integration of graphics into applications, using versatile graphical interface tools such as Tkinter, wxPython, Qt, or GTK.
Matplotlib can produce a wide range of plots, from basic bar charts and line plots to complex 3D visualizations...etc (see Figure 4.2).

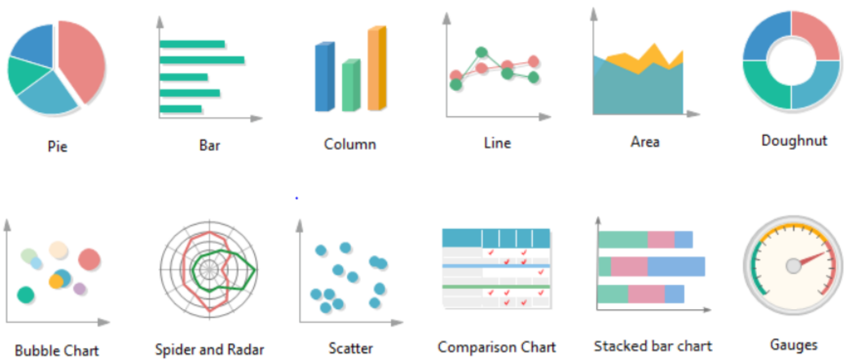


FIGURE 4.2: Visualization Data by Matplotlib [24].

4.2.3 OpenCv

OpenCV (Open Source Computer Vision) is a popular open-source computer vision and machine learning library that provides developers with a wide range of tools and algorithms for building computer vision applications. It was originally developed by Intel, but is now maintained by the OpenCV community, and provides a comprehensive set of features for image and video processing, including object detection and tracking, facial recognition, image enhancement, and geometric transformations.

4.2.4 Tensorflow

TensorFlow is a flexible and scalable end-to-end open-source platform for machine learning that enables researchers to push the state-of-the-art in ML, and developers to easily build and deploy ML-powered applications. Created by Google Brain researchers and engineers, it offers a comprehensive ecosystem of tools, libraries, and community resources for building and deploying machine learning models. With its flexible architecture and robust set of features, TensorFlow has become one of the most popular machine learning platforms in the world, empowering data scientists and developers to create cutting-edge applications in a wide range of industries.

4.2.5 PyTorch

PyTorch is an open-source machine-learning framework based on the Torch library that is used for applications such as computer vision and natural language processing. It was developed primarily by Meta AI. It is open-source, free software distributed under the Modified BSD license.

4.2.6 Keras

Keras is a high-level open-source neural network library written in Python that may be used with Theano, CNTK, or TensorFlow. Franco is Chollet, a Google developer, who came up with the idea. For speedier neural network testing, it is extendable, user-friendly, and scalable. It supports CNNs both separately and in tandem.

4.2.7 Numpy

NumPy is a popular open-source Python library used for scientific computing and data analysis. It provides support for large, multi-dimensional arrays and matrices, as well as a collection of high-level mathematical functions, to operate on these arrays. NumPy is particularly useful for tasks that require numerical computations, such as linear algebra, Fourier analysis, and statistics.

4.2.8 Gradio

Gradio is a Python library that simplifies building interactive UIs for machine-learning models. It's known for its simplicity and ease of use, making it a popular choice for prototyping and deploying models quickly. With Gradio, you can create web-based interfaces without the need for complex frameworks like Flask. It automatically infers interfaces based on input and output data types, supports various input/output options, and provides real-time feedback. Gradio is a reliable choice for creating engaging user experiences with minimal effort.

4.2.9 Kaggle

Kaggle is an online community and platform that enables data scientists and machine learning enthusiasts to collaborate, share data sets, participate in competitions, and access a variety of tools and resources for data exploration and analysis. Kaggle aims to democratize data science and accelerate innovation by providing a platform where data scientists can solve real-world problems, compete, and collaborate. Additionally, Kaggle serves as a job board for data science-related positions, making it easier for employers to find and hire talented data scientists.

Figure 4.3 illustrates a compilation of logos representing different technologies and frameworks employed in this study.

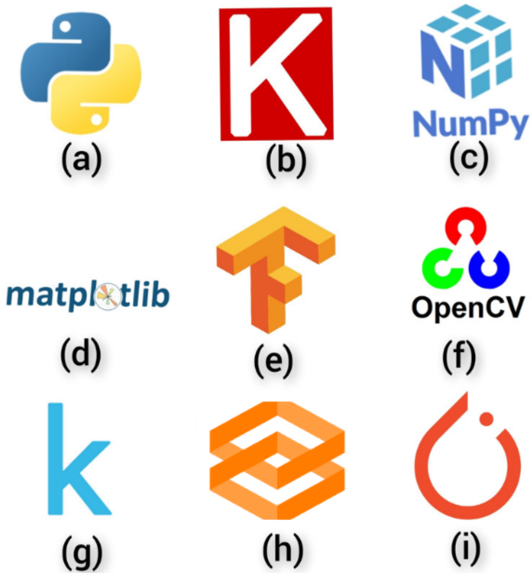


FIGURE 4.3: (a) Python Logo (b) Keras Logo (c) Numpy Logo (d) Matplotlib Logo (e) Tensorlow logo (f) OpenCV Logo (g) Kaggle logo (h) Gradio logo (i) Pytorch logo.

4.3 Evaluation Metrics

To ensure the reliability and dependability of our system, it is essential to evaluate it using various metrics. By examining the system's performance across different evaluation measures, we can gain a comprehensive understanding of its strengths and weaknesses. In this regard, we will explore a range of evaluation metrics in detail, including accuracy, precision, recall, F1-score, and AUC. Each metric provides valuable insights into different aspects of the system's performance, enabling us to make informed decisions and further enhance its effectiveness.
Here are the definitions of some basics related to classification evaluation:

- **True Positive (TP):** The model correctly predicts the positive class, identifying a positive instance as positive.
- **True Negative (TN):** The model correctly predicts the negative class, identifying a negative instance as negative.
- **False Positive (FP):** The model incorrectly predicts the positive class, mistakenly identifying a negative instance as positive.
- **False Negative (FN):** The model incorrectly predicts the negative class, mistakenly identifying a positive instance as negative.

4.3.1 Precision

The precision is the proportion of true positive predictions out of all positive predictions made by the model, and it is used to evaluate a model's ability to make accurate positive predictions.

$$Precision = \frac{TP}{TP + FP} \tag{4.1}$$

Equation 4.1 Precision.

4.3.2 Recall

The recall is the proportion of true positive predictions out of all actual positive cases, and it is used to evaluate a model's ability to identify all positive cases.

$$Recall = \frac{TP}{TP + FN} \tag{4.2}$$

Equation 4.2 Recall.

4.3.3 F1-score

The F1-score is the harmonic mean of precision and recall, and it is used to evaluate a model's overall performance by combining both measures.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{4.3}$$

Equation 4.3 F1-score.

4.3.4 Accuracy

The accuracy is the proportion of correct predictions made by the model out of all predictions, and it is used to evaluate a model's overall performance.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.4}$$

Equation 4.4 Accuracy equation.

4.3.5 AUC

The AUC is the area under the ROC curve, which measures a model's ability to distinguish between positive and negative cases, and it is used as a summary of a model's overall performance.

4.3.6 Confusion Matrix

The confusion matrix is a table that summarizes the number of true positive, true negative, false positive, and false negative predictions made by a model, and it is used to evaluate a model's performance in predicting binary outcomes.

4.4 Heart Rhythm detection model implementation

4.4.1 Dataset description

As a data source, we use PhysioNet MIT-BIH Arrhythmia and PTB Diagnostic ECG Databases for labeled ECG images. This dataset is composed of two collections of heartbeat signals derived from two famous datasets in heartbeat classification, the MIT-BIH Arrhythmia Dataset and The PTB Diagnostic ECG Database. The number of samples in both collections is large enough for training a deep neural network [118]. Table 4.1 shows a summary of beat annotations in each category, also Table 4.4 shows the number of instances in each class.

