AUTOMATIC RECOGNITION OF LEFT VENTRICULAR STRUCTURES AND CARDIAC CYCLES IN 2D ECHOCARDIOGRAPHY IMAGES USING DEEP REINFORCEMENT LEARNING

By

MEHDI SAMIEIYEGANEH

Thesis presented to the Universiti Putra Malaysia in fulfillment of the requirements for the degree of Doctor of Philosophy

May 2024

FSKTM 2024 22

DEDICATION

TO:

My father, who has been my support throughout my life, and he is my role model in life.

My wife, who patiently and kindly helped and motivated me throughout.

My mother, who has always helped me with good prayers.

My son, who during this time by drawing beautiful paintings, gave me spirit and increased my motivation.

My wife's father, mother and sisters who have always been my support and helper.

My Professor, Prof. Rahmita, who always guided me with valuable guidance and high knowledge.

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MEHDI SAMIEIYEGANEH

May 2024

Chairman : Professor Rahmita Wirza binti O. K. Rahmat, PhD
Faculty : Computer Science and Information Technology

Understanding the anatomical structures on the left side of the heart, particularly the Left Atrium (LA) and Left Ventricle (LV), including the Endocardium (LV_{Endo}) and Epicardium (LV_{Epi}), is essential for evaluating cardiac function. Manual segmentation of these structures in echocardiography remains the standard practice but is time-consuming, operator-dependent, and prone to variability. Developing automatic segmentation and identification methods for echocardiography images is crucial to enhance diagnostic accuracy, reduce subjectivity, and streamline clinical workflows.

This thesis presents a novel Deep Reinforcement Learning (DRL) framework designed to address the challenges in segmenting cardiac structures in 2D echocardiography images. The proposed framework integrates a Convolutional Neural Network (CNN) for the identification of cardiac cycles (End-Diastolic (ED) and End-Systolic (ES) phases) with the DRL approach for precise segmentation of LV Endocardium, LV Epicardium, and LA. Unlike conventional Deep Learning (DL) techniques that rely on static, pre-labelled datasets, DRL dynamically interacts with the environment, enabling adaptive learning of complex spatial and temporal patterns inherent in Transthoracic Echocardiography (TTE). This adaptability makes DRL particularly effective in handling variations and complexities associated with TTE imaging, where external factors often degrade image quality. The research makes several key contributions to the field of echocardiography image analysis which are, A novel integration of a fully connected neural network as an actor in the Actor-Critic (A-C) framework to enhance the precision of capturing actions and improve segmentation accuracy. Development of a robust DRL algorithm trained iteratively on the CAMUS dataset, a publicly available dataset of 450 clinical cases, to achieve accurate segmentation without manual intervention. And A tailored CNN-based approach to identify ED and ES cardiac cycles, enabling phase-specific segmentation and overcoming ambiguities caused by the similarity of ED and ES images.The DRL framework was rigorously evaluated using metrics such as Dice Similarity Coefficient (DSC), Hausdorff Distance (HD), Jaccard Index, and Mean Absolute Error (MAE), demonstrating superior performance compared to traditional DL methods. Results highlight the model's capability to adapt to varying imaging conditions and its potential to transform clinical cardiology by providing a scalable, accurate, and efficient solution for cardiac structure recognition. This thesis addresses a critical gap in the application of DRL to medical imaging, setting a foundation for further exploration and development in this domain.

Keyword: Deep Reinforcement Learning (DRL), Echocardiography, Left Ventricle (LV) Segmentation, Medical Imaging, Transthoracic Echocardiography (TTE)

SDG: GOAL 3: Good Health and Well-being, GOAL 4: Quality Education, GOAL 9: Industry, Innovation, and Infrastructure.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

KITARAN JANTUNG DALAM IMEJ ECHOCARDIOGRAPHY 2D MENGGUNAKAN PEMBELAJARAN PENGUATAN MENDALAM

Oleh

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Memahami struktur anatomi di bahagian kiri jantung, terutamanya Atrium Kiri *(LA)* dan Ventrikel Kiri *(LV),* termasuk Endokardium *(LV_{Endo})* dan Epikardium *(LV_{Epi}),* adalah penting untuk menilai fungsi jantung. Segmentasi manual struktur ini dalam ekokardiografi kekal sebagai amalan piawai tetapi memakan masa, bergantung kepada pengendali, dan terdedah kepada variasi. Pembangunan kaedah segmentasi dan pengenalan automatik untuk imej ekokardiografi adalah penting untuk meningkatkan ketepatan diagnostik, mengurangkan subjektiviti, dan merampingkan aliran kerja klinikal.

Tesis ini mempersembahkan rangka kerja Pembelajaran Pengukuhan Mendalam *(DRL)* yang inovatif, direka untuk menangani cabaran dalam segmentasi struktur jantung dalam imej ekokardiografi 2D. Rangka kerja yang dicadangkan mengintegrasikan Rangkaian Neural Konvolusi *(CNN)* untuk pengenalan kitaran jantung (fasa End-Diastolik (*ED*) dan End-Sistolik (*ES*)) dengan pendekatan *DRL* untuk segmentasi tepat pada Endokardium *LV*, Epikardium *LV*, dan *LA*. Tidak seperti

teknik Pembelajaran Mendalam (*DL*) konvensional yang bergantung pada dataset yang dilabel secara statik, *DRL* berinteraksi secara dinamik dengan persekitaran, membolehkan pembelajaran adaptif terhadap corak spatial dan temporal kompleks yang wujud dalam Ekokardiografi Transtorasik (*TTE*). Keupayaan adaptasi ini menjadikan *DRL* amat berkesan dalam menangani variasi dan kerumitan yang dikaitkan dengan pengimejan *TTE*, di mana faktor luaran sering menjejaskan kualiti imej.

Penyelidikan ini memberikan beberapa sumbangan utama dalam analisis imej ekokardiografi yang merupakan ,Integrasi inovatif rangkaian neural yang bersambung sepenuhnya sebagai pelakon dalam rangka kerja *Actor-Critic (A-C)* untuk meningkatkan ketepatan dalam menangkap tindakan dan meningkatkan ketepatan segmentasi. Pembangunan algoritma *DRL* yang kukuh dan dilatih secara iteratif menggunakan dataset *CAMUS*, dataset awam yang mengandungi 450 kes klinikal, untuk mencapai segmentasi tepat tanpa campur tangan manual. Dan Pendekatan khusus berdasarkan *CNN* untuk mengenal pasti kitaran jantung *ED* dan ES, membolehkan segmentasi khusus fasa dan mengatasi kekaburan yang disebabkan oleh persamaan imej *ED* dan *ES*.

Rangka kerja *DRL* ini dinilai secara teliti menggunakan metrik seperti *Dice Similarity Coefficient* (*DSC*), *Hausdorff Distance* (*HD*), Jaccard Index, dan *Mean Absolute Error* (*MAE*), menunjukkan prestasi yang lebih baik berbanding kaedah *DL* tradisional. Hasilnya menonjolkan keupayaan model untuk menyesuaikan diri dengan keadaan pengimejan yang berubah-ubah dan potensinya untuk mengubah kardiologi klinikal dengan menyediakan penyelesaian yang boleh diskalakan, tepat, dan cekap untuk pengiktirafan struktur jantung. Tesis ini menangani jurang kritikal dalam aplikasi *DRL* kepada pengimejan perubatan, menyediakan asas untuk penerokaan dan pembangunan lanjut dalam domain ini.

Kata kunci: Pembelajaran Pengukuhan Mendalam (*DRL*), Ekokardiografi, Segmentasi Ventrikel Kiri (*LV*), Pengimejan Perubatan, Ekokardiografi Transtorasik (*TTE*)

SDG: MATLAMAT 3: Kesihatan dan Kesejahteraan yang Baik, MATLAMAT 4: Pendidikan Berkualiti, MATLAMAT 9: Industri, Inovasi, dan Infrastruktur.

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For the others who have directly or indirectly helped me in the completion of my work, I thank you all.

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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Date: 24 February 2025

Declaration by the Graduate Student

I hereby confirm that:

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Declaration by Members of the Supervisory Committee

This is to confirm that:

- the research and the writing of this thesis were done under our supervision;
- supervisory responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 are adhered to.

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LIST OF ABBREVIATIONS

2D	Two Dimensional
3D	Three Dimensional
A-C	Actor-Critic
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
ASMs	Active Shape Models
CAD	Computer-Aided Diagnosis
CNN	Convolutional Neural Network
CT	Computed Tomography
CVDs	Cardiovascular Diseases
DBN	Deep Belief Networks
DDPG	Deep Deterministic Policy Gradient
DSC	Dice similarity coefficient
DL	Deep Learning
DNNs	Deep Neural Networks
DQN	Deep Q Network
DRL	Deep Reinforcement Learning
ED	End Diastolic
EF	Ejection Fraction
ELU	Exponential Linear Unit
ES	End Systolic
FN	False Negative
FP	False Positive
F-C	Fully Connected

FCN	Fully Convolutional Network
GPU	Graphical Processing Unit
HD	Hausdroff Distance
IOU	Intersection over Union
LA	Left Atrium
LSTM	Long Short-Term Memory
LV	Left Ventricle
LV_{ENDO}	Left Ventricular Endocardium
LV_{EPI}	Left Ventricular Epicardium
MAE	Mean Absolute Error
MHz	Megahertz
ML	Machine Learning
MRI	Magnetic Resonance Imaging
NLP	Natural Language Processing
NN	Neural Network
RA	Right Atrium
ReLU	Rectified Linear Unit
RL	Reinforcement Learning
RNN	Recurrent Neural Network
ROI	Region of Interest
RV	Right Ventricle
SARSA	State-Action-Reward-State-Action
SL	Supervise Learning
SMC	Sequential Monte Carlo
Tanh	Hyperbolic Tangent
TD	Temporal Difference
TEE	Transesophageal Echocardiography

TN	True Negative
TP	True Positive
TTE	Transthoracic Echocardiography
UL	Unsupervised Learning
WHO	World Health Organization

CHAPTER 1

INTRODUCTION

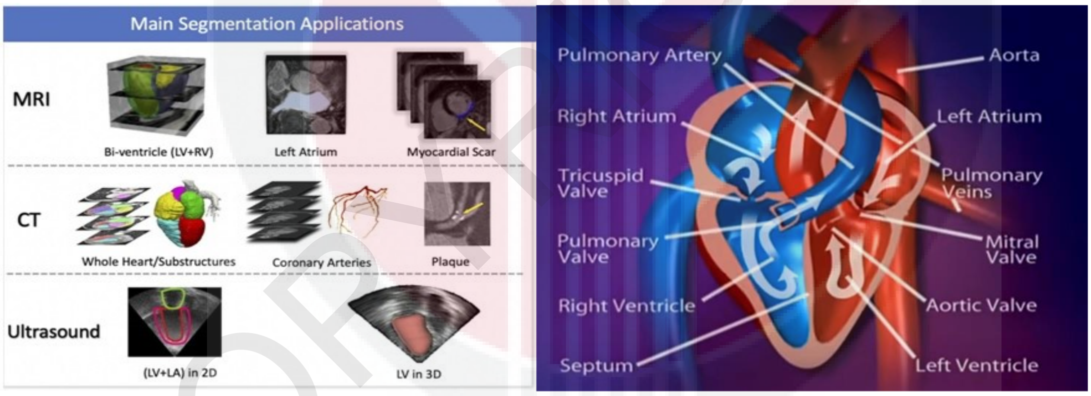
In this chapter, a brief overview of Machine Learning (ML), Deep Learning, and Deep Reinforcement Learning concepts is presented. In fact, to understand the topics related to Deep Reinforcement Learning (RL), prerequisites for studying are needed, which include Machine Learning, Reinforcement Learning, and Deep Learning. The rest of this chapter provides a concise summary of echocardiography and details key aspects of the human heart and its functioning. Additionally, it delves into the overview of our technique for cardiac ultrasound segmentation employing Deep Reinforcement Learning as outlined in this thesis, then addressing the motivation, objectives, contribution, scope, and constraints involved in employing DRL algorithms for medical image segmentation.

1.1 Introduction

1.1.1 Background

In various applications, cardiac image segmentation plays a vital role as the initial stage. It involves dividing the image into semantically meaningful regions based on anatomical criteria. Through this segmentation, various measurements can be extracted, including myocardial mass and wall thickness. The anatomical structures commonly targeted for segmentation in cardiac imaging include the Left Ventricle (LV), Right Ventricle (RV), LA, and Right Atrium (RA)(Leclerc et al., 2019). This thesis focuses on the Left Ventricle (LV), the heart's primary chamber responsible for pumping oxygenated blood throughout the body. By visualizing the Left Ventricle, clinicians can evaluate its size, shape, and functionality, which is essential for diagnosing conditions such as heart failure, cardiomyopathy, and valvular diseases.

Figure 1 provides an outline of the usual tasks associated with cardiac image segmentation. It displays the applications of the three frequently utilized modalities, namely, Computed Tomography (CT) , Magnetic Resonance Imaging (MRI) and Ultrasound and the sections related to the heart wall and related terms used in this thesis are shown. To enhance comprehension, the anatomy of the heart is provided on the Right side.



(A) (B)

Figure 1: (A) Usual tasks associated with cardiac image segmentation. (B) Heart wall sections
(Chenet al., 2019**)**

The application of image segmentation technology in medical image analysis and processing has significantly improved physicians' ability to make more accurate diagnoses. The manual segmentation of medical images is a labor-intensive task performed by professionals and is subject to subjectivity. As a result, there is a critical need to develop an advanced segmentation method. Artificial Intelligence (AI) methods play a vital role in computer-aided diagnosis (CAD) by facilitating medical image segmentation. This technology assists radiological experts in clinical diagnosis and treatment planning. Image segmentation involves extracting the Region of Interest (ROI) and dividing a medical image into various pixel-level areas based on specific requirements. This technique is especially effective for segmenting body organs and tissues, making it valuable for applications like border detection, tumours segmentation, and mass identification in medical imaging.

Cardiovascular diseases (CVDs) are the primary cause of mortality worldwide, according to the World Health Organization (WHO). In 2016 alone, CVDs claimed the lives of around 17.9 million people, primarily due to heart disease and stroke. Unfortunately, this figure continues to rise each year. In recent times, there have been significant advancements in cardiovascular research and practices with the goal of improving the diagnosis and treatment of cardiac ailments, as well as reducing the mortality rate associated with CVDs. Non-invasive techniques of medical imaging, including MRI, CT, and ultrasound, are now widely utilized for assessing cardiac anatomical structures and functions. These imaging techniques are invaluable in aiding with the diagnosis, treatment planning, disease monitoring, and prognosis of CVDs (Chen et al., 2019).

Echocardiography, commonly referred to as Cardiac Ultrasound imaging, is an essential tool in the clinical assessment of cardiovascular function. In clinical practice, the analysis of 2D Echocardiographic images is critical for determining cardiac morphology, function, and diagnosis. This analysis depends on interpreting clinical indices obtained through low-level image processing techniques, like tracking and segmentation. Its real-time capability, affordability, and portability make it a preferred choice for primary imaging examinations. However, traditional methods such as level-sets, active shape models and active contours commonly used for automating the segmentation of anatomical structures in ultrasound images, often exhibit limited accuracy due to the inherent complexities and challenges associated with ultrasound imaging.

These challenges include a low signal-to-noise ratio, varying intensities of speckle noise, poor image contrast—especially between the myocardium and blood pool—edge dropouts, and shadows caused by dense structures like muscles and ribs. As a result, due to the limited accuracy and reproducibility of fully automatic cardiac segmentation methods, manual annotation or semi-automatic remains the standard practice in routine clinical settings.

However, these methods are time-intensive and susceptible to variations both within and between observers. (Leclerc et al., 2019). The challenges in segmenting echocardiographic images are widely recognized and include low contrast between the myocardium and blood pool, brightness inconsistencies, variations in speckle patterns due to probe orientation, the presence of trabeculae and papillary muscles with similar intensities, differences in tissue echogenicity across individuals, and significant variations in the shape, intensity, and motion of cardiac structures across patients and pathological conditions.

Machine Learning (ML) has achieved remarkable success in recent years, with sequential decision-making emerging as a key area of focus. These tasks involve determining a sequence of actions based on experience within uncertain environments to achieve specific goals. Sequential decision-making spans a wide range of applications, including healthcare, robotics, finance, and many other fields. The design and feature extraction process in ML relied on manually defined (handcrafted features)(Rabinowitz et al., 2018), which is a significant limitation of this model.

ML includes 4 steps, in the first stage of Machine Learning, we clean the data. Then we select the appropriate algorithm and train the model. Then, with the new data, the model should make the appropriate prediction. Therefore, the general steps of doing work in Machine Learning are as follows:

1. Clean the Data.
2. Select the proper algorithm.
3. Train the model.
4. Predict new cases.

In Machine Learning we have a series of keywords that understand the concept of them will be useful, which are:

1. Observation: Each row of the data set, that is, each part of the data that is used to train the model, is called an observation.
2. Features: Each of the columns in the dataset is features.
3. Label: It is a column in the data set that our model is supposed to predict in the future based on other features. In Table 1, the keywords for a hypothetical data set are specified.

Table 1: Example of ML keywords

Feature → Age; Label → class; Observation → row "34, F, B"

Age	Gender	class
34	F	B
47	M	C

Machine Learning (ML) methods can be classified into three main categories: Supervised Learning (SL), Unsupervised Learning (UL), and Reinforcement Learning (RL). (Samieiyeganeh et al., 2022). Until the 1960s, there was considerable confusion regarding the distinction between Reinforcement Learning (RL) and Supervised Learning (SL). This issue was later clarified by Sutton and Barto (Sutton & Barto, 1998), who provided clear solutions. In Supervised Learning, the data must be trained to produce feature vectors, where each piece of data is labelled by an external supervisor. Using machine learning algorithms, a predictive model is then generated. In contrast, Supervised Learning focuses on discovering the natural structure of training data so that new data can be grouped into appropriate clusters without requiring labelled training data. Reinforcement Learning, on the other hand, refers to a process where an agent learns by interacting with its environment and receiving feedback based on its actions. An agent refers to a software application that acquires the ability to make informed and intelligent choices. In the context of Reinforcement Learning, an agent can be seen as a learner. The environment represents the domain in which the agent operates, encompassing its entire scope of interaction. The agent remains confined to this environment throughout its learning process. A state refers to a specific location or moment within the environment where the agent is situated. It is crucial to recognize that the agent's presence is confined to the environment, and within this realm, there exist numerous potential locations where the agent can exist, known as states. a state denoted by the symbol s. The agent engages in interactions with the environment, transitioning from one state to another through the execution of actions. Actions are represented by the symbol a. The agent interacts with the environment by executing actions, facilitating transitions between states. These actions, in turn, result in the agent receiving a reward, represented as a numerical value, such as *+1* for favorable actions and *-1* for unfavorable ones. Reward is symbolized as r. Figure 2 shows the SL, UL, and RL.

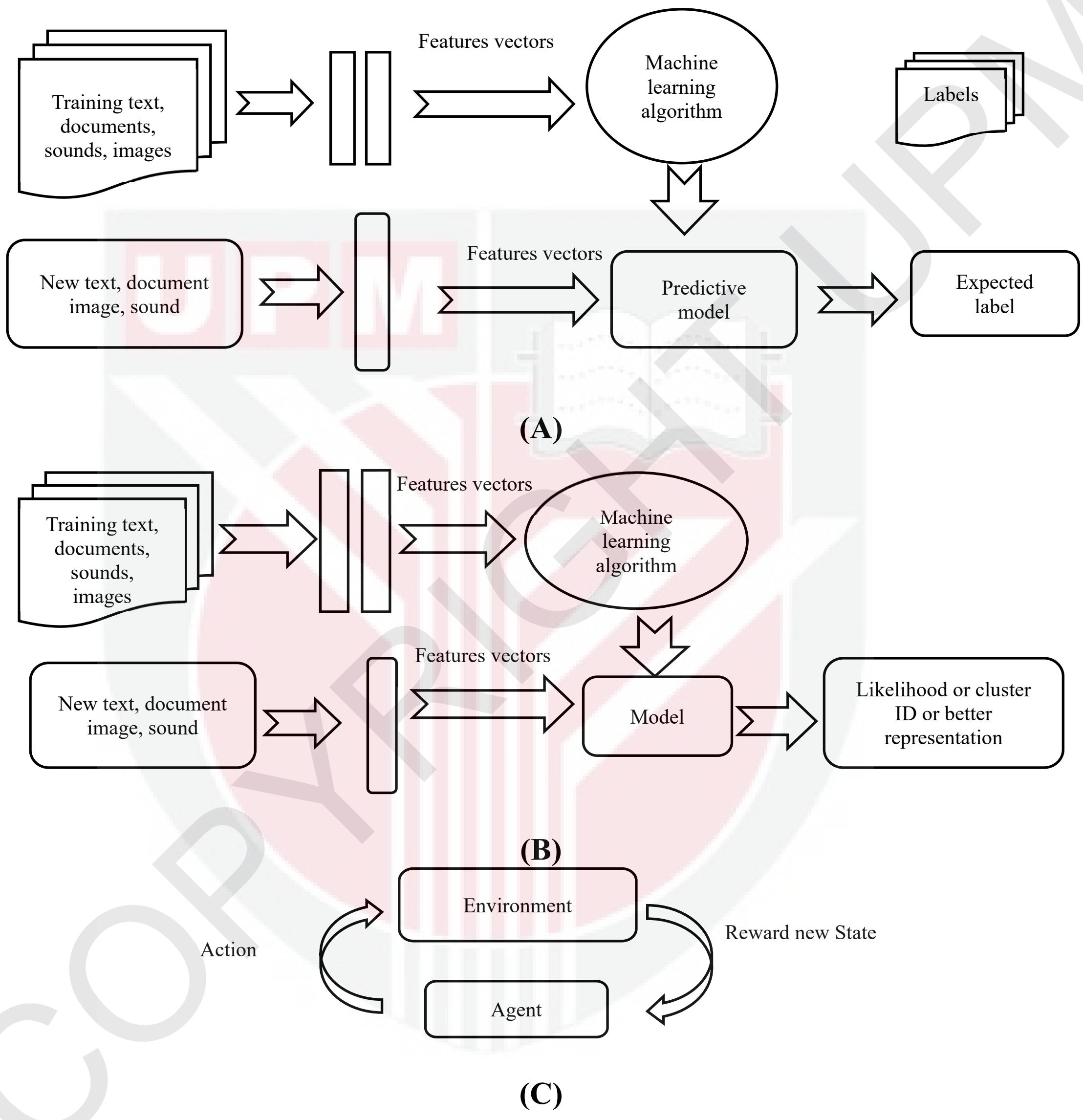


Figure 2: (A) Supervised Learning. (B) Unsupervised Learning (C) Reinforcement Learning

Since 2000, DL has made significant strides in image processing, thanks to advancements in computer hardware, yielding outstanding outcomes (Hesamian et al., 2019). Neural Networks (NNs) are a crucial component of DL, as they can efficiently capture concise representations of data with high dimensions. Consequently, the issue of manual feature engineering in Machine Learning will be resolved in such scenarios (Hernandez-Leal et al., 2019) and (Altaf et al., 2019). Deep Neural Networks (DNNs) are composed of interconnected layers of neurons or perceptron, forming a multi-layer structure (Altaf et al., 2019). Deep Reinforcement Learning is an amalgamation of Deep Learning and Reinforcement Learning techniques. In fact, in the brain of the agent we are using Deep Neural Networks.

