UNIVERSITY OF KASDI MERBAH OUARGLA
Faculty of New Information Technologies and Communication
Department of Electronic and Telecommunication

ACADEMIC MASTER DISSERTATION

Domain : Science and Technology

Field : Electronics

Specialty : Electronics and Embedded system

Topic

Heart failure analysis using Artificial Intelligence

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Publicly defended on : 13 June 2024

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University year: 2023/2024

Abstract

In this master's thesis, we aim to develop a diagnostic support system that enables the detection of heart failure using a medical dataset. Accurate diagnosis of heart failure is a complex task that requires a series of clinical examinations and tests to verify the signs and symptoms of the disease. Therefore, the objective of this project is to design an automated diagnostic system for the early detection of heart failure using a medical dataset, focusing on distinguishing between heart failure patients and healthy individuals. The proposed system relies on two main stages: the first is feature extraction, and the second is classification using artificial intelligence. The selected discriminative features include two main parameters: the feature extraction process and the neural network model parameters. The classification process employs several deep learning models and classifiers such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Long Short-Term Memory networks (LSTM), hybrid CNN-LSTM models, and Artificial Neural Networks (ANN).

Feature extraction and the classification process were implemented using Visual Studio Code. The heart failure database used in our experiments was manually structured from a previous database. Performance measures used in this study include accuracy, loss curve, and accuracy curve. The results obtained showed varying performance across different models.

Keywords — : Heart failure disease ,Medical dataset ,Accurate diagnosis ,Early detection ,Feature extraction ,Classification ,Deep learning ,Neural network model parameters ,CNN ,SVM ,LSTM ,CNN-LSTM ,ANN ,Visual Studio Code.

ملخص

في هذه الأطروحة للماجستير، نهدف إلى تطوير نظام دعم تشخيصي يمكّن من اكتشاف مرض فشل القلب باستخدام مجموعة بيانات طبية. يعتبر التشخيص الدقيق لمرض فشل القلب مهمة معقدة تتطلب سلسلة من الفحوصات والاختبارات السريرية للتحقق من علامات وأعراض المرض. لذا، فإن الهدف من هذا المشروع هو تصميم نظام تشخيصي آلي يتيح الكشف المبكر عن مرض فشل القلب باستخدام مجموعة بيانات طبية، مع التركيز على التمييز بين مرضى فشل القلب والأفراد الأصحاء.

يعتمد النظام المقترح على مرحلتين رئيسيتين: الأولى هي استخراج الميزات، والثانية هي التصنيف باستخدام الذكاء الاصطناعي. تشمل الميزات التمييزية المختارة معلمين رئيسيين: عملية استخراج الميزات، ومعلمات نموذج الشبكة العصبية. تعتمد عملية التصنيف على عدة نماذج ومصنفات تعلم عميق مثل: الشبكات العصبية التلافيفية (CNN)، آلات المتجهات الداعمة (SVM)، الشبكات العصبية التكرارية (LSTM)، النموذج الهجين من الشبكات العصبية التلافيفية-التكرارية (CNN-LSTM)، والشبكات العصبية الاصطناعية (ANN).

تم تنفيذ عملية استخراج الميزات والتصنيف باستخدام Visual Studio Code، وتم استخدام قاعدة بيانات مرض فشل القلب التي تم إعدادها يدويًا من قاعدة بيانات سابقة في التجارب. تم تقييم الأداء باستخدام مقاييس الدقة، منحنى الفقد، ومنحنى الدقة، وأسفرت النتائج عن تنوع في الأداء المستخلص من النماذج المختلفة.

الكلمات المفتاحية-- امرض قصور القلب، مجموعة البيانات الطبية، التشخيص الدقيق، الكشف المبكر، استخراج الميزات، التصنيف، التعلم العميق، معلمات نموذج الشبكة العصبية، CNN، SVM، LSTM، CNN-LSTM، ANN، كود Visual Studio

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Resume

Dans cette thèse de master, nous visons à développer un système de soutien au diagnostic permettant de détecter l'insuffisance cardiaque à l'aide d'un ensemble de données médicales. Le diagnostic précis de l'insuffisance cardiaque est une tâche complexe nécessitant une série d'examens cliniques et de tests pour vérifier les signes et les symptômes de la maladie. Par conséquent, l'objectif de ce projet est de concevoir un système de diagnostic automatisé permettant la détection précoce de l'insuffisance cardiaque à l'aide d'un ensemble de données médicales, en se concentrant sur la distinction entre les patients atteints d'insuffisance cardiaque et les individus en bonne santé.

Le système proposé repose sur deux phases principales : l'extraction des caractéristiques et la classification utilisant l'intelligence artificielle. Les caractéristiques discriminantes sélectionnées comprennent deux composants principaux : le processus d'extraction des caractéristiques et les paramètres du modèle de réseau de neurones. Le processus de classification repose sur plusieurs modèles et classificateurs d'apprentissage profond tels que les réseaux de neurones convolutionnels (CNN), les machines à vecteurs de support (SVM), les réseaux de neurones récurrents (LSTM), le modèle hybride des réseaux de neurones convolutionnels-récurrents (CNN-LSTM) et les réseaux de neurones artificiels (ANN).

Les processus d'extraction des caractéristiques et de classification ont été mis en œuvre en utilisant Visual Studio Code, et l'ensemble de données sur l'insuffisance cardiaque utilisé a été préparé manuellement à partir d'une base de données précédente dans les expériences. Les performances ont été évaluées à l'aide de mesures de précision, de courbes de perte et de courbes de précision, ce qui a donné une variété de résultats de performance provenant de différents modèles.

- Mots-clés: Insuffisance cardiaque, ensemble de données médicales, diagnostic précis, détection précoce, extraction de fonctionnalités, classification, apprentissage en profondeur, paramètres du modèle de réseau neuronal, CNN, SVM, LSTM, CNN-LSTM, ANN, Visual Studio Code.

ACKNOWLEDGMENTS

Above all, we express gratitude to **ALLAH**

who gave us the joy of success after striving and diligently

I would like to thank my distinguished Dr. **KHALED BENSID**

The supervisor who oversees this topic showed kindness and dedication, and spared no effort in providing us with his valuable advice and guidance.

my sincere thanks to dr. **MAROUANE DIDA**

For his patience, dedication, and significant contribution to the advancement of this research, leading to successful outcomes in our study, as well as the culmination of this remarkable academic year.

We would like to express our deep gratitude to the members of the judging committee for agreeing to review and evaluate our humble work. We also extend our sincere thanks to Dr. Ibtissem LATI,Dr. Hisham Al-Qud, Dr. Hamshawi,Dr. Malika IDJA, and Dr. Kahal for their companionship and guidance throughout this period.

We take this opportunity to express our appreciation to all of our teachers for their ongoing cooperation, availability, and empathy during the teaching process. Your support and guidance have been invaluable to us throughout our academic journey.

DEDICATIONS

We dedicate this modest work as a testimony of affectation, of admiration :

To My Family

my soul and heart , my mather ,without her none of my succes would be possible .my father for his support and continued encouragement .my loving sister aicha allah yrhamha .my bestfriend massi allah yarhmou. my sisters and my brathers. my cousin bachir.

Dear friends

my friend for their support , encouragement and faith in me marouan mouman ,taha , abdo, oussama ,krimo , hmida ,chaker , and artist samara all the teacher who once tought me specially ms chrifa , mr khlifa ,ms zregragba ,dr.ben said , mr marouan . to the people we love to all with warm regards .

Zine EL Abidine

DEDICATIONS

We dedicate this modest work as a testimony of affectation, of admiration :

To My Familly

I thank my dear father for your constant support and encouragement. for me My brothers, for your love and motivation, each in his name, Lakhdar, Abdel Ghani, chaima, Youssef, Abdel Razak, and Ibtisam, the little girl, and to my soul mate, Safa, may ALLAH protect you.

Dear friend

To my friends, Wissal, Amira, Sarah, Zine Al-Abidine, and the Invisible Soldiers for their support, encouragement, and trust. Thank you for your accompaniment throughout this journey. Your presence Make every moment valuable. My friend Nourhane , thank you for your encouragement and belief in me. You have always been my help and best friend I thank my supervisor Dr Khaled BENSID for his tireless guidance This achievement is the result of your efforts and support.

Maroua

DEDICATIONS

We dedicate this modest work as a testimony of affectation, of admiration :

To My Familly

To my parents, for their unwavering support and sacrifices. To my father, for teaching me hard work and perseverance, and to my mother, for her kindness and support.
To my beloved brothers and sisters Safouane, Moatassim, Sana, Sadil and my lovely samou for their constant encouragement and support, being my source of strength and determination.

Dear friend

To my best friends Maroua, Safa, Imane, Meriem, Khaoula, Nassira,Yousra and Atona for their support during difficult times, and for their understanding and encouragement.
To my professors, for their valuable knowledge and guidance, serving as role models and sources of inspiration.
I thank everyone who contributed to this achievement; it is thanks to all of you that I have reached where I am today.

Ouissal

DEDICATIONS

We dedicate this modest work as a testimony of affectation, of admiration :

To My Familly

To my father no dedication can express the love, esteem, dedication and respect I have always had for you. This work is the fruit of the sacrifices you made for my education and training. I dedicate this work to you as a token of my deep love. To my dear mother, honorable, kind, you represent for me the symbol of goodness par excellence, the source of tenderness and the example of devotion who has never ceased to encourage me, your prayers and blessings have been a great help to me in carrying out my studies. No dedication could be eloquent enough to express what you deserve for all the sacrifices you have made since my birth, during my childhood and even into adulthood. To my dear brothers Youcef and Mohamed, and my dear sister Imane, Hanane and Intissar as a token of the attachment and love I bear for you, you are always in my heart, thank you for being the shoulder I can always count on. To my beloved grandmother, whose prayers are unparalleled. May you enjoy good health and a long, happy life.

Dear friend

To my best friends Amina, Manel, Rym, Elisabeth and all my others friends, thank you for always being there for me. Thank you for your unconditional love, support, and encouragement, Love you all.

Amira Asma

DEDICATIONS

We dedicate this modest work as a testimony of affectation, of admiration :

To My Familly

This thesis is dedicated to my parents who have always supported me in all my endeavours especially my mom, my sisters

Dear friend

my best friends whose their unwavering encouragement and belief in me have been my great source of strength and my supervisors Dr khaled ben sid ,dida marouan Whose guidance and support have been invaluable throughout this process.

Sarah

List of abbreviation

HF :	Heart failure
ESC :	European Society of Cardiology
WHO:	World Health Organization
AI:	Artificial Intelligence
DL:	Deep learning
ML:	Machine learning
ANN :	Artificial Neural Network
CNN :	Convolution neural networks
RNNs :	Recurrent neural networks
RV :	Right ventricle
SP :	Septal Perforator
SVM :	Support Vector Machine
LSTM :	Long Short-Term Memory
Train :	Training
val :	valition
TP :	True Positive
TN :	True Negative
FP :	False positive
FN :	False negative

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General Introduction

Introduction

The heart stands as a vital organ within the human body, crucial for sustaining life and maintaining overall health. Heart diseases, globally known as one of the main causes of illness and death, it casts its significant shadow over public health concerns, encompassing a wide range of conditions affecting the heart and blood vessels [1].

The last stage of the development of the many heart diseases is heart failure (HF) [2]. Heart failure (HF) is a chronic progressive condition in which the heart muscle weakens due to multiple factors, resulting in an inadequate delivery of blood to meet the body's oxygen needs. According to research conducted by the European Society of Cardiology (ESC), heart failure affects 26 million adults worldwide, with approximately 3.6 million new diagnoses identified each year [3] .

Around 3–5 % of hospital admissions are associated with incidents of heart failure, making it the primary reason for admission in clinical practice. The financial burden is significant, accounting for up to 2% of total healthcare costs in developed nations, heart failure does not mean that the heart has stopped working altogether, but rather that it is not pumping blood as efficiently as it should. With proper management and treatment, many people with heart failure can lead active and fulfilling lives. Treatment typically involves a combination of medications, lifestyle changes, and sometimes medical procedures to help improve heart function and alleviate symptoms. However, early diagnosis and ongoing management are crucial to improving outcomes and quality of life for individuals living with heart failure. Therefore, constructing an effective disease management strategy entail analyzing a significant volume of data, early disease detection, assessing severity, and predicting adverse events at an early stage. This will hinder the disease from getting worse, enhance patients' quality of life, and cut down on medical expenses [4].