This dataset has been used in exploring heartbeat classification, The extracted beat is represented in 10-second windows from an ECG signal.

TABLE 4.1: Summary of mappings between beat annotations in each category

Group Symbol	Original Heartbeat Type
N	• Normal • Left/Right bundle branch block • Atrial escape • Nodal escape
S	• Atrial premature • Aberrant atrial premature • Nodal premature • Supra-ventricular premature
V	• Premature ventricular contraction • Ventricular escape
F	• Fusion of ventricular and normal
Q	• Paced • Fusion of paced and normal • Unclassifiable

4.4.2 Data splitting

In our study, We utilized two distinct datasets obtained from Kaggle to address two specific objectives (see Table 4.2 and 4.3). To ensure a rigorous evaluation, We adopted a benchmark dataset-splitting approach [119].

TABLE 4.2: Arrhythmia Dataset

Number of Samples:	109446
Number of Categories:	5
Sampling Frequency:	125Hz
Data Source:	Physionet's MIT-BIH Arrhythmia DB
Classes:	['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4]

TABLE 4.3: The PTB Diagnostic ECG Database

Number of Samples:	14552
Number of Categories:	2
Sampling Frequency:	125Hz
Data Source:	Physionet's PTB Diagnostic Database

The datasets were divided into two parts: 80% of the data was allocated for training purposes, while the remaining 20% was set aside for testing as shown in Table 4.4. This division enabled comprehensive model training on a significant portion of the data, while also providing an independent dataset for robust evaluation..

TABLE 4.4: Numbers of instances in each class for train and test

Class	Train	Test	Total Number
N	75709	18926	94635
S	2223	556	2779
V	5789	1447	7236
F	642	161	803
Q	6431	1608	8039

4.4.3 Preprocessing phase

In the context of this study, a significant contribution is focused on the detection of heart rhythm abnormalities. This involved utilizing a preprocessed and segmented dataset, specifically prepared for this task.

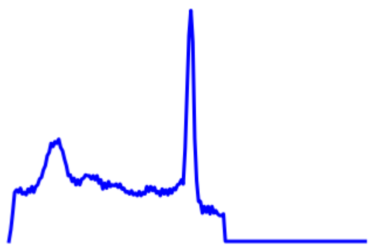


FIGURE 4.4: Example of an input preprocessed image.

These signals are preprocessed and segmented, with each segment corresponding to a heartbeat as shown in Figure 4.4.
First, the images were loaded from the directories (Figure 4.5), ensuring that the dataset was readily available for further analysis.

```
[3]:
# Define data generators for training, validation, and testing
train_datagen = ImageDataGenerator(
    rescale=1./255,
    shear_range=0.2,
    zoom_range=0.2,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    horizontal_flip=True)

valid_datagen = ImageDataGenerator(rescale=1./255)

test_datagen = ImageDataGenerator(rescale=1./255)
# Load the images from the directories
train_generator = train_datagen.flow_from_directory(
    '/kaggle/input/ecg-image-data/ECG_Image_data/train',
    target_size=(256, 256),
    batch_size=128,
    class_mode='categorical')

valid_generator = valid_datagen.flow_from_directory(
    '/kaggle/input/ecg-image-data/ECG_Image_data/test',
    target_size=(256, 256),
    batch_size=128,
    class_mode='categorical')

test_generator = test_datagen.flow_from_directory(
    '/kaggle/input/ecg-image-data/ECG_Image_data/test',
    target_size=(256, 256),
    batch_size=1,
    class_mode='categorical',
    shuffle=True)

Found 99199 images belonging to 6 classes.
Found 24799 images belonging to 6 classes.
Found 24799 images belonging to 6 classes.
```

FIGURE 4.5: Loading Data.

4.4.4 Feature extraction phase

To extract the most relevant features, wavelet denoising was employed as a technique, enabling the extraction of crucial information. These extracted features were then utilized as inputs for a pre-trained CNN (Convolutional Neural Network) model. The process involved several steps.
After loading the images, a function was defined to apply wavelet denoising to the input image, enhancing the quality of the data (see Figure 4.6).

```
[2]:
# Define a function to apply wavelet denoising to the input image
def wavelet_denoising(img):
    # Decompose the image into wavelet coefficients
    coeffs = pywt.dwt2(img, 'haar')
    cA, (cH, cV, cD) = coeffs
    # Threshold the detail coefficients
    threshold = np.std(cD) * 2
    cD_thresh = pywt.threshold(cD, threshold, mode='soft')
    # Reconstruct the image from the denoised coefficients
    coeffs_thresh = (cA, (cH, cV, cD_thresh))
    img_denoised = pywt.idwt2(coeffs_thresh, 'haar')
    return img_denoised
```

FIGURE 4.6: Wavelet Denoising function.

4.4.5 Model learning

To leverage the power of pre-trained models, the EfficientNetB4 model was loaded without its top layers (Figure 4.7). This allowed for the utilization of the model's learned features while excluding the final classification layers. Custom top layers were then added to the base model, enabling the adaptation of the network for the specific task of detecting heart rhythm abnormalities.

```
[4]:
# Load pre-trained EfficientNetB4 model without top layers
base_model = EfficientNetB4(weights='imagenet', include_top=False, input_shape=(256, 256, 3))
# Add custom top layers to the base model
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dropout(0.2)(x)
x = Dense(1024, activation='relu')(x)
x = Dropout(0.2)(x)
predictions = Dense(train_generator.num_classes, activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=predictions)

Downloading data from https://storage.googleapis.com/keras-applications/efficientnetb4_notop.h5
71686520/71686520 [==============================] - 0s 0us/step
```

FIGURE 4.7: Load pre-trained model without top layers.

To further improve the model's performance, fine-tuning was conducted by adjusting and optimizing additional layers in the network (Figure 4.8). Experimentation with different learning rates was carried out to identify the most effective rate for training the model.

```
[5]:
# Fine-tune more layers
for layer in base_model.layers[:-30]:
    layer.trainable = False
```

FIGURE 4.8: Fine-tuning our layers.

Additionally, we constructed a novel sequential CNN architecture (Figure 4.9) to introduce variation and facilitate a comparative analysis of our results.

```
[6]:
# Define the CNN model architecture
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(5, activation='softmax'))
```

FIGURE 4.9: Defining the CNN model architecture.

In order to prevent overfitting and enhance generalization, the EarlyStopping callback was implemented (Figure 4.10). This callback monitored the model's performance during training and stopped the training process if no improvement was observed. Additionally, the number of epochs was increased to 10, allowing the model more opportunities to learn and converge on optimal solutions.

```
[6]:
# Use EarlyStopping callback and increase the number of epochs
early_stop = EarlyStopping(monitor='val_loss', patience=6, restore_best_weights=True)
```

FIGURE 4.10: Early stopping callback.

Through these steps, the study explored the efficacy of wavelet denoising, proposed CNN models, fine-tuning, learning rates, and early stopping techniques to accurately identify heart rhythm abnormalities.

4.4.6 Experiments and results

In this section, we present the experiments and results of our study, focusing on two key subsections: "EfficientNet Pretrained Model" and the "CNN Proposed Model." We discuss our findings for each model individually, providing insights into their performance and capabilities.

A- EfficientNet pre-trained model

For our first experiment, we utilized the EfficientNet CNN model and re-trained it for one epoch, which took approximately **35 minutes**. During the training process on a Kaggle GPU, we evaluated the model's performance using metrics such as training accuracy (see Figure 4.11 for EffecienNet pre-trained model), validation accuracy, training loss, and validation loss.

