MINISTRY OF INDUSTRY & TRADE

INDUSTRIAL UNIVERSITY OF HO CHI MINH CITY



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CORONARY VESSEL SEGMENTATION AND ABNORMAL DETECTION TO AID IN DIAGNOSIS

DISSERTATION SUMMARY

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Phản biện 1:.....

Phản biện 2:.....

Phản biện 3:.....

Phản biện độc lập 1:.....

Phản biện độc lập 2:.....

Luận án sẽ được bảo vệ trước Hội đồng chấm luận án cấp Cơ sở đào tạo họp tại

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1. Thư viện Tổng hợp Quốc gia Tp.HCM
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CHAPTER 1 OVERVIEW

1.1 Medical image

1.2 Medical image processing model

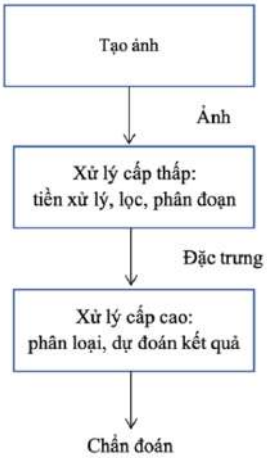


Figure 1.1 Model for medical imaging diagnostic system [1].

1.3 Coronary artery

The right and left coronary arteries supply blood to the heart [1]. They are the first branches of the aorta, which is the main artery in the body. These arteries and their branches supply blood to all parts of the heart muscle. Each artery contains many branches:

- Right Coronary Artery (RCA): The RCA supplies blood to the right atrium and right ventricle (where deoxygenated blood goes before reaching the lungs). Its branches supply the sinoatrial (SA) and atrioventricular (AV) nodes.
- Left Main Coronary Artery (LMCA): The LMCA supplies blood to the left atrium and left ventricle. This is where oxygenated blood from the lungs arrives before the heart pumps it to the rest of the body. Its branches supply 2/3 of the interventricular septum.

The structure of the coronary artery branches varies from person to person. The coronary arteries are typically surrounded by a layer of fat, but in some individuals, the arteries are embedded within the heart muscle itself; the blood supply to the SA and AV nodes comes from the LMCA, not the RCA, in about 10% of people; sometimes a single coronary artery arises from the aorta, then divides into right and left branches. Most of these variants are harmless and do not cause symptoms. However, in rare cases (less than 1% of people), abnormalities in the coronary arteries can lead to serious problems or even death.

The main coronary arteries usually have a diameter from 3mm to 4mm, slightly smaller than the width of a straw. The size of the arteries varies slightly depending on gender,

body weight, and even ethnicity. The walls of all arteries, including the coronary arteries, have three layers:

- Tunica intima: The inner layer that touches the blood and keeps it flowing smoothly through the arteries.
- Environment: The middle elastic layer, so it expands and contracts to maintain proper blood pressure in the artery.
- Adventitia: The outer layer contains small vessels that supply oxygen and nutrients from the blood to the cells in the heart.

Coronary Artery Disease (CAD) is the most common condition affecting the coronary arteries. CAD typically results from atherosclerosis, which is the accumulation of plaque within the arteries. This blockage can impede blood flow to the heart and potentially lead to a heart attack. Acute coronary syndrome is a condition where there is a sudden reduction in blood flow to the heart through the coronary arteries. Myocardial infarction is one type of acute coronary syndrome. Like CAD, these conditions are also a result of atherosclerosis, as shown in figure 1.1. Less common conditions affecting the coronary arteries include:

- Arterial aneurysm: bulging in the vessel wall.
- Congenital abnormalities in the arteries.
- Coronary artery spasm: Sudden tightening of the muscles within the artery. When these muscles constrict or spasm, the arteries are temporarily blocked. This can lead to chest pain known as Prinzmetal's angina.

CAD is a chronic disease. Plaque buildup takes many years, even decades. However, as the arteries narrow, patients may experience mild symptoms. These symptoms indicate that the heart is working harder to pump oxygen-rich blood to the body. Atherosclerosis causes coronary artery disease. Atherosclerosis is the gradual accumulation of plaque within the arteries throughout the body. When plaque affects blood flow in the coronary arteries, the patient develops coronary artery disease. The plaque consists of cholesterol, waste, calcium, and fibrin (a substance that helps with blood clotting). As plaque continues to build up along the artery walls, the arteries of the patient become narrow and stiff.

Plaque can obstruct or damage the arteries, restricting or stopping blood flow to a particular part of the patient's body. When plaque builds up in the coronary arteries, the heart muscle does not receive enough blood. As a result, the heart cannot obtain the necessary oxygen and nutrients to function normally. This condition is known as myocardial ischemia. It leads to discomfort in the chest (angina) and increases the risk of a heart attack.

Figure 1.2 illustrates arterial narrowing. With X-ray imaging of the coronary arteries, doctors can determine whether the vessels are obstructed or not, or which treatment method is most appropriate for the patient. However, it is very difficult to visually interpret X-ray images due to the overlapping of blood vessels around the heart (figure

1.3 (b)) or due to the contrast between the blood vessels and the background. This has been a significant challenge for many years.

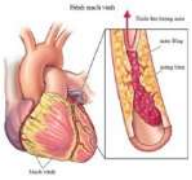


Figure 1.2 Coronary artery disease [2].



(a)



(b)

Figure 1.3 Coronary angiography: (a) narrow and (b) overlap.

Currently, there are no routine invasive or non-invasive tests used to identify vulnerable plaques in living patients [3]. Vulnerable plaques may be calcified or not, thereby complicating the assessment of cardiovascular risk through calcification screening. There is a rational appeal for directly assessing the coronary arteries, rather than relying on indirect measures such as age, circulating cholesterol levels, and other traditional risk factors. Advances in CT technology now allow for non-invasive visualization of calcification in the coronary artery walls in living patients.

Currently, there are two basic equivalent methods for imaging and quantifying coronary artery calcification - Electron Beam Computed Tomography (EBCT) and Multidetector Computed Tomography (MDCT). Both EBCT and MDCT are large and complex X-ray imaging systems. Through image analysis captured from Cardiac Catheterization - a diagnostic method using X-ray imaging of blood vessels by injecting a contrast agent, to study the heart [3]. Physicians can determine whether the blood vessels are obstructed, to use the most appropriate treatment method for the patient. However, due to the nature of X-ray imaging, there is often low contrast between the blood vessels and the background, with image noise from the shadows of the ribs and surrounding tissues. Additionally, the shape of the blood vessels is not definitive, the width of the vessels depends on the type of vessel, and the width usually varies along the vessel; as well as the patient's physique, race, etc.; especially, the timing of the image also affects the vessel images, because if the image is taken when blood is passing through, the vessel wall will be visible, but if the image is taken after the blood has passed, the vessel wall collapses making the vessel nearly transparent and very difficult to see clearly.

Due to the complexity of the coronary vessels (figure 1.3) as presented, it is very difficult to directly detect abnormalities on the coronary vessels, therefore the dissertation focuses on proposing methods for detecting abnormalities on the coronary vessels to support disease diagnosis.

1.4 Problem

Based on the complexity of the coronary artery images, the dissertation proposes two approaches to detect abnormalities in the coronary arteries:

- An approach based on developing algorithms with image processing knowledge.
- A deep learning approach.

