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# MULTICLASS SEGMENTATION IN CARDIAC MRI IMAGES USING FC-DENSENET: AN ISLAMIC PERSPECTIVE

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Abstract: This study developed an automatic multi-class segmentation model for cardiac MRI images using the FC-DenseNet architecture. The model was trained on a dataset of 1,322 images from patients with various cardiovascular conditions and healthy subjects. Data augmentation techniques, including rotation, shifting, zooming, and flipping, were employed to enhance generalization. High training accuracy and decreasing loss over 30 epochs indicate effective learning, highlighting the model's promise for clinical application in cardiac MRI analysis. This research resonates with the teachings of Surah Al-Maidah, verse 32, which emphasizes the significance of saving and protecting life. By improving diagnostic capabilities in cardiology, this model not only contributes to better treatment planning for heart diseases but also embodies the moral responsibility to use technology for the benefit of humanity. The model achieved Dice Coefficient scores of 0.83 for the right ventricle (RV), 0.78 for the myocardium (Myo), and 0.71 for the left ventricle (LV), demonstrating satisfactory segmentation performance. To further enhance the model's accuracy and reliability, strategies such as advanced data augmentation, ensemble modeling, hyperparameter optimization, and attention mechanisms could be explored, ultimately supporting improved diagnosis and treatment planning in cardiology.
Keywords: Cardiac MRI Segmentation, FC-DenseNet Architecture, Data Augmentation, Heart Disease Diagnosis.

## 1. Introduction

Cardiovascular Disease (CVD) remains one of the leading causes of death worldwide. In 2022, approximately 422.7 million people globally suffered from CVD, with 19.8 million deaths attributed to the disease. In the Qur'an, it is emphasized that efforts to save and preserve life are of great value: ―…and whoever saves a life, it is as though he had saved all mankind... (Qur'an, Surah Al-Ma'idah: 32). This verse reflects the importance of contributing to human welfare through medical advancements.

Cardiac Magnetic Resonance Imaging (MRI) is a crucial non-invasive tool for evaluating cardiac volume and function. This evaluation is vital for assessing treatment in patients with serious heart conditions, such as heart failure that requires transplantation or the implantation of an artificial heart. Islam encourages endeavors that benefit humanity, including in the medical field. As the Prophet Muhammad (peace be upon him) said: ―Indeed, your body has a right over you‖ (HR. Bukhari), highlighting the responsibility of maintaining and seeking the best for one's health.

MRI is recognized as the gold standard for evaluating cardiac morphology and function, making it the optimal choice for non-invasive cardiac volume measurement and ejection fraction (EF) calculation, both of which require accurate cardiac boundary segmentation. Manual segmentation by clinicians is often time-consuming and prone to inter- and intra-observer variability. Therefore, a reliable automatic cardiac segmentation method is needed to expedite the diagnosis and monitoring process for patients. In this context, Islam supports the use of technology to improve the quality of healthcare, as long as its use brings benefits to society.

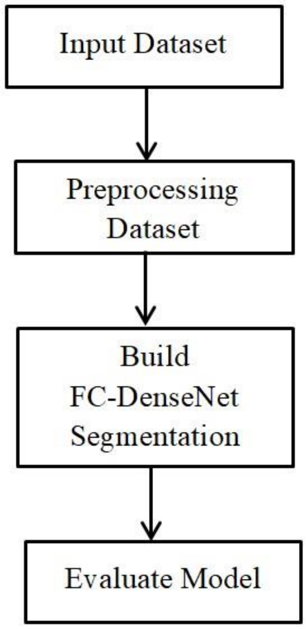
Cardiac segmentation is a challenging task due to the unclear boundaries of the heart and significant variation in the shape and intensity of cardiac tissue, especially in pathological cases. These challenges are compounded by the complexity of the heart's anatomical structure, which includes various components such as the muscular walls, heart chambers, and major blood vessels. In the Islamic perspective, advancing knowledge and technology to better understand God's creations, such as the complex structure of the heart, is part of the effort for tafakkur (reflection) and tadabbur (contemplation) upon the universe that Allah has created. As mentioned in the Qur'an: "And on the earth are signs for the certain [in faith] and in yourselves. Then will you not see?" (Qur'an, Surah Adh-Dhariyat: 20-21).

