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Thesis

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Prediction of heart disease using deep learning

By:

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Dedication

To my mother, Daira Houria.

To all the teachers who have guided me to this day,

Thank you for your support.

Résumé

Les maladies cardiaques sont une condition grave et sont considérées comme la principale cause de mortalité dans de nombreux pays. Sans détection précoce, l’état des patients atteints de maladies cardiaques peut se détériorer jusqu’à ce qu’il soit trop tard pour un traitement efficace. Une méthode de diagnostic qui peut aider à la détection précoce des maladies cardiaques est l’électrocardiographie (ECG), en raison de son faible coût. Cependant, l’interprétation des signaux ECG est difficile et prend du temps. Les récents progrès en apprentissage profond offrent une solution potentielle en aidant les médecins et les patients à détecter précocement les maladies cardiaques grâce à la classification des enregistrements ECG.

Dans ce travail, nous avons discuté des maladies cardiaques, de l’ECG et de ses limites, ainsi que des approches d’apprentissage automatique et d’apprentissage profond utilisées dans ce domaine, chacune ayant ses propres avantages. Dans notre projet, nous avons proposé un modèle d’autoencodeur LSTM pour soutenir la prédiction précoce de la maladie. Le modèle a été entraîné sur un ensemble de données ECG et a obtenu des résultats prometteurs.

Mots-clés: Maladie cardiaque, classification, électrocardiogramme, apprentissage automatique, apprentissage profond, diagnostic, traitement, LSTM, autoencodeur, maladies cardiovasculaires, détection précoce.

Abstract

Heart disease is a serious condition and is considered the leading cause of death in many countries. Without early detection, the condition of patients affected by heart disease can worsen until it becomes too late for effective treatment. One diagnostic method that can aid in the early detection of heart disease is electrocardiography (ECG), due to its low cost. However, interpreting ECG signals is challenging and time-consuming. Recent advances in deep learning offer a potential solution by assisting both doctors and patients in the early detection of heart disease through the classification of ECG records.

In this work, we discussed heart disease, ECG and its limitations, as well as machine learning and deep learning approaches used in this field, each with its own strengths. In our project, we proposed an LSTM Autoencoder model to support early prediction of the disease. The model was trained on an ECG dataset and achieved promising results.

Keywords: Heart disease, classification, Electrocardiogram, Machine Learning, Deep Learning, Diagnosis, Treatment, LSTM, Autoencoder , Cardiovascular diseases, Early detection.

ملخص

مرض القلب هو حالة خطيرة جدا ويعتبر السبب الرئيسي للوفاة في العديد من الدول في العالم. ومن دون الكشف المبكر، قد تتدهور حالة المرضى المصابين بأمراض القلب حتى تصبح فرص العلاج الفعّال ضئيلة أو معدومة. واحدة من الوسائل التشخيص التي يمكن أن تساعد في الكشف المبكر عن أمراض القلب هي تخطيط القلب الكهربائي(ECG) ، وذلك نظراً لتكلفته المنخفضة. و لكن، تفسير إشارات تخطيط القلب يُعتبر أمرا معقدا ويستغرق وقتاً طويلاً. وقد أظهرت التطورات الحديثة في مجال التعلم العميق إمكانية تقديم حل فعّال من خلال مساعدة الأطباء والمرضى في الكشف المبكر عن أمراض القلب عبر تصنيف سجلات تخطيط القلب.

في هذا العمل، ناقشنا أمراض القلب وتخطيط القلب الكهربائي ومحدوديته، بالإضافة إلى أساليب التعلم الآلي والتعلم العميق المستخدمة في هذا المجال، وكل واحدة منها بنقاط قوة خاصة بها. في مشروعنا، اقترحنا نموذج LSTM Autoencoder لدعم التنبؤ المبكر بالمرض. تم تدريب النموذج على مجموعة بيانات لتخطيط القلب وحقق نتائج واعدة

الكلمات المفتاحية: مرض القلب ، تصنيف، تخطيط القلب الكهربائي، تعلم الآلة،التعلم العميق،تشخيص ،العلاج،الذاكرة طويلة قصيرة المدى،شبكة الترميز التلقائي،أمراض القلب والأوعية الدموية،الكشف المبكر.

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General Introduction

General context

In the medical field, the need to detect a disease as soon as a patient develops or shows symptoms is of great importance, as the increased chance of recovery depends on early detection. For example, the early detection of heart diseases can both save the patient life and avoid any future health complications. However, due to the subtle nature of the symptoms of heart disease, many patients don’t notice they have developed it before it's too late.

To address this issue, deep learning can be of great help by enabling faster and earlier detection of the disease, assisting both the patient and the doctor. Deep learning models are effective at detecting anomalies, such as those present in a sick heart, by analyzing data like ECGs or heart scans. We chose this work to help patients discover they are suffering from heart disease before it’s too late.

Problematic

The heart is a vital organ necessary for sustaining human life. However, it may malfunction due to various factors, such as damage to the blood vessels, which can pose a serious threat to the patient's life if left untreated for an extended period. This thesis aims to develop a model to facilitate the early prediction of heart disease using electrocardiogram (ECG) signals.

Objective of the work

The main objective of our work is to develop a deep learning model that can aid in predicting presence of heart diseases.

The research is structured as follow:

- **Chapter 1: Heart Diseases and Electrocardiography.** This chapter discusses heart diseases, including their types, causes, diagnostic methods, and treatments. It also explores electrocardiography as a diagnostic tool, covering its waveforms, rhythms, and lead placements.
- **Chapter 2: Machine and Deep learning approaches.** This chapter discusses machine learning and its types, and explores deep learning approaches that are commonly used in the field of heart disease prediction.

- **Chapter 3: Design of the approach.** This chapter presents our proposed model and explains the dataset that was used.
- **Chapter 4: Implementation and results.** This chapter explains the implementation of the model and its results, along with a comparison to related works.

Chapter 1:
Heart Diseases and Electrocardiography

Chapter 1 Heart Diseases and Electrocardiography

1.1. Introduction

Heart diseases more commonly referred to in the medical field as cardiovascular diseases are considered a major type of chronic illness affecting many people around the world. According to the European Society of Cardiology, heart diseases are the most common cause of death within ESC member countries, accounting for 45% and 39% of all deaths in females and males, respectively [1].

As part of the diagnostic and monitoring process for these conditions, electrocardiography (ECG) plays a vital role. As a widely accessible diagnostic tool, ECG provides valuable insights into the electrical activity of the heart, enabling clinicians to detect various cardiac abnormalities early.

In this chapter, we aim to discuss cardiovascular diseases (heart diseases), their types, and possible treatments.

1.2. Cardiovascular diseases (Heart diseases)

Cardiovascular diseases (heart diseases) refer to a group of anomalies that negatively affect the heart and blood vessels, potentially leading to severe complications such as heart failure and heart attacks [2] if left untreated. They often disrupt the normal blood circulation, preventing it from functioning properly and delivering oxygen and nutrients to vital organs. These conditions often arise due to risk factors like smoking, diabetes, obesity, and high blood pressure, factors that have become increasingly prevalent in today’s society, largely due to the modern work environment.

1.3. Types of cardiovascular diseases

There are over 30 types of cardiovascular diseases, but most fall under four main categories [3]:

- Coronary heart disease.
- Stroke.
- Peripheral arterial disease.
- Aortic disease.

1.3.1. Coronary heart disease (CAD)

1.3.1.1. Definition

It is a heart condition in which the coronary arteries become blocked or narrowed due to atherosclerosis (the buildup of fatty material and plaque inside the coronary arteries) [3], which leads to decreased myocardial perfusion [4].

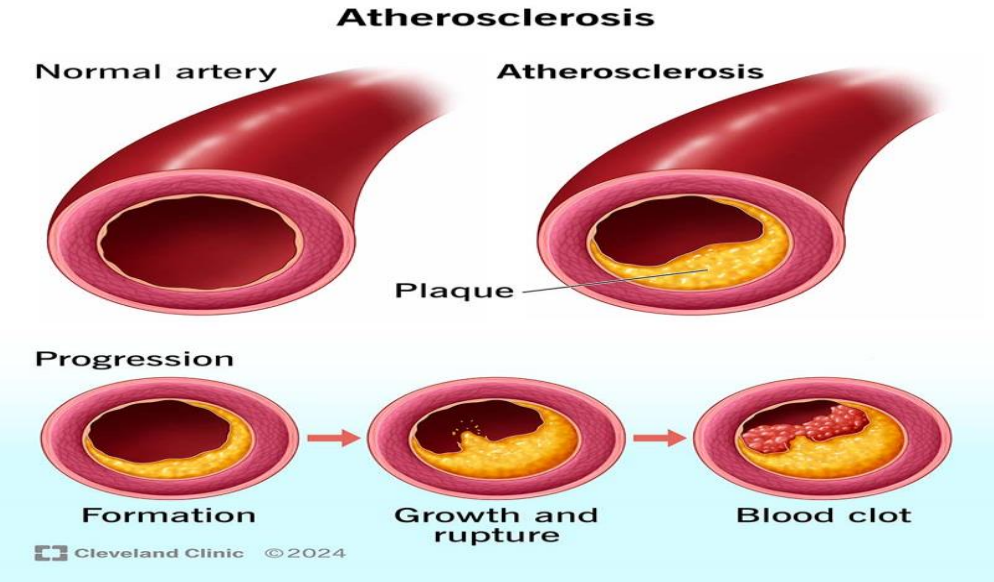


Figure 1.1: Atherosclerosis formation [94]

1.3.1.2. Cause

Coronary artery disease (CAD) is influenced by multiple factors, including no modifiable factors such as gender, age, family history, and genetics, as well as modifiable risk factors such as hypertension, smoking, obesity, dyslipidemia, and psychosocial stress [5]. In addition, unhealthy dietary habits and lack of physical activity are significant contributors that should not be overlooked.

These risk factors initiate and sustain a chronic inflammatory process, beginning with the early formation of fatty streaks and progressing to the development of fibrous atheromas, ultimately leading to arterial narrowing, impaired blood flow, [6]and increased risk of acute coronary syndromes.

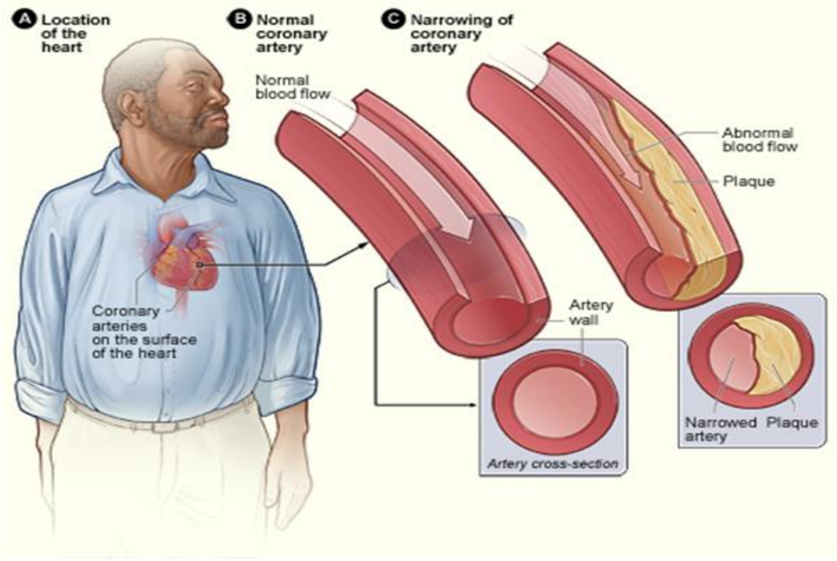


Figure 1.2: Arterial narrowing process [95].

1.3.1.3. Symptoms

CAD symptoms can vary depending on the severity of the illness but common ones include [7]:

- Chest discomfort or pain
- Upper body pain
- Stomach pain
- Shortness of breath
- Nausea and vomiting

1.3.1.4. Diagnostic

There are many tests used to diagnose CAD, here are some of the most used ones:

- **Electrocardiogram (ECG or EKG):** ECG is a paper recording of the heart's electrical activity [8], typically captured through electrodes placed on the skin at specific points on the chest, arms, and legs. This electrical activity occurs when the heart is depolarized to trigger its contraction during a heartbeat [9]. This test provide essential information such as the heart's rate, rhythm, and axis to help detect heartbeat issues [5].
- **Stress Test:** It is a very common test to reveal cardiovascular abnormalities that are not apparent at rest and to assess how well the heart is functioning [10]. It involves recording the electrocardiogram (ECG) before, during, and after subjecting the patient to varying levels of physical stress, in order to identify any anomalies that may arise during the procedure.

- **Cardiac catheterization:** This test is considered one of the most accurate methods for evaluating coronary artery disease (CAD). The procedure involves inserting a long, thin, flexible tube called a catheter into a blood vessel, followed by taking X-rays of the coronary arteries using a technique known as coronary angiography, which highlights any blood vessels that are narrowed or blocked [11].
- **Nuclear scanning:** Nuclear scanning is a diagnostic imaging technique in which radioactive material is injected into a vein. A special camera then tracks the radiotracer as it travels through the bloodstream and accumulates in the heart muscle, helping to assess blood flow and detect abnormalities [7].

1.3.1.5. Treatments

Coronary artery disease (CAD) is treated in various ways depending on the severity of the condition. For milder cases, treatment focuses on managing symptoms by addressing major modifiable risk factors, such as smoking, high blood pressure, diabetes mellitus, and hypercholesterolemia. Lifestyle improvements, including dietary adjustments and maintaining a healthy weight, are also essential.

For patients with more serious conditions, treatment often involves medications. Antiplatelet agents and low-dose aspirin are typically the first-line options, while statins are used to lower cholesterol levels. Both β-blockers and angiotensin-converting enzyme (ACE) inhibitors help prevent cardiac events. In extremely severe cases, myocardial revascularization may be considered. This surgical procedure bypasses blocked arteries and creates a new path for blood to flow to the heart.

It should be noted that several new treatments have emerged in recent years, such as PCSK9 inhibitors for lowering LDL cholesterol, but these have not yet achieved widespread use [12].

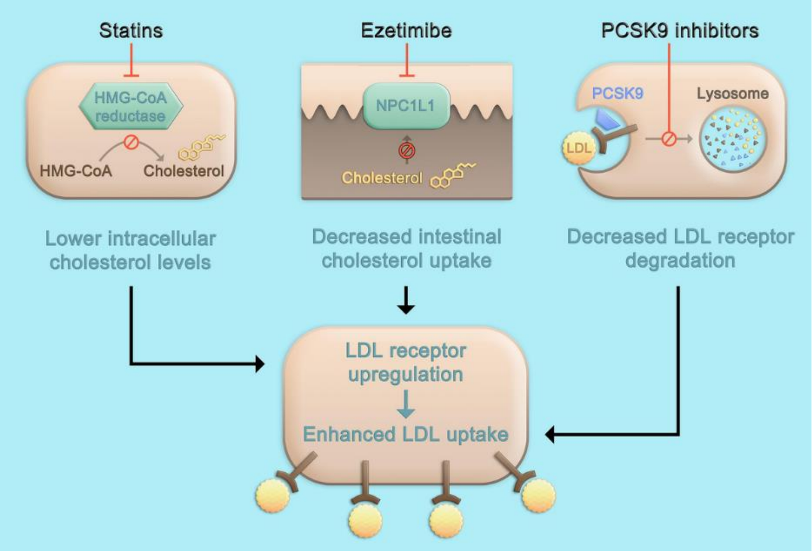

Statins
Ezetimibe
PCSK9 inhibitors
HMG-CoA reductase
HMG-CoA
Cholesterol
NPC1L1
Cholesterol
PCSK9
Lysosome
LDL
Lower intracellular cholesterol levels
Decreased intestinal cholesterol uptake
Decreased LDL receptor degradation
LDL receptor upregulation
Enhanced LDL uptake

Figure 1.3: Pharmacologic approaches to treat CAD by lowering cholesterol [96].

1.3.2. Stroke

1.3.2.1. Definition

Stroke is a condition that falls under both cardiovascular and neurological diseases [13], occurring when the blood supply to the brain is disrupted. This disruption can result from various causes, such as a blockage (ischemic stroke) or the rupture of a blood vessel (hemorrhagic stroke) [14]. Such events can lead to a range of serious consequences, including loss of vision or speech, paralysis, and confusion. Moreover, stroke is considered one of the most life-threatening complications of cardiovascular disease, second only to coronary artery disease (CAD).

1.3.2.2. Cause

Stroke is influenced by multiple risk factors that are either non-modifiable (age, sex, ethnicity, genetics) or modifiable (hypertension, diabetes mellitus, smoking, hyperlipidemia, alcohol consumption, obesity, inflammation) [15]. These risk conditions cause reduced blood flow to the brain due to problems with the blood vessels, leading to either ischemic or hemorrhagic strokes. Ischemic stroke occurs when there is a deficiency in blood and oxygen supply to the brain. One type of ischemic stroke, thrombotic stroke, occurs when the build-up of plaque in the arteries constricts the vascular chamber and forms clots, blocking blood flow to the brain.The second type of ischemic stroke, embolic stroke that happen because of decreased blood flow to the brain region causing an embolism. Meanwhile, hemorrhagic stroke is caused by bleeding or leaky blood vessels, resulting from the rupture of weakened blood vessels, leading to bleeding within or around the brain. Hemorrhagic stroke is classified under either intracerebral and subarachnoid hemorrhage. In intracerebral hemorrhage (ICH), blood vessels rupture, leading to an abnormal buildup of blood within the brain. In subarachnoid hemorrhage, blood gathers in the subarachnoid space of the brain, often caused by an injury to the head or a cerebral aneurysm [16].

1.3.2.3. Symptoms

There are many symptoms of strokes depending on the severity of the current situation of the patient and the type of stroke, the following are the most general common symptoms [33] :

- A sudden feeling of weakness
- Numbness and paralysis
- Speech and language problems
- Vision problems
- Dizziness and trouble walking

1.3.2.4. Diagnostic

Some of the diagnostic methods mentioned in the last section can be used to diagnose stroke, but computed tomography (CT) and magnetic resonance imaging (MRI) are considered the main diagnostic tools [17].

- **Magnetic resonance imaging (MRI):** MRI is a non-invasive imaging diagnostic method that relies on the magnetic properties of the body to create detailed images of internal organs and tissues. It primarily uses hydrogen nuclei (single protons) due to their abundance in water and fat [18]. The main advantage of MRI is its higher sensitivity in detecting anomalies associated with stroke compared to CT, but it is less commonly used because the process takes longer [17].
- **Computed tomography (CT):** CT is an image-based procedure that uses X-rays and advanced algorithms to provide precise information about the internal body. The process starts with the rotation of an X-ray tube and a detector array, which capture multiple X-ray projections from different angles around the patient's body. These projections are then used to generate cross-sectional images [20] that help detect anomalies associated with stroke conditions. Although this process carries the risk of high radiation doses, it is more commonly used due to its low cost and the speed at which results can be obtained [21].

1.3.2.5. Treatments

The treatment of stroke includes managing risk factors to limit any irreversible injury. A medical professional then decides on the appropriate treatment based on the type and severity of the stroke. For example, in hemorrhagic stroke (HS), where the patient has high blood pressure, blood pressure (BP) management may be recommended. This involves lowering BP using beta-blockers (labetalol, esmolol), an ACE inhibitor (enalapril), a calcium channel blocker (nicardipine), or hydralazine to reach a target of 150/90 mmHg.

Another treatment option for this type of stroke is hemostatic therapy, which helps reduce the progression of the hematoma. During this therapy, patients with elevated prothrombin time (INR) receive intravenous vitamin K and fresh frozen plasma (FFP) or prothrombin complex concentrates (PCCs), while patients with thrombocytopenia receive platelet concentrates.

On the other hand, for patients who experience HS-related seizures, which occur in about 30% of cases, antiepileptic therapy is recommended using antiepileptic drugs. In addition, cerebroprotection is an important treatment approach, as most patients who experience HS injuries suffer from inflammation and oxidative stress. To address this, pioglitazone, misoprostol, and celecoxib are used to reduce inflammatory damage, while edaravone, flavonoids, and nicotinamide mononucleotide can be used to reduce oxidative stress.

Surgery in HS cases is typically considered only in severe situations. Depending on the case, a doctor may decide to remove part of the skull to access and evacuate the hematoma or to relieve pressure on the brain. Other surgical procedures, such as endoscopic aspiration or catheter aspiration, may also be considered [22].Meanwhile, for patients suffering from ischemic stroke, two therapies are mainly considered ,which are intravenous thrombolysis with TPA (tissue-type plasminogen activator) or a more invasive procedure called mechanical thrombectomy [23]. It should be noted that treatment using tenecteplase (TNK) can be an alternative to TPA. TNK has the advantage of remaining in the body longer than TPA, and the injection procedure is faster, taking only around 5 seconds [24].

1.3.3. Peripheral arterial disease (PAD)

1.3.3.1. Definition

PAD is a medical condition that causes reduced blood flow through the arteries, which manifests as pain in the thighs or calves during walking [25]. This happens as a result of a loss of vessel elasticity or a narrowing of the arterial lumen [26]

1.3.3.2. Cause

PAD occurs due to various causes, such as atherothrombotic occlusion or stenosis of the lower limb arteries [27], which usually results from atherosclerotic plaque buildup. The body tries to compensate by dilating the vessels to preserve blood flow. However, this response eventually becomes insufficient [24]. This condition develops due to several risk factors, including smoking, diabetes, older age, dyslipidaemia, hypertension, obesity, and chronic kidney disease. In recent years, gender has also been considered a risk factor, with studies showing that women are more likely to develop PAD than men between the ages of 45 and 70 years [27].

