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Neural Network and Discret Meyer's Wavelet Approach in Identifying Heart Abnormalities on 12 Lead ECG Images

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ABSTRACT
The heart is very important in the organ systems of the human body. So everyone tries to keep their heart condition healthy. If there is an error in the function of the heart, it will be fatal to the human body system. This study tried to offer to examine related heart defects using 12 Lead ECG images. ECG data used is in the form of images. The method used in the Pre-processing stage to convert ECG image data is transformed into a signal. Feature extraction uses Wavelet Transformation Decomposition with a five-level level. The mother wavelet used is Discret Mayer. The classification stage compares two neural network methods, namely the radial basis function method and backpropagation by looking at the level of accuracy, sensitivity, and specificity. The level of accuracy related to system validation using K-Fold Cross Validation, where for K = 5 with 80% training data sharing and 20% testing. Results obtained from the entire system where ANN-RBF with an accuracy rate of 95.26%, Sensitivity of 93.33% and Specificity of 96.32%. While ANN-Backpropagation obtained accuracy of 92.31%, sensitivity of 88.89% and specificity of 94.12%.
KEYWORDS: *electrocardiogram, wavelet discret Meyer, RBF, backpropagation, k-fold cross validation*
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I. INTRODUCTION

Cardiovasculor disease is the leading cause of death in the world, therefore human heart health has been a topic of interest for decades. Cardiac activity forms electrical potential wave signals in the heart that can be recorded using an electrocardiogram (ECG) [1]. A signal electrocardiogram (ECG) is a comprehensive, noninvasive method for determining heart health. Various health practitioners use ECG signals to ascertain important information about the human heart [2]. An electrocardiograph is a graphic signal to record potential electrical activity [3]. Electrocardiogram (ECG) signals are important physiological signals that contain cardiac information and are the basis for diagnosing heart-related diseases [4]. Poor electrocardiographic signal quality can result in misinterpretation and improper results, compromising correct diagnosis information [5].

The results of ECG signals can determine the conditions and abnormalities experienced by the heart, such as arrhythmias [1]. Arrhythmias are rhythm disturbances in heterogeneous conditions in which there is abnormal electrical activity of the heart, which refers to disturbances in the frequency, regularity, location of origin, or conduction of the heart's electrical impulses [6]. Various abnormalities in the morphology and rhythm of an electrocardiogram (ECG) are commonly known as arrhythmias. Arrhythmias result in severe heart problems if left untreated. Morbidity and mortality rates are higher in arrhythmia cases [7]. Electrocardiogram (ECG) is very useful for diagnosing arrhythmias that can lead to serious complications in heart health [8]. Meanwhile, according to [9], the majority of people who have a heart attack are most commonly ischemia. On this ECG it will appear where the ST segment is abnormally high or low.

Research to determine the markers of the development of cardiovascular pathology in the early stages, especially in ischemia [10]. The development of wavelet transformations was realized and successfully applied earlier, namely the creation of histograms and spectral power density calculations in order to extract additional diagnostically important information from the studied electrocardiac signals. The results of his research contribute to the achievement of goals regarding the search for new markers of the development of ischemia heart disease, especially in the early stages. Research is to help early find out his heart condition for ischemia heart disease and avoid heart attack complications by showing the accuracy of classification results [11]. The proposed device is used for recording heart signals by processing digital signals using discrete wavelet transforms. The classification process categorizes signals into 2 classes, namely normal and ischemia. By testing using two data containing ECG wave peaks and 5-scale decomposition obtained from processing with dicrete wavelet transform. Classification results are obtained from testing with the best classification results.

Wavelet transformation describes a signal that can compress ECG signals and reduce noise without loss of clinically important information that can be achieved by medical personnel [1].This study tried to perform trait extraction with discretmayer wavelets and identification by comparing radial basis function and backpropagation based on 12-lead ECG images.