Artificial Intelligence (AI) has revolutionized the intricate decision-making processes across various fields, notably in medicine. Drawing from diverse disciplines such as logistics, biology, linguistics, computer science, mathematics, engineering, and psychology, AI has become a cornerstone in medical innovation. Its remarkable advancements in speech and facial recognition, natural language processing, intelligent robotics, and image recognition have significantly contributed to enhancing healthcare delivery. By streamlining diagnostic procedures, optimizing treatment plans, and analyzing vast medical datasets, AI has empowered medical professionals to make more accurate and timely decisions, ultimately improving patient outcomes and revolutionizing healthcare practices.

Machine learning (ML), a key technique, has facilitated this advancement. It enables computers to learn autonomously, drawing insights from past experiences and data. As data volumes surge, efficient data handling becomes imperative. Humans often struggle to extract insights manually from raw data due to its inconsistencies and complexities. Machine learning (ML) addresses this challenge by extracting valuable insights from vast datasets. Its demand has soared with the rise of big data, offering more accurate and consistent information. Ultimately, machine learning aims to empower machines to learn independently, without exhaustive programming. Over recent decades, it has made significant strides in various fields, refining preprocessing techniques and learning algorithms.

Deep learning (DL) is one of those remarkable advancements that has made AI even smarter. It is a branch of machine learning named in 2006, inspired by the structure of the human brain, which contains neural networks. Deep learning (DL) employs a data-processing method that utilizes a multi-layered technique. The functioning of these layers involves receiving weighted input, transforming it primarily into nonlinear functions, and then transmitting the output to the next layer. It assists in addressing long-standing issues in artificial intelligence and excels at uncovering complex structures in vast amounts of data. Hence, it finds applications across various fields such as science, business, and government. With its ability to extract valuable patterns and information from data, it can also play a significant role in diagnosing and treating cardiovascular diseases [5].

Contribution

We are contributing to the design of a diagnostic aid system that enables the early detection of heart failure using a medical dataset. In this work, we aim to classify patients based on features extracted from the medical data.

The classification relies on classifiers powered by convolutional neural networks (CNNs), SVM, LSTM, CNN-LSTM, and ANN. The classification process is conducted using VS Code software. The data used in this study consists of a medical database of individuals with heart failure. The performance is evaluated using model accuracy through the loss curve and accuracy curve .

Memory organization

Our work is organized as follows :

The first chapter: This chapter provides an overview of the heart and heart failure, and explains key concepts for understanding heart failure.

The second chapter: This chapter provides an overview of artificial intelligence and explains its basic concepts.

The third chapter: is dedicated to the experimental results and discussion.

Conclusion and perspectives.

Chapter 1

Generalities about the heart and heart failure

I.1 introduction

The human heart is considered the centre of life in the human body. It is one of the body's most effective organs, yet heart disease is a common source of illness and death in both developed and poor countries [6].

Heart disease, which includes heart attacks or heart failure, is one of the main causes of death globally. According to estimates from the World Health Organization (WHO), cardiovascular-related illnesses cause for approximately 17.9 million deaths globally each year, or 32% of all fatalities worldwide. Due to the fact that this represents a large portion of the global death rate, cardiac problems must be prevented and treated. These conditions include irregular blood flow, blood vessel issues, and heart function issues. Using massive datasets, artificial intelligence has been applied extensively in the medical industry to assist doctors in forecasting and making critical decisions [7].

I.2 The human body

The human body is defined as the entire structure of a human being, comprising various cells that form tissues, organs, and organ systems as shown in Figure 1.

It consists of systems of organs that combine these organs and others. Tissues in the human body are specialized and fulfil specific functions, and these are called organs. Organs in the human body can be classified based on their functions and locations in systems: Internal organs, digestive organs, reproductive organs, evacuation organs, respiratory organs, circulation organs, and sense organs. Internal organs in the human body are located within the ribcage and abdominal region. Our internal organs include the trachea, exophages, lungs, heart, stomach, liver, gallbladder, duodenum, pancreas, intestines, large intestine, rectum, spleen, kidneys, and appendix [8].

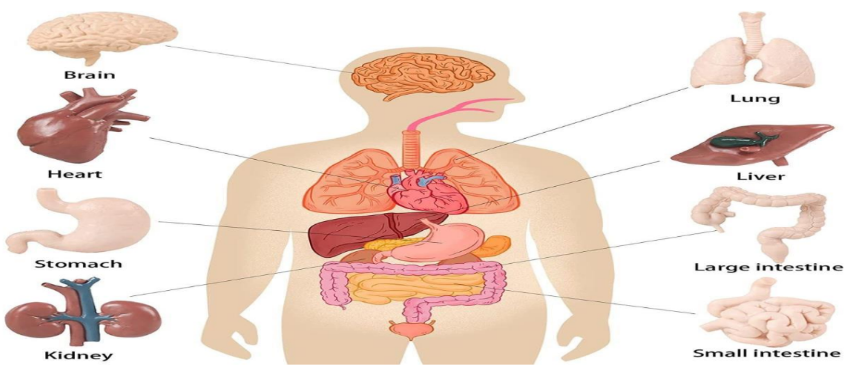

Figure 1: human body

1. The human heart

The human heart serves as the primary pump of the circulatory system, propelling blood throughout the body via its intricate network of vessels. It plays a vital role in supplying tissues with oxygen and nutrients while eliminating waste products such as carbon dioxide. Positioned centrally in the chest, slightly to the left of the sternum, it resides between the lungs and is enveloped by a protective double-walled sac known as the pericardium. This sac not only shields the heart but also secures it within the chest cavity. Pericardial fluid acts as a lubricant between its outer and inner layers, facilitating smooth contractions and movements during respiration.

In humans, the heart is approximately the size of a large fist and varies in weight, averaging between 10 and 12 ounces in men and 8 to 10 ounces in women. Comprising four chambers two atria and two ventricles it effectively segregates oxygen-rich blood from oxygen-poor blood. The heart's structure is partitioned by a muscular wall called the septum, which separates the left and right sides. Its outer wall consists of three layers: the epicardium, forming the inner pericardial wall the myocardium, containing the contracting muscle Fibers and the endocardium, lining the heart chambers, collectively ensuring its functionality and integrity [9].

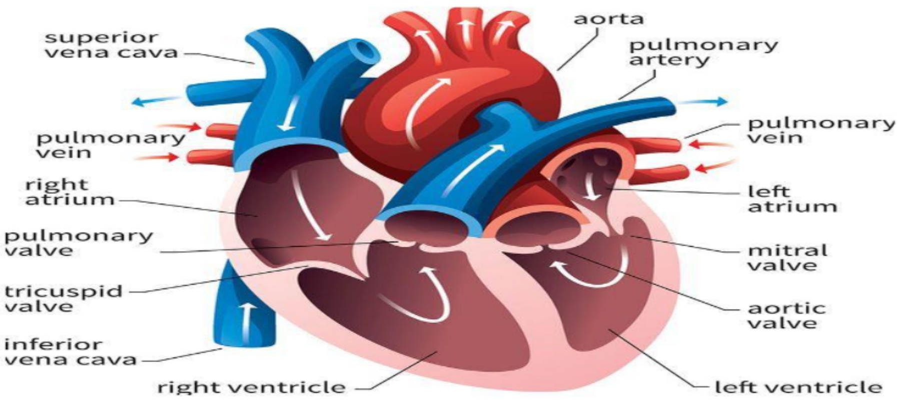

Figure 2: The human heart

I.3 Function and anatomy

The heart plays a paramount role in sustaining life through its remarkable function as the body's primary pump. Every heartbeat fuels the intricate network of blood vessels, delivering oxygen and essential nutrients to every cell while carrying away waste products. In essence, the heart's function is synonymous with vitality, ensuring the body's survival and optimal functioning.

The heart consists of four chambers: the left and right ventricles, and the left and right atria. The atria receive blood returning from the body, while the ventricles pump blood out to the body. The heart also has four valves that ensure blood flows in the correct direction [10].

The heart's pumping action is controlled by electrical signals that originate in the sinoatrial (SA) node, the heart's natural pacemaker. These signals cause the heart muscle to contract and relax in a coordinated manner, resulting in the heartbeat. The heart beats around 60 to 100 Pulse per minute at rest, increasing during exercise.

The heart's pumping action is crucial for maintaining blood pressure, which is necessary for blood to reach all parts of the body. The heart's pumping action also ensures that oxygen-rich blood is delivered to the body's tissues and that waste products are removed [11].

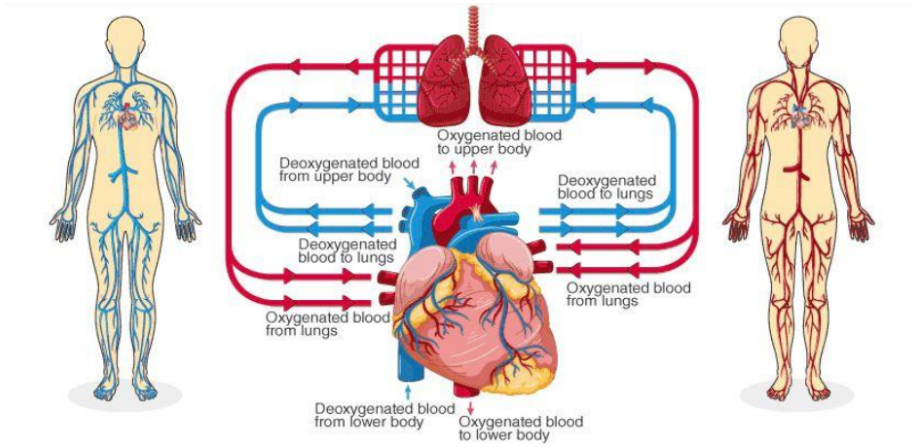

Figure 3: Human circulatory system transportation

I.3.a The heart Walls

The walls of the heart consist of several layers that work in Harmony to ensure proper cardiac function. The inner layer, known as the endocardium, lines the inner parts of the heart and provides a smooth surface for blood flow. The middle layer is the myocardium, or cardiac muscle, responsible for the contraction and relaxation processes that propel blood into the blood vessels. The outer layer is called the epicardium, a thin layer of tissue that surrounds and protects the heart from external stress.

These layers work together to maintain an optimal balance between strength and flexibility, allowing the heart to efficiently pump blood with stability. The muscular tissues provide the necessary strength for contraction, while the epicardium provides protection

and support to maintain the shape and function of the heart.
The walls of the heart play a crucial role in cardiac function, and when any of these layers are damaged or compromised, it can lead to heart failure [12].

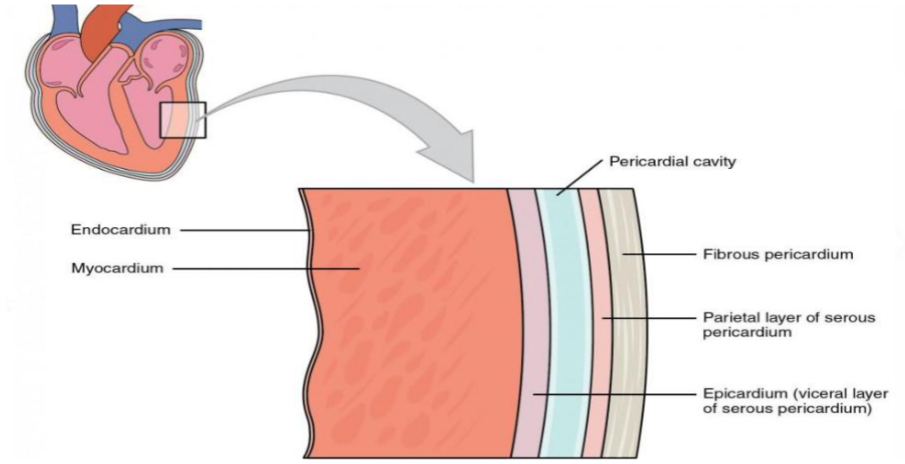

Figure 4: The Layers of the Heart Wall

I.3.b the heart valves

The heart consists of four chambers, two atria (upper chambers) and two ventricles (lower chambers). There is a valve through which blood passes before leaving each chamber of the heart. The valves prevent the backward flow of blood. These valves are actual flaps that are located on each end of the two ventricles (lower chambers of the heart). They act as one-way inlets of blood on one side of a ventricle and one-way outlets of blood on the other side of a ventricle. Normal valves have three flaps, except the mitral valve, which has two flaps. The four heart valves include the Following [13].

