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A New Method For Classifying Heart In Multiview Echocardiographic Images

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| Article Information | Abstract |
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| Submitted :10 Aug 2022 Reviewed : 12 Aug 2022 Accepted : 17 Aug 2022 | Echocardiography is a test that uses high-frequency sound waves to describe the structure of the heart. Echocardiography is used by doctors to analyze the movement of the walls in the heart chambers and identify heart disease. Several images, including the long-axis, short-axis, 2-chamber and 4- |
| Keywords | chamber left ventricle, can be used to check heart function. Many studies that have been carried out, including cardiac evaluation, are still carried out |
| Echocardiography, Multi View, Good Feature, Support Vector Machine, Optical Flow | conventionally and require a certain level of accuracy. In this research, several methods proposed to achieve object extraction are used to build a classification system, the steps start with image enhancement, segmentation, tracking, extraction, output characteristics, validation and classification. Imaging enhancement aims to improve the echocardiographic image, thereby clarifying the edges of the heart wall. In addition, the images are reprocessed to separate the left ventricle from the heart wall and generate ventricular contours, at the segmentation stage. The contours are obtained by looking for the good features on each heart wall. In this approach, good features are identified only on the first image of the left ventricular slice. The good feature points used are 24 point which will be grouped into 6 segments. In addition, all images will be processed using the optical flow method to track the movement of the walls of the heart. Optical flow tracing will generate direction and distance features and find a suitable classification |

algorithm that is combined using different validation techniques, namely Kfold and Leave-one-out. In its implementation, Classifier Support Vector Machine (SVM) with rbf core achieves the highest accuracy. The SVM classification algorithm with validation techniques, namely k-fold crossvalidation and leave-one-out cross-validation, reaches an accuracy value of

100% and 100%.

A. Introduction

The heart is an organ consisting of a set of muscles that pumps blood throughout the body. In humans, the heart is divided into four segments: the upper right atrium, the upper left atrium, the lower right ventricle, and the lower left ventricle. In general, the right atrium and ventricle is called the right heart and the rest is called the left heart. In a healthy heart, blood flows in one direction through the veins. In 2016, cardiovascular disease accounted for approximately 17.9 million deaths, of which cases accounted for 31% of all deaths worldwide. Based on data from the World Health Organization (WHO) [1], 85% of the death were due to heart attack and stroke cases. Heart disease is a disease that still threatens the world and is the main cause of death in the world. According to the 2018 Basic Health Research (Riskesdas) data, the number of people with heart and blood vessel disease is increasing from year to year. At least 15 out of 1,000 people or about 2,784,064 people in Indonesia have heart disease[2]. In this case, accurate screening tools are essential for diagnosing heart disease and finding potential sources. A heart exam usually uses an echocardiogram, with sound waves, to depict body spaces.

Checking the condition of the heart can be done from various angles. The American Heart Association (AHA) recommends imaging studies of the twochamber, four-chamber, long axis, and short axis of the left ventricle[3]. Measuring left ventricular movement from diastolic to systolic can provide a variety of parameter values for doctors to identify and diagnose heart conditions. Current cardiac function testing methods mainly focus on ejection fraction[4]. The Simpson method is a popular method for examining the heart from a two-chamber and four-chamber perspective. This method aims to obtain the volume of the left ventricular cavity.

However, it should be noted that the Simpson method still relies on manual detection of the heart chambers, which requires high accuracy. Experiments have been carried out by previous studies involving automatic segmentation of cardiac chambers. Anwar[5] segmented the two-chamber and four-chamber heart cavities through an iterative process to obtain the contours of the cavity. The results of segmentation in this study get an accuracy of 89.409%. Another study performed automatic segmentation on the short axis using collinear and triangle equation methods, and was able to obtain the short axis cavity [6][7].

The movement of the walls of the heart can be seen by observing the left ventricular valve. Systolic pressure describes the contractile response of the ventricles. During systole, there is diastole, which causes the ventricles to relax. Understanding the movement of ventricular pressure is essential to understanding movement based on visual data. The motor definition can be seen in the systolic and diastolic phases, in the systolic phase the left ventricle begins to contract, so that the left ventricular pressure exceeds the pressure in the left atrium causing the mitral valve to close. During diastole, the left ventricle continues to contract until it is below left atrial pressure, causing the mitral valve to open.