II. RELATED WORKS

Some studies related to ECG include [1], His research compared the best performance in detecting ECG signals using various wavelet transformations and optimal threshold values based on empirical methods to obtain R peaks and R-R interval features. Various wavelet transformations are used including Daubechies (db4), Symlets (sym4), Coiflets (coif4), and Biorthogonal (bior3.7) with four types of Detail and Approximate levels; they are Level 1, 2, 3, and 4. The comparison results for the best performance of various wavelet transformations were using Daubechies wavelets, and biorthogonal wavelets with an accuracy percentage of 100% at level 2 to diagnose arrhythmias and 93.1% at level 1 for normal diagnosis from 31 data for arrhythmias and 18 for Normal sourced from the MIT-BIH Database. Thus, the total accuracy result obtained from all tested data is 96.55%.

Furthermore, propose a new approach to inter-patient ECG classification using Self-ONN 1D by exploiting morphological and time information in the cardiac cycle. He used the MIT-BIH arrhythmia benchmark database, the proposed method achieves the highest classification performance [12].In the same year [2], a swarm intelligence approach was used in the biomedical signal processing sector to improve adaptive hybrid filters and empirical wavelet transformation (EWT). The honey badge optimization (HBO) algorithm is used to optimize the functionality of the EWT window and the weight parameters of adaptive hybrid filters. The experimental results suggest that an HBO approach powered by EWT and adaptive hybrid filters can be efficiently used for denoising cardiovascular signals. SQA classification method based on three-layer wavelet scattering network and LSTM was proposed in his research, This proposed method shows high computational accuracy, robustness, and efficiency [13].

Used continuous wavelet transformation (CWT) to detect arrhythmias. Signals taken from the MIT-BIH database are used for testing. CWT is connected to standard deviation (SD) and Shannon entropy (SE) for the feature extraction stage. For classification, thresholds are recommended to distinguish between different arrhythmias [8]. Propose a hybrid technique that integrates the concepts of sparsity, wavelet transformation, and extreme machine learning in a single framework. A comparative analysis of the proposed method was carried out on the MIT-BIH Arrhythmia database [14].Research describes a modified approach to detect heart defects and QRS complexes using machine learning and classification with SVM [15]. Proposes ECG signals based on continuous wavelet transformations (CWT) and convolutional neural networks (CNNs) [16]. The proposed method can build the time frequency of the ECG signal using CWT. Next, it was incorporated into the CNN model. By utilizing the GoogLe Net network model for recognition, it establishes accurate mapping to recognize different ECG signals. In addition, this method shows higher recognition accuracy than other methods.

Study to improve ECG signal quality using wavelet transformation (sym4) and adaptive filter [17]. Research focuses on reviewing publications from the last decade, namely related to prediction, detection, and classification using wavelets and artificial intelligence (AI) [18]. In this work [19], an end-to-end deep learning framework based on convolutional neural networks (CNNs) is proposed for ECG signal processing and arrhythmia classification. The experimental results showed that the proposed model achieved better performance than most baselines. Research conducted digital filtering-based noise removal, wavelet transformation-based feature extraction and machine learning-based classification approaches, and the findings resulted in 99.4% accuracy [20]. Proposed a new adaptive power threshold function to achieve ECG signal denoising [21]. The results are evident from both quantitative and qualitative aspects that the proposed method has advantages in removing ECG signal noise compared to traditional threshold functions.Investigated continuous and discrete wavelet transformations to determine the corresponding features of ECG signals with temporal and spatial variable components. Approach and refinement of wavelet coefficients of different frequency sub-bands are used to eliminate noise at high frequencies, compress signals, and classification [22].

The proposed approach aims to demonstrate the superiority of kernel capabilities from Kernel Principal Component Analysis (KPCA) and Kernel Independent Component Analysis (KICA) in the wavelet domain. In this work, experiments were conducted using five different categories of heartbeats. Supervised classifiers such as feed-forward neural network (FNN), backpropagation neural network (BPNN), and K-nearest neighbor (KNN) statistically evaluate the impact of discrete wavelets with KPCA and KICA on trait extraction.

