Echocardiogram Image Quality Enhancement using Upsampling and Histogram Matching Methods

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Abstract— The prevalence of heart disease has been increasing in the last ten years. One of the cardiac diagnostic tools is echocardiography. Echocardiogram medical images provide essential information, including shape, size, pumping capacity, heart function abnormalities, and location of heart damage, but echocardiogram images have high noise content and poor contrast, as well as limitations due to differences in anatomy or body mass. This will affect the reading results of patient diagnosis. Therefore, image quality improvement is needed by removing noise and increasing image contrast. This research has improved image quality using a method with low mathematical complexity and a fast computational process. The method used is the Upsampling method to generate a reference image. The quality of the image produced was the Nearest Neighbor upsampling method: 2.8 dB, Bi-linear Interpolation: 2.78 dB, and Bi-cubic Interpolation: 2.73 dB. Furthermore, the image with the highest SNR value is processed with Histogram Matching to accelerate improving image quality. The Histogram Matching image increases quality by more than 50% with a SSIM value of 0.54. The required computational process to apply this method to each medical image has an average duration of 0.4 s. This result provides a higher value than several methods using linear scaling and speckle reducing.

Keywords— echocardiogram; histogram matching; image contrast; upsampling

I. Introduction

Echocardiography is the most common image modality used to analyze the size and function of the heart but it has limitations in defining normal heart structure and function. The New York Heart Association, European Association of Cardiovascular Imaging, and American Society of Echocardiography have defined normality in Echocardiography by providing standardized values for normal conditions in left ventricular, right ventricular, right atrial, and left atrial [1]. The standardization process in previous research which was done by designing an echocardiogram image standardization mechanism, matching the intensity distribution histogram regarding the distribution, is considered to be the best to characterize the echocardiogram image. The idea of histogram specification is used to build a model for standardization, namely, a prototype of the shape and scale parameter set of the considered distribution of a representative image [2]. Echocardiography is a cardiac diagnostic tool that assists physicians in analyzing the heart based on recording the heart in 2D images and incorporates low-cost portable instrumentation and rapid image acquisition without the risk of ionizing radiation [1]. The results of echocardiography, namely echocardiogram images, can provide information on the anatomy of the heart without performing surgery, including shape, pump capacity, and size of the heart to the location of damage to the heart [2].

The utilization of echocardiography tools has increased substantially over the past decade. 2D echocardiogram images have become the initial reference recommendation for patients with heart failure symptoms, not only for prognostics but also to guide the invasive management of patients before catheterization [3]. The results of a 2D echocardiogram can be an accurate evaluation of primary or secondary catheter abnormalities [4].

Echocardiogram has the potential to determine the condition of the left ventricular and right ventricular muscles. However, the accuracy value depends on the image quality and is affected by the image recording frame rate [5]. Operators with specialized training carry out recording the heart using echocardiography, so the quality of the recording image is highly dependent on the operator's skill in clinical settings and settings for each patient condition [6]. Automatic boundary extraction from echocardiograms is essential in the clinic to obtain the most effective results. Many researchers have identified the boundaries of echocardiograms but it is still a challenge because heavy noise and artifacts make feature extraction and tracking difficult. Echocardiogram images have high noise content and poor contrast, limited acoustic window due to anatomical differences or body mass [7].

There are two fundamental operations in image processing: downsampling and upsampling. Downsampling is a method of reducing spatial resolution while maintaining the exact two-dimensional (2D) representation. It is used to reduce the storage and transmission requirements of the image. Upsampling is an increase in spatial resolution by retaining the 2D representation of an image used to enlarge small regions and eliminate pixel effects that appear whenever a low-resolution image is displayed on a relatively large frame. This technique applies the reverse process of the previous one and consists in obtaining an output image with a higher resolution than the input image. In practice, the focus lies on obtaining images that do not present unwanted artifacts and maintain a high level of detail [8]. The standard methods for downsampling or upsampling are

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decimation or duplication and bi-linear interpolation. Several studies have applied bi-linear or bi-cubic interpolation for upsampling and downsampling [9].

Research on ultrasound image of standardization has not been widely studied [10]. Some studies have applied linear scaling standardization and provided better segmentation of ultrasound images [11], [12]. Research on echocardiogram image quality improvement has applied linear intensity scaling without considering the gray color texture distribution. This results in the loss of true organ reflective information [13]. Previous study has applied a method of reducing speckle noise by applying Speckle Reducing Anisotropic Diffusion (SRAD). This method is carried out before logarithmic transformation. The next stage is the guide filter and the last stage with exponential transformation. The combination of several transformations, and this method results in Structural Similarity (SSIM) of 0.76 and there is an image improvement of 24%. This study on this lesion and speckle gives good results on edge detection. However, it has the disadvantage that there are additional stages in the form of filtered images converted to additive noise while there must be additional noise [14]. Other research on image contrast enhancement has been carried out by applying the Squeeze Box Filter (SBF) method with the pre-processing stage of adding white Gaussian noise. The results showed that the Signal Noise Ratio (SNR) value is 9.12 dB and SSIM value is 0.42. This research has good results in removing outliers but the improvised value based on the average value of an image region cannot represent the overall value distribution [15]. Fuzzy logic computational models have also been applied to reduce speckle noise for image quality improvement. However, a pre-processing stage in calculating local statistical parameters must consider in image processing. In this case, the researcher's subjectivity will affect the results of parameter selection; the research developed resulted in SSIM: 0.54 [16].