Given the complexity of the coronary system where blood is moved in one direction and the images of the coronary arteries depend heavily on the environment (as presented above), the dissertation needs to address two problems: (1) segmenting the coronary arteries to obtain images of the arteries with clear boundaries, from which data this will address the second problem (2) detecting abnormalities on the coronary artery walls using both approaches. The dissertation presents the methods for solving these as shown in figure 1.4.

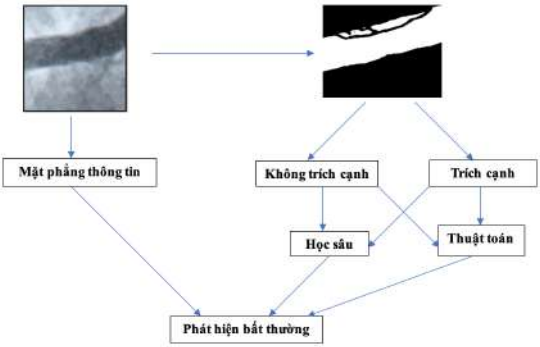


Figure 1.4. Our method for detecting abnormalities in coronary angiography.

1.5 Dataset

The data was provided by Chonnam National University Hospital, South Korea. This data has been approved by the hospital's ethical board, as well as by the patients themselves. The data initially consists of 48 patients, each image being a color image (gray color) with a resolution of 512×512 pixels, Figure 1.5, for the extraction of coronary vessels (segmentation). The dataset is called dataset A. Dataset A received expert support to have ground-truth for validation. After segmenting dataset A, the dissertation constructs a new dataset where each image is a segment of the coronary vessel (dataset B).

Figure 1.5, to determine whether the coronary arteries are abnormal or not? The dataset B has 124 coronary artery segments with a size of 100×100 pixels, of which 102 are abnormal and 22 are normal. With dataset B, the small number of images is inadequate for classification and at the same time, the data is imbalanced. The dissertation uses a data generating method through Affine transformations to create dataset C, which has 1404 abnormal images and 1115 normal images. Afterthat, the dissertation collects additional data from the hospital so that dataset D has 2906 abnormal images and 3022 normal images.



Figure 1.5 A coronary artery segment after segmentation.

CHAPTER 2 THEORETICAL FOUNDATION

Chapter 2 of the dissertation presents the theoretical foundations used in the dissertation such as the artificial neural network, deep learning, especially Unet, and the skeleton extraction method.

2.1 Skeleton extraction method

From the skeleton of the object, we can obtain information about the original shape of that object. There have been many methods proposed for skeleton extraction. The skeleton extraction algorithm proposed by authors Zhang-Suen in 1984 is the most widely used algorithm, serving as the foundation for many subsequent studies

2.2 Artificial neural network

Inspired by the operation of human neural networks, computer algorithms mimic these biological structures and are called Artificial Neural Networks (ANN). In the conventional approach in programming, the computer will know what to do, breaking down large problems into many small tasks, from clear definitions of tasks that the computer can easily perform through commands. Conversely, in a neural network, the computer will have to learn how to solve the problem from the information learned through data via the model.

2.3 Deep learning

Deep learning is a part of machine learning, so the nature of deep learning also carries the characteristics of machine learning, but it allows for learning deeper information based on improvements in the model and algorithms through many more hidden layers. Deep learning models can: (1) automatically extract features from data and (2) link near and distant information in the model to learn deeper information.

2.4 Unet

Unet is a convolutional neural network developed from the CNN model initially intended for medical image segmentation, created by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015 [2]. Unet is one of the standard CNN architectures for image classification tasks, where we need not only to identify the entire image by classes but also to segment areas of the image by classes. Moreover, Unet is trained end-to-end with characteris is that it does not require much data.

2.5 Conclusion

Based on the theoretical foundation in this chapter, the dissertation develops adaptive Unet models to address the problem of coronary vessel image segmentation from coarse to fine approach, as well as classifying whether coronary segments are abnormal or not using two approaches: developing algorithms and deep learning to solve the two problems posed in the dissertation.

CHAPTER 3 CORONARY VESSEL IMAGE SEGMENTATION PROBLEM

3.1 Approaches

3.2 Proposed model

Based on the nature of coronary vessels: blood flows only one direction, and the coronary structure is hierarchical from the main vessel to the branches. Coronary images appear with a lot of noise, while the contrast between the blood vessels and the background is very low, especially in smaller vessel areas. Therefore, using a single algorithm for segmentation would not be effective. Moreover, the coronary structure is very complex, with vessel widths varying depending on the timing of the image capture and the amount of blood moving. However, with the blood vessel structure running vertically from top to bottom and narrowing, the dissertation will build a vascular skeleton to segment smaller vessels and group them to form a complete vascular tree. Therefore, the dissertation proposes an approach to the problem by segmenting blood vessels from coarse to fine. This means that the dissertation will extract parts that are definitively blood vessels. Then, from the 'coarse' part previously detected, it will sequentially search for smaller vessels within a certain limited area (branch vessels), which can be understood the step of extracting finer vessels.

With main and branch vessels having different properties, a single Unet model cannot be used for segmentation to achieve the best results, so the dissertation proposes a model that processes each part, each part being a corresponding Unet model. First, the dissertation proceeds with the extraction of the main vessels along with basic features such as the skeleton and junction points. The skeleton is defined as the central line of the blood vessel. Junction points are the intersections between sections of blood vessels within the skeleton. Then, based on the main vessels, the dissertation continues the process of extracting all the vessels connected to the main vessel through the junction points, also known as secondary vessels. Finally, the dissertation achieves blood vessel segmentation results. The processing model includes three main steps: extracting the main vessel, extracting secondary vessels, and reconstructing the vascular tree, as detailed in Figure 3.1.

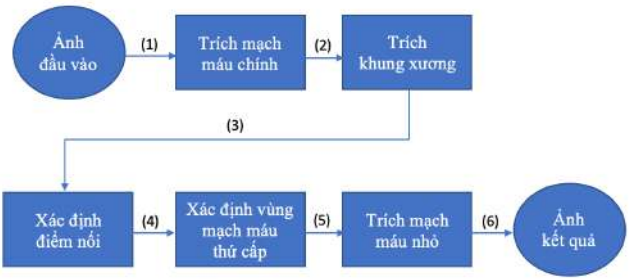


Figure 3.1 Proposed model for coronary segmentation.

3.3 Building Model

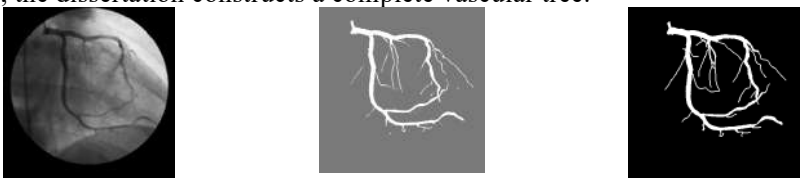
3.3.1 Main coronary vessel extraction

- Main coronary vessel segmentation: The dissertation utilizes a trained Unet model with a private custom design for segmenting the main coronary vessels, it was called Unet main (algorithm 3.1), as shown in figure 3.1.
- Skeleton extraction: After identifying the main coronary vessels, to determine the junction points, the dissertation needs to identify the skeleton of the vessels. However, the vessels after segmentation may be interrupted due to the timing of the imaging, varying blood movement, uneven vessel regions, or because the doctor handling the imaging device is unstable. To address this problem, the dissertation proposes an improvement of the Zhang-Suen algorithm [4], algorithm 3.2, with results shown in figure 3.2.
- Junction point determination: The dissertation proceeds to identify critical joint points (including junctions and the start and end points of the vessels) using algorithm 3.3, with results as shown in figure 3.3.