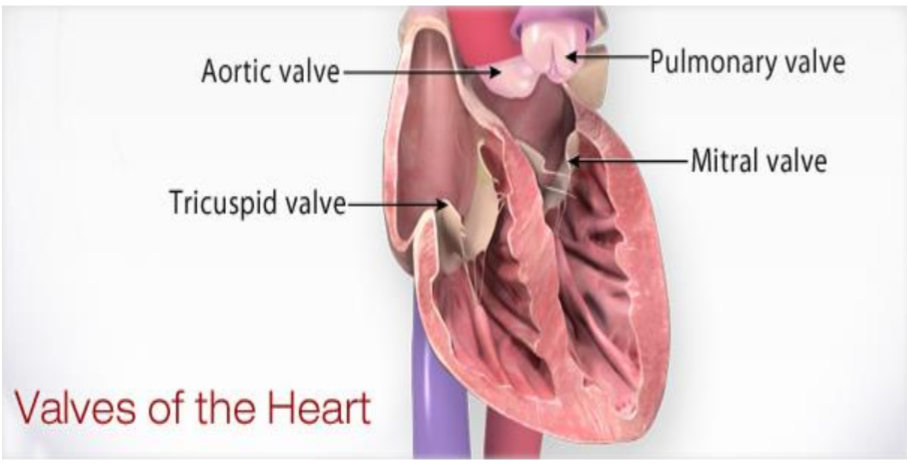

Figure 5: Picture showing heart valves

I.3.c Electrical conduction system of the heart

The cardiac conduction system encompasses the propagation of electrical signals starting from the sinoatrial node, then passing through the atrioventricular node, down the bundle of His, and along the Purkinje fibers. This electrical activity triggers myocardial contraction in the adjacent myocardial tissue as it spreads through the heart's conduction network [14]:

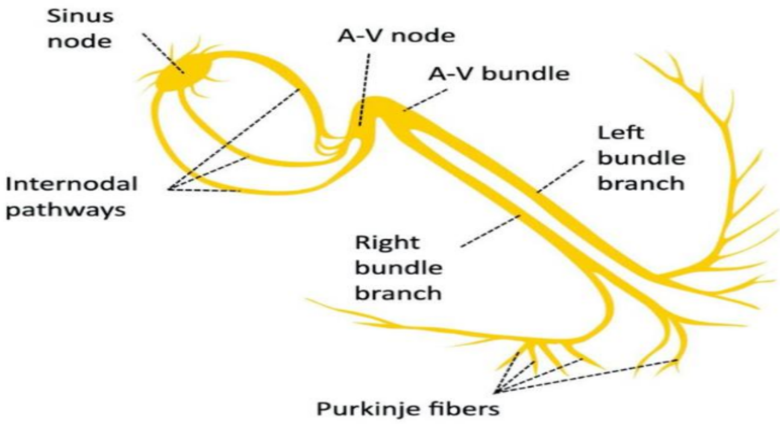

Figure 6: The electrical conduction system of the heart

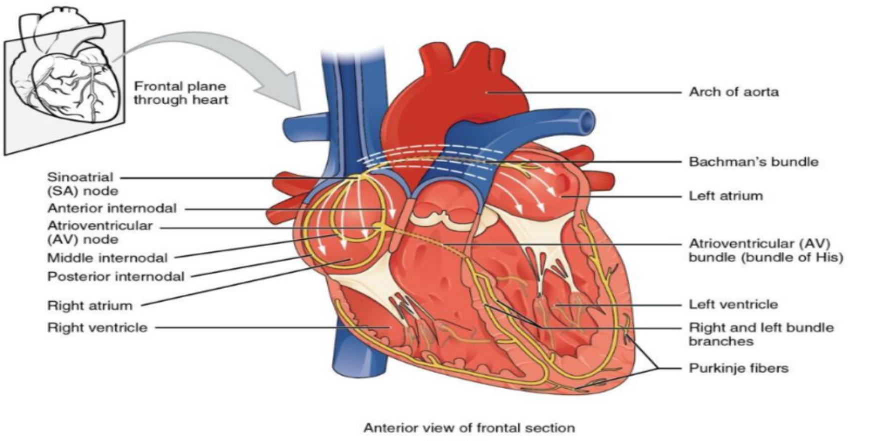

Figure 7: cardiac conduction system

1. Sinoatrial Node (SA Node)

The sinoatrial node (SAN) is a cluster of cells situated near the junction of the right atrium and the superior vena cava. Serving as the heart's natural pacemaker, the SAN governs heart rate. [14],[15], It autonomously generates electrical impulses, which propagate to both the right and left atria, prompting contraction of the atrial myocardium.

Notably, atrial muscle conducts these impulses relatively swiftly at a rate of 0.5m/sec [16].

2. Atrioventricular Node (AV Node)

The atrioventricular node (AVN) consists of specialized cells located in the atrioventricular septum, positioned just above the opening of the coronary sinus. Functionally, the AVN [14],[15], receives electrical impulses from the atria and subsequently conveys them to the ventricles. Its slower conduction velocity (0.05m/sec) compared to the atria facilitates optimal ventricular filling before contraction [16].

3. Bundle of His (Atrioventricular Bundle)

The bundle of His comprises specialized heart muscle cells for electrical conduction, receiving input from the AVN. It divides into left and right bundle branches, which run along the interventricular septum. These branches transmit impulses to the left and right ventricles, ultimately terminating as multiple Purkinje fibers [14],[15].

4. Purkinje Fibers

Purkinje fibers, located in the sub endocardium, conduct electrical impulses to the ventricular myocardium, initiating ventricular contraction [14],[15].

I.4 The heart parameters

1 Location of the heart

The heart is nestled within the protective thoracic cavity, positioned behind the sternum and costal cartilages, and resting on the superior surface of the diaphragm. Enclosed by the two lungs occupying the pleural cavities, it resides within the mediastinum, a central area in the chest cavity. The mediastinum is divided into superior and inferior parts by the transverse thoracic plane, extending from the sternal angle to the space between thoracic vertebrae T4 and T5. This plane serves as a crucial reference point, intersecting key structures like the tracheal bifurcation, the top of the pericardium, the base of the aorta, and the split of the pulmonary trunk.

The human heart is positioned obliquely within the thorax, with approximately two-thirds of its mass to the left of the body's midline. Its orientation forms a plane from the right shoulder to the left nipple. The heart's base lies below the third rib near the sternum (notably, the sternal angle aligns with the second rib). The base points upwards and towards the right, while the apex extends leftwards and forwards. Consequently, the heartbeat is most palpable between the fifth and sixth ribs, just below the left nipple [17].

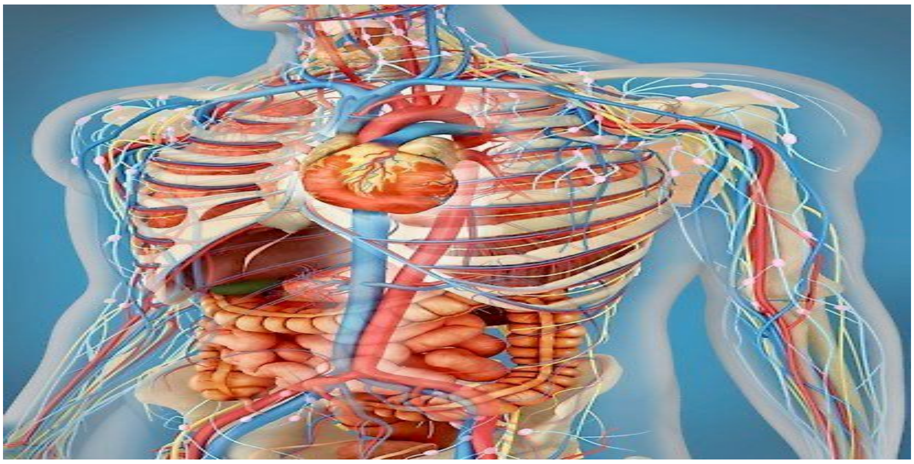

Figure 8: Position of heart in the thorax

2 Size of the heart

The heart resembles a pinecone in shape, wider at the top and tapering to the apex. Typically, it's about the size of a clenched fist, measuring around 12 cm (5 in) in length, 8 cm (3.5 in) wide, and 6 cm (2.5 in) thick. There's a variance in size between sexes, with a female heart weighing approximately 250-300 grams (9 to 11 ounces) and a male heart weighing around 300-350 grams (11 to 12 ounces) [18].

3 Electrical tension

The heart pumping function relies on the coordinated contraction of billions of muscle cells. This intricate process cannot occur without extensive communication and synchronization among these cells. To ensure precise timing of each heart segment's contraction, a complex signalling system regulates activation. Although the mathematical models we develop may not focus on this conduction system, a fundamental grasp of signal propagation in the heart is crucial for understanding ECG characteristics.

Electrical signalling in the heart originates from the sinoatrial (SA) node, situated above the right atrium. The cells within the SA node, known as self-oscillatory or pacemaker cells, generate action potentials spontaneously, independent of external stimuli. The frequency of these action potentials is modulated by external signals, such as adjusting heart rate according to various activity levels [19].

The electrical stimulation of the SA node triggers neighboring atrial muscle cells. These muscle cells are interconnected by gap junctions, large proteins forming channels between adjacent cells. These channels permit the flow of electrical current, primarily ions, establishing a direct electrical pathway between neighboring cells. When one cell depolarizes, this coupling affects neighboring cells' potentials, potentially surpassing the threshold value for action potential initiation. Thus, stimulating a small area of the atria results in a propagating wavefront of depolarization, activating the entire atria and prompting their contraction [19].

I.5 Heart failure

Heart failure (HF) is a cardiac disorder resulting from dysfunction in its function, and it is considered one of the common diseases in clinical practice. Heart failure is a chronic, progressive illness where the heart's muscle weakens for a variety of reasons, making the blood supply insufficient to fulfil the body's oxygen needs [20].

Heart failure is a serious disorder that affects the heart's function as a blood-pumping organ in the body. This disorder occurs due to structural or functional abnormalities in the heart, hindering its ability to efficiently pump blood to meet the body's needs. This impairment can result from various factors such as high blood pressure within the heart or inadequate cardiac output, whether at rest or during physical activity. This disorder is associated with a range of bothersome symptoms that may progress to serious complications if proper medical intervention is not sought.

Early detection of these changes and prompt intervention can play a crucial role in improving clinical outcomes for patients, reducing mortality rates, and enhancing the quality of life [21].

I.6 Heart disorders and changes

1 Arrhythmia

Cardiac arrhythmia occurs when the heart's normal rhythm is disrupted. This article outlines the typical sinus rhythm of the heart and explores various deviations from this rhythm, elucidating how dynamical systems can aid in understanding the heart's behavior under such circumstances [22].

The heart serves the crucial function of pumping blood, laden with oxygen, nutrients, immune cells, and regulatory molecules, to various organs throughout the body. Its rhythm is regulated by the sinoatrial (SA) node, a cluster of cardiac muscle cells located in the right atrium, which acts as a natural pacemaker. However, this rhythm is subject to modulation by nerves and circulating hormones, which influence heart rate through a network of control circuits aimed at maintaining optimal blood pressure and oxygen levels. Structurally, the heart comprises two upper chambers, known as the atria, and two lower chambers, the ventricles [22].