Based on the background, this research aims to standardize images by matching histograms on echocardiogram images with proper intensity distribution. The idea of histogram specification built a standardization model. The distribution's prototype shape and scale parameter sets are considered from representative images. This set of parameters constructed the Cumulative Distribution Function (CDF) [17]. Similarity matrices based on the statistical properties of the images have been applied mainly based on the distance between the CDF of the images and have proven to be effective, stable, and efficient [18], [19].

The CDF value obtained is the transfer function for the testing image. It is assumed that the echocardiogram image follows a mixture distribution. This study proposes Histogram Matching to overcome the bias caused by dynamic range transformation. Histogram Matching is a technique to ensure that two or more images are properly normalized and has been applied to research on applying Histogram Matching-based Local Binary Patterns (LBP) features to improve image selection [20]. Other research has applied this method to ultrasound images, impacting general imaging based on quantitative values [21].

Research on interpolation techniques is of particular value in the medical imaging domain, whereby the quality and resolution of images obtained on magnetic resonance imaging (MRI) must be highly valued. Reconstruction of non-uniform sample volumes is done with the help of interpolation [22]. Some techniques, such as Computer-Assisted Diagnostics (CAD) and Computer-Assisted Surgery (CAS), impose certain resolution constraints, either to identify patterns in diagnostics or to provide high-fidelity imaging [8]. Quantitatively, image quality can be determined using SNR. Based on this value, poor image quality can still be improved [23].

This research aims to enhance the quality of echocardiogram images. An image's displayed dynamic range and information enables normalized comparison among image formation methods using histogram matching. Section II describes the upsampling method, histogram matching, general research, and quantitative methods for echocardiography image analysis. Section III is an analysis of the research results. Section IV is a research conclusion on the results of applying the method and the future research planned.

II. METHOD

Some existing studies have performed quality improvement stages using local statistical parameters, average reference values, adding noise, and fuzzy classification methods. This research differs from previous research because the initial stage is to use the upsampling method by applying several methods that aim to increase the ratio of image value to noise.

The echocardiogram image processing process has several stages, namely: the first stage is upsampling the image using Nearest Neighbor, Bi-linear Interpolation, and Bi-cubic Interpolation; the second stage determines the image with the highest SNR value as the Histogram Matching testing image and the third stage performs standardization by adjusting the CDF value of the upsampled image with a representative image. The dataset in this study uses HMC-QU is the results from collaborative research on Myocardial Infarction conducted by Hamad Medical Corporation (HMC), Tampere University, and Qatar University. This dataset is publicly accessible at www.kaggle.com and has been used by several researchers to research other echocardiogram images, with an initial image size of 636x422 pixels. The images in this dataset consist of echocardiography recordings with apical two heart chambers and apical four heart chambers views [24]–[26].

A. Upsampling

This research applies three upsampling methods as the first step to improve image quality: Nearest Neighbor, Bi-linear Interpolation, and Bi-cubic Interpolation. The upsampling process with Nearest Neighbor is the most basic. Nearest Neighbor performs by taking the information value of the Nearest Neighbor's pixel while ignoring other neighbors. So, $h(x)$ is the distance between the two-pixel points (1). Because of this simple upsampling process, Nearest Neighbor has a speedy turnaround time [27]. Locating the Nearest Neighbor used the euclidean distance algorithm (2) where $d(p,q)$ are two euclidean points, $q_i - p_i$ is the euclidean vector and n is the number of distances. The image before the upsampling process using Nearest Neighbor is shown in Figure 1 and Figure 2.

$$h(x) = \begin{cases} 1, |x| < \frac{1}{2} \\ 0, |x| < \frac{1}{2} \end{cases} \quad (1)$$

$$d(p,q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \quad (2)$$

The following upsampling process applies Bi-linear Interpolation. In contrast to Nearest Neighbor, Bi-linear Interpolation takes four pixels in the nearest neighbor, where $h(x)$ is the distance between the two pixels (3). The result of the Upsampling process using Bi-linear Interpolation is shown in Figure 3. The processing time is longer than Nearest Neighbor due to the more complex computation [27].

$$h(x) = \begin{cases} 1, |x| \leq \frac{1}{2} \\ 0, \frac{1}{2} \leq |x| \end{cases} \quad (3)$$

The last upsampling process applies Bi-cubic Interpolation. This process has a more complex computation than Bi-linear Interpolation because it uses the average of the 16 nearest pixels (4x4) to estimate the new pixel value, $u(x)$ is the distance between the two pixels (4) [27]. The results of the upsampling process using Bi-cubic Interpolation is shown in Figure 4.