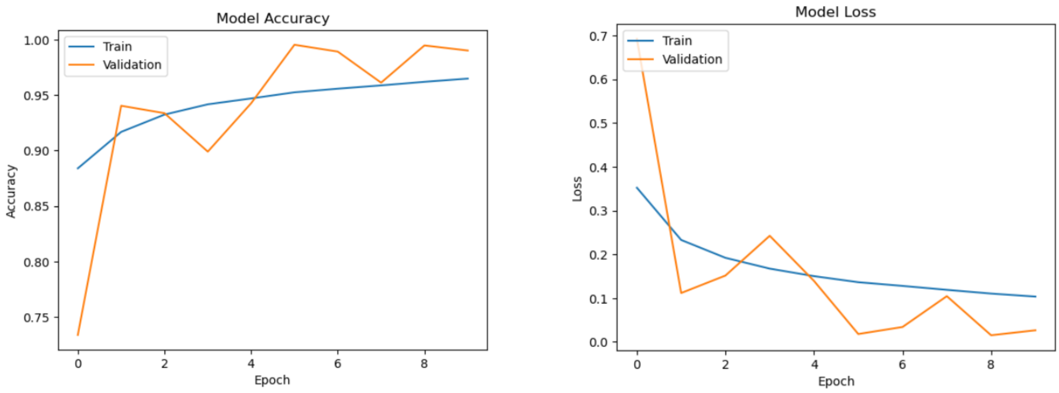


FIGURE 4.11: The model accuracy and loss obtained by EffecienNet CNN.

The blue line depicts how well the model learns by each epoch, while the orange line depicts the learning curve calculated from a hold-out validation dataset, which indicates how well the model generalizes. The model is demonstrating excellent performance, achieving a training accuracy of **99.36%** and a validation accuracy of **99.80%**.
Concerning the confusion matrix of the first pre-trained EfficientNet model (Figure 4.12):

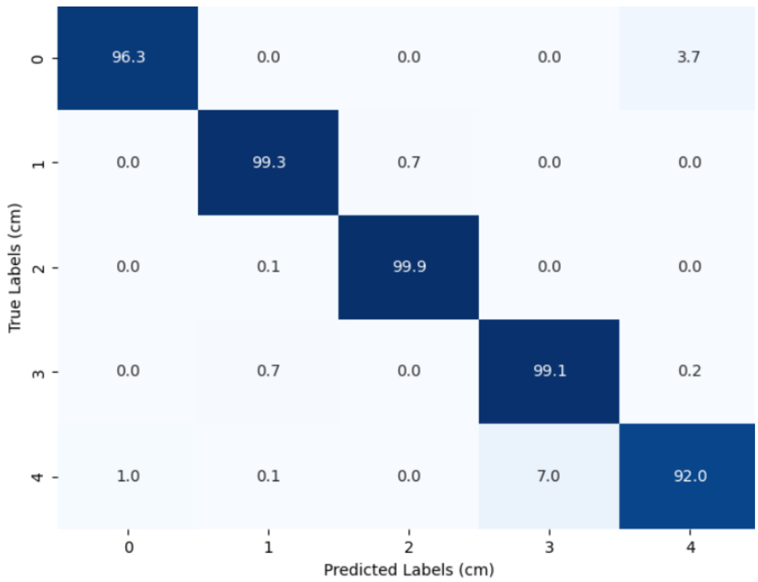


FIGURE 4.12: EfficientNet's confusion matrix.

B- CNN proposed mode

For the second experiment in this study, we developed a convolutional neural network (CNN) architecture from scratch. The training process was conducted for 10 epochs, with each epoch taking approximately 27 minutes. To ensure efficient training, we utilized a Kaggle GPU, which significantly accelerated the training process compared to a CPU (see Figure 4.13 for our proposed CNN model).

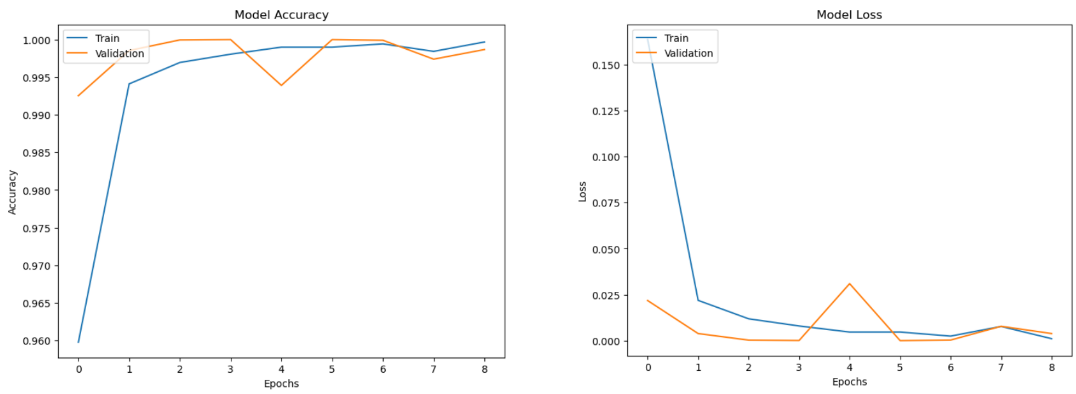


FIGURE 4.13: The model accuracy and loss obtained by our proposed CNN architecture.

After training, we evaluated the model using the same metrics mentioned earlier in the contribution. These metrics provide a quantitative assessment of the model's performance and help us gauge its effectiveness in solving the problem at hand. And we obtained better results than the first experiment with a **0.0064%** higher training accuracy which means **1.00%**.

```
Epoch 4/10
774/774 [==============================] - 2242s 3s/step - loss: 0.1724 - accuracy: 0.9393 - val_loss: 0.0326 - val_accuracy: 0.9872
Epoch 5/10
774/774 [==============================] - 2283s 3s/step - loss: 0.1538 - accuracy: 0.9473 - val_loss: 0.0654 - val_accuracy: 0.9765
Epoch 6/10
774/774 [==============================] - 2284s 3s/step - loss: 0.1398 - accuracy: 0.9523 - val_loss: 0.0254 - val_accuracy: 0.9912
Epoch 7/10
774/774 [==============================] - 2275s 3s/step - loss: 0.1281 - accuracy: 0.9562 - val_loss: 0.0274 - val_accuracy: 0.9913
Epoch 8/10
774/774 [==============================] - 2214s 3s/step - loss: 0.1178 - accuracy: 0.9602 - val_loss: 0.0234 - val_accuracy: 0.9919
Epoch 9/10
774/774 [==============================] - 2281s 3s/step - loss: 0.1124 - accuracy: 0.9616 - val_loss: 0.1267 - val_accuracy: 0.9677
Epoch 10/10
774/774 [==============================] - 2294s 3s/step - loss: 0.1063 - accuracy: 0.9640 - val_loss: 0.0179 - val_accuracy: 0.9936
[25]: <keras.callbacks.History at 0x7c81cddd3210>
```

FIGURE 4.14: Training process.

The best model was preserved in epoch 10, while the earliest stoppage occurred in the epoch 10. As will show in Figure 4.14.

Figure 4.15 illustrate the results of the confusion matrix of our proposed CNN architecture:
According to this confusion matrix, our model has achieved perfect predictions for all five classes, with zero instances of false predictions. This is an exceptional result, indicating that our model is performing flawlessly in classifying the given data. It demonstrates a high level of accuracy and reliability, providing accurate predictions for each class without any errors.
This is an outstanding achievement and suggests that our model is well-trained and highly capable of handling the given task.