1.1.2 Echocardiography

Echocardiography is a non-invasive medical imaging technique that utilizes sound waves to generate detailed images of the heart, offering crucial insights into its structure and function while ensuring safety for patients.

During an echocardiogram, a trained technician or a doctor called a sonographer performs the procedure. They use a device called a transducer, which emits high-frequency sound waves, typically between 2 and 18 Megahertz (MHz) that are beyond the range of human hearing. The transducer is placed on the chest or sometimes inserted into the esophagus to obtain clearer images. In fact, we have two types of echocardiography which are TTE and Transesophageal echocardiography (TEE). TTE is done by placing the ultrasound probe on the wall of chest. TEE involves passing a flexible probe with an ultrasound transducer on its tip through the mouth and into the esophagus, which lies directly behind the heart. This allows for closer proximity to the heart and provides clearer and more detailed images compared to TTE in certain situations. our focus in this thesis is based on TTE echocardiography images because the process of taking the images is Non-invasive and TTE is the most performed echocardiographic technique and widely available, and in compared to TEE, TTE images have a lower quality due to the interference of lung tissue, ribs, and other structures between the probe and the heart (Carerj et al., n.d.2002). Therefore, segmentation of low-quality images is more significant.

When the sound waves encounter different tissues and structures in the heart, such as heart valves, walls, and chambers, they bounce back as echoes. These echoes are then detected by the transducer and converted into electrical signals. In fact, Echocardiography utilizes the principles of ultrasound to create images of the heart. Ultrasound is a form of imaging that uses high-frequency sound waves to produce detailed pictures of structures within the body. These sound waves are emitted by the transducer, which is a small handheld device that is pressed against the skin or inserted into the esophagus.

The signals are processed by a computer, which generates real-time images of the heart on a monitor. These images, known as echocardiograms, provide detailed information about the heart's size, shape, and movement. They can also show the flow of blood through the heart and identify any abnormalities or diseases.

Echocardiography is extensively utilized for diagnosing and managing a range of heart conditions, such as heart valve diseases, heart failure, congenital heart defects, and cardiac tumours. It serves as an essential tool for assessing overall heart function and aiding in treatment planning. The images produced by echocardiography can be Two-Dimensional (2D) or Three-Dimensional (3D). 2D echocardiograms show cross-sectional slices of the heart, allowing doctors to visualize the different chambers, valves, and walls. 3D echocardiograms provide a more comprehensive view of the heart by creating a three-dimensional image, enabling a more accurate assessment of complex structures and volumes (Subramani, 2022). In our thesis, we focused on 2D echocardiography images because they are widely used compared to 3D echocardiography. 3D echocardiography is demanding and requires specialized equipment and expertise for acquisition and interpretation. 3D echocardiography has Longer acquisition times than 2D echo may limit its utility in certain clinical scenarios, particularly in critically ill patients. An image of the echocardiogram device is shown in Figure 3.

Figure 3: The Echocardiogram device

In this thesis we used The CAMUS [1]dataset, which is a publicly available and clinically annotated standard dataset from the University Hospital of St. Etienne, France. CAMUS acquired from GE Vivid E95 ultrasound scanners, with a GE M5S probe. The

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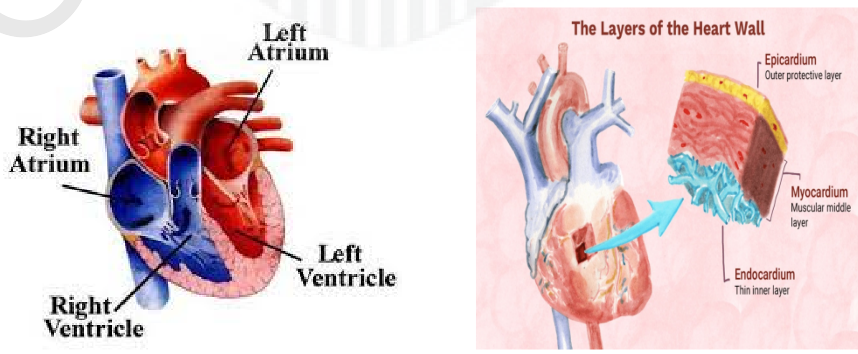
[1] https://www.creatis.insa-lyon.fr/Challenge/camus/

GE Vivid E95 ultrasound system is a versatile cardiovascular imaging platform that supports both transthoracic echocardiography and transesophageal echocardiography. The GE M5S probe, which is compatible with the Vivid E95 system, is primarily used for Transthoracic echocardiography. This probe is designed for imaging through the chest wall and provides high-quality images of the heart's structure and function from the outside of the body.

1.1.3 Structure of the heart

The heart is an essential organ that ensures blood circulation throughout the body. It is a muscular organ located in the chest cavity, between the lungs, and slightly tilted towards the left side of the chest. The heart's structure can be divided into four main chambers, valves, major blood vessels, and the surrounding protective layers. Considering that our focus in this thesis is based on Left Ventricular Endocardium, Epicardium, and Atrium in End-Diastolic and End-Systolic, we briefly define the four heart chambers shown in Figure 4 part (A) and also the LV $_{Endo}$, LV $_{Epi}$, in End- ED, and ES shown in Figure 4 part (B).



(A) (B)

Figure 4: (A) 4 Heart Chambers. (B) Layers Of the Heart Wall
(Sanjeevi et al., 2024a)

1. Chambers of the heart:

i. Right Atrium: This is the right upper chamber of the heart, which receives deoxygenated blood from the body through two major veins: the superior vena cava and the inferior vena cava.

ii. Right Ventricle: Positioned beneath the Right Atrium, the Right Ventricle receives deoxygenated blood from the RA and pumps it to the lungs via the pulmonary artery for oxygenation.

iii. LA: Positioned on the upper left side of the heart, the Left Atrium collects oxygen-rich blood from the lungs via the pulmonary veins.

iv. Left Ventricle: Located below the left atrium (LA), the left ventricle (LV) receives oxygen-rich blood from the LA and pumps it to the rest of the body through the aorta, the body's main artery.

2. Layers of the heart wall:

LV_{Endo} is the inner layer of the LV, while LV_{Epi} is the outer layer. In End-Diastole, the ventricle is filled with blood, and in End-Systolic, it contracts to pump blood out.

LV is more important because it pumps oxygen-rich blood into the entire body, supplying vital organs. Its thicker muscle ensures it can withstand higher pressure, crucial for systemic circulation. In contrast, the Right Ventricle primarily pumps blood to the lungs for oxygenation, serving a vital but more localized function. Diseases affecting LV are often more serious and prevalent compared to those affecting RV. Conditions such as coronary artery disease, cardiomyopathy, and hypertension more commonly impact the LV, leading to significant morbidity and mortality(Schwarz et al., 2013).

1.2 Fundamentals of Deep Reinforcement Learning techniques

DRL enhances the existing RL framework by incorporating the expressive capabilities of Deep Neural Networks to learn a series of actions that optimize the anticipated reward. Recent studies have showcased the significant possibilities of DRL in the fields of medicine and healthcare. RL provides a structure for acquiring knowledge about a series of actions that aims to optimize the anticipated reward Sutton & Barto, 1998.[5]. DRL is the outcome of combining DL and RL methodologies (Bernstein & Burnaev, 2018). Figure 5 shown the structure of DRL.

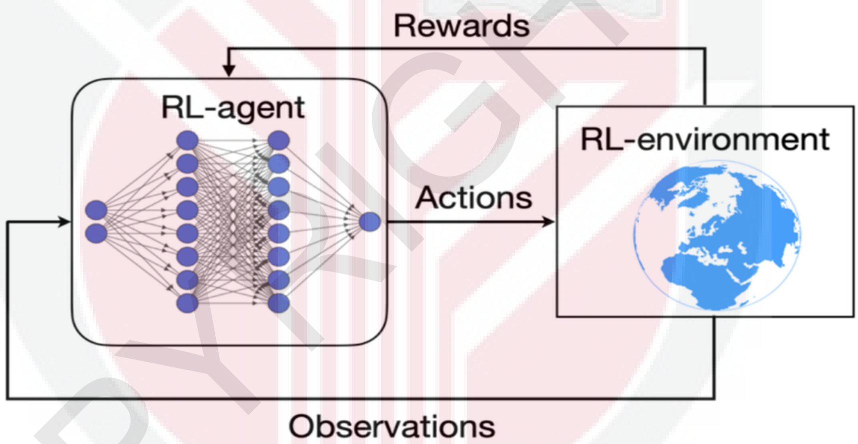


Figure 5: The structure of DRL
(Samieiyeganeh et al., 2022)

The fusion of these two formidable technologies presently represents a cutting-edge framework within the field of AI. Traditional RL algorithms such as Q-Learning, State-Action-Reward-State-Action (SARSA), Monte Carlo Methods and Temporal Difference (TD) Learning often face challenges when applied to complex and high-dimensional environments(Sutton & Barto, 1998). The use of DNNs in DRL addresses these challenges by providing a more expressive and flexible representation of the problem domain. DRL enables the application of RL techniques to tackle complex problems that were previously difficult or impossible to solve. By incorporating DNNs, DRL enhances the representational power of RL algorithms, allowing them to handle larger, more challenging problem domains. In both 2013 and 2017, MIT Technology Review acknowledged DL and RL as part of their prestigious selection of 10 groundbreaking technologies (Zhou et al., 2020). In the past few years, there has been notable advancement in DRL, leading to substantial enhancements in various domains such as computer vision(Bernstein & Burnaev, 2018), gaming(Mnih et al., n.d,2013.), Natural Language Processing (NLP) (Luketina et al., 2019), and Robotics (Finn et al., 2016).In contrast to SL, the DRL framework possesses the capability to handle sequential decision-making and learn from delayed feedback, where the outcome of a decision becomes known only after several time steps. Additionally, DRL is adept at dealing with non-differentiable metrics. For instance, it can be utilized to search for the optimal architecture or parameter settings of a Deep Neural Network (DNN), maximizing classification accuracy, even though the choice of non-linear functions or the number of layers is not differentiable. Another application of DRL involves finding efficient search sequences to expedite detection or identifying optimal transformation sequences to enhance registration accuracy. DRL can also address the challenge of high memory consumption when processing high-dimensional medical images. For instance, a DRL-based object detection system can focus on processing small image regions at a time, reducing the memory footprint, and subsequently determine the next regions to process. While DRL has achieved notable achievements, its implementation in the field of medical imaging is still largely unexplored (Zhou et al., 2020). This can be attributed, in part, to a limited understanding of the specific strengths and limitations of DRL when applied to medical data.

Considering that in this thesis we have used DL and specifically Fully Connected (F-C) NNs and we have also used two DRL algorithms which are A-C and DQN, in the following sections we will give a brief explanation about these three parts.

1.2.1 Deep Learning

Deep Learning-based image segmentation has become a well-established and reliable tool for effectively segmenting images. It has found extensive application in separating homogeneous regions, serving as a crucial initial step in diagnostic and treatment pipelines. There has been significant growth in the use of Deep Learning-based image segmentation in biological fields(Hesamian et al., 2019).

Before the advent of deep learning (DL), traditional machine learning (ML) methods, such as model-based techniques like active shape and appearance models, as well as atlas-based approaches, achieved notable success in cardiac image segmentation. However, these methods typically required substantial feature engineering or prior domain knowledge to achieve acceptable accuracy. (Chen et al., 2020). In the following, we will examine DL and its understanding.

DL falls within the realm of ML and revolves primarily around NNs. Although Deep Learning has existed for approximately ten years, its current surge in popularity can be attributed to advancements in computing power and the widespread availability of vast amounts of data. Capitalizing on these extensive datasets, DL algorithms have proven to outperform traditional ML algorithms. DL-based algorithms excel in autonomously detecting intricate features in data for tasks such as object detection and segmentation. These features are learned directly from the data using a versatile learning process, enabling DL-based algorithms to be effortlessly applied to various image analysis applications. With the aid of advanced computer hardware, such as Graphical Processing Units (GPUs), alongside the availability of abundant training data, DL-based segmentation algorithms have progressively surpassed traditional methods, establishing themselves as the preferred choice in research. DL models refer to Artificial Neural Networks (ANNs) that possess multiple layers, including an input layer, an output layer, and several hidden layers.

A Convolutional Neural Network (CNN) is a specialized type of Deep Neural Network designed to analyse and process visual data, such as images. CNNs have demonstrated exceptional performance in a wide range of computer vision tasks, including object detection, image classification and image segmentation.(Hesamian et al., 2019).

The architecture of CNN is inspired by the visual processing mechanism of the human brain. It consists of multiple layers, each performing specific operations on the input data. The main building blocks of a CNN are convolutional layers, pooling layers, and fully connected layers.

Convolutional layers are designed to capture and learn local patterns and features from the input data. They employ a set of learnable filters, also known as convolutional kernels, which slide across the input image to perform convolution operations. In fact, each input image is encoded as a matrix consisting of pixel values. In addition to the input matrix, there exists another matrix known as the filter matrix, which is alternatively referred to as a kernel or filter. By convolving the filters with the input, these layers capture local correlations and extract meaningful features. Convolutional layers help the network detect edges, textures, and higher-level visual representations.

Pooling layers decrease the spatial dimensions of the feature maps produced by convolutional layers. This is achieved through down sampling, which condenses the feature maps into smaller but meaningful representations. The most common pooling method is max pooling, where only the maximum value within each pooling window is preserved, and the remaining values are discarded. Pooling layers play a crucial role in ensuring translation invariance and reducing the computational load of the network.

Fully Connected layers are often integrated into the final stages of a Convolutional Neural Network (CNN). These layers, also known as dense layers, are responsible for performing classification or regression tasks using the features extracted by the preceding convolutional and pooling layers. The output from the last pooling layer is flattened into a one-dimensional vector, which is then passed through one or more fully connected layers. In these layers, each neuron is connected to every neuron in both the previous and subsequent layers, allowing the network to capture complex relationships and patterns within the feature space.

The strength of CNNs lies in their capability to automatically learn hierarchical features from raw visual data, allowing them to identify relevant patterns and generate precise predictions. With their effectiveness in computer vision tasks, CNNs have revolutionized the field of image analysis and paved the way for numerous applications, including autonomous vehicles, facial recognition, medical imaging, and more. The CNN architecture is depicted in Figure 6.

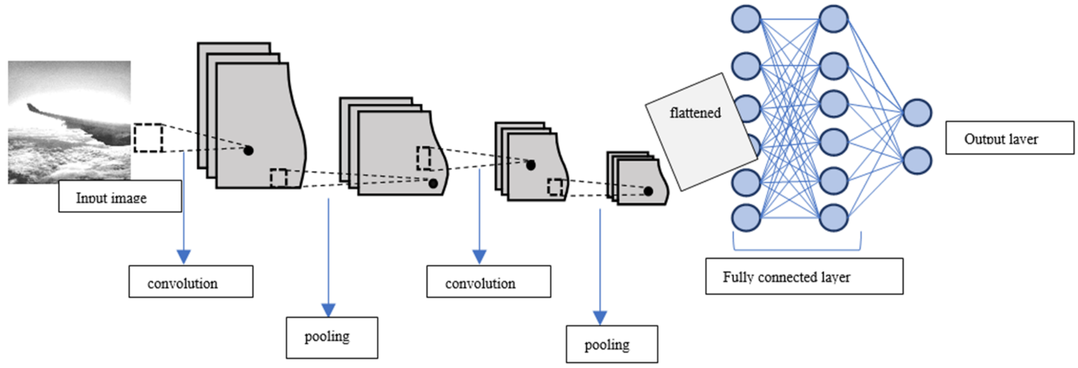


Figure 6: CNN architecture
(Ravichandiran, 2020)

In CNNs, activation functions are crucial components that introduce non-linearity into the network, enabling it to learn complex patterns in data(Zhou et al., 2020). An activation function, also known as a transfer function, is a mathematical function applied to the output of each neuron (or unit) in a neural network, including CNNs. The purpose of the activation function is to introduce non-linearity into the network, enabling it to learn complex patterns in the data. Activation functions determine whether a neuron should be activated or not, based on whether the input to the neuron meets a certain threshold. If the input exceeds the threshold, the neuron is activated and transmits information to the next layer of the network; otherwise, it remains inactive.

Common types of activation functions used in CNN include Rectified Linear Unit (ReLU), Leaky ReLU, Exponential Linear Unit (ELU) , Sigmoid, and Hyperbolic Tangent (Tanh) and Soft Max. (Ravichandiran, 2020). Each activation function has its own characteristics, advantages, and disadvantages, and the choice of activation function can significantly impact the performance and training dynamics of the neural network. In this thesis we used Soft Max and ReLU as activation functions. ReLU accelerates the convergence of training by allowing the model to learn faster compared to other activation functions like sigmoid and tanh. Figure 7 shows the Rectified Linear Unit function.

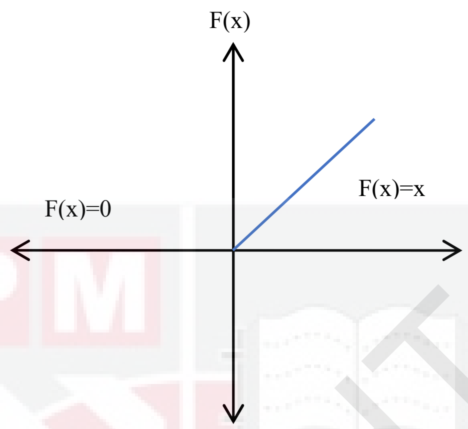


Figure 7: Rectified Linear Unit function

As depicted in the previous diagram, when a negative input is given to the ReLU function, it is transformed into zero.

The soft max function is an extension or generalization of the sigmoid function. It is typically used in the final layer of a network for multi-class classification tasks. It provides the probability of each class as output, ensuring that the sum of soft max values always equals 1.

The soft max function transforms its input into probabilities as shown in Equation 1-1.

Equation 1-1:

$$f(x_i) = \frac{e^{x_i}}{\sum_j e^{x_i}}$$

In our thesis we have two-part, first part is related to the identification of ED and ES based on DL method and second part is related to segmentation heart structure based on DRL method. For identifying the ED and ES phases, we utilized a CNN due to its high capability in extracting visual features. This network can detect complex patterns in cardiac images and assist in phase identification. The structure of the phase identification model is as follows: it includes inputs, which are echocardiography images prepared during the preprocessing stage; convolutional layers, which extract various features from the images such as the shape and size of cardiac chambers, wall thickness, and the position of cardiac structures; and F-C layers, which are added after the convolutional layers to combine the extracted features and perform the final classification. An output layer with two nodes is used to represent the two phases, ED and ES. For classification, the Softmax activation function is employed to calculate the probability of each image belonging to a specific phase.

Fully Connected Neural Networks (F-C NNs), also referred to as Dense Neural Networks (DNNs) or Fully Connected layers, are utilized as our Deep Learning (DL) model in the second part of this study. An F-C NN is a type of Artificial Neural Network (ANN) where each neuron in a given layer is connected to every neuron in the next layer. This structure ensures that all neurons in one layer have direct connections to all neurons in the subsequent layer.