1.3.3.3. Symptoms

There are many symptoms of PAD, and some individuals may be asymptomatic. The following are the most common symptoms [27]:

- Pain in the calf induced by walking and relieved by rest.
- Pain at other lower limb sites.
- Leg pain unrelated to walking.

- Numbness of the leg and paresthesia.

1.3.3.4. Diagnostic

There are various diagnostic methods to detect PAD, depending on the situation. MRI and CT, which are already described in another section [28], are among them. Aside from those two, the following are the most common methods [29]:

- ❖ **Exercise Treadmill Testing:** It is a cardiovascular stress test that uses electrocardiography while monitoring blood pressure during exercise [30]. In the case of detecting PAD, resting measurements of ankle pressure and the Ankle-Brachial Index (ABI) are taken by the doctor before and after exercise to detect any anomalies, such as a drop in their values, which is common for PAD. The test also measures how much the patient can walk before experiencing pain, which helps determine the severity of condition [31].
- ❖ **Ankle-Brachial Index (ABI):** This test uses a hand-held continuous wave Doppler ultrasound device to measure systolic blood pressure at two positions in the leg, the posterior tibial or dorsalis pedis arteries. The result is then compared to the highest brachial pressure from either arm. A normal ABI value ranges from 0.90 to 1.40. Any value lower than this indicates the presence of PAD [29]. This test has the advantage of being quick and cost effective.
  - ❖ **Duplex Ultrasonography:** It is a safe, noninvasive, and cost-effective imaging technique that combines B-mode imaging with PW and CW Doppler modes to provide detailed information about the anatomy and hemodynamic function of the vascular system. It stands out for its high success rate in detecting peripheral artery disease (PAD), ranging from 79.7% to 97% [49].

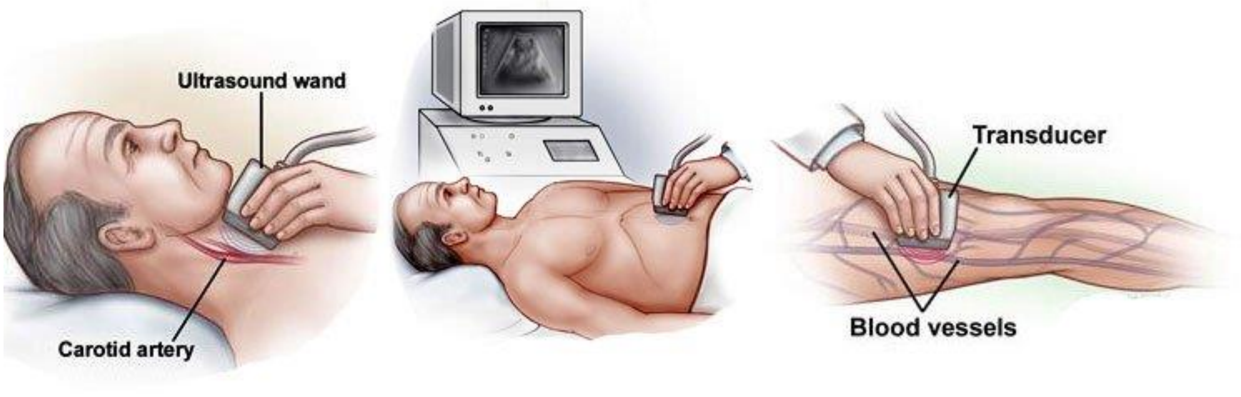


Figure 1.4: Overview of the Duplex Ultrasonography Process[97].

- **Digital Subtraction Angiography:** Digital Subtraction Angiography is an invasive, image-based technique that produces images containing blood vessels, bones, and other structures after the injection of a contrast medium. These images are then digitally subtracted from the pre-contrast images, effectively removing distracting structures to enhance visualization of the blood vessels [50].

1.3.3.5. Treatments

The treatment of PAD involves managing risk factors, such as eating a healthy diet and quitting smoking. In addition, lipid-lowering therapies, including statins, may be recommended to achieve an LDL goal of less than 1.4 mmol/L. PCSK9 inhibitors may also be considered as part of this therapy. Another treatment is antihypertensive therapy, which is advised for blood pressure above 140/90 mmHg. Angiotensin-converting enzyme inhibitors (ACEi) and angiotensin receptor blockers (ARBs) are commonly used medications in this type of therapy. Calcium channel blockers and thiazide diuretics are often used alongside one of them to help reach a healthy blood pressure. If blood pressure remains high despite their use, spironolactone is often considered a last resort.

For patients suffering from symptomatic PAD, antiplatelet therapy may be recommended using either aspirin or clopidogrel to reduce symptoms and improve the patient's chances of survival. On the other hand, for patients suffering from diabetes, antidiabetic therapy is advised to control glucose levels and achieve an HbA1c of <7% or <53 mmol/mol. This can be done using either sodium-glucose co-transporter 2 (SGLT2) inhibitors or glucagon-like peptide-1 receptor agonists (GLP-1 RAs), which are especially effective for patients with type 2 diabetes in reducing PAD events [27].

Lastly, for people suffering from chronic limb-threatening ischemia (CLTI), which occurs in the latest stages of PAD, a revascularization procedure is performed to avoid leg loss. However, this procedure carries a higher risk of failure in patients between the ages of 75 and 80 years [32].

1.3.4. Aortic disease

1.3.4.1. Definition

Aortic disease refers to a group of medical conditions that primarily affect the aorta and can range from acute to life-threatening, posing serious risks to the cardiovascular system [34]. These conditions are typically classified into four categories based on their underlying pathology, which are thoracic aortic aneurysm and dissection (TAAD), acute aortic syndrome (AAS), connective tissue diseases, and vasculitis [37]. TAAD is characterized by an enlargement of the aortic diameter by 1.5 times or more compared to its normal size [34]. AAS includes three critical conditions namely acute aortic dissection (AAD), which involves a tear in the aortic wall, intramural hematoma (IMH), resulting from bleeding within the aortic wall without an intimal tear, and penetrating aortic ulcer (PAU), caused by an atherosclerotic ulcer eroding into the media layer of the aorta [35]. Connective tissue diseases, which affect the structural tissues of the body, are marked by chronic inflammation and fibrosis of the connective tissue [36]. Finally, vasculitis represents an acute inflammatory condition involving the swelling and irritation of blood vessels, further complicating aortic health [37].

1.3.4.2. Cause

Aortic diseases have multiple causes depending on the type and location. For example, thoracic aortic aneurysms (TAAs) are caused by progressive weakening and dilation of the aortic wall, particularly involving the intima, media, and adventitia layers [38]. This degeneration results from four key biological processes which are infiltration of the vessel wall by lymphocytes and macrophages, destruction of elastin and collagen by proteases such as matrix metalloproteinases, loss of smooth muscle cells (SMCs) with medial thinning, and neovascularization. Additionally, genetic disorders like Marfan syndrome (MFS) and Loeys–Dietz syndrome (LDS) contribute to TAA formation by disrupting structural integrity and activating abnormal signaling pathways [39].

Another closely related type is aortic dissection, which occurs because of a tear in the aortic intima that exposes the medial layer to pulsatile blood flow. This separation of the aortic wall layers results in the formation of a false lumen, which can lead to serious complications such as aortic rupture in the case of adventitial disruption. Alternatively, the false lumen may re-enter the true lumen through another intimal tear, sometimes maintaining perfusion and stabilizing the patient. In some cases, the false lumen ends blindly, leading to blood clot formation, which can impair systemic blood flow [40].

On the other hand, acute aortic syndrome (AAS) can occur for various reasons depending on its type. For example, acute aortic dissection happens for similar reasons to those already discussed for classic aortic dissection. Meanwhile, for other types such as intramural hematoma (IMH), it was traditionally linked to vasa vasorum rupture, but recent findings of microintimal tears suggest shared mechanisms with AAD, differing only by the lack of a large enough reentrant tear to preserve the false lumen's patency. Finally, the last type of AAS, called penetrating aortic ulcer (PAU), results from atherosclerotic plaque formation. This process leads to destruction and inflammation of the intima and penetrates outwardly through the layers of the aortic wall [35].

The third type of aortic disease, which are diseases caused by connective tissue disease, develops through several mechanisms, some of which are not directly related to the aorta. For the conditions that are related , they are a result from problems in the connective tissues that support the aortic wall, mainly involving the proteins collagen and elastin. One example is vascular Ehlers-Danlos Syndrome, where a gene mutation weakens type III collagen, making blood vessel walls fragile and more likely to develop serious complications. Another issue occurs when a signaling system called TGFβ does not function properly, leading to abnormal tissue repair and cell death in the aortic wall. Both of these problems weaken the aorta and increase the risk of rupture [41].

The final condition, vasculitis, encompasses a broad spectrum of disorders, some of which do not effect aortic diseases. However, a particular subset known as large vessel vasculitis directly affects the aorta and gives rise to a condition called aortitis. Aortitis can be caused by various factors, including rheumatologic conditions, infectious causes (resulting from direct infection of the aorta), non-infectious causes (resulting from an immune system reaction), or isolated cases with unclear origins, although drug use is a suspected contributing factor. Many researchers remain uncertain whether the mechanisms involved in these isolated cases truly fall within the definition of aortitis [42].

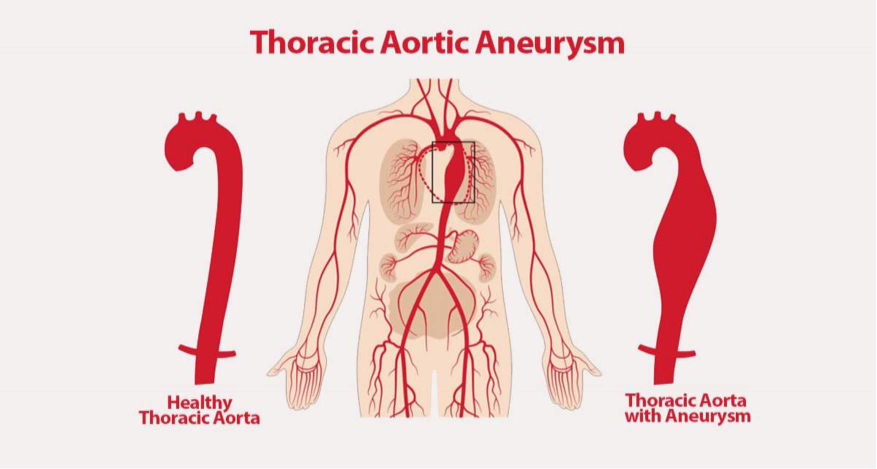


Figure 1.5: Morphological Comparison of a Healthy Thoracic Aorta and One Affected by Aneurysm[98].

1.3.4.3. Symptoms

General symptoms of aortic disease are the following ones [43]:

- Sudden stabbing.
- Radiating pain.
- Fainting.

- Difficulty breathing.
- Nausea and vomiting.
- Chest pain.
- Jaw pain.

1.3.4.4. Diagnostic

Various methods are used to detect aortic disease, such as MRI and CT, which are already described in other sections. The following are the most common ones in addition to those [44]:

- **Transthoracic Echocardiography (TTE):** Transthoracic echocardiography **(**TTE) is the most commonly used diagnostic method for early, non-emergency evaluation of the thoracic aorta. It helps detect anomalies in the aortic root and ascending aorta and is useful in assessing aortic valve anatomy and function.
- **Transesophageal Echocardiography (TEE):** Transesophageal echocardiography (TEE) is an image-based evaluation tool that provides very high-resolution imaging, allowing for detailed visualization of aortic valve anatomy and function. It is particularly useful in evaluating patients with acute aortic syndromes (AAS) and in assessing true and false lumen flow both before and immediately after aortic repair.
- **Abdominal Ultrasound:** Abdominal ultrasound is a fast, image-based diagnostic method that uses B-mode imaging, color Doppler, and spectral waveform analysis. It is primarily used for the diagnosis and surveillance of abdominal aortic aneurysm (AAA) due to its high sensitivity in detecting aneurysms, but it can also be used to identify other aortic diseases
- **Intravascular Ultrasound:** Intravascular ultrasound is a minimally invasive diagnostic method that offers high-resolution intraluminal imaging. It helps reveal aortic size, tortuosity, plaque burden, calcification, branch vessel ostia, and intravascular filling defects (e.g., thrombus or dissection flap). It also helps identify patients at higher risk of failure from surgical treatment.

1.3.4.5. Treatments

Treatment for aortic disease depends on its specific type and underlying cause, though many forms share a common approach centered on managing risk factors, either by eliminating them or controlling them with medication. In the case of thoracic aortic aneurysm and dissection (TAAD), treatment often involves beta blockers to reduce stress [45] and maintain a heart rate of approximately 60 beats per minute[46]. However, the management of each condition diverges significantly beyond initial stabilization. For thoracic aortic aneurysm, lipid-lowering agents like statins are mainly used to decrease the rate of rupture. Emergency surgeries are also considered an option to prevent dissection or rupture of the aneurysm for patients who need immediate surgical correction. For patients with an ascending aorta of 5.5 cm and a descending aorta of 6.5 cm, elective surgery is considered more suitable. Lastly, for patients with an aneurysm in the upper part of the aorta, an open surgery is performed to replace the aorta [45].

In contrast, for thoracic aortic dissection (TAD), analgesic therapy with morphine is recommended to control pain and reduce sympathetic tone. Other treatments, such as managing hypotension, are also advised for patients. This typically involves intravenous fluid resuscitation. However, excessive fluid can increase pressure on the aortic wall, potentially worsening the patient's condition. Surgical treatments are also an option, depending on the type and severity of TAD. For instance, urgent surgical intervention may be required for a tear in the ascending aorta, involving procedures such as excision of the intimal tear, aortic replacement, and aortic valve assessment and repair. Other surgeries may be necessary to repair a tear in the descending aorta, which involve procedures such as endovascular stent-grafting or surgical repair [46].

Aortic diseases caused by connective tissue diseases are treated in multiple ways. One option is open surgical repair [47], which is a very invasive procedure that allows for the complete replacement of the diseased aortic segment[48] but carries a high risk of death. Another, less invasive procedure is called endovascular treatment, which is considered a last option only for patients who are not suitable for open surgical repair due to its low success rate. β-blockers are also considered to have a significant impact on managing the risk factors [47].

Lastly, for aortic diseases caused by vasculitis, such as aortitis, treatment is done using antibiotics for patients suffering from infectious aortitis. Open aortic surgery is considered a last option due to its high death rate. Patients suffering from non-infectious aortitis are recommended corticosteroids and immunosuppressive drugs to control the inflammation. For conditions associated with large-vessel vasculitis, a glucocorticoid dose of 40-60 mg/day is initially prescribed, which should then be reduced to a dose of ≤5-10 mg once the disease stabilizes [42].

1.4. Complications of heart disease

Like any other disease, patients suffering from heart disease experience multiple health complications. The following are some of the most common ones [4]:

- Death
- physical disabilities
- life-threatening arrhythmias
- paralysis

- limb ischemia

1.5. Prevention of heart disease

Heart disease prevention involves many lifestyle changes, such as following a healthy diet that is rich in vegetables, fruits, nuts, whole grains, lean vegetable or animal protein, and fish, while minimizing the intake of trans fats, red meat, and processed meats. Maintaining a healthy weight is also essential. Another key step is engaging in at least 150 minutes of physical activity per week. Avoiding risk factors such as smoking is also very important. For patients with high cholesterol levels (≥190 mg/dL), statin therapy may be recommended by a healthcare professional [52].

1.6. Electrocardiography (ECG)

We already explained ECG as a diagnosis method for many cardiovascular diseases but in the following section, we will go more in depth and explain its components and how it works.

1.6.1. Definition

An electrocardiogram (EKG or ECG) is a paper-based recording of the heart's electrical activity, primarily generated by the cardiac conduction system, especially the sinoatrial node (SAN) [83], which acts as the heart's natural pacemaker. The ECG was invented by Willem Einthoven in 1902 [84], and his dedicated work in clinical studies led to its official recognition as a diagnostic method. The ECG works by recording where electrical impulses start and how they flow through the heart, which allows a professional doctor to examine these recordings to assess the heart's rhythm and detect abnormalities in the electrical conduction system.

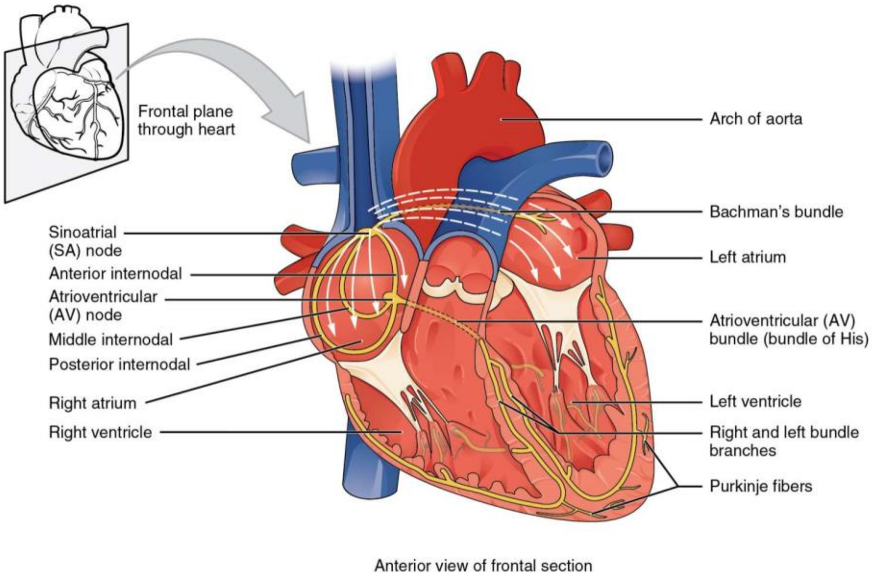


Figure 1.6: Overview of Sinoatrial and Atrioventricular Heart Nodes [99].

1.6.2. ECG Signal Components

A heartbeat is the result of the activity of the cardiac conduction system, beginning in the right atrium at the sinoatrial node (SAN). This specialized group of cells generates electrical signals that propagate throughout the heart. The signal first travels from the atria to the atrioventricular (AV) node, which then transmits it to a network of fibers in the ventricles. These fibers conduct the electrical impulse to all parts of the lower chambers, the ventricles [85]. This coordinated electrical activity produces the characteristic waveform observed in an electrocardiogram (ECG), made up of several key components including the P wave, the QRS complex, and the T wave [8].

- **P wave:** It represents electrical activation, called depolarization, of the atrial muscle.
- **QRS complex:** It records the impulse spreading throughout the ventricles resulting in ventricular contraction.
- **T wave:** It is the return (repolarization) of the ventricular muscle to its resting electrical state.

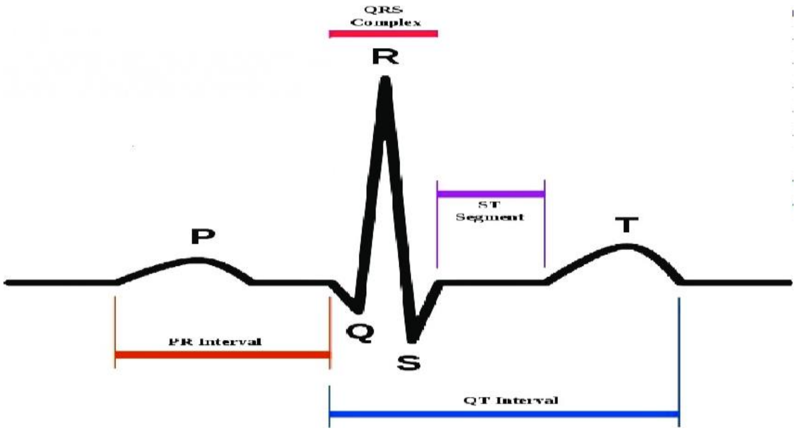


Figure 1.7: ECG waves forms[100].

1.6.3. ECG Rhythms

ECG patterns are generally characterized by the sequence and timing of electrical signals produced by the heart, reflected in the recurring waves and intervals on the ECG tracing. These patterns form what is known as the cardiac rhythm, which represents the heart's regular or irregular beating pattern. The most common and normal rhythm is the sinus rhythm, where electrical impulses originate from the sinoatrial (SA) node, resulting in a consistent and orderly pattern of P waves followed by QRS complexes and T waves. However, when the heart suffers from abnormalities, the electrical conduction system is disturbed, resulting in patterns that deviate from the normal sinus rhythm. These are called irregular rhythms [8] ,although not all of them are indication about the presence of heart disease.

1.6.3.1. Regular Rhythms

There are various regular rhythms but the following are the most common ones [8]:

- **Sinus rhythm:** Sinus rhythm is a regular heart rhythm that indicates the cardiac conduction system is working normally. It is characterized by a heart rate between 60 and 100 beats per minute. In sinus rhythm, each QRS complex is preceded by a P wave, indicating proper atrial depolarization. The rhythm is regular, the PR interval ranges from 0.12 to 0.20 seconds, and the QRS complex duration is typically between 0.06 and 0.10 seconds [87].
- **Narrow complex tachycardia:** Narrow complex tachycardias (NCTs) are a type of regular heart rhythm characterized by a heart rate greater than 100 beats per minute (bpm) and a QRS complex duration of less than 120 milliseconds (ms) [89]. They typically originate above the ventricles, often arising from the sinus node, atria, or atrioventricular (AV) junction.