3.3.2 Secondary circuit coronary vessel extraction

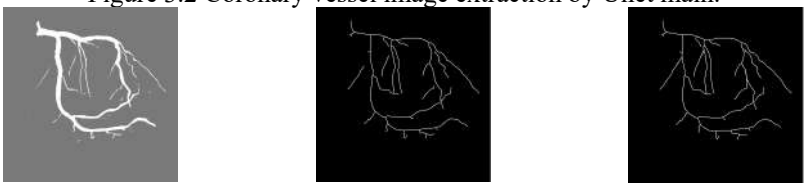
- Selecting vascular regions: The dissertation develops an algorithm for selecting regions to extract secondary circuit coronary vessels from *joint* points between vessel segments, algorithm 3.4. A window is used to cut from the image including two points: *point i* and *point j*, with the width being $w = |(x_i - x_j)|$ and the length being $h = |(y_i - y_j)|$. However, extracting rectangles from the initial joint points is not effective for the segmentation process. Therefore, the dissertation extends the area by Δp pixels to ensure better results, as shown in figures 3.4 and 3.5.
- Extracting secondary circuit coronary vessels: The dissertation uses a trained model Unet with a private custom design for segmenting secondary circuit coronary vessels, it was called the Unet branch.

3.3.3 Constructing the complete vascular tree: From the results of the two steps above, the dissertation constructs a complete vascular tree.



a. Input b. Using Unet main c. Ground truth

Figure 3.2 Coronary vessel image extraction by Unet main.



a. Input b. Skeleton extraction by Zhang-Suen algorithm c. Skeleton extraction by improved Zhang-Suen algorithm

Figure 3.3 Result of skeleton extraction by improved Zhang-Suen algorithm.



a. Joint points on skeleton



b. Joint points on main vessel

Figure 3.4 The junctions between vessel branches.

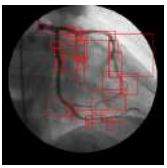


Figure 3.5 Choice windows from *joints*.

3.4 Experiments

The dissertation chooses parameters for the algorithms as shown in tables 3.1, 3.2 and 3.3.

Table 3.1 Values of Unet main model parameters.

Parameters	Values	Meaning
Filter1	64	Number of filters for the first convolutional layer
Activation1	ReLU	Activation function
learning_rate1	1e-4	Learning rate
output_activation1	sigmoid	Activation function at the output layer

Table 3.2 Values of Unet branch model parameters.

Parameters	Values	Meaning
Filter2	16	Number of filters for the first convolutional layer
Activation2	ReLU	Activation function
learning_rate2	1e-4	Learning rate
output_activation2	sigmoid	Activation function at the output layer

Bảng 3.2 Values of parameters for constructing the vascular skeleton.

Parameters	Values	Meaning
γ	116	Minimum size of coronary vessels
Δp	20	Extend the rectangle from the joint point

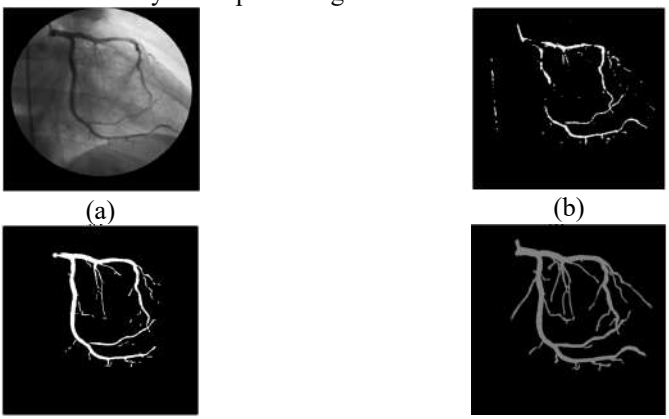
3.5 Results and evaluation

The results of the dissertation show that the proposed method is indeed more effective than previous methods. The coarse-to-fine approach with two Unet models has brought about positive results, table 3.4.

Table 3.4 Comparison.

Methods	Dice coefficient (%)
DFB based segmentation [5]	45,50 ± 1,31%
Coarse-to-fine based DFB and Otsu [6]	71,34 ± 0,80%
Baseline U-net [7]	73,64 ± 1,32%
Our proposed method	**76,40 ± 1,02%**

The method for segmenting main coronary arteries produces good results. The segmentation performance is independent of size, achieving 80.17%. The method also detects a large number of small and thin coronary vessels with an average efficiency of 76.40%. Figure 3.9 shows a comparison of the segmentation results, including the mean value ± standard deviation. The results of the dissertation demonstrate that the proposed method is indeed more effective than previous methods. The coarse-to-fine approach with two Unet models has yielded promising results.



(a) (b)

(c) (d)

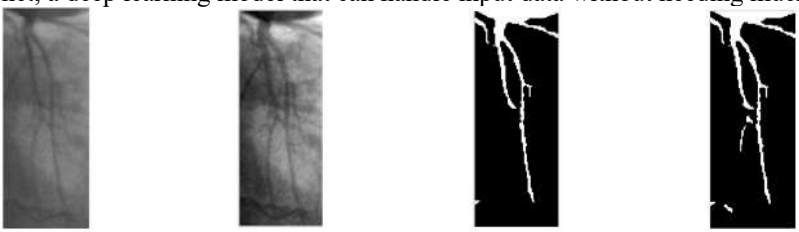
Figure 3.9 Comparing segmentation results (a) Input, (b) Result of [5]
(c) Result of [6], (d) Result of dissertation.

The proposed method achieves better segmentation results and outperforms standard methods. With the segmentation method based on DFB, it leads to interrupted coronary vessels and does not improve small coronary vessels compared to the approach of the dissertation and cannot detect small coronary vessels with low intensity, as well as large coronary vessels missing components. The method of the dissertation detects both large and small vessel; even in cases where there is a significant difference in intensity between large coronary vessels (high contrast objects) and small coronary vessels (low contrast objects). The method proposed in [6] can extract large blood vessels very well, but it leads to the omission of small, thin vessels and vessels with low contrast. The basic Unet provides higher accuracy than the DFB and Otsu methods. However, the basic Unet method also misses small coronary vessels.

The dissertation method addresses this issue by separately detecting large and small coronary vessels based on a hierarchical technique through the main and branch Unet model. Segmentation based on a coarse-to-fine strategy ensures that large coronary vessels are accurately extracted.

However, errors occur when processing small vessels; these errors occur when there are different contrast enhancements and depend on the quality of the image. Particularly, the traditional method, which enhances contrast, will have increased errors because the background is also enhanced. In the data of the dissertation, some images of small vessels are affected by lighting and noise, such as conditions of weak light, low contrast (at the time of capturing the image due to blood moving within the vessels, or environmental conditions). Figure 3.10 shows the image of small blood vessels affected by increased light intensity and contrast. Some small vessel branches are missing.