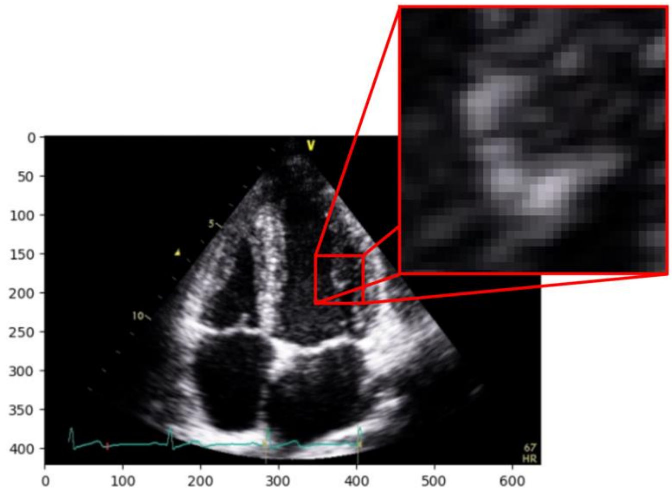

Figure 1. Image before upsampling

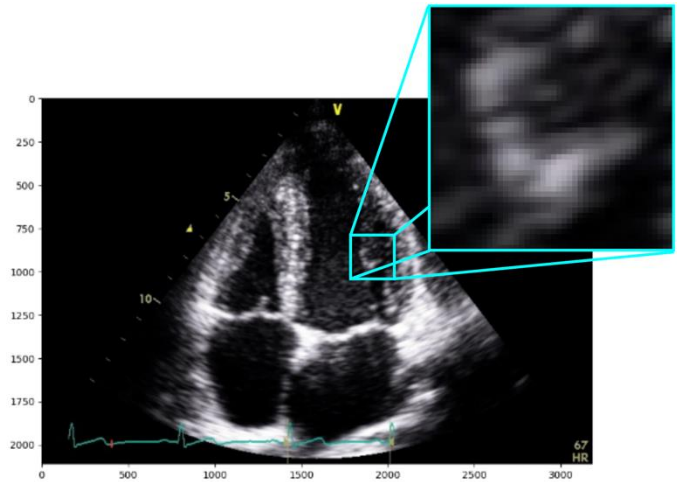

Figure 2. Upsampling of nearest neighbor

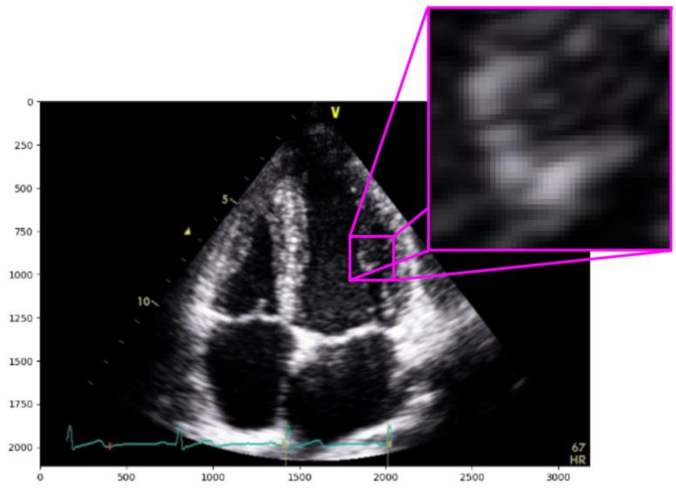

Figure 3. Upsampling of bi-linier interpolation

$$u(x) = \begin{cases} \frac{3}{2}|x|^3 - \frac{5}{2}|x|^2 + 1, & if\ 0 \leq |x| \leq 1 \\ \frac{-1}{2}|x|^3 + \frac{5}{2}|x|^2 - 4|x| + 2, & if\ 1 \leq |x| \leq 2 \\ 0\ , & if\ |x| > 2 \end{cases} \quad (4)$$

B. Histogram Matching

The stage of this research is to adjust the image contrast value referring to the results of the reference image generated from the upsampling process. The reference image is selected and intended for gray-level parameters. Therefore, the input image that is lower or higher than the reference image will change according to the level of the reference image. The difference in gray values can be seen in Figure 5 for the input image gray histogram, and Figure 6 for the reference image histogram, where 0 is the black pixel value, and 255 is the white pixel value. The method used to adjust the standardized gray value is using the Histogram Matching method. This adjustment is made because there are differences in CDF values. The CDF value is the distribution value of the pixel value of the echocardiogram image. This image information is used as input to adjust the CDF reference value.

CDF value retrieval on image input using (5), where C_x is the initial value variable of the gray level value of each pixel. Then x_j is the number of intensity values of the input image and has been grouped. N is the total number of pixels. In comparison, K is the value of the possibility that is in an image of the value in question, such as $\{0,1,2,\dots L-1\}$ [21].