Movement of the walls of the heart through diastole and systole can identify signs of heart disease. Pandian [8] discussed the findings of a violation with the detection of asymmetric left ventricular wall motion and wall thickening. The highfrequency sounds captures the structure of the heart as an image. Echocardiogram results are used to identify underlying heart disease. In echocardiography, images have speckle noise and need a repair process. Noise is a fine grained texture resembling the pattern seen on echocardiography, and indeed in all clinical ultrasound modalities. The applications of various ultrasonic imaging techniques have been explored in the literature, and the general goal is to reduce or eliminate the spectral components while preserving the image structure. The median filter is a nonlinear filter used to smooth the signal. This is excellent for removing pulsations from the signal. There are several variations of this filter, and the bidirectional variant is commonly used in digital signaling systems to remove point noise from an image. Previous studies using median filters [9][10] have shown that median filters can be used to deal with noise.

In image processing, we often want to emphasize the high frequency components that represent the image. Brightness is used to highlight certain parts of the heart chambers. The high-boost filter can be used to increase the high frequency component while maintaining the low frequency component[11][12]. This filter is performed at high frequencies and at low frequencies retains the value of the image. As a result of this filter, it is possible to sharpen the edges of the image and get a clearer image. The height enhancing filter can be expressed in equation (1-3) where A is the value of the constant that affects the brightness of the image. Threshold is a simple method for image segmentation, a nonlinear operation that converts a grayscale image into a binary image, where two levels are assigned to pixels lower or higher than a specified threshold value. The resulting image segmentation has a line which is the boundary between two different image areas, sharp edge detection is an image processing method used to detect edges in the image. Sigit [13] used a smart filter to capture the short axis of the heart chambers. The results obtained show that the intelligent edge detection method can adapt to many different environments. However, it is still necessary to improve the smart edge detection to remove the line around the cavity, improve the edge line using aligned regions and areas[12][14]

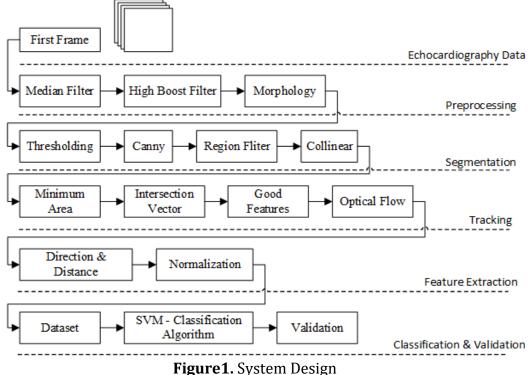
In addition, previous studies have focused on tracking and visualizing the left ventricular movement of the heart. Reference[11] automatically proposes cardiac cavity segmentation at a short axis point of view. The segmentation process uses the active shape model method. The starting point in the cavity is used to monitor the movement of the heart via optical flow. The tracking process uses the optical flow method to produce direction and distance characteristics. Anwar [15] using 24 good features that produce 4 data, namely the distance and direction of each good feature so that the total features in each dataset is 96 data in one point of view. In previous studies, researchers conducted research from each perspective, such as the classification of heart conditions from the long axis point of view by Cicik., the classification result was 80%, with 11 training data and 10 test data[16]. Then Adam [17] classified heart conditions from a short axis perspective with 11 data sets, which achieved classification results of 81.82 with the neural network learning method and 72.73 with the support vector learning method.

Based on previous research that discusses feature extraction using 24 good feature points. This study proposes the development of good feature points by optimizing by grouping 24 good feature points into 6 segments which will produce 12 data in each view and 48 data in each dataset. This study uses ultrasonic which

utilizes high-frequency sound waves to obtain multi-view images of the heart, namely Long Axis, Short Axis, 2 chambers and 4 chambers. And uses 42 data and has one class per data. The amount of data for the abnormal class is 21 and the normal class is 21. The results of object extraction are analyzed to determine the characteristics of the resulting data and find the appropriate classification algorithm using authentication specifications, namely k-fold and leave one out. This system is expected to be able to classify cardiovascular health problems very accurately.

B. Research Method

The design of the system implementation can be described in the form of system design. The system design describes the entire process contained in the system which can be shown in the following figure 1.