Traditional segmentation methods are often susceptible to noise, false edges, and weak edges. They also heavily depend on the registration process, which can affect the accuracy of the segmentation results. In recent years, Convolutional Neural Networks (CNNs) have demonstrated superior performance in large-scale visual recognition challenges like ImageNet. CNNs can automatically extract complex semantic features, which are useful for segmenting various cardiac structures, and have been successfully applied in medical image segmentation.

In recent years, many studies have used deep learning approaches for cardiac segmentation. For example, Fully Convolutional Network (FCN) architectures and other architectures like Fully Convolutional DenseNet (FC-DenseNet) have been applied for the automatic segmentation of cardiac images. FC-DenseNet utilizes dense blocks that allow each layer to receive input from all previous layers within the same block, thereby enhancing information flow and model efficiency. This research aims to perform multi-class segmentation on the heart chambers, separating three distinct parts: the right ventricle (RV), myocardium (Myo), and left ventricle (LV).

This study proposes the use of FC-DenseNets for the automatic segmentation of cardiac images from MRI. The model is designed to process input images end-to-end and produce segmentation maps that indicate the category of each pixel in the image. The training process for the cardiac segmentation model involves data augmentation methods to increase the variety and number of available training datasets. The experimental results are expected to show that this method is effective in achieving more accurate and efficient cardiac segmentation. Through this research, it is hoped to contribute to facilitating the diagnosis and treatment of heart diseases, ultimately serving as a means of preserving and protecting human life—a noble task in Islamic teachings.

## 2. Research Methods




`Figure 1: Flow diagram of the FC DenseNets method.

The flowchart of the FC-DenseNet method for automatic heart segmentation from a cardiac MRI dataset can be seen in Figure 1. This method consists of several key stages. First, Input Dataset: the cardiac MRI image dataset is input into the system. Second, during the Dataset Preprocessing stage, the images are resized to 224×224 pixels to match the input size of the FC- DenseNet model. Additionally, data augmentation is applied using `ImageDataGenerator` to enhance data diversity and generalization through techniques such as rotation, flipping, and zooming.

Next, in the Building the FC-DenseNet Segmentation Model stage, the FC-DenseNet segmentation model is constructed and trained using the preprocessed dataset. The goal is to learn features from the cardiac MRI images and perform accurate segmentation. Finally, in the Model Evaluation stage, the performance of the segmentation model is assessed using metrics such as the Dice Coefficient and Intersection over Union (IoU). These metrics are used to measure how well the model detects and labels heart regions, including the Right Ventricle (RV), Myocardium (Myo), Left Ventricle (LV), and Background. These four stages will be discussed further in the following sections.

### 2.1 Inputing the Dataset

In the first stage, the cardiac MRI image dataset is input into the system for further processing. This dataset consists of a series of images that will be used to train and test the segmentation model. These images are the primary input required for the entire segmentation process, as the quality and diversity of the dataset significantly influence the final outcome of the model.

### 2.2 Preprocessing the Dataset

The preprocessing stage includes several key steps to prepare the data for use by the segmentation model. First, all images are resized to 224×224 pixels to match the input size of the FC-DenseNet model. This step ensures that all images have consistent dimensions, allowing them to be processed efficiently by the model. Next, data augmentation is applied using ImageDataGenerator to enhance the diversity of the training dataset. The augmentation techniques used include rotation, flipping, and zooming of the images, aiming to simulate various conditions and variations that may occur in real-world data. This augmentation is crucial for improving the model's generalization ability and reducing the risk of overfitting by introducing a broader range of variations into the training process.