The input layer comprises neurons representing the input features, with each neuron corresponding to a specific feature in the input data. The hidden layers, positioned between the input and output layers, act as intermediate processing layers responsible for learning and extracting patterns from the input data.

Each neuron in a hidden layer takes inputs from all the neurons in the preceding layer and processes them using an activation function to generate its output. Similarly, the output layer, which produces the network's final predictions, is fully connected to the neurons in the previous layer. Both hidden and output layer neurons typically apply an activation function to the weighted sum of their inputs. This activation function introduces non-linearity into the network, enabling it to capture and learn complex patterns within the data. Khened et al., 2019[18].

In Chapter Three, which focuses on our methodology, all the steps undertaken are explained in detail.

1.2.2 Deep Q Network and Actor-Critic Algorithms

In this section, we're diving into one of the most popular techniques in Deep Reinforcement Learning named Deep Q Network. Understanding DQN is crucial because many cutting-edge DRL methods are built upon it. Back in 2013, researchers at Google's DeepMind introduced the DQN algorithm in their paper "Playing Atari with DRL. Mnih et al., n.d.2013.[14] .They detailed its architecture and clarified why it's so adept at achieving human-level accuracy in playing Atari games.

Deep Q Network is typically considered a Model-free approach in DRL. In Model-free RL, the algorithm learns directly from interacting with the environment, without explicitly building a model of the environment's dynamics. Instead, it focuses on learning an optimal policy, based solely on observed states and rewards. Model-based reinforcement learning involves learning or having access to a model of the environment's dynamics. This model represents how the environment behaves, including how states transition from one to another and the associated rewards. Ravichandiran, 2020.[17].

In RL, our aim is to discover the best strategy, known as the optimal policy, which yields the highest total rewards over episodes. To determine this policy, we start by Q function. Once we've obtained the Q function, we can derive the policy by choosing the action with the highest Q value for each state. So, we utilize DQN to estimate the Q value for each action within a provided input state. The desired Q value we aim for is the optimal Q value. we can compute the optimal Q value by Bellman equation Ravichandiran, 2020.[17]. (Equation 1-2 and 1-3).

Equation 1-2:

$$Q^*(s,a) = E_{s' \sim p}[R(s,a,s') + \gamma \max_{a'} Q^*(s',a')]$$

where $R(s,a,s')$ represents the immediate reward r that we obtain while performing an action a in state s and moving to the next state s' , so we can just denote $R(s,a,s')$ by r . (Equation 1-3).

Equation 1-3:

$$Q^*(s,a) = E_{s'\sim p}[r + \gamma \max_{a'} Q^*(s',a')]$$

Deep Q Network is typically used for discrete action spaces. It's particularly effective in scenarios where the action space is discrete. Our agent’s actions are also discreet, which is a collection of labels. For this reason, we did not use other Model -free algorithms such as Deep Deterministic Policy Gradient (DDPG). DDPG is an extension of Deep Q Network designed to handle continuous action spaces and unlike DQN which is more suitable for discrete action spaces Tian et al., 2020.[19]. We will examine this case in the methodology section.

Another intriguing technique, known as the A-C approach, is employed to discover the most advantageous strategy (optimal policy). The A-C method incorporates elements from both value-based and policy-based methodologies. Within the value-based approach, the optimal policy is derived by leveraging the Q function. Conversely, in policy-based methodology, the optimal policy is computed without relying on the Q function. The A-C technique stands as a highly acclaimed algorithm in the realm of DRL. Numerous contemporary DRL algorithms draw inspiration from Actor-Critic methodologies. The A-C methodology comprises two distinct networks, namely the Actor network and the Critic network, as implied by its name. The Actor network is responsible for determining the optimal policy, while the Critic network evaluates the policy generated by the actor network. Consequently, the Critic network can be envisioned as a feedback mechanism, assessing and directing the Actor network in its pursuit of the optimal policy, as depicted in Figure 8.

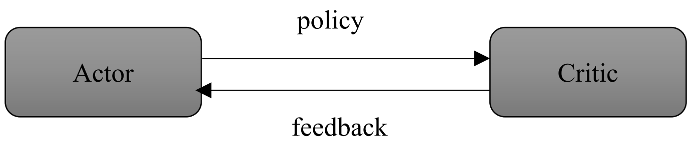


Figure 8: The Actor-Critic network

The Actor network, also referred to as the policy network, employs a policy gradient method to ascertain the optimal policy. Conversely, the Critic network, acting as the value network, estimates the state value. Consequently, the Critic network employs the state value to evaluate the action generated by the Actor network and provides feedback to the Actor Ravichandiran, 2020.[17]. The Actor-Critic architecture, including algorithms like DQN can be considered Model-free RL methods. Using Model-free mechanisms like A-C and Deep Q-networks (DQNs) can be advantageous in scenarios where the agent cannot perceive the entire environment directly Ravichandiran, 2020.[17].

The cardiac environment is highly complex and dynamic, involving various anatomical structures and physiological processes. Echocardiography images typically have a limited field of view, meaning that the entire heart or relevant structures might not be captured in a single frame. The agent, therefore, cannot perceive the entirety of the cardiac environment from just one image and it may be challenging for the agent to fully comprehend the entire cardiac environment due to the limitations of the imaging modality.

In such cases, using model-free mechanisms like A-C and DQN allows the agent to learn directly from its interactions with the environment without explicitly modelling the environment dynamics or having full observability. These mechanisms enable the agent to explore and exploit the available information to make decisions based on its learned knowledge and experiences. By leveraging DRL techniques, the agent can adapt and optimize its behaviour over time, even in environments with partial observability or complexity. This can be particularly useful in medical applications like echocardiography analysis, where the full understanding of the environment may be challenging or not feasible with conventional modelling approaches.

Combining A-C with DQN-like value function approximation can lead to more stable and efficient learning compared to using each method independently(Mnih et al., n.d.2013.[14].

1.3 Motivation

segmentation image of cardiac is a critical task in medical imaging, serving as a foundation for diagnosing and treating cardiovascular diseases. Accurate segmentation of structures such as the LV $_{Endo,}$ LV $_{Epi}$, and LA is essential for evaluating cardiac function, including assessing size, shape, and performance. However, existing methods often rely on manual or semi-automated segmentation, which is time-consuming and prone to variability due to operator dependency. These limitations can significantly impact the accuracy and efficiency of clinical diagnoses, especially when analyzing TTE images, which pose additional challenges due to external imaging constraints.

Traditional ML and DL approaches have achieved notable advancements in cardiac image segmentation. However, these methods typically rely on static, pre-labeled datasets, limiting their adaptability to new imaging scenarios and complex spatial-temporal patterns. Specifically, the lack of an explicit actor component in conventional A-C algorithms reduces their ability to accurately learn intricate cardiac features, resulting in suboptimal segmentation performance. Additionally, the complexity of ventricular boundaries in TTE images remains a significant challenge, necessitating innovative solutions to address these limitations.

This research is motivated by the need to overcome these challenges through the integration of advanced DRL methodologies. DRL, by enabling dynamic learning through interaction with the environment, offers significant advantages over static DL techniques. It allows the model to adapt to variable and complex patterns in cardiac imaging, providing a robust solution for segmenting and identifying cardiac structures, particularly in challenging TTE datasets. By combining DRL with a CNN for phase identification, this work addresses the critical gap in existing segmentation methods and enhances clinical decision-making by automating the segmentation and identification of cardiac structures with greater precision and reliability.

The proposed approach not only aims to improve the Actor-Critic algorithm for better representation and learning but also leverages the dynamic capabilities of the DRL framework to iteratively refine segmentation results. These objectives align with the goal of achieving precise, automated, and efficient segmentation of cardiac cycles in 2D echocardiography images, setting a new benchmark for medical image analysis.

1.4 Problem statement

Accurate segmentation and identification of cardiac structures in echocardiographic images are critical for assessing cardiac function and diagnosing cardiovascular diseases (Hesamian et al., 2019) However, existing methodologies face significant challenges:

A-C algorithms lack an explicit actor component within the DQN framework, which limits their ability to effectively learn complex spatial and temporal patterns in 2D cardiac imaging data (Mnih et al., n.d.2013). This limitation reduces the efficiency and adaptability of these methods in dynamic and intricate imaging contexts (Orr & Dutta, 2023).

Automated segmentation of the LV in echocardiograms, particularly in TTE, often relies on geometric approaches that require user intervention. This manual involvement introduces subjectivity and variability, adversely affecting segmentation accuracy. Moreover, the complexity of ventricular boundaries in TTE images poses additional challenges for existing ML techniques (Mortada et al., 2023).

TTE presents inherent challenges in accurately identifying cardiac structures and cycles, such as the endocardium, epicardium, and atrium, during both ES and ED phases. Due to the external imaging nature of TTE, image quality is often affected by noise and anatomical variations Liu et al., 2020[44]. Existing identification techniques, which predominantly rely on manual or semi-automated methods, are time-consuming, operator-dependent, and prone to variability, thus reducing the accuracy and efficiency of clinical diagnoses (Mortada et al., 2023).

Addressing these challenges requires innovative approaches that enhance the adaptability, accuracy, and efficiency of cardiac structure segmentation and identification in echocardiographic imaging.

1.5 Objectives

1. To increase efficiency and versatility of the A-C algorithm in capture and learn complex spatial and temporal patterns inherent in cardiac imaging data at the LV $_{Endo}$, LV $_{Epi}$, and LA in cardiac cycles (ED and ES) phases of 2D echocardiography images.
2. To design and develop DQN with A-C framework automated segmentation DRL algorithm for accurately delineating the Left Ventricle structures in echocardiogram images, with a specific focus on addressing the challenges associated with Transthoracic echocardiograms.
3. To design an identification DL algorithm capable of accurately delineating cardiac cycles (ED and ES) in echocardiogram images obtained through Transthoracic echocardiography.

1.6 Contribution

1. Enhancing the algorithm's precision in capturing actions and integrating a fully connected neural network as an actor in the A-C algorithm addresses the limitations of current A-C methods in cardiac image segmentation.
2. The DRL algorithm was trained iteratively on the dataset to accurately segment LV structures without manual intervention.
3. Effective DL algorithm to identify cardiac cycles, which adapted to the variations and complexities of TTE imaging data

1.7 Scope and limitation

The scope of this thesis encompasses the development and implementation of a novel framework for automatically segmenting and identifying the Left Ventricular LV $_{Endo}$, LV $_{Epi}$, and LA in both ED and ES phases of 2D echocardiography images. This research leverages advanced DL techniques, specifically DRL, to address the challenges associated with accurate and robust segmentation of cardiac structures in echocardiographic data. The thesis focuses on utilizing DRL methodologies, specifically the Deep Q-Network and Actor-Critic algorithms, to train an autonomous agent for segmenting cardiac structures in 2D echocardiography images. The DQN algorithm will be employed to approximate the optimal action, while the Actor-Critic architecture will provide a mechanism for states selection. The primary objective is to develop a segmentation model capable of accurately delineating the boundaries of the LV $_{Endo}$, LV $_{Epi}$, and LA across different cardiac phases. Quantitative metrics, including, DSC, HD, Jaccard index, and MAE used to assess the accuracy of the segmentation and identification results. The segmentation framework will be designed to operate effectively in both the ED and ES phases of the cardiac cycle. This ensures comprehensive coverage of cardiac motion and enables the assessment of dynamic changes in the left ventricular morphology throughout the cardiac cycle. The thesis will entail the training of the DQN and Actor-Critic models using a curated dataset of 2D echocardiography images annotated by expert cardiologists.

The efficacy of this thesis is profoundly contingent upon the presence of a diverse and suitably extensive dataset comprising 2D echocardiography images. This dataset must be augmented with meticulously annotated ground truth information pertaining to the Left Ventricular structures under investigation. The precision of the segmentation and identification procedures is significantly hinged upon the caliber and uniformity of the expert annotations encompassed within the dataset. Annotations characterized by inaccuracies or inconsistencies have the potential to introduce errors that may adversely affect the model's performance. The employment of DRL models necessitates substantial computational resources, both in terms of hardware and time. The availability of high-performance hardware components, notably Graphics Processing Units and an ample allocation of computational time, are essential prerequisites for the efficient training and deployment of the model.

1.8 Summary

In this chapter, we provide a foundational understanding of the concepts and challenges associated with cardiac image segmentation, particularly focusing on the Left Atrium LA and Left Ventricle LV, including their LV $_{Endo}$ and LV $_{Epi}$. It emphasizes the critical importance of accurately identifying and segmenting these cardiac structures for diagnosing and treating cardiovascular diseases. Traditional manual segmentation methods, though widely used, are highlighted as time-consuming, operator-dependent, and prone to variability, necessitating the development of automated solutions.

The chapter introduces the role of ML, DL, and DRL in addressing these challenges. we explain the advantages of DRL over conventional DL methods, particularly its ability to dynamically learn from complex spatial and temporal patterns through interaction with the environment. This adaptability is especially crucial for Transthoracic TTE, where image quality is often affected by external factors, making segmentation difficult.

A detailed overview of the echocardiography process and its clinical relevance is provided, with a specific focus on TTE imaging. The challenges of segmenting echocardiographic images, including low contrast, noise, and anatomical variations, are discussed. The chapter highlights the limitations of traditional methods and the potential of advanced techniques such as CNNs and DRL in overcoming these issues.

Additionally, in this chapter we outline the use of the CAMUS dataset, a clinically annotated standard dataset, which serves as the foundation for training and evaluating the proposed models. The dataset ensures robust benchmarking of segmentation results.

Chapter one concludes by introducing the proposed DRL framework, which integrates CNN for phase identification and A-C and DQN architectures for segmentation. It sets the stage for the methodology, objectives, and contributions discussed in subsequent chapters, emphasizing the framework's potential to significantly enhance the accuracy, efficiency, and automation of cardiac image segmentation.

CHAPTER 2

LITERATURE REVIEW

Our focus in this thesis is on the segmentation of 2D TTE Left Ventricular echocardiography image using Deep Reinforcement Learning method. Due to the significant advances in the field of Deep Learning and DRL compared to traditional segmentation methods, in this chapter, we review papers that have used DL to segment 2D Left Ventricular echocardiography images. However, at the beginning of the chapter, we also did a brief review of methods that are not based on DL and DRL which are based on traditional methods. The review section of the research done in the DL methods is divided into two parts. In the first part, the papers that were done before the publication of the data set used in this thesis are mentioned, and in the second part, we have reviewed the papers that are exactly done on the data set used in this thesis with DL methods for segmentation. (Our used data set published in September 2019). It is important to note that the use of Deep Reinforcement Learning method in segmenting 2D echocardiography images has not been done before writing this thesis, therefore, in the review of papers related to DRL, we have reviewed papers that segment medical images in other types of images such as MRI. Furthermore, we discuss the challenges related to DL and DRL methods in medical image segmentation.

2.1 Traditional Approaches

Numerous examinations of segmentation techniques for echocardiography, specifically focusing on 2D and 3D images, have been suggested (Noble &

Boukerroui, 2006.) (Bernard et al., 2016).The majority of documented approaches have concentrated on segmenting the LV $_{Endo}$ border. Out of these reviews, the study conducted by (Bernard et al., 2016).

In 2016 stands out as it assessed various techniques using the same dataset, ensuring a balanced comparison. In this research, the authors presented the outcomes achieved by nine distinct methods. These methods can be classified into two primary groups: those with minimal prior assumptions and those with significant prior assumptions. The initial category comprises modest assumptions, such as spatial, intensity, motion, or anatomical data. This encompasses techniques such as image-based methods with multi-scale quadrature filter, Kalman filter in motion-based approaches, and a graph cut in graph-based method. The second category employs methods with robust priors, including a Hough Forest shape prior, an active appearance model, an atlas-based technique, and a random forest ML algorithm, (Keraudren et al., 2014); (Milletari et al., 2014).

Traditional approaches for LV echocardiography images segmentation often face several challenges due to the complexity of the images and the variability in anatomical structures and imaging conditions. Traditional methods may struggle to accurately delineate the boundaries of the LV due to variations in shape, size, and intensity of the LV cavity and surrounding tissues. Many traditional approaches rely on handcrafted features or heuristics to distinguish between LV tissue and surrounding structures. These features may not fully capture the complexity of the images, leading to suboptimal segmentation results. Echocardiography images are often affected by noise, speckle, and artifacts, which can degrade the performance of traditional segmentation algorithms. These methods do not effectively handle noise and artifacts, leading to inaccurate segmentation results. Traditional methods require manual intervention or user-defined parameters, making them time-consuming and less suitable for large-scale or real-time applications. (Zhang et al., 2001), (Bazi et al., 2007.), (Miller et al., 2013),(Wang et al., 2014).

2.2 Deep Learning-Based Segmentation Techniques in 2D Echocardiography images

Medical image segmentation seeks to identify the precise outline of an anatomical or pathological structure depicted in a medical image. In its broadest sense, image segmentation involves attributing semantic labels to individual pixels, thereby achieving object segmentation by grouping pixels sharing the same label(Zhou et al., 2020).

Cardiac ultrasound imaging, also called echocardiography, is a very important tool for physicians to check how well the heart is working. It's often the first test done because it's portable, doesn't cost much, and shows results immediately. Though there have been efforts to use computer programs to help analyze ultrasound images, they aren't always accurate because ultrasound images can be tricky to read due to problems like not enough clear signal, different kinds of noise, not much contrast between parts of the image, missing edges, and shadows from things like bones and muscles.(Noble & Boukerroui, 2006).

Recently, several DL methods have been suggested to enhance how accurately and quickly we can outline structures in heart ultrasound images. Most of these methods concentrate on segmentation of LV, but only a few deal with finding and outlining the LA.

The high resolution of echocardiography poses a significant challenge for voxel-based tissue classification. To tackle this issue, a fusion of DL and deformable models has been employed for LV segmentation in 2D images. (Carneiro et al., 2010), (Carneiro et al., 2012), (Nascimento & Carneiro, 2017), (Nascimento & Carneiro, 2014),(Nascimento & Carneiro, 2019) (Gopalkrishna Veni; et al,2018).(Carneiro & Nascimento, 2013) Instead of relying on manually crafted features, trained DNNs were employed to enhance both accuracy and resilience by extracting features. Several studies have utilized DL within a two-step process. Initially, they localize the ROI by employing rigid transformation of a bounding box, followed by segmenting the target structure within the identified ROI. The utilization of this dual-stage approach decreases the search area for segmentation and enhances the overall robustness of the segmentation framework. In (Carneiro et al., 2010) and(Carneiro et al., 2012). Initially, this DL framework was employed to segment the LV in apical long-axis echocardiograms. The approach utilizes Deep Belief Networks (DBN)(Klein et al., 2018) for forecasting both the rigid transformation parameters to localize and the deformable model parameters for segmentation. The outcomes illustrated the resilience of DBN-driven feature extraction against fluctuations in image appearance. In 2012, (Carneiro et al., 2012) devised a two-step DL approach to segment the LV endocardium in 2D echocardiographic images, specifically focusing on acquisitions limited to four-chamber views. Utilizing a maximum, a posteriori framework, the authors structured the LV segmentation issue into two sequential stages: first: Automatically identifying multiple areas within the tested image that encompasses the complete LV $_{Endo}$. Second: Automatically delineating the contour of the LV $_{Endo}$ from the regions selected beforehand. These two stages utilized DBN. The approach was trained on 400 images sourced from 12 distinct patient sequences exhibiting diverse pathologies and validated on 50 images from 2 sequences of healthy subjects. They achieved an approximate average Hausdorff distance of 18 mm and an average mean absolute distance of 8 mm for the LV $_{Endo}$.

(Nascimento & Carneiro, 2017) decreased the training and inference complexity of the DBN-based framework even further by incorporating sparse manifold learning in the rigid detection phase.

In 2017 (Smistad et al., 2017) demonstrated that the U-Net CNN technique could effectively undergo training for the segmentation of the LV in 2D ultrasound images. Nevertheless, because of insufficient training data, the network underwent training using the output generated by a cutting-edge deformable model segmentation technique. (Smistad & Lindseth,2014). The findings on a test set that underwent manual segmentation indicated that both the network and the deformable model achieved equivalent accuracy, yielding a Dice score of 0.87.

To further minimize computational complexity, certain studies conduct segmentation in a single step without employing the two-stage method. (Nascimento & Carneiro, n.d,2017) utilized sparse manifold learning in segmentation, revealing decreased training and search complexity compared to their prior method, while retaining the same segmentation accuracy level. (Gopalkrishna Veni; et al,2018) employed a Fully Convolutional Network (FCN) to generate initial coarse segmentation masks, subsequently refining them using a level-set-based technique. A FCN is a type of neural network commonly used for semantic segmentation tasks. Unlike traditional CNNs, FCNs retain spatial information throughout the network by replacing fully connected layers with convolutional layers.(Shelhamer et al., 2017).