1. Preprocessing

Image enhancement on video echocardiogram using median filter, high-boost filter, and morphology reduces speckle noise that interferes with vision. Then noise reduction will be emphasized to clarify the information contained in the image. The first stage uses an median filter with a multiplier of 21 x 21. The use of a large multiplier is intended to reduce noise. However, it preserves image margins and increases left ventricular margins, even when the resulting image is blurred[18]. After reducing the noise, the brightness of the heart wall in the image should be further increased. The second step involves the use of a high-boost filter whose working principle is to increase the value at high frequencies and maintain low frequencies at the image value[19].

2. Segmentation

Echocardiographic image segmentation is used to separate the left ventricle from the heart wall, but the echocardiographic image has a grainy type of noise, so it needs to be improved with image enhancement to improve image quality. The image enhancement process involves several stages starting from the median filter, high-boost filter, and morphometric operations, resulting in an echocardiographic image with a clear distinction between the heart wall and the center of the heart, left ventricle and low noise. Furthermore, at the segmentation stage which aims to separate the left ventricle from the heart wall, the overall segmentation process includes the thresholding method, canny filter, region filter, watershed for long axis and collinear method, the left ventricle is clean from noise.

3. Tracking

Echocardiographic monitoring was used to obtain characteristic values of left ventricular wall motion during diastole to systole. To monitor the left ventricle, a good features point is needed, this study uses the contour obtained from the segmentation results as a good features point. These points are good features that will be used as points in the optical flow to monitor heart wall motion and the number of good features used in this study is 24. Overall, follow-up imaging of echocardiographic images includes several steps ranging from minimal surfaces, vector intersections, good features, and optical flow. The results of monitoring the movement of the heart wall will be displayed live so that it can distinguish normal and abnormal heart movements. In this research, the good features of the left ventricular wall were used for optical flow monitoring using the Lucas-Kanade method. Reference [20], uses a good line obtained from a transverse line on the contour used for left ventricular monitoring. The proposed method provides calculation results with a sensitivity of 83.27%, accuracy of 91.51%. Lucas-Kanade is a method used to predict the motion of an object based on the intensity of light in an image.

4. Feature Extraction

Cardiac abnormalities can be assessed visually based on the movement of the walls of the heart from diastole to systole. From the observations made, a normal heart has large and fast movements, while an abnormal heart has small and slow movements. The parameters used to determine the health status of the heart are the distance and direction from the characteristics of the right side of diastole to the results of systolic monitoring. The resulting intersection vector with the left ventricular contour produces features that have both left and right sides, so that the resulting tracking distances and migration directions have different outputs. Heart movement can be used as a parameter to assess heart health. Left ventricular flow optical monitoring, capable of producing directional and distance features from the good features shown in the first image. To get the characteristic values for the direction of parietal heart motion, the researchers proposed a simple algorithm as shown in Figure 2.

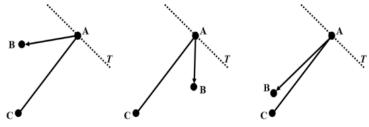


Figure 2. Direction Feature

Left ventricular wall motion abnormalities are common in various diseases; Pandian[21]describe asymmetric movement of the left ventricular wall, revealing cardiac abnormalities. From observations, a healthy heart has a fast movement from systole to diastole, while an abnormal heart has a slow movement. Evaluation of cardiac function can use the optical flow method to monitor the movement from diastole to systole. Thus, thickening of the walls of the heart indicates abnormal heart function. Optical flow monitoring will provide characteristics of left ventricular displacement and distance using good features. The characteristics are obtained by using equation (1) (2) for the direction and distance characteristics.

$$\cos\cos A = \frac{b^2 + c^2 - a^2}{2bc}$$
(1)

$$d_{(i,j)} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$
(2)

The feature then normalized to scale the data. Min-max normalization is one of the most popular ways to normalize data. This method converts the feature's minimum value to 0, the maximum value is converted to 1, and all other values are converted to values between 0 and 1. The min-max normalization can be expressed by Equation (3).

$$N = \frac{x - \min(x)}{(x) - \min(x)} \tag{3}$$

Normalization is done by finding the min and max values for each object and then scaling it to a value between 0 and 1.

