Deep Learning Model for Estimation of LV Ejection Fraction from Echocardiogram

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Abstract

Heart failure, a leading global cause of death, poses challenges for early prediction of cardiac dysfunction, especially ejection fraction (EF). This study employs Convolutional Neural Networks (CNNs), utilizing ResNet and MobileNet architectures, on the CAMUS dataset with 500 patient records (2CH and 4CH). The goal is to aid healthcare professionals in accurately measuring EF. The CAMUS dataset, comprising multi-modality cardiac imaging and segmentation data, serves as the foundation. The CNN, ResNet, and MobileNet models are fine-tuned through transfer learning and their performance is evaluated based on accuracy. This comparative analysis identifies the model with the best predictive capabilities for EF, showcasing their potential for earlier diagnosis and intervention. Deep learning techniques enhance cardiac healthcare by providing reliable, noninvasive means of predicting heart failure, reducing its impact on patients and healthcare systems.

Keywords: Deep learning, Convolution Neural Network, ResNet, MobileNet, Ejection Fraction

DOI: https://doi.org/10.36548/jaicn.2024.2.006
Received: 08.04.2024, received in revised form: 02.05.2024, accepted: 16.05.2024, published: 25.05.2024

1. Introduction

Heart failure, a complex and debilitating cardiovascular condition, continues to be a significant public health challenge worldwide. In order to effectively manage and treat patients with heart failure, timely diagnosis and accurate prediction of cardiac dysfunction, in particular with regard to ejection fraction, are essential. Deep learning techniques, specifically the utilization of deep neural networks, have emerged as powerful tools in the field of medical imaging and diagnostics. In this study, we embark on a journey to predict heart failure with a particular focus on EF using three prominent deep learning models: Convolutional Neural Networks (CNN), Residual Networks (ResNet), and MobileNets. To exploit the capacities of those models to develop robust predictive tools that leverage the wealth of CAMUS (Cardiac Atlas Multi-Modality and Segmentation for Understanding Structure-Function Relations) data in order to serve medical professionals is a primary objective of this research. Heart failure poses a significant burden on global healthcare systems, leading to reduced quality of life and increased mortality rates. Medical imaging is a key factor in addressing this problem, as it assesses heart function. A key indicator for heart failure's severity is EF, a measurement of how effectively the heart pumps blood. Precise prediction of the EF from cardiac imaging, which is also a guide to treatment decisions and ensures that patients are appropriately treated, results in earlier identification as well as more effective diagnosis. In this field, a collection of heterogeneous multi-modality heart imaging data and comprehensive segmentation information are an invaluable resource that is available in the CAMUS database. This dataset is carefully compiled and essential for training and evaluation of machine learning models in cardiac applications. In our research, we are preparing the CAMUS dataset to be used for Model Learning, implementing CNN, ResNet and MobileNet Architectures while optimizing those model by using techniques of Transfer Learning. In this way, appropriate features and patterns of the cardiac images that reflect EF can be inferred to provide a baseline for accurate forecasts.

The field of medical imaging analysis has gained popularity with deep learning models such as CNN, ResNet and MobileNet. CNNs are of particular interest for image data, because they can be automatically trained to recognize the relevant features. ResNet, with its skip connections, can effectively solve the problem of vanishing gradients and is able to be used in deep architectures. On the other hand, MobileNet is a technology that can be used in applications where computational resources are limited due to its efficiency. Convolutional Neural Network is a deep learning model that precisely targets the processing and analysis of semantic grid-like data, such as images and videos. CNNs have revolutionized computer vision, enabling tasks like image classification, object detection, and face recognition, while also being instrumental in natural language processing and speech recognition for sequential data. The ResNet architecture, short for "Residual Networks," is a complex convolutional algorithm that addresses the issue of decreasing gradients in very deep neural networks by introducing residual blocks with shortcut connections, allowing the network to efficiently detect minor changes in data and improve performance by adding this functionality to the original input. The MobileNet family is a CNN architecture designed for efficient, lightweight deep learning on mobile and embedded devices. Optimized for tasks like image classification and object detection, it consumes minimal computing resources, memory, and power. Developing a machine learning model for predicting heart failure offers several benefits: it provides a noninvasive, effective detection method, reduces patient discomfort, aids in therapy planning and patient management, and allows early detection and intervention, potentially improving patient outcomes.

In this work, we shall also assess deep learning technology's capacity to predict EF in heart failure cases and perform a comprehensive evaluation of its performance for determining which model is most effective. The results of this study could change the way doctors treat cardiac conditions by making it possible to introduce revolutionary and accurate diagnostic tools that would have a large impact on patients' well being and healthcare system efficiency.

2. Literature Survey

Dr. Neal Yuan and colleagues developed a model to predict Coronary Artery Calcium (CAC) using echocardiograms, collecting data from Cedars Sinai Medical Center and Stanford Healthcare. They processed video frames from transthoracic echocardiograms (TTEs) using Convolutional Neural Networks (CNN), achieving 95% accuracy. The study indicates that CAC predictions from TTEs can distinguish between one and two years of mortality in high-incidence cancer patients, suggesting potential for future coronary artery disease risk stratification and preventive therapy.