2 Cardiomyopathy

Cardiomyopathy is a condition characterized by structural and functional abnormalities in the heart muscle, leading to potential heart muscle or electrical malfunction. It encompasses a diverse range of diseases that often result in progressive heart failure, posing significant health risks. These conditions can either be primary, stemming from genetic, mixed, or acquired factors, or secondary, arising from issues like infiltration, toxicity, or inflammation [23].

The primary types include dilated cardiomyopathy, hypertrophic cardiomyopathy, restrictive cardiomyopathy, and arrhythmogenic right ventricular cardiomyopathy. While symptoms may not manifest in the early stages, they eventually mirror those typical of heart failure, such as breathlessness, fatigue, coughing, difficulty lying flat, sudden nighttime breathing difficulties, and swelling [23].

Diagnostic procedures typically involve assessing B-type natriuretic peptide levels, baseline serum chemistry, electrocardiography, and echocardiography. Treatment aims to alleviate heart failure symptoms and decrease related hospitalizations and mortality rates. Options include medication, implantable cardioverter-defibrillators, cardiac resynchronization therapy, and heart transplantation. Lifestyle adjustments such as limiting alcohol intake, weight management, regular exercise, smoking cessation, and adopting a low-sodium diet are also recommended [23].

3 Congestive heart failure

Congestive heart failure (CHF) is a prevalent clinical condition characterized by pulmonary vascular congestion and diminished cardiac output. It should be considered in the diagnostic evaluation of any adult experiencing dyspnea and/or respiratory distress. Diagnosis typically involves a thorough medical history, physical examination, and evaluation of chest radiographs for characteristic findings. The integration of serum brain natriuretic peptide levels and echocardiography has significantly enhanced diagnostic accuracy. Treatment strategies for CHF aim to restore normal cardiopulmonary function and alleviate the hyperadrenergic state. A key component of therapy involves a combination approach utilizing an angiotensinconverting-enzyme inhibitor alongside gradual titration of a blocker. Patients with CHF are susceptible to pulmonary complications such as obstructive sleep apnea, pulmonary edema, and pleural effusions. Management of CHF exacerbations often includes interventions like continuous positive airway pressure and non-invasive positive-pressure ventilation to improve respiratory function and patient outcomes [24].

4 Coronary artery disease

Coronary artery disease (CAD) is the primary cause of death in developed countries, responsible for nearly 20% of all deaths. Its profound effects on health, mortality, and economic factors make early and precise diagnosis and cost-effective treatment essential. A literature review focused on key elements of diagnosis, risk evaluation, and treatment of chronic CAD patients was conducted using the PubMed database, highlighting articles on chronic CAD or stable angina. The review emphasizes the significant impact of new imaging methods, drug treatments, and both percutaneous and surgical revascularization in managing chronic CAD. Although medication is the cornerstone of treatment, revascularization remains important. With changing economic conditions and healthcare reforms, the careful application of revascularization is crucial. The review discusses when revascularization is appropriate and evaluates the benefits and risks of percutaneous versus surgical methods, providing insight into current CAD management strategies.

5 Heart attack

Arteries, particularly the coronary ones, are susceptible to the buildup of plaque, a condition known as atherosclerosis. If this plaque becomes unstable, it can lead to the formation of a fissure, paving the way for vessel blockage (occlusion) that disrupts blood flow. This interruption in blood flow deprives the heart muscle of oxygen, resulting in distress signals from the heart tissue cells, often perceived as chest pain—this is a heart attack. Such blockages can occur at any point along the three major coronary arteries, putting the heart tissue downstream from the blockage at significant risk of damage. A complete blockage (100 percent occlusion) in a coronary artery, occurring early on, can lead to a severe heart attack because oxygenated blood is unable to reach a substantial portion of the heart muscle beyond the blockage [25].

6 Heart valve disease

When a semilunar valve is functioning properly, its leaflets are pushed into the sinuses during myocardial contraction (systole), facilitating the exit of blood from the ventricles. As the myocardium relaxes and ventricular pressure decreases below that of the arteries (the aorta or pulmonary artery), the valve promptly closes. This closure typically occurs shortly after ventricular systole but before complete heart relaxation, ensuring that during diastole, when the chambers are refilling via the atrioventricular valves, the semilunar valve leaflets remain firmly shut. A positive pressure gradient between the aorta and the coronary sinus, located within the right atrium, permits blood flow through the coronary vasculature. Hence, it's important to note that the heart muscle receives perfusion when the semilunar valves are closed and cardiac myocytes are relaxing [26].

7 Blood pressure

Blood pressure, also known as blood force or pressure on the walls of your arteries, is measured as blood pressure (BP). Consider it analogous to water in a garden hose. Water exerts pressure on the hose's interior (the arteries) as it passes through Placing an inflatable cuff over your upper arm allows you to test your blood pressure. A measurement of the force of blood flow through the artery in your arm is made while the cuff deflates There are variations in the blood pressure within your blood vessels. Because it rises and falls with every beat, blood pressure is represented by two digits. The first, or higher, figure is the systolic blood pressure, which is the measurement taken as the heart contracts and forces blood out. The second, or lower, value is the diastolic blood pressure, which is the lowest pressure that occurs when the heart relaxes in between beats.

I.7 Symptoms of heart disease

Coronary artery disease, ”congestive heart failure”, and ”heart attacks” represent a spectrum of heart-related ailments, each demanding specialized treatment strategies. Although these conditions are distinct, they often present with similar preliminary warning signs, such as chest discomfort, shortness of breath, and fatigue. It is imperative to consult a healthcare professional without delay when these symptoms arise. Prompt medical evaluation is essential to accurately identify the specific heart issue at hand and to initiate the appropriate therapeutic measures as soon as possible. Early detection and management are key to improving outcomes and preventing complications associated with these serious cardiovascular disorders.

IV. Conclusion

understanding heart failure goes beyond recognizing it as a medical condition; it’s a global challenge affecting millions daily. Awareness and modern healthcare tools like AI can improve diagnosis and treatment, enhancing patients’ quality of life .

In this chapter covered heart failure comprehensively, discussing its basics, related disorders, causes, and impacts.

In the next chapter will delve into Artificial Intelligence and data analysis techniques for heart failure detection, providing guidance on utilizing our system for effective diagnosis and management.

Chapter 2

Artificial Intelligence

II. introduction

Before the emergence of artificial intelligence (AI) in medicine, healthcare heavily relied on human expertise and knowledge. Scientists and physicians leaned on previous studies, personal experiences, and clinical evaluations to diagnose and treat patients. However, the Tools and technologies available were limited, potentially leading to inaccuracies in diagnosis and suboptimal treatment outcomes. Data collection and analysis were manual processes, often time-consuming and labour-intensive, which could result in delays in critical medical decisions and hinder the development of optimal treatment plans.

With the emergence of artificial intelligence (AI), particularly in the field of cardiovascular medicine, significant advancements have occurred. AI enables the utilization of advanced analytical techniques to process vast amounts of medical data rapidly and accurately.

Artificial intelligence algorithms enhance diagnostic accuracy by identifying intricate patterns in data. This integration accelerates diagnosis and improves treatment outcomes, especially in heart failure cases. AI also aids in risk assessment and disease progression prediction, enabling personalized care and tailored treatment plans for heart failure patients [27].

II.1 Artificial intelligence

An artificial intelligence (AI) program is a computational program that can perform tasks that are considered typical of human intelligence, like pattern recognition, image identification, object recognition, programming, and problem solving .

Artificial Intelligence (AI) enables a device to make decisions on its own using previously obtained data. This relates to facts in medical practice that are utilized to create diagnoses or choose the best course of therapy.

The medical community has access to a wealth of scientifically recorded data in the current era of evidence-based medicine, which forms the basis for therapeutic alternatives. Precision medicine is about to follow.

Precision medicine takes a comprehensive approach to cardiovascular prevention and therapy, taking into consideration a patient's lifestyle, genetic makeup, and exposure to environmental influences to shape their unique cardiovascular condition.

AI operates outside of the aphaeretic perspective, which makes the arbitrary assumption that patients with similar disease characteristics have the same Patho phenotype and, as a result, will benefit from the same treatment. In precision medicine, and specifically in the field of heart failure (HF), artificial intelligence (AI) plays a crucial role in identifying and rearranging the components of this massive data set that seem to be useful and can be linked to favourable clinical outcomes [28].

II.2 Machine learning

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that enables machines to learn autonomously from data and past experiences. It involves extracting patterns from data to make predictions with minimal human intervention. ML algorithms benefit from iterative processes to extract useful information from massive datasets, learning directly from data rather than relying on predefined models. Deep Learning, a branch of ML, offers superior performance compared to traditional methods through the use of complex algorithms.

ML encompasses a variety of methods, including supervised, unsupervised, semi-supervised, and reinforcement learning. Supervised learning involves training machines on labelled datasets to predict outcomes based on provided training, while unsupervised learning trains machines on unlabelled datasets to predict outcomes without guidance. Semi-supervised learning combines features of both supervised and unsupervised learning, while reinforcement learning involves learning based on feedback where AI agents learn from experiences to maximize rewards.

ML has seen recent advancements, making it indispensable in various fields such as computational finance, computer vision, computational biology, automotive and aerospace industries, manufacturing, natural language processing, and even in the field of heart failure. In the healthcare domain, understanding basic ML terminologies is essential for healthcare professionals to comprehend the role of artificial intelligence in daily clinical practice [28].

II.3 Deep learning

Deep learning (DL) is a specific type of machine learning that utilizes artificial neural networks (ANN) to generate predictions automatically directly from internal data. In the context of medical image analysis, deep learning primarily relies on convolutional neural networks (CNNs), which are networks frequently used for classifying and segmenting images.

Deep learning networks, such as CNNs, consist of multiple layers, including the input, convolutional, activation, and output layers. These networks maintain a hierarchical structure similar to traditional neural networks but incorporate additional layers to extract and process more features.

Each layer in the network performs distinct processing tasks, with simplifications in connections to improve computational efficiency. The input layer receives multidimensional internal data, preserving the underlying structural details in the image data.

The convolutional layer uses convolutional hierarchies to process internal samples and extract features, such as lines and details, from the data. Convolution hierarchies can change with the network's depth, affecting the extracted features. The quality of the extracted information is influenced by the location of the convolutional layer within the network.

Essentially, deep learning uses complex neural networks, such as CNNs, to learn and extract meaningful patterns and features directly from internal data, making it a powerful tool for tasks such as image analysis and natural language processing, especially in the field of heart failure [28].

II.4 Artificial Neural Network

Artificial Neural Networks (ANNs), a subset of Machine Learning (ML), are computational models inspired by the structure and function of the human brain. They consist of a network of interconnected nodes, called artificial neurons, which process input information and generate output. Each artificial neuron receives one or more inputs and processes them using an activation function that determines the neuron's output.

The output of each neuron is transmitted to other neurons through weighted connections, which are used to adjust the contribution of each neuron to the final output. During

ANN training, the model adjusts the weights of the connections between neurons to minimize the difference between the desired and actual output, using optimization algorithms such as gradient descent. ANNs are used in a wide range of ML applications, including image classification, natural language processing, and time series prediction. They have also been used in solving complex problems such as deep learning, and the creation of recurrent and convolutional neural networks [29].

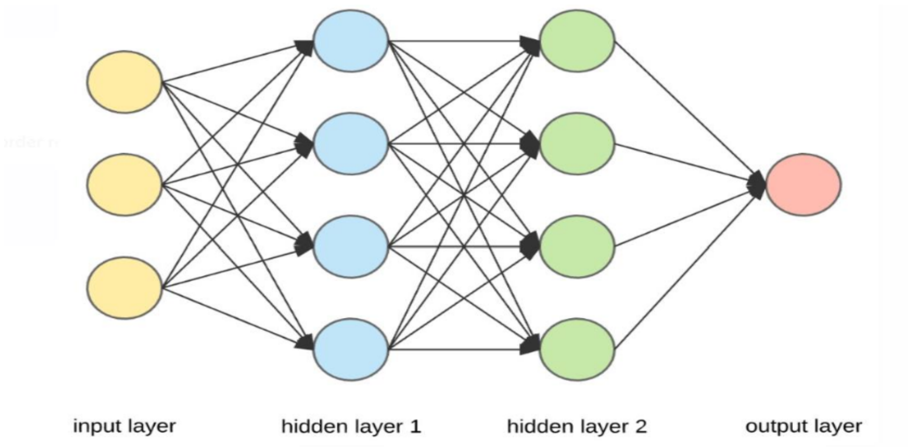

Figure 9: Style of Neural Computation

1 Input layers

The concept of input layers in neural networks is fundamental for receiving and processing data. In artificial neural networks, the input layer is the first layer that receives input data from the external world and transforms it into a format that the network can understand. This layer typically consists of artificial neurons that receive input, such as images, text, or video, and pass this information to the next layer in the network, usually a hidden layer. During the training phase, the processing of input data can be adjusted, allowing the network to adapt and improve its predictive capabilities over time. In the context of deep learning, input layers serve as the entry point for data into the neural network. They can vary in structure based on the type of data being processed, such as 2-D images, 3-D images, sequences, features, custom formats, point clouds, or regions of interest for object detection. These layers play a crucial role in shaping how information flows through the network and are essential for the network to learn and make predictions based on the input data [30].