### 2.3 Building the FC-DenseNets Segmentation Model

Dense Convolutional Networks (DenseNets) are a modern CNN architecture based on the principle that directly connecting two layers in a feed-forward manner improves the accuracy and efficiency of the network. DenseNets consist of dense blocks and pooling operations, where each dense block is an iterative concatenation of the previous feature maps [17].

To enhance the flow of information between layers, DenseNets propose a more effective connection pattern where each layer is connected to all subsequent layers. First, the heart input image x0 (or the output image from a transition down (TD)) with m feature maps is fed into the first layer, producing an output x1 with k feature maps. Then, the k feature maps are combined with all previous feature maps and used as input to the second layer. This operation is repeated i times, where the i-th layer receives feature maps from all preceding layers as input:

$$xl=Hl([x0,x1,...,xi-1])$$

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where $[x_0, x_1, \ldots, x_{i-1}]$ represents the concatenation of the feature maps generated from layers 0 to $i-1$ [37].

Dense blocks within FC-DenseNets are used to extract features from cardiac images more efficiently. By utilizing dense connections, the vanishing gradient problem can be mitigated, feature propagation is enhanced, feature reuse is achieved, and the number of parameters is significantly reduced. The layers between blocks, known as transition layers, combine convolution and pooling operations to reduce the spatial scale of the feature maps and perform down-sampling. When the size of the feature maps is reduced during the transition down (TD) blocks, the feature map size needs to be restored through upsampling for semantic segmentation, which is the function of the transition up (TU) blocks [17].

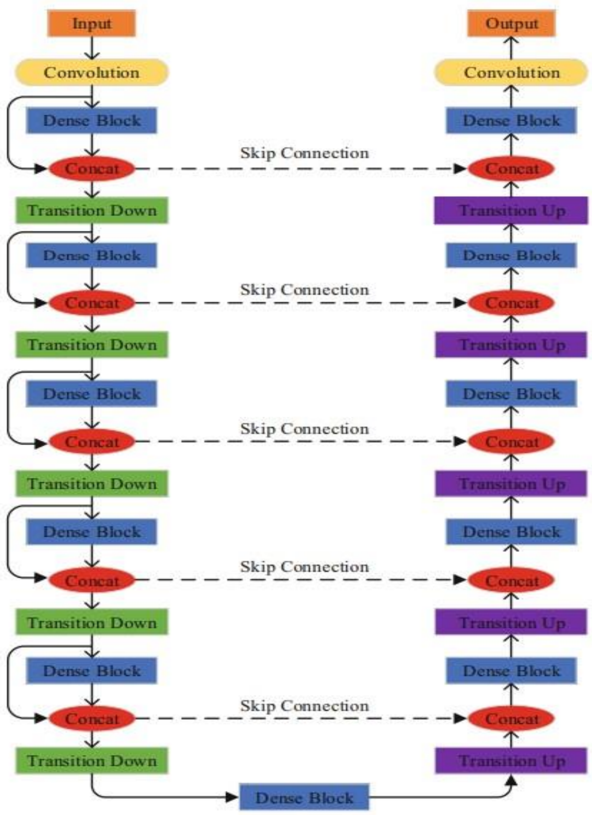


Figure 2: Architecture of FC DenseNets method.

The FC-DenseNets architecture is configured with a specific number of sub-blocks in each dense block to achieve optimal segmentation results. For instance, the number of sub- blocks in the dense blocks is set as [4, 5, 7, 10, 12, 15, 12, 10, 7, 5, 4], with a growth rate of (k=16), to minimize model complexity while ensuring adequate segmentation outcomes[17].

To enhance segmentation accuracy and reduce overfitting, techniques such as transfer learning and data augmentation are applied during the training of FC-DenseNets. Data augmentation includes operations like rotation, horizontal and vertical flipping, width and height shifting, and zooming [18].