In paper [2], Lindsay and her team developed a machine learning model for mitral regurgitation (MR) detection in echocardiography using data from a Philips CX50 machine with an S5-1 transducer probe. The dataset included 2,229 video clips and 66,330 still frames from 227 subjects' echocardiograms. They used Python and the GDCM library to extract metadata from the DICOM echocardiographic data. The approach involved two steps: view classification to identify the parasternal long-axis (PLAX) view and MR detection within the PLAX-C view, using CNN models DenseNet and ResNet. The MR detection CNN achieved 86% accuracy, with limitations in differentiating MR severity. The CNN was particularly effective in detecting MR in pediatric patients with low ejection fraction (EF), achieving 90.3% accuracy, which is valuable as traditional methods may not be suitable for these patients.

In paper [3], a machine learning based approach for predicting 1 year survival after myocardial infarction-MI is proposed in a paper "One Year Survival Prediction of Myocardial Infarction". MI is a disease in which the heart's blood vessels are blocked, causing damage to its cardiac muscle. It is a leading cause of death worldwide. To reach this error, compared to the RBFN that achieved its lowest mean square errors of 10 seconds”, BPNN needed a longer training period '20 seconds'. The convergence of the BPNN1000 epoch and the accuracy of 96.9% was approximately the same as that of the RBFN50 epoch and the accuracy of 98.5%.

In paper [4], machine learning is increasingly pivotal in heart disease prediction, leveraging extensive patient datasets to identify disease patterns with high precision. Various machine learning algorithms, including Decision Trees, Random Forests, Support Vector Machines (SVMs), Logistic Regression, and Naive Bayes, are employed.

In paper [5], combining machine learning and deep learning enhances heart disease prediction accuracy. Machine learning identifies crucial data features, while deep learning makes predictions from these features. The study evaluates various machine learning algorithms (RF, LR, kNN, SVM, DT) alongside deep learning, comparing their results. Without feature selection and outlier detection, SVM achieves 84.09% accuracy and deep learning 76.7%. With feature selection, RF reaches 88% accuracy and deep learning 86.8%. With both feature selection and outlier detection, kNN achieves 84.86% accuracy and deep learning 94.2%. Overall, deep learning outperforms machine learning, showing promise for heart disease prediction as the field continues to evolve.

In paper [6], the RPeak Altered Detection method for QRS complex detection in ECG signals improves upon the Pan-Tompkins algorithm by being more resistant to noise. The ECG signal is preprocessed to remove DC offset and high-frequency noise, then a derivative filter extracts slope information, and the squared signal measures signal energy. R peaks are recorded as localized maximum frequencies. This modified algorithm is more resistant to noise, integrates signal power to mitigate errors, and is efficient in detecting QRS complexes with high precision, making it suitable for portable devices due to its low computational requirements.

In paper [7], a novel method estimates heart rate using Seismocardiography (SCG) independently of ECG during low and high lung volume phases. Involving seven healthy subjects, the study recorded SCG, ECG, and respiratory signals simultaneously. The method showed a low bias of 0.08 bpm compared to standard ECG measurements.

In paper [8], Dr. Manimurugan and colleagues proposed a two-stage model for medical data classification and prediction. The first stage classified ECG data from medical sensors using a hybrid linear discriminant analysis with modified ant lion optimization (HLDA-MALO), achieving 96.85% accuracy for normal data and 98.31% for abnormal data. The second stage classified echocardiogram images from the UCI database using a hybrid Faster R-CNN with SE-ResNeXt-101 transfer learning model, achieving 99.15% accuracy. Future improvements may include advanced deep transfer learning models like SqueezeNet and EfficientNet and using larger datasets for better analysis.

In paper [9], the study compared the accuracy of 3D echocardiography (3D echo) with 3 Tesla Cardiac Magnetic Resonance Imaging (CMRI) in estimating end-systolic Left Ventricular Ejection Fraction (LVEF). Both methods, non-invasive for cardiac function assessment, showed strong correlation in LV volumes and LVEF measurements. While 3D echo displayed slightly different values, it proved precise for cardiac evaluation. Larger, diverse population studies, especially for complex diagnostics, are recommended to validate these findings further.

In paper [10], Ouyang et al. introduce the EchoNet-Dynamic Cardiac Motion Video dataset, containing 10,271 apical 4-chamber echocardiography videos with tracings and labels of cardiac function. Acquired from the University Hospital Echocardiography Lab, images were processed using various ultrasound machines and stored in the Philips Xcelera system. Preprocessing techniques included quality control and interpolation using OpenCV. A CNN model achieved 90% accuracy in detecting wall motion. While comprehensive, future work could expand the dataset to include additional echocardiographic views, link ECG data, incorporate patients' cardiovascular history, and assess disease progression over time.

In paper [11], Farhad et al. developed a CNN model to detect cardiac abnormalities using CAMUS and CardiacPhase datasets. CAMUS included 100 images, and CardiacPhase, created for the study, contained echocardiograms from 35 patients in ED and ES phases. ResNet achieved 92% accuracy on CAMUS, while VGG-16 reached 79% on CardiacPhase.

In paper [12], the discussion focuses on machine learning's role in diagnosing cardiac diseases via echocardiography images. Echocardiography, a non-invasive imaging method, aids in diagnosing heart failure, vascular and coronary artery diseases. Machine learning algorithms analyze these images to detect indicators like heart chamber size and valve movement. The study achieved a 90% accuracy in categorizing echocardiography images from chronic heart disease patients. Employing HPT-Xception_MLP and HPT-Xception_RF models, accuracies of 89.38% and 99.84% were reached. This research underscores machine learning's potential to improve cardiovascular disease diagnosis accuracy and efficiency through echocardiography image analysis.