2 Activation Function

Activation function in neural networks is a mathematical function that determines the output of a neuron based on its input. As the name suggests, it is some kind of function that should "activate" the neuron. Whether it will be convolutional neural networks or recurrent neural networks, the activation function decides how to proceed. Just as neurons in the brain receive signals from the body and make decisions on how to process them, neurons in artificial neural networks work in a similar manner. They act as transfer functions, receiving input values and producing corresponding output values [31].

3 Type Activation Functions

There are several types of activation functions commonly used in artificial neural networks, each with its own characteristics and applications.

a Sigmoid Activation function

The sigmoid function is a smooth, continuously differentiable function that maps real-valued inputs to a range between 0 and 1. It has an "S"- shaped curve that asymptotes to 0 for large negative numbers and 1 for large positive numbers, making it suitable for binary classification problems. The function is defined by the formula:
f(x) = 1 / (1 + e(̃-x)) [32].

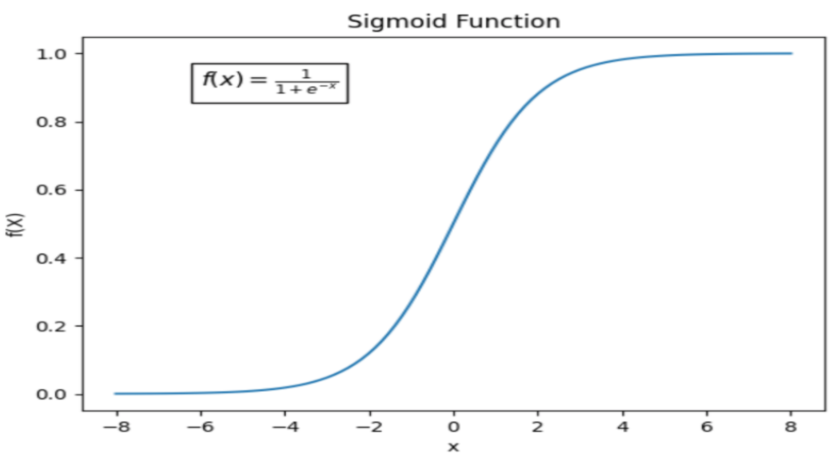

Figure 10: Sigmoid Activation function.

b Output layer

The output layer in a convolutional network is crucial for producing the final results based on the specific problem being addressed. It plays a key role in shaping the output of the network according to the task at hand. Different types of output layers are utilized depending on the nature of the problem, such as binary or multiple classification, predictive tasks, image synthesis, and more. The output layer employs various transition functions to generate the desired results effectively. Common transition functions used in the output layer of a convolutional network include the softmax function for multi-class classification tasks, the sigmoid function for binary classification tasks, and the linear function for regression tasks. These functions are essential in determining the final output of the network based on the problem's requirements[33].

II.5 Convolution neural network

Convolutional Neural Network (CNN), also referred to as CNN Net, is a deep learning algorithm used to identify images by processing them as inputs and extracting features, learnable weights, and other features from the images. The CNN is designed to automatically learn and adapt spatial hierarchies of features using back propagation through multiple blocks, such as sublayers, convolutional spectra, pooling layers, and fully connected layers. This algorithm consists of three types of layers, namely convolution, aggregation, and fully connected layers, and is constructed[34].

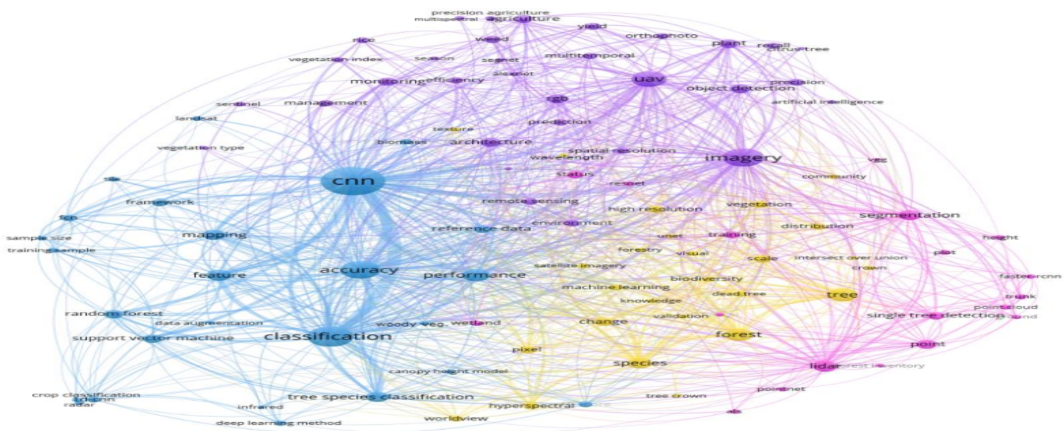

Figure 11: Network analysis on terms contained in title and abstracts of the reviewed studies. The frequency of the terms is represent by their size and their colour represents statistically derived clusters (determined using the node-repulsion LinLog method Noack, 2007). The analysis was performed using VOS viewer (Van Eck and Waltman, 2010). A detailed description of the corresponding workflow is given in the Appendix.

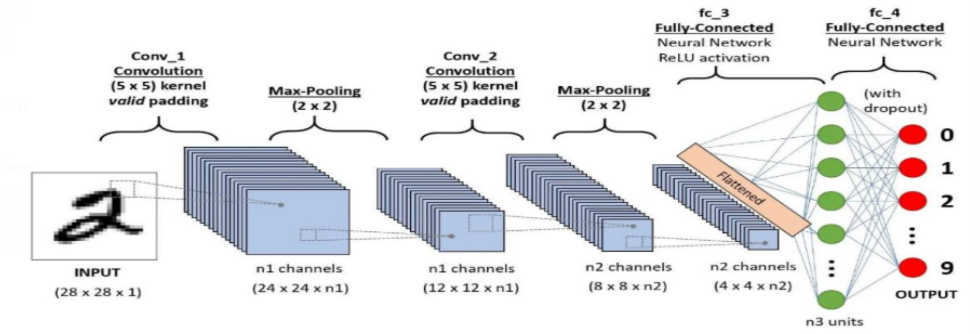

Figure 12: Convolutional neural network architecture

1 Convolution Layer

Convolution layers in Convolutional Neural Networks (CNNs) are responsible for performing non-linear transformations on input data, such as images or videos, to extract relevant features. These layers use a mathematical operation called convolution, which involves applying a filter or kernel to the input data to produce a feature map. The filter moves across the input data, performing element-wise multiplication and summing the results to generate a new value for each position in the output feature map. This process helps to identify and highlight important features in the input data, such as edges, shapes, or textures, by amplifying the response of specific features while suppressing others. Aggregation layers in CNNs, on the other hand, are responsible for learning through low-fidelity representation, which enables efficient training on large inputs. These layers are often used in combination with convolutional layers to create a hierarchical structure, where the output of one layer is used as the input for the next layer, allowing the network to learn increasingly complex features. Aggregation layers can also be used to reduce the dimensionality of the input data, which helps to improve the efficiency of the network and reduce the risk of overfitting. In summary, convolution layers in CNNs are responsible for extracting features from input data, while aggregation layers are responsible for learning through low-fidelity representation and reducing dimensionality. Together, these layers enable CNNs to efficiently process large inputs and learn complex features, making them highly effective for tasks such as image and video recognition[35].

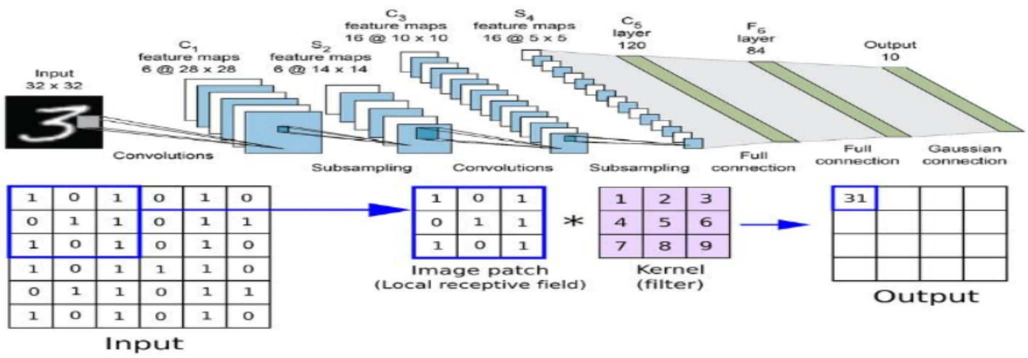

Figure 13: representation of a convolutional layer

2 Pooling Layer

Pooling in deep convolutional neural networks (CNNs) plays a crucial role in reducing spatial dimensions and improving computational efficiency. It is responsible for the invariance to data variation and perturbation, making CNNs more robust to translation and elastic distortions. The pooling layer is typically obtained through a pooling operation that scans the feature map and aggregates information within each local region. This information aggregation can be achieved through various pooling operators, such as average pooling or max pooling, which take the average or maximum value of the local region, respectively. Recent research has focused on improving the pooling layer by proposing novel pooling methods that adaptively learn and extract relevant features from specific datasets. These custom pooling layers aim to address the limitations of traditional pooling operations, which may not be suitable for all applications and data types. For example, a new pooling method called T-Max-Avg has been proposed, which combines the advantages of max pooling and average pooling by incorporating a learning parameter T to compute the K pixels with the highest representational capacity within each local region. This method has been shown to improve the performance of CNNs, especially in tasks that require accurate preservation of features, such as image classification and object detection. In addition to traditional pooling methods, there are several novel pooling methods that have been proposed in recent years. For example, compact bilinear pooling, spectral pooling, per-pixel pyramid pooling, and Rank-based average pooling are all pooling methods that have been shown to improve the performance of CNNs in various applications. These methods aim to capture higher-order information, spatial or structural information, and better discriminative power than traditional pooling methods. In conclusion, pooling is an essential component of deep convolutional neural networks, and recent research has focused on improving the pooling layer by proposing novel pooling methods that adaptively learn and extract relevant features from specific datasets. These custom pooling layers aim to address the limitations of traditional pooling operations and improve the performance of CNNs in various applications[36].

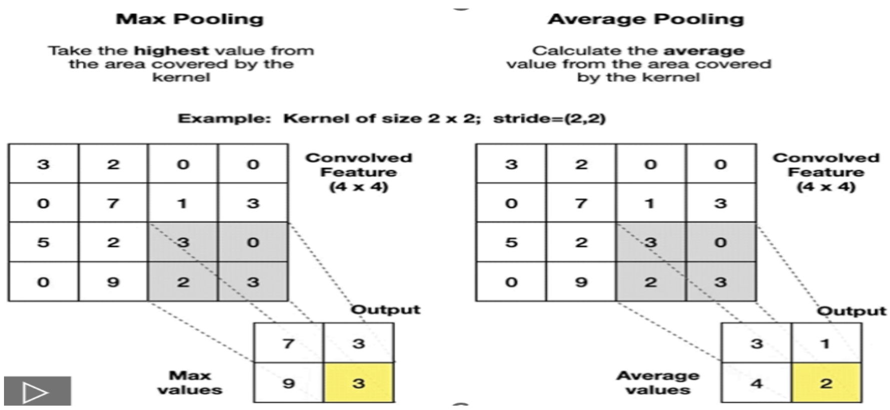

Figure 14: Example of pooling layer (max pooling)

3 Fully Connected Layer

Binarized Convolutional Neural Networks (CNNs) have gained popularity in recent years due to their ability to reduce memory consumption and replace arithmetic operations with bitwise operations, leading to a substantial increase in power efficiency. These networks have weights and activations constrained to -1,+1 at runtime, making them energy-efficient.