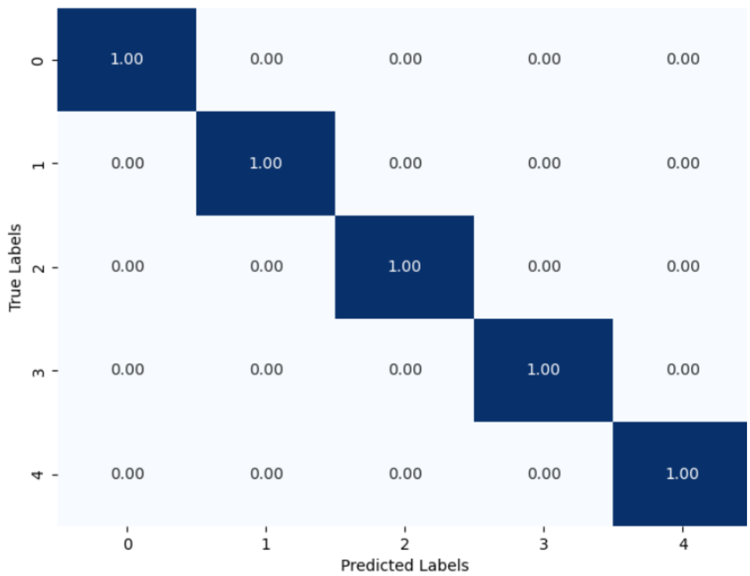


FIGURE 4.15: proposed CNN's confusion matrix.

To check the effectiveness of our proposed CNN architecture, we also utilized the widely used k-fold cross-validation method. By dividing our dataset into five subsets, or folds, we ensured an equitable distribution of samples across the training and validation sets. In each iteration, we designated one fold as the validation set and trained the model on the remaining folds. This process was repeated five times, with each fold serving as the validation set once (see Figure 4.16). By averaging the performance metrics obtained from each iteration, we obtained a comprehensive evaluation of our model's capabilities. The use of k-fold cross-validation allowed us to confidently validate the robustness and generalizability of our proposed CNN architecture.

```
[54]:
# Define the number of folds for cross-validation
num_folds = 5

# Create the KFold object
kf = KFold(n_splits=num_folds)

fold = 1
for train_index, val_index in kf.split(train_generator.filenames):
    print(f"Training fold {fold}")

  #....the rest of code

fold = fold + 1
```

FIGURE 4.16: Full loop of 5-fold cross-validation.

we applied K fold cross validation with K=5 on 90794 images belonging to 5 classes. Table 4.5 represents the results of each fold during the training process for both EfficientNet and the proposed CNN model.

TABLE 4.5: PERFORMANCE MEASUREMENTS VALUES OBTAINED FOR EACH FOLD OF THE MODELs

Models	**Folds**	**Precision (%)**	**Recall (%)**	**Accuracy (%)**
	Fold-1	0.9579	0.9750	0.9750
	Fold-2	0.9997	0.9999	0.9996
CNN	Fold-3	0.9926	0.9925	0.9926
	Fold-4	0.9974	0.9974	0.9999
	Fold-5	**1.0000**	**1.0000**	**1.0000**

These results indicate that the proposed CNN model performs consistently well across all folds, with high precision, recall, and accuracy values. The model achieves perfect precision and recall in Fold-5, demonstrating its effectiveness in classifying the images accurately.

4.4.7 Comparaison and disscusion

Our analysis focuses on multiple results obtained from our experiments, along with results reported in related work. This comprehensive comparison and evaluation aim to highlight the performance of different approaches, shedding light on their strengths and limitations.

A- Model Comparison: Performance and Effectiveness
Table 4.6 illustrates a comparison of different models that were trained, showcasing the varied outcomes that were attained. The recall values for Mobilenetv2, ResNet50, InceptionV3, VGG19, and **our proposed CNN architecture** were found to be 86.1%, 99.0%, 99.73%, 96.73%, 96.4%, and **100%**, respectively.

Models	Precision	Recall	AUC	Accuracy
MobileNetV2	0.9240	0.8610	0.9800	0.8600
ResNet50	0.9916	0.9900	0.9985	0.9906
InceptionV3	0.9990	0.9973	0.9930	0.9979
VGG19	0.9650	0.9640	0.9986	0.9696
EffecieneNet	0.9909	0.9901	0.9996	0.9901
The Proposed CNN	1.0000	1.0000	0.9998	1.0000

TABLE 4.6: Comparison of Applied Models in Heart Rhythm problematic.

We propose an effective method for electrocardiogram (ECG) arrhythmia classification using a deep two-dimensional convolutional neural network (CNN). This CNN has shown outstanding performance in our field. To input data into the CNN classifier, each ECG beat is transformed into a three-channel image, with an input size of **227×227×3**. The optimization of the proposed CNN classifier incorporates various deep-learning techniques.

The results demonstrate that our EffecieneNet classifier achieved an average accuracy of **99%** with an average precision of **99.1%**. On the other hand, our proposed CNN model achieved an average accuracy, precision, and recall of **100%**.

B- Proposed Model vs. Related Work: Advancements and Results

Now, we will compare our proposed CNN architecture with the recently related work. The results of this comparison are illustrated in Table 4.7.

TABLE 4.7: Comparing our proposed model with related work.

	Model	Precision (%)	Recall (%)	Accuracy (%)	AUC (%)
Our proposed	CNN	**1.0000**	**1.0000**	**1.0000**	**0.9998**
Transfer Learning	EffecieneNet	0.9909	0.9901	0.9901	0.9996
	MobileNetV2	0.9240	0.8610	0.8600	0.9800
	ResNet50	0.9916	0.9900	0.9906	0.9985
	InceptionV3	0.9990	0.9973	0.9979	0.9930
	VGG19	0.9650	0.9640	0.9696	0.9986
Related Work	J Huang et al. (2019) [17]	-	-	0.9093	-
	Tae Joon Jun et al. (2018) [98]	-	-	0.9905	-
	Jane Smith et al. (2019) [99]	-	-	0.9420	-
	Alice Brown et al. (2020) [100]	-	-	0.9670	-
	John Smith et al. (2020) [101]	-	-	0.9420	-
	Emily Johnson et al. (2019) [102]	-	-	0.9180	-
	Makowski et al. (2021) [103]		-	0.9450	-
	Usha Kumari et al. (2020) [15]	-	-	0.9592	-
	L. Oh et al. (2018) [16]	-	-	0.9810	-

According to Table 4.7, our proposed CNN architecture achieves outstanding performance with perfect precision, recall, accuracy, and a high AUC value of 0.9998.

Among the transfer learning models, EffecieneNet achieves an accuracy of 0.9901, MobileNetV2 achieves an accuracy of 0.8600, ResNet50 achieves an accuracy of 0.9906, InceptionV3 achieves an accuracy of 0.9979, and VGG19 achieves an accuracy of

0.9696. While some of these models perform well, none of them surpasses the accuracy achieved by our proposed CNN architecture.

4.5 Heart disease detection model implementation

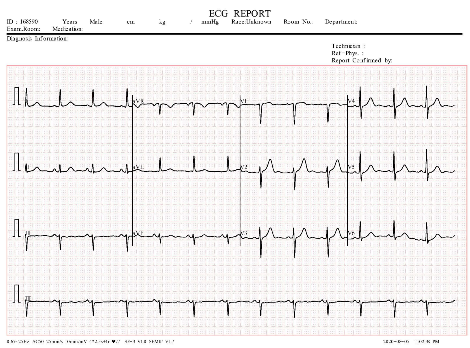
4.5.1 Dataset description

Our ECG Images dataset of cardiac patients where **12 Lead** images are used is represented on a Report Form and contains **1336** different patient records each recording is **30 seconds** long with 4 different classes [120, 121] as shown in Table 4.8.