C. Result and Discussion

This section discusses the analysis and implementation of the system. The process begins with data acquisition, preprocessing, segmentation, tracking, feature extraction, classification and validation.

1. Result of Preprocessing

The study implemented median filter, high-boost filter, and morphology methods to reduce speckle noise. The preprocessing result shown in Figure 3.

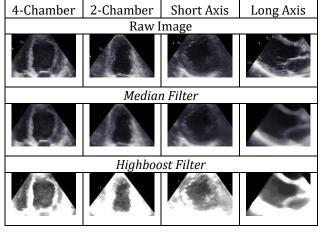




Figure 3. Preprocessing result

2. Result of Segmentation

At the segmentation stage which aims to separate the left ventricle from the heart wall, the overall segmentation process involves thresholding, canny filter, region filter, and collinear methods which produce a clean left ventricular contour from noise. The segmentation result shown in Figure 4.

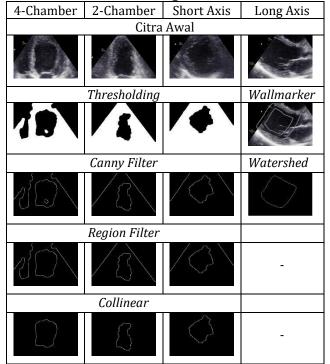
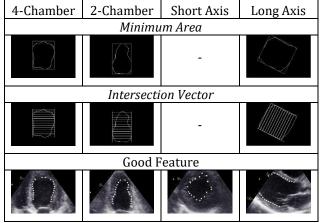


Figure 4. Segmentation result

3. Result of Tracking

Figure 5 is the process for get good features in each view. In general, the echocardiographic image tracking process involves several stages, starting from the minimum area, intersection vector, good feature and optical flow.



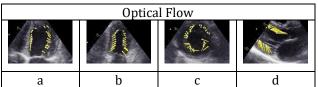


Figure 5. Result tracking using Lucas Kanade (a) Four-Chamber (b) Two-Chamber (c) Short Axis (d) Long Axis

4. Result of Feature Extraction

This research uses 24 good features which are grouped into 6 segments as shown in table 1 for tracking, resulting in 48 features consisting of 6 segments in each view, in each segment there are 2 data, namely distance and direction data so that a total of 48 features are obtained for each dataset consisting of 4 views. From the observations made, the normal heart has large and fast movements, while the abnormal heart has small and slow movements. The parameters used to determine the health status of the heart are the distance and direction.