Recent research has focused on improving the accuracy of binary CNNs, which often suffer from significant accuracy degradation compared to their full-precision counterparts. One approach to address this issue is to find the best approximation of full-precision convolution using multiple binary operations and employing multiple binary activations to allow more information passing through.

In the context of embedded systems, binarized CNNs have been implemented on FPGA platforms for real-time inference on resourceconstrained devices. This approach eliminates the need for floatingpoint multiplications and additions, decreasing both the computational load and the memory footprint compared to a full-precision network implemented in floating point.

One example of a binarized CNN implementation on an FPGA platform is the VGG-11 benchmark CNN for the CIFAR10 image classification task. This implementation eliminates internal fully connected (FC) layers, except for the last one, and inserts a binarized average pooling layer, which can be realized by a majority circuit for binarized (1/0) values. The weight memory is replaced with a 1's counter, resulting in a compact and faster CNN than conventional ones.

Compared with conventional binarized implementations on an FPGA, this approach achieves almost the same classification accuracy, with a performance per power efficiency that is 5.1 better, a performance per area efficiency that is 8.0 times better, and a performance per memory that is 8.2 times better .

In summary, binarized CNNs offer significant benefits in terms of power and area efficiency, making them an attractive option for embedded systems. Recent research has focused on improving the accuracy of binary CNNs while maintaining their energy-efficiency, with promising results[37].

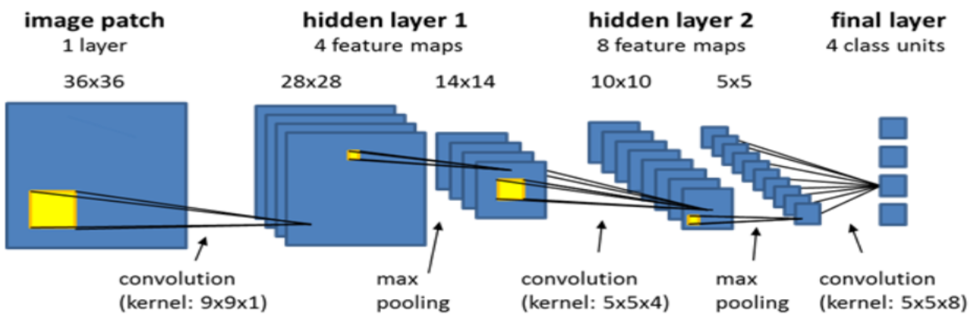

Figure 15: Below is an example showing the layers needed to process an image of a written digit, with the number of pixels processed in every stage. This is a very simple image, larger and more complex images would require more convolutional/pooling layers.

4 Support Vector Machine

A Support Vector Machine (SVM) is a supervised learning algorithm utilized in machine learning for tasks such as classification and regression. SVMs aim to establish an optimal decision boundary, called a hyperplane, to segregate data points into distinct classes, with the goal of maximizing the margin between classes. They accomplish this by transforming data into higher-dimensional spaces through kernel functions, thereby enabling the classification of both linearly and non-linearly separable data. SVMs are effective for analyzing complex datasets and are renowned for their efficiency in handling high-dimensional data [38].

5 Long Short-Term Memory

LSTM (Long Short-Term Memory) is a specific type of recurrent neural network (RNN) designed to model temporal sequences. It is used in deep learning to process and predict data sequences. LSTM was designed to address the problem of vanishing gradients in traditional recurrent neural networks, which occurs when errors are propagated through multiple layers, leading to the loss of important information. LSTM utilizes a gated cell structure that enables the network to control the amount of information stored and forgotten at each time step, making it particularly suitable for processing long-term data sequences. LSTMs have been successfully applied in various deep learning applications such as natural language processing, speech recognition, text generation, and time series prediction[39].

II.7 Per-trained Convolutions Neural Networks

Convolutional neural networks (CNNs), a particular kind of neural network in artificial intelligence intended to carry out particular tasks, are one such method. CNN is made up of a collection of networks that operatewell with itsstructure to carry out the activities needed forlearning and training procedure, including feature extraction and categorization.

IV. Conclusion

our chapter sheds light on the importance of understanding the concepts of artificial intelligence and the diversity of its branches. It represents a comprehensive field contributing to advancements in various domains, especially in medicine.
We provided a definition of artificial intelligence and its various branches, including artificial neural networks (ANN), convolutional neural networks (CNN), long short-term memory networks (LSTM) and Support Vector Machines (SVM), along with an explanation of the feature extraction process and its significance in data analysis.
In the next chapter, we will present works and systems similar to ours, analysing their results and elucidating the differences and similarities to deepen understanding in this field.

Chapter 3

Experimentation and Results

III.1 Introduction

In this study, we propose a system for diagnosing heart failure using a medical dataset. The aim of the system is to detect heart failure in its early stages, which reduces the severity of the disease and facilitates early treatment. The method involves extracting features from the dataset and feeding them to a neural network trained for classification. We will discuss the process of training the neural network model and evaluate the proposed system using accuracy, sensitivity, and the F1 score. Finally, we will present and discuss the results obtained from our experiments, providing insights into the effectiveness of our approach.

III.2 State of the Art about heart failure using artificial intelligence

Authors	title	Year	Methodes	data set	Accuracy%
Ahmet Çınar Seda Arslan Tuncer	Classification of normal sinus rhythm, abnormal arrhythmia and congestive heart failure ECG signals using LSTM and hybrid CNN-SVM deep neural networks	2021	SVM-KNN LSTM AlexnetSVM	data (MIT-BIH 2020).MIT-Bosnia and Herzegovina	86.75% 90.67% 96.77%
Asma Baccouche , Begonya GarciaZapirain Cristian Castillo Olea	Ensemble Deep Learning Models for Heart Disease Classification: A Case Study from Mexico	2020	CNN	Darta set taken from medica norte hospitalin Mexico	91%..96%
Gjoreski, M., Gradišek, A., Budna, B., Gams, M., & Poglajen, G	Machine Learning and End-to-End Deep Learning for the Detection of Chronic Heart Failure From Heart Sounds	2020	PhysioNet	Our dataset (UKC-JSI)	92.90%
LI, Dengao, LI, Xuemei, ZHAO, Jumin	Automatic staging model of heart failure based on deep learning	2019	CNN-RNN	The dataset used in this paper is from the chest pain centers (CPCs) of Shanxi Academy of Medical Sciences.	97.60%

III.3 System Design

In the study presented, we suggest that a set of data be used for people to detect heart failure. This methodology is described as follows: First, we collect a series of analyses of people containing information: age, animea, cretinne phosphkinase, diabetes, ejection fraction, high blood pressure, platelets, serum cretinine, serum sodium, sex,smoking,time) and then put this information in a database called haert failure clinical recorde dataset:Two, we're using models of learning the robot and the deep learning that's been trained before.(CNN , ANN , LSTM, SVM) Third: The aforementioned works are used where the classification model is defined by type, and the process of sorting is then carried out and then the decision is made at last and applied to the test of two illusions (sick, no sick).

Figure 16: System design

III.4 Experimental data

This is a study of a system of detection of heart failure using an internet database of kaggle called "heart failure clinical recorde dataset" which was obtained through the collection of 12 clinical features of 5,000 people and includes these features (age, animia,cretinine phosphkinase, diabities, ejection fraction, high blood pressure, platelets,serum creatinne,serum sodium, sex, smoking,time) We've divided the database file into two files: the training file, which consists of 4,000 people's data and the remaining 1,000 people's data, drawn into a test file to conduct our study.

1.Experimental SETUP

2.DEVELOPMENT HARDURE

We have implemented the detection system of VS Code The operating system used is Windows 11, 64 bit, The system was equipped with an :

- **CPU:** Ppocessor intel(R) Core(TM) i5-10310U CPU @ 1.70GHz 2.21 GHz
- **RAM:** 16,0 GB.

3.DEVELOPMENT SOFTWARE:

- **the program used:** Visual Studio Code

Visual Studio Code is a source code editor that can be used with a variety of programming languages, including Java, JavaScript, Go, Node.js and C++. It is based on the Electron cadre, which is used to develop Web Node.js applications that operate on the Blink display driver. Visual Studio Code uses the driver's name (code Monaco) in Azure DevOps (an application includes Visual Studio Online and Visual Studio Team Services). The logic includes charging the Windows Subsystem for Linux and, as an example, the programmer facilitates the C/C++ installation in Windows 10.

4.METHOD SETUP

5.Data Split

In order to prepare the data for use in the proposed detection system, the first step involved organizing and categorizing it into six distinct categories, consisting of both negative and positive samples. These categories were further divided into two sets, namely the "Train" and "Val" sets, which also contained both negative and positive samples.

III.5 Classification methods:

In our proposed system, the classification process represents the final stage, where a CNN model is chosen based on its individual coefficient and classification methodology. Specifically, we employed the following models: ANN, CNN, SVM, LSTM, and CNN-LSTM.

- **ANN:** Using a pre-trained Artificial Neural Network (ANN) model with modifications to the "epoch" and "batch size" parameters.
- **CNN:** Using a pre-trained Convolutional Neural Network (CNN) model with modifications to the same parameters.
- **SVM:** Using a Support Vector Machine (SVM) to classify databases .
- **LSTM:** Using a pre-trained Long Short-Term Memory (LSTM) model to analyze sequential data.
- **CNN-LSTM:** Using a model that combines Convolutional Neural Networks and Long Short- Term Memory (CNN-LSTM) to achieve higher classification accuracy.

In this proposed system, the models aim to classify data to determine whether it reflects healthy conditions or heart failure cases, aiding in early diagnosis and therapeutic intervention.

III.6 Experimental metrics

The developed system aimed to detect heart failure using deep learning methods. The performance of the model was evaluated using the SPEC-DATA dataset, as previously mentioned. Results from the proposed classifiers or classification models were compared and displayed.

- **Accuracy:** It was used as the primary performance measure to evaluate the effectiveness and responsiveness of the medical decision-making system. Other performance measures used included:

$$\text{Accuracy}(\%) = \frac{TP}{TNTP + TN + FP + FN} \times 100 \tag{1}$$

- **Sensitivity:** The probability of diagnosing abnormal samples as positive, expressed as follows:

$$\text{Sensitivity } (\%) = \frac{TP}{TP + FN} \times 100 \tag{2}$$

- **Specificity:** The probability of correctly selecting normal samples, expressed as follows:

$$\text{Specificity}(\%) = \frac{TN}{TN + FP} \times 100 \tag{3}$$

Where TP,TN,FP and FN are :

- **True positive (TP):** the pathogenic nature of the speech sample is indicated by the signal.
- **True negative (TN):** refers to the sound sample being normal and being correctly identified as such.
- **False positive (FP):**refers to a normal sound sample being incorrectly identified as pathogenic.
- **False negative (FN):** refers to a pathogenic vocal process being identified as healthy.
- **F1 Score:** The degree of F1 expresses the accuracy of the model in a binary classification system, where the samples are classified as positive or negative.

$$F1 \text{ Score } = 2 \times \frac{\text{Precision } \times \text{ sensitivity}}{\text{precision } + \text{ sensitivity}} [?]. \tag{4}$$

where the Precision is given by :

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5}$$

III.7 accuracy And loss comparison

1 accuracy curve

Accuracy is a standard metric used to evaluate the performance of a neural network model and its ability to interpret data. In deep learning, the accuracy curve represents the percentage of correct predictions made by the model during training. This curve is typically depicted as a graph with accuracy values on the y- axis and epochs or time gradient on the x-axis. Monitoring the accuracy curve throughout the training process allows for tracking the model's performance, providing insights into whether its accuracy is improving or if there are issues that need addressing.