- **Broad complex tachycardia:** A broad complex tachycardia (WCT) is a cardiac rhythm characterized by a heart rate exceeding 100 beats per minute and a QRS complex duration greater than or equal to 0.12 seconds [88]. Structural changes in the heart can create alternative conduction pathways, allowing electrical impulses to travel in abnormal directions, including retrograde (backward) and antidromic (opposite to the normal route). These altered pathways affect how electrical activity appears on the ECG, often resulting in a widened QRS complex. WCT can present with either a regular or irregular rhythm, depending on the underlying conduction pattern and mechanism, but it is considered regular most of the time.
- **Complete heart block (Third-Degree AV Block):** Complete heart block (third-degree heart block) is a type of regular ECG rhythm that occurs when no electrical impulses from the atria reach the ventricles. This block can occur at the AV node or below it. As a result, the ventricles generate their own slow escape rhythm (30–45 beats per minute) [86], while the atria continue to beat independently at a faster rate (60–100 beats per minute). This leads to AV dissociation, where the atria and ventricles contract separately without coordination.

1.6.3.2. Irregular Rhythms

There are various irregular rhythms but the following are the most common ones [8]:

- **Sinus arrhythmia:** Sinus arrhythmia is a common variation of the heart’s normal rhythm, where the time between heartbeats changes by more than 0.12 seconds. The P waves remain consistent, showing that the heart’s atria are activated normally by the sinus node. This irregularity happens because the vagus nerve is intermittently active during breathing, causing the heart rate to vary from one beat to the next. Usually, having sinus arrhythmia is a sign of a healthy heart [85].

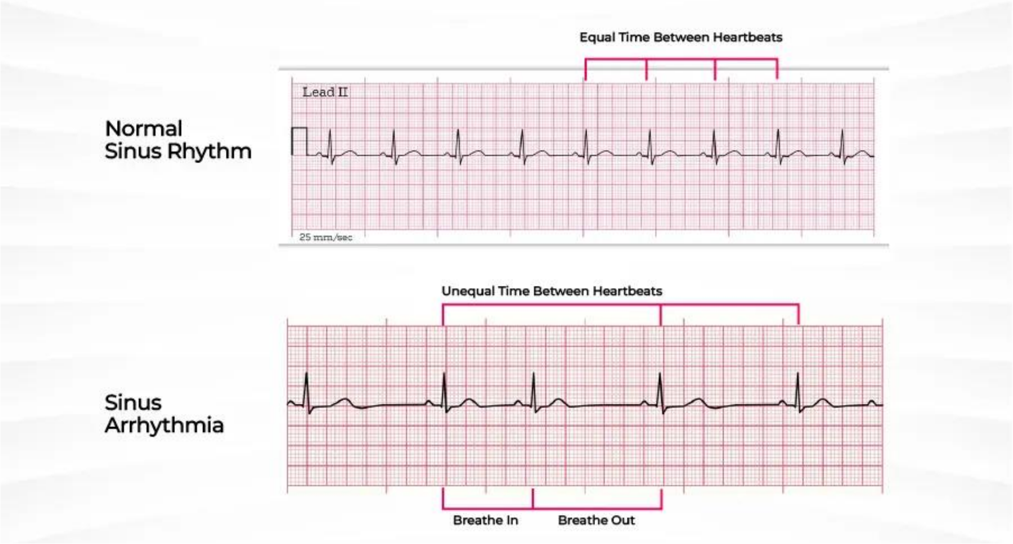


Figure 1.8: Comparison of ECG Patterns in Sinus Arrhythmia and Normal Sinus Rhythm [101].

- **Extrasystoles :** Extrasystoles are extra heartbeats that occur earlier than the normal heartbeat. They may originate from the ventricles, the atria, or the AV node [8]. This condition is often characterized by a sinus rhythm with occasional early beats, making the rhythm irregular.

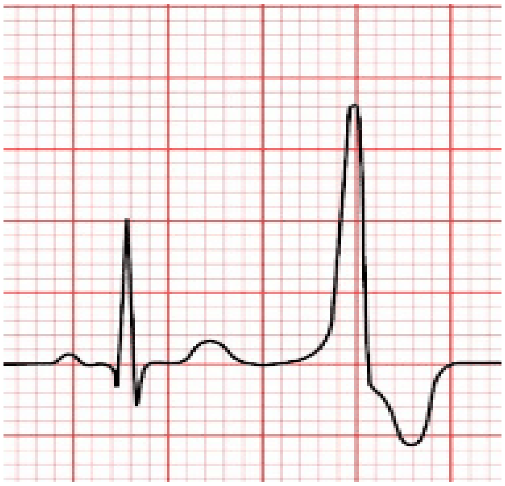


Figure 1.9: Electrocardiogram illustrating ventricular extrasystole, a subtype of cardiac extrasystoles [102].

- **Atrial fibrillation:** In atrial fibrillation, the atria have chaotic electrical activity with multiple small reentrant circuits causing no true P waves and a flat or slightly wavy baseline on the ECG. The AV node receives over 500 impulses per minute [86] but only allows some through at irregular intervals, resulting in an irregularly irregular heartbeat, typically between 120–180 beats per minute.

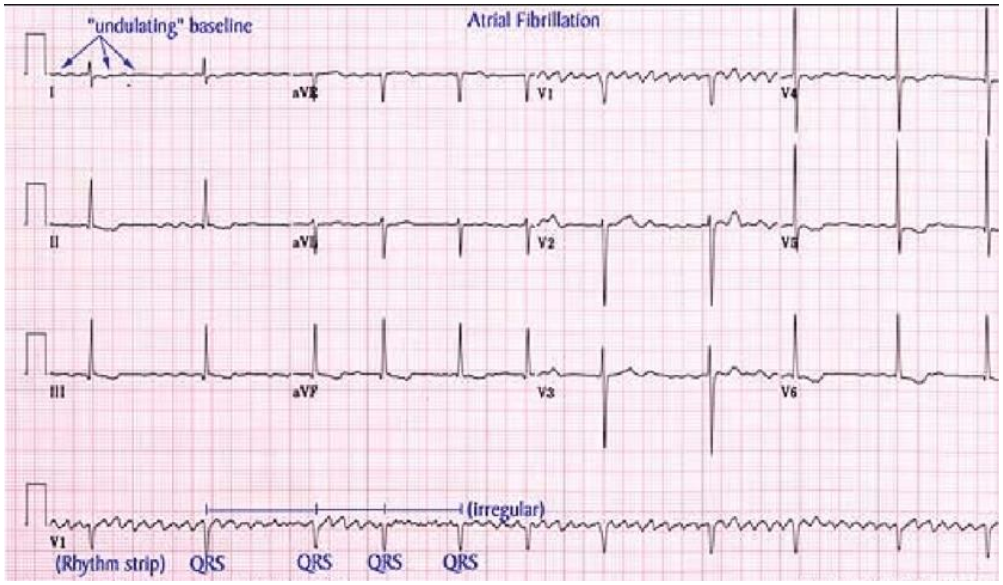


Figure 1.10: ECG demonstrating Atrial Fibrillation[103].

- **Ventricular fibrillation:** Ventricular fibrillation is a fatal arrhythmia that usually occurs in dying hearts. It is the most common rhythm in cases of sudden adult death. In this condition, the ECG either jerks about spasmodically (coarse ventricular fibrillation) or undulates gently (fine ventricular fibrillation) [86], without true QRS complexes. Since it produces no cardiac output, immediate CPR and defibrillation are required.

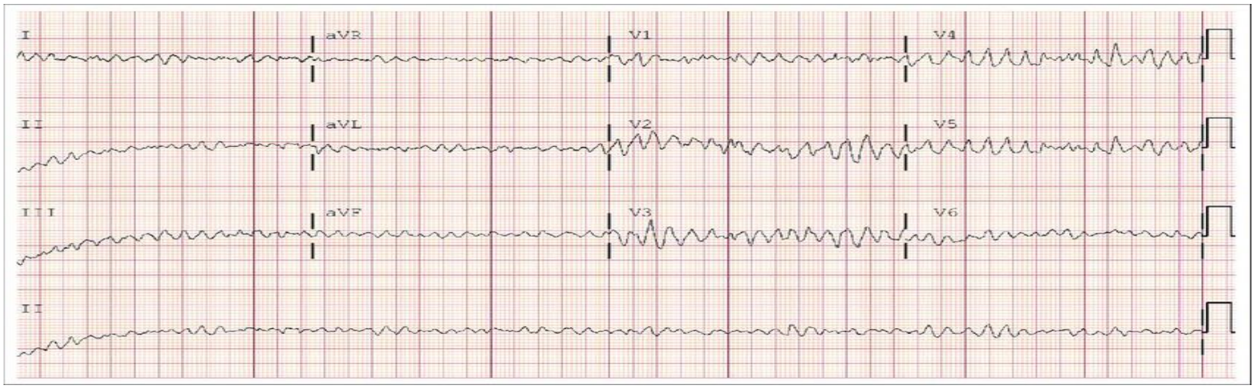


Figure 1.11: Electrocardiogram showing ventricular fibrillation [104].

1.6.4. Electrocardiogram Lead Setup

Electrocardiogram (ECG) Lead Setup is a vital step in obtaining accurate ECG recordings. It involves the careful placement of electrodes on specific locations of the patient’s chest and limbs to monitor the heart’s electrical activity. These small conductive pads, called electrodes, detect electrical signals from the heart from various angles, allowing for a comprehensive evaluation of cardiac function. During this setup, the bipolar arrangement of two electrodes, one positive and one negative, is referred to as a lead [90]. By using multiple leads placed around the chest and limbs, the ECG captures a complete picture of the heart's electrical function from different perspectives, which aids in the accurate diagnosis of cardiac conditions.

1.6.5. Electrode Placement

The conventional ECG machine consists of 12 leads divided into two types [84], which are the following two:

- **Limb Electrodes:** Limb electrodes are essential components of the standard 12-lead electrocardiogram (ECG) system. Four electrodes placed on the right arm, left arm, right leg, and left leg are used to generate six leads that view the heart in the frontal (vertical) plane. These include three bipolar leads (I, II, and III) and three augmented unipolar leads (aVR, aVL, and aVF) [84].

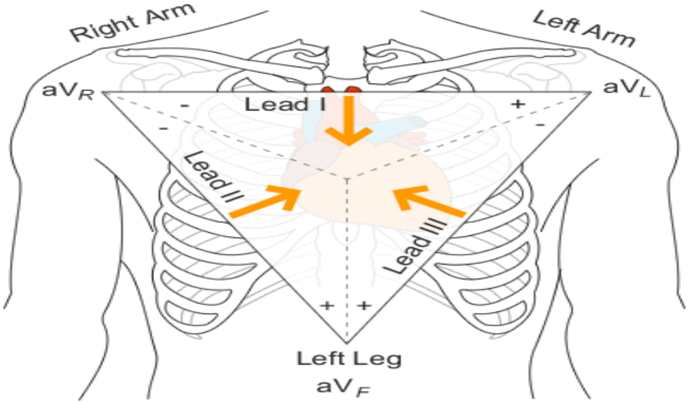


Figure 1.12: Illustration of Einthoven's Triangle Showing Bipolar Leads (I, II, III) and Augmented Unipolar (aVR, aVL, aVF) Limb Leads[105].

- **Precordial (Chest) Electrodes:** In a standard 12-lead electrocardiogram (ECG), the precordial electrodes are used to capture the heart's electrical activity in the horizontal plane. To achieve this, six precordial electrodes labeled V1 through V6 are placed at specific locations on the chest [84].

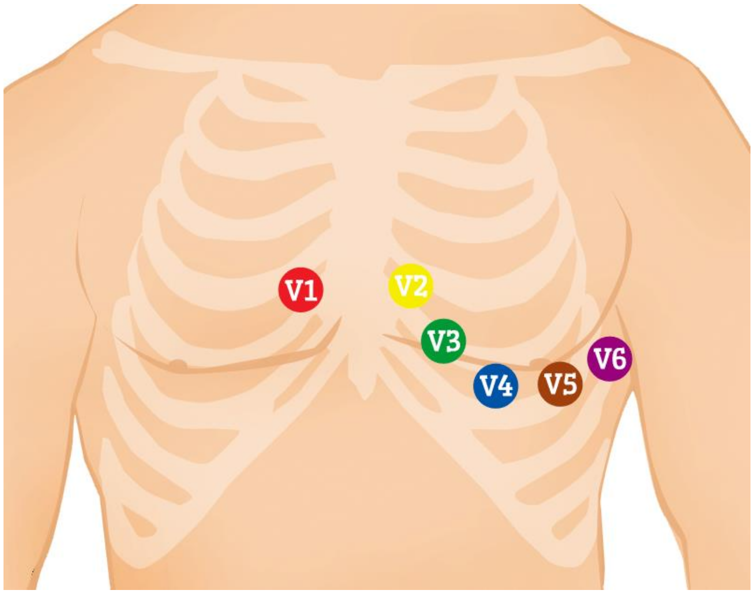


Figure 1.13: Illustration of Precordial Electrode Placement for Electrocardiography [106].

1.6.6. ECG Limitations

ECG is a very valuable diagnostic method, but like any diagnostic tool, it is not perfect and suffers from several limitations, such as limited sensitivity and an inability to detect certain heart conditions. Additionally, some patterns, such as the right bundle-branch block pattern [92], can be challenging to interpret even for expert doctors due to a lack of training during formal medical education [91]. Additionally, improper filter application is a significant issue affecting many clinical recordings. As demonstrated by Kligfield and Okin in their study, only 62% of clinical recordings applied an increased low-frequency cutoff [93], which resulted in recordings being affected by noise and interference, such as electromyographic signals from muscle activity. This interference compromises the accurate interpretation of these recordings.

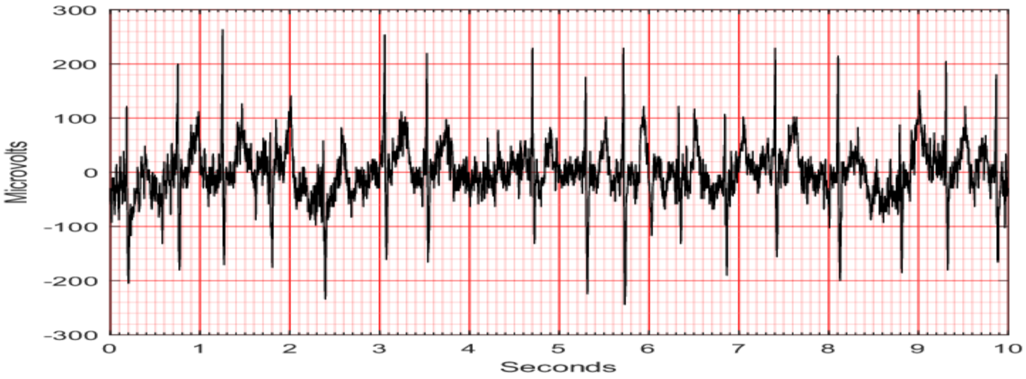


Figure 1.14: Example of an Electrocardiogram (ECG) Signal Distorted by Noise[107].

1.7. Conclusion

In this chapter, we presented the most common types of heart conditions, explaining their causes, diagnostic methods, treatments, and preventive measures. We then explored ECG in greater depth, describing its waveforms and rhythms, as well as how to properly place the electrodes on the body.

We learned that heart disease is a very dangerous condition and is considered the leading cause of death. Early diagnosis significantly improves patient outcomes, and ECG has proven to be a valuable and cost-effective tool for detecting heart conditions. However, it does have some limitations that can make interpreting the recordings challenging.

Chapter 2:

Machine and Deep learning approaches

2.1. Introduction

In recent years, artificial intelligence (AI) has rapidly evolved, driven by advancements in machine processing power and technology, revolutionizing the healthcare system by assisting both patients and doctors in the identification and diagnosis of diseases. This progress has been made possible through the development of highly complex algorithms that can analyze vast amounts of medical data with remarkable accuracy and speed. AI tools are now used to detect early signs of illnesses such as heart disease, interpret medical images, and predict patient outcomes, helping healthcare professionals make more informed decisions. In this chapter, we will discuss machine learning and deep learning, and explore other works that also aim to address the challenge of heart disease prediction.

2.2. Machine Learning

Machine learning (ML), a subfield of artificial intelligence (AI), enables machines to replicate the human ability to learn and recognize patterns. It was developed to solve complex problems that traditional programming struggles with, as defining solutions through precise mathematical instructions can be challenging. One of ML's key strengths is its adaptability, making it especially useful for problems that change over time. This flexibility is particularly valuable in dynamic fields like healthcare, where data is constantly evolving.

One of the early works of AI is considered to be the development of an early version of an artificial neural network (ANN) in 1943, which drew from physiological insights, propositional logic, and the theory of computation [54]. This early research helped create some of the first computer programs capable of playing chess and solving logical problems, which in turn helped popularize machine learning.

Currently, there are five types of machine learning, which we will discuss in full detail in the following sections.

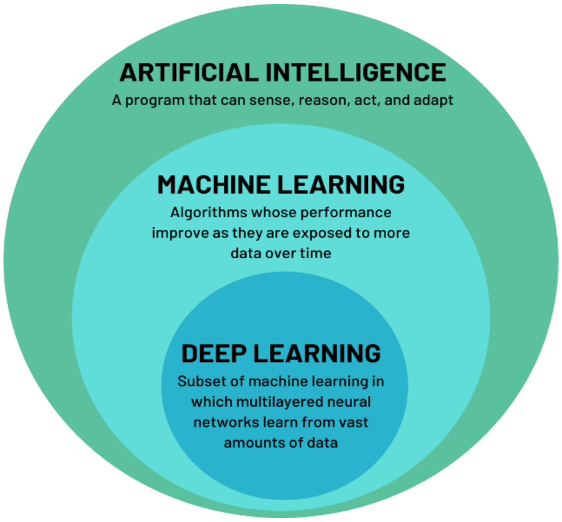

ARTIFICIAL INTELLIGENCE
A program that can sense, reason, act, and adapt
MACHINE LEARNING
Algorithms whose performance improve as they are exposed to more data over time
DEEP LEARNING
Subset of machine learning in which multilayered neural networks learn from vast amounts of data

Figure 2.1: AI, ML, and Deep Learning Hierarchy.[108]

2.2.1. Types of Machine Learning

2.2.1.1. Supervised learning

Supervised learning is a category of machine learning that aims to train algorithms using labeled data to learn patterns and relationships between inputs and outputs [55]. This process enables the model to make predictions on new, unlabeled data. There are two categories of supervised learning which depend on the type of output variable. The first category is regression, which deals with quantitative output, and the second is classification, which involves qualitative output.

- **Regression:** In regression, the input type can be either quantitative or qualitative, but the output must be quantitative, meaning its values are continuous. There are several common regression algorithms, such as linear regression, ridge regression, and lasso regression [56].
- **Classification:** In classification, the input variable can be either quantitative or qualitative, but the output has to be qualitative, meaning its values are from a finite set. We refer to those possible output values as classes or labels. There are several common types of classification, such as binary classification, multiclass classification, multi label classification, and imbalanced classification [57].

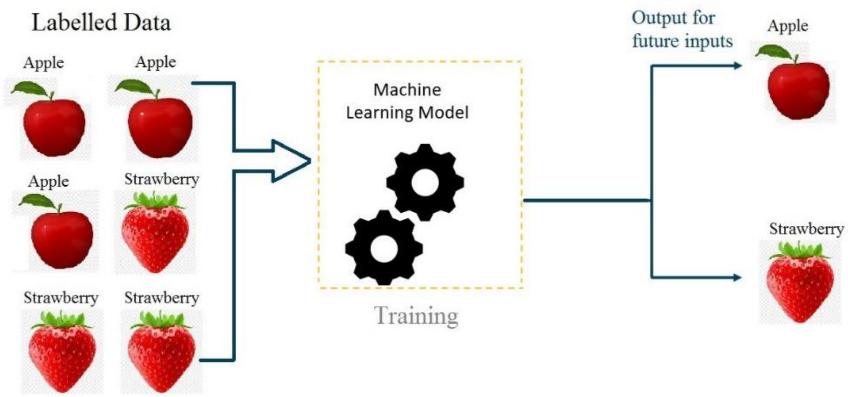


Figure 2.2: Supervised Learning Pipeline Diagram[109].

2.2.1.2. Unsupervised learning

Unsupervised learning is a category of machine learning that aims to train algorithms using unlabeled or unstructured data to learn and detect patterns without the help of a supervisor. It is better at solving complex problems that lack labeled data compared to supervised learning, but it generally has lower accuracy on average [58]. There are three main types of unsupervised learning, which will be explained below [58].

- **Association Rule:** It is a technique mainly used to uncover associative relationships between variables in massive datasets.
- **Clustering:** It is a technique used to group unlabeled data based on their similarity, organizing the data into overlapping fuzzy sets.
- **Dimensionality Reduction:** It is a method that aims to reduce the number of features while preserving as much information as possible without losing relevant details.