Cardiac ultrasound information is commonly captured in a series of consecutive images over time. Various methods strive to utilize consistency among adjacent frames to enhance the precision and resilience of LV segmentation. (Carneiro & Nascimento, 2013) introduced a dynamic modeling approach utilizing a Sequential Monte Carlo (SMC) or particle filtering framework, incorporating a transition model. This model ensures that the segmentation of the current cardiac phase is influenced by preceding phases. The outcomes indicate that this method outperforms the prior approach (Carneiro et al., 2010), which neglects temporal information. In a recent study, (Jafari et al., 2018)merged U-net, long-short term memory (LSTM), and inter-frame optical flow to incorporate several frames in segmenting a single target frame, illustrating enhancements in overall segmentation accuracy. Additionally, the approach exhibited greater resilience to fluctuations in image quality across a sequence compared to using U-net with individual frames. U-Net is a convolutional neural network architecture widely utilized for biomedical image segmentation tasks. It features a contracting path to capture contextual information and a symmetric expanding path to achieve accurate localization. Its design facilitates precise segmentation even with limited training data.(Ronneberger et al., 2015). Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) architecture designed to capture long-term dependencies and handle sequential data by maintaining a memory cell that can retain information over time. It includes gates to control the flow of information, enabling effective learning and processing of sequential patterns, making it particularly useful for tasks like natural language processing and time series prediction(Hesamian et al., 2019). Recurrent Neural Network (RNN) is a type of ANN designed to process sequential data by maintaining internal memory. It operates on sequences, processing each element while retaining information about previous elements, making it suitable for tasks such as speech recognition, language modeling, and time series prediction. (Hesamian et al., 2019). The effectiveness of CNNs in segmentation has inspired the assembly and labeling of vast datasets. Table 2 shows the reviewed papers based on Deep Learning Methods.

Table 2: Comprehensive overview of the reviewed studies

Application	Selected works	Method	Structure	Imaging modality
2D LV	(Carneiro et al., 2010), (Carneiro et al., 2012)	DBN with tow-step approach: localization and fine segmentation	LV	2D A2C, A4C
	(Nascimento & Carneiro, 2017)	Deep belief networks (DBN) and sparse manifold learning for the localization step	LV	2D A2C, A4C
	(Nascimento & Carneiro, 2014)	DBN and sparse manifold learning for one-step segmentation	LV	2D A2C, A4C
	(Veni et al. 2018)	FCN (U-net) followed by level-set based deformable model	LV	2D A4C
	(Carneiro & Nascimento, n.d., 2013)	DBN and particle filtering for dynamic modeling	LV	2D A2C, A4C
	(Jafari et al., 2018)	U-Net and LSTM with additional optical flow input	LV	2D A4C
	(Smistad et al., 2017)	Real time CNN view-classification and segmentation	LV	2D A2C, A4C
A[X]C is short for Apical [X]-chamber view.				

In the second part of the literature review, we consider papers that report the application of DL to segment echocardiography images on the CAMUS data set.

(Leclerc et al., 2019)Evaluated various DL techniques for segmenting the Left Ventricular endocardium and myocardium, showing that encoder-decoder architectures outperformed existing non-DL methods. (Moradi et al., 2019) employed the U-Net model to enhance the segmentation of the LV through modifications to the U-Net architecture, known as MFP-U-Net. The updated CNN included additional convolutional layers to generate feature maps and enhance the segmentation performance of the LV. (Kim et al., 2021) targeted the segmentation of both the LV endocardium and myocardium. Their algorithms were tailored based on porcine images but evaluated on human images. While achieving satisfactory results, a notable constraint was that the developed method was validated on open-chest pigs, which typically offer superior image quality compared to human echocardiographic images.(Girum et al., 2021) integrated a customized U-Net structure with an FCN encoder to enhance feature extraction capabilities and enable the system to learn from its errors. Liu et al., 2020[44]. employed a bilateral segmentation network for deep feature extraction, coupled with a pyramid local attention mechanism to amplify features within confined and limited surrounding contexts. (Alam et al,2022) introduced a dual pipeline approach for segmenting ED and ES frames, employing the DeepResU-Net architecture. In contrast to other approaches, (Saeed & Yaqub, 2022). utilized DeepLapV3, SimCLR, BOYL, and U-Net to delineate the left ventricle, addressing the shortage of annotated data.(Zhuang et al., 2021) employed the YOLOv3 algorithm, an object detection technique, to identify three key points within the ventricular chamber and subsequently segment the ventricles. Finally, (Mortada et al., 2023) used YOLOv7 and U-Net for segmentation of LA, LV_{Epi} and LV_{Endo}.

Even though the methods were innovative and demonstrated high performance, most of these investigations except (Mortada et al., 2023) concentrated on segmenting the ventricle itself, neglecting certain anatomical structures within it and also LA. In (Mortada et al., 2023) Although they have emphasized on the segmentation of the LV structures, the segmentation of the LV structures in End-Systolic and End-Diastolic has not been done. Furthermore, it is important to note that in the studies reviewed in Table 3, different structures of the Left Ventricle have been individually analysed using the methods proposed in those studies. However, in this thesis, using a DNN mechanism explained in Chapter Three, we first identify the LV in ED and ES phases, and then utilize the DQN mechanism for segmentation.

Table 3 shows the reviewed papers based on Deep learning methods on CAMUs data set.

Table 3: Reviewed papers using DL methods on CAMUs data set

Ref.	Dataset	Dataset Split	Classes	Method
(Leclerc et al. 2019)	CAMUS	10-fold cross-validation	LV_{Endo} and LV_{Epi}	U-Net
(Moradi et al., 2019)	(1) CAMUS (2) Custom dataset	5-fold cross-validation	LV	MFP-U-Net
(Kim et al., 2021)	(1) custom dataset (2) CAMUS	n.a.(Not applicable)	LV_{Endo} and LV_{Epi}	SegAN
(Girum et al., 2021)	CAMUS	Static data division	LA, LV_{Endo} and LV_{Epi}	LFB-Net
(Liu et al., 2020)	(1) EchoNet-Dynamic (2) CAMUS	Static data divison	LV_{Endo} and LV_{Epi}	PLANet
(Alam et al,2022)	Custom dataset	Static data division	LV	Deep Res-U-Net
(Saeed & Yaqub, n.d.2022)	(1) EchoNet- Dynamic (2) CAMUS	Static data division	LV	DeepLabV3
(Zhuang et al., 2021)	custom dataset	n.a.	LV_{Endo}	YOLOV3 (Darknet53)
(Mortada et al., 2023)	CAMUS	Static data division	LA, LV_{Endo} and LV_{Epi}	YOLOv7 and U-Net

2.2.1 Challenges of Deep Learning-Based Segmentation Techniques

Advanced Neural Network architecture and enhanced computational hardware have enabled Deep Learning techniques to achieve comparable or superior performance to previous state-of-the-art methods across diverse cardiac segmentation applications.

Considering this swift progression, one might question whether DL methods can be promptly implemented in real-world scenarios to alleviate clinicians' workload. However, we propose that there is still a significant journey ahead.

Using DRL can overcome the challenges in DL methods. In DRL method, the agent is dynamically and continuously interacting with its environment. In each episode, the agent uses its experiences in previous episodes and improves its performance during training phase (Ravichandiran, 2020). Deep learning methods lack this feature. As a result, DL may not have the necessary precision in extracting important features, and it will not be possible to modify them in the training phase. Deep Learning systems pose challenges in interpretation and transparency, unlike symbolic AI systems. After training, these systems function as "black boxes," yielding predictions that lack direct interpretability. Consequently, this characteristic renders the model unpredictable, complicating model verification and ultimately undermining trustworthiness. (Yin et al., 2023).

The limited availability of annotated data poses a major obstacle for DL methodologies (Zhou et al., 2020). To overcome this problem, in our thesis we use data from 450 patients at a hospital in France, taken with GE Vivid E95 ultrasound scanners and GE

M5S probes. Cardiac structures were manually labeled during End Diastole and End Systole using at least one full cardiac cycle for each patient in each view.

Overfitting can make the model unpredictable and untrustworthy because it may produce unreliable predictions when presented with new, unseen data. Additionally, overfitted models are difficult to verify and may not perform well in real-world applications due to their lack of generalization. Overfitting happens when a model focuses on learning noise and random variations in the training data rather than identifying the true underlying patterns. As a result, the model achieves high accuracy on the training data but struggles to perform well on new, unseen data. Indicators of overfitting include excellent performance on the training set but noticeably lower accuracy on the validation or test set.(Hesamian et al., 2019).

To overcome the Overfitting problem, we used 10-fold cross-validation technique(Berrar, 2018) . In 10-fold cross-validation, we split our dataset into 10 equal parts called folds. We train our model on 9 of these folds and test it on the remaining one. We repeat this process 10 times, each time using a different fold for testing. This helps us evaluate our model's performance more accurately by using all data for both training and testing. (Figure 9).

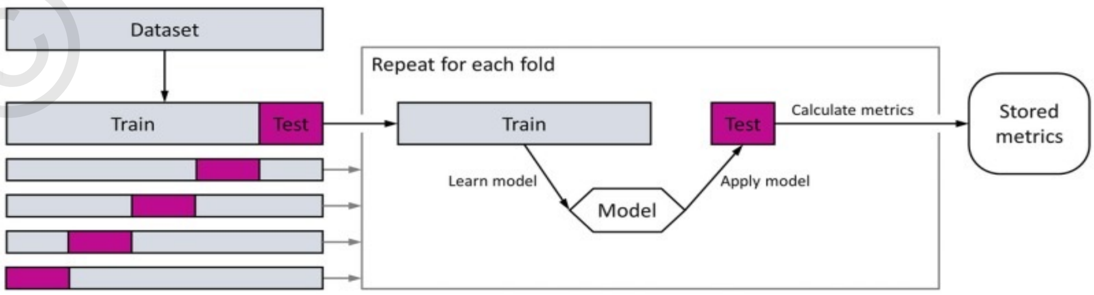


Figure 9: 10-fold cross-validation technique

2.3 Deep Reinforcement Learning-Based Segmentation Techniques and their challenges

Insufficient labeled data poses a significant obstacle in medical image segmentation. To address this challenge and enhance the diversity of available training samples, augmentation techniques are frequently employed in existing methods(D. Yang et al., 2020;), (Ravishankar et al., 2017).Nevertheless, data augmentation has been utilized as a pre-processing step, but its optimality is not assured. Data augmentation helps to improve model performance by reducing overfitting and enhancing generalization to unseen data. Essentially, it artificially expands the dataset to provide more varied examples for the model to. In order to achieve optimal augmentation within an end-to-end segmentation framework, (Qin et al., 2020)suggest training both augmentation and segmentation modules concurrently. They utilize errors generated during the segmentation process as feedback to adapt the augmentation module accordingly. Table 4 shows a summary of reviewed papers related to segmentation in DRL.

Table 4: Summary of papers in segmentation task using DRL

Task	Ref	Modality	Remark
Image segmentation	(H. Yang et al., 2020) (Qin et al., 2020)	3D ultrasound Kidney Tumor Segmentation	DQN-driven catheter segmentation Automatic data augmentation via DRL

One of the challenges in DRL is defining the reward mechanism. Defining a reward function for a given task is often challenging due to the need for knowledge spanning various domains, which might not always be accessible. A reward function with significant delays complicates the training process, while assigning rewards to individual actions demands meticulous manual design. Additionally, obtaining intermediate rewards at each time step isn't consistently feasible, resulting in a lack of feedback on performance improvement within an episode and the identification of optimal action sequences leading to maximum final rewards. The reward mechanism designed in this thesis is obtained according to the steps taken by the agent in each episode. In each episode, the agent will have steps equal to the total number of pixels in the image. In each episode, the agent improves its learning according to the previous episodes. As a result, the number of steps will gradually decrease according to different episodes. In DRL methods, a final and significant reward is given to the agent. In fact, the goal of the agent is to achieve the cumulative reward.

2.4 Summary

In Chapter Two we reviewed the evolution of segmentation techniques for 2D echocardiographic images, focusing on the Left Ventricle (LV) and emphasizing the transition from traditional methods to modern DL and DRL approaches. Traditional methods, while foundational, face challenges due to their reliance on handcrafted features, sensitivity to noise, and limited adaptability to anatomical and imaging variations. These limitations underscore the need for more robust and automated solutions.

DL-based methods have significantly advanced segmentation accuracy, leveraging architectures like U-Net and its variants, including MFP-U-Net and PLANet. These methods improved feature extraction and segmentation robustness but often remained limited to specific datasets and failed to address segmentation across different cardiac phases, such as ED and ES.

The potential of DRL in medical image segmentation was also explored. DRL's dynamic learning capability through interaction with the environment offers significant advantages over static DL methods. It addresses key challenges like overfitting and improves adaptability in complex imaging scenarios. However, defining reward mechanisms and handling limited annotated datasets remain significant challenges.

This chapter establishes the foundation for the proposed approach in this thesis, which integrates CNN for phase identification and DRL frameworks (DQN and Actor-Critic). By addressing gaps in the existing literature, the proposed method aims to enhance segmentation accuracy and adaptability, providing a comprehensive solution for LV segmentation across ED and ES phases in echocardiographic imaging.

CHAPTER 3

METHODOLOGY

In this chapter, steps related to data Pre-processing on CAMUS data set which is a publicly available data set, our DL method for identification of ED and ES which are the cardiac cycle and our DQN and A-C methods used for segmentation of LV $_{Endo}$, LV $_{Epi}$ are fully explained. At the end of this chapter, we will examine the research method in terms of being quantitative or qualitative.

3.1 Data Set and Preprocessing

The analysis of 2D echocardiographic images is of utmost importance in clinical practice as it serves multiple purposes: measuring cardiac morphology and function, as well as aiding in the diagnostic process. This analysis relies on the interpretation of clinical indicators, which are derived from low-level image processing techniques like segmentation and tracking. A specific example is the extraction of the Ejection Fraction (EF) of the Left Ventricle, which necessitates precise delineation of the Left Ventricular Endocardium during both ED and ES. Currently, in routine clinical practice, semi-automatic or manual annotation methods are still prevalent due to the limitations in accuracy and reproducibility associated with fully automated cardiac segmentation methods. Consequently, these tasks are time-consuming and susceptible to variations in observations made by different observers, both within and across individuals. (Armstrong et al., 2015).

The CAMUS dataset utilized in this thesis consists of clinical examinations from 450 patients, collected at the University Hospital of St. Etienne in France. The dataset was acquired in compliance with the regulations established by the local ethical committee, ensuring complete anonymization of the data. To preserve clinical realism, no prerequisites or data selection criteria were applied.

The dataset consists of a training set with data from 400 patients and corresponding manual references provided by a clinical expert. Additionally, there is a testing set containing data from 50 new patients. The raw input images are provided in the raw/mhd file format. The images were acquired using GE Vivid E95 ultrasound scanners with a GE M5S probe. The imaging protocol followed clinical routine, and standard cardiac views (2D apical four-chamber and two-chamber views) were exported from EchoPAC analysis software. It is important to mention that, no new data collection was conducted as part of this study.

Manual annotation of cardiac structures at ED and ES phases was carried out using at least one complete cardiac cycle for each patient and for each view. The manual contours were delineated on the apical four-chamber and two-chamber views at ED and ES, following the guidelines provided by the American Society of Echocardiography and the European Association of Cardiovascular Imaging.

Specific contouring protocols were followed for different structures. For LV $_{Endo}$, conventions were used for the LV wall, mitral valve plane, trabeculations, papillary muscles, and apex. For LV $_{Epi}$, there were no specific recommendations, so the epicardium was outlined as the interface between the pericardium and myocardium in specific segments. Regarding LA segmentation, recommendations for assessing the full LA area were not applicable to this dataset, so the contouring protocol involved starting the LA contour from the points where the valve leaflets hinge and having it pass along the LA inner border(Leclerc et al., 2019). It is worth mentioning that the download link for the dataset, which is publicly available, is provided in Section 1.1.2 of Chapter 1 and in the footnote for downloading. Figure 10 shows one sample of a Dataset image with its label.

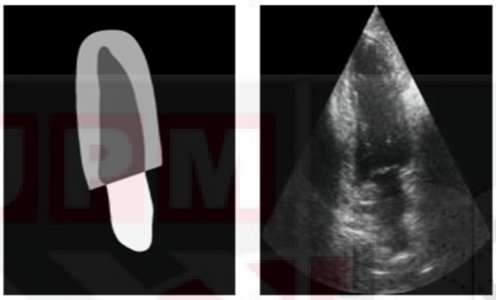


Figure 10: Sample of Dataset image and it's label

3.1.1 Pre-processing

In this thesis, two stages of Pre-processing have been performed on the dataset images. In the following, we will examine them. Both these two steps have been taken to create conditions that the agent can perform better in the environment.

The first stage of Pre-processing is that considering that the images in the data set were of different sizes, we normalize all the images to 500 * 350-pixel sizes. By examining the images of the data set, we came to the conclusion that by changing the size to the said size, no important information from the image will be lost.

The second stage of image Pre-processing is to make all the images of the data set clearer and actually increase the intensity in all the images of the data set.in fact we do enhancing contrast using histogram equalization which is a technique used to improve the visual quality of an image by redistributing its pixel intensities across the entire available range. The goal is to make the image look more visually appealing and easier to analyze by stretching out the range of pixel values, thereby increasing the difference between dark and bright regions.

The result of applying histogram equalization is an image with improved contrast, making the details more distinguishable. Dark regions in the image will be made darker, and bright regions will become brighter .The action mechanism of our agent in this thesis is pixel by pixel based on the neighborhood matrix of the three surrounding pixels in the target pixel of LV $_{Endo}$ and LV$_{Epi}$ in both ED and ES imagesand the use of histogram equalization in Pre-processing will help the agent to segment more accurately. This technique is particularly useful for images with low contrast or those that have a significant portion of their intensity levels clustered in a specific range. Figure 11 shows the effect of using the histogram equalization on a sample dataset image . The left image is the original image of the Dataset, and the right image is generated after using histogram equalization.

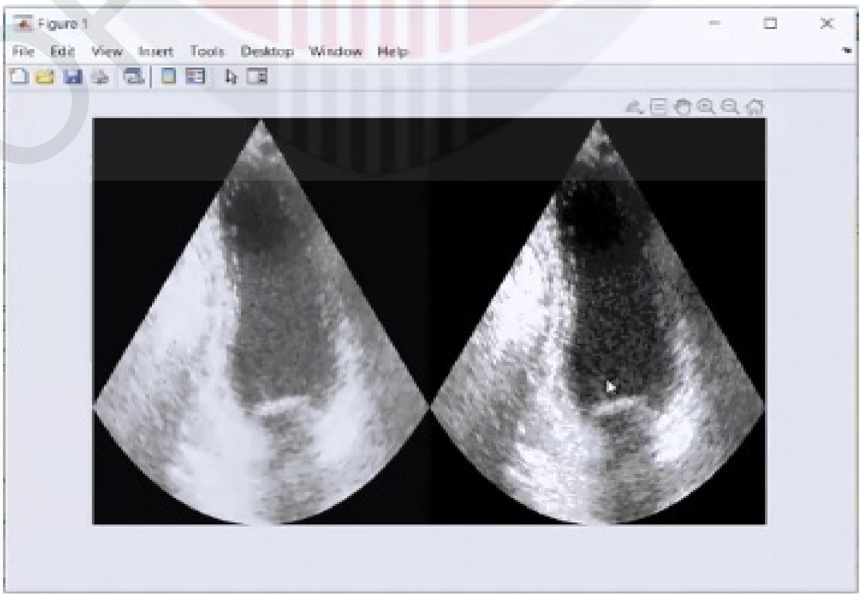


Figure 11: Effect of using the histogram equalization on a sample dataset image

we specify 4 classes in the Dataset images, class one is related to the background of the image (margins around the Region of Interest), As we have specified in Figure 12, the four image classes are the black part around the ROI, the inner and upper part of the ROI which is marked with green color (Left Ventricle Endocardium), the halo part around it which is marked with red color (Left Ventricle Epicardium) and the bottom part which is marked with blue color (Left Atrium).

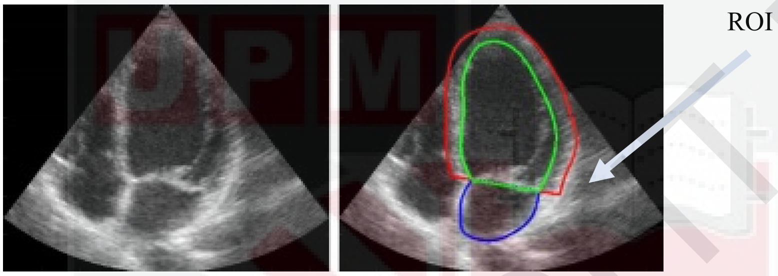


Figure 12: 4 Classes in the data set images

3.1.2 Dataset Limitations

Segmenting echocardiographic images presents several well-documented challenges, including: (i) poor contrast between the myocardium and the blood pool, (ii) inconsistencies in brightness across the image, (iii) variations in speckle patterns caused by the orientation of the cardiac probe, (iv) the presence of trabeculae and papillary muscles with intensities closely resembling the myocardium, (v) significant variability in tissue echogenicity between individuals, and (vi) differences in the shape, intensity, and motion of cardiac structures across patients and various pathological conditions.

The lack of large, publicly available datasets has hindered comprehensive evaluations of the potential of DL methods in estimating clinical indices. Although these techniques have been successfully implemented in other imaging modalities, only one notable challenge has specifically addressed cardiac ultrasound image segmentation. However, this challenge, conducted in 2014, did not incorporate CNNs or DRL, as these methods had not yet become widely adopted in the field of medical imaging.