2 Loss curve

The loss curve tracks the loss calculated between the expected values and the model's predicted values, reflecting the model's ability to learn and adapt from the data. The primary goal of the loss curve is to minimize loss during testing by adjusting and updating the neural network's weights and parameters. This curve is typically depicted as a graph with the loss value on the y-axis and the epochs or temporal gradient on the x-axis. At the beginning of training, the loss value is usually high, but it gradually decreases as the training progresses and the model improves.

III.8 Results and discussions

The proposed system was used to classify heart failure patients using deep learning methods from the previously mentioned SPE-DATA dataset, aiming to identify the most common cases. The exact and optimal model for this task was determined through comparative analysis of five pre-trained network models: ANN, CNN, SVM, LSTM, and CNN-LSTM. Each model's performance was evaluated, showcasing its unique features.

- We had a 80% of the dataset was used as training data.
- while 20% of the dataset was reserved for testing purposes.
- EPOCH settings ranged from 10 to 100, and BATCHSIZE ranged from 16 to 256 for all CNN models.

Finally, we present the performance results of the five models: ANN, CNN, SVM, LSTM, and CNN-LSTM. These models were evaluated using EPOCH, BATCHSIZE, and other metric parameters. The methods used to measure classification accuracy are detailed in the following table

-Results of CNN:

Table 1: Results of CNN

Batch-size/epoch	10	40	60	100
16	94.88	95.50	95.39	95.71
32	93.62	95.93	95.91	95.87
64	93.65	95.38	95.46	95.37
128	90.57	95.34	94.96	94.71
256	86.59	93.41	92.16	93.95

The proposed system for detecting heart failure using the CNN algorithm, Convolutional Neural Network (CNN), achieved automatic classification of heart failure with an accuracy of up to 95.93% using a data set of epoch = 40 and batch size = 32.

a accuracy curve CNN

As in the CNN accuracy curve, as shown in the figure01, the validation accuracy curve indicates the stability of the model in accuracy during validation and shows how well the model generalizes to new data in the context of the CNN model. The increase in the training curve indicates the success of the model in providing correct answers during the training process. The stability of the validation accuracy curve between 96% and 98% indicates consistent performance in generalizing new data, which demonstrates the reliability of the model in making accurate predictions beyond the training range

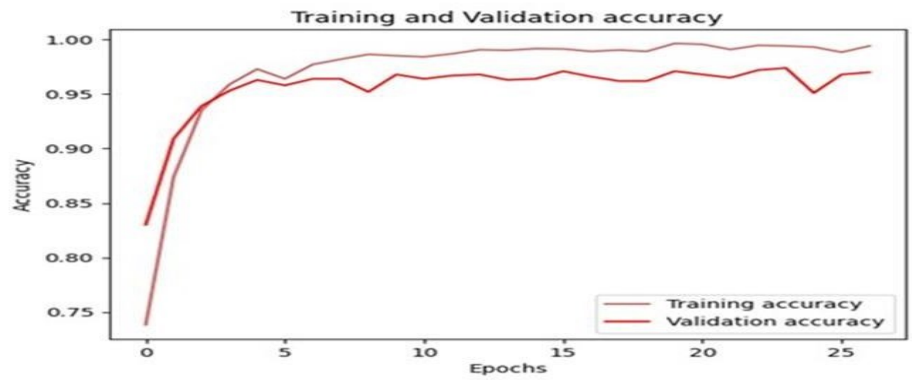

Figure 17: Accuracy curve to CNN

b Loss curve CNN

In the CNN loss curve, we notice proportionality in all curves to test and then achieve the accuracy curve, as the percentage was high at the beginning of training, reaching 55. Then we notice a decrease in this percentage, i.e. a decrease in the loss percentage, and it is clear in the following figure02, so that we notice its stability as a loss percentage at about 0%, and stability at the end. the operation.

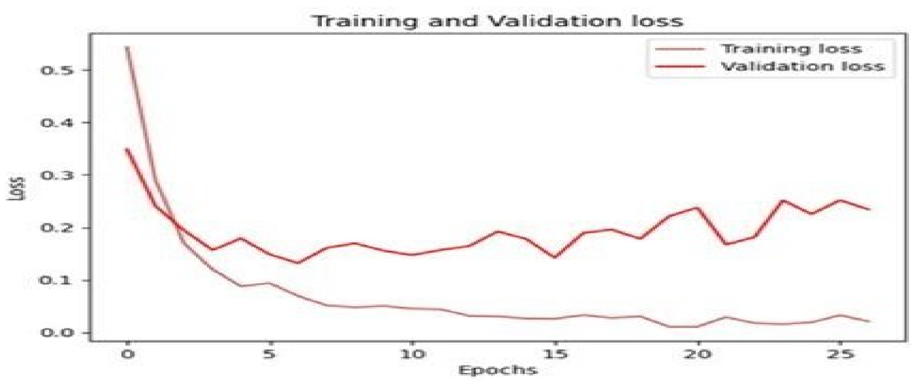

Figure 18: Loss curve to CNN

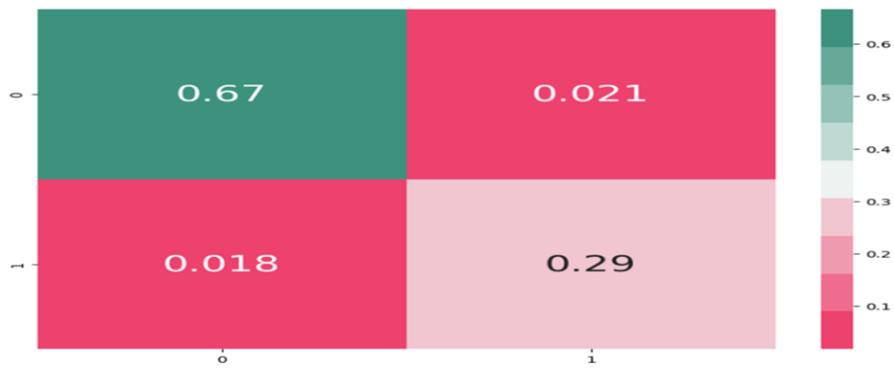

Figure 19: Confusion matrix CNN

-We will discuss another group model, which is ANN:

Table 2: Results of ANN

Batch-size/epoch	10	40	60	100
16	96.16	97.22	96.90	97.48
32	94.79	96.75	97	96.88
64	94.81	96.65	96.72	96.56
128	93.48	96.11	96.21	96.37
256	90.24	95.41	95.76	95.65

The table above shows the results of detecting heart failure using an artificial neural network (ANN), an automatic classification with an accuracy of up to 97.48% when using a set of data epoch = 100 and batch size = 16. This model showed promising results in diagnosing heart disease, which demonstrates the capabilities of neural network models in prediction. Results in cases of heart failure.

c accuracy curve ANN

In the accuracy curve of the ANN model, as shown in the figure03, an increase in the curve indicates giving correct answers during the training process, and the model showed a response in training. We also notice stability in the accuracy curve between 96% and 98%.

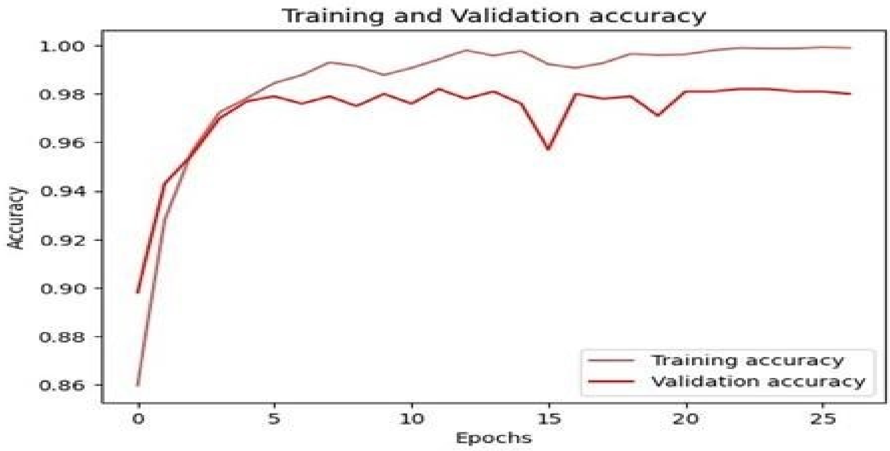

Figure 20: Accuracy curve to ANN

d Loss curve ANN

In the ANN loss curve we observe a fit in the from to test and accuracy curveWe notice a decrease in both curves, and then we notice a loss curve to test stability at 13% and a significant increase at other times.The training loss curve decreases sharply and stabilizes at 0% at the end of the training process.

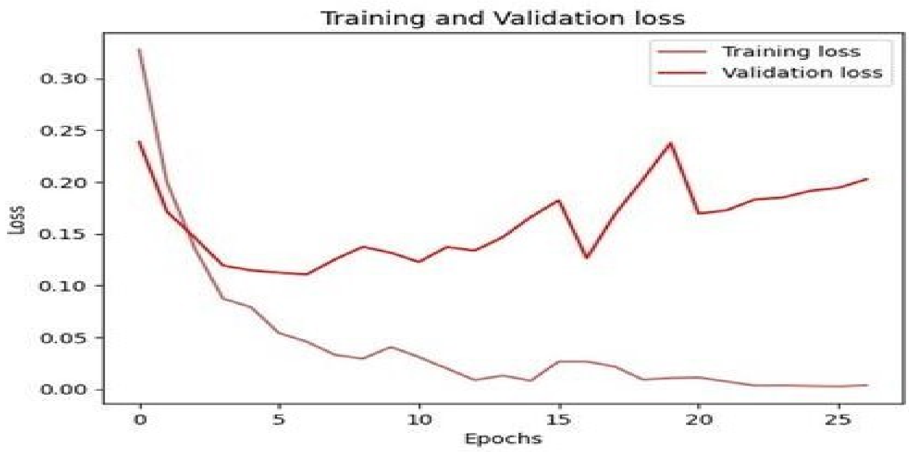

Figure 21: Loss curve to ANN

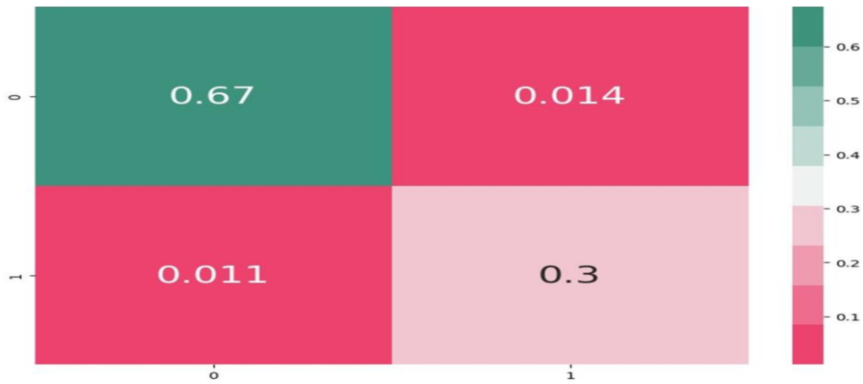

Figure 22: Confusion matrix ANN

-Results of LSTM:

Table 3: Results of LSTM

Batch-size/epoch	10	40	60	100
16	92.13	95.63	96.08	94.35
32	87.17	92.14	91.65	92.35
64	83.38	88.89	83.62	88.46
128	77.85	84.56	83.62	84
256	69.64	78.38	76.76	74.95

The table above shows the results of detecting heart failure using LSTM, an automatic classification with an accuracy of up to 96.08% when using the data set epoch = 60 and batch size = 16. This model showed promising results, and this can be improved in the future in diagnosing heart diseases.

e accuracy curve LSTM

As in the LSTM accuracy curve, as shown in the figure05, the validation accuracy curve indicates the stability of the model in accuracy during validation and shows how well the model generalizes to new data in the context of the CNN model. The increase in the training curve indicates the success of the model in providing correct answers during the training process. The stability of the validation accuracy curve between 95% and 97.50% indicates consistent performance in generalizing new data, which demonstrates the reliability of the model in making accurate predictions beyond the training range.