| Table 1. Number of Features | | | | | | | |
|------------------------------------|---|--|--|--|--|--|--|
| View | Good Feature | Movement | Feature | Value | | | |
| | 1 - | Direction | F1 | 1.448106 | | | |
| | | Distance | F2 | 1.990686 | | | |
| Long Axis | | | | | | | |
| _ | 6 - | Direction | F11 | 2.208333 | | | |
| | | Distance | F12 | 2.002899 | | | |
| | 1 - | Direction | F13 | 1.66875 | | | |
| | | Distance | F14 | 3.24856 | | | |
| Short Axis | | | | | | | |
| _ | 6 - | Direction | F23 | 2.4875 | | | |
| | | Distance | F24 | 3.72152 | | | |
| | 1 - | Direction | F25 | 6.25 | | | |
| _ | | Distance | F26 | 11.41494 | | | |
| 4 Chamber | | | | | | | |
| _ | 6 | Direction | F35 | 5.025 | | | |
| | | Distance | F36 | 13.1406 | | | |
| | 1 - | Direction | F37 | 1.66875 | | | |
| | | Distance | F38 | 3.037637 | | | |
| 2 Chamber | | | | | | | |
| - | 6 - | Direction | F47 | 3.2375 | | | |
| | | Distance | F48 | 3.17551 | | | |
| | | | | | | | |
| | View Long Axis Short Axis 4 Chamber 2 Chamber | ViewGood FeatureLong Axis1Long Axis61Short Axis614 Chamber612 Chamber66666666666666 | $\begin{tabular}{ c c c c } \hline View & Good \\ \hline Feature & Movement \\ \hline Feature & Movement \\ \hline \\ \hline \\ 1 & Direction \\ \hline \\ 0 & Direction \\ \hline \\ 0 & Direction \\ \hline \\ 0 & Distance \\ \hline \\ 1 & Direction \\ \hline \\ 0 & Distance \\ \hline \\ 1 & Direction \\ \hline \\ 0 & Distance \\ \hline \\ 4 \ Chamber & & \\ \hline \\ 4 \ Chamber & & \\ \hline \\ 6 & Direction \\ \hline \\ 0 & Distance \\ \hline \\ 1 & Direction \\ \hline \\ 0 & Distance \\ \hline \\ 2 \ Chamber & & \\ \hline \\ 6 & Direction \\ \hline \\ 0 & Direction \\ \hline \\ 0 & Distance \\ \hline \\ 1 & Direction \\ \hline \\ 0 & Distance \\ \hline \\ 2 \ Chamber & & \\ \hline \\ 6 & Direction \\ \hline \\ 0 & Direction \\ \hline \\ 0 & Distance \\ \hline \\ 0 & Direction \\ \hline \\ 0 & Distance \\ \hline \\ 0 & Distance \\ \hline \end{array} \end{tabular}$ | $\begin{tabular}{ c c c c c } \hline View & \hline Good \\ \hline Feature & Movement & Feature \\ \hline \\ \hline Peature & Direction & F1 \\ \hline Distance & F2 \\ \hline \\ \hline \\ Long Axis & $$\dots$ & \dots & \dots & \dots \\ \hline \\ \hline \\ \hline \\ \hline \\ \hline \\ \\ \hline \\ \\ \hline \\ \hline \\ \hline \\ \\ \hline \hline \\ \hline \\ \hline \\ \hline \\ \hline \hline \\ \hline \\ \hline \\ \hline \\ \hline \hline \\ \hline \\ \hline \\ \hline \\ \hline \\ \hline \hline \hline \hline \\ \hline \hline \hline \\ \hline \hline \\ \hline \hline$ | | | |

5. Result of Classification and Validation

Table 2 show the test results with the k-fold cross-validation technique show that the classification algorithm using the SVM method obtains validation results with the best accuracy value of 100 with 100% accuracy, 100% recovery and 100% f1 score and second is using NN(MLP Backpro) method that have accuracy value 96% and 91.41% Fscore.

| I able 2 | Table 2. Classification Algorithm with K-Fold Valuation | | | | | | | |
|------------------------|---|-----------|--------|--------|-------------|--|--|--|
| K-Fold Validation | Accuracy | Precision | Recall | FScore | Kappa Score | | | |
| SVM | 100% | 100% | 100% | 100% | 100% | | | |
| Decision Tree | 89% | 92.45% | 88.33% | 88.75% | 76.15% | | | |
| KNN | 89% | 92.91% | 89.16% | 90.92% | 78.31% | | | |
| Naïve Bayes | 93% | 95.41% | 92.5% | 93.86% | 85.45% | | | |
| Logistic Regression | 95.5% | 97.08% | 97.08% | 95% | 90.45% | | | |
| NN (MLP Backpro) | 96% | 97.08% | 95.83% | 96.41% | 91.60% | | | |

Table 2. Classification Algorithm With K-Fold Validation

Table 3 show the test results with the Leave-One-Out validation technique show that the classification algorithm with the SVM method obtains validation results with the best accuracy value 100% and 100% f1 score and second is using NN(MLP Backpro) that have 97.61% accuracy and 97.67% f1score.

K-Fold Recall **Kappa Score** Accuracy Precision **FScore** Validation 100% 100% 100% 100% 100% SVM **Decision Tree** 83.3% 83.33% 83.4% 83.37% 66.67% KNN 88.1% 88.1% 90.38% 89.22% 76.19% Naïve Bayes 92.9% 92.9% 92.9% 92.9% 85.71% Logistic 95.2% 95.2% 95.65% 95.44% 90.47% Regression NN 97.6% 97.6% 97.72% 97.67% 95.23% (MLP Backpro)

Table 3. Classification Algorithm With Leave-One-Out Validation

D. Conclusion

Determination in the selection of classification algorithm parameters using the grid search method. The classification algorithm assessment uses several validation techniques, namely k-fold cross validation and leave one out cross validation which obtains an accuracy value of 100% and 100% using the SVM method classification algorithm with the rbf kernel produces the best level of accuracy compared to other classification algorithms.

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