When using FC-DenseNets for cardiac image segmentation, the output images have the same size as the input images. However, the binary segmentation results from FC- DenseNets may not always be sufficient. To address this, the segmentation output is generated as a probability map. Each pixel in the segmented image represents the probability that the corresponding pixel in the original cardiac image belongs to the heart, with each probability ranging between 0 and 1. This probability map is then multiplied by 255 to produce a probability image, which is used as input for the level set method [17].

### 2.4 Evaluating Model

In the evaluation stage, the trained segmentation model is assessed to measure its performance. The evaluation is conducted using metrics such as the Dice Coefficient and Intersection over Union (IoU) to determine how well the model detects and labels heart regions in MRI images. These metrics are calculated for each class (RV, Myo, LV, Background), and the results provide insights into the model's effectiveness in segmentation. This analysis helps in understanding the strengths and weaknesses of the model and determines whether further adjustments are needed to improve segmentation accuracy and reliability in the future.

## 3. Experiments and Result

### 3.1 Inputing the Dataset

After understanding the theoretical foundation, the next step is to collect cardiac MRI datasets from patients with various cardiovascular conditions and normal subjects. This data was obtained from the University Hospital of Dijon and has been anonymized in accordance with the regulations set by the hospital's local ethics committee.

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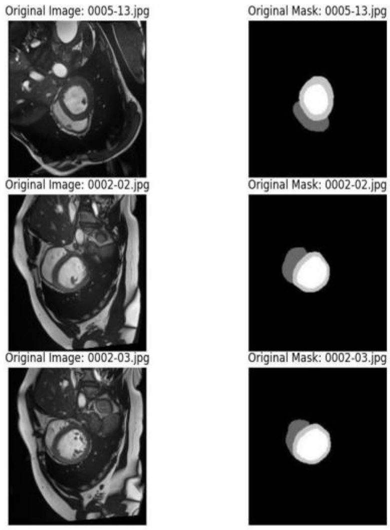


Figure 3: Original Datasets

This dataset is crucial as it includes a wide range of well-defined pathologies and a sufficient number of cases to train machine learning methods and assess the variation of key physiological parameters from cine-MRI, such as diastolic volume and ejection fraction. The dataset consists of 1,322 images, including 676 images in the ED_training folder and 646 images in the ES_training folder. This data will be used to train and test the developed Deep Learning model [19].

### 3.2 Preprocessing the Dataset

Here is the flowchart illustrating the data processing procedure for this cardiac MRI image processing study.

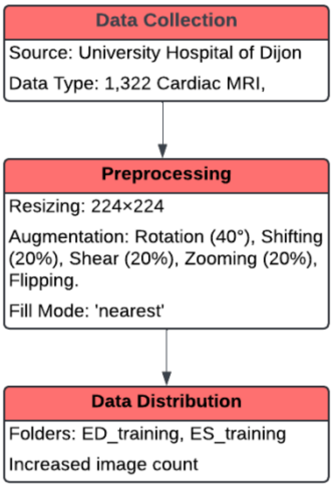


Figure 4: Workflow of Data Processing for Cardiac MRI Images.

### 3.2.1 Resizing Images

Resizing Images is a crucial step in the preprocessing phase to ensure consistency in the input to the segmentation model. Cardiac MRI images, which initially have varying sizes, are resized to a uniform dimension of 224×224 pixels. This process ensures that all images have the same dimensions, which is necessary to optimally utilize the FC-DenseNet model architecture.
To provide a clear illustration of the changes, Figure 4 shows an example of cardiac MRI images before and after resizing. The original images have varying dimensions depending on the data source, whereas the resized images demonstrate how the entire dataset has been standardized to 224×224 pixels. This process not only helps maintain data uniformity but also facilitates further processing by the segmentation model.