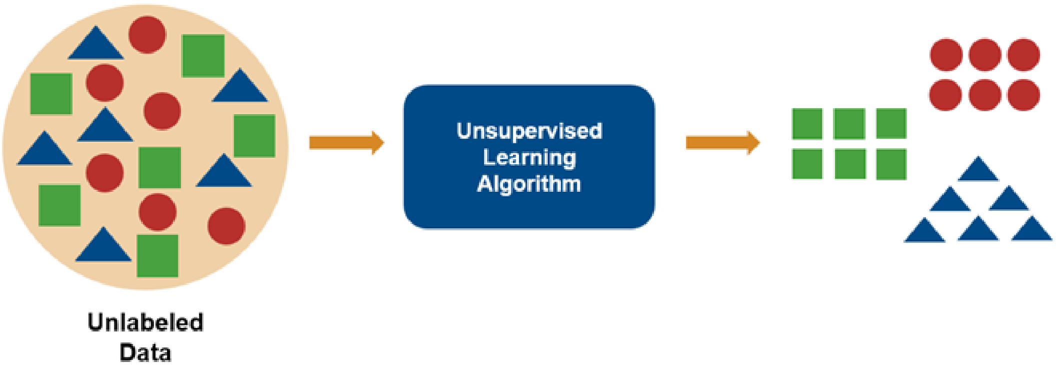


Figure 2.3: Unsupervised Learning Pipeline Diagram [110].

2.2.1.3. Semi-supervised learning

Semi-supervised learning is a type of machine learning that combines key aspects of both supervised and unsupervised learning by using both labeled and unlabeled data to enhance the predictive performance of the ML model [54] and compensate for the weaknesses of each type. It is mostly used when labeling data is expensive, so both labeled and unlabeled data are used to train the model, which allows it to make better use of the available data.

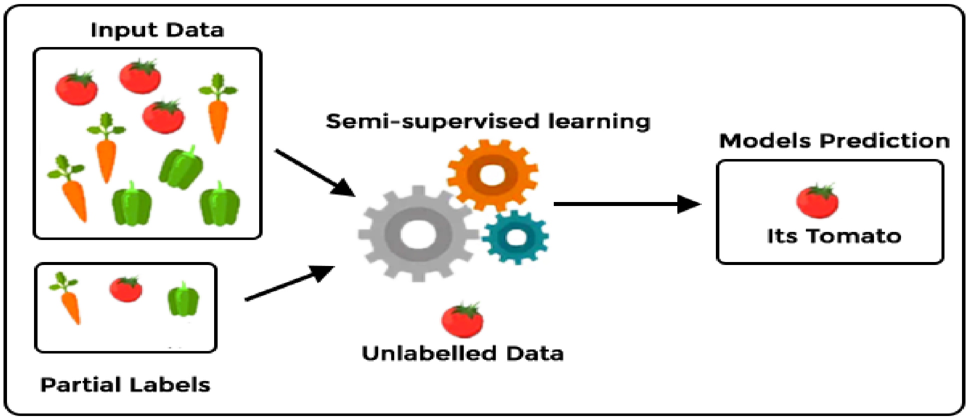


Figure 2.4: Semi-supervised Learning Pipeline Diagram [110].

2.2.1.4. Self-supervised learning

Self-supervised learning is a type of machine learning that uses unlabeled data. Its main idea is to use parts of the data to predict other parts. For example, a part of the data is masked, and the model will try to predict it based on the surrounding context. This way of working makes it great for NLP tasks because it helps models learn useful patterns and structures in language [55].

2.2.1.5. Reinforcement learning

Reinforcement learning is a type of machine learning algorithm that aims to find actions that maximize specific rewards within an environment [54]. It was developed to mimic humans' and animals' ability to make decisions based on their surroundings. Reinforcement learning consists of four main concepts: an agent that must make decisions, an environment with which the agent interacts, a reward that indicates a correct action,a value function that specifies the expected cumulative reward an agent can obtain starting from a particular state, and a policy to determine the best action [59].

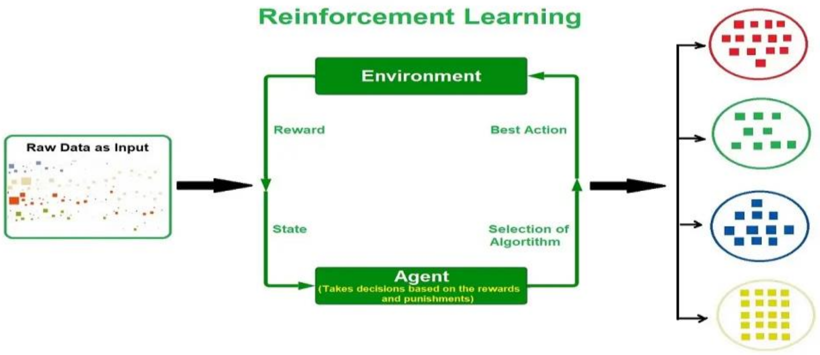


Figure 2.5: Reinforcement learning Pipeline Diagram [111].

2.3. Deep learning

Deep learning is a subset of machine learning based on layered neural architectures that enable machines to extract complex features from big data [53]. These architectures are composed of multiple interconnected layers of artificial neurons, allowing the model to gradually learn patterns, starting from simple ones and moving toward more abstract and meaningful insights. This makes deep learning especially effective for tasks such as classification, generation, and anomaly detection.

We shall discuss some of the deep learning architectures that have demonstrated significant success in the field of heart disease prediction in the following section.

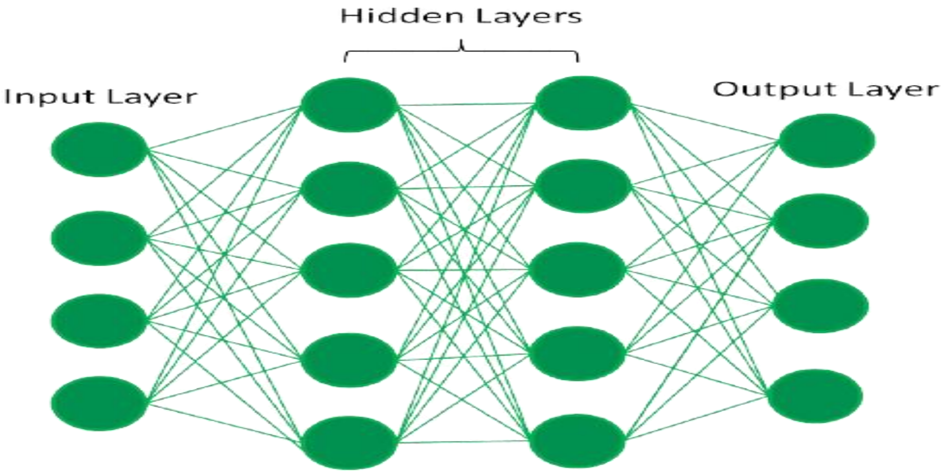


Figure 2.6: General deep learning architecture [112].

2.3.1. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are a deep learning architecture initially introduced by Kunihiko Fukushima in 1980. They gained widespread popularity later when Krizhevsky et al. demonstrated the strong performance of their CNN model, AlexNet [60]. CNNs are typically structured as feedforward neural networks, where data flows in one direction from input to output. Their core mathematical operations are mainly convolution and pooling, which help extract and condense important features from the input data, enabling them to generalize well. This makes CNNs particularly powerful for analyzing structured grid data such as images. A typical CNN architecture consists of four main layers, which are the convolutional layer, the pooling layer, the fully connected layer, and the output layer [61]. Each of these plays an important role in feature extraction and classification.

- **Convolutional layer:** It is considered to be the main core of CNN. It works by applying a set of kernels to the data to extract meaningful features.
- **The pooling layer:** It applies pooling operations that reduce the image dimensions, which helps improve the model's performance and reduces computational power usage.
- **The fully connected layer:** After applying the previous layers, a fully connected layer is used where all neurons are connected to every neuron in the previous layer to make the final prediction for the model.

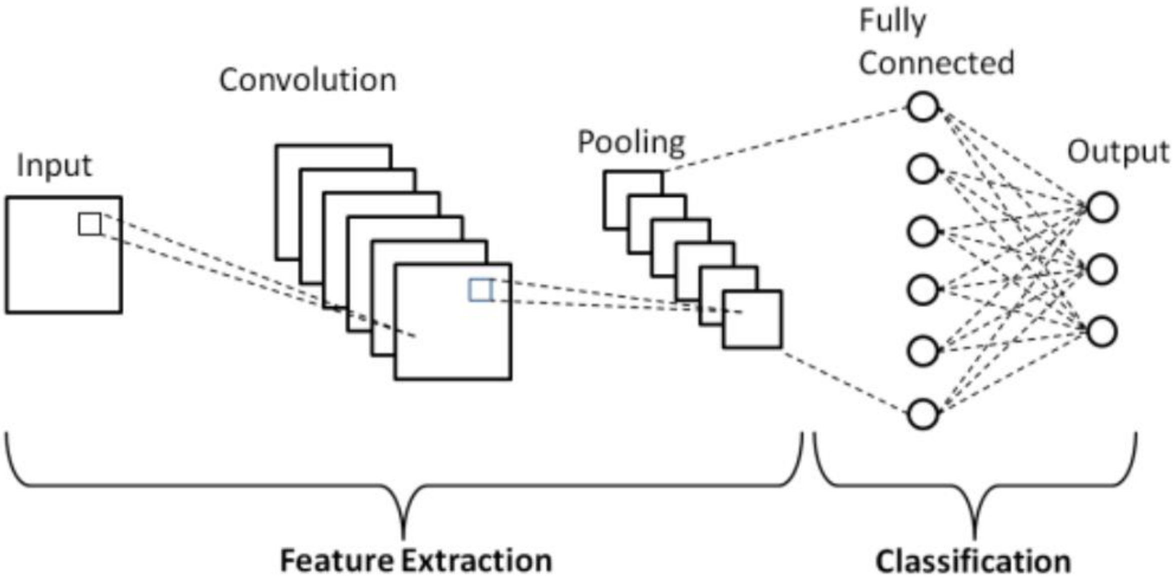


Figure 2.7: General CNN architecture [113].

2.3.2. Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are a type of deep learning architecture specifically designed to process sequential data, such as time series, by maintaining a hidden state that captures information from previous inputs. Unlike feedforward networks, which transmit information in a single direction, RNNs incorporate feedback loops that allow information to be fed back into the network [62]. This cyclical structure enables RNNs to retain a memory of past inputs when making predictions.

Despite their effectiveness in various applications, RNNs face significant challenges, particularly the vanishing and exploding gradient problems [63]. These issues occur during training when the gradients used to update the network's weights through backpropagation either become too small (vanish) or grow excessively large (explode) [62]. This happens because, during backpropagation through time, gradients are repeatedly multiplied by the recurrent weight matrices and the derivatives of activation functions. When these values are less than one, the gradients gradually shrink and vanish. When the values are greater than one, the gradients grow rapidly and explode. This makes the model unstable and hinders the learning process.

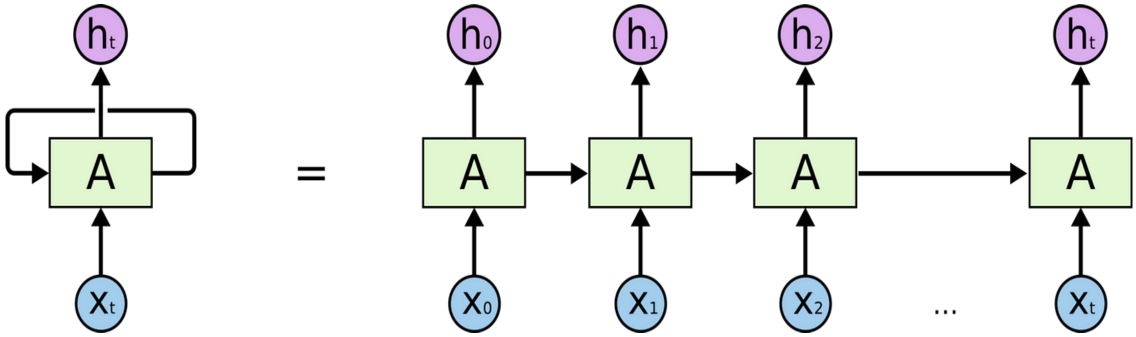


Figure 2.8: General RNN architecture [65].

2.3.3. Long Short-Term Memory (LSTM)

Long short-term memory (LSTM) is a type of recurrent neural network (RNN) introduced by Hochreiter and Schmidhuber in 1997. It aims to address the vanishing and exploding gradient problems by introducing a memory unit and a gating mechanism that enables the model to capture long-range dependencies in a sequence [64]. The gating mechanism consists of three gates, which are forget, input, and output gates. The forget gate determines which information from the previous cell state should be discarded and which should be retained, using a sigmoid layer to produce values between 0 and 1 that represent the degree of forgetting. The input gate decides which new information should be stored in the cell state [65], using a combination of sigmoid and Tanh layers to update the long-term memory. Finally, the output gate determines the next hidden state, again using a combination of sigmoid and Tanh layers.

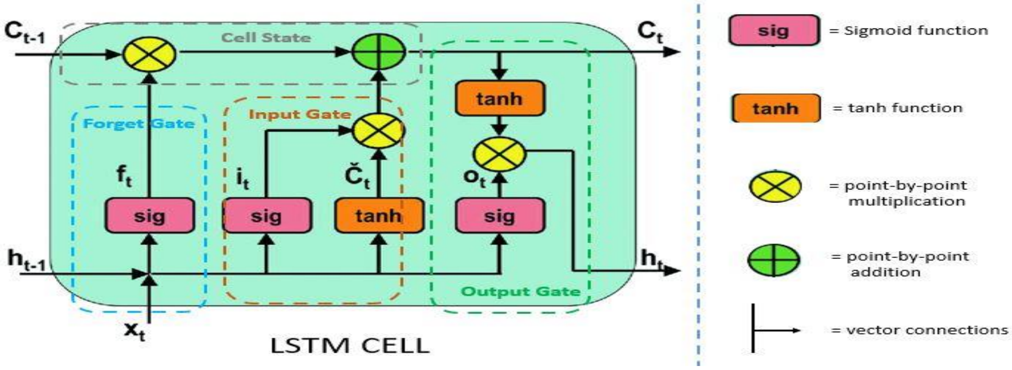


Figure 2.9: General LSTM architecture [114].

2.3.4. Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is a simplified variant of LSTM introduced by Cho et al. (2014) [65], designed to enhance computational efficiency, particularly when working with large datasets. GRU simplifies the architecture by combining the forget and input gates into a single update gate, which regulates the flow of information across time steps. It also merges the cell state with the hidden state to further reduce complexity. In addition to the update gate, GRU introduces a reset gate, which determines how much of the previous hidden state should be forgotten [71] when computing the new candidate activation. This approach helps reduce training time and memory usage, making it useful in specific situations, although there is no clear consensus on whether LSTM or GRU delivers better performance.

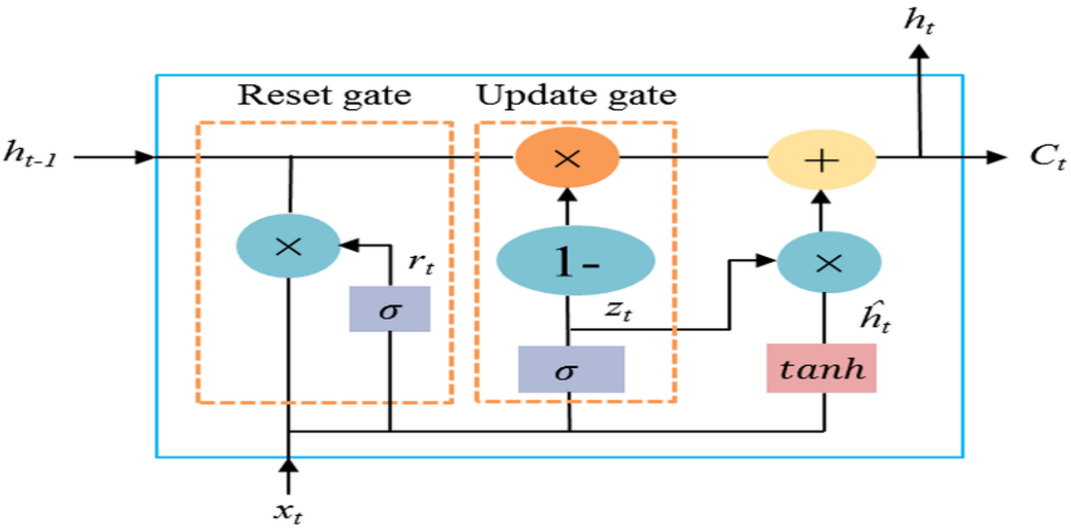


Figure 2.10: general GRU architecture [115].

2.3.5. Autoencoder

Autoencoders are a type of deep learning that was introduced by Rumelhart, Hinton, and Williams in 1986 [66]. They were made with the aim of learning how to reconstruct data with the smallest possible error, which is useful for many tasks such as anomaly detection. Through learning to reconstruct healthy samples, the model can identify abnormal ones. Autoencoder architecture is mainly composed of three parts, which are an Encoder, Decoder [67], and Bottleneck layer. The Encoder's role is to compress the input by lowering the number of units in each successive layer. The Bottleneck is the central layer of the architecture with the smallest number of units. Its role is to store the compressed representation of the information. The Decoder is the last part of this architecture, and its role is to convert the encoder representation back to its original dimensions by gradually increasing the number of units in each successive layer.

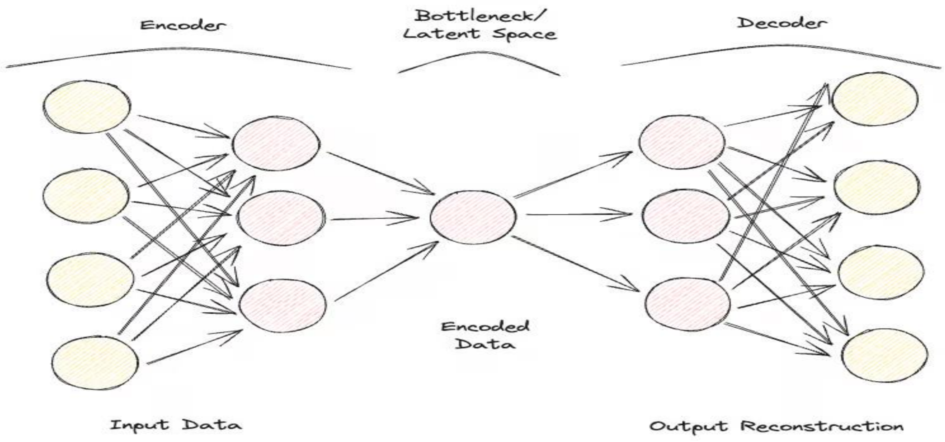


Figure 2.11: General Autoencoder architecture[116].

2.3.6. LSTM-Autoencoder (LSTM-AE)

The LSTM-Autoencoder is a hybrid deep learning architecture that combines the capabilities of both LSTM networks and autoencoders. Its overall structure typically follows that of traditional Autoencoder models, with the key difference being that both the encoder and decoder layers are composed of LSTM units instead of standard neurons. This design takes advantage of LSTM's ability to capture long-term temporal dependencies in sequential data, while leveraging the autoencoder's strength in learning compact representations and reconstructing inputs. As a result, it is particularly effective for tasks such as anomaly detection.

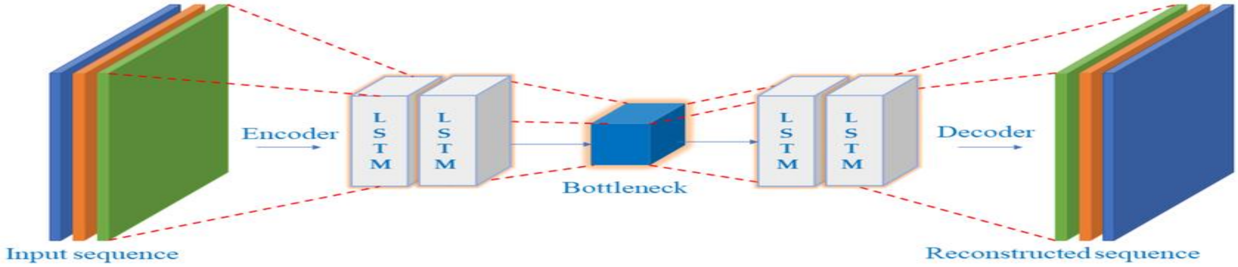


Figure 2.12: General LSTM-Autoencoder architecture [51].

2.4. Related Works

The problem of detecting heart disease using AI has interested many researchers due to the substantial benefits it offers to the healthcare system. As a result, numerous solutions have been proposed, each achieving varying levels of success. In the following section, we will explore some of the research efforts that aimed to address this problem and examine the results they achieved.

2.4.1. CNN-FWS: A Model for the Diagnosis of Normal and Abnormal ECG with Feature Adaptive

This paper was published in 2022 by Junjiang Zhu, Jintao Lv, and Dongdong Kong [68]. It proposes a CNN-FWS model, which consists of three convolutional neural networks trained separately to extract features from the input. These features are then fed into a weight-based recursive feature elimination module, which operates in an adaptive manner to remove redundant features. Finally, a fully connected layer is connected to the output layer to make the final prediction.

The dataset used in this study was obtained from PTB-XL, which consists of 21,837 clinical 12-lead ECG recordings from 18,885 patients. The proposed model achieved an F1 score of 0.902, a recall of 0.889, and an accuracy of 90.05%.