In "Nature Communications," a paper explores using video data to predict postoperative right ventricular failure (PORVF) after heart surgery. Deep learning is employed to analyze videos capturing right ventricle movement, likely using Convolutional Neural Networks. This research compiles patient videotapes to develop a predictive model distinguishing PORVF cases. Considerations include data quality, size, and diversity. The study results in a predictive model for assessing PORVF risk, potentially aiding post-surgery patient management. Emphasizing video-based deep learning's value in predicting PORVF, the paper underscores the need for further research to enhance model accuracy and clinical application [13].

In paper [14], a semiautomatic diagnosis network employing deep learning algorithms detects Left Ventricular Hypertrophy (LVH) in echocardiograms. The study included 1610 echocardiograms from 724 patients, diagnosed by two clinicians. ResNet and U-net++ architectures were introduced for classification and segmentation tasks, achieving excellent performance. The model achieved a perfect AUC of 1.0 for view classification and 0.98 for LVH detection, with high sensitivity and specificity. Etiology identification models showed good discriminatory abilities, and the integrated framework achieved an average AUC of 0.91 for classifying four conditions, demonstrating machine learning's potential in cardiac diagnosis and patient care enhancement.

In paper [15], deep learning techniques are applied to echocardiogram analysis, focusing on distinguishing between normal and abnormal regurgitation and classifying regurgitation types using 2D and 3D Doppler images, along with videographic images. 1070 2D and 540 3D Doppler images are used, with 10% for verification and the rest for training. Testing excludes 38 2D and 10 Doppler images. Two deep learning methodologies, RNN (LSTM-based) and Auto-encoder (VAE-based), are employed. Results show deep learning outperforms SVM, with VAE excelling in static images and LSTM in video graphics. This research underscores deep learning's potential in echocardiogram analysis advancement.

In paper [16], a Deep Learning model is developed for automated Left Ventricular Ejection Fraction (LVEF) measurements using 2D echocardiography images from three centers. The CAMUS dataset includes 500 2DE studies, while EchoNet Dynamic comprises 10,030 grayscale videos. Two modules were used for algorithm development and generalization testing. DPSNet showed high effectiveness in LV segmentation and LVEF measurements across phenotypes and echo systems. Studywise evaluation revealed better LV segmentation performance with DPSNet v2 compared to EchoNet_dynamic algorithm ($p = 0.008$). DPSNet achieved good correlation and agreement for LVEF measurement, indicating its potential in automated LVEF assessment.

3. Dataset Description

The dataset (Figure1) is composed of 500 patients as follows: 406 patients with good/medium image quality, 94 patients with poor image quality, 246 patients with an ejection fraction lower than 45%, 97 patients with an ejection fraction higher than 55%. For all these data, the corresponding manual references given by one cardiologist expert along with additional information (diastolicsystolic phase instants) are provided. The dataset concerns the segmentation of echocardiographic images. The dataset consists of clinical exams from 500 patients, acquired at the University Hospital of St Etienne (France). The acquisitions were optimized to perform left ventricle ejection fraction measurements. 19% of the images have a poor quality (based on the opinion of one expert). The full dataset was acquired from GE Vivid E95 ultrasound scanners, with a GE M5S probe. For each patient, 2D apical four-chamber and two-chamber view sequences were exported from EchoPAC analysis software.

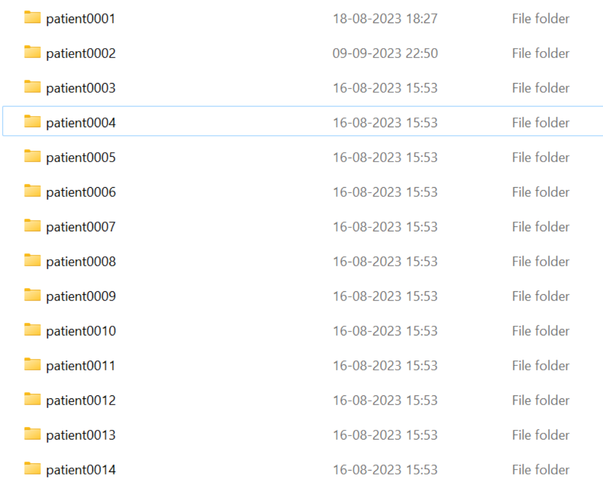


Figure 1. Dataset

For each patient, 2D apical four-chamber and two-chamber view sequences were available. CAMUS includes manual expert annotations for the left ventricle endocardium (LVEndo), the myocardium (epicardium contour more specifically, named LVEpi) and the left atrium (LA).

- **Diastole**: Period of Relaxation.
- **Systole**: Period of Contracion.
- **End Diastole**: The ventricles are completely filled with blood.
- **End Systole**: The ventricles have pushed out the maximum amount of blood.
- **Ejection Fraction**: The ejection fraction is calculated by comparing the volume of blood present in the left ventricle at the end of diastole and the volume of blood remaining in the ventricle at the end of systole.
- **Endocardium**: Endocardium is the innermost layer of the heart's wall.