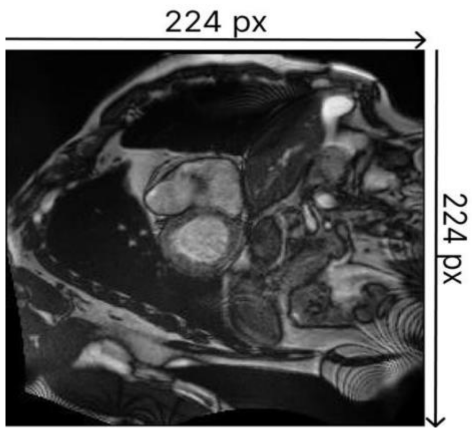


Figure 5: Example of cardiac MRI images after resizing.

### 3.2.2 Data Augmentation

The data augmentation process applied to cardiac MRI images includes several techniques to enhance the diversity of the training dataset and improve the generalization capability of the segmentation model. Figure 4 shows the original cardiac MRI images followed by versions that have undergone augmentation with various techniques. These techniques include rotation, shifting, shearing, zooming, and flipping.

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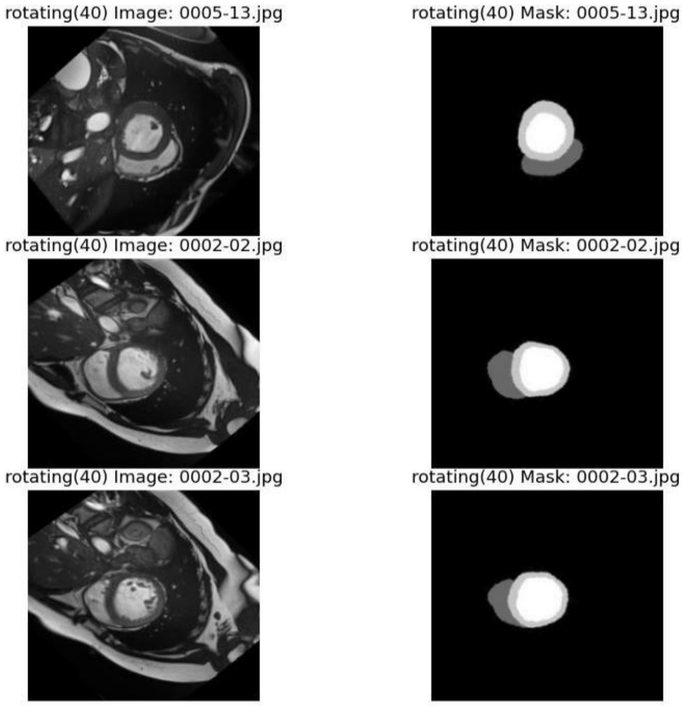
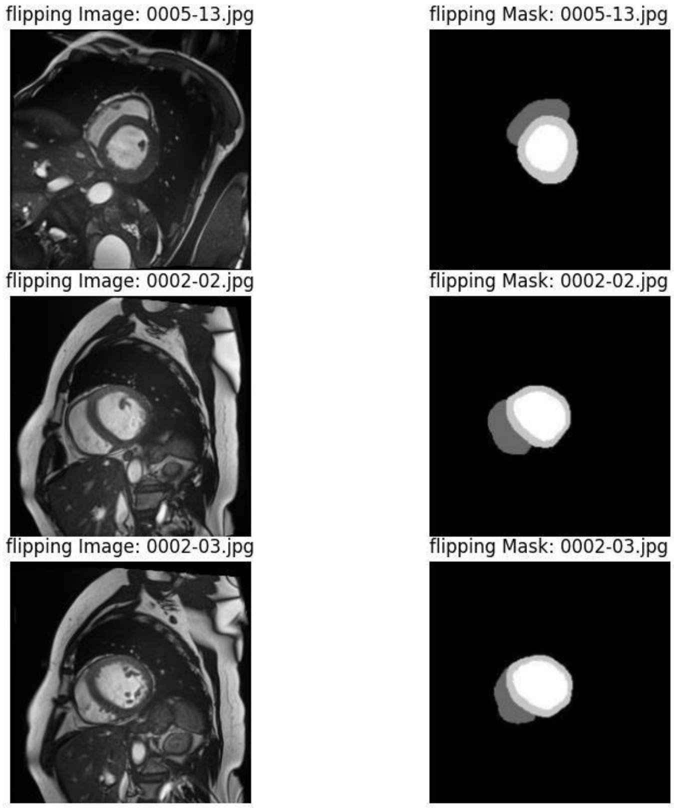