The scarcity of well-annotated echocardiographic datasets can be attributed to the difficulties in exporting data from clinical ultrasound equipment and obtaining a large volume of carefully annotated images by cardiologists, given the nature of echocardiography as mentioned earlier. In addition to CAMUS data set, which pertains to 2D images Currently, only one echocardiographic dataset has undergone broad validation. This dataset was released in conjunction with the Challenge on Endocardial 3D Ultrasound Segmentation (CETUS[2]) during the MICCAI 2014 conference (Leclerc et al., 2019).

The CETUS dataset comprises 45 3D echocardiographic sequences, with 15 for training and 30 for testing. These sequences are equally distributed among three different subgroups: healthy subjects, patients with previous myocardial infarction (examined at least 3 months after the event), and patients with dilated cardiomyopathy. Each data entry in the dataset includes two reference meshes of the Left Ventricular Endocardium (one at ED and one at ES). These references represent the mean shape derived from annotations by three experienced cardiologists (Leclerc et al., 2019).

[2] https://www.creatis.insa-lyon.fr/Challenge/CETUS/databases.html

3.2 Architecture Model

Deep Reinforcement Learning was chosen over traditional Deep Learning methods in this thesis due to its suitability for addressing the specific challenges associated with the segmentation of cardiac structures in 2D echocardiographic images. Unlike static DL approaches, DRL offers dynamic learning capabilities, allowing the model to interact with its environment and adapt to the complex spatial and temporal patterns inherent in echocardiographic data. This adaptability is critical for dealing with the variability in transthoracic echocardiography (TTE) images caused by factors such as probe orientation, patient-specific anatomical differences, and noise.

Furthermore, DRL is designed for sequential decision-making tasks, making it well-suited for region-based segmentation processes. By leveraging an Actor-Critic architecture, the DRL framework can optimize cumulative rewards, ensuring precise and efficient segmentation of structures like the Left Ventricular Endocardium, Epicardium, and Left Atrium during both End-Diastolic and End-Systolic phases. The reward mechanism in DRL provides the flexibility to incorporate complex feedback, enabling the agent to refine its actions and achieve accurate boundary delineations. This capability surpasses traditional DL methods, which may lack the adaptability to handle such nuanced objectives.

Another key advantage of DRL is its ability to generalize beyond the training dataset. Given the limited availability of labelled echocardiographic datasets and the variability between patients, DRL's off-policy learning capability ensures robust performance even under unseen conditions. This feature is particularly valuable in medical imaging, where achieving consistency across diverse clinical scenarios is essential.

The model design process for this thesis consists of two parts. In the first part, using a DL model, we initially identify the cardiac cycle structures, which include ED and ES. Then the architecture of the implementation for segmentation of LV structures which is based on Deep Reinforcement Learning methods named Deep Q Network with Actor-Critic (Ravichandiran, 2020) . In chapter one, we briefly explained these two methods. For a better understanding of these methods, we will examine these two methods with their complete details.

3.2.1 DL model for identification of cardiac cycles

For the part that identifies and separates ED and ES images, we used a DL module, which is responsible for recognizing ED and ES phases. This module is placed at the beginning of the process, categorizing images into ED and ES phases before passing the data to the Actor-Critic network.

For identifying ED and ES phases, we employed the Convolutional Neural Network (CNN) architecture due to its superior ability to extract image features. This network can identify complex patterns in cardiac images and assist in phase recognition.

The structure of the model is as follows:

- Inputs: The input consists of echocardiographic images prepared during the pre-processing stage.
- Convolutional Layers: These layers extract various features from the images, such as the shape and size of cardiac chambers, wall thickness, and the positions of cardiac structures.
- Fully Connected Layers: These layers combine the extracted features and perform the final classification.

- Output Layer: A two-node output layer is used, representing the two phases, ED and ES. The Softmax activation function is employed to determine the probability of the image belonging to each phase.

For training the model, we used the Categorical Cross-Entropy loss function, as this is a binary (two-class) classification problem. Optimization was performed using Adam, which is highly effective for faster convergence in convolutional neural networks. Based on the data size and computational power, we selected 100 epochs and a batch size of 64.

With accurate identification of ED and ES phases, the segmentation model can perform better, and more precise operations based on the specific features of each phase. By recognizing the phases, the model can overcome ambiguities arising from the similarities between ED and ES images, providing more accurate results. After this step, the segmentation of ED and ES images will be performed as described in the next section.

The architecture used in the phase identification process is illustrated in the figure 13.

Input Layer: (Image 500x350 pixels)

↓

Convolutional Layer 1: 32 filters, 3x3 kernel, ReLU activation

↓

Max Pooling Layer 1: 2x2 pool size

↓

Convolutional Layer 2: 64 filters, 3x3 kernel, ReLU activation

↓

Max Pooling Layer 2: 2x2 pool size

↓

Fully Connected Layer 1: 128 neurons, ReLU activation

↓

Fully Connected Layer 2: 64 neurons, ReLU activation

↓

Output Layer: 2 neurons (ED or ES), Softmax activation

Figure 13: Neural Network Diagram for Phase Identification

3.2.2 Deep Q Network and Actor-Critic

The Deep Q-Network algorithm is a Reinforcement Learning method that falls under the category of model-free, online, and off-policy approaches. Unlike model-based methods, which require an explicit model of the environment, DQN learns directly from interactions with the environment without assuming knowledge of its dynamics. Being online means that it updates its policy continuously as it receives new data, allowing for real-time learning and adaptation. Moreover, being off policy enables

DQN to learn from past experiences, even those not following the current policy, enhancing sample efficiency and robustness. These characteristics make DQN advantageous in scenarios where obtaining a model of the environment is challenging or impractical, and where continuous learning and the ability to leverage past experiences are crucial for effective decision-making and adaptation. A DQN agent is a value-based reinforcement learning (RL) model that employs a critic to estimate the expected cumulative long-term reward, discounted over time, while adhering to the optimal policy. As an extension of Q-learning, DQN incorporates both a target critic and an experience replay buffer to enhance training stability and performance. (Mnih et al.2013).

The DQN algorithm employed in our thesis operates without needing a predefined model of the environment, making it adaptable to diverse scenarios and data variations. DQN's online nature allows it to update its policy continuously, ensuring real-time learning and adaptation to new data, which is critical in dynamic environments like cardiac cycles in 2D echocardiography. By being off-policy, DQN can utilize past experiences effectively, even if they deviate from the current policy, thereby enhancing sample efficiency and robustness of the segmentation and identification process. DQN's ability to learn directly from interactions with the environment without needing an explicit model makes it advantageous in scenarios like echocardiography, where obtaining a comprehensive model of the complex dynamics is challenging. The characteristics of DQN enable effective decision-making and adaptation in real-time medical imaging tasks, ensuring accurate segmentation and identification of cardiac structures like the Left Ventricular Endocardium, Epicardium, and Atrium in 2D echocardiography at both End-Diastolic and End-Systolic phases.

As mentioned above DQN is a derivative of Q-learning, including a target critic and an experience buffer. In order to better understand why we have used the DQN method in our thesis in comparison with Q-learning, in the following we will briefly review the Q-learning method and explain the difference between Q-learning method and DQN method.

Q-Learning algorithm is a value-based approach based on Q-Table. Value-based approaches in RL emphasize the importance of estimating the value of states or state-action pairs to guide the agent's decision-making process towards maximizing long-term rewards. The Q-learning algorithm is model-free, off-policy Reinforcement Learning, which finds appropriate action according to the agent's current state. Based on the agent's position within the environment, it decides what the next action will be. The Q-Table determines the highest potential future reward for each action within every state. Utilizing this data, we can select the action that promises the greatest reward. We don't adhere to a static method for calculating Q values. Rather, we enhance the Q-table through an iterative process, known as training or learning. We update the Q value with an update formula that is called the Bellman Equation (Equation 1-1 at chapter 1). In fact, one of the most well-known value functions is the Q-function (also known as the action-value function), which estimates the expected cumulative reward of taking a particular action in a given state and then following a specific policy thereafter. The Q-function is typically represented as $Q(s, a)$, where: s is the state, a is the action, $Q(s, a)$ represents the expected cumulative reward obtained by taking action a in state s and following the current policy thereafter.

The formula for updating the Q-function varies depending on the algorithm being used. For example, in Q-learning, one common update rule is the Bellman Equation (Equation 3-1) (Ravichandiran, 2020), which is:

Equation 3-1:

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma max_{a'} Q(s',a') - Q(s,a))$$

Where: $Q(s,a)$ is the Q-value for state-action pair (s, a), α is the learning rate, r is the immediate reward obtained after taking action a in state s, γ is the discount factor, s' is the next state after taking action a in state s, a' is the next action chosen in state s', $max_{a'} Q(s',a')$ represents the maximum Q-value of all possible actions in the next state s'. The learning rate (α) in the Bellman equation represents the proportion by which the Q-value is updated towards the newly estimated value. It determines the rate at which the agent incorporates new information into its value function during learning.

DQN extends the principles of Q-learning by replacing the traditional Q-table with a Neural Network. This network receives a state as input and approximates the Q-values corresponding to all possible actions for that state. The motivation for this approach lies in the scalability limitations of the classic Q-table. While a Q-table may suffice for simple environments, it becomes infeasible in complex scenarios, such as 2D echocardiography images, where the number of states and actions increases significantly. To address this, we use a Deep Neural Network that processes the input state and efficiently predicts Q-values for all available actions. The action corresponding to the highest Q-value is then selected. While the learning process remains similar to the iterative update approach, instead of updating a Q-table, the neural network's weights are adjusted to improve its output over time. (Ravichandiran, 2020). Figure 1۴ shows the difference between Q-learning and DQN.

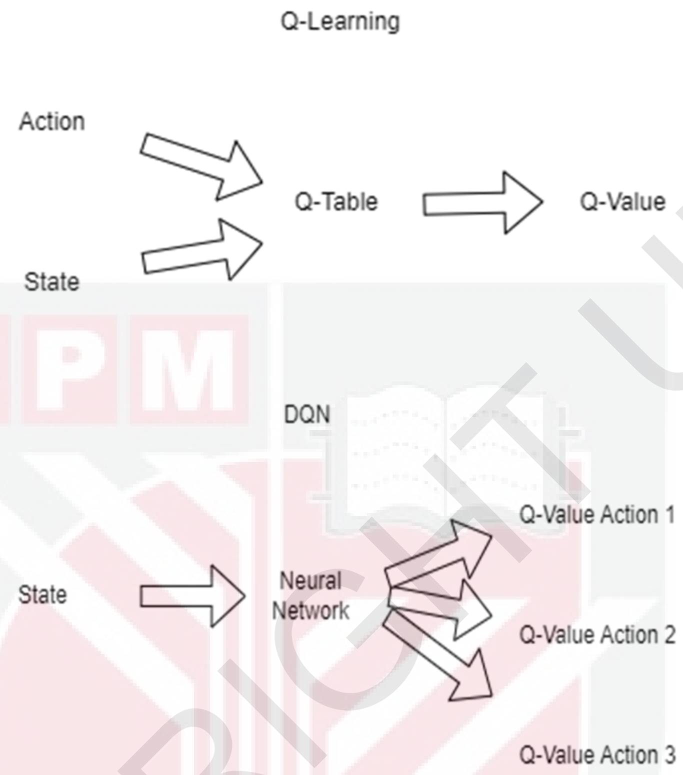


Figure 14: Q-Learning Vs. DQN

DQN agents can be trained in environments with continuous or discrete observation and discrete action spaces.In our thesis agents' environment is discrete because it works based on pixels and pixel by pixel trace 2D echocardiography images and also our agent's action space is discrete because agent actions are labels that agent will put for each pixel.

The Actor-Critic algorithm is a model-free, online, and on-policy reinforcement learning method. It aims to optimize the policy using the actor while concurrently training the critic to evaluate the expected cumulative discounted future rewards.

(Mnih et al,2013). The Actor-Critic agent resembles a policy gradient agent coupled with a baseline. However, the key distinction lies in A-C's utilization of a fully bootstrapping critic, which involves updating the value estimate of a state according to the value estimates of subsequent states. Actor-critic agents can be trained in environments with the Discrete or continuous observation and Discrete or continuous action spaces.(Mnih et al. 2013). Training, an actor-critic include 2 steps: first estimate probabilities of taking each action in the action space and randomly selects actions based on the probability distribution. And then interacts with the environment for multiple steps using the current policy before updating the actor and critic properties.

In our thesis, the purpose of using the A-C mechanism is to find the state- value for the DQN. Due to the fact that it is very difficult to define the state value in such problems, we have used the A-C method to better estimate the state value for DQN. DQN agent uses the Q-value function critic Q (S, A). DQN agent does not use an Actor. DQN typically utilizes only the critic part of the Actor-Critic framework because its primary focus is on learning Q-values, which represent the expected return for taking a particular action in a given state.

The problem we faced in this thesis was that our action space was discrete, and we had to use the DQN method. On the other hand, to find the action of agent, we needed to use the Actor section in the A-C method. The definition of actions in our DQN mechanism is to find the correct labels, which are discrete in nature. Therefore, we added the Actor section to DQN. For each pixel in the image, the agent must assign one of 4 labels. The number of pixels in the image is 500 * 350 and it creates a very large state and action space, so we have used the actor part or the policy network to select the action by the agent with epsilon-greedy mechanism. In other words, the Actor, through its optimized policy, selects a better path for segmentation and avoids unnecessary actions, which not only increases the model's efficiency but also reduces processing time.

The training process of our agent in the DQN framework involves the following steps:

1. **Critic Update:** The critic's parameters are updated at every time step throughout the learning process to improve its accuracy in estimating action values.
2. **Exploration of Action Space (Actor):** The agent explores the action space using the epsilon-greedy strategy. During each control interval, it selects a random action with probability ϵ\epsilon or chooses the action that maximizes the action-value function (greedy action) with probability 1−ϵ1-\epsilon. The greedy action corresponds to the one with the highest estimated action-value.
3. **Experience Replay:** The agent stores past experiences in a circular experience buffer. During training, the critic is updated using a mini-batch of experiences that are randomly sampled from the buffer.

These steps form the basis of the training algorithm, ensuring effective learning, exploration, and optimization of the agent's performance.

1. For the current observation S, choose a random action A with a probability of ϵ; otherwise, select the action that maximizes the critic value function.

Equation 3- 2:

$$A = \underset{A}{\operatorname{argmax}}\, Q(S, A)$$

2. Execute action *A*. Observe the reward *R* and next observation *S′*.
3. Store the experience (*S*,*A*,*R*,*S′*) in the experience buffer.

4. Sample a random mini-batch of M experiences (S_i,A_i,R_i,S'_i) from the experience buffer.

For all experiences in the minibatch, if S'_I is a terminal state, set the value function target y_i to R_i. Otherwise, set it to

Equation 3-3:

$$A_{max} = \underset{A'}{\operatorname{argmax}}\, Q(S'_i, A')$$

$$y_i = R_i + \gamma Q_t(S'_i, A_{max})$$

$$y_i = R_i + \gamma \max_{A'} Q_t\,(S'_i, A')$$

5. Update the critic parameters by one-step minimization of the loss L across all sampled experiences.

Equation 3-4:

$$L = \frac{1}{2M}\sum_{i=1}^{M}(y_i - Q(s_i, A_i))^2$$

In this study, hyperparameter optimization was employed to identify the optimal values for critical parameters such as learning rate, batch size, and discount factor. This process ensures that the model achieves its best performance by systematically exploring the parameter space.

The impact of hyperparameter optimization was evident in the improved performance metrics of the model.

3.2.3 Implementation Details

Actions of the agent are labels that are assigned to each pixel. The nature of the actions performed by the agent is discrete. Labels can have values 1, 2, 3 and 4. The value of 1 is equal to pixel zero, which is the same as the black borders around the ROI. The other three values are assigned to the three different classes that exist in the dataset images. As we have specified in Figure 12. To define the value of each state in agent environment which is TTE 2D echocardiography images, we use the Actor Critic (A-C) mechanism. A-C method is useful when definition of state-value are complex and it is impossible to distinguish values of states(Tian, Si, Zheng, Chen, & Li, 2020) . The agent starts from the first pixel in the image and moves forward (Left to Right) one pixel at each step. Our agent mechanism is pixel by pixel. As we have already mentioned in the explanation of the pre-processing steps, we normalize all the images and make them 500 * 350 pixels. So the agent steps are equal to total numbers of pixels in the image.

When the agent is in each pixel, the agent sees a neighborhood matrix or observation matrix around that pixel. This is the neighborhood of three pixels around the pixel that the agent is in, which is three pixels up, three pixels down, three pixels right, and three pixels left in ED and ES images. This neighborhood matrix is given to the agent as input of agent, which is the agent's observation. In fact, instead of giving the whole image to the agent, we provide the agent with an observation of the image. This causes the agent to explore its environment in smaller parts. So the agent in each pixel receives this neighborhood matrix as input, and the agent's action is the label that is supposed to be given to each pixel. As mentioned earlier, there are four different classes in the data set, and as a result, there can be four labels for each pixel. As we have specified in Figure 12, the four image classes are the black part around the ROI which is related to class 1, the inner and upper part of the ROI which is marked with green color (Left Ventricle Endocardium) which is related to class 2, the halo part around it which is marked with red color (Left Ventricle Epicardium) which is related to class 3 and the bottom part which is marked with blue color (Left Atrium) which is related to class 4.

The mechanism of DQN in this thesis is that it takes the input which is the observation matrix, and the output is the action that the agent must perform. In fact, by obtaining the optimal policy, it determines what action should be taken in each state. We use the Critic mechanism in such a way that it gives us the mapping of observation to state-value.

Our Actor mechanism in this thesis is that it takes two inputs which are the observation matrix along with action in previous time step (Action $_{T-1}$). The output of Actor network is the action which is selected with epsilon-greedy mechanism, and we use this action in Critic network, In addition to the output of the Actor (Policy Network), which is used as one of the Critic (Value Network) inputs, Critic section has two other inputs which include observation matrix and True Labels (annotated images) and the output of Critic network is state-value. In fact, it gives us the expected long-term Q or value for an action per observation matrix. The overall architecture is shown in Figure 1۵. The training process in DRL is iterative and the agent uses its experiences in previous episodes and updates its decisions in different steps and episodes. The role of Evaluator in the diagram shown in Figure 15 is updating Critic Parameters.

The structure of the A-C shown in Figure 16 is as follows, in Actor network we used convolutional layer 3*3 and fully connected layer consists of 100 layers. In actor Network we used convolutional layer 3*3 along with Relu as active function and 2 fully connected layers consist of 100 and 400 layers.

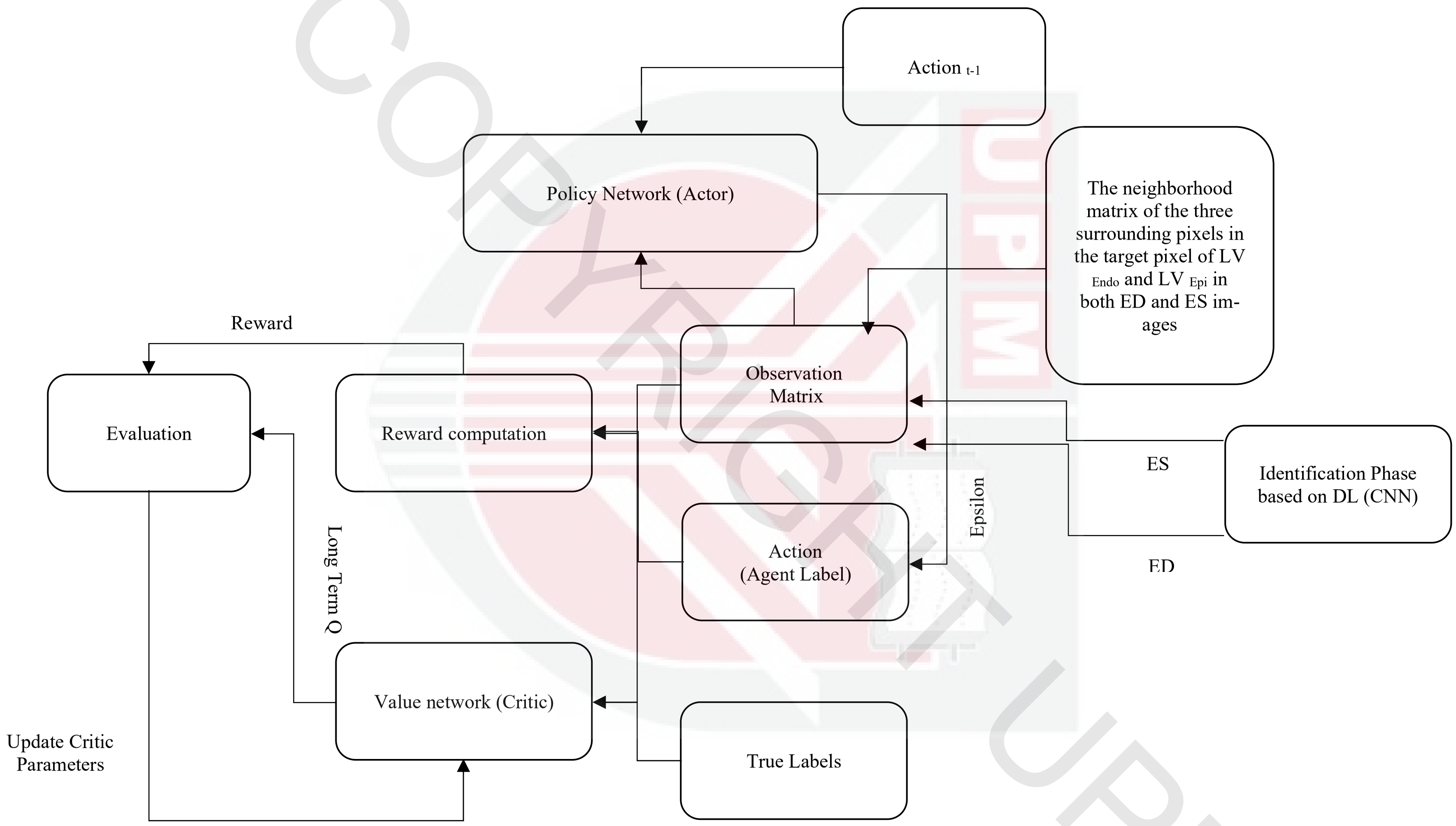


Figure 15: The overall architecture of proposed model

Our Actor and Critic networks also shown in Figure 16, part (A) is related to the Actor Network, and part (B) is Critic Network.