$$C_x(k) = \sum_{j=0}^{k} p_x(j) = \frac{1}{N}\sum_{j=0}^{k} x_j \quad (5)$$

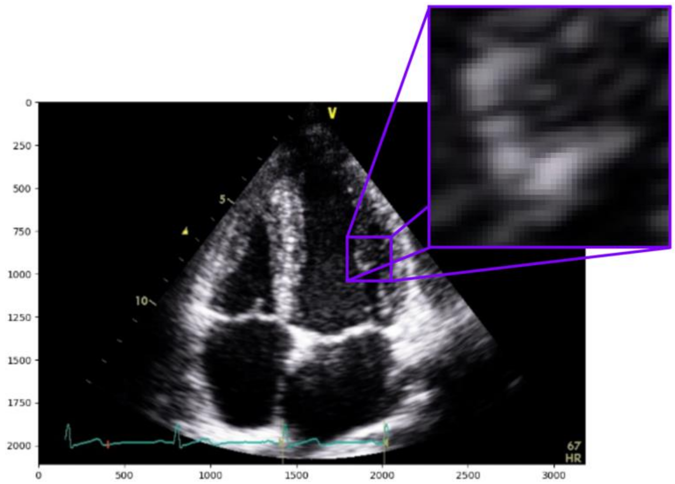

Figure 4. Upsampling of bi-cubic interpolation

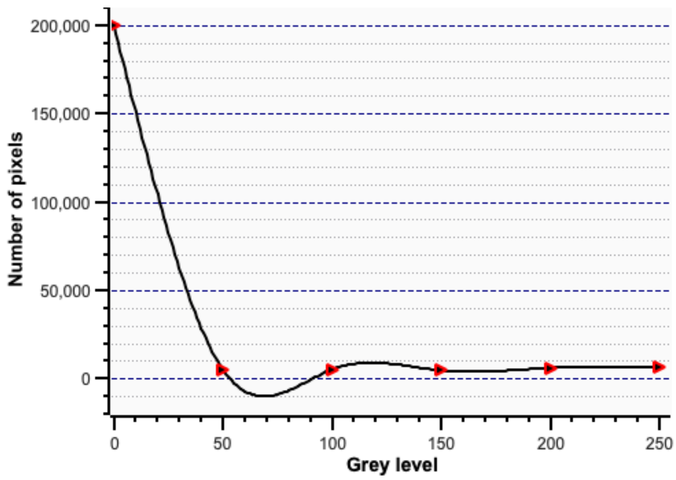

Figure 5. Histogram of image input

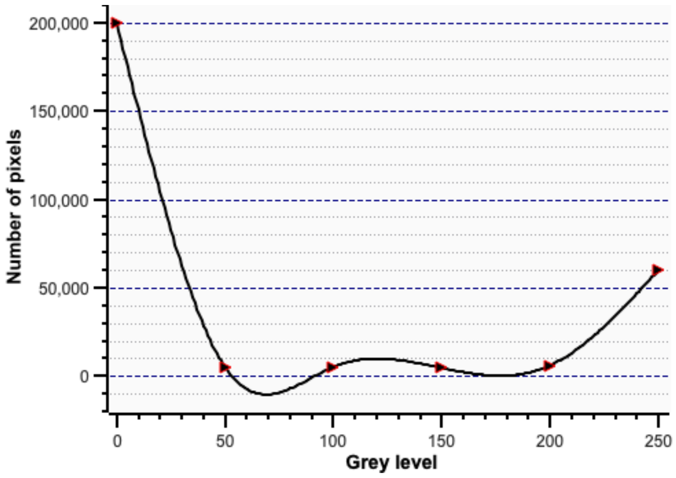

Figure 6. Histogram of image reference

Deriving the CDF value used as a reference refers to (6). Where C_z is the variable gray level value of the reference image. Thus, z_j is the sum of the number of intensity values of the input image and has been grouped. N is the total number of pixels. In contrast, K is the different possible values in an image, such as $\{0,1,2,\ldots L-1\}$ [21]. Figure 7 is the CDF graph of the input and reference images. The red graph is the CDF of the input image and the blue graph is the CDF of the reference image. The graph indicates that the input and reference images have very different CDF values.

$$C_z(l) = \sum_{j=0}^{l} p_z(j) = \frac{1}{N}\sum_{j=0}^{l} z_j \tag{6}$$

C. Metrics Evaluation

This research used evaluation metrics to determine changes in image information before and after the enhancement process. The evaluation metrics used are Peak Signal Noise Ratio (PSNR) and SSIM. PSNR is to determine the value of information loss after processing in PSNR, determined by the Mean Squared Error (MSE) value in (7) and (8), where I is the reference image and I' is the image that passed through the intensity enhancement process. L is the maximum value of possible pixels obtained as 255 in an 8-bit RGB image [27].

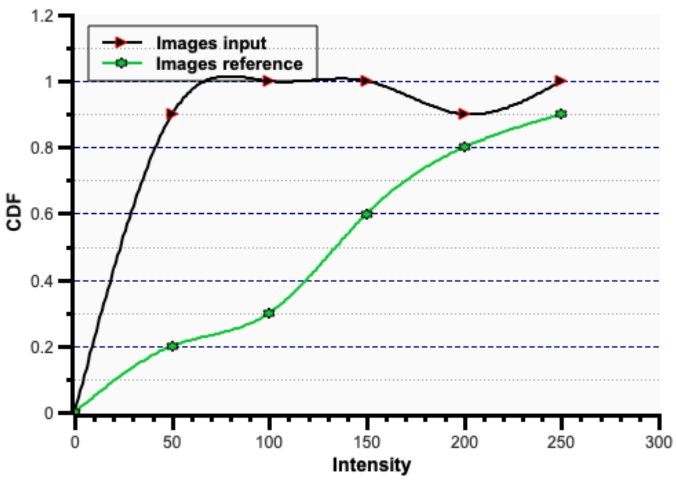

Figure 7. Input and reference graph

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(I(i) - I'(i))^2) \tag{7}$$

$$PSNR = 10.\log_{10}\left(\frac{L^2}{MSE}\right) \tag{8}$$

The subsequent metric evaluation used SSIM. This evaluation aims to obtain information on the match value between the reference and processed images. In (9), μ_I is the average of the pixel values, σ_I which is the standard deviation of the image I. $\sigma\ I\ I'$ is the covariance between the reference image and the processed image. The value of C_1C_2 is the constant limit of pixel value stability [27].