Figure 6: Example of cardiac MRI images after 40 degree rotation

Rotation is applied within a range of up to 40 degrees, allowing the image to be rotated within this angular range. This technique is crucial for simulating variations in orientation, enabling the model to recognize cardiac features from different viewpoints and not just from a single image orientation. Horizontal and vertical shifting is applied within a range of up to 20%, ensuring that the model can recognize cardiac features despite changes in the image position. Shearing is applied with a range of up to 20%, which alters the image shape by flattening some areas and enlarging others, helping the model handle distortions and changes in feature shapes. Zooming is performed within a range of up to 20%, allowing the model to focus on specific details and manage variations in the scale and position of features by enlarging the image.




Vertical flipping involves flipping the image vertically, which helps the model handle symmetry in the cardiac structure and recognize features from inverted or symmetric positions. The fill mode is set to nearest, which fills empty pixels after the transformation with the nearest pixel values, ensuring that the image remains visually natural.

Applying these augmentation techniques introduces additional variations into the training dataset. These techniques help the model to recognize and detect cardiac features under various conditions and orientations. The augmentation enhances the model's generalization capability, reduces the risk of overfitting, and ensures that the model can handle a range of variations in previously unseen data.

### 3.2.3 Data Distribution Post-Augmentation

Data augmentation significantly impacts the dataset distribution by increasing the number of images available for training and enhancing data diversity. Your dataset includes two main folders: "ED_training" and "ES_training". The "ED_training" folder containscardiac MRI images taken at the End-Diastole (ED) phase, when the heart is fully filled with blood and has its maximum volume. The "ES_training" folder contains images taken at the End-Systole (ES) phase, when the heart has its minimum volume after contraction.

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Table 1: Image Count Before and After Data Augmentation.

| Folder | Before Augmentation | After Augmentation |
|---|---|---|
| ED_training | 676 images | 2,028 images |
| ES_training | 646 images | 1,938 images |
| **Total** | **1,322 images** | **4,966 images** |

### 2.3 Building the FC-DenseNets Segmentation Model

In this study, an automatic cardiac segmentation model was developed using the FC- DenseNet architecture, implemented through the TensorFlow framework.

#### 2.3.1 Model Implementation Using TensorFlow

Using the Keras API from TensorFlow, the FC-DenseNet model was implemented by defining the number of dense blocks, the number of layers in each block, and the number of filters in each convolutional layer. Leveraging TensorFlow-Keras enables the development of a flexible and efficient model, facilitating experimentation with various architectural configurations.

#### 2.3.2 Training Parameters

To achieve optimal performance, training parameters were carefully selected based on technical considerations. This parameter selection aims to ensure optimal and stable convergence during the training of the medical image segmentation model.

Table 2: Model Training Parameters

| Parameter | Nilai |
|---|---|
| Optimizer | Adam |
| Learning Rate | 0.001 |
| Batch Size | 4 |
| Epoch | 30 |
| Fungsi Loss | Dice Loss |

1. The Adam optimizer was chosen for weight updates during training due to its ability to achieve fast and stable convergence. Adam combines the

advantages of momentum and RMSprop methods, providing an efficient adaptive learning rate.