The study of the dissertation has other limitations, namely the limitation in the number of datasets, which is a drawback of the deep learning method, although the dissertation uses Unet, a deep learning model that can handle input data without needing much.



(a) (b) (c) (d)

Figure 3.10 Segmentation errors in small vessel images due to the influence of light.
(a) Inputr, (b) Contrast enhanced image
(c) Result of Unet model, (d) Result of our method.

3.6 Conclusion

The dissertation successfully develops a coronary vessel segmentation method using a coarse-to-fine approach with two models, Unet main and Unet branch for branch vessels. The research results of the coronary vessel segmentation problem have been published in a scientific article titled “Coronary Vessel Segmentation by Coarse-to-Fine Strategy using U-Nets” in the SCIE journal “BioMed Research International” [CT2].

CHAPTER 4 DETECTING ABNORMALITIES IN CORONARY ARTERIES

4.1 Approaches

4.2 Proposed general model

The first approach of the dissertation is to construct a model, Figure 4.1, to detect whether coronary arteries are abnormal or not in two ways: with edge detection and without edge detection, using segmented coronary artery segments as input based on computational models and deep learning.

The second approach uses deep learning models to learn and classify whether coronary arteries are abnormal or not on the information planes of the original coronary artery images segments, Figure 4.2. Each information plane will be trained and classified, then the results from each are combined using a soft voting method for the final outcome.

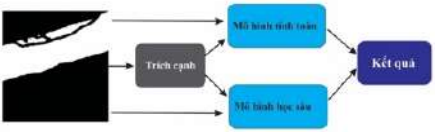


Figure 4.1 First approach for coronary anomaly detection.

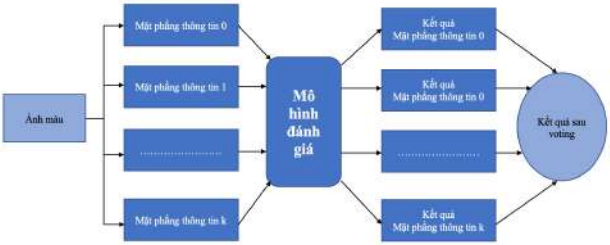


Figure 4.2 Second approach for coronary anomaly detection.

4.3 Approach without image preprocessing

4.3.1 Building algorithms based on image processing knowledge

The dissertation develops algorithms to normalize images (Figure 4.4), then identifies abnormal candidates, finds abnormal points (the algorithm is named t*he vessel wall browsing algorithm*) to achieve results as shown in Figure 4.5 (with data before and after edge extraction).



(a) (b)

Figure 4.4 Coronary artery location standardization: (a) Input; (b) Result.

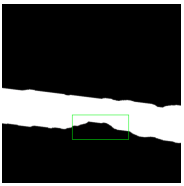


Figure 4.5 Abnormal test results.

4.3.2 Deep learning

The dissertation built a CNN model with two output layers: normal or abnormal vascular segments, using the MSE loss function to evaluate the model's performance. During backpropagation, the dissertation employs an algorithm to update the weights.

4.4 Approach with image preprocessing

4.4.1 Edge extracting

After segmentation, the coronary artery edges may be discontinuous or noisy; they are affected by many factors. In many cases, there is noise inside, outside, or at the edges of the boundaries. Therefore, the dissertation extracts the upper and lower edges of the coronary artery boundaries as inputs for processing, as shown in Figure 4.7, and normalizes the positions (Figure 4.7 (c)) which will be the input data to apply the anomaly detection method using an approach based on image processing knowledge and deep learning. The dissertation uses two edge extraction methods: the classical method (Canny) and deep learning with Dense Extreme Inception (DexiNed) for edge extraction.



(a) (b) (c)

Figure 4.7 Preprocessing: (a) input; (b) edge extracting; (c) result.

4.4.2 Anomaly detection with the vessel wall browsing algorithm

The dissertation applies the vessel wall browsing algorithm, section 4.3.1 to determine whether the coronary artery is abnormal or not.

4.4.3 Deep learning model

The dissertation builds a 2D-CNN model, which has 03 layers based on the size of the image. It has been redesigned to suit the size and characteristics of the coronary artery. The model uses the MSE loss function and is optimized by the Adam algorithm.

4.5 Information plane approach

Color images are composed of: (1) bit planes [5]; (2) three color layers RGB [5]. Each plane carries different information, these information planes are combined then we have the complete information of the image, objects, etc., is obtained. Based on this characteristic, the dissertation proposes a model to evaluate information planes to select

the appropriate plane for the problem, as shown in Figure 4.11. From these information planes, the dissertation builds a model to classify which coronary images may have abnormalities. The dissertation considers two types of information planes: bit planes and color planes for classification. For bit planes, there are 08 information planes, and for color planes, there are 03 information planes. These planes are evaluated for their contribution to the classification results, and these contributions are synthesized by a soft voting method to have the final decision.

4.6 Experiments

The code of program was implemented using the Python programming language with version 3 on the Google Colab enviroment platform.

4.7 Results

4.7.1 Result of the vessel wall browsing algorithm without edge extracting

The dissertation implements the vessel wall browsing algorithm with data that has not yet had edges extracted, resulting in measurement values as shown in Table 4.2 and accuracy as shown in Table 4.3, Figure 4.11.

Table 4.2 Result of values TP, TN, FP và FN.

	Abnormal	Normal	Total
Abnormal	1003 (TP)	401 (FP)	1404
Normal	175 (FN)	940 (TN)	1115

Table 4.3 Measurement results.

	Recall	Precision	F1-score
Abnormal	0,851	0,714	0,777
Normal	0,701	0,843	0,765

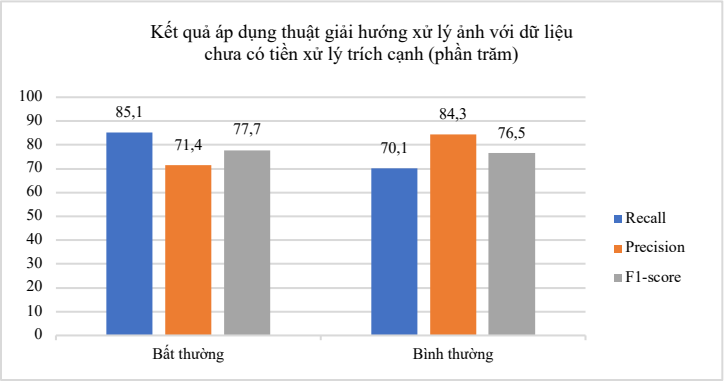
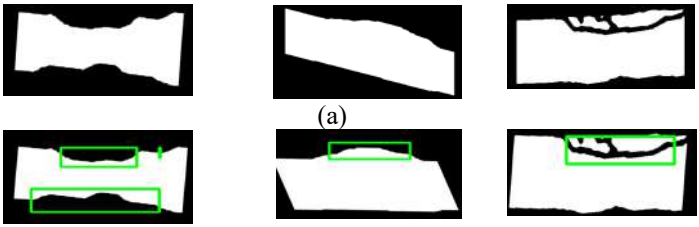


Figure 4.11 Graph of measurement results.

For example, the detection results using the vessel wall browsing algorithm are shown in Figure 4.12 (correct abnormality detection), Figure 4.13 (a)(b) (missing abnormal area

detection or failing to detect anomalies), and Figure 4.14 (normal vessels incorrectly detected as abnormal).