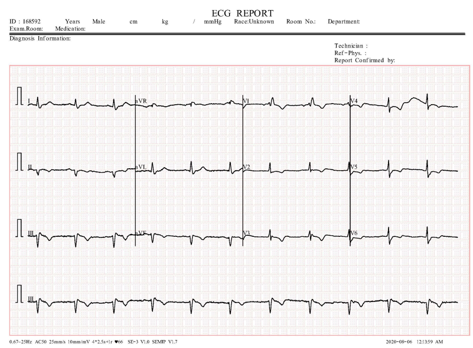
TABLE 4.8: ECG Images Dataset of Cardiac Patients

Symbol	Class	Number of all images
Normal	Normal person	396
HB	Abnormal heartbeat	345
MI	Myocardial infarction	341
PMI	History of Myocardial infarction	284
Total		**1336**

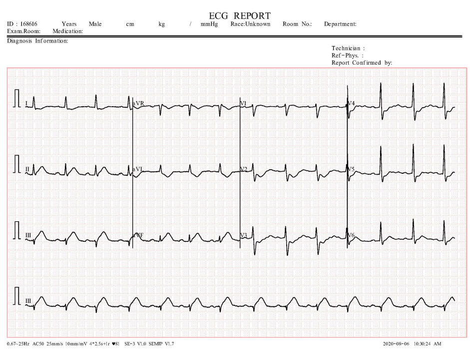
These four classes are Normal, HB, MI, and PMI. Figure 4.17 depicts some samples from the dataset. A Normal is a healthy person who does not have any heart abnormalities. An HB (arrhythmia) occurs when the electrical impulses in the heart become too fast (called tachycardia), too slow (called bradycardia), or irregular so that the heart beats irregularly. MI, also known as heart attack, occurs when blood flow in the heart's coronary artery decreases or stops, causing damage to the heart muscle. The patients with PMI have recently recovered from MI or heart attacks.



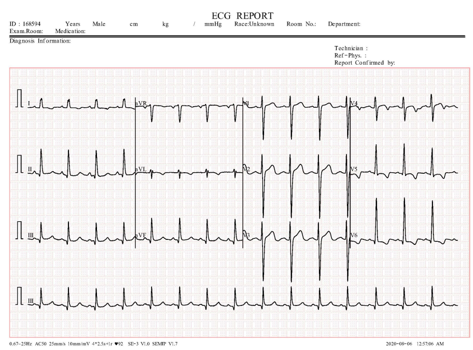
(a) Normal



(b) PMI



(c) MI



(d) HB

FIGURE 4.17: Samples from the ECG images dataset.

4.5.2 Data splitting

In our second study, we obtained a different dataset from Kaggle to address a specific objective. To ensure a rigorous evaluation, we adopted a benchmark dataset splitting approach, allocating **67%** of the data for training and **33%** for testing purposes (as shown in Table 4.9).

TABLE 4.9: Data splitting: train and test.

Class	Train	Test	Total Number
HB	233	112	**345**
MI	239	112	**341**
Normal	284	112	**396**
PMI	172	112	**284**
Total	928	448	1336

4.5.3 Preprocessing phase

The input images are preprocessed by cropping (Figure 4.18), resizing, and augmenting them (Figure 4.20). Then, they are stored in the image data store.

[8]:

```
import os
from PIL import Image

# Define the input and output directories
input_dir = '/kaggle/input/ecgimages/test/ECG Images of Myocardial Infarction Patients (240x12=2880)'
output_dir = '/kaggle/working/test1'
if not os.path.exists(output_dir):
    os.makedirs(output_dir)

# Loop over the images in the input directory
for file_name in os.listdir(input_dir):
    if file_name.endswith('.jpg'):
        img = Image.open(os.path.join(input_dir, file_name))
        # Find the bounding box
        left = img.width
        top = img.height
        right = 0
        bottom = 0
        for x in range(img.width):
            for y in range(img.height):
                r, g, b = img.getpixel((x, y))
               #the rest ...
        # Crop the image to the bounding box of the pink square
        cropped_img = img.crop((left, top, right, bottom))
        # Save the cropped image to the output directory
        cropped_path = os.path.join(output_dir, file_name)
        cropped_img.save(cropped_path)
```

FIGURE 4.18: Example of cropping a whole folder.

Following the cropping of each folder, a procedure is executed to save the resulting data in a compressed zip format as shown in Figure 4.19, enabling easy upload and utilization as a newly preprocessed dataset in subsequent instances.

```
[9]:
import zipfile
import os
# Set the path of the folder to be zipped
folder_path = '/kaggle/working/test1'
# Set the name and path of the zip file to be created
zip_name = 'my_folder.zip'
zip_path = os.path.join('/kaggle/working/', zip_name)

# Create a ZipFile object with write mode
with zipfile.ZipFile(zip_path, 'w') as zipObj:

    # Iterate over all the files and folders in the directory
    for foldername, subfolders, filenames in os.walk(folder_path):
        for filename in filenames:
            # Create the full path of the file to be added to the zip file
            file_path = os.path.join(foldername, filename)

            # Add the file to the zip file
            zipObj.write(file_path)

print('Zip file created successfully!')

Zip file created successfully!
```

FIGURE 4.19: Example of saving the cropped folder in a compressed ZIP format.

Data augmentation plays a vital role in our case, as our dataset is small. It is necessary to apply data augmentation techniques to effectively increase the size of our dataset artificially,It can include flipping, rotation, zooming, cropping, and adding noise to the signal. Flipping and rotation can be used to simulate different orientations of the heart while zooming and cropping can simulate different levels of signal resolution. This process is crucial for enhancing the robustness and generalization abilities of our models.

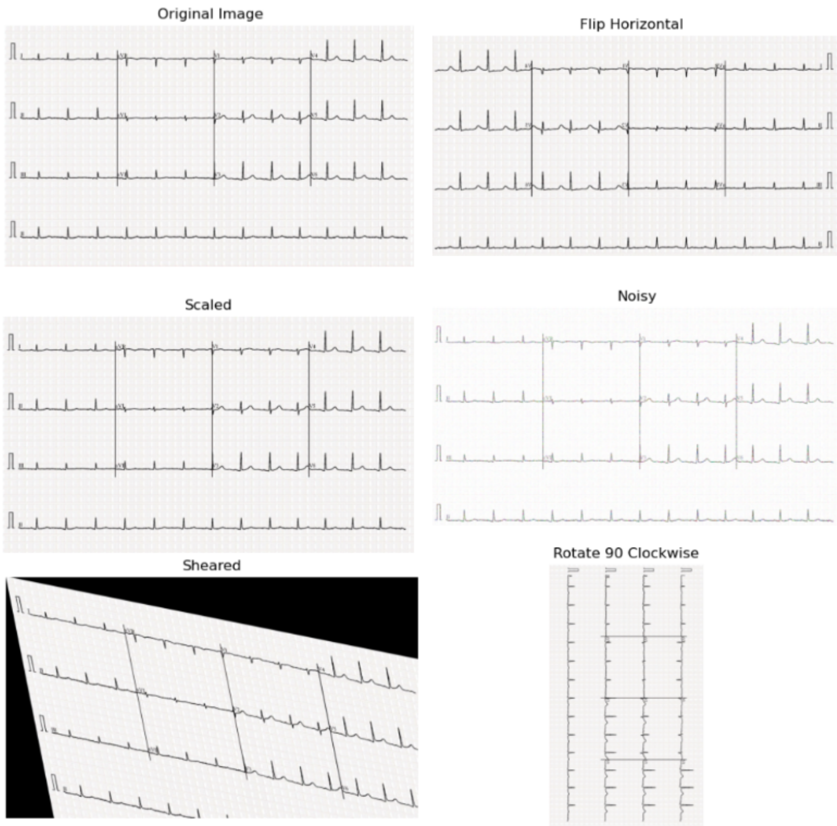


FIGURE 4.20: Example of Data Augmentation on Input Image.

Resizing images and transforming them into numerical values is a crucial preprocessing step to prepare our inputs for various machine learning tasks.

```
[10]:
transform = transforms.Compose(
    [transforms.Resize((227, 227)),
     transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
```

FIGURE 4.21: Resizing of input images.