2. The learning rate was set to 0.001, based on initial experiments indicating that this value provides a balance between fast convergence and weight update stability.
3. A batch size of 4 was selected to maximize memory utilization and training speed.Smaller batch sizes allow the model to update weights more frequently, improving its ability to adapt to the training data.
4. The training process was conducted for 30 epochs. This number of epochs was chosen based on preliminary experiments showing that the model could learn important features without overfitting within this number of iterations.

### 2.3.3 Loss Function and Optimizer

Dice Loss was chosen as the primary loss function due to its advantages in handling class imbalance and its ability to maximize overlap between predictions and ground truth, which is essential for image segmentation, particularly in cardiac MRI images. Additionally, the Adam optimizer was used for weight updates because its adaptive nature allows for more efficient and stable convergence compared to conventional optimization methods, enabling the model to achieve optimal performance during the learning process.

### 2.3.4 Training Process

During the training process, the model received pre-processed and augmented MRI heart images as input. Data augmentation techniques such as rotation, shifting, zooming, and flipping were applied to increase the diversity and generalization ability of the model across different image variations. The model was trained with a batch size of 4 and a learning rate of 0.001 over 30 epochs.


Figure 8: Training Loss and Accuracy

The graph you provided shows the training loss and accuracy over these epochs. The blue line, representing training loss, sharply decreases initially and then continues to decline gradually, indicating that the model is effectively learning from the training data and improving its prediction accuracy. The red line, representing training accuracy, remains consistently high throughout the training, suggesting that the model achieves a stable and high accuracy early in training. This could indicate a robust training process where the model quickly adapts to the patterns in the data.

## 2.4 Evaluating and Testing Model

The evaluation of the FC-DenseNet segmentation model was conducted to assess its performance in detecting and marking the heart regions in MRI images. In this study, the data was divided into two parts: training data and test data, without using a separate validation set. The evaluation metrics employed include the Dice Coefficient and Intersection over Union (IoU), which are standard metrics in medical image segmentation tasks. The Dice Coefficient measures the degree of similarity between the model's predicted regions and the ground truth, providing insight into how well the model performs segmentation. Meanwhile, IoU assesses the overlap between the model's predictions and the ground truth, indicating the precision of the model's segmentation.

Table 3: Segmentation quality performance

| | |
|---|---|
| RV Dice Coefficient | 0.83808884 |
| RV IoU | 0.77785892 |
| Myo Dice Coefficient | 0.78156806 |
| Myo IoU | 0.67560733 |
| LV Dice Coefficient | 0.71466263 |
| LV IoU | 0.64441163 |

The trained segmentation model produced quite good performance metrics on the test data. For the right ventricle (RV), the model achieved a Dice Coefficient of 0.83 and an IoU of 0.77, indicating very strong segmentation capabilities in this area. For the myocardium (Myo), the model obtained a Dice Coefficient of 0.78 and an IoU of 0.67, demonstrating reasonably accurate segmentation of the myocardium. As for the left ventricle (LV), the model achieved a Dice Coefficient of 0.71 and an IoU of 0.64, which, although slightly lower compared to RV and Myo, still indicates adequate performance. Overall, these metrics suggest that the model is capable of effectively segmenting the heart chambers, though some areas may still require further improvement.