4. Pre - Processing

The aim of the project to find cardiovascular abnormality with the Ejection fraction level in Left Ventricle using CNN, ResNet, MobileNet, before entering model feature must be extracted, so some pre-processing techniques were used in this research.

A. Convert NifTi File

To store 3D images of the human brain, a "NIfTI" file (Figure 2) is a common file format used for neuroimaging and medical imaging. It's called "NIfTI" for Neuro Imaging Informatics Technology Initiative. The components of the filename extension represent: ".nii": this part represents a file format called NIfTI. NIfTI is a standard format for representing neuroimaging data, and it includes important information about the image, such as image dimensions, voxel sizes, and header information.".gz": This part of the extension signifies that the file has been compressed using the gzip compression algorithm.

Figure 2. NIfTI File Info

Compression is frequently utilized to reduce the file sizes of brain imaging data, which can be particularly large and complex in neuroimaging. The input images are in .nii.gz format, so we convert them into .png format using the "nib" library, as illustrated in Fig. 3. These processes will be performed for 500 patients.

Figure 3. Output .png Images

B. Change Background Colour

After converting the images, the background color will be changed. In this project, only the Left Ventricle is needed, which is the darkest portion, so the color of other dark areas will be changed. Changing the background color enhances the accuracy of the extraction. This was the second step in the preprocessing technique of the project. The background of the images is changed to white, as shown in Figure. 4. This process will be done for 500 patients.

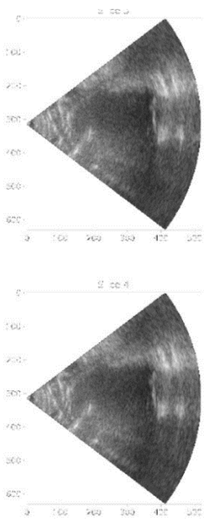


Figure 4. Background Changing Image

C. Bounding Box Implementation

The third process is to apply a bounding box to each image to extract the left ventricle. In the 2CH view, it contains both the left ventricle and the left atrium. The algorithm first detects the two darkest portions and applies a bounding box to the second largest portion, cropping that area. Each patient has more than 12 frames; bounding boxes are applied to all frames for all 500 patients, as shown in Figure 5.

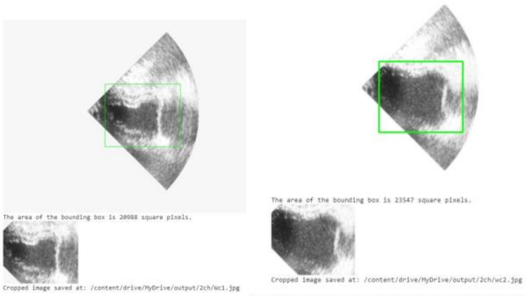


Figure 5. Bounding Box Implementation

D. Contour Implementation

The fourth step in the model involves applying contours. Contours represent the outline of objects or shapes in an image and are crucial for image processing and computer vision tasks. After applying contours, the area of the contour portions is calculated, with the smallest contour representing End Systole and the largest representing End Diastole, crucial for calculating Ejection Fraction (EF). Smallest and largest images are stored for further analysis, as depicted in Figure 6 and 7.

Formulae for calculating

Area = 0.5 * Σ(x[i]*y[i+1] - x[i+1]*y[i])

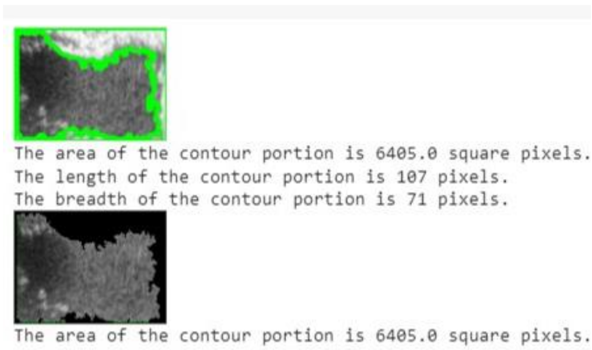


Figure 6. Contour Implementation for ES

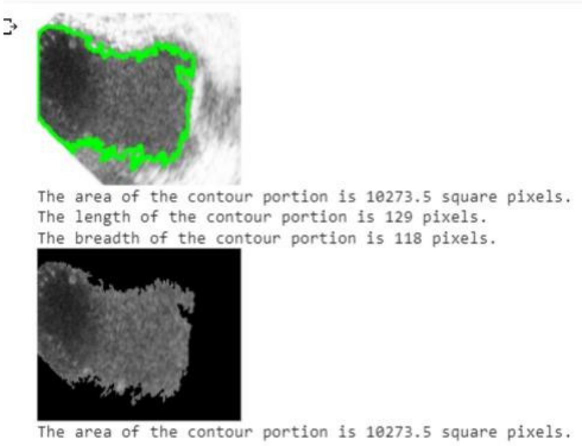


Figure 7. Contour Implementation for ES

E. Segmentation in 4CH View

The same preprocessing techniques were used in 4CH Left Ventricle segmentation: conversion from .nii.gz to .png images, background color change, application of bounding boxes, and contouring. Additionally, cropping was used to extract the region of interest, as the 4-ch view includes the left ventricle, left atrium, right ventricle, and right atrium. In this project, we predict Left Ventricle Ejection Fraction (LVEF), and the cropping technique is employed to isolate the left side of the heart, as shown in Figure 8. The cropping technique is applied before applying the bounding box.