$$SSIM(I,I') = \frac{(2\ \mu\ I\ \mu\ I\prime + C_1)(\sigma\ I\ I\prime + C_2)}{(\mu_I^2 + \mu_{I\prime}^2 + C_1)(\sigma_I^2 + \sigma_{I\prime}^2 + C_2)} \tag{9}$$

D. Proposed Model

This research model determines the echocardiogram image data selected as a total of 20 image data for the upsampling process to improve the sharpness and pixel density values. Figure 8 is a proposed upsampling process diagram by applying three selected methods, namely: Nearest Neighbor, Bi-linear Interpolation, and Bi-cubic Interpolation. After the three methods, the best upsampling method was selected for the enhancement process of 20 image data. This enhancement has determined the initial image data with information dimensions of 636x422 pixels and has increased dimensions to 3180x2170 pixels—this process is shown in Figure 9. The overall research stages can be seen in Figure 10.

The output of the upsampling process was used as input data for Histogram Matching. Figure 11 shows the performance diagram of Histogram Matching. Input is data that has passed the optimal upsampling stage. The reference image is the data that becomes the contrast reference value. The Histogram Matching method is robust in adjusting the CDF value or the cumulative distribution value of the gray level value between the input and reference.

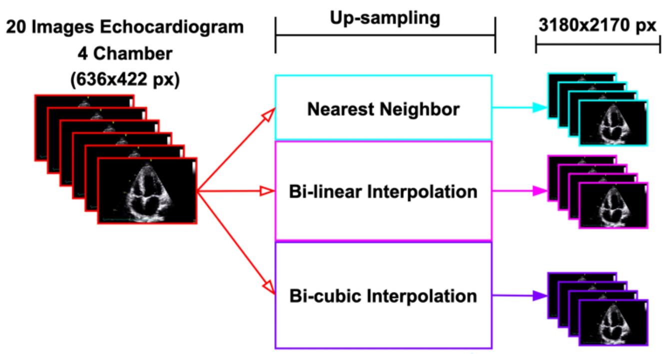

Figure 8. Flowchart of upsampling process

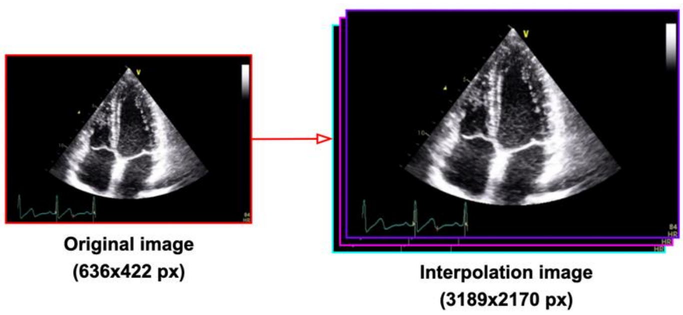

Figure 9. Improved pixel dimensions

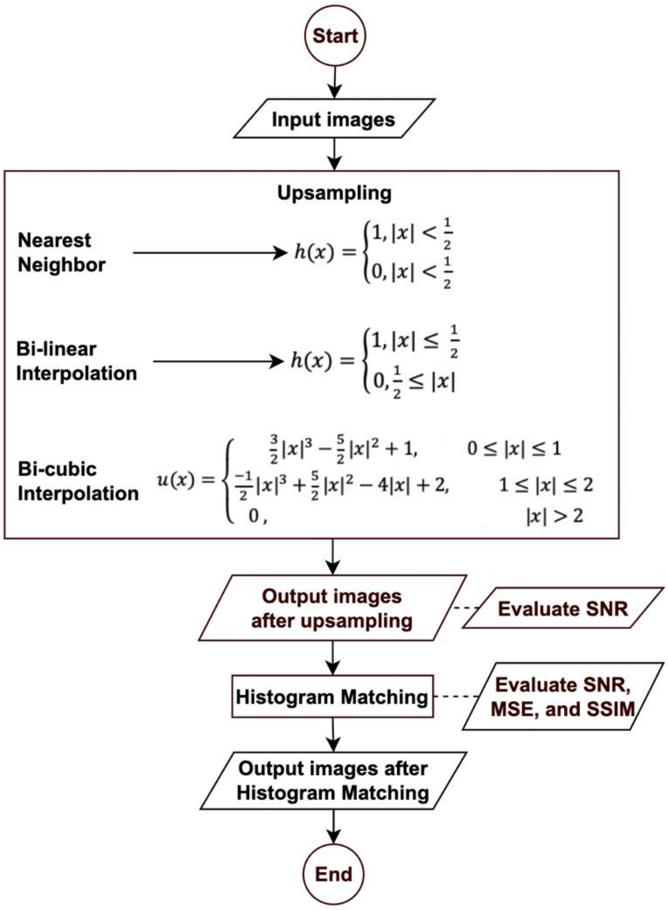

Figure 10. Research flowchart

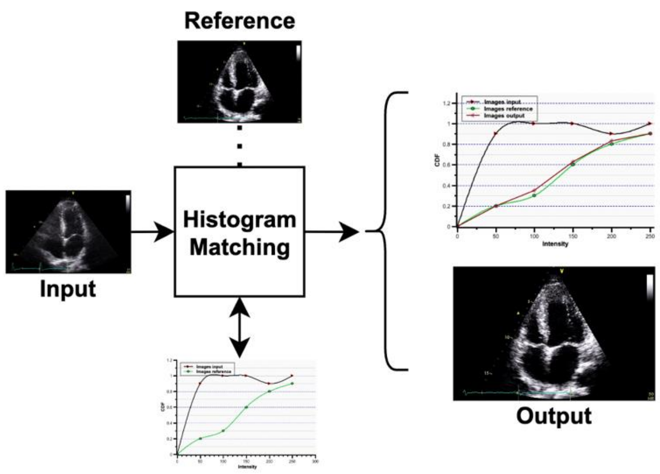

Figure 11. Process of histogram matching

III. Results and Discussion

This research test explains that echocardiogram images have low visual quality, hence the importance of quantitatively knowing the initial image quality value. The initial stage to determine the composition of the image is conducted metric testing with SNR. After testing the image, the image quality was increased to 3180x2170 pixels by applying upsampling. The upsampling process is applied with three methods, namely: Nearest Neighbor, Bi-linear Interpolation and Bi-cubic Interpolation. Furthermore, metric testing is carried out again to determine the quality of the new image in SNR, so that it can determine the value of the improvement that occurs. The output image with the best results from the three upsampling methods will be used as a reference image to improve contrast quality using Histogram Matching.

A. Upsampling Result

The upsampling results in Figure 9 show the difference in pixel dimensions after upsampling. After acquiring the best and selected image enhancement, testing is then performed to determine information on the quality change of the image. Figure 12 shows the SNR test graph result by testing 8-bit to 256-bit.

B. Histogram Matching Result

The results of the contrast value change in applying Histogram Matching are shown as a CDF. The Histogram Matching method estimates the CDF that matches the reference CDF value. The Histogram Matching method is highly robust in changing the CDF value without performing a complex computational process since it only refers to the reference value. This process will exactly match the reference distribution but is very vulnerable to outliers in the reference data since all values are replicated in the target or output [28]. Figure 13 green graph transforms the estimated input CDF values into reference CDF values.