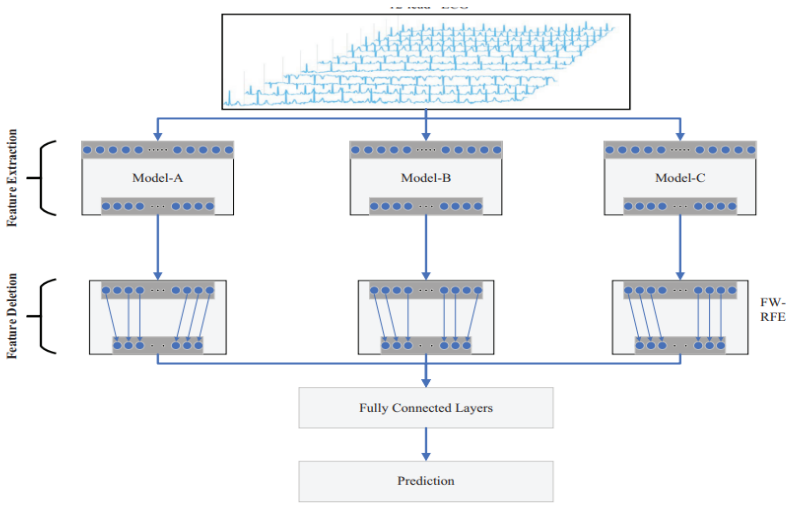


Figure 2.13: Architecture of the proposed model [68].

2.4.2. Dynamic prediction of cardiovascular disease using improved LSTM

This paper, published by Junwei Kuang et al. [69], proposes an LSTM-based model combined with a target repeat prediction method. In this approach, the hidden layer output at each time step is used to compute the diagnosis prediction via a Sigmoid activation function. The prediction loss at each time step is then calculated by comparing the predicted and actual classification labels. Finally, the overall loss function is defined as a weighted combination of the losses from all time steps and the loss from the final time step, which is used to update the model parameters.

The dataset used in this study was obtained from the Hospital Information System (HIS) of a hospital and included patients' medical information such as age, sex, 23 test indicators, and corresponding heart disease diagnoses. The proposed model achieved an accuracy of 89.6%, an F1 score of 60.8%, a recall of 81.1%, and a precision of 49.2%.

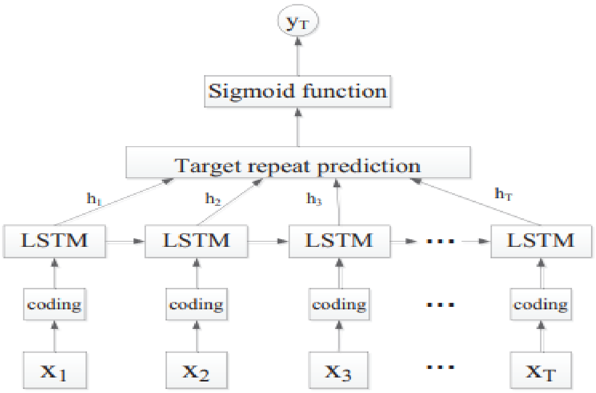


Figure 2.14:Architecture of the proposed LSTM model [69].

2.4.3. A CNN based model for heart disease detection

This paper was published by Kingsley Ifeanyi Chibueze et al. [70]. It proposes a CNN model that takes 224×224×3 images as input, normalizes them using a rescaling layer, and extracts features through a series of Conv2D and MaxPooling2D layers with increasing filter sizes. A dropout layer is included to reduce overfitting, followed by flattening and two dense layers. The final dense layer uses a softmax activation function to classify the input into one of five target classes.

The study applied multiple preprocessing methods to improve training results. These methods include image resizing, normalization, data color normalization, cropping, data compression, and conversion. To improve generalization, the study used an MRI dataset obtained from two different sources. The first source was Enugu State University Teaching Hospital, specifically at Park Lane in Enugu State, Nigeria. The second source was the CAD Cardiac MRI Dataset available on Kaggle. The proposed model achieved an accuracy of 94.13%.

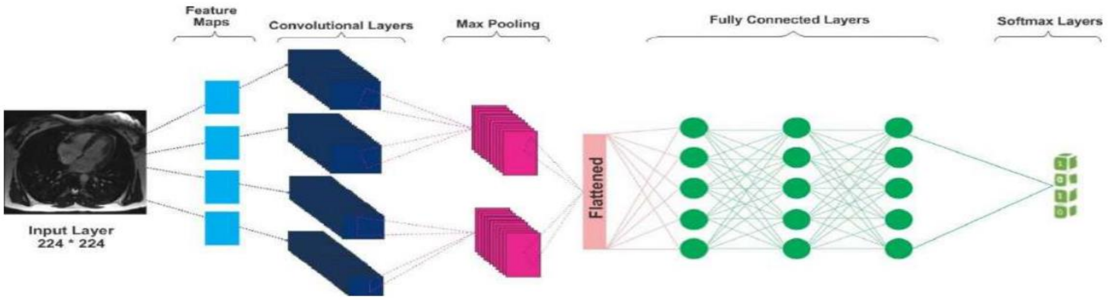


Figure 2.15:Architecture of the proposed CNN model [70].

Table 2.1 Comparison of related works on heart disease prediction using deep learning techniques

Study	Year	Method	Dataset	Preprocessing	Accuracy
The Diagnosis of Normal and Abnormal ECG with Feature Adaptive	2022	CNN-FWS	21,837 ECG sample from PTB-XL	band-pass filter	90.05%
Dynamic prediction of cardiovascular disease	2019	LSTM	A data set that contains age, sex, 23 test indicators and nine disease diagnosis labels	z-score standardization, time Series length adjustment, record filtering, one-hot encoding	89.6%
Heart disease detection	2024	CNN	MRI dataset from Kaggle and Park Lane in Enugu State	image resizing, normalization, data color normalization, cropping, data compression, conversion	94.13%.

2.5. Conclusion

In this chapter, we presented machine learning and its types, and delved deeper into deep learning approaches, exploring some of the most successful architectures for heart disease detection and how each model works. Furthermore, we discussed recent advancements in the field to highlight the various techniques currently being employed. We observed that each approach has its strengths under the right conditions but also comes with limitations that must be carefully considered.

Chapter 3:

Design of the approach

3.1. Introduction

The advancement of Artificial Intelligence (AI) has aided many fields, such as healthcare, in various aspects by using machine learning and deep learning techniques. These techniques have started showing promising results in facilitating professional jobs, such as diagnosing and treating patients, by automating many time-consuming steps during the process. As previously explained, heart disease is a very dangerous condition that poses a serious risk to many people's lives, which is why we saw an opportunity to develop a deep learning model to help with the early prediction of this disease. In this chapter, we present the system design, the dataset used, the preprocessing phase, and the proposed LSTM Autoencoder architecture.

3.2. General workflow

In order to create our model that helps predict heart disease, we began by obtaining the data. Afterward, we cleaned and preprocessed it to make it easier for the machine to understand. Then, we split the data into a training set, which the model used to detect patterns, and a test set, which was used to verify the model's accuracy.

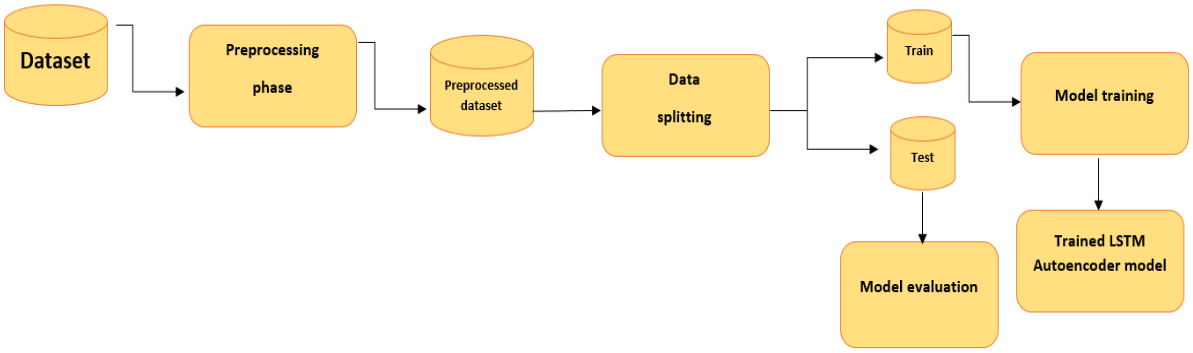


Figure 3.1:General workflow.

3.3. Dataset

- The dataset that was used is available on Kaggle [118] and it was donated by Y. Chen , E. Keogh.
- The dataset contains 5,000 samples of ECG signals from people with either a healthy heartbeat or heart disease.

- The dataset have 140 features (different electrical signals) that determine if the patient has a heart disease or not.

3.3.1. Dataset structure

In this dataset there are 5 classes which are:

1: Normal heartbeat.

2, 3, 4: Abnormal heartbeat.

5: Unclassified heartbeat.

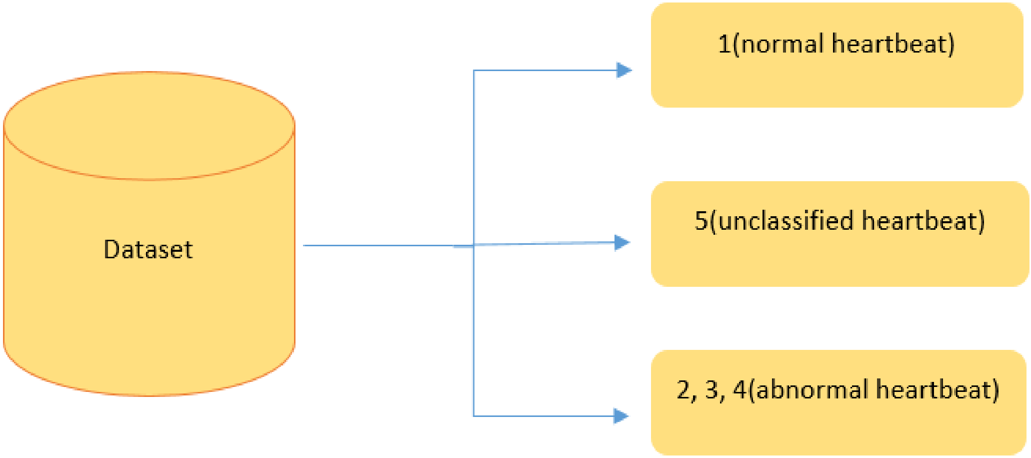


Figure 3.2:Dataset structure.

3.4. Preprocessing

- **Data filtering**

In this step, we examine the dataset to identify if there are any null values present in any of the rows. Null values can cause issues in data processing and analysis, so it's important to address them early. If we find any row containing one or more null values, we remove that entire row to ensure the dataset remains clean for future steps.

- **Standardizing data types**

In this step, we ensure that the entire dataset contains only float values. This is crucial because the model requires numeric input to function correctly and to prevent errors during training. By converting the data types appropriately, we guarantee smooth processing and more accurate results from the model.

- **Selection of output targets**

In this step, we identify and isolate the specific columns or features in the dataset that will serve as the output targets for the model. These targets represent the variables that the model is expected to predict or classify.

- **Data Reshaping**

The data must be reshaped into a format compatible with the LSTM architecture, which is why we will add one dimension to match the general LSTM shape of (samples, time steps, features).

3.5. Proposed model

The model begins with an input layer of size 140, followed by an encoder composed of two LSTM layers. The first LSTM layer has 64 units, and the second has 32 units. The encoder's output is passed to the bottleneck, which includes a repeat vector. An attention mechanism is applied to both the first LSTM layer and the repeat vector, and the result is then passed to the decoder. The decoder mirrors the encoder, starting with an LSTM layer of size 32, followed by another with 64 units. The final output layer generates the reconstructed sequence with a size of 140.

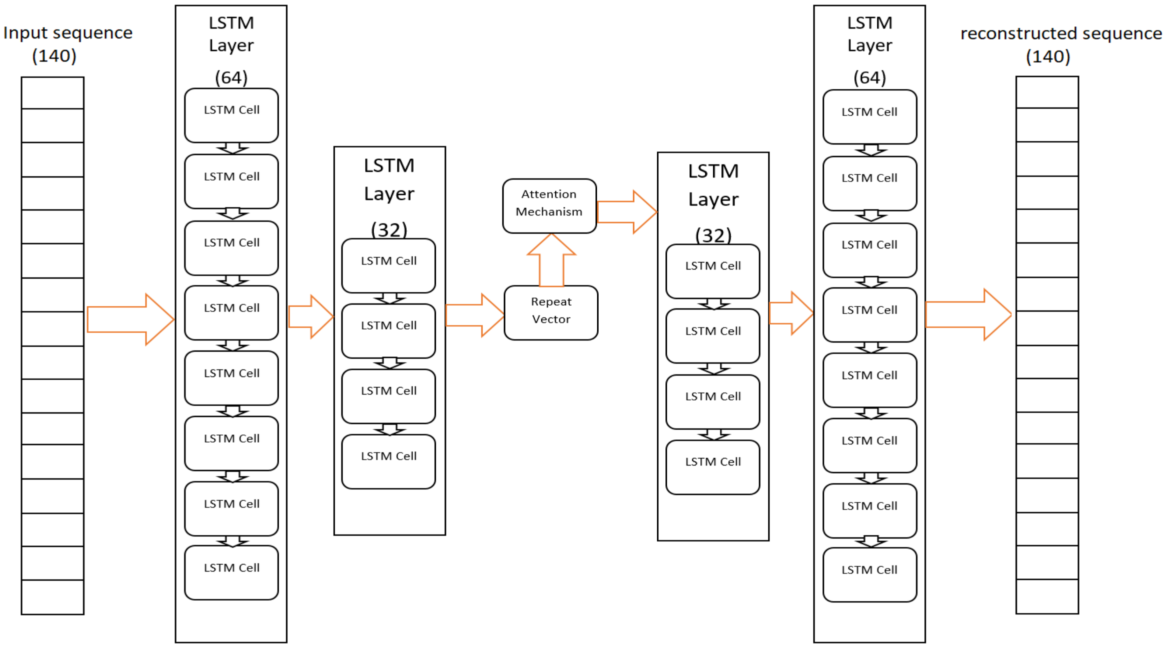


Figure 3.3: General architecture of our proposed model.

After preprocessing our dataset, we use it to train our proposed model, which is an LSTM Autoencoder that employs a slight Multi-head Attention mechanism to improve the model’s performance. We then use the model to predict whether the patient is healthy or suffers from an abnormal heartbeat. We chose this model because LSTMs are well-suited for time-series tasks such as ECG analysis, and Autoencoders are effective for anomaly detection, which is our goal here.

3.5.1. Attention Mechanism

We enhance the decoder's ability to focus on the most relevant parts of the encoded sequence during input reconstruction by incorporating a Multi-head Attention [117]. This mechanism enables the model to selectively pay more attention to specific segments of the input sequence when generating each output element, rather than treating all input elements equally. It operates by comparing a query with a set of key-value pairs and computing an attention score for each key. These scores are then used to calculate a weighted sum of the corresponding values, resulting in a context vector that highlights the most relevant parts of the input.

3.5.2. Activation Functions

The activation function is a mathematical function applied to the output of a neuron or a neuron layer in a neural network. It transforms the raw output, which is typically the weighted sum of inputs plus a bias, into a new value that becomes the neuron's final output. In our model, we mostly used Tanh functions, but sigmoid functions are also widely used in this type of models. Since the ECG values in our normalized dataset range from -1 to 1 and our goal is to reconstruct the input, the Tanh function is well-suited for this task, as its output also ranges from -1 to 1.

Below is the mathematical formula used to define the Tanh activation function [119]:

$$Tanh(z) = \frac{\sinh(z)}{\cosh(z)} = \frac{exp\ (z)\ -\ exp(-z)}{exp\ (z) +\ exp(-z)}$$

3.5.3. Learning rate

Learning rate is a hyperparameter that determines how much the model adjusts its parameters, such as weights, during each training step. In the case of our model, we use a learning rate of 0.0001. We chose this low value because other tests with higher learning rates, such as 0.01 or 0.1, made the model overshoot the optimal weights, while the 0.0001 learning rate allowed the model to learn the optimal weights in a stable manner. Not to mention, a low learning rate is very ideal for LSTM, as it helps prevent the model from falling into the vanishing gradient problem, allowing the gate mechanisms to effectively retain and control the flow of long-term dependencies during training.

3.5.4. Optimization Algorithm

Optimization algorithms are responsible for tuning the model parameters and updating their values during training. For our model, we chose the Adam optimizer due to its efficient performance and relatively low computational cost compared to other optimizers.

Below is the Adam algorithm as defined in the paper “Adam: A Method for Stochastic Optimization” [121], where both β_1 and β_2 are exponential decay rates for the moment estimates, and $f(\theta)$ is the stochastic objective function.

Algorithm 3.1 Adam optimizer [121]

```
Input : The values of $\alpha$, $\beta_1$, $\beta_2$, $f(\theta)$, $\theta_0$
Output: Next set of optimized weights.
$m_0 \leftarrow 0$ (Initialize 1st moment vector)
 v0 ← 0 (Initialize 2nd moment vector)
$t \leftarrow 0$ (Initialize timestep)
while $\theta_t$ not converged do
    $t \leftarrow t + 1$
    $g_t \leftarrow \nabla\theta f_t(\theta t{-}1)$ (Get gradients w.r.t. stochastic objective at timestep t)
    $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$ (Update biased first moment estimate)
    $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$ (Update biased second raw moment estimate)
    $\hat{m}_t \leftarrow m_t/(1 - \beta_1^t)$ (Compute bias-corrected first moment estimate)
    $\hat{v} \leftarrow vt/(1 - \beta_2^t)$ (Compute bias-corrected second raw moment estimate)
    $\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \hat{m}_t/(\sqrt{\hat{v}_t} + \epsilon)$ (Update parameters)
end while
return $\theta_t$ (Resulting parameters)
```

3.5.5. Loss Function

A loss function is a mathematical function that aims to evaluate how well the model performs. In the case of your model, we are using mean squared error (MSE). We used MSE because it heavily penalizes large errors, which is suitable for our case since the model aims to reconstruct healthy samples with a very small error margin. Large errors are exactly what we want to avoid, making MSE a good choice.

Below are the mathematical formulas used to define it, where y is the true value and ŷ is the predicted value [120]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (1)$$

3.5.6. Prediction

After the completion of training, the model will be capable of reconstructing healthy heartbeats with a minimal error margin. Any reconstructed sample with an error margin exceeding a predefined threshold will be classified as an abnormal heartbeat.

3.5.7. Evaluation metrics

Evaluation metrics are a very important part of measuring model performance because they provide objective standards for assessing model quality and performance. The choice of evaluation metrics depends on the type of model and the specific outcomes it aims to achieve. In our study, we will use four evaluation metrics, which are F1-Score, Accuracy, Recall, and Precision [72].

Below are the mathematical formulas used to calculate these metrics, where TP means true positives, TN means true negatives, FP means false positives, and FN means false negatives.

$$F1 - Score = \frac{2*precision*Recall}{precision+Recall} \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

3.6. Conclusion

In this chapter, we presented our workflow and explained our dataset classes and their sources. We then described the steps involved in the preprocessing phase of our data, followed by a detailed explanation of our proposed model architecture and its parameters. Finally, we outlined the metrics we will use to evaluate our model’s performance.

In the following chapter, we will delve deeper into the implementation of the model, including all relevant code, instructions, and libraries, along with testing and evaluating the model’s performance.

Chapter 4:
Implementation and results

4.1. Introduction

This chapter focuses on the implementation of our proposed deep learning model. It begins with an overview of the tools, libraries, and frameworks utilized in the development process. We then evaluate the performance of our model using various evaluation metrics and conclude with a comparative analysis against related works.

4.2. Implementation frameworks, tools and libraries

- **Python**

Python is an object-oriented, high-level programming language with dynamic semantics that make it save a lot of time during the development of very complex applications. Python also supports many modules and libraries, which provide extensive functionalities for various tasks such as web development, data analysis, machine learning, automation, and more [73].

- **Jupyter Notebook**

Jupyter Notebook is a development environment that enables users to write and execute live code, as well as visualize results. It is commonly used in data science and research [74].

- **NumPy**

NumPy is a Python library mainly used for array-related tasks [75].

- **Pandas**

Pandas is an open-source Python library that facilitates data analysis and data manipulation [76].

- **Seaborn**

Seaborn is a Python library that offers statistical data visualization [77].

- **Tensorflow**

TensorFlow is an open-source framework developed by Google researchers and designed to help with machine learning tasks [78].

- **Keras**

Keras is the high-level API within the TensorFlow platform, providing a user-friendly and efficient interface for tackling machine learning tasks, especially those involving modern deep learning techniques [79].

- **Matplotlib**

Matplotlib is a Python library used for plotting tasks [80].

- **Scikit-learn**

Scikit-learn is a Python library designed for machine learning tasks [81].

- **Scipy**

SciPy is a scientific Python library that uses NumPy underneath. It provides many useful functions for optimization, integration, interpolation, and more [82].

- **Flask**

Flask is a micro web framework written in Python. It aims to offer an easy way to create web applications quickly with minimal code. We used it in our project mainly to design the interface [122].

- **Flask-CORS**

Flask-CORS is a Flask extension that facilitates the handling of Cross-Origin Resource Sharing (CORS) in Flask applications [19].