(a)

(b)

Figure 4.12 (a): normal; (b) correct detection of abnormalities.



(a) (b)

Figure 4.13 (a) failing to detect anomalies; (b) missing abnormal area detection.

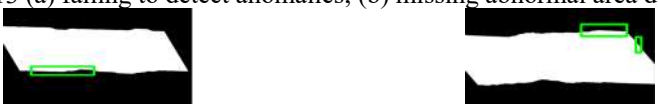


Figure 4.14 Normal image falsely detected as abnormal.

4.7.2 Result of the vessel wall browsing algorithm with edge extracting

The dissertation implements the vessel wall browsing algorithm with pre-extracted edge data, resulting in Table 4.4 and Figure 4.15. From 1404 abnormal images, the algorithm correctly identified 1047 images and incorrectly identified 357 images. Out of 1115 normal images, the algorithm correctly classified 855 images and incorrectly classified 260 images. The average processing time is about 0.34 seconds and 0.45 seconds for the abnormal and normal datasets, respectively. And the percentages of measurements are in Table 4.5. Abnormal images are correctly classified but lack location (Figure 4.16), showing that the algorithm does not fully detect all abnormal locations, or normal images are classified as normal or incorrectly as abnormal (Figure 4.17).

Table 4.4 Result of values TP, TN, FP và FN.

	Abnormal	Normal	Total
Abnormal	1047	357	1404
Normal	260	855	1115

Table 4.5 Measurement results.

	Recall	Precision	F1-score
Abnormal	0,801	0,746	0,773
Normal	0,705	0,767	0,735

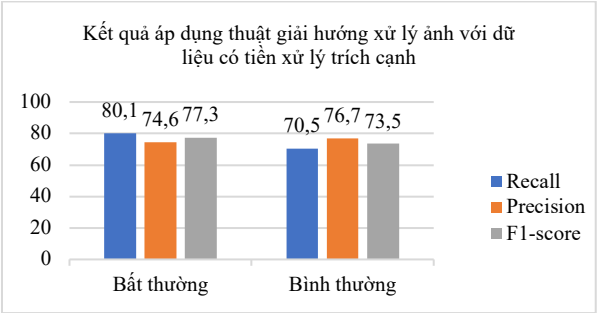
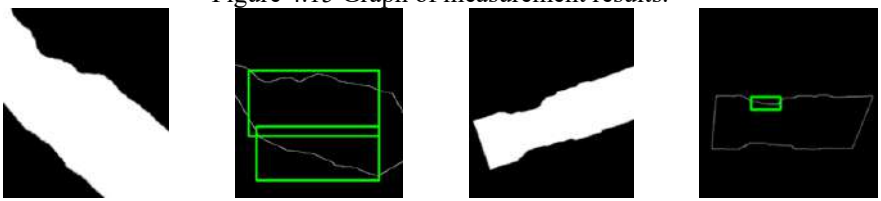


Figure 4.15 Graph of measurement results.



(a) (b) (c) (d)

Figure 4.16 abnormal: (a) input; (b) correct result;
(c) input; (d) correct result but missing abnormal area detection.



(a) (b) (c) (d)

Figure 4.17 normal: (a) input; (b) correct result;
(c) input (d) incorrect result.

4.7.3 Result of the deep learning method without edge extracting

The dissertation divides the data into two parts for training and testing with a ratio of 65% (training), 15% (validation), and 20% (testing) as shown in Table 4.6.

Table 4.6 Amount of data used for the model.

	Training	Validation	Testing	Total
Abnormal	912	211	281	1404
Normal	725	167	223	1115

The training results are shown in Figures 4.18 and 4.19. And accuracy values are the Table 4.7 and Figure 4.20.

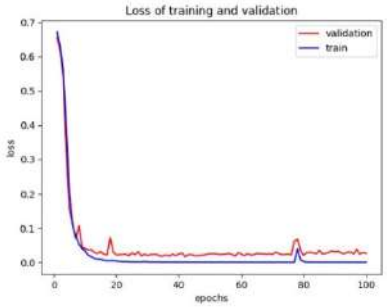


Figure 4.18 loss value.

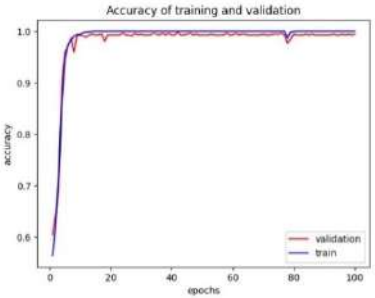


Figure 4.19 accuracy value.

Table 4.7 Result of values TP, TN, FP và FN.

	Abnormal	Normal	Total
Abnormal	190	91	281
Normal	44	179	223

Bảng 4.8 Measurement results.

	Recall	Precision	F1-score
Abnormal	0,812	0,676	0,738
Normal	0,663	0,803	0,726

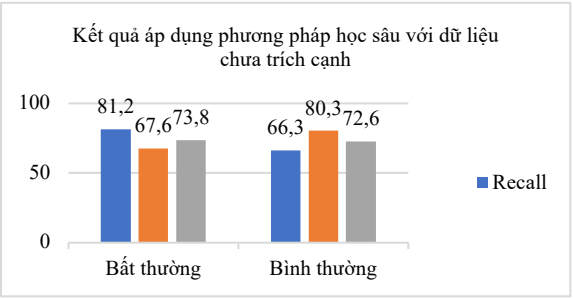


Figure 4.20 Graph of measurement results.

4.7.4 Result of the deep learning method with edge extracting by Canny method

The dissertation divides the data into two parts for training and testing with a ratio of 65% (training), 15% (validation), and 20% (testing) as shown in Table 4.9.

Table 4.9 Amount of data used for the model.

	Training	Validation	Testing	Total
Abnormal	912	211	281	1404
Normal	725	167	223	1115

The experimental results for the CNN model with preprocessed edge-extracted data as shown in Table 4.10, Table 4.11, Figure 4.21, Figure 4.22, and Figure 4.23, there are correct and incorrect result.

Table 4.10 Result of values TP, TN, FP và FN.

	Abnormal	Normal	Total
Abnormal	212	69	281
Normal	55	168	223

Table 4.11 Measurement results.

	Recall	Precision	F1-score
Abnormal	0,794	0,754	0,773
Normal	0,709	0,753	0,730

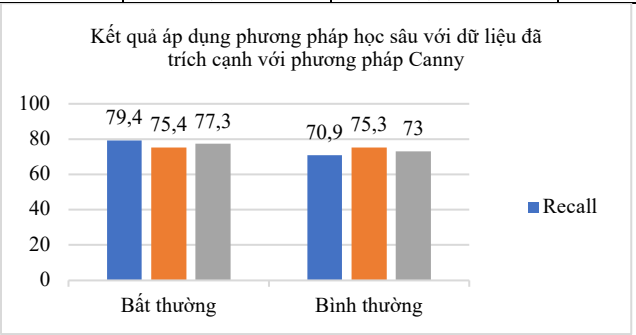
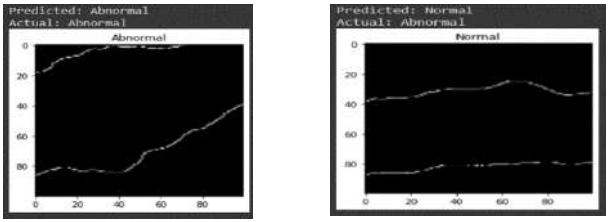
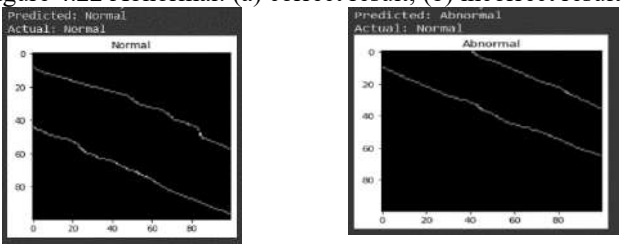


Figure 4.21 Graph of measurement results.