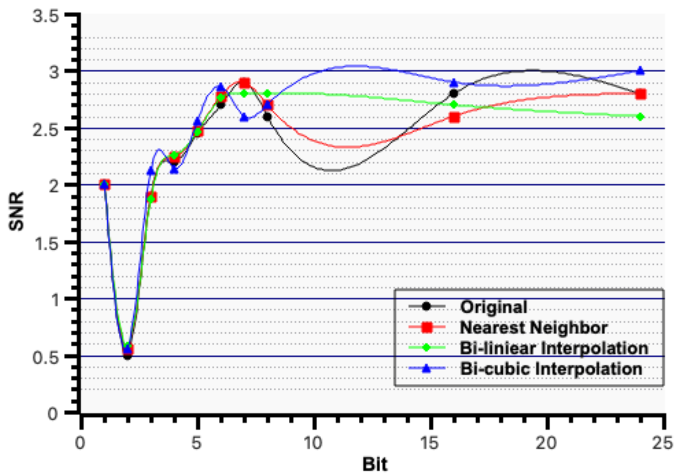

Figure 12. SNR test graph

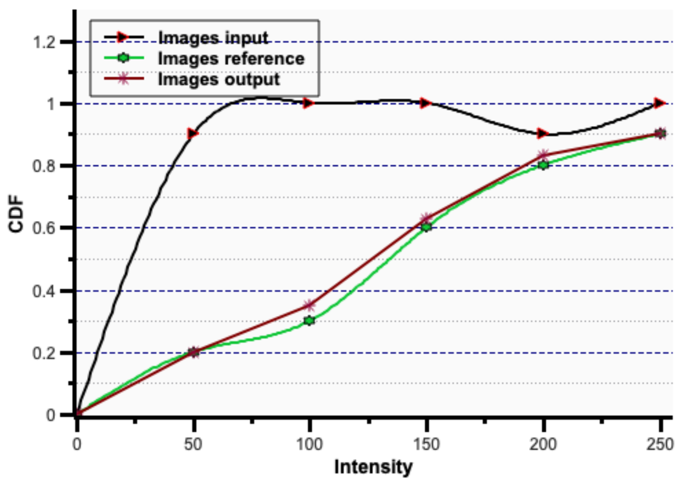

Figure 13. Reference-output CDF graph

TABLE I. MSE PSNR SSIM METRICS TESTING

Images	Input vs Input			Input vs Reference			Input vs Histogram Matching		
	MSE	PSNR	SSIM	MSE	PSNR	SSIM	MSE	PSNR	SSIM
1	0	inf	1	3384.92	12.84	0.57	7415.08	9.43	0.50
2	0	inf	1	3376.52	12.85	0.57	7395.50	9.44	0.50
3	0	inf	1	3402.22	12.81	0.57	7458.21	9.40	0.50
4	0	inf	1	3507.44	12.68	0.57	7519.25	9.37	0.50
5	0	inf	1	3560.34	12.62	0.57	7578.64	9.33	0.50
6	0	inf	1	3608.76	12.56	0.57	7609.31	9.32	0.50
7	0	inf	1	3596.26	12.57	0.57	7501.24	9.38	0.50
8	0	inf	1	3609.07	12.56	0.56	7410.21	9.43	0.51
9	0	inf	1	4102.08	12.00	0.62	7240.62	9.53	0.59
10	0	inf	1	3022.01	13.33	0.69	7361.09	9.46	0.62
11	0	inf	1	2967.62	12.41	0.59	7285.76	9.51	0.54
12	0	inf	1	3885.06	12.24	0.67	7627.45	9.31	0.62
13	0	inf	1	3414.98	12.80	0.67	7778.44	9.22	0.60
14	0	inf	1	3879.69	12.24	0.60	7380.32	9.45	0.58
15	0	inf	1	4200.44	11.90	0.59	7123.19	9.60	0.55
16	0	inf	1	3520.64	12.66	0.63	7245.38	9.53	0.60
17	0	inf	1	3006.03	13.35	0.57	6858.73	9.77	0.51
18	0	inf	1	2778.54	13.69	0.62	6848.56	9.77	0.58
19	0	inf	1	2761.80	13.72	0.61	7158.84	9.58	0.56
20	0	inf	1	2760.30	13.65	0.61	7167.76	9.67	0.57
average	0	inf	1	3451.81	12.72	0.60	7357.67	9.46	0.54

TABLE II. SNR UPSAMPLING TESTING

No.	Sampling	Pixel (px)	Time (s)	SNR (dB)
1	Original	636x434	1.30	2.69
2	Nearest Neighbor	3180x2170	4.82	2.80
3	Bi-linear Interpolation	3180x2170	5.72	2.78
4	Bi-cubic Interpolation	3180x2170	5.83	2.73

The SNR test result for selecting the best upsampling process with a value of 2.8 dB is the Nearest Neighbor with a computation time duration of 4.82 s. Furthermore, this result is used as a reference image in the Histogram Matching process. The time required for processing image data using Histogram Matching is 0.4 s. The computation process used a Macbook Air M1 2020 8-core CPU device. The test results of MSE, PSNR and SSIM are shown in Table I. Then, this research has also conducted quantitative testing on the improvement of Histogram Matching image quality towards the reference image based on the following t-test: p-value 6.628×10^{-28} and t-count 28.016. The hypothesis is accepted based on the absolute value of t-count > t-table. Meanwhile, based on the p-value < 0.05, the hypothesis is accepted. This test concludes that this research is quantitatively to enhance the quality value of echocardiogram images.

The results of testing echocardiogram images were processed through the Histogram Matching process using Nearest Neighbor upsampling. The results of testing the echocardiogram image by comparing the input image with the input image have an SSIM value: of 1 means that the image has no change due to the similarity value 1. The results of the input image compared to the reference image have an average value of SSIM: 0.6. This indicates that there are differences between the input image and the reference image by 40% and