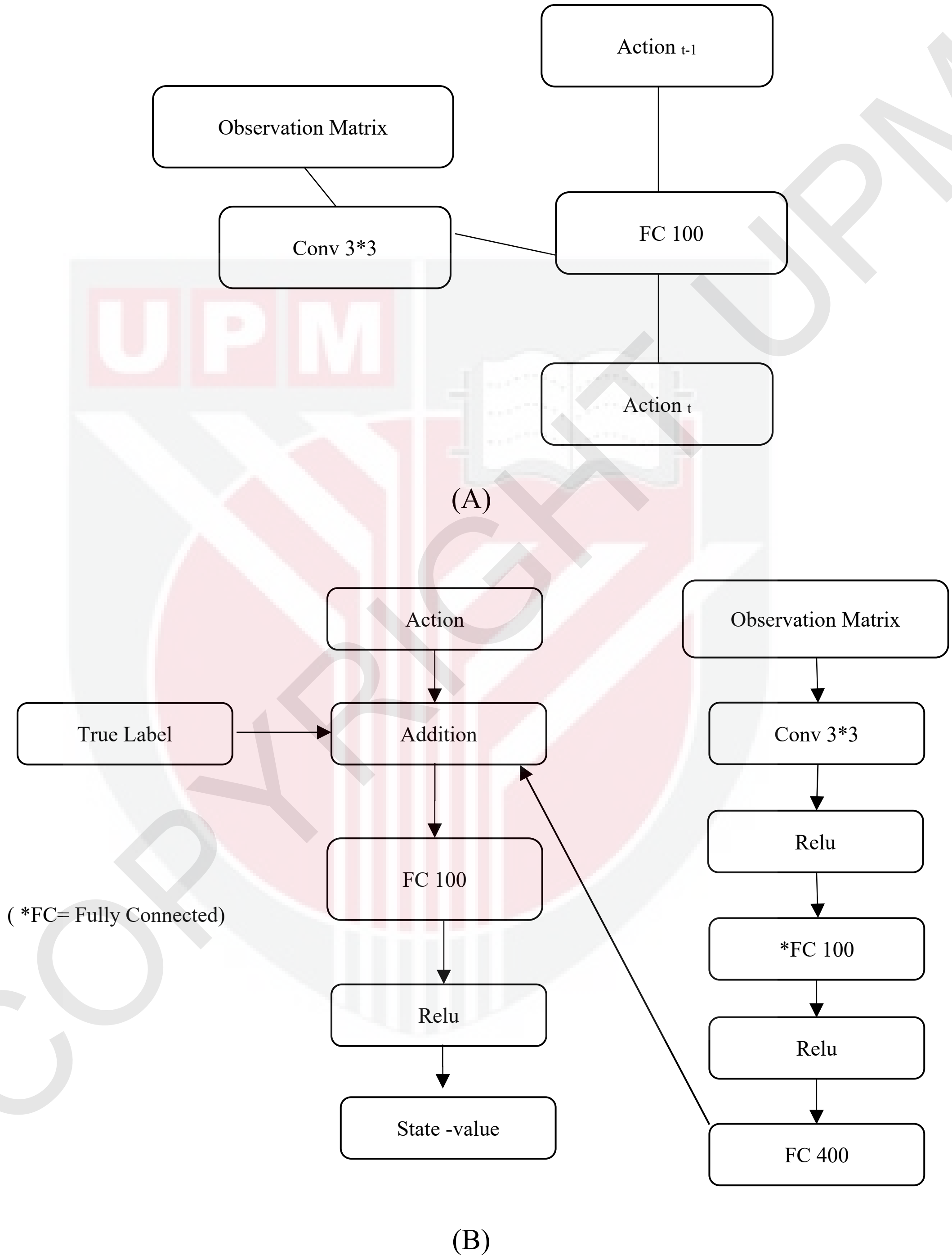


Figure 16: Part (A) Actor Network, Part (B) Critic Network

As mentioned in the previous part, due to the large number of states, it is not possible to use the Q-learning mechanism and we cannot create the Q-table, that's why we use Deep Neural Networks with the A-C mechanism. Furthermore, DQN agent does not use an Actor section, but to specify the action we involved the actor part also in our model. Because in each pixel agent can select 4 different actions and the number of our pixels is equal to the total image size therefore, we have large numbers of actions.

In Reinforcement Learning, we do not explicitly instruct the agent on specific actions or their execution; instead, we employ a reward-based system. For every action the agent takes, it receives a corresponding reward. A positive reward is assigned to the agent for performing beneficial actions, while a negative reward is given for unfavorable actions.

Initially, the agent explores by taking random actions, and when a positive outcome is achieved, it receives a positive reward, enabling it to recognize the value of that action and subsequently repeat it. Conversely, if the agent's action leads to undesirable outcomes, a negative reward is given, prompting the agent to comprehend the inadvisability of that action and avoid its repetition. Consequently, in RL learning process, is based on exploration, agent explores different actions and gradually learns the optimal actions that yield positive rewards.

The reward mechanism in the implementation of this thesis is as follows:

When each label by the agent is applied to the pixel that the agent is in, it creates a change in accuracy. Because it is possible that the agent mistakenly assigns a label to the pixel in which it is located. We have a series of labels as true labels which are the same as annotated images in the data set and a series of labels are assigned to the image by the agent in each step. The label that the agent applies to the image pixels naturally creates a new segmented image. We calculate the accuracy by comparing the segmented image that the agent creates with the true labels. We multiply the accuracy value by negative one, which becomes the agent's reward. In fact, the base reward that we have set for the agent is minus one. In other words, we get the accuracy or the degree of similarity of the original labeled image in the data set with the image labeled by the agent and multiply the base reward by the difference. The difference is the amount of difference between the image labeled by the agent and the image labeled in the data set. We calculate the absolute value of this difference.

The values that the difference can have are 0, 1,2 and 3. We multiply the difference value by minus one, which is the reward for each action performed by the agent. The bigger the difference is (for example, suppose it is 3), in this case, the agent will receive a negative amount of three fines. But if this value is zero, the best state has been formed. When the agent reaches the point where the similarity of the labeled image with the original labeled image in the data set is 90%, the agent will receive a final reward of 7000, which is the same final reward that we give to the agent, and this reward expresses that the agent's work for labeling the image is finished and the work for segmenting the next image begins. We have chosen this value of 90% because the agent has found the segmentation pattern. In fact when the agent can correctly label 90% of the pixels in the image, it indicates that the agent has reached the right pattern for image segmentation. Infact The 90% threshold was chosen as a scientifically meaningful point where the agent has demonstrated a high level of segmentation accuracy. This threshold indicates that the agent has successfully identified and segmented the majority of the relevant structures in the image (e.g., LV_{Endo}, LV_{Epi}, and LA) and is ready to move to the next task. It also ensures a balance between computational efficiency and segmentation precision.

The value 7000 represents a predefined terminal reward that the agent receives when it achieves a segmentation accuracy of 90%, signifying that the agent has successfully learned the segmentation pattern for the current image. This value is designed to act as a clear and significant signal, ensuring the agent understands that the task for the current image is complete, and it can proceed to the next. DRL operates on an iterative process, where the agent refines its understanding of the environment and task through rewards. A large, terminal reward like 7000 provides a strong positive reinforcement for achieving the desired accuracy level. This clear boundary between success and continuation helps the agent focus on optimizing its actions toward the correct segmentation.

As mentioned above, In each iteration or episode agent interacts with its environment by doing action in each step, In the next episode, the agent uses the knowledge gained in the previous episode and improves its work process.

Due to the fact that the total number of steps in this problem is equal to the total number of pixels in the image, and also because the agent in each episode uses the knowledge gained in the previous episode, which makes the agent in the next episode go through fewer steps, we have specified a balance to get the final reward of the agent between the steps traveled by the agent in each episode, which is the final reward of 7000.

In the realm of Reinforcement Learning (RL), adherence to the conditions of the Markov chain is imperative. In this specific problem, since the agent's actions in each step are independent of the previous steps, the Markov chain conditions are satisfied.

Cross-validation, employed in ML, assesses a model's performance on new data by segmenting the available data into numerous folds or subsets. One of these subsets acts as the validation set while the model trains on the rest. This procedure iterates multiple times, each time utilizing a different subset for validation. Ultimately, the outcomes from each validation iteration are averaged, yielding a more reliable assessment of the model's performance. Cross validation stands as a crucial phase in machine learning, ensuring the chosen model is resilient and adept at generalizing to novel data. The primary aim of cross-validation is to counteract overfitting, a situation wherein a model is excessively trained on the training data, resulting in subpar performance on fresh, unseen data. Through assessment on various validation sets, cross-validation furnishes a more authentic evaluation of the model's generalization capability, namely, its proficiency in performing effectively on new, unseen data. Cross-validation and static data division are techniques used for assessing the performance of machine learning models. In static data division, the dataset is split into two parts: a training set and a test set. Typically, a certain percentage (e.g., 70-80%) of the data is used for training, and the remaining portion is used for testing. The model is trained on the training set and evaluated on the test set. This approach is simple and easy to implement but may lead to variability in performance metrics depending on how the data is divided.

Another technique in cross-validation is 5-fold cross-validation. 5-fold cross-validation follows a similar approach to 10-fold cross-validation (Refers to chapter 2 part 2.2.1) but with 5 folds instead of 10. Advantages of 10-fold cross-validation over static data division and 5-fold cross-validation include:

i. Better Utilization of Data: 10-fold cross-validation allows for better utilization of the available data by using multiple train-test splits, leading to more reliable performance estimates.

ii. Reduced Variability: With 10 iterations and averaging of performance metrics, 10-fold cross-validation provides a more stable estimate of model performance compared to 5-fold cross-validation and static data division.

iii. Balanced Evaluation: Each instance in the dataset gets a chance to be in the test set exactly once in 10-fold cross-validation, ensuring a more balanced evaluation of the model across different data samples.

To avoid overfitting problem we used 10-fold cross-validation technique. According to the advantages of 10-fold cross-validation technique method and as specified in Table 3 in chapter two Section 2.2, only one paper used the 10-fold cross-validation technique.

As shown in figure 14, according to the objectives of this thesis, we used the DQN method using the A-C to segment and identify the structures in the LV during the cardiac cycle. By adding the Actor section to find the action, we improved the DQN mechanism, which is used in discrete environments. The advantage of the DRL method used in this thesis compared to DL methods is that the agent is dynamically interact with its environment and in each episode it uses the knowledge gained from the previous episodes and improve the accuracy of segmentation and identification task. This continuous interaction with the environment does not exist in DL methods, and if the wrong features are extracted by the Deep Neural Network, It cannot be modified in the learning process. The better results of our proposed method used in this thesis compared to DL methods show the same issue.

Figure 17 shows the Stages of agent training in different Episodes. As it is known, the agent has increased its knowledge over time, and this increase the agent's knowledge has led to receiving more rewards in the next episodes.

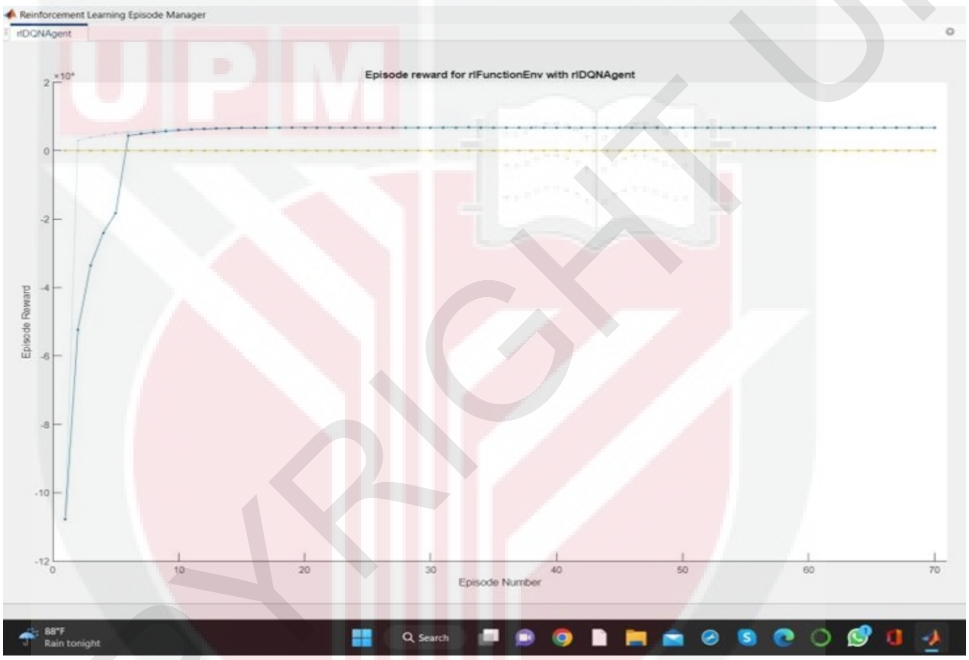


Figure 17: The Stages of agent training in different Episodes

3.3 Research Method

The research method in this thesis is quantitative for the reasons that we mention at the following.

1. The thesis aims to "automatically segment and identify" specific structures within echocardiography images. This objective suggests a focus on precise measurement, classification, and identification of anatomical structures, which aligns with the objectives of quantitative research.

2. The thesis involves the analysis of medical images (2D echocardiography). The goal is to accurately identify and measure different structures, which is a quantitative endeavor. The use of "Deep Reinforcement Learning (DRL)" indicates a focus on developing a computational model that can learn to perform specific tasks through data-driven optimization. Deep Learning, which involves neural networks and computational processing of data, is a characteristic of quantitative research methods.

3. The thesis's focus on "segment and identify" implies the measurement of specific features and attributes of the heart structures in question. Quantitative research is concerned with measuring and quantifying variables. The research is involved statistical analysis, such as assessing the accuracy of the automated segmentation method, comparing results with manual segmentations, and potentially calculating performance metrics. The expected outcome of the thesis would be quantitative in nature, involving measurements, accuracy rates, and potentially statistical comparisons.

3.4 Summary

In this chapter, we explained the two stages of pre-processing on the dataset images. The first step is to normalize the dataset images to 500 * 350. The second step is to improve the brightness of the data set images. The data set contains 450 two-dimensional echocardiography images. We have explained the two methods of A-C and DQN, we have used the A-C mechanism to obtain State-Value.

The advantage of the DRL method used in this thesis compared to DL methods is that the agent is dynamically interact with its environment and in each episode it uses the knowledge gained from the previous episodes and improve the accuracy of segmentation and identification task. This continuous interaction with the environment does not exist in DL methods.

To avoid overfitting problem based on advantages of 10-fold cross-validation technique we used this method.

CHAPTER 4

RESULTS AND DISCUSSION

In this chapter, First, we explain the metrics used to evaluate the accuracy of the segmentation and identification of our proposed model which are Dice similarity coefficient (DSC), Jaccard index ,Hausdorff's Distance (HD) as segmentation metrics, and Mean Absolute Error , F1 Score and Intersection over Union (IoU) which are useful metrics for cardiac cycle analysis because they provide a comprehensive evaluation of the performance of our proposed model to identify specific phases within echocardiographic images. After that, we compare results of our method with results of other papers that used our dataset in this thesis.

4.1 Geometrical Metrics of Segmentation

The metrics for measuring accuracy in image segmentation are very diverse. The reason we have used these metrics is that in most papers related to image segmentation with DL methods, used these metrics which are Dice similarity coefficient (DSC), Jaccard index and Hausdorff's Distance (HD)(Leclerc et al., 2019) .

4.1.1 Dice similarity coefficient (DSC)

The Dice coefficient, also referred to as the Dice similarity coefficient or Dice index, is a widely used metric for evaluating image segmentation tasks. It quantifies the degree of similarity or overlap between the predicted segmentation and the ground truth segmentation. The Dice coefficient is particularly useful for evaluating binary segmentation tasks, where each pixel is classified as either foreground (positive class) or background (negative class). It is defined as the ratio of the intersection of the predicted foreground and the ground truth foreground to the average size of the two regions:

Dice coefficient = 2 * (Area of Intersection) / (Area of Prediction + Area of Ground Truth)

Here, the "Area of Intersection" refers to the number of pixels that are correctly classified as foreground in both the predicted segmentation and the ground truth. The "Area of Prediction" and "Area of Ground Truth" represent the total number of pixels classified as foreground in the prediction and the ground truth, respectively.

A higher Dice coefficient indicates better segmentation accuracy and similarity between the prediction and the ground truth. The Dice coefficient is commonly used in medical image segmentation tasks and other binary segmentation applications because it provides a robust measure of segmentation performance, especially when dealing with class imbalance or when the foreground class is much smaller than the background class.

4.1.2 Jaccard Index

The Jaccard Index, also referred to as the Jaccard similarity coefficient, is a commonly used metric in image segmentation tasks. It quantifies the similarity between the predicted segmentation and the ground truth segmentation, functioning similarly to the Dice coefficient.

Similar to the Dice coefficient, the Jaccard Index is highly effective for assessing binary segmentation tasks, where pixels are categorized as either foreground (positive class) or background (negative class). It is calculated as the ratio of the intersection between the predicted foreground and the ground truth foreground to the union of these two regions:

Jaccard Index = (Area of Intersection) / (Area of Union)

Here, the "Area of Intersection" refers to the number of pixels that are correctly classified as foreground in both the predicted segmentation and the ground truth. The "Area of Union" represents the total number of pixels classified as foreground in either the predicted segmentation or the ground truth or both. A higher Jaccard Index indicates better segmentation accuracy and similarity between the prediction and the ground truth.

4.1.3 Hausdorff Distance (HD)

Hausdorff Distance (HD) is a metric used to evaluate the similarity between two sets of points, typically in the context of image segmentation. In the context of segmentation, it quantifies the dissimilarity between a reference (ground truth) segmentation and a predicted segmentation. That's how it works: Consider two sets of points, A and B. In the context of segmentation, A represents the points belonging to the ground truth segmentation, and B represents the points belonging to the predicted segmentation. For each point in set A, find the closest point in set B, and vice versa. This yields two distance sets: d (A, B) and d (B, A), representing the distances from each point in set A to its nearest neighbor in set B, and vice versa. The Hausdorff Distance is defined as the maximum of these two distances: H (A, B) =max (sup (d (A, B)), sup (d (B, A)). Where *sup* denotes the supremum, which is the least upper bound.

4.2 Clinical Metrics of Measurement in End Diastole (ED) and End Systole (ES)

We assess the effectiveness of the methods by utilizing one clinical index. Which is Mean Absolute Error (MAE) (Leclerc et al., 2019).

4.2.1 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a metric commonly used to evaluate the performance of a machine learning model, it measures the average absolute difference between the predicted segmentation and the ground truth segmentation of the images.

In the context of heart echo image segmentation, MAE quantifies how accurate the model's predictions are in terms of the actual boundaries of the left ventricular endocardium, epicardium, and atrium (or any other structures of interest). It calculates the absolute difference between each pixel in the predicted segmentation and the corresponding pixel in the ground truth segmentation, then takes the average of all these absolute differences.

The MAE is defined by the following formula:

Equation 4-1

$$MAE = (1 / N) * \Sigma|P\_i - GT\_i|$$

Where:

N is the total number of pixels in the segmentation masks.

P_i represents the pixel value of the *i-th* pixel in the predicted segmentation mask.

GT_i represents the pixel value of the *i-th* pixel in the ground truth segmentation mask.

Σ represents the sum of all the absolute differences between the predicted and ground truth pixel values.

A lower MAE indicates better performance, as it means the model's predictions are closer to the ground truth annotations. MAE provides a straightforward and easily interpretable measure of segmentation accuracy, making it a common choice for evaluating segmentation models in medical imaging tasks, including heart echo image analysis.