(a) (b)

Figure 4.22 Abnormal: (a) correct result; (b) incorrect result.



(a) (b)

Figure 4.23 Normal: (a) correct result; (b) incorrect result.

4.7.5 Result of the deep learning method with edge extracting by DexiNed method

The dissertation divides the data into two parts for training and testing with a ratio of 65% (training), 15% (validation), and 20% (testing) as shown in Table 4.12.

Table 4.12 Amount of data used for the model.

	Training	Validation	Testing	Total
Abnormal	1889	436	581	2906
Normal	1965	453	604	3022

The dissertation trains the DexiNed model to extract edges of coronary segments, Figures 4.24, 4.25. The results after the extraction are shown in Figures 4.26, 4.27. After edge extraction, the dissertation uses morphological methods to enhance edge information, results shown in Figures 4.27, 4.28.

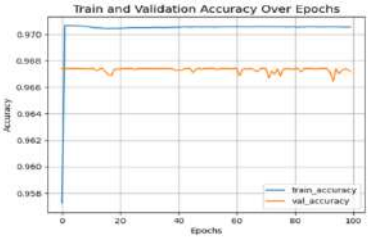


Figure 4.24 Accuracy value.

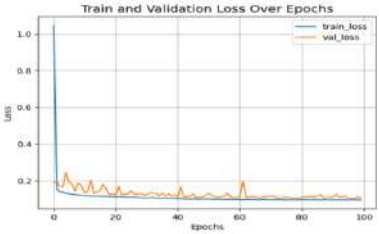


Figure 4.25 loss value.



Figure 4.26 Normal coronary to edge extraction.



Figure 4.27 Abnormal coronary to edge extraction.

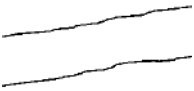


Figure 4.28 Normal coronary to enhance.



Figure 4.29 Abnormal coronary to enhance.

The dissertation uses a CNN model to train and classify whether coronary segments are abnormal or not, with the input data being coronary segments that have been edge-detected using the DexiNed model, Figure 4.30, Figure 4.31.



Figure 4.30 accuracy value.

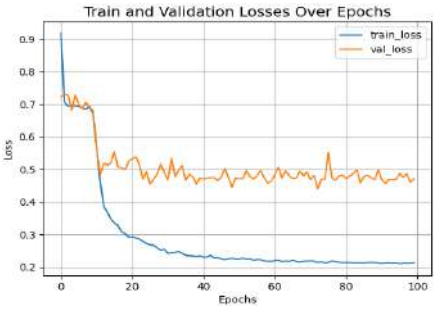


Figure 4.31 loss value.

Table 4.13 Result of values TP, TN, FP và FN.

	Abnormal	Normal	Total
Abnormal	512	69	581
Normal	38	566	604

Table 4.14 Measurement results.

	Recall	Precision	F1-score
Abnormal	0,931	0,881	0,905
Normal	0,891	0,937	0,913

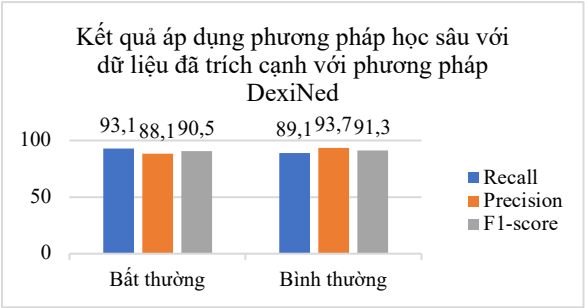


Figure 4.32 Graph of measurement results.

4.7.6 Result of the deep learning method with bit plane

The dissertation divides the data for training and testing in the ratios of 65%, 15%, and 20%, as shown in Table 4.15. Experiments were conducted on each bit plane to achieve the results as in Table 4.16.

Table 4.15 Amount of data used for the model.

	Training	Validation	Testing	Total
Abnormal	1889	436	581	2906
Normal	1965	453	604	3022

Table 4.16 The accuracy results of the prediction model for each bit plane.

Bit plane	Training	Validation	Testing
7	0,771	0,570	0,604
6	0,688	0,535	0,546
5	0,487	0,540	0,596
4	0,451	0,443	0,420
3	0,419	0,506	0,471
2	0,402	0,379	0,371
1	0,352	0,440	0,335
0	0,301	0,255	0,295

The dissertation finds that the bit planes in lower positions contribute less to accuracy, therefore, it removes the last five-bit planes and retains the first three bit planes for the soft voting method. Bit plane 7 corresponds to Figures 4.33, 4.34; and the accuracy results from the test set, Table 4.17. Bit planes 6 and 5, the dissertation has corresponding results as Figures 4.35, 4.36, Table 4.18 and Figures 4.37, 4.38, Table 4.19.

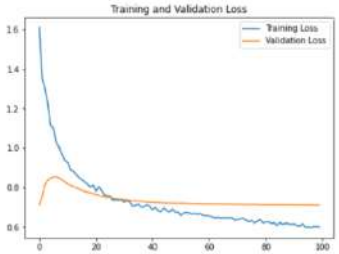


Figure 4.33 loss value of bit plane 7.



Figure 4.34 accuray value of bit plane 7.

Table 4.17 Measurement result with bit plane 7.

	Recall	Precision	F1-Score
Abnormal	0,626	0,604	0,615
Normal	0,631	0,652	0,641

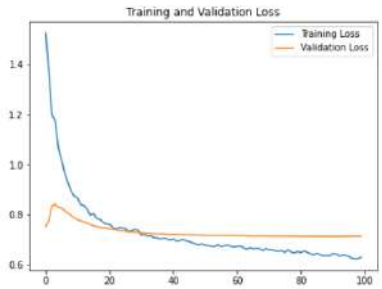


Figure 4.35 loss value of bit plane 6.

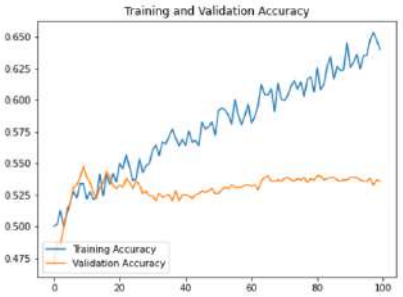


Figure 4.36 accuracy value of bit plane 6.

Table 4.18 Measurement result with bit plane 6.

	Recall	Precision	F1-Score
Abnormal	0,588	0,546	0,566
Normal	0,591	0,632	0,611

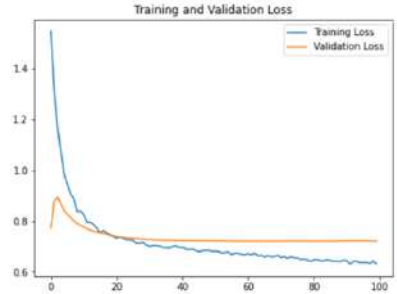


Figure 4.37 loss value of bit plane 5.