has been compared as the final result of this study by comparing the input image with poor image quality with the image of histogram matching results which have an SSIM value: 0.54. This indicates 54% image similarity and 46% image improvement—the overall results are shown in Table II. There are several time comparisons on several upsampling methods, with the fastest time and the highest value of SNR produced by the Nearest Neighbor method with a time of 4.88 s. The overall time required for the enhancement process is the total of the Nearest Neighbor time, followed by Histogram Matching with a processing time of 0.4 s, the total enhancement time was 5.22 s. Based on existing research on contrast image enhancement, there is an optimization method using the World Cup Optimization Algorithm for skin cancer images for 9.17 s, brain tumor images for 8.28 s, liver cancer images for 9.76 s and breast cancer images for 10.13 s [29].

This study applied three metrics: MSE to determine the error value between the original image and the image that has been improved and the contrast adjustment process, PSNR to determine the information on the increase and change in image quality in dB, and SSIM to determine the similarity value of the output image data with the reference image data. The results of the MSE Histogram Matching value are significantly different from the input image value. This proved that the image has many changes in the value of each pixel. The SSIM value is used to determine the image's similarity before processing and after Upsampling and Histogram Matching. The low quality of the input image compared to the Upsampling reference image results in an SSIM value of 0.60. The quality of the input image is also compared to the output image of Histogram Matching, resulting in a value of 0.54. This result showed an increase in image quality because the similarity value is 54% compared to the input image, which has low quality.

There is 11% improvement in the quality of the Histogram Matching image compared to the upsampled reference image. This value results from the difference in the SSIM value (Input vs. Reference) compared to (Input vs. Histogram) from 0.60 to 0.54. The echocardiogram image results that have undergone quality improvement by applying the proposed method are shown in Figure 14 (a), and Figure 14 (b) is the original image before improvement. The results of the echocardiogram image that was generated in this study by applying Bi-cubic Interpolation upsampling and Histogram Matching provided PSNR: 9.46 dB, SSIM: 0.54, and 54% image improvement, better when compared to several previous methods. Research [2] has applied the Nakagami SSIM algorithm of 0.85 with an image improvement of 15% and the pre-processing stage of Texture Echo Clustering using Fuzzy, which is quite complex [30]. Another study applied the anisotropic diffusion method to remove speckle noise with an average SSIM: of 0.76 with an image improvement of 24% [14].