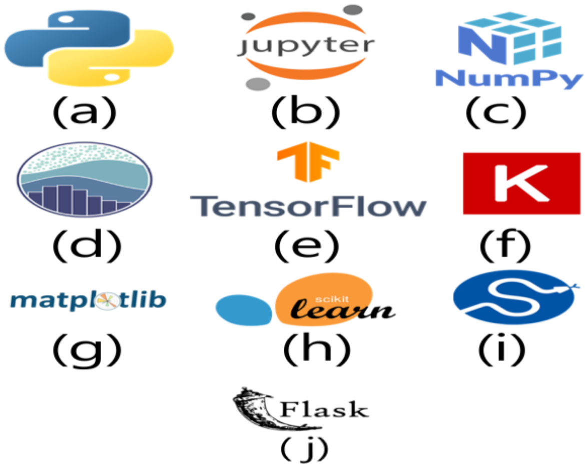
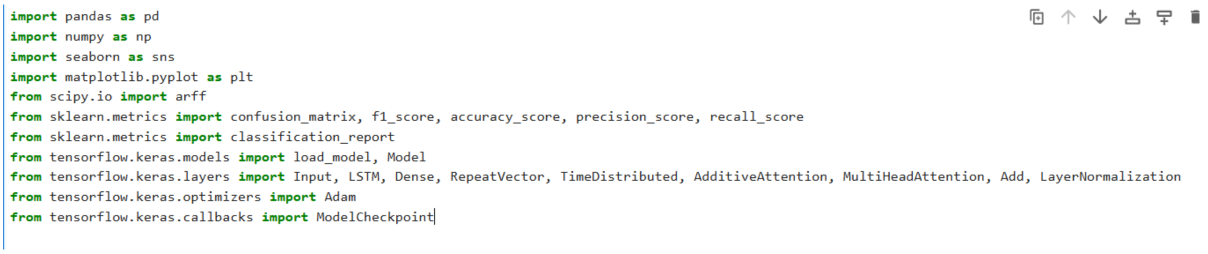


Figure 4.1: Python logo (a),Jupyter notebook logo (b),Numpy logo (C),Searborn logo (d),Tensorflow logo (e),Keras logo (f),Matplotlib logo (g), Scikit-learn logo (h),Scipy logo (i),Flask(j).

4.3. Implementation phases

For the purpose of implementing our model, we need to import essential libraries that aid in its construction.



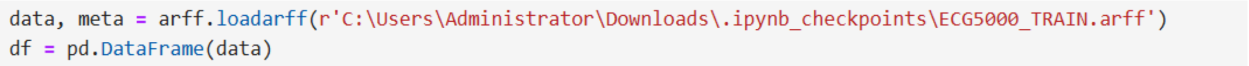
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.io import arff
from sklearn.metrics import confusion_matrix, f1_score, accuracy_score, precision_score, recall_score
from sklearn.metrics import classification_report
from tensorflow.keras.models import load_model, Model
from tensorflow.keras.layers import Input, LSTM, Dense, RepeatVector, TimeDistributed, AdditiveAttention, MultiHeadAttention, Add, LayerNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ModelCheckpoint
```

Figure 4.2:Model libraries.

After we import these libraries, we shall use them for various tasks, starting with loading the data, then preprocessing it, and finally building our model and testing its performance.

4.3.1. Loading dataset

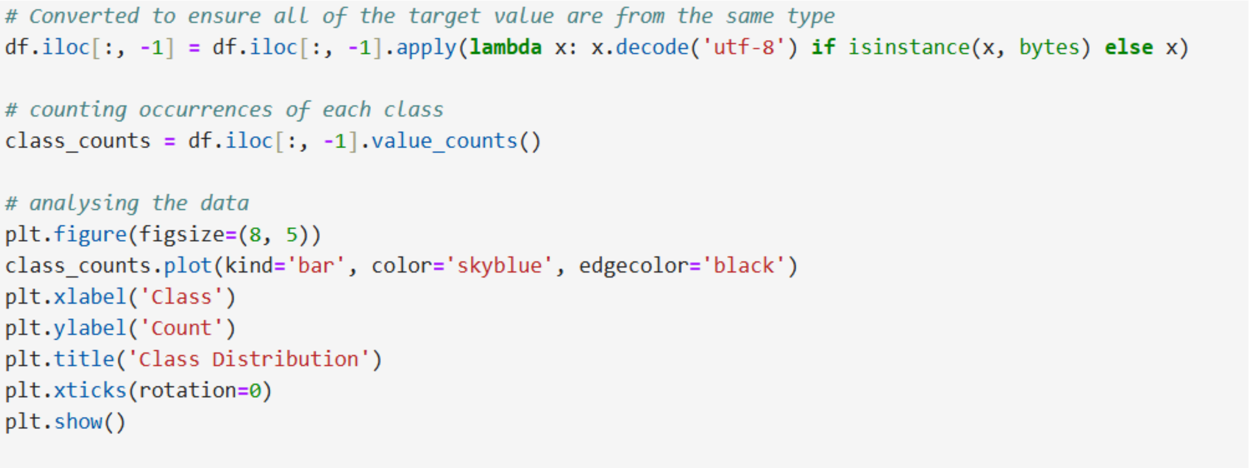
In order to load the data, we will use SciPy (scipy.io) to open the ARFF file, then use pandas to convert the data into a DataFrame to facilitate manipulating it later on.



```
data, meta = arff.loadarff(r'C:\Users\Administrator\Downloads\.ipynb_checkpoints\ECG5000_TRAIN.arff')
df = pd.DataFrame(data)
```

Figure 4.3: Code for loading the dataset.

After that, to visualize how many samples each class has, we use the instruction below.n.



```
# Converted to ensure all of the target value are from the same type
df.iloc[:, -1] = df.iloc[:, -1].apply(lambda x: x.decode('utf-8') if isinstance(x, bytes) else x)

# counting occurrences of each class
class_counts = df.iloc[:, -1].value_counts()

# analysing the data
plt.figure(figsize=(8, 5))
class_counts.plot(kind='bar', color='skyblue', edgecolor='black')
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('Class Distribution')
plt.xticks(rotation=0)
plt.show()
```

Figure 4.4: Code to plot our data classes.

After we execute these instructions, we obtain this plot that visualizes our data.

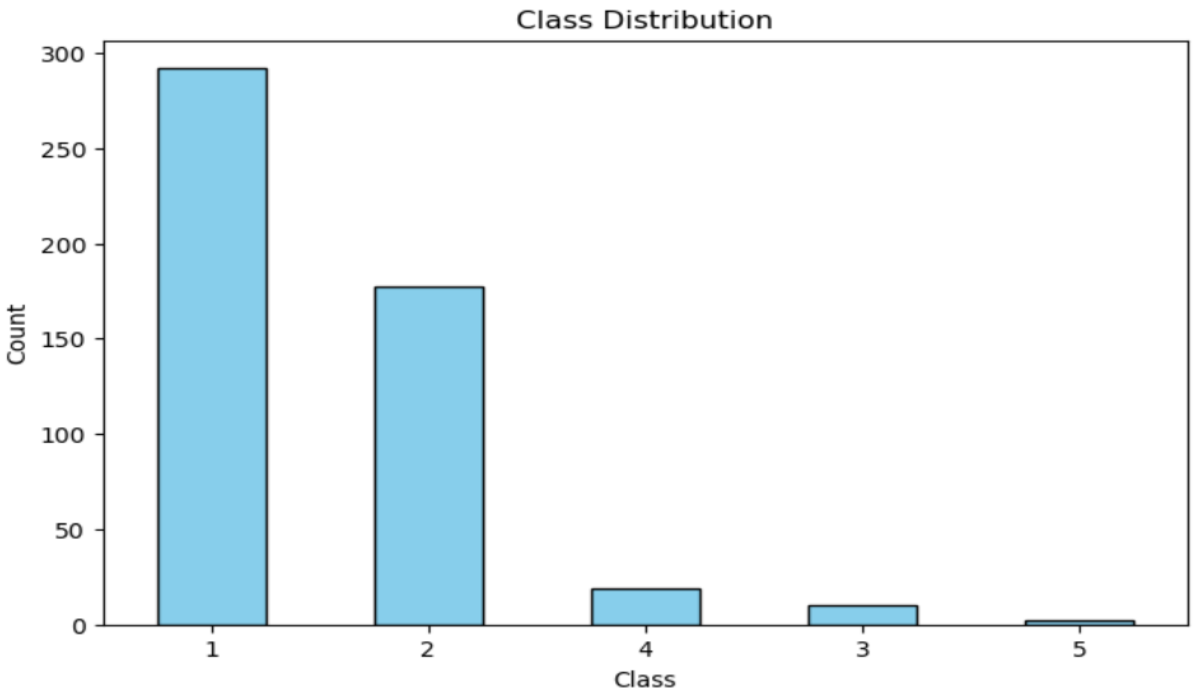
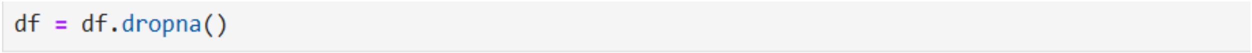


Figure 4.5: Distribution of Classes in the Dataset.

4.3.2. Preprocessing

4.3.2.1. Data Filtering

In order to ensure our data is free from any null values, we use this code to drop any columns with nulls.

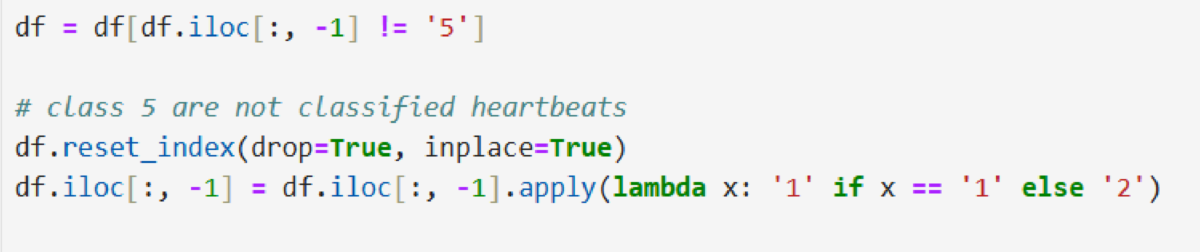


```
df = df.dropna()
```

Figure 4.6:Code for filtering the dataset.

4.3.2.2. Selection of input features and output target

The dataset contains 140 features representing ECG signals, with each entry labeled by a corresponding diagnosis. A label of 1 indicates a normal heartbeat, while labels 2, 3, and 4 represent different types of abnormal heartbeats. Label 5 refers to heartbeats that are not classified. For model training, labels 2, 3, and 4 are combined into a single class labeled as 2, since they all indicate abnormal heart activity. Label 5 is removed from the dataset because it is not relevant to the objectives of this study.

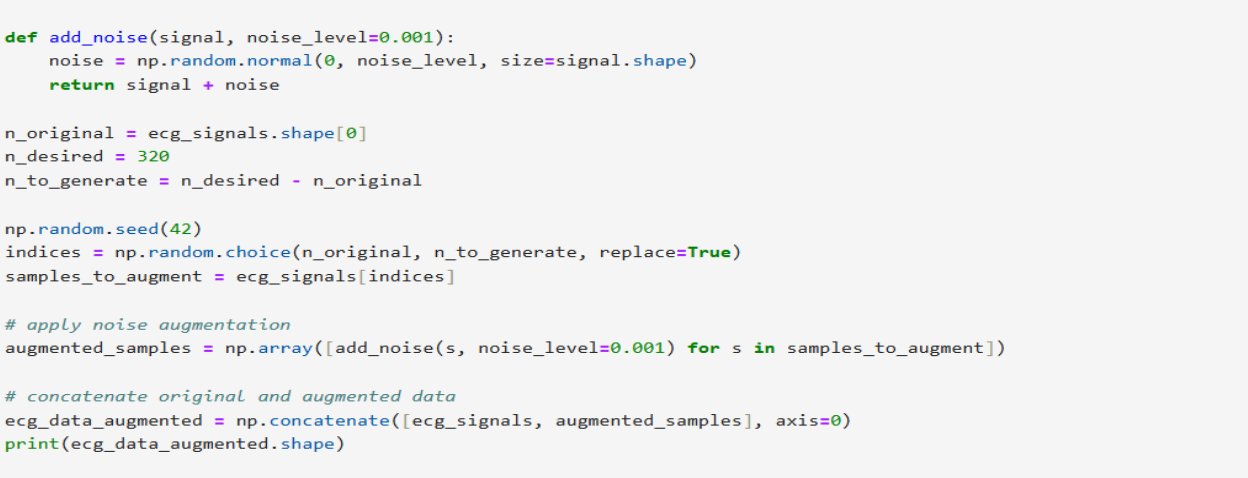


```
df = df[df.iloc[:, -1] != '5']

# class 5 are not classified heartbeats
df.reset_index(drop=True, inplace=True)
df.iloc[:, -1] = df.iloc[:, -1].apply(lambda x: '1' if x == '1' else '2')
```

Figure 4.7: Code for selection of the input featured and output target.

4.3.2.3. Data augmentation

Due to the limited size of our training dataset, we employ a function that generates additional data instances by introducing noise to the original data, thereby augmenting the dataset.



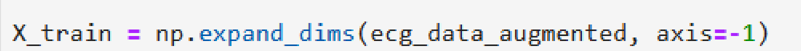
```
def add_noise(signal, noise_level=0.001):
    noise = np.random.normal(0, noise_level, size=signal.shape)
    return signal + noise

n_original = ecg_signals.shape[0]
n_desired = 320
n_to_generate = n_desired - n_original

np.random.seed(42)
indices = np.random.choice(n_original, n_to_generate, replace=True)
samples_to_augment = ecg_signals[indices]

# apply noise augmentation
augmented_samples = np.array([add_noise(s, noise_level=0.001) for s in samples_to_augment])

# concatenate original and augmented data
ecg_data_augmented = np.concatenate([ecg_signals, augmented_samples], axis=0)
print(ecg_data_augmented.shape)
```

Figure 4.8: Code for data augmentation.

A random subset of data instances is selected to reach the desired total of 320. Noise is then applied to these instances, and they are concatenated with the original data to form the final dataset used for training.

4.3.2.4. Data Reshaping

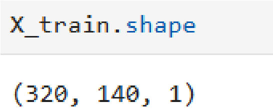
LSTM-based models expect a 3D input shape with the dimensions (number of samples, number of time steps, number of features). Since our data currently has a 2D shape (number of samples, number of features), we need to add one dimension to match the required input shape.



```
X_train = np.expand_dims(ecg_data_augmented, axis=-1)
```

Figure 4.9: Code to reshape the data.

After reshaping our data, the new shape of the data will be:



```
X_train.shape
```

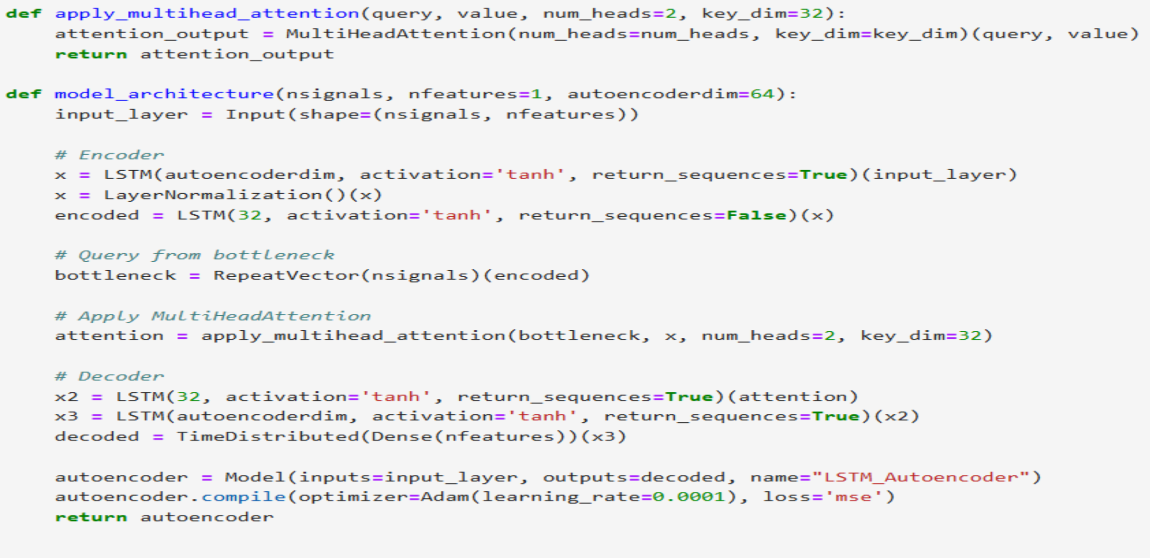
```
(320, 140, 1)
```

Figure 4.10: The model training data after reshaping it.

4.3.2.5. LSTM Autoencoder Model

After loading the dataset, preprocessing it, splitting it, and augmenting it, we will use the training portion of the dataset that we already loaded to train our LSTM Autoencoder model.

Our model architecture is defined below:

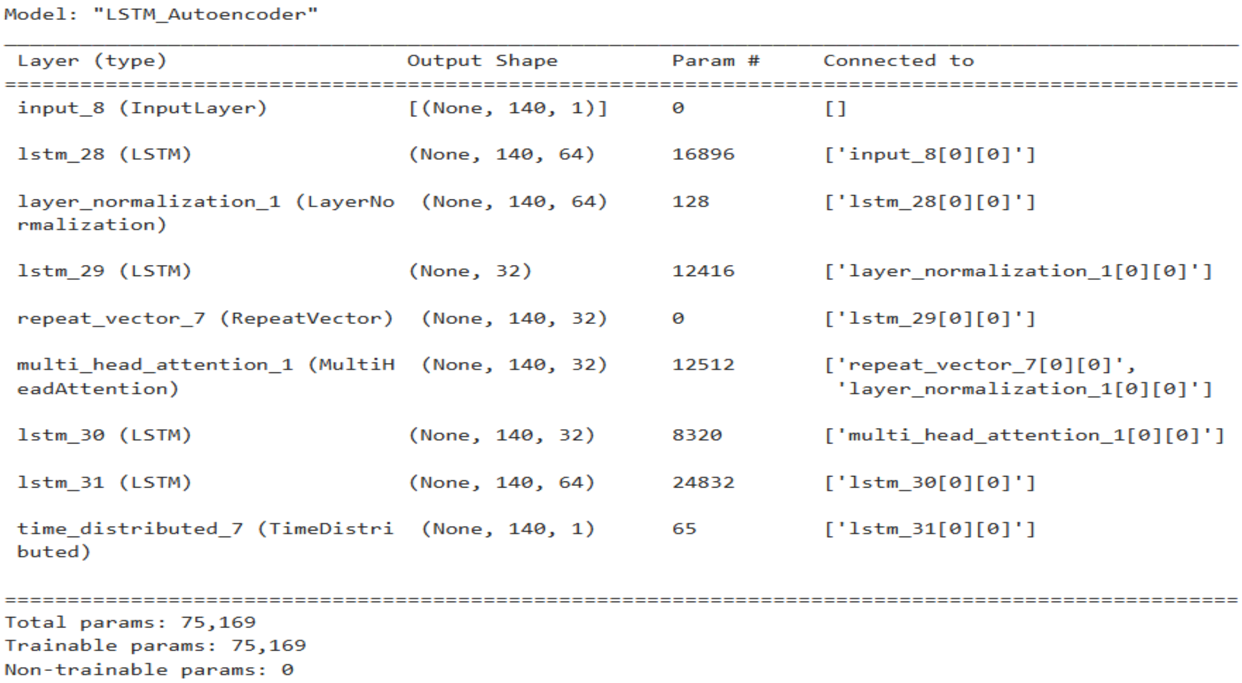


```
def apply_multihead_attention(query, value, num_heads=2, key_dim=32):
    attention_output = MultiHeadAttention(num_heads=num_heads, key_dim=key_dim)(query, value)
    return attention_output

def model_architecture(nsignals, nfeatures=1, autoencoderdim=64):
    input_layer = Input(shape=(nsignals, nfeatures))

    # Encoder
    x = LSTM(autoencoderdim, activation='tanh', return_sequences=True)(input_layer)
    x = LayerNormalization()(x)
    encoded = LSTM(32, activation='tanh', return_sequences=False)(x)