4.3 Metrics of identification

The cardiac cycle describes the series of events that take place during one complete heartbeat, encompassing both the systole (contraction phase) and diastole (relaxation phase). Within the cardiac cycle, identifying the end-systolic and end-diastolic phases involves determining specific points in time corresponding to the maximum contraction and maximum relaxation of the heart chambers, respectively. In this case, the objective is to analyse echocardiographic images, to detect specific events within the cardiac cycle.

F1 Score and Intersection over Union (IoU) are useful metrics for cardiac cycle analysis because they provide a comprehensive evaluation of the performance of algorithms designed to identify specific phases within echocardiographic images(Sanjeevi et al., 2024b).

4.3.1 F1 Score

The F1 Score combines both precision and recall into a single metric, providing a balanced evaluation of algorithm performance. In cardiac cycle analysis, it's essential to achieve a balance between correctly identifying the end-systolic and end-diastolic phases (high recall) while minimizing false detections (high precision). F1 Score quantifies the trade-offs between precision and recall, helping to assess the overall effectiveness of the detection algorithm.

4.3.2 Intersection over Union (IoU)

IoU measures the spatial overlap between the detected phases and the ground truth annotations. In cardiac cycle analysis, it assesses how well the identified phases match the expected regions of interest, such as the timing of ventricular contraction and relaxation. IoU is robust to variability in phase durations and signal noise, making it suitable for evaluating algorithm performance under real-world conditions.

4.4 Comparing Results

In this section, the results obtained by this thesis are shown in Table 5 with the results obtained by 9 papers that used CAMUS data set. In addition, the results related to clinical metrics based on our proposed method also shown in this table. The results of our proposed in this thesis show more accuracy than the models proposed in other 9 papers. In addition, the results related to the identification of ED and ES are also shown in Tables 6. In the following, 3 examples of results obtained by our proposed model are shown in Figure 18. These results include both ED and ES images. Along with these images, the original images, also shown. Right side images are original data set images.

Table 5: comparing results with pervious study and results of our clinical metric

Ref.	Dataset Split	Classes	Method	Performance (on CAMUS Dataset)		
				LA	LV_{EPI}	LV_{ENDO}
(Leclerc et al. 2019)	10-fold cross-validation	LV_{ENDO} and LV_{EPI}	U-Net	n.a.	ED: DSC=95.4 HD=6.0 ES: DSC=95.4 HD=6.1	ED: DSC=93.9 HD=5.3 ES: DSC=91.6 HD=5.5
(Moradi et al., 2019)	5-fold cross-validation	LV	MFP-U-Net	n.a.	DSC=95.3 HD=3.5	
(Kim et al., 2021)	n.a.	LV_{ENDO} and LV_{EPI}	SegAN	n.a.	DSC=85.9 HD=6.2	DSC=91.7 HD=5.1
(Girum et al., 2021)	Static data division	LA, LV_{ENDO} and LV_{EPI}	LFB-Net	DSC=92.0 HD=4.8	DSC=88.0 HD=7.1	DSC=94.0 HD=5.6
(Liu et al., 2021)	Static data division	LV_{ENDO} and LV_{EPI}	PLANet	n.a.	ED: DSC=96.2 HD=4.6 ES: DSC=95.6 HD=4.6	ED: DSC=95.1 HD=4.2 ES: DSC=93.1 HD=4.3
(Alam et al,2022)	Static data division	LV	Deep Res-U-Net	n.a.	ES: DSC = 82.1 JAC=66.9 HD=23.8 ED: DSC = 86.5 JAC=63.7 HD=19.7	

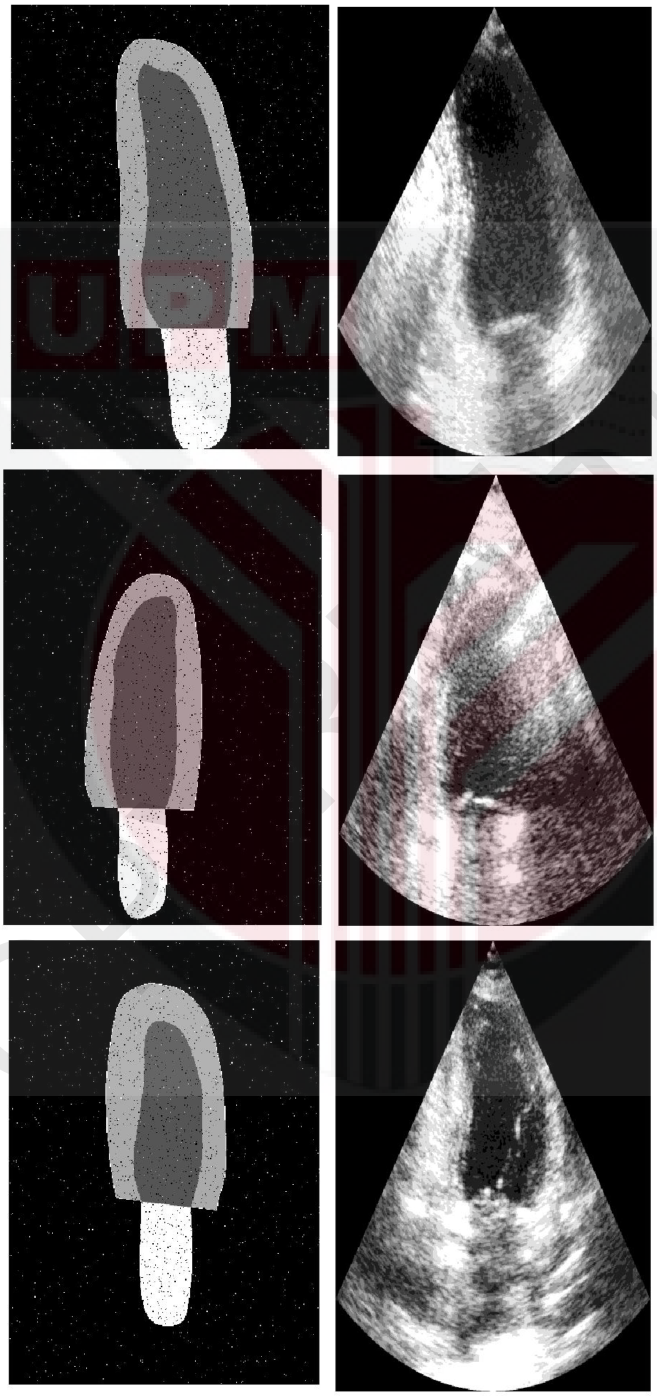
Table 5: Continued

(Saeed & Yaqub, n.d.2022)	Static data division	LV	DeepLabV3	n.a.	DSC = 93.1	
(Zhuang et al., 2021)	n.a.	LV_{ENDO}	YOLOV3 (Darknet53)	n.a.	n.a.	DSC=93.6 HD=6.7
(Mortada et al., 2023)	Static data division	LA, LV_{ENDO} and LV_{EPI}	YOLOv7 and U-Net	DSC=87.6 JAC=79.8 HD=4.1	DSC =85.6 JAC=75.4 HD=5.0	DSC =92.6 JAC=86.8 HD =3.8
This study	**10-fold cross-validation**	**LA, LV_{ENDO} and LV_{EPI} In ED AND ES**	**DQN using A-C**	**LA, LV_{ENDO} and LV_{EPI} (Metrics for Segmentation)** **ED: DSC: 97.26 HD: 4.24 JAC:94.67** **ES: DSC: 97.22 HD: 4.47 JAC:94.60**		
				Measurements Metrics:(MAE) **ES** / **ED** **LA: 1.29** / **LA: 0.175** **LV_{EPI}: 5.14** / **LV_{EPI}: 3.14** **LV_{ENDO}: 4.10** / **LV_{ENDO}: 3.39**		

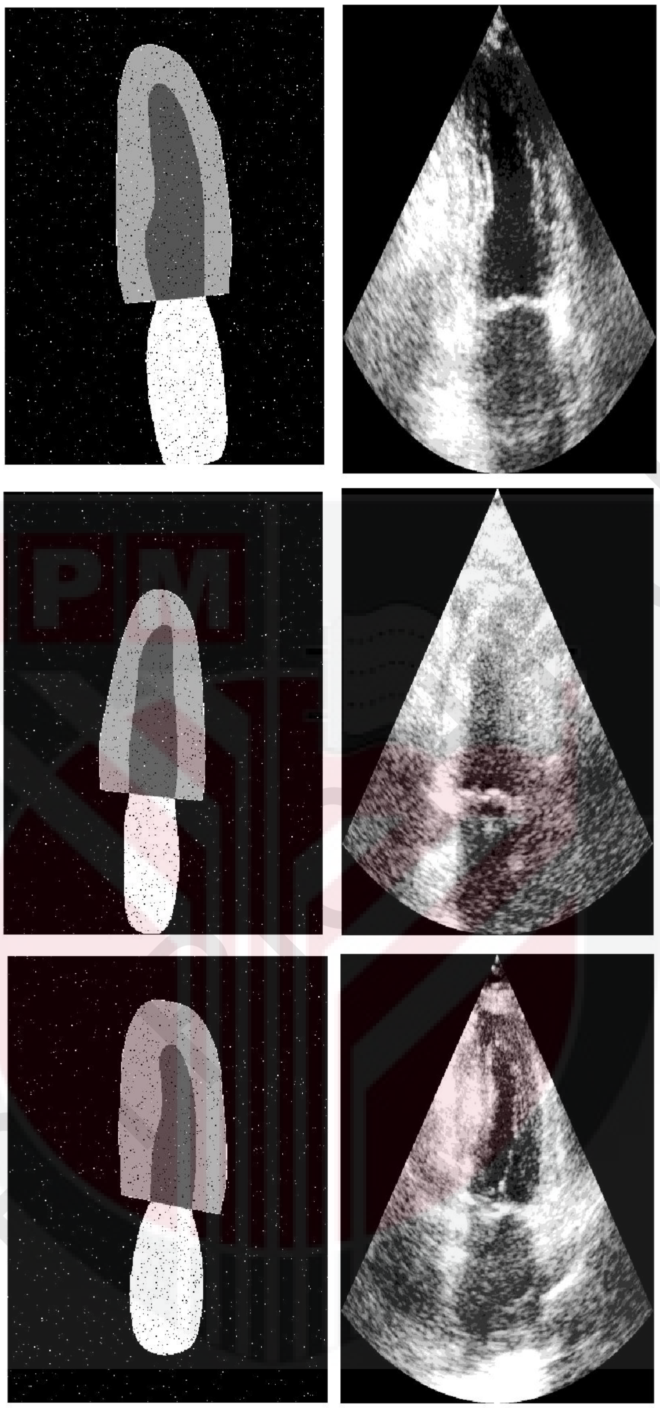
n.a-(Not applicable)

Table 6: Results related to the identification of ED and ES

	ES	ED
F1 Score	97.66	97.75
IoU	87.48	87.56



(A)



(B)

Figure 18: Results of images in cardiac cycles. Part A(ED) and Part B(ES)

4.5 Discussion

This research focuses on the segmentation of anatomical structures of the heart, particularly the Left Ventricle and Left Atrium, which are crucial for diagnosing cardiac conditions. By employing Deep Reinforcement Learning on 2D Transthoracic Echocardiography images, this study addresses the challenges associated with these non-invasive but lower-quality imaging techniques. Unlike existing studies that primarily focus on segmenting the LV alone, this work introduces a comprehensive framework capable of segmenting LV structures, including the Endocardium (LV_{Endo}), Epicardium (LV_{Epi}), and LA, during the End-Diastole and End-Systole phases. This novel approach employs a Deep Q-Network within an Actor-Critic framework, leveraging DRL's unique ability to dynamically interact with the environment and learn iteratively from prior experiences. This dynamic and adaptive learning capability enables the agent to improve its accuracy and efficiency progressively.

The method also integrates a Convolutional Neural Network for identifying cardiac cycles (ED and ES), making phase-specific segmentation more accurate.

Quantitative evaluation metrics such as Dice Similarity Coefficient, Hausdorff Distance, and Mean Absolute Error were used to validate the methodology. Results demonstrated that the proposed DRL framework outperformed traditional methods, particularly in dealing with the variability and complexities inherent in TTE imaging. This study demonstrates the potential of DRL to transform clinical cardiology by providing a reliable, accurate, and scalable solution for the automatic segmentation of cardiac structures under diverse imaging conditions, minimizing the dependency on manual intervention and improving diagnostic workflows.

4.6 Summary

In this chapter, segmentation and identification metrics for the accuracy Automatically segment and identify the Left Ventricular Endocardium, Epicardium and Atrium in End-Diastolic and End-Systolic Left Ventricular In 2d TTE Echocardiography using Deep Reinforcement Learning are shown in Tables 5 and 6. The results obtained by the proposed method in this thesis were compared with 9 other papers that used the same data set. In Figure 17, the images obtained by the proposed method were shown along with the original images available in the dataset for comparison.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Future Work

Future work for 2D heart image segmentation in echocardiography images using Deep Reinforcement Learning can encompass several research directions and practical advancements. Here are some specific areas for further investigation:

1. Multi-View and Temporal Segmentation: Extend the DRL model to handle multi-view and temporal sequences of echocardiography images. This could involve incorporating information from different imaging planes or analyzing image sequences to improve segmentation accuracy and capture cardiac motion.

2. Transfer Learning and Domain Adaptation: Explore methods for transferring knowledge from related medical imaging domains or pretraining on other datasets to improve the segmentation performance on echocardiography images.

3. Cardiac Pathology Segmentation: Extend the DRL model to segment specific cardiac pathologies, such as myocardial infarction, hypertrophy, or valve abnormalities, to assist in diagnosing and monitoring various heart conditions.

4. Multi-Task Learning: Explore multi-task learning setups where the DRL model performs related tasks simultaneously, such as segmentation and landmark detection, to leverage shared representations and improve performance.

5.2 Conclusion

This study addresses the significant challenges associated with the automatic segmentation and identification of cardiac structures in echocardiography images, specifically focusing on the Left Ventricular Endocardium و Epicardium, and Left Atrium during End-Diastolic and End-Systolic phases. Utilizing the CAMUS dataset, which includes clinically annotated data from 450 patient cases, the research ensured clinical realism and concentrated on achieving high segmentation accuracy. The novelty of this work lies in the implementation of a Deep Reinforcement Learning چ framework combined with a Convolutional Neural Network. Unlike traditional Deep Learning چ methods that rely on static datasets, DRL leverages dynamic interactions with the environment, enabling robust and adaptive learning. The integration of an Actor-Critic چ architecture within a Deep Q Network چprovided a sophisticated approach to refine the segmentation and identification processes.

The proposed DRL framework demonstrated remarkable success, as evidenced by quantitative evaluations using Dice Similarity Coefficient, Hausdorff Distance, Jaccard Index, and Mean Absolute Error. The model excelled in delineating LV $_{Endo}$, LV $_{Epi}$, and LA structures across ED and ES phases, effectively addressing the complexities of ventricular boundaries. The dynamic training process allowed the agent to continuously learn and adapt, overcoming challenges posed by noise, low contrast, and the anatomical variability inherent in echocardiography. This adaptability and precision underline the clinical relevance of the research, offering an automated solution that reduces dependency on manual annotation, minimizes inter-observer variability, and improves diagnostic efficiency.

The research contributes a novel perspective to the field of medical imaging by combining DRL and CNN to address specific challenges in transthoracic echocardiography. The methodology not only enhances segmentation accuracy but also sets a precedent for future explorations in more complex scenarios, such as three-dimensional echocardiography or multi-phase cardiac imaging. This work establishes a scalable, reliable, and clinically impactful solution, paving the way for advancements in automated diagnostic tools within cardiovascular care. By demonstrating the potential of DRL to handle the intricate and variable nature of cardiac imaging, this thesis marks a significant step forward in the development of intelligent medical imaging systems.

In summary, in the table 11, Problem statement, objectives and contributions are briefly explained.

Table 7: Problem Statement, objectives and contributions in brief

Problem statement	Accurate segmentation and identification of cardiac structures in echocardiographic images are critical for assessing cardiac function and diagnosing cardiovascular diseases Hesamian et al., 2019.[6] However, existing methodologies face significant challenges: A-C algorithms lack an explicit actor component within the DQN framework, which limits their ability to effectively learn complex spatial and temporal patterns in 2D cardiac imaging data Mnih et al., n.d.2013.[14]. This limitation reduces the efficiency and adaptability of these methods in dynamic and intricate imaging contexts Orr & Dutta, 2023[56]. Automated segmentation of the LV in echocardiograms, particularly in TTE, often relies on geometric approaches that require user intervention. This manual involvement introduces subjectivity and variability, adversely affecting segmentation accuracy. Moreover, the complexity of ventricular boundaries in TTE images poses additional challenges for existing ML techniques Mortada et al., 2023.[48] TTE presents inherent challenges in accurately identifying cardiac structures and cycles, such as the endocardium, epicardium, and atrium, during both ES and ED phases. Due to the external imaging nature of TTE, image quality is often affected by noise and anatomical variations Liu et al., 2020[44]. Existing identification techniques, which predominantly rely on manual or semi-automated methods, are time-consuming, operator-dependent, and prone to variability, thus reducing the accuracy and efficiency of clinical diagnoses Mortada et al., 2023.[48] Addressing these challenges requires innovative approaches that enhance the adaptability, accuracy, and efficiency of cardiac structure segmentation and identification in echocardiographic imaging.

Table 7: Continued

objectives and contributions	1. To increase efficiency and versatility of the A-C algorithm in capture and learn complex spatial and temporal patterns inherent in cardiac imaging data at the LV Endo, LV Epi, and LA in cardiac cycles (End-Diastolic and End-Systolic) phases of 2D echocardiography images. 2. To design and develop DQN with A-C framework automated segmentation DRL algorithm for accurately delineating the Left Ventricle structures in echocardiogram images, with a specific focus on addressing the challenges associated with Transthoracic echocardiograms. 3. To design an identification DL algorithm capable of accurately delineating cardiac cycles (ED and ES) in echocardiogram images obtained through Transthoracic echocardiography. Contributions: 1. Enhancing the algorithm's precision in capturing actions and integrating a fully connected neural network as an actor in the A-C algorithm addresses the limitations of current A-C methods in cardiac image segmentation. 2. The DRL algorithm was trained iteratively on the dataset to accurately segment LV structures without manual intervention. 3. Effective DL algorithm to identify cardiac cycles, which adapted to the variations and complexities of TTE imaging data

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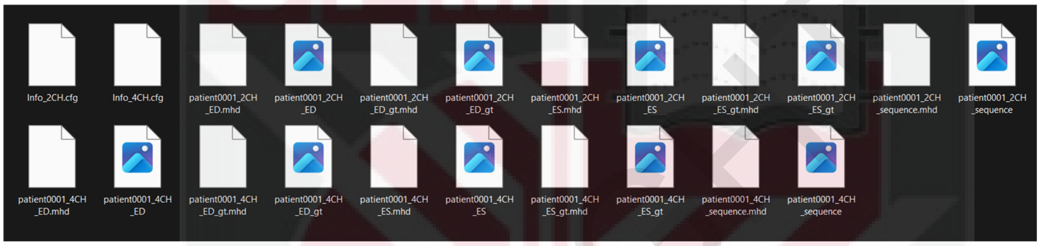
APPENDICES

Appendix 1

Samples of Data set Images

The CAMUS data set include ground truth for ED and ES of 2Chamber and 4 Chamber images and sequence of 2Chamber and 4Chamber images at ED and ES for 450 patients. The following images are sample of patient 1 images.



Software used for implementation:

MATLAB software: MATLAB R2023a

System requirements:

Operating System: Windows 11 Home Single Language 64-bit

Ram: 16GB

GPU: NVIDIA GeForce GTX 1650

Appendix 2

Experiments

The experiments conducted in this thesis involved several stages aimed at identifying and segmenting cardiac structures in 2D echocardiographic images. Initially, a pixel-by-pixel method was implemented, where each pixel in the image was processed independently. The Actor-Critic architecture was used for this approach, where the Actor was responsible for making decisions about each pixel, and the Critic provided feedback to refine the learning policy. The algorithm classified each pixel into one of three main classes: Endocardium, Epicardium, or Left Atrium. Despite its theoretical precision, this method faced significant challenges. The similarity in pixel intensities between the Endocardium and Epicardium reduced accuracy, while noise and variations in contrast further disrupted performance. Moreover, processing each pixel independently resulted in high computational costs and made this method impractical for real-time applications. Due to these limitations, the pixel-by-pixel approach was abandoned.

After abandoning the pixel-by-pixel method due to its numerous challenges, the neighbouring matrix method with six surrounding pixels was introduced. In this method, each pixel, along with its six neighbours (top, bottom, left, right,), was analysed. The aim was to enhance segmentation accuracy by analysing local relationships and addressing the challenges of the pixel-by-pixel method.

However, despite improvements over the pixel-by-pixel method, this approach encountered several issues in its performance. One of the primary challenges of this method was the large search space. Analysing six neighbouring pixels in each step expanded the search area, which not only increased computational complexity but also led to inaccuracies in identifying complex or ambiguous boundaries. This larger search space caused the algorithm to struggle in accurately detecting the boundaries of cardiac structures, such as the endocardium and epicardium, resulting in insufficient segmentation precision.