Other research on speckle noise reduction has been performed using the SBF method resulting in SNR values: of 9.12 dB, SSIM: of 0.42, and image enhancement changes of 58%. However, this method requires a pre-processing stage by adding white Gaussian noise [15]. Existing research [18] applies computation to remove noise with the pre-processing stage of local statistical parameters followed by the Fuzzy Uncertainly Modeling (FUM) method resulting in SNR values: of 16.59 dB, SSIM: of 0.54 with 46% image improvement Table III shows a comparison of several previous studies.

IV. CONCLUSION

This study provided an algorithm model to enhance the quality of the intensity Echocardiogram image using upsampling and Histogram Matching methods. The results significantly provided different values compared to low-quality input images. With the Nearest Neighbor method, the upsampling method can improve the image quality value by 2.8 dB. Furthermore, the image data was adjusted by the Histogram Matching method. The SSIM results indicated the difference between the low-quality input image, the reference image, and the Histogram Matching image. Applying the Histogram Matching method improved image quality by 11% compared to the upsampling method. The processed time required to apply this method was 0.4 s. Overall this method is expected to improve image quality by 54%, whicsh has a higher value when compared to several other enhancement methods with high complexity, among others: fuzzy, linear scaling, and anisotropic diffusion. The following research segments the left ventricle area to diagnose heart function abnormality.

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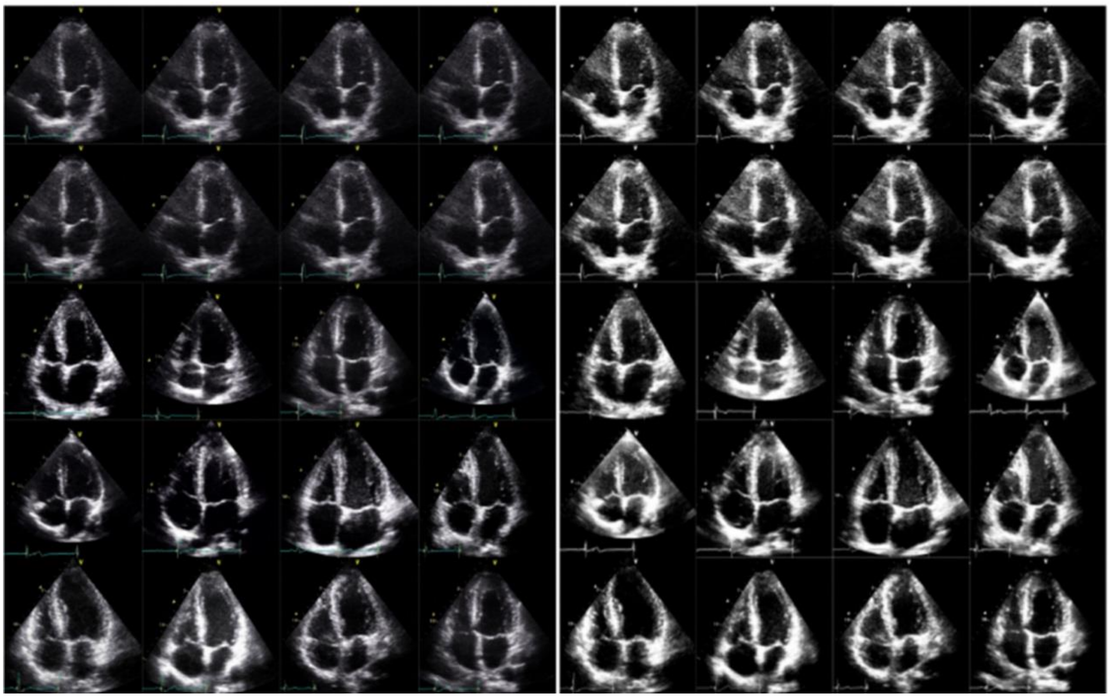
TABLE III. COMPARISON OF SEVERAL PREVIOUS STUDIES

No.	Reference	Pre-processing	Methods	Result
1	[2]	Clustering Texture Echo Using Fuzzy	Linier Scaling, Generalized Gamma and Nakagami	Linear Scaling with SSIM: 1.34, PSNR Index: 0.94 dB, CPI: 0.59 and Entropy: 2.71. Generalized Gamma with SSIM: 1.19, PSNR: 0.96 dB, CPI: 0.61 and Entropy: 2.65. Nakagami with SSIM: 0.85, PSNR: 0.96 dB, CPI: 0.65 and Entropy: 3.04.
2	[16]	-	Speckle Reducing Anisotropic Diffusion	PSNR: 25.98 dB, SSIM: 0.76 (improvement 24%)
3	[18]	Local Statistical Parameters	FUM	SNR: 16.59 dB, SSIM: 0.54 (improvement 46%)
4	[30]	Directional Filter Group	Spatial-frequency domain-based algorithm	Contrast value has improved 21.26%
5	[31]	Gaussian Fuction and Contourlet Transform	Combined Galactic Swarm Optimization with Particle Swarm Optimization	Contrast value has improved 15%
6	Proposed method	Upsampling: Nearest Neighbor, Bi-liniear interpolation and Bi-cubic interpolation	Histogram Matching	PSNR: 9.46 dB and SSIM: 0.54 (improvement 54%)



(a) (b)

Figure 14. Image result (a) before histogram matching and (b) after histogram matching

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