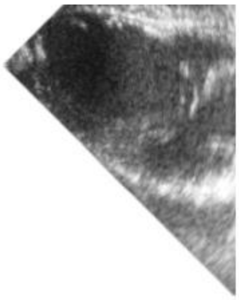


Figure 8. Cropping Technique

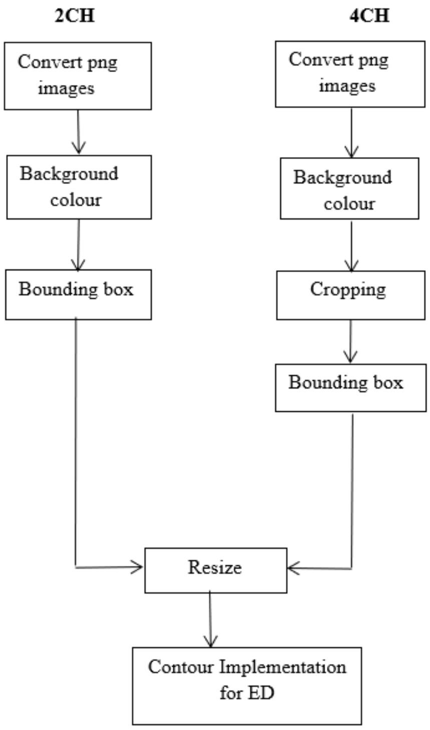


Figure 9. Flow Graph of Preprocessing Technique

F. Resize Image

Both 4 - CH contour images and 2 - CH contour images are resize because all images are different size. So, use this technique to resize all image (length = 200, width= 200).

G. Ejection Fraction (EF)

Left ventricular ejection fraction (LVEF) is a crucial measurement used in cardiology to assess the pumping efficiency of the heart's left ventricle, which is responsible for pumping oxygenated blood to the body's various tissues and organs. The amount of LVEF is calculated by each heartbeat, and quantifies the volume of blood that has been released from the left ventricle. Medical imaging techniques such as echocardiography, cardiac magnetic resonance Imaging MRI are commonly used to measure the left ventricle ejection fraction, which is a vital indicator of heart function. The calculation of LVEF shall be carried out in the following ways:

$$EF = (EDA - ESA)/EDA \times 100\%$$

H. EF Calculation

To find a smallest contour image and largest contour image in both 4CH and 2CH based on contour area. Largest image is End Diastole and smallest is End systole as shown in Figure 9 and 10 and calculate Ejection fraction using formula 2 as shown in Figure 11

Figure 9. Area of ES

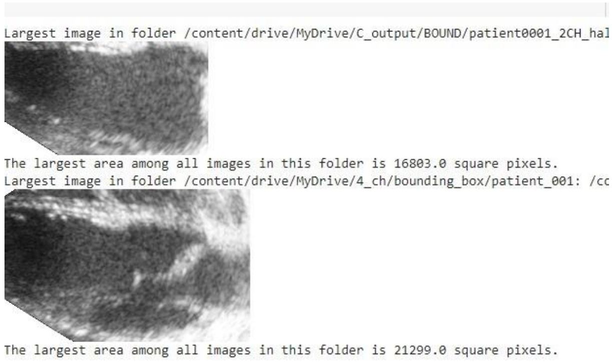


Figure 10. Area of ED

- **End-Diastolic(ED):** This is the volume of blood present in the left ventricle at the end of the diastolic phase, when the ventricle is fully relaxed and filled with blood.
- **End-Systolic (ES):** This is the volume of blood remaining in the left ventricle at the end of the systolic phase, when the ventricle has contracted and pumped blood out.

```
Folder: /content/drive/MyDrive/C_output/BOUND/patient0001_2CH_half_sequence.nii
Percentage Difference: 37.75218710944474%
Folder: /content/drive/MyDrive/4_ch/bounding_box/patient_001
Percentage Difference: 35.738767078266584%
```

Figure 11. Calculation of Ejection Fraction

5. Feature Extraction

Table.1 below shows the details of features extracted

Table 1. Feature Extraction

Class	EF Level	Dataset Samples (Number of patients)
Normal	50 % to 70%	94
Mild	40 % to 49%	246
Moderate	30% to 39 %	100
Severe	Below 29 %	65

6. System Architecture

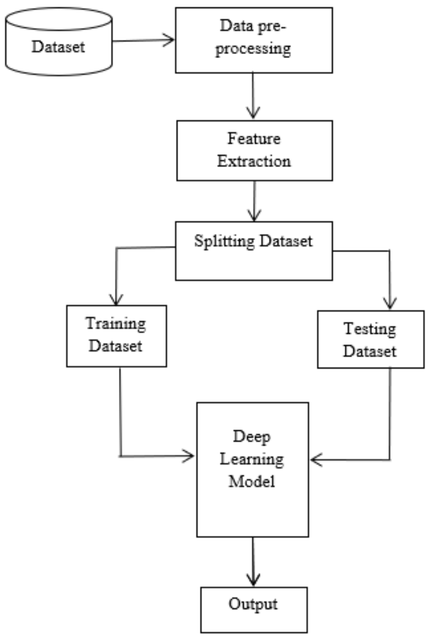


Figure 12. System Architecture

7. Model Building

A. Delete Poor Quality Images

In 2CH, 75 patient images were of poor quality, and in 4CH, 45 patient images were of poor quality. These poor quality images were then deleted.