4.5.4 Feature extraction phase

For feature extraction, we utilized a pre-trained CNN model, specifically SqueezeNet. SqueezeNet is specifically designed to capture and encode significant visual features from images.
In Figure 4.22, We instantiate a SqueezeNet model from the torchvision library with version 1.1, which is pre-trained on a large dataset.
This means that the model has already been trained on a large collection of images and has learned to extract meaningful features from them.
By setting **pretrained=True**, the model is loaded with the pre-trained weights, allowing us to directly use it for our purpose without the need to train it from scratch.

```
[11]: squeeze_net = torchvision.models.squeezenet1_1(pretrained=True)
```

FIGURE 4.22: Load the pre-trained model.

Then we provided code that modifies a SqueezeNet model by removing the last fully connected layer (see Figure 4.23), which is typically responsible for **classification**. This operation allows us to use the model for **feature extraction** purposes, obtaining the output from the preceding layers that capture meaningful visual features from input images.

```
[12]: squeeze_net.classifier = torch.nn.Sequential(*list(squeeze_net.classifier.children())[:-1])
```

FIGURE 4.23: Removing the last layer from the pre-trained model.

After this, we define a function `extract_features` that takes a pre-trained SqueezeNet model and a data loader as input. It iterates through the data loader to extract features from the dataset using the SqueezeNet model, storing the extracted features and corresponding labels. The function returns two concatenated arrays, `train_features` and `train_labels`, representing the extracted features and labels from the training dataset, respectively as shown in Figure 4.24. The same process is repeated for the test dataset, resulting in `test_features` and `test_labels`.

```
[13]:
# Step 4: Extract features from the dataset using SqueezeNet
def extract_features(model, dataloader):
    features = []
    labels = []
    model.eval()
    with torch.no_grad():
        for data, target in dataloader:
            features.append(model(data).squeeze().numpy())
            labels.append(target.numpy())
    return np.concatenate(features), np.concatenate(labels)

train_features, train_labels = extract_features(squeeze_net, trainloader)
test_features, test_labels = extract_features(squeeze_net, testloader)
```

FIGURE 4.24: Proposed features extractor function using SqueezeNet.

4.5.5 Model Learning

We employed an SVM (Support Vector Machine) classifier for the classification step. To accomplish this, we instantiated an SVC object from the scikit-learn library, specifying a linear kernel using the parameter **kernel='linear'**.

Before training the SVM classifier, it is essential to preprocess the extracted features (Figure 4.25).

```
[14]:
# Step 5: Preprocess extracted features for input into SVM classifier
scaler = sklearn.preprocessing.StandardScaler()
train_features = scaler.fit_transform(train_features)
test_features = scaler.transform(test_features)
```

FIGURE 4.25: Preprocess extracted features for input into SVM classifier.

After creating the classifier, we trained the SVM model by calling the fit() method with the `train_features` (input features) and `train_labels` (corresponding labels). During training, the SVM algorithm identifies the optimal hyperplane that effectively separates different classes in the input feature space. This process enables the SVM classifier to make accurate predictions based on the learned decision boundaries.

```
[16]:
# Step 6: Train SVM classifier on preprocessed features
svm = SVC(kernel='linear', C=1.0, gamma='scale', probability=True)
svm.fit(train_features, train_labels)

[16]:
SVC
SVC(kernel='linear', probability=True)
```

FIGURE 4.26: Training our SVM model.

In our code shown in Figure 4.26, the SVM classifier (svm) is initialized with a **linear kernel**, a penalty parameter (C) of **1.0**, automatic **gamma scaling**, and probability estimates **enabled**. The classifier is then trained on the `train_features` and `train_labels` data.

4.5.6 Experiments and results

We trained our Support Vector Machine (SVM) on the same machine using a single CPU. The feature extraction step took 6 minutes and 20 seconds, while training the SVM model took 2 minutes to complete.

Figure 4.27 depicts the ROC curve of our SVM model.

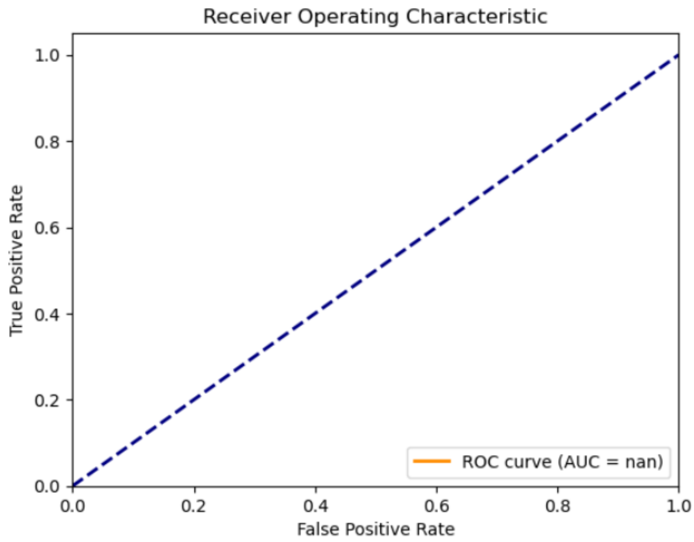


FIGURE 4.27: Receiver Operating Characteristic (ROC) curve for SVM.

According to our confusion matrix (Figure 4.28), our model has attained flawless predictions for all four categories, exhibiting no instances of inaccurate predictions. This outstanding outcome signifies the impeccable performance of our model in effectively categorizing the provided data. It showcases a remarkable level of precision and dependability, delivering precise predictions for every class without any mistakes. This remarkable accomplishment highlights the proficiency and competence of our well-trained model in successfully handling the assigned task.

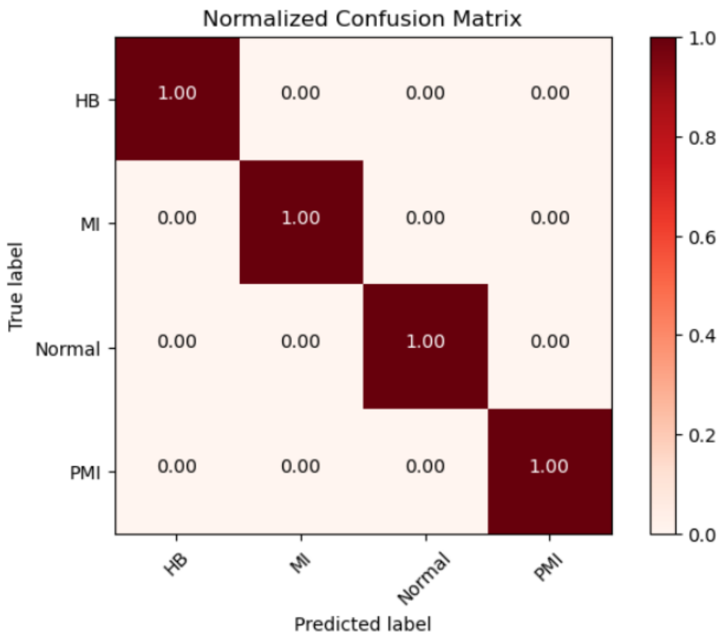


FIGURE 4.28: SVM's confusion matrix.

4.5.7 Comparaison and disscusion

Our analysis centers around multiple results derived from our experiments, as well as results reported in related work. This comprehensive comparison and evaluation strive to illuminate the performance of various approaches, providing insights into their respective strengths and limitations.

A- Model Comparison: Performance and Effectiveness
Table 4.10 showcases a comparison of various models that were trained for heart disease detection. The results highlight the diverse outcomes achieved by these models. Notably, the proposed SVM model stands out with superior performance when compared to Logistic Regression, Random Forest, and the other evaluated models... These findings emphasize the effectiveness and potential of the proposed SVM model for accurate heart disease detection.