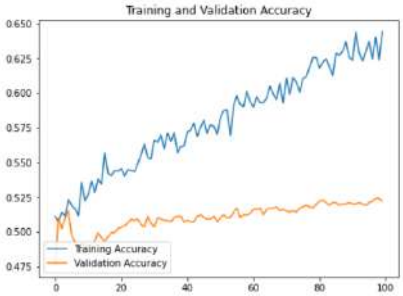


Figure 4.38 accuracy value of bit plane 5.

Table 4.19 Measurement result with bit plane 5.

	Recall	Precision	F1-Score
Abnormal	0,626	0,596	0,611
Normal	0,628	0,657	0,642

After using the soft voting method, the dissertation obtained results as shown in Table 4.21 and Figure 4.39, for example, the classification results using the bit plane combination method with soft voting, as shown in Figure 4.28.

Table 4.20 Result of values TP, TN, FP và FN.

	Abnormal	Normal	Total
Abnormal	456	125	581
Normal	156	418	604

Table 4.21 Measurement result with 03-bit planes were combined by soft voting.

	Recall	Precision	F1-Score
Abnormal	0,71	0,785	0,746
Normal	0,77	0,692	0,729

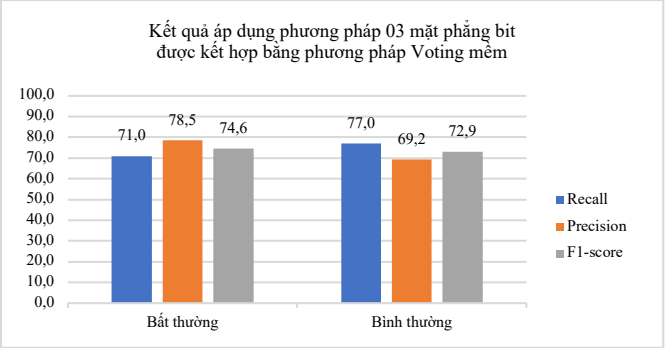
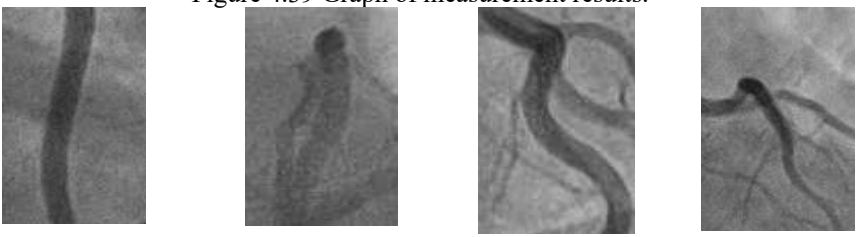


Figure 4.39 Graph of measurement results.



(a) (b) (c) (d)

Figure 4.40 Prediction by bit plane method: (a) normal to normal; (b) normal to abnormal; (c) abnormal to normal; (d) abnormal to abnormal.

4.7.7 Result of the deep learning method with color plane

Using the original color image, the dissertation conducts experiments on data as shown in Table 4.15 for each color plane, with the results regarding the accuracy of the model for each color plane presented in Table 4.22.

Table 4.22 The accuracy results of the prediction model for each color plane.

Color plane	**Training**	**Validation**	**Testing**
Red	0,945	0,617	0,723
Green	0,932	0,619	0,706
Blue	0,932	0,610	0,739

The dissertation trains and tests for each color plane: red, with results as shown in Figure 4.41, 4.42, Table 4.23; green, with results in Figure 4.43, 4.44, Table 4.24; blue, with results in Figure 4.45, 4.46, Table 4.25.

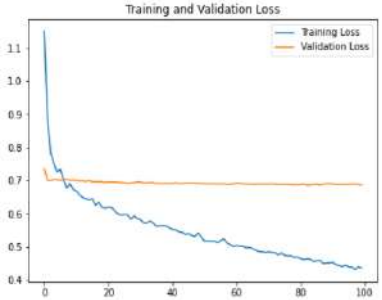


Figure 4.41 loss value of red plane.

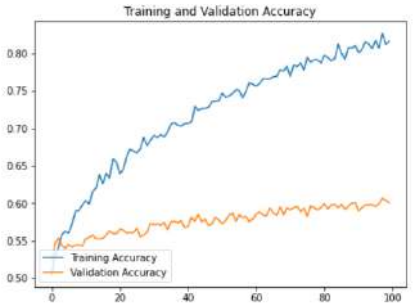


Figure 4.42 accuracy value of red plane.

Table 4.23 Measurement result with red plane.

	Recall	Precision	F1-Score
Abnormal	0,676	0,723	0,699
Normal	0,715	0,667	0,690

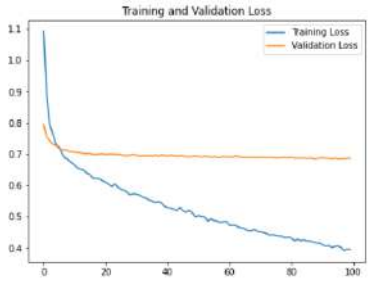


Figure 4.43 loss value of green plane.

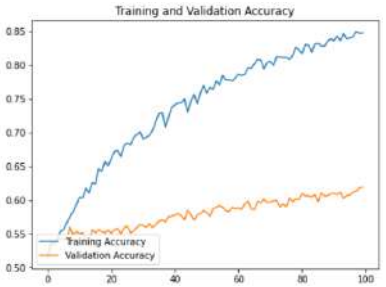


Figure 4.44 accuracy value of green plane.

Table 4.24 Measurement result with green plane.

	Recall	Precision	F1-Score
Abnormal	0,660	0,706	0,682
Normal	0,697	0,651	0,673

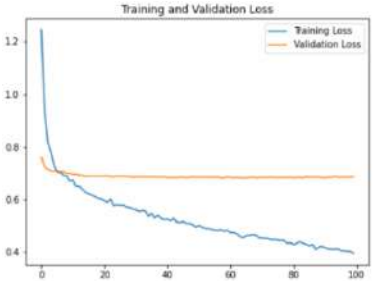


Figure 4.45 loss value of blue plane.

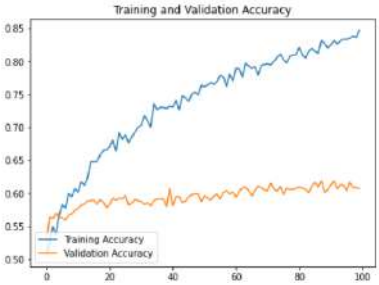


Figure 4.46 accuracy value of blue plane.

Table 4.25 Measurement result with blue plane.

	Recall	Precision	F1-Score
Abnormal	0,697	0,740	0,718
Normal	0,734	0,690	0,711

The dissertation applies the soft voting combined results of 03 color planes, resulting in the outcomes shown in Tables 4.26 and 4.27, and Figure 4.47. An example of the classification result using the color planse with soft voting is shown in Figure 4.48.

Table 4.26 Result of values TP, TN, FP và FN.