B. Splitting Data

Before implementing the model, the data were split for training and testing. The input comprises 776 images. Only End Systole and End Diastole images are provided, meaning each patient has only 2 images, as Ejection Fraction is calculated using End Diastole and End Systole. Thus, the number of images is reduced. There are 776 images in the training set and 112 images in the testing set.

C. Model Implementation

Deep Learning," a subfield of machine learning and AI, focuses on developing highly intelligent Artificial Neural Networks capable of human-like tasks. This involves using multiple layers, or a deep architecture, in neural networks to automatically learn hierarchical features from data. In this project, CNN (Convolutional Neural Network), ResNet, and MobileNet are employed.

1. CNN (Convolution Neural Network)

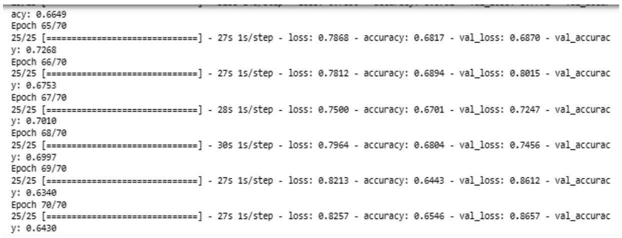
A Convolutional Neural Network is a Deep Learning Architecture which has been specially formulated for the Processing of Grid like Data, such as images and videos. CNNs can be used especially well for tasks such as image classification, object recognition or segmentation because they consist of convolution layers that are automatic to detect hierarchical patterns and characteristics in the input data. Some layer are available in CNN model. In these project we use 14 layers and accuracy of these model is 63%.

```
Epoch 1/15
40/40 [==============================] - 21s 525ms/step - loss: 0.9992 - accuracy: 0.5938
Epoch 2/15
40/40 [==============================] - 21s 515ms/step - loss: 1.0492 - accuracy: 0.5500
Epoch 3/15
40/40 [==============================] - 20s 506ms/step - loss: 0.9880 - accuracy: 0.6000
Epoch 4/15
40/40 [==============================] - 21s 512ms/step - loss: 0.9537 - accuracy: 0.6313
Epoch 5/15
40/40 [==============================] - 20s 508ms/step - loss: 1.0911 - accuracy: 0.5063
Epoch 6/15
40/40 [==============================] - 21s 511ms/step - loss: 1.0922 - accuracy: 0.5312
Epoch 7/15
40/40 [==============================] - 21s 519ms/step - loss: 1.0245 - accuracy: 0.6250
Epoch 8/15
40/40 [==============================] - 22s 545ms/step - loss: 1.0923 - accuracy: 0.5250
Epoch 9/15
40/40 [==============================] - 21s 521ms/step - loss: 1.0480 - accuracy: 0.5750
Epoch 10/15
40/40 [==============================] - 21s 520ms/step - loss: 1.0347 - accuracy: 0.5688
Epoch 11/15
40/40 [==============================] - 21s 529ms/step - loss: 0.9955 - accuracy: 0.5875
Epoch 12/15
40/40 [==============================] - 21s 521ms/step - loss: 0.9924 - accuracy: 0.5938
Epoch 13/15
40/40 [==============================] - 21s 520ms/step - loss: 1.0963 - accuracy: 0.5250
Epoch 14/15
40/40 [==============================] - 21s 523ms/step - loss: 1.0134 - accuracy: 0.5750
Epoch 15/15
40/40 [==============================] - 21s 513ms/step - loss: 0.9842 - accuracy: 0.6313
```

Figure 13. CNN Accuracy

2. ResNet Model

ResNet, by introducing residual connections that allow information to bypass a single layer or multiple layers, addresses this problem. To do so, you add a layer input to output of the next layer that in this way creates what is known as "a short window" allowing data to be moved. The ResNet model has four layers which achieve an accuracy of 65 %.

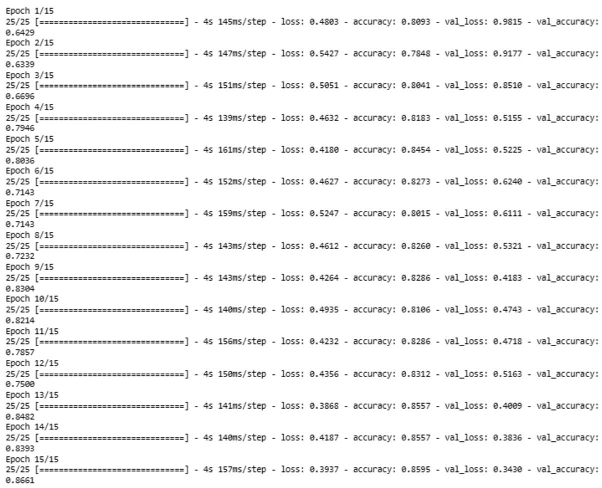


```
acy: 0.6649
Epoch 65/70
25/25 [==============================] - 27s 1s/step - loss: 0.7868 - accuracy: 0.6817 - val_loss: 0.6870 - val_accurac
y: 0.7268
Epoch 66/70
25/25 [==============================] - 27s 1s/step - loss: 0.7812 - accuracy: 0.6894 - val_loss: 0.8015 - val_accurac
y: 0.6753
Epoch 67/70
25/25 [==============================] - 28s 1s/step - loss: 0.7500 - accuracy: 0.6701 - val_loss: 0.7247 - val_accurac
y: 0.7010
Epoch 68/70
25/25 [==============================] - 30s 1s/step - loss: 0.7964 - accuracy: 0.6804 - val_loss: 0.7456 - val_accurac
y: 0.6997
Epoch 69/70
25/25 [==============================] - 27s 1s/step - loss: 0.8213 - accuracy: 0.6443 - val_loss: 0.8612 - val_accurac
y: 0.6340
Epoch 70/70
25/25 [==============================] - 27s 1s/step - loss: 0.8257 - accuracy: 0.6546 - val_loss: 0.8657 - val_accurac
y: 0.6430
```