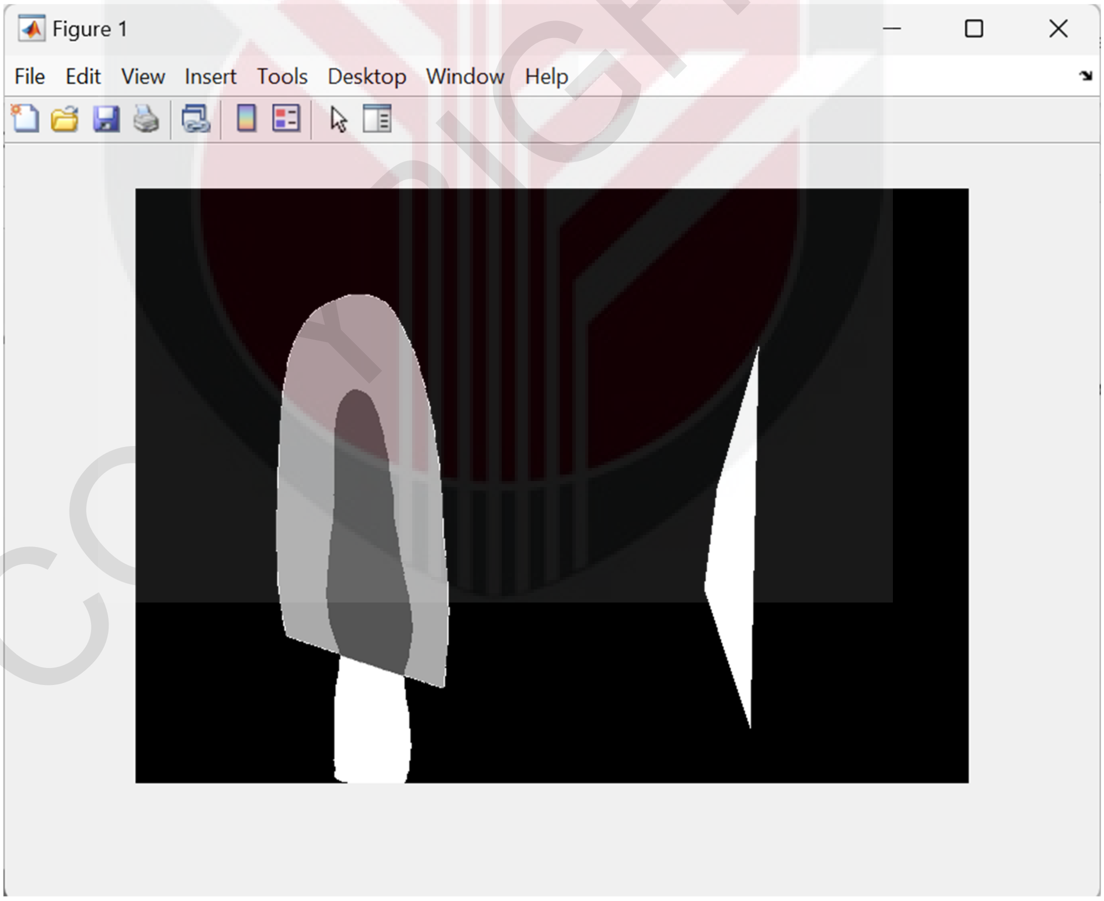
Additionally, incorporating six neighbouring pixels in regions with gradual intensity variations or similar pixel intensities created ambiguities in class assignments. For instance, the algorithm sometimes failed to distinguish clearly between the endocardium and epicardium because the larger search space included more information, which could lead to incorrect assignments. This issue was particularly evident in noisy images or those with low contrast.

To address these limitations, the search space was optimized by reducing the number of neighbours to three pixels. In the neighbouring matrix method with three pixels, only the neighbouring pixels above, below, and the target pixel were analysed. This change proved effective for several reasons:

1. Reduced Search Space: By analysing fewer pixels, the algorithm was able to make more accurate decisions and avoid considering unnecessary information that could lead to ambiguities.
2. Improved Boundary Detection: The reduced search space allowed the algorithm to perform better in detecting the boundaries of cardiac structures, as it focused on more local and relevant information.
3. Lower Computational Complexity**:** This method not only increased the segmentation speed but also performed more efficiently in high-resolution images or clinical scenarios.

The neighbouring matrix method with three pixels successfully addressed the challenges of the previous methods and established a balanced approach between accuracy, efficiency, and computational complexity. These adjustments demonstrate the importance of optimizing the search space and leveraging local analysis to improve the performance of segmentation algorithms in medical imaging tasks. The images obtained from these two methods are shown in the figure below. Part (A) corresponds to the pixel-by-pixel method, and part (B) represents the six-pixel neighborhood method.

Part A: 3 samples results of pixel-by-pixel method.



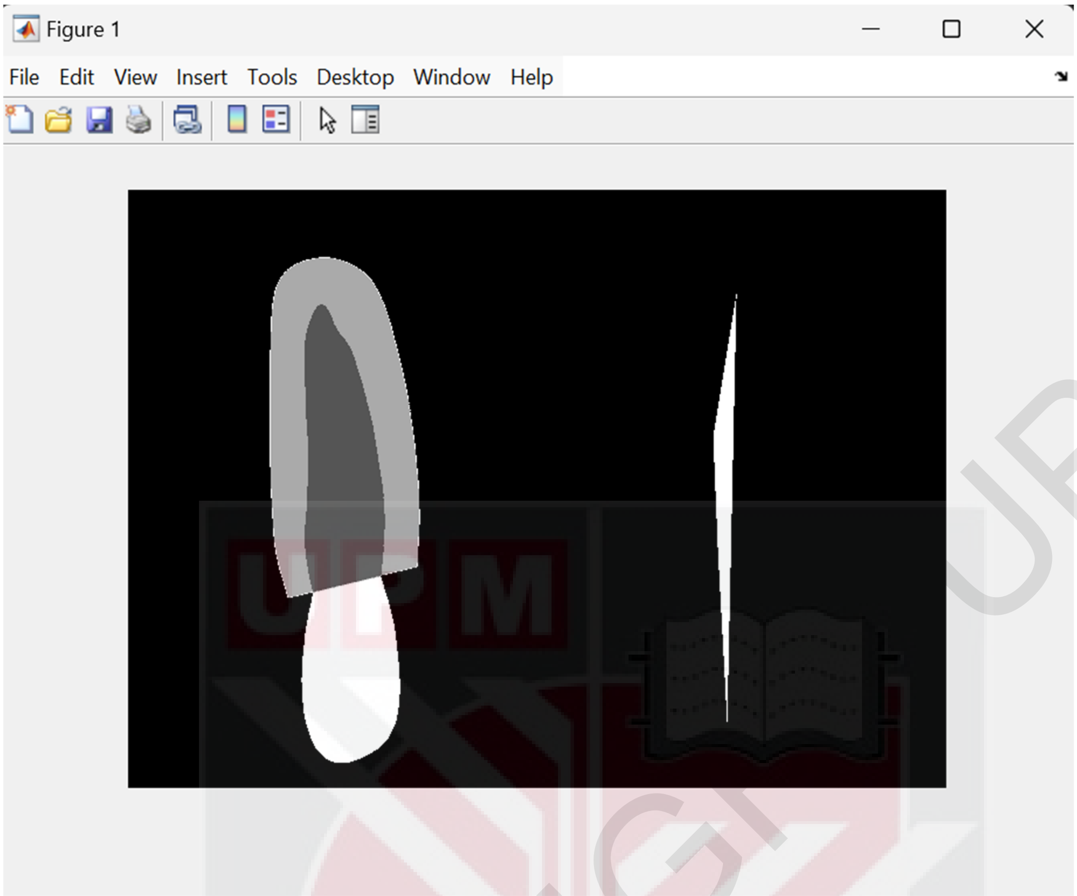


Figure 1
File Edit View Insert Tools Desktop Window Help

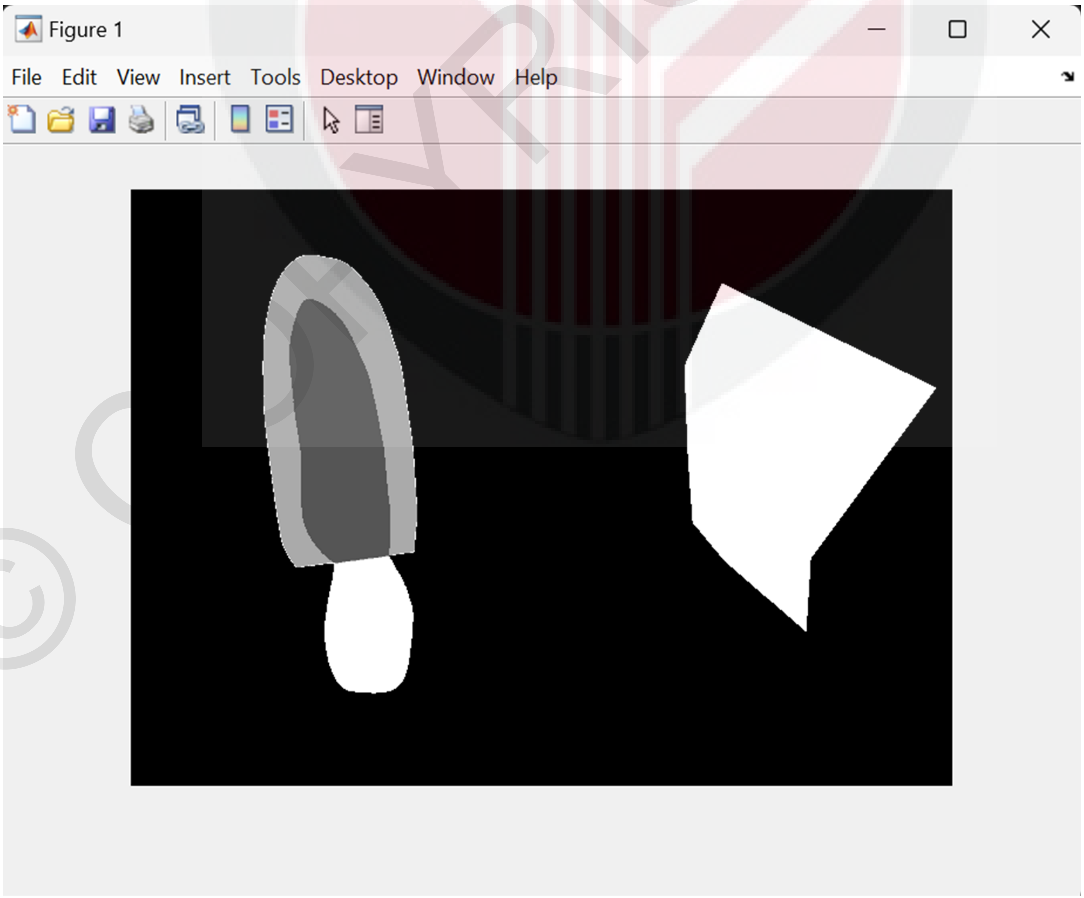
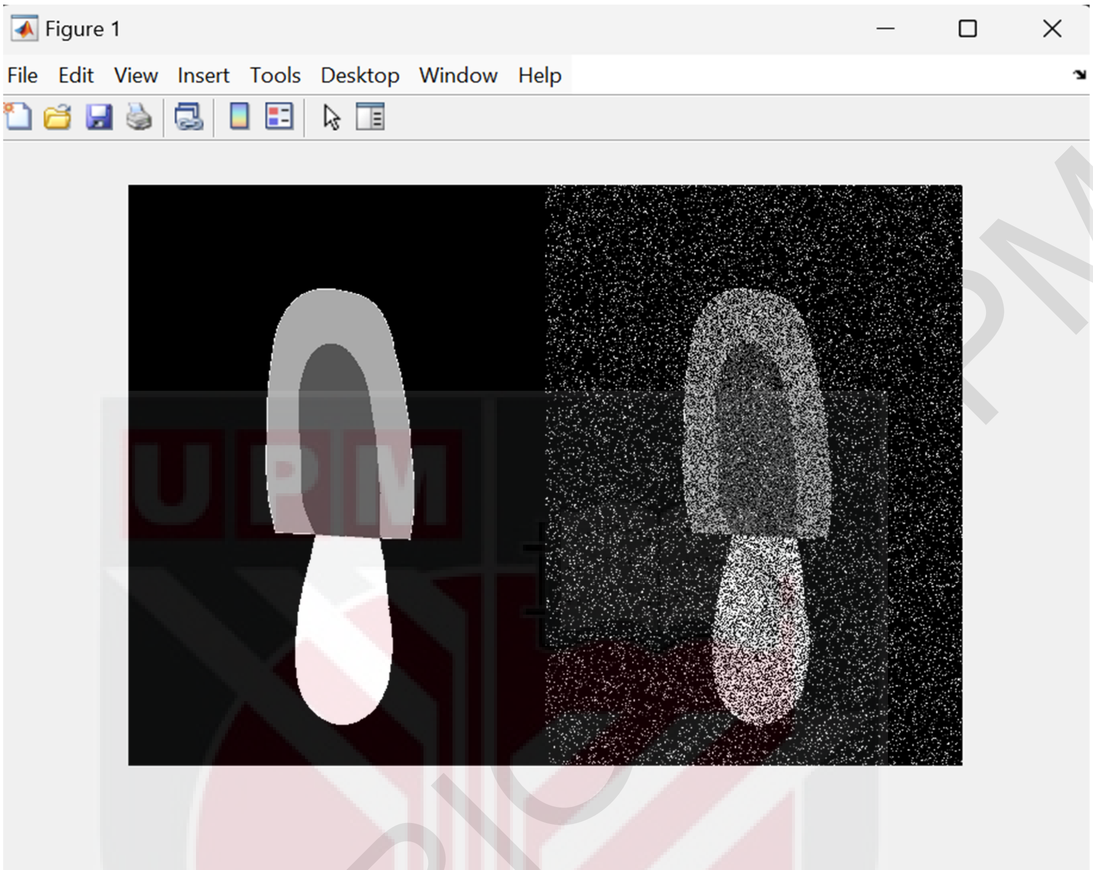
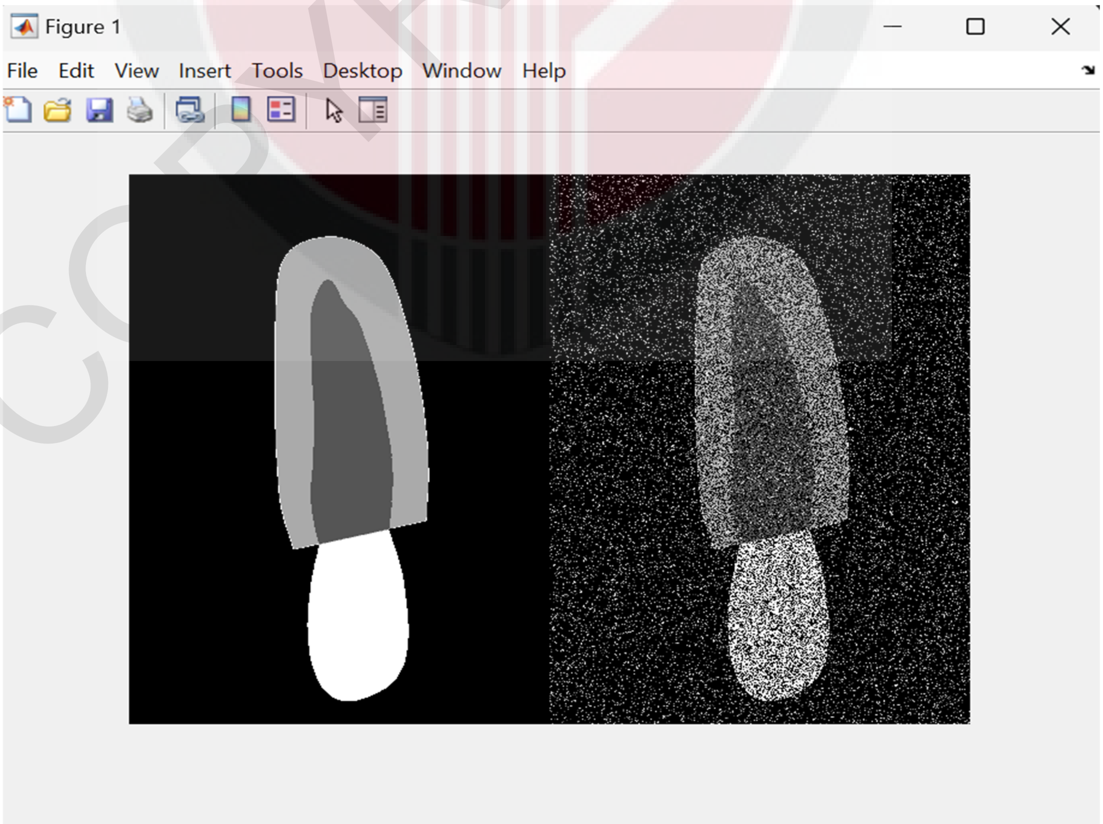


Figure 1
File Edit View Insert Tools Desktop Window Help

Part (B): 3 Samples results of six-pixel neighborhood method.





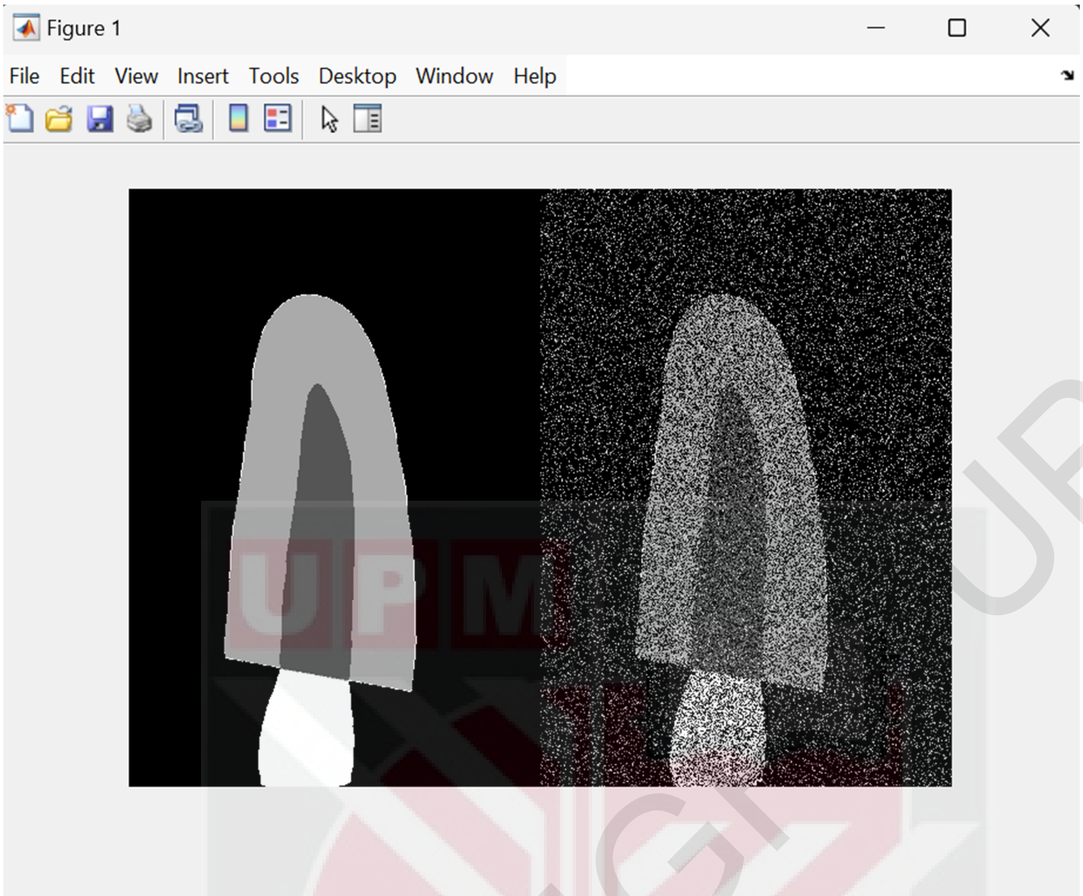


Figure 1
File Edit View Insert Tools Desktop Window Help

BIODATA OF STUDENT

Mehdi Samieiyeganeh completed his bachelor's degree in software engineering from 2005 to 2009 at the Islamic Azad University, Toisarkan Branch, Iran. In 2010, he joined Jawaharlal Nehru Technology University in Hyderabad (JNTUH), India for his master's degree (M-Tech) and completed his master's degree in software engineering in 2012 with a first-class average. After returning to Iran, he taught as a lecturer in various public and private universities for 6 years, and during this time he became faculty member of Ganjnameh Higher Education Institute, Hamedan,iran. For 4 years, he was the head of the Computer Department at Ganjaneh Institute of Higher Education. In 2018, due to his interest in continuing his studies outside of Iran, he resigned from his job at university and entered the University Putra Malaysia (UPM) as doctoral student. Published papers with their citations are available in Google Scholar link.

https://scholar.google.com/citations?user=ZzwzYOcAAAAJ&hl=en

LIST OF PUBLICATIONS

Samieiyeganeh, M. E. H. D. I., Rahmat, R. W. B. O. K., Khalid, F. B., & Kasmiran, K. B. (2022). Deep reinforcement learning to multi-agent deep reinforcement learning. *J Theor Appl Inf Technol*, *100*, 990-1003.

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