    # Query from bottleneck
    bottleneck = RepeatVector(nsignals)(encoded)

    # Apply MultiHeadAttention
    attention = apply_multihead_attention(bottleneck, x, num_heads=2, key_dim=32)

    # Decoder
    x2 = LSTM(32, activation='tanh', return_sequences=True)(attention)
    x3 = LSTM(autoencoderdim, activation='tanh', return_sequences=True)(x2)
    decoded = TimeDistributed(Dense(nfeatures))(x3)

    autoencoder = Model(inputs=input_layer, outputs=decoded, name="LSTM_Autoencoder")
    autoencoder.compile(optimizer=Adam(learning_rate=0.0001), loss='mse')
    return autoencoder
```

Figure 4.11:The code of the model architecture.

Our model is an LSTM-based autoencoder enhanced with multi-head attention and is composed of three main parts which are the encoder, the attention mechanism, and the decoder. The encoder consists of two LSTM layers. The first layer has a size of 64 and the second has a size of 32. Both layers use the tanh activation function, and layer normalization is applied to the first layer to improve performance. The bottleneck includes a repeat vector that uses the output of the encoder. After that, an attention mechanism is applied to the bottleneck using multi-head attention which helps create a connection between the first LSTM layer after normalization and the bottleneck. The decoder mirrors the structure of the encoder. It begins with an LSTM layer of size 32 that uses the attention output and then continues with an LSTM layer of size 64. Finally, a TimeDistributed layer wrapper provided by Keras is applied to output a 2D reconstruction of the input data since during the LSTM process the data had a 3D shape. When compiling the model, we use the Adam optimizer with a learning rate of 0.0001.

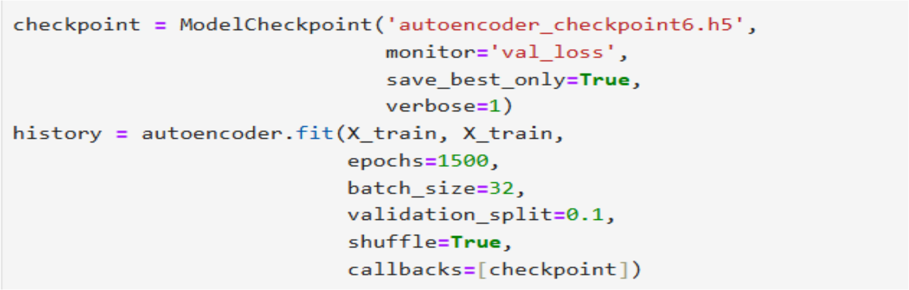
A general summary of our model would look like this:



```
Model: "LSTM_Autoencoder"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_8 (InputLayer)           [(None, 140, 1)]     0           []

 lstm_28 (LSTM)                 (None, 140, 64)      16896       ['input_8[0][0]']

 layer_normalization_1 (LayerNo  (None, 140, 64)     128         ['lstm_28[0][0]']
 rmalization)

 lstm_29 (LSTM)                 (None, 32)           12416       ['layer_normalization_1[0][0]']

 repeat_vector_7 (RepeatVector)  (None, 140, 32)     0           ['lstm_29[0][0]']

 multi_head_attention_1 (MultiH  (None, 140, 32)     12512       ['repeat_vector_7[0][0]',
 eadAttention)                                                    'layer_normalization_1[0][0]']

 lstm_30 (LSTM)                 (None, 140, 32)      8320        ['multi_head_attention_1[0][0]']

 lstm_31 (LSTM)                 (None, 140, 64)      24832       ['lstm_30[0][0]']

 time_distributed_7 (TimeDistri  (None, 140, 1)      65          ['lstm_31[0][0]']
 buted)

==================================================================================================
Total params: 75,169
Trainable params: 75,169
Non-trainable params: 0
```

Figure 4.12: Model Summary.

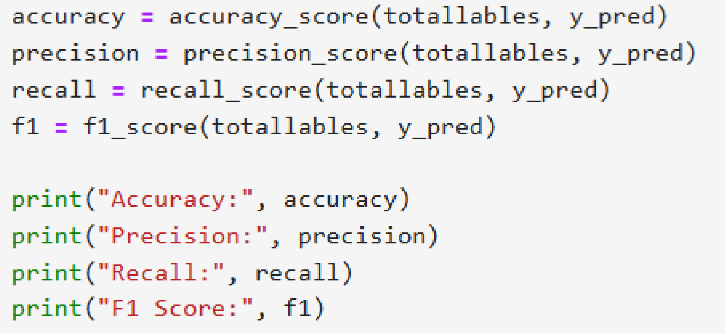
Model.fit is a function used to train our model on the training data subset of the dataset. It takes the training data as input and iteratively updates the model's internal parameters (weights) to minimize the loss function, thereby improving the model's accuracy.



```
checkpoint = ModelCheckpoint('autoencoder_checkpoint6.h5',
                             monitor='val_loss',
                             save_best_only=True,
                             verbose=1)
history = autoencoder.fit(X_train, X_train,
                          epochs=1500,
                          batch_size=32,
                          validation_split=0.1,
                          shuffle=True,
                          callbacks=[checkpoint])
```

Figure 4.13: Code for training the model.

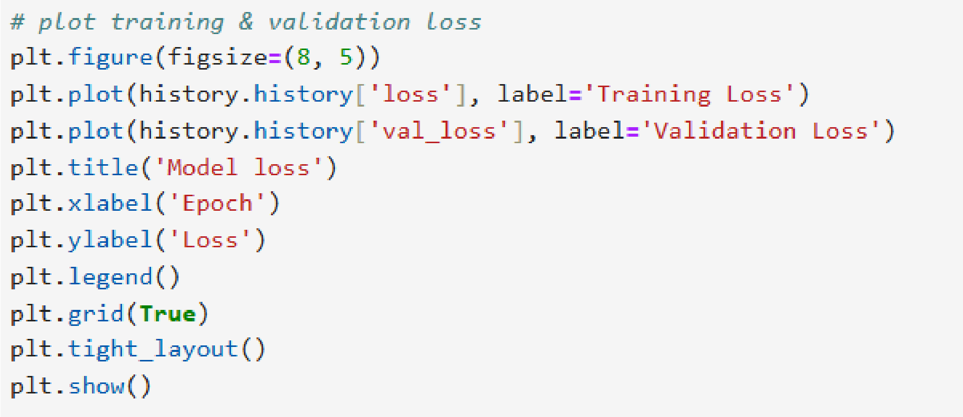
The evaluation of the model is performed using metrics already explained in previous sections, such as F1-Score, Accuracy, Recall, and Precision, provided by scikit-learn. These metrics evaluate the trained model on the test portion of the dataset, which is in a separate file that we open and preprocess in a similar way to how we handled the training data.



```
accuracy = accuracy_score(totallables, y_pred)
precision = precision_score(totallables, y_pred)
recall = recall_score(totallables, y_pred)
f1 = f1_score(totallables, y_pred)

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

Figure 4.14: Code for the evaluation metrics applied on the test dataset.

To visualize how well our model's training loss converged, we use the following code:



```
# plot training & validation loss
plt.figure(figsize=(8, 5))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

Figure 4.15: Code to plot the model training loss.

4.4. Results

After explaining how we implemented our model, we will present the results and performance obtained from evaluating it.

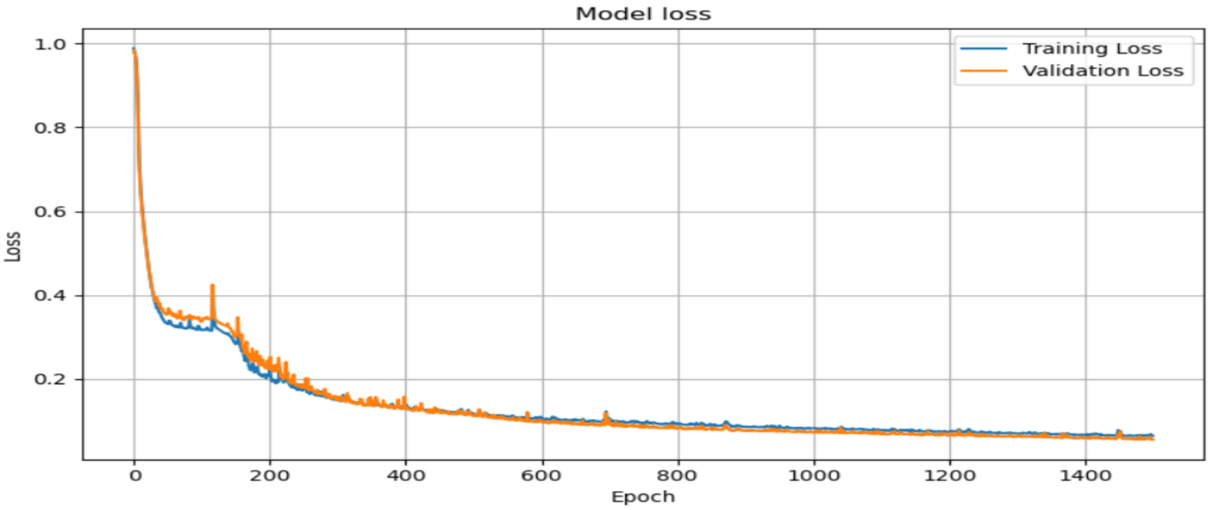
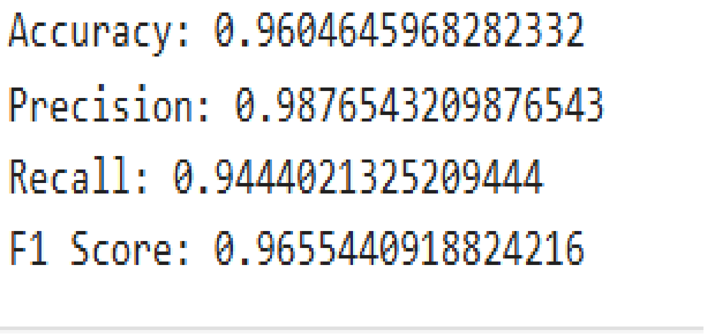


Figure 4.16: Training vs Validation Loss.

This plot of the model loss shows a good fit because both the training loss and validation loss converge to similar values.

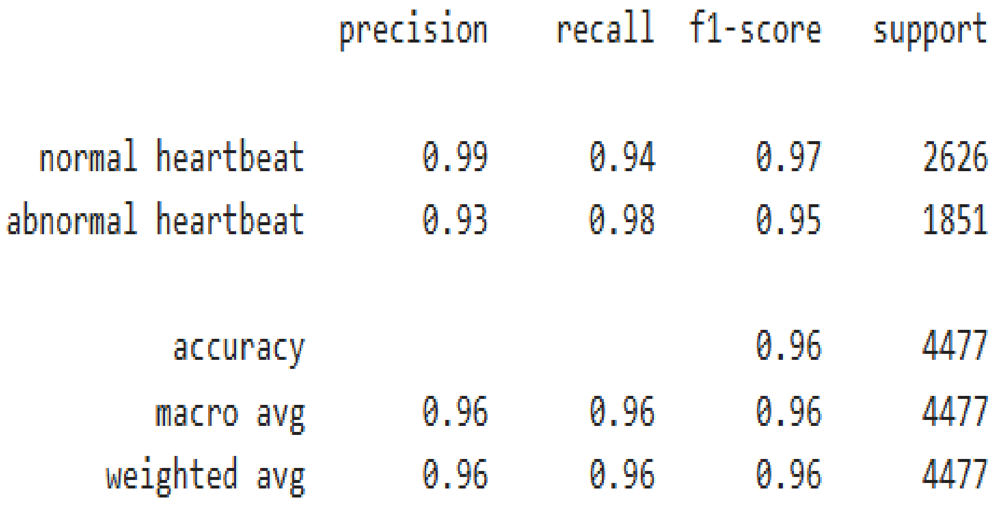
After testing our trained model on the training dataset, we achieved the following results:



```
Accuracy: 0.9604645968282332
Precision: 0.9876543209876543
Recall: 0.9444021325209444
F1 Score: 0.9655440918824216
```

Figure 4.17: Model Evaluation Results (Accuracy, Precision, Recall, F1-Score).

A more detailed look at the evaluation metrics yields the following results:



```
                   precision    recall  f1-score   support

  normal heartbeat      0.99      0.94      0.97      2626
abnormal heartbeat      0.93      0.98      0.95      1851

          accuracy                          0.96      4477
         macro avg      0.96      0.96      0.96      4477
      weighted avg      0.96      0.96      0.96      4477
```

Figure 4.18: Model Evaluation Results on each class (Accuracy, Precision, Recall, F1-Score)

From these results, we can see that our model achieved good performance and the following:

- Total precision is 98.76% for normal heartbeats and 93% for abnormal heartbeats, indicating a low overall false positive rate. The model mostly predicts healthy heartbeats correctly, but there are a few false positives for abnormal heartbeats.
- Total recall is 94.44%, with 97% for normal heartbeats and 95% for abnormal heartbeats, indicating very balanced classification.
- Total F1 score is 96.55%, indicating a good balance between precision and recall.

- Total accuracy is 96.05%, meaning the model correctly predicts 96.05% of the samples.

4.4.1. Confusion matrix

A confusion matrix is a table that illustrates the performance of a machine learning model. We use it to clearly demonstrate how well our model performs.

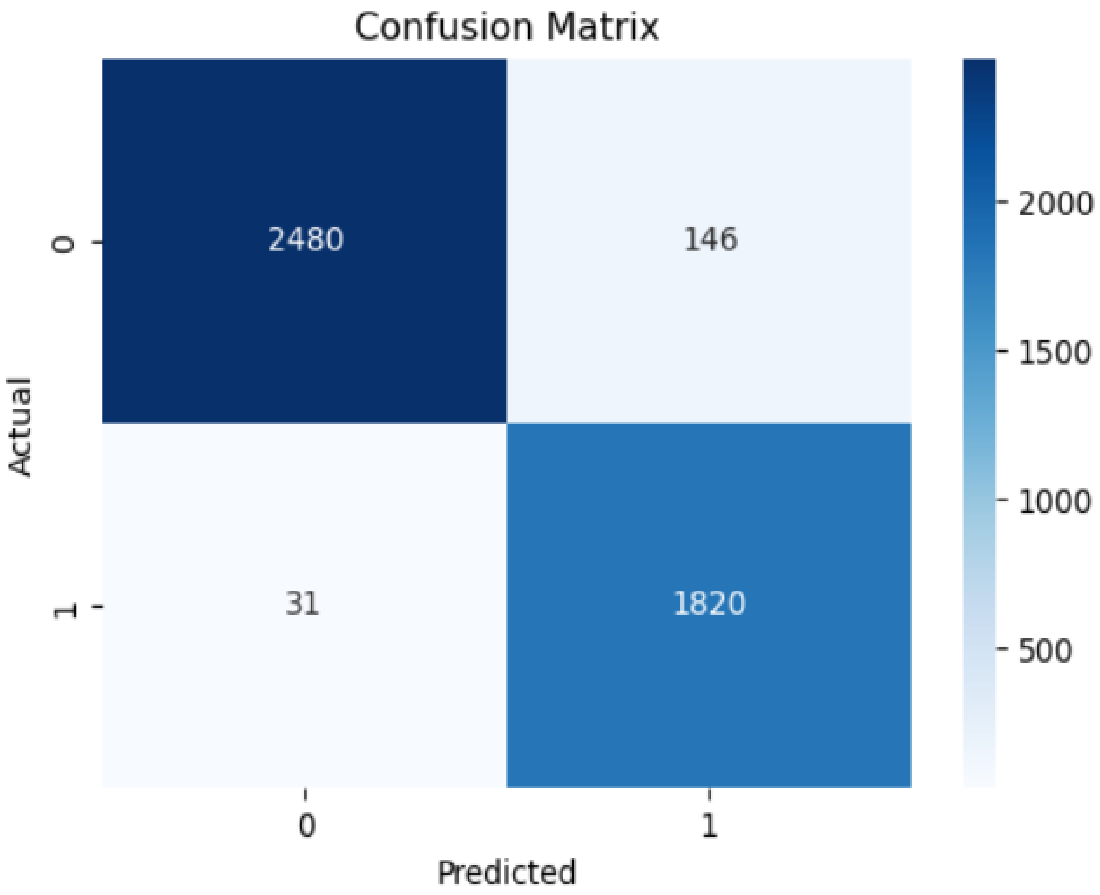


Figure 4.19:Confusion matrix.

The model correctly predicted 2,480 normal heartbeats, which is the majority of the normal heartbeat samples, while only 146 predictions were incorrect.

The model also correctly predicted 1,820 abnormal heartbeats, with only 31 incorrect predictions.

4.4.2. Comparison with other related works

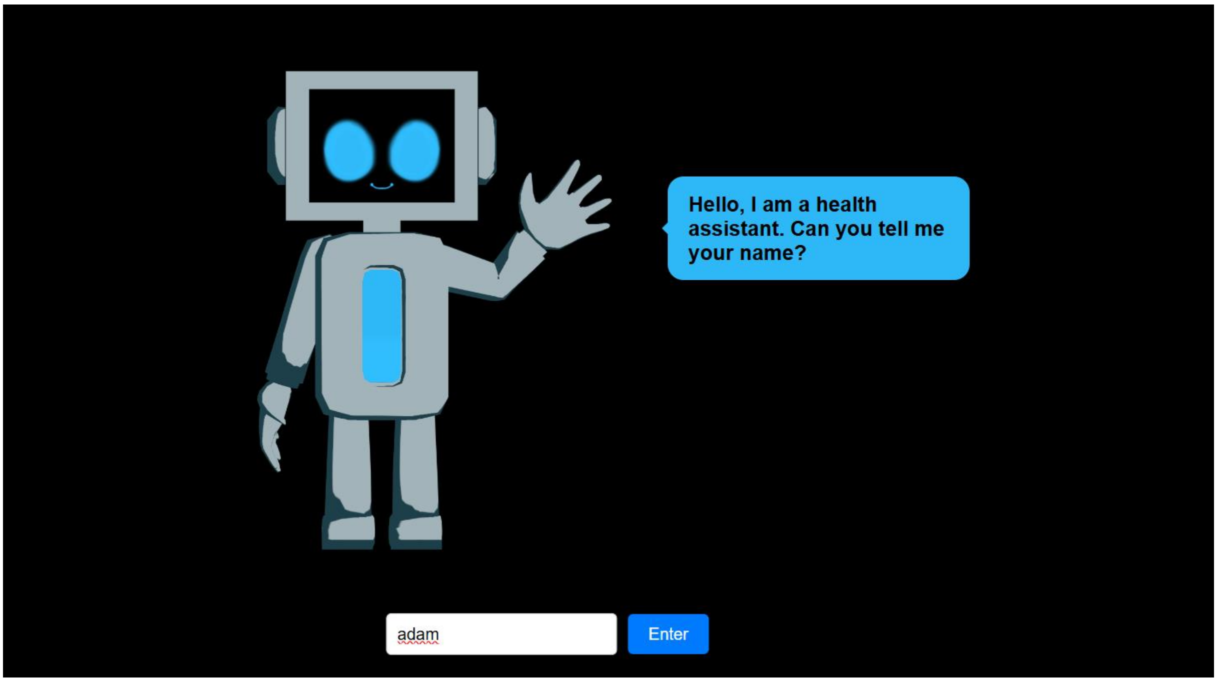
In order to put the evaluation of our model into the perspective of the overall deep learning field, we will compare its performance to other related studies in the field, highlighting the strengths of each method.

Table 4.1 Performance comparison between related works and our proposed method.

	Accuracy	F1_score	Recall	Precision
Our Model	96,05%	96,55	94,44%	98,76%
A CNN based model for heart disease detection by Kingsley Ifeanyi Chibueze ,Amarachi Favour Didiugwu,Nwamaka Georgenia Ezeji,Nnaemeka Ugwu [70] (2024)	94.13%	Nope	Nope	Nope
CNN-FWS: A Model for the Diagnosis of Normal and Abnormal ECG with Feature Adaptive by Junjiang Zhu 1,*, Jintao Lv 1 and Dongdong Kong 2 [68] (2022)	90,05%	90,2%	88,9%	91,15
Dynamic prediction of cardiovascular disease using improved LSTM by Junwei Kuang, Hangzhou Yang,Liu Junjiang , Zhijun Yan. [69] (2019)	89,6%	60.8%	81.1%	49,2%

4.5. Interface Design

In order to demonstrate how our model can be executed, we designed an interface where the user is greeted by a virtual health assistant. The assistant asks for the user's name, then greets them using their name and proceeds to ask what they would like to do today. The user can click a button labeled “Interpret my ECG data.” After that, a brief animation appears, revealing a text box where the user can enter their ECG data and then press a button to submit it. The interface uses the model to make a prediction and informs the user whether they have a healthy heart or are experiencing an abnormal heartbeat. It then provides simple advice accordingly. Below is a simple demonstration of this interaction.

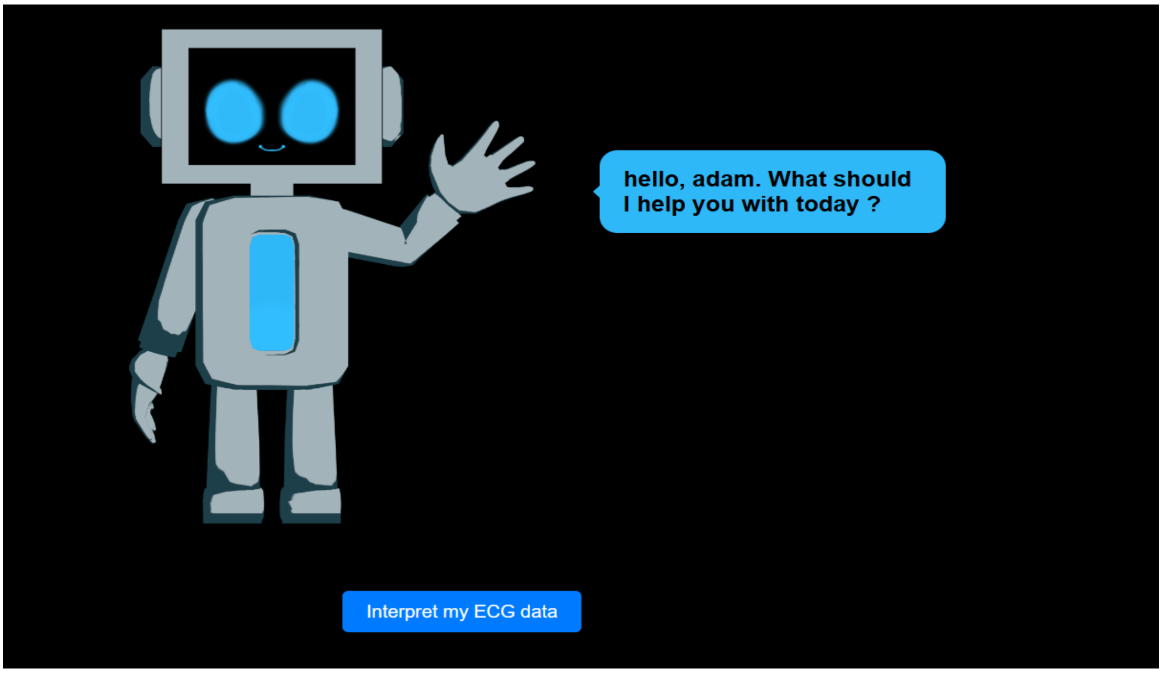


Hello, I am a health assistant. Can you tell me your name?

adam

Figure 4.20: Initial user interaction with virtual assistant.

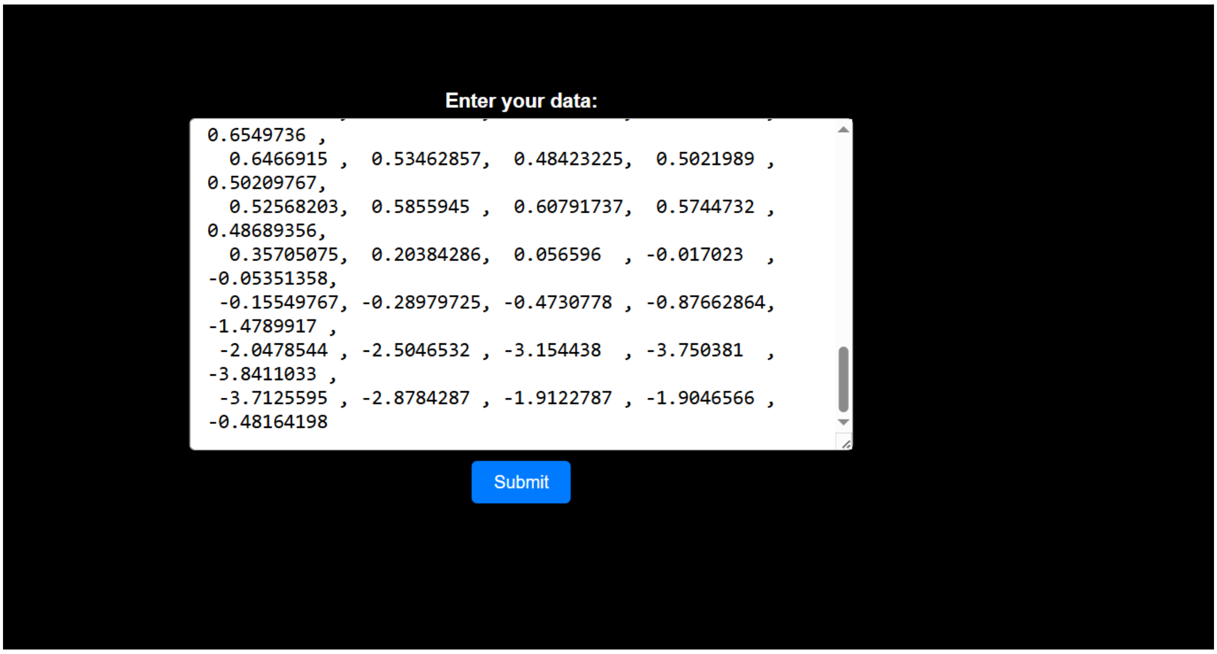
The user is greeted by the virtual health assistant, which asks for their name to create a comfortable and welcoming experience. An input text box is provided for the user to enter their name, followed by a button to confirm their choice.



hello, adam. What should I help you with today ?

Figure 4.21: Virtual assistant awaiting user instruction.

Afterward, as shown on the following screen, the virtual assistant greets the user by name and then asks what it should do next. The user is then presented with the option to press a button to have their ECG data interpreted.

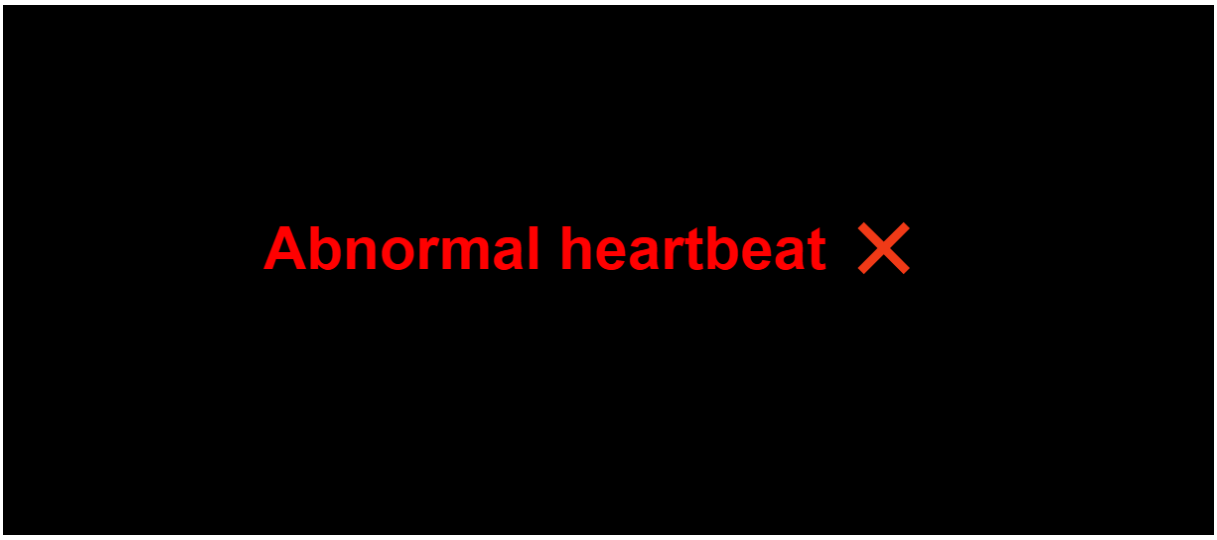


Enter your data:

```
0.6549736 ,
  0.6466915 ,  0.53462857,  0.48423225,  0.5021989 ,
0.50209767,
  0.52568203,  0.5855945 ,  0.60791737,  0.5744732 ,
0.48689356,
  0.35705075,  0.20384286,  0.056596  , -0.017023  ,
-0.05351358,
 -0.15549767, -0.28979725, -0.4730778 , -0.87662864,
-1.4789917 ,
 -2.0478544 , -2.5046532 , -3.154438  , -3.750381  ,
-3.8411033 ,
 -3.7125595 , -2.8784287 , -1.9122787 , -1.9046566 ,
-0.48164198
```

Figure 4.22: User input screen for ECG data submission.

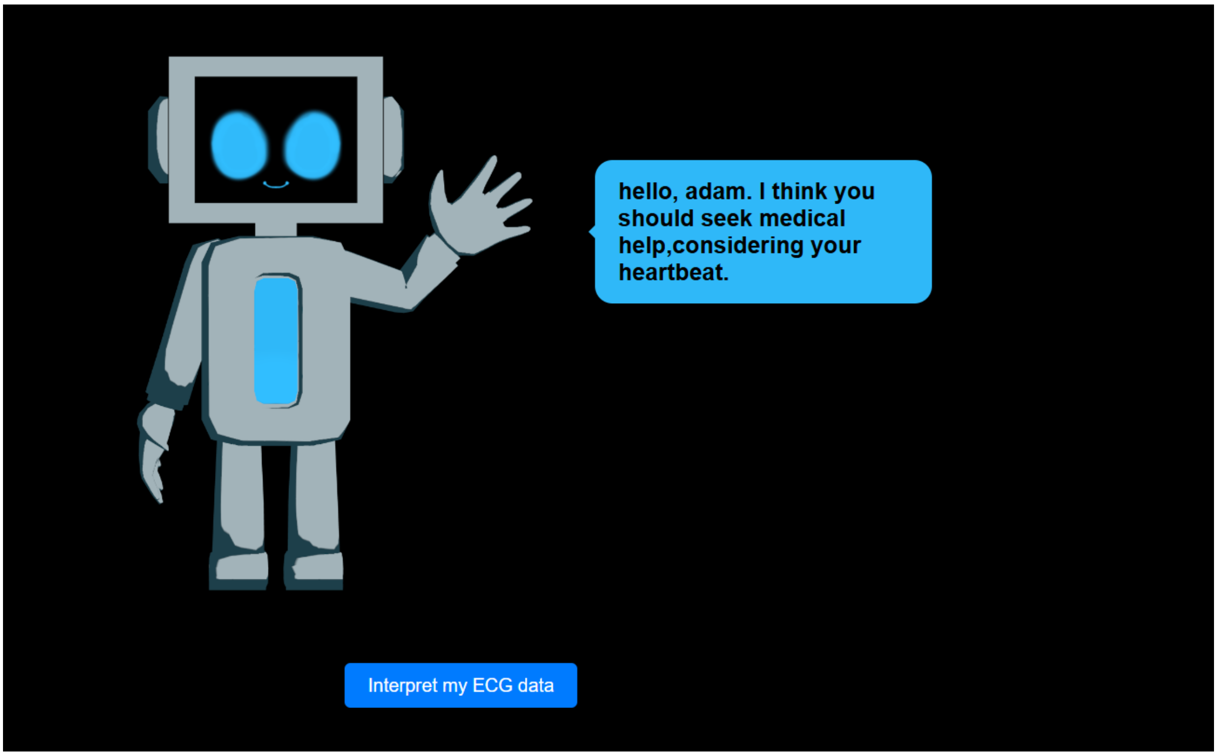
Next, a brief animation transitions the user to this interface, where they can enter their ECG data and then press the submit button to confirm their input.



Abnormal heartbeat ✗

Figure 4.23: Outcome screen displaying ECG analysis prediction.

Once the user enters their ECG data, the interface uses the model to predict whether they are healthy or have an abnormal heartbeat. In this example, the user is diagnosed with an abnormal heartbeat.



hello, adam. I think you should seek medical help,considering your heartbeat.

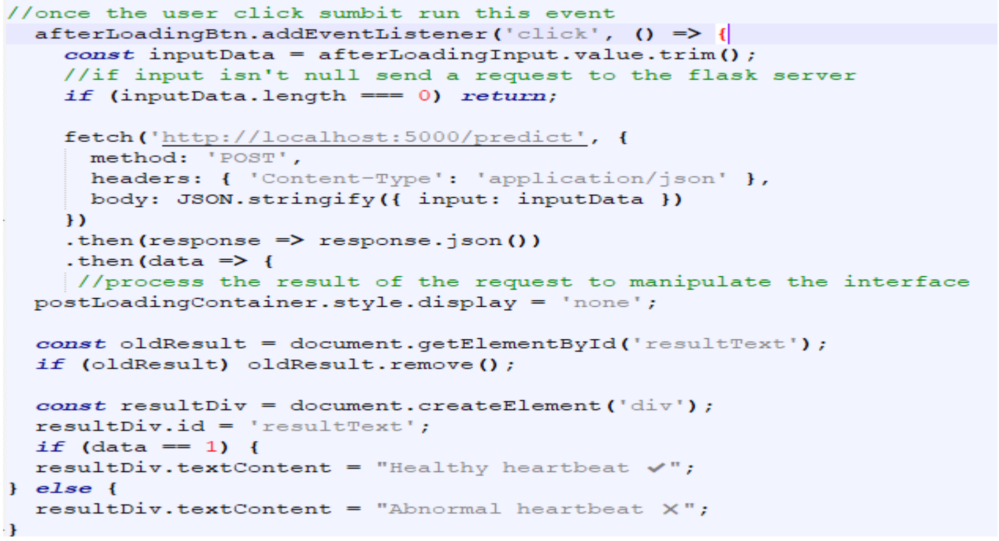
Figure 4.24: An interface presenting recommendations by the virtual assistant.

Then, the health assistant provides advice to the user if an abnormal heartbeat is detected, as in this case.

4.6. Model Integration and System Deployment

4.6.1. Model Integration

The interface is connected to our LSTM Autoencoder through a Flask backend. When the user submits their ECG, the JavaScript component of the interface sends a request to the Flask server hosting the LSTM Autoencoder. The server processes the request using the model and returns a response indicating 1 if the user has a healthy heartbeat or 2 if not.

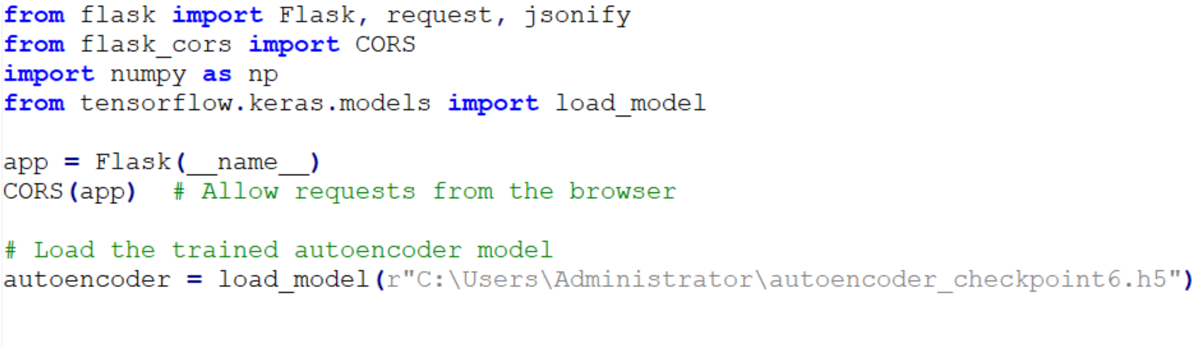


```
//once the user click sumbit run this event
  afterLoadingBtn.addEventListener('click', () => {
    const inputData = afterLoadingInput.value.trim();
    //if input isn't null send a request to the flask server
    if (inputData.length === 0) return;

    fetch('http://localhost:5000/predict', {
      method: 'POST',
      headers: { 'Content-Type': 'application/json' },
      body: JSON.stringify({ input: inputData })
    })
    .then(response => response.json())
    .then(data => {
     //process the result of the request to manipulate the interface
  postLoadingContainer.style.display = 'none';

  const oldResult = document.getElementById('resultText');
  if (oldResult) oldResult.remove();

  const resultDiv = document.createElement('div');
  resultDiv.id = 'resultText';
  if (data == 1) {
  resultDiv.textContent = "Healthy heartbeat ✓";
} else {
  resultDiv.textContent = "Abnormal heartbeat ✕";
}
```

Figure 4.25: JavaScript Code for Sending Prediction Request to Flask API of our model.

4.6.2. System Deployment

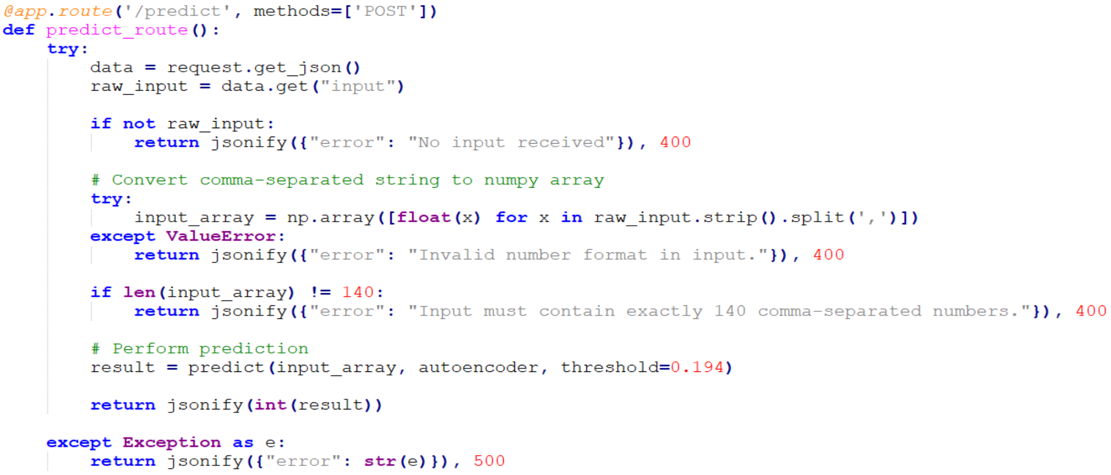
The backend server is started by running the app.py Flask script, which launches an API at http://localhost:5000/predict. During execution, app.py imports the necessary libraries, creates a Flask application, enables Cross-Origin Resource Sharing using CORS(app), and then loads the trained model using the following code:



```
from flask import Flask, request, jsonify
from flask_cors import CORS
import numpy as np
from tensorflow.keras.models import load_model

app = Flask(__name__)
CORS(app)  # Allow requests from the browser

# Load the trained autoencoder model
autoencoder = load_model(r"C:\Users\Administrator\autoencoder_checkpoint6.h5")
```

Figure 0.26: Python backend server code that imports libraries, creates the Flask app, enables CORS, and loads the model.

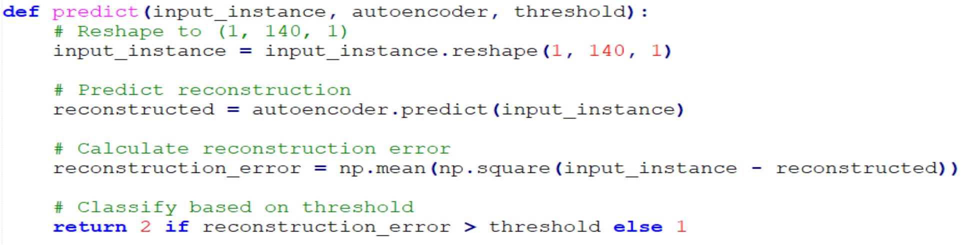
The user request is handled by a function mapped to the route using the @app.route decorator. The function first validates the input format, then splits the input into an array and passes it to the predict function. After generating the prediction, the result is sent to the JavaScript component of the interface.



```
@app.route('/predict', methods=['POST'])
def predict_route():
    try:
        data = request.get_json()
        raw_input = data.get("input")

        if not raw_input:
            return jsonify({"error": "No input received"}), 400

        # Convert comma-separated string to numpy array
        try:
            input_array = np.array([float(x) for x in raw_input.strip().split(',')])
        except ValueError:
            return jsonify({"error": "Invalid number format in input."}), 400

        if len(input_array) != 140:
            return jsonify({"error": "Input must contain exactly 140 comma-separated numbers."}), 400

        # Perform prediction
        result = predict(input_array, autoencoder, threshold=0.194)

        return jsonify(int(result))

    except Exception as e:
        return jsonify({"error": str(e)}), 500
```

Figure 4.27: The Python function responsible for processing the user request.

The predict function will take the user input, adjust its shape to be compatible with the model, and then use the model to make a prediction where 1 means a healthy heartbeat and 2 means an unhealthy heartbeat.



```
def predict(input_instance, autoencoder, threshold):
    # Reshape to (1, 140, 1)
    input_instance = input_instance.reshape(1, 140, 1)

    # Predict reconstruction
    reconstructed = autoencoder.predict(input_instance)

    # Calculate reconstruction error
    reconstruction_error = np.mean(np.square(input_instance - reconstructed))

    # Classify based on threshold
    return 2 if reconstruction_error > threshold else 1
```

Figure 4.28: The Python function responsible for generating a prediction using the model.

4.7. Conclusion

In this chapter, we explained the implementation of our proposed model and provided the corresponding code. We then demonstrated the model's performance using evaluation metrics such as accuracy, F1-score, precision, and recall. Finally, we compared our model's performance with other related works. The results showed that the model performed well and demonstrated strong capabilities in detecting heart diseases.

General Conclusion

Heart disease is a dangerous condition that threatens many lives if left untreated, which is why our study aimed to develop a deep learning model to assist with the early detection of this disease. To achieve our objective, we proposed a model based on an LSTM Autoencoder architecture. Comparative analysis with existing models demonstrated that our proposed model achieved better accuracy. The automation of ECG analysis using our model proves to be very useful, as it enables a faster and easier way to detect abnormal heart activity without the need for constant expert supervision. This not only reduces the diagnostic burden on healthcare professionals but also facilitates early intervention, potentially saving lives by identifying heart disease in its initial stages, which helps patients get treatment early before their situation becomes too serious.

Despite the model's promising results, there is still room for improvement, particularly in designing models that can operate effectively using more readily accessible and widely available technologies such as ECG watches, although their use isn’t common yet. These devices often provide lower-resolution signals with limited leads and are more prone to noise and motion artifacts, which can significantly impact the performance of deep learning models like LSTM Autoencoders. Therefore, future work should focus on developing robust architectures capable of handling such noisy, real-world data while maintaining diagnostic accuracy. This also includes optimizing models to be adaptable and consume less computing power, and improving generalization across diverse populations, taking into account the variability in ECG patterns. Bridging this gap between high quality clinical- data and widely accessible consumer devices is crucial for enabling scalable, continuous, and real-time heart disease monitoring in everyday settings. Incorporating explainable AI techniques would also be valuable to allow doctors in the field to trust and understand the model better, which in turn increases its use in the medical field.

In conclusion, deep learning models hold great promise in supporting medical professionals. Their accuracy and utility are expected to improve continuously as they are exposed to more diverse data and patterns, making them increasingly valuable tools in the future of healthcare.

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