Figure 14. ResNet Accuracy

3. MobileNet Model

MobileNet is an efficient and light architecture for neural networks, which are mainly designed to operate on mobile or embedded devices. MobileNet models are designed to achieve a balance of model accuracy and computational efficiency, which makes them appropriate for applications that do not have sufficient computational resources or the size of their models. There are four layers in these model. This model achieve 85% accuracy.



```
Epoch 1/15
25/25 [==============================] - 4s 145ms/step - loss: 0.4803 - accuracy: 0.8093 - val_loss: 0.9815 - val_accuracy:
0.6429
Epoch 2/15
25/25 [==============================] - 4s 147ms/step - loss: 0.5427 - accuracy: 0.7848 - val_loss: 0.9177 - val_accuracy:
0.6339
Epoch 3/15
25/25 [==============================] - 4s 151ms/step - loss: 0.5051 - accuracy: 0.8041 - val_loss: 0.8510 - val_accuracy:
0.6696
Epoch 4/15
25/25 [==============================] - 4s 139ms/step - loss: 0.4632 - accuracy: 0.8183 - val_loss: 0.5155 - val_accuracy:
0.7946
Epoch 5/15
25/25 [==============================] - 4s 161ms/step - loss: 0.4180 - accuracy: 0.8454 - val_loss: 0.5225 - val_accuracy:
0.8036
Epoch 6/15
25/25 [==============================] - 4s 152ms/step - loss: 0.4627 - accuracy: 0.8273 - val_loss: 0.6240 - val_accuracy:
0.7143
Epoch 7/15
25/25 [==============================] - 4s 159ms/step - loss: 0.5247 - accuracy: 0.8015 - val_loss: 0.6111 - val_accuracy:
0.7143
Epoch 8/15
25/25 [==============================] - 4s 143ms/step - loss: 0.4612 - accuracy: 0.8260 - val_loss: 0.5321 - val_accuracy:
0.7232
Epoch 9/15
25/25 [==============================] - 4s 143ms/step - loss: 0.4264 - accuracy: 0.8286 - val_loss: 0.4183 - val_accuracy:
0.8304
Epoch 10/15
25/25 [==============================] - 4s 140ms/step - loss: 0.4935 - accuracy: 0.8106 - val_loss: 0.4743 - val_accuracy:
0.8214
Epoch 11/15
25/25 [==============================] - 4s 156ms/step - loss: 0.4232 - accuracy: 0.8286 - val_loss: 0.4718 - val_accuracy:
0.7857
Epoch 12/15
25/25 [==============================] - 4s 150ms/step - loss: 0.4356 - accuracy: 0.8312 - val_loss: 0.5163 - val_accuracy:
0.7500
Epoch 13/15
25/25 [==============================] - 4s 141ms/step - loss: 0.3868 - accuracy: 0.8557 - val_loss: 0.4009 - val_accuracy:
0.8482
Epoch 14/15
25/25 [==============================] - 4s 140ms/step - loss: 0.4187 - accuracy: 0.8557 - val_loss: 0.3836 - val_accuracy:
0.8393
Epoch 15/15
25/25 [==============================] - 4s 157ms/step - loss: 0.3937 - accuracy: 0.8595 - val_loss: 0.3430 - val_accuracy:
0.8661
```

Figure 15. MobileNet Accuracy

8. Result and Inference

A. Model Comparison

Convolutional Neural Networks (CNNs), ResNet (Residual Network), and MobileNet are all deep learning architectures designed for image-related tasks, but they differ in terms of their network structures, design philosophies, and use cases.

Table 2. Model Comparison

S.No	Pre-processing Technique	Algorithm	Accuracy
1	Image Conversion, Background ‘Colour Change,	CNN	63.3%
2	Bounding box, Cropping , Resize	ResNet	65%
3	Image, Contour Apply	MobileNet	85%

The MobileNet model outperforms CNN and ResNet on the CAMUS dataset with significantly higher accuracy (85%). This suggests that the MobileNet architecture, known for its efficiency and lightweight design, is well-suited for medical image classification tasks. The comparatively lower accuracies of CNN (63.3%) and ResNet (65%) may indicate challenges in capturing relevant features or overfitting due to the dataset's size, emphasizing the importance of choosing a model architecture tailored to the specific characteristics of the medical imaging dataset.