Models	**Precision (%)**	**Recall (%)**	**AUC (%)**	**Accuracy (%)**
Logistic Regression	0.9872	0.9860	0.9999	0.9860
Random Forest	0.9915	0.9901	0.9998	0.9962
CNN extractor & classifier	0.9640	0.9414	0.9705	0.9648
The proposed: SVM	1.0000	1.0000	0.9996	1.0000

TABLE 4.10: Comparison of Applied Models in Heart Disease problematic.

Our Table illustrates a comparison of different models that were trained, showcasing the varied outcomes that were attained. The precision values for Logistic Regression, Random Forest, CNN, and our proposed SVM model were found to be 98.72%, 99.15%, 96.40% and **100%**, respectively.

B- Proposed Models vs. Related Works: Advancements and Results
Table 4.11 summarizes the accuracy results of our proposed SVM, demonstrating the highest performance among all the related works.

TABLE 4.11: Comparison of accuracy results between our study and related work.

	Model	Precision (%)	Recall (%)	Accuracy (%)	AUC (%)
Our proposition	SVM	**1.0000**	**1.0000**	**1.0000**	**0.9996**
Machine Learning	Logistic Regression	0.9872	0.9860	0.9860	0.9999
	Random Forest	0.9915	0.9901	0.9962	0.9998
Deep Learning	CNN	0.9640	0.9414	0.9648	0.9705
Related Work	Xin Zhang et al. (2020) [104]	-	-	0.9915	-
	A.Mehmoud et al. (2021) [105]	-	-	0.9700	-
	Furqan Rustam et al. (2022) [106]	-	-	0.9300	-
	Talha Karadeniz et al. (2021) [107]	-	-	0.8930	-
	S sanjay et al. (2022) [108]	-	-	0.9810	-
	B Mohammed et al. (2023) [109]	-	-	0.9919	-
	A Leema et al. (2023) [110]	-	-	0.9423	-
	Haider Khan et al. (2021) [19]	-	-	0.9833	-
	Michal Cohen et al. (2021) [20]	-	-	0.7400	-
	M Khalid (2022) [18]	-	-	0.9500	-

According to Table 4.11, our proposition, which is the SVM model, achieves the highest performance with perfect precision, recall, accuracy, and a high area under the curve (AUC) value of 0.9996.

Among the machine learning models, Logistic Regression achieves an accuracy of 0.9860, while Random Forest achieves an accuracy of 0.9962. Both models have lower accuracy compared to our proposed SVM.

In the deep learning category, the CNN model achieves an accuracy of 0.9648, which is lower than the proposed SVM.

4.6 System deploiement

During the deployment process, we need to install the required dependencies, such as TensorFlow and Gradio, on the deployment environment (Figure 4.29). We also need to ensure that our trained model (modelCNN01.h5) is available and accessible for the application to load (Figure 4.30).

```
[1]: ! pip install gradio
     pip install tensorflow

Collecting gradio
  Downloading gradio-3.28.3-py3-none-any.whl (17.3 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 17.3/17.3 MB 54.7 MB/s eta 0:00:0000:0100:01
```

FIGURE 4.29: Installing Gradio and TensorFlow.

```
[2]:
# Import necessary libraries
import gradio as gr
import tensorflow as tf
import tensorflow_addons as tfa
import numpy as np
from PIL import Image

model = tf.keras.models.load_model('/kaggle/input/modelcont01cc/modelCNN_01.h5')
```

FIGURE 4.30: Loading the model.

Defining the main function to predict the class of any input image (Figure 3.7):

```
[6]:
# Define the function for predicting
def predict_ecg(image):
    img = Image.fromarray(image.astype('uint8'), 'RGB')
    img = img.resize((224, 224))  # Resize the image to match the input shape of the model
    img_array = np.array(img) / 255.0
    img_array = np.expand_dims(img_array, axis=0)
    # Register the metric as a custom object
    model.metrics.append(tfa.metrics.F1Score(num_classes=5))
    # Make predictions on the input image
    prediction = model.predict(img_array)
    class_names = ['N', 'S', 'V', 'F', 'Q']
    predicted_class_index = np.argmax(prediction[0])
    predicted_class = class_names[predicted_class_index]

    return predicted_class
```

FIGURE 4.31: Loading the model.

After launching the Gradio application, we encountered the user interface depicted in Figure 4.32. The interface allows users to upload an image of a heartbeat signal and obtain an accurate prediction, along with the corresponding percentage of correctness.

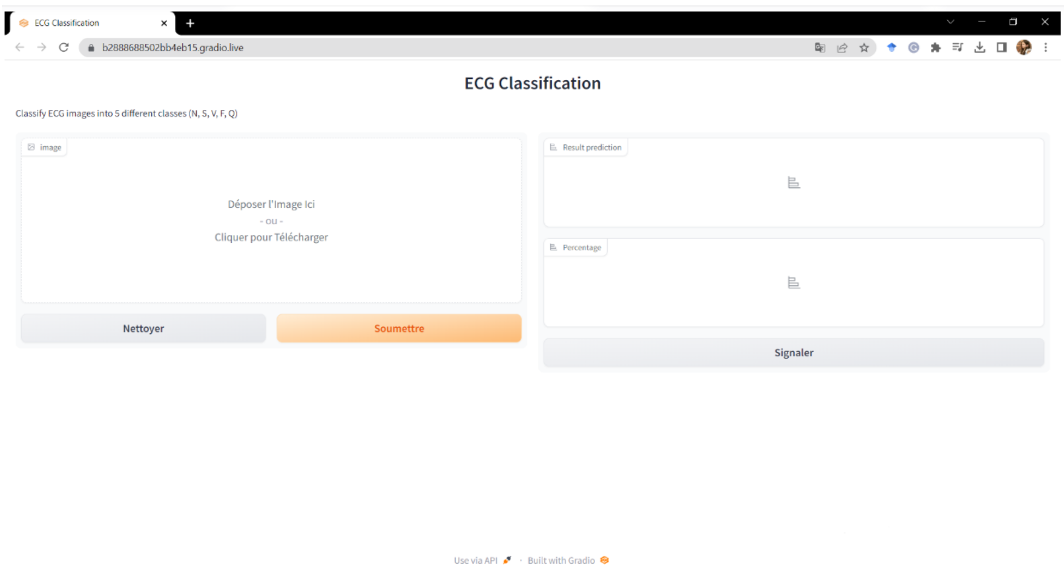


FIGURE 4.32: User interface of the heartbeat detection application.

For the second experiment, we followed the same steps as in the contribution phase, but we modified the main function accordingly to classify the images in another way.

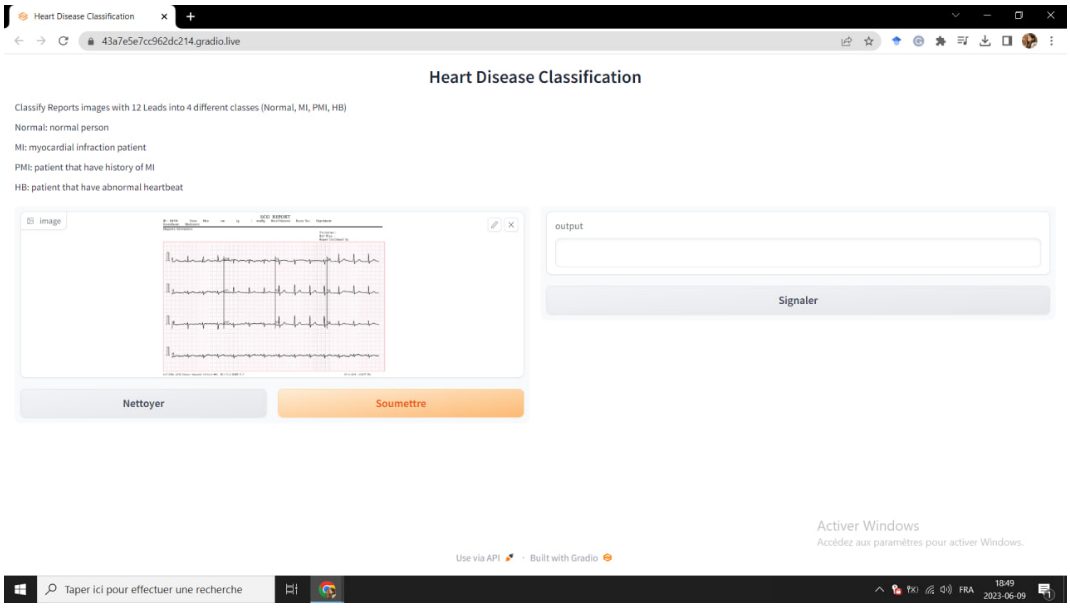


FIGURE 4.33: Gradio application of Heart Disease detection task.