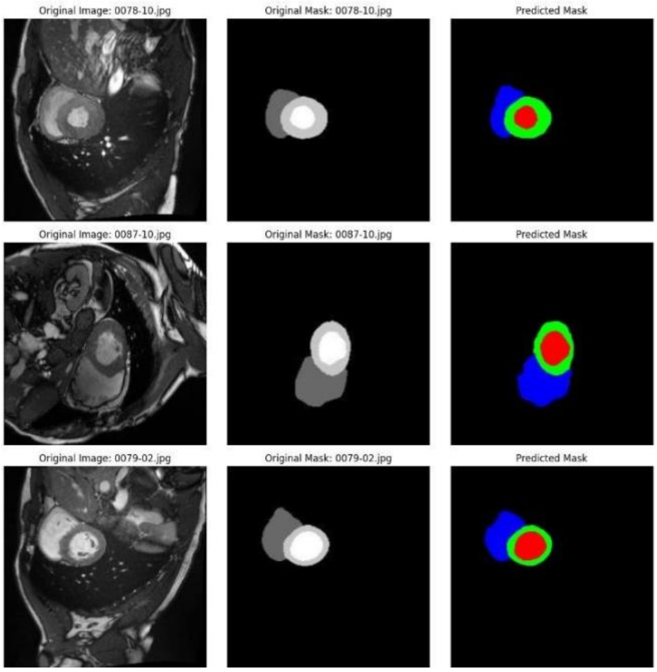


Figure 9: Output of Data Testing

The image above shows the segmentation results of the test data alongside the original mask. The model's segmentation closely resembles the original mask overall, but there are still some areas where the segmentation is not entirely accurate. For instance, some edge details and fine features of the original mask are not fully captured in the segmentation results, indicating the need for a more diverse dataset.

## 4. Discussion

The experimental results indicate that the developed FC-DenseNet model successfully achieved good performance in segmenting the heart chambers in MRI images, with a Dice Coefficient of 0.83 for the right ventricle (RV), 0.78 for the myocardium (Myo), and 0.71 for the left ventricle (LV). However, the model's performance varied significantly across different regions of the heart, with left ventricle segmentation presenting greater challenges in capturing complex or variable anatomical structures.

Based on the previously shown training loss and training accuracy graphs, it can be observed that the model reached a very high training accuracy from the beginning, with accuracy values approaching 100%. Meanwhile, the training loss values consistently decreased throughout the training process. These results indicate that the model learned effectively from the training data and minimized prediction errors.

This research has significant implications in the context of Islam, particularly in line with the meaning of Surah Al-Maidah, verse 32, which emphasizes the importance of efforts to save and protect life. By developing a more accurate segmentation method for MRI images, this research contributes to the improvement of diagnosis and treatment of heart disease, which, in turn, can save patients' lives.

The findings of this study not only advance the field of medical technology but also reflect our moral responsibility as Muslims to use knowledge and technology for the benefit of humanity. Every advancement in accurate diagnosis allows us to contribute to saving lives, in accordance with the Islamic principles that prioritize the value of life.

Therefore, further improvement strategies, including the use of more advanced data augmentation techniques, ensemble models, and hyperparameter optimization, are crucial to enhancing the model's performance in clinical applications. With these steps, it is hoped that the segmentation of heart chambers in MRI images can be conducted more accurately and consistently, supporting more effective diagnosis and treatment planning. Thus, this research aligns with Islamic teachings that encourage us to contribute to the safety and well-being of humanity.

## 5. Conclutions

This study developed an automatic segmentation model for heart chambers using the FC-DenseNet architecture on cardiac MRI images. With a dataset of 1,322 images from patients with various cardiovascular conditions and healthy subjects, the model achieved satisfactory Dice Coefficient scores: 0.83 for the right ventricle, 0.78 for the myocardium, and 0.71 for the left ventricle, indicating its clinical potential.

Training loss and accuracy graphs show that the model reached nearly 100% training accuracy early on, with a steady decrease in loss over 30 epochs. While these results suggest effective learning, the high accuracy raises concerns about potential overfitting, highlighting the need for validation on unseen data.

This research reflects the teachings of Surah Al-Maidah, verse 32, emphasizing the importance of saving and protecting life. By improving diagnostic capabilities in cardiology, the model significantly aids in treatment planning for heart diseases, ultimately contributing to saving lives.

Despite these successes, further improvements through advanced augmentation techniques, ensemble modeling, and optimization methods are essential for addressing challenges in complex anatomical areas like the left ventricle. Ongoing refinement of these approaches will enhance the model's accuracy and reliability, reinforcing the ethical obligation to use technology for the greater good.

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