9. Conclusion and Future Works

The analysis of ejection fraction (EF) using the CAMUS dataset with 2-chamber (2ch) and 4-chamber (4ch) views revealed valuable insights. Three models—CNN, ResNet, and MobileNet—were assessed for accuracy in the CAMUS dataset, with MobileNet standing out at 85%. This promising accuracy and efficiency make MobileNet a strong candidate for clinical applications. These findings have broad implications, improving cardiovascular condition diagnosis and monitoring with precise and efficient EF estimation. Machine learning can reduce the need for costly and invasive procedures, enhancing healthcare accessibility and cost-effectiveness. The application of machine learning, particularly MobileNet, can revolutionize cardiology. Ongoing research is expected to yield more reliable diagnostic and management tools, benefiting patients and healthcare delivery. Future research, improve the accuracy of model and may also explore EF-based diagnosis and management of heart diseases like Congestive Heart Failure and Hypertrophy Heart Disease.

References

[1] Yuan, N., Kwan, A.C., Duffy, G., Theurer, J., Chen, J.H., Nieman, K., Botting, P., Dey, D., Berman, D.S., Cheng, S. and Ouyang, D., 2023. Prediction of coronary artery calcium using deep learning of echocardiograms. Journal of the American Society of Echocardiography, 36(5), pp.474-481.

[2] Edwards, L.A., Feng, F., Iqbal, M., Fu, Y., Sanyahumbi, A., Hao, S., McElhinney, D.B., Ling, X.B., Sable, C. and Luo, J., 2023. Machine learning for pediatric echocardiographic mitral regurgitation detection. Journal of the American Society of Echocardiography, 36(1), pp.96-104.

[3] Helwan, A., Ozsahin, D.U., Abiyev, R. and Bush, J., 2017. One-year survival prediction of myocardial infarction. International Journal of Advanced Computer Science and Applications, 8(6).

[4] Gavhane, A., Kokkula, G., Pandya, I. and Devadkar, K., 2018, March. Prediction of heart disease using machine learning. In 2018 second international conference on electronics, communication and aerospace technology (ICECA) (pp. 1275-1278). IEEE.

[5] Bharti, R., Khamparia, A., Shabaz, M., Dhiman, G., Pande, S. and Singh, P., 2021. Prediction of heart disease using a combination of machine learning and deep learning. Computational intelligence and neuroscience, 2021.

[6] Palaniappan, Y., Vishanth, V.A., Santhosh, N., Karthika, R. and Ganesan, M., 2020, July. R-peak detection using altered pan-Tompkins algorithm. In 2020 International Conference on Communication and Signal Processing (ICCSP) (pp. 1501-1505). IEEE.

[7] Taebi, A., Bomar, A.J., Sandler, R.H. and Mansy, H.A., 2018, April. Heart rate monitoring during different lung volume phases using seismocardiography. In SoutheastCon 2018 (pp. 1-5). IEEE.

[8] Manimurugan, S., Almutairi, S., Aborokbah, M.M., Narmatha, C., Ganesan, S., Chilamkurti, N., Alzaheb, R.A. and Almoamari, H., 2022. Two-stage classification model for the prediction of heart disease using IoMT and artificial intelligence. Sensors, 22(2), p.476.

[9] Benameur, N., Arous, Y., Ben Abdallah, N. and Kraiem, T., 2019. Comparison between 3D echocardiography and cardiac magnetic resonance imaging (CMRI) in the measurement of left ventricular volumes and ejection fraction. Current Medical Imaging, 15(7), pp.654-660.

[10] Ouyang, D., He, B., Ghorbani, A., Lungren, M.P., Ashley, E.A., Liang, D.H. and Zou, J.Y., 2019, December. Echonet-dynamic: a large new cardiac motion video data resource for medical machine learning. In NeurIPS ML4H Workshop: Vancouver, BC, Canada.

[11] Farhad, M., Masud, M.M., Beg, A., Ahmad, A., Ahmed, L. and Memon, S., 2023. Cardiac phase detection in echocardiography using convolutional neural networks. Scientific Reports, 13(1), p.8908.

[12] Negi, P., John, D., Vimal, V. and Prasad, V., 2023. Machine Learning-Based Analysis of Echocardiography Images for Cardiac Disease Diagnosis. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), pp.08-1.

[13] Shad, R., Quach, N., Fong, R., Kasinpila, P., Bowles, C., Castro, M., Guha, A., Suarez, E.E., Jovinge, S., Lee, S. and Boeve, T., 2021. Predicting post-operative right ventricular failure using video-based deep learning. Nature communications, 12(1), p.5192.

[14] Yu, X., Yao, X., Wu, B., Zhou, H., Xia, S., Su, W., Wu, Y. and Zheng, X., 2021. Using deep learning method to identify left ventricular hypertrophy on echocardiography. The International Journal of Cardiovascular Imaging, pp.1-11.

[15] Wahlang, I., Maji, A.K., Saha, G., Chakrabarti, P., Jasinski, M., Leonowicz, Z. and Jasinska, E., 2021. Deep Learning methods for classification of certain abnormalities in Echocardiography. Electronics, 10(4),

[16] Liu, X., Fan, Y., Li, S., Chen, M., Li, M., Hau, W.K., Zhang, H., Xu, L. and Lee, A.P.W., 2021. Deep learning-based automated left ventricular ejection fraction assessment using 2-D echocardiography. American Journal of Physiology-Heart and Circulatory Physiology, 321(2), pp.H390-H399.