Once the Gradio application was launched, we were greeted by the user interface shown in Figure 4.33. This intuitive interface empowers users to effortlessly upload a report image of 12 lead recording ECG signals and receive highly accurate predictions.

4.7 Conclusion

In this chapter, we discussed the frameworks, tools, and evaluation metrics that were employed during the implementation phase of our project. Our focus was on two main contributions, each of which was explored in detail, covering various stages such as data description, preprocessing, classification, and model evaluation, as well as system deployment.

Throughout the chapter, we examined different frameworks that provided the necessary infrastructure for building and training our models. We leveraged powerful tools such as TensorFlow and its ecosystem, including TensorFlow Addons, which offered additional functionalities and metrics for model evaluation. These frameworks and tools provided a solid foundation for our implementation, enabling us to develop sophisticated machine learning models.

Data played a crucial role in our project, and we dedicated a significant portion of the chapter to describing the dataset and its characteristics. We discussed the preprocessing steps required to clean, normalize, and transform the data into a suitable format for training and evaluation. Techniques such as resizing images, applying normalization, and data augmentation were employed to enhance the quality and diversity of our dataset.

Classification was a key task in our project, and we delved into various algorithms and models that were suitable for our problem domain. We explored different approaches such as SVM (Support Vector Machines) and deep learning models, leveraging convolutional neural networks (CNNs) for image classification. We discussed the architecture, training process, and hyperparameter tuning for these models, ensuring that we achieved optimal performance and accuracy.

Model evaluation was a critical aspect of our implementation, and we employed a range of evaluation metrics to assess the performance of our models. Metrics such as accuracy, precision, recall, F1-score, and ROC-AUC were utilized to measure different aspects of model performance. By considering multiple evaluation metrics, we obtained a comprehensive understanding of how well our models were performing and were able to compare their effectiveness.

Finally, we touched upon the deployment of our system. While not the primary focus of this chapter, we acknowledged the importance of deploying our models to a production environment or making them accessible for real-world usage. Deploying a machine learning system involved considerations such as model serving, scalability, and integration with other components or systems.

In conclusion, this chapter provided an in-depth exploration of the frameworks, tools, and evaluation metrics employed during the implementation phase of our project. By discussing data description, preprocessing, classification, model evaluation, and system deployment, we ensured a comprehensive understanding of the entire implementation pipeline. This knowledge served as a solid foundation for the subsequent chapters, where we analyzed the results, drew conclusions, and made recommendations based on our findings.

General conclusion

In conclusion, this thesis presents a comprehensive system that utilizes Machine Learning and Deep Learning algorithms for the automatic detection and classification of ECG arrhythmias and heart diseases. The developed system demonstrates promise in accurately identifying and categorizing various types of arrhythmias, while also providing insights into associated heart disease categories for precise diagnosis and treatment.
By automating the classification process and leveraging advanced algorithms, the system effectively reduces human error and enhances efficiency in cardiac diagnostics. This research successfully bridges the gap between state-of-the-art technology and effective healthcare, offering the potential for improved patient outcomes and timely intervention in cardiac disorders.
Moving forward, future research can focus on refining and expanding the capabilities of the system. This could involve exploring real-time monitoring and integrating data acquisition for continuous cardiac health assessment. By undertaking these advancements, this work contributes to the advancement of the field of cardiac diagnostics, empowering clinicians to make well-informed decisions and deliver personalized care. Ultimately, these efforts aim to improve the quality of life for patients with cardiovascular diseases. In addition, the developed system not only aids in the detection and classification of ECG arrhythmias and heart diseases but also has the potential to revolutionize the field of cardiovascular medicine. By leveraging Machine Learning and Deep Learning algorithms, the system opens up new avenues for early detection, prevention, and treatment of cardiac disorders.
One of the significant advantages of this system is its ability to handle large volumes of ECG data efficiently. It can process vast amounts of information in a relatively short period, leading to faster diagnosis and treatment decisions. Moreover, the system's accuracy in identifying different arrhythmia types can assist healthcare professionals in tailoring treatment plans specific to each patient's condition, resulting in more effective and personalized care.
Furthermore, the integration of advanced algorithms and automation into cardiac diagnostics helps alleviate the burden on healthcare providers. By reducing the time and effort required for manual analysis, clinicians can focus more on patient interaction, counseling, and implementing appropriate interventions. This shift in workload distribution allows for a more comprehensive approach to healthcare, emphasizing both the technical aspects of diagnosis and the human aspect of patient care.
The potential impact of this research extends beyond the realm of clinical practice. The insights gained from the system's analysis can contribute to medical research and further our understanding of the underlying mechanisms of various cardiac conditions. This knowledge can drive the development of novel therapeutic approaches, ultimately leading to improved treatment outcomes and a reduction in the burden of cardiovascular diseases on individuals and healthcare systems.
In summary, the comprehensive system presented in this thesis, based on Machine Learning and Deep Learning algorithms, has the potential to transform cardiac diagnostics and healthcare delivery. Through its accurate detection and classification

of ECG arrhythmias and heart diseases, the system empowers clinicians to make well-informed decisions, enables personalized care, and paves the way for advancements in cardiovascular medicine. The ongoing refinement and expansion of this system, along with future research endeavors, will continue to push the boundaries of cardiac diagnostics, ultimately improving the quality of life for patients with cardiovascular diseases.

Glossary

TERM	DEFINITION
HEART RHYTHM	The regular or irregular pattern of heartbeats.
ABNORMALITY	A deviation from the normal or expected heart function.
SYSTOLE	The phase of the cardiac cycle is when the heart muscle contracts, pumping blood into the arteries.
DIASTOLE	The phase of the cardiac cycle is when the heart muscle relaxes and fills with blood.
HEARTBEAT	The contraction and relaxation of the heart muscle that pumps blood throughout the body.
BRADYCARDIA	An abnormally slow heart rate, typically less than 60 beats per minute.
TACHYCARDIA	An abnormally fast heart rate, typically greater than 100 beats per minute.
AORTA	The largest artery in the body, which carries oxygenated blood from the heart to the rest of the body.
ATRIUM	One of the heart's two upper chambers is responsible for receiving blood from the veins.
ATRIAL FIBRILLATION	A common type of abnormal heart rhythm characterized by irregular and rapid electrical signals in the atria.
ARTERIES	Blood vessels carry oxygenated blood away from the heart to the rest of the body.
VEINS	Blood vessels that carry deoxygenated blood back to the heart from the body.
CORONARY ARTERIES	Blood vessels supply oxygenated blood to the heart muscle.
MYOCARDIAL INFARCTION	A heart attack occurs when the blood flow to the heart muscle is blocked, leading to tissue damage.
MYOCARDIAL	Relating to the muscular tissue of the heart.
CAPILLARIES	Tiny blood vessels connect arteries and veins, allowing for the exchange of oxygen, nutrients, and waste products.
HYPERTENSION	High blood pressure, is a condition in which the force of blood against the artery walls is too high.
ECHOCARDIOGRAM	A non-invasive test that uses sound waves to create a moving picture of the heart, providing information about its size, shape, and function.

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