	Abnormal	Normal	Total
Abnormal	453	128	581
Normal	174	430	604

Table 4.27 Measurement result with color planes by soft voting.

	Recall	Precision	F1-Score
Abnormal	0,722	0,780	0,750
Normal	0,771	0,712	0,740

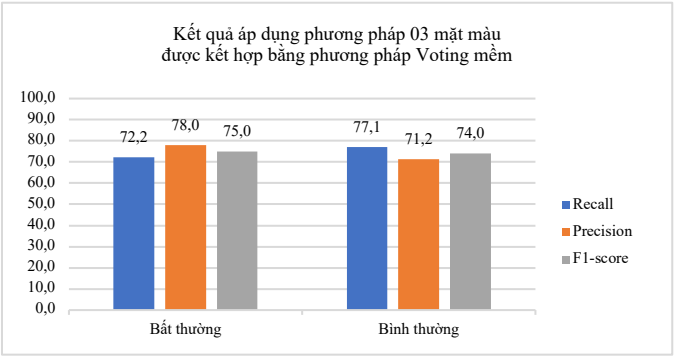
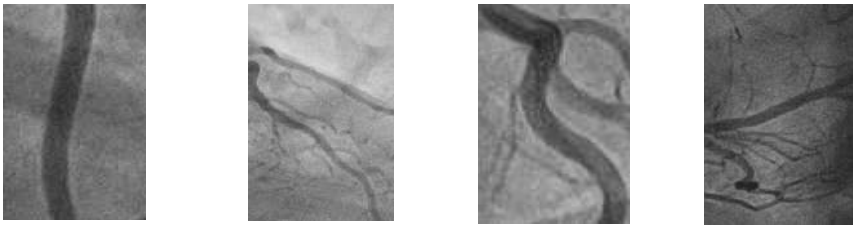


Figure 4.47 Graph of measurement results.



(a) (b) (c) (d)

Figure 4.48 Prediction by bit plane method: (a) normal to normal; (b) normal to abnormal; (c) abnormal to normal; (d) abnormal to abnormal.

4.8. Evaluation

The method of navigating along coronary edges to detect abnormalities depends heavily on the transition threshold of the edge, so choosing the threshold is very difficult to achieve high accuracy. Although edge extraction helps reduce navigation costs and increases accuracy by about 3% in the case of abnormal edges, it reduces accuracy by nearly 8% in the case of normal edges, which may be mistaken for abnormal ones when the segmentation results are not entirely accurate or if the segment of the circuit cuts off and slightly changes the direction of movement.

In terms of using deep learning methods, the results clearly show the complexity of coronary artery images when edges are not extracted, resulting in fairly low anomaly detection accuracy (lower than with the edge-based method). However, the accuracy of identifying normal edges is better by about 4% compared to data that has been edge-extracted using traditional methods (Canny) but not as good as with deep learning (DexiNed), with deep learning and data edge-extracted by DexiNed exceeding by more than 9%. Deep learning methods for anomaly detection with data edge-extracted by deep learning yield the best results, over 13% better than the second-best method. This indicates that edge extraction using deep learning provides richer information compared to traditional methods (as Canny also uses thresholds for edge extraction) and deep learning without edge extraction. It not only performs best for classifying abnormalities but also ensures results for classifying normal images. For the data of unsegmented coronary segments used for soft voting with results from the information planes: bit plane and color plane. Due to the complexity of the coronary image segments, even though the information planes are separated, these pieces of information cannot be isolated for each information plane but still have correlations with each other.

Finally, if we consider the average accuracy for each approach, the deep learning approach with edge extraction still holds the advantage.

4.9 Conclusion

The approach builds algorithms that combine the edge relations of pixels on coronary segments to consider whether the directional variability of the pixels on the edges exceeds the threshold to decide whether the coronary segment is abnormal or not. In this approach, the dissertation considers the input data as coronary segments that have been segmented: without edge extraction and with edge extraction. The second approach uses

deep learning, specifically CNNs, to detect whether the segment is abnormal or not? The input data also has two types: without edge extraction and with edge extraction. However, with edge-extracted data, the dissertation considers using two edge extraction methods: Canny and DexiNed. In this approach, the dissertation examines the classification results of the information planes and combines the results based on soft voting methods to have the final decision. With the results of the research, the dissertation indicates that the method of detecting abnormalities using deep learning, the deep learning method using data of coronary segments after segmentation and edge extraction by deep learning methods, will yield the best results. This promises that future research may apply the results in real treatment. The research results of the dissertation have been published in 02 scientific articles in Scopus [CT3] and SCIE [CT1] journals and one international conference under IEEE [CT5].

CHAPTER 5 CONCLUSION AND FUTURE WORK

5.1 Conclusion

The dissertation has achieved its goal of addressing two problems based on a new method:

- Segmenting coronary arteries as a basis for solving the problem.
- Detecting anomalies in the arterial segment (if any).

For the first problem, the dissertation proposed a coarse-to-fine approach based on different Unet models for segmenting objects with complex data types and successfully segmented the coronary arteries. From the segmentation results, the dissertation proposed two approaches to solving the problem of detecting anomalies in the coronary artery segment:

- An approach to building the vessel wall browsing algorithm based on direction change and gradient to decide whether the arterial segment is abnormal or not. With input data being the arterial segment that has been segmented: not edge-extracted and edge-extracted.
- A deep learning approach, the dissertation builds the CNNs model with input data being the arterial segment that has been segmented: not edge-extracted and edge-extracted. For edge extraction, the dissertation uses two methods: traditional – Canny and deep learning – DexiNed. Additionally, the dissertation also considers using information planes to detect anomalies in the coronary artery segment through the soft voting method to combine the results of the information plane's results.

The dissertation achieved several specific scientific significances as follows:

- Proposed a coarse-to-fine approach for deep learning Unet models [CT2].
- Built the vessel wall browsing algorithm to detect abnormal arteries [CT3].
- Applied the algorithmic approach with data being the edge-extracted coronary artery segment, using both traditional and deep learning methods [CT5].
- Proposed a deep learning method to detect abnormal areas [CT3].
- Proposed a deep learning method to detect abnormal areas with edge-extracted input data, using both traditional and deep learning methods [CT5].
- Proposed a deep learning model combined with a soft voting method for data being the information planes of unsegmented coronary artery segment images [CT1].

In terms of practical significance, the results of the dissertation could serve as a foundation for a reasonable approach for research groups with good equipment to further increase accuracy. Initially, doctors could use it for quick reference for diagnoses.

5.2 The future work

The problem of coronary segmentation and abnormality detection on coronary arteries remains very challenging, as it is a rather complex issue and there is not much data available. In subsequent studies, the author will focus on the following content:

- Collaborating reputable medical centers to collect data for practical implementation.
- Working with experts to integrate specialized knowledge into the segmentation model to achieve better results, laying the groundwork for rapid classification of whether coronary arteries are abnormal or not.

THE CONTRIBUTION

SCIE journal

[CT1] Le Nhi Lam Thuy, Vo Hoang Trong, Huynh Trung Hieu, Pham The Bao, "Detection of Abnormality in Coronary Artery Magnetic Resonance Imaging using Bit Plane Slicing and Deep Learning", Current Medical Imaging, vol. 20, pp. 1 – 12, 2024. http://dx.doi.org/10.2174/0115734056252243231025113221, Q3, IF = 1.315.

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Scopus journal

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