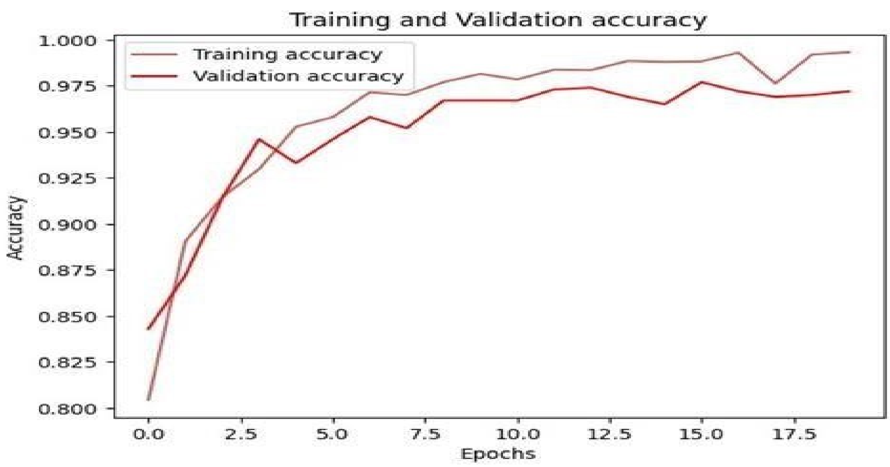

Figure 23: Accuracy curve to LSTM

f Loss curve LSTM

In the LSTM loss curve, there is a gradual decrease in the loss curve in the learning process, which indicates that the model is being trained correctly and that the loss continues until then, reaching 0% at the end of learning.While a loss curve appears to test a gradual decrease between 35% and 12%, the loss value remains stable between 15 and 10 and remains stable until the end of training.

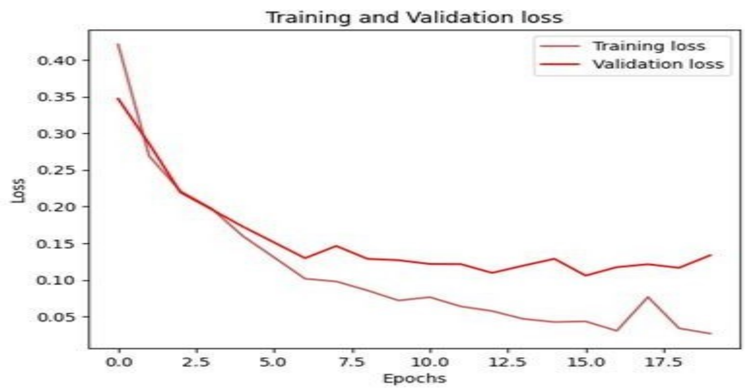

Figure 24: Loss curve to LSTM

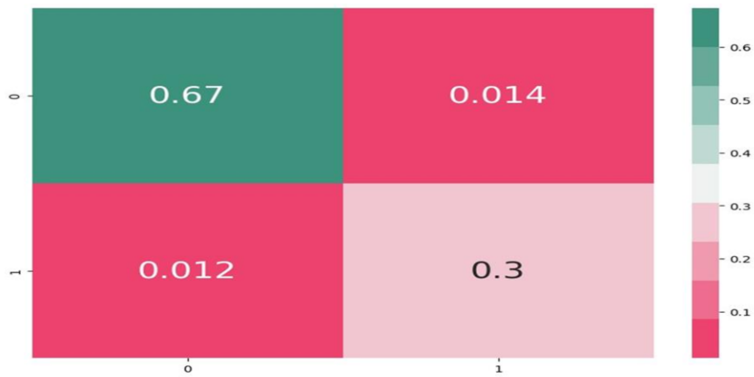

Figure 25: Confusion matrix LSTM

-Results of CNN- LSTM:

Table 4: Results of CNN- LSTM

Batch-size/epoch	10	40	60	100
16	92.47	95.27	95.25	96.48
32	88.26	93.04	93.26	93.02
64	80.74	88.88	87.65	88.26
128	70	78.92	79.40	78.04
256	68.89	67.71	68.81	70.19

The proposed system for detecting heart failure using the convolutional neural network (CNN) algorithm and long short-term memory(LSTM) achieved automatic classification with an accuracy of up to 96.08% when using the data set epoch=60 and batch size=16. Other models can be used to help doctors confirm their diagnosis.

h accuracy curve CNN-LSTM

In the accuracy curve of the ANN model, as shown in the figureO7, an increase in the curve indicates giving correct answers during the training process, and the model showed a response in training. We also notice stability in the accuracy curve between 95% and 97.50%.

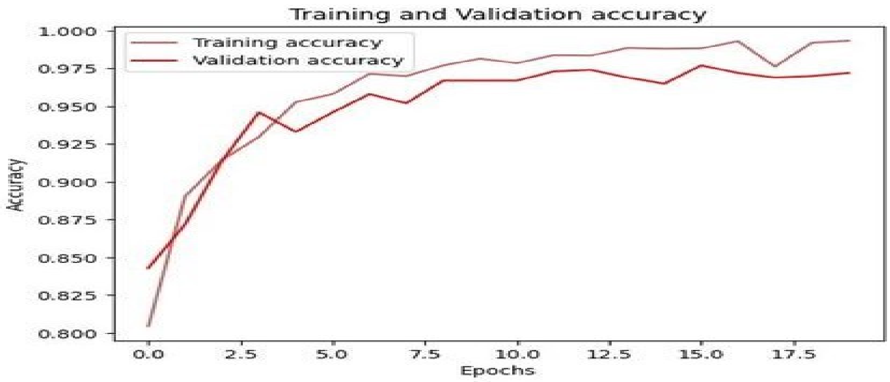

Figure 26: Accuracy curve to CNN-LSTM

j Loss curve CNN-LSTM

In the CNN-LSTM loss curve, we notice proportionality in all test curves, and an accuracy curve was achieved, as the percentage was high at the beginning of training, reaching 60%. Then we see a decrease in this percentage, i.e. a decrease in the loss percentage, shown in the figure08, so that we notice a stability of the loss percentage in the curve at 0 and stability at The end of the training process, but in the loss curve of the test we notice a stability of accuracy between 1% and 2%, which is a low loss rate in the model.

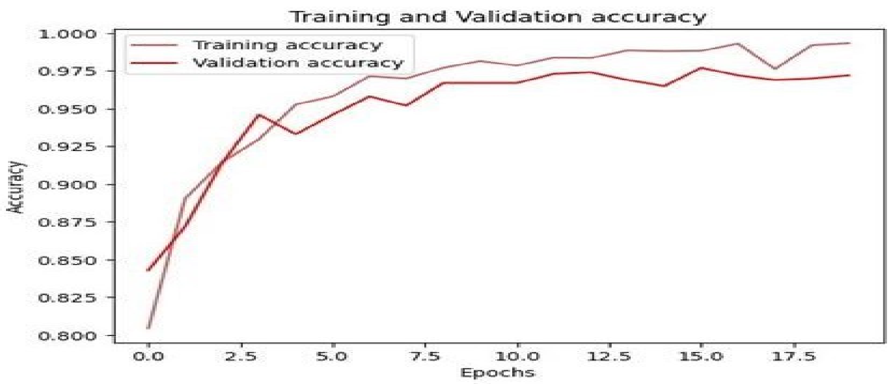

Figure 27: Loss curve to CNN-LSTM

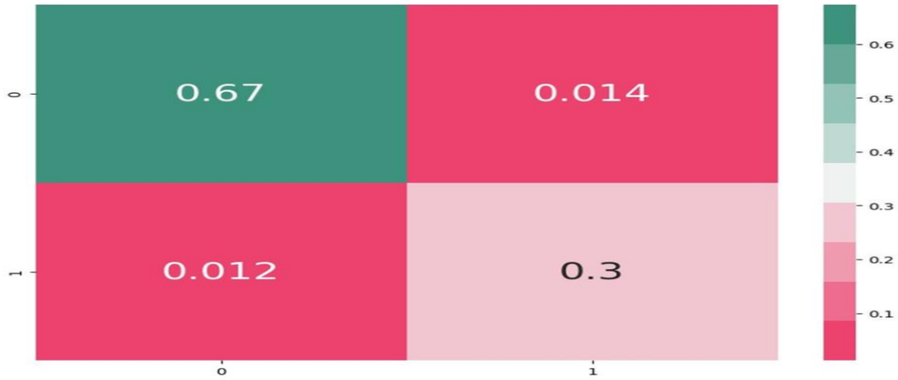

Figure 28: Confusion matrix CNN-LSTM

Other models can be used to help doctors confirm their diagnosis . The best results in all the models we've used:

Table 5: Results of The best results in all the models we've used

Classifier	Epoch	Batch-Size	Accuracy%
ANN	100	16	97.48
LSTM-CNN	100	16	96.48
LSTM	60	16	96.08
ANN-CNN	40	32	95.93
SVM	nothing	nothing	95

The table shows the best system for detecting heart failure, as we achieved the best detection accuracy in ANN, as it detected affected individuals with an accuracy of 97.48% which achieved strong performance and good generalization on the real data set.
This does not mean that it is not possible to rely on other algorithms to detect disease, such as in our research, which gave similar results, such as CNN-LSTM with an accuracy of 96.48%.
-The model's best result :

Table 6: The model's best result ANN

Classifier	Epoch	Batch-Size	Accuracy%
ANN	100	16	97.48%
LSTM-CNN	100	16	96.48%

We note in the following table study of the best result and the best model, where the

ANN classifier obtained the best accuracy of 97.48% in our system compared to the other classifiers.

III.9 Comparison

In curves 7, 4, 1 and 10, we note a difference in the accuracy curve in the ann model above the accuracy curve in other models, such as lstm and cnn-lstm, where ann achieved the accuracy of 100% training and 98% test accuracy, which is better and plus a loss curve as shown in the 8,2 and 11 curves. And as for the test loss curve, ann was also one of the best models, so when the results are close to 100% and the accuracy of 0% in the loss is perfect. We can say that the higher the accuracy of the system and the lower the loss rate, the better the accuracy curve, the better the loss curve.

III.10 Conclusion:

our project aims to classify a medical dataset for heart failure detection using feature extraction and convolutional network classifiers in deep learning. By utilizing a medical dataset, we evaluated the performance of CNN and ANN models by varying the parameters. The results showed that most of the tested models achieved high accuracy, with the best model achieving an accuracy of ..., followed by another model with an accuracy of .... However, we acknowledge that the evidence used in the proposed work may not be sufficient to achieve better results. Therefore, the use of new and good evidence can always contribute to improving the accuracy and efficiency performance of our system or similar systems, leading to better results. We hope that these findings will contribute to the development of more effective diagnostic tools for early detection of heart failure and improvement of patient care.

General Conclusion

The heart failure is one of the most dangerous and complex diseases, leading to the death of many people worldwide. Scientists and doctors have tried to discover early diagnostic methods to limit its spread. In the search for effective methods for early detection of heart failure, modern technologies have leaned towards using artificial intelligence, particularly deep learning and convolutional neural networks (CNN), due to their efficiency and accuracy in detection.

In this work, we proposed using a set of medical data and training them on CNN models.

Our study was as follows:

We proposed a system for detecting heart failure using a set of medical data and training CNN models such as (ANN, LSTM-CNN, LSTM, CNN, SVM).

We used deep learning and convolutional networks techniques. We compared classifiers (ANN, LSTM-CNN, LSTM, CNN, SVM).

We obtained a set of results in this work, proving the accuracy and excellent performance of this system.

Finally, the experimental results were applied to our system, with the LSTM-CNN model achieving an accuracy of 96.48% while the ANN model achieved an accuracy of 97.47%, making it the best. Factors such as the number of training epochs, batch size, and number of layers play a crucial role in the results.

This study demonstrates the effectiveness of our system in detecting heart failure using AI , which can be a significant motivator for continuing research and development in this field. These advanced models can bring a qualitative shift in medical decision-making systems, helping to achieve more accurate and faster diagnostic results, thereby improving the quality of healthcare provided to patients.

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