Performance evaluation also compares results with existing techniques. The results obtained confirmed the supremacy of the combination of wavelet, kernel, and KNN approaches, resulting in a classification success rate of 99.7% [23].

Study analyzed and compared noise removal using different decomposition rates of non-disintegrating wavelet transformations (UWT) and discrete wavelet transformations (DWT) based on different types of parent wavelets such as orthogonal (Haar, Daubechies, Coiflets, Symmlet) and biorthogonal, while other artifacts that were low-frequency carriers have been removed from the signal [24]. Research presents improved P wave crest algorithms, onset and offset detection in electrocardiogram (ECG) [25]. For ECG signals, the denoising algorithm is based on the Generalized Minmax Concave (GMC) penalty.

Present a method to classify each baseline-wander segment of an ECG signal as minimal, medium or large, using the C4.5 algorithm to model the classifier [26]. Testing of the proposed method on ECG signals obtained from the MIT-BIH arrhythmia database. The classification results showed that the model classifier achieved an average sensitivity of 97.36%, specificity of 99.50%, and overall accuracy of 98.89% in classifying baseline-wander noise in ECG signals.

Paper proposed a simple method to eliminate power line interference (PLI) based on wavelet decomposition (sym8), without using threshold techniques [27]. Twenty synthetic ECG signals with different features and eight real ECG signals, obtained in the Physionet Challenge 2011, were used in the experiment. The proposed method performs better for 75% synthetic signals and 100% real signals.Propose the extraction of new features and machine learning schemes for ECG imaging. The evaluation results show better detection accuracy compared to other studies of real-time processing [28].

In his research he used methods to exploit redundancy in signals. The algorithm for one-dimensional cases is modified and applied to compress ECG data. The parsed signal is compressed using thresholding and run-length encoding. Various types of wavelets such as daubechies, haars, coiflets and symlets are applied for decomposition. Compression using HAAR wavelets and local thresholds were found to be optimal in terms of compression ratio [29]. Research related to Wavelet &; Arrhythmia: [4], [7], and [30].From several literature reviews that have been submitted above, there are two studies that researchers think are very interesting to follow up, namely the research of [8] and [19]. stated that the results of their research will open up opportunities to continue by choosing other wavelet transformations in detecting heart abnormalities [8]. Meanwhile, suggest that future research should focus on identifying by adding other heart defects [19].

Based on these suggestions ([8] and [19]), this study tried a new approach related to heart abnormalities using 12-lead ECG images. The 12-lead ECG image was scanned at the pre-processing stage and transformed into a signal according to the method carried out by [31], then the results as input for feature extraction. Feature extraction using wavelet transformation decomposition, using Discret Meyer's mother wavelet. The results of characteristic extraction become input material for the classification process using Artificial Neural Networks. At the classification stage here by comparing the two methods of radial basis function and the method of backpropagation. Both neural network methods are used to distinguish normal ECG data, Ischemia abnormalities and Arrhythmia abnormalities. The final result of this study is the level of accuracy, sensitivity, and specificity of the two methods (radial basis function and backpropagation).

III. PROPOSED METHOD

The method proposed in this study consists of three stages, including Pre-processing, feature extraction and identification (Figure 1). Meanwhile, to see the level of validation using the K-Fold Cross Validation method to obtain the percentage level of accuracy, sensitivity, and specificity. K-Fold Cross Validation method with K = 5, where the division of each K with a composition of 80% Training data and 20% Testing data. The 12-lead ECG data in this study was taken from the hospitalSardjito Yogyakarta with a total of 45 patient data, with normal ECG data, Ischemia and Arrhythmia abnormalities of 15 ECG data each. One patient in the ECG print-out has 12 leads (I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5 and V6), so there will be 12 images per ECG. The composition of each heart condition can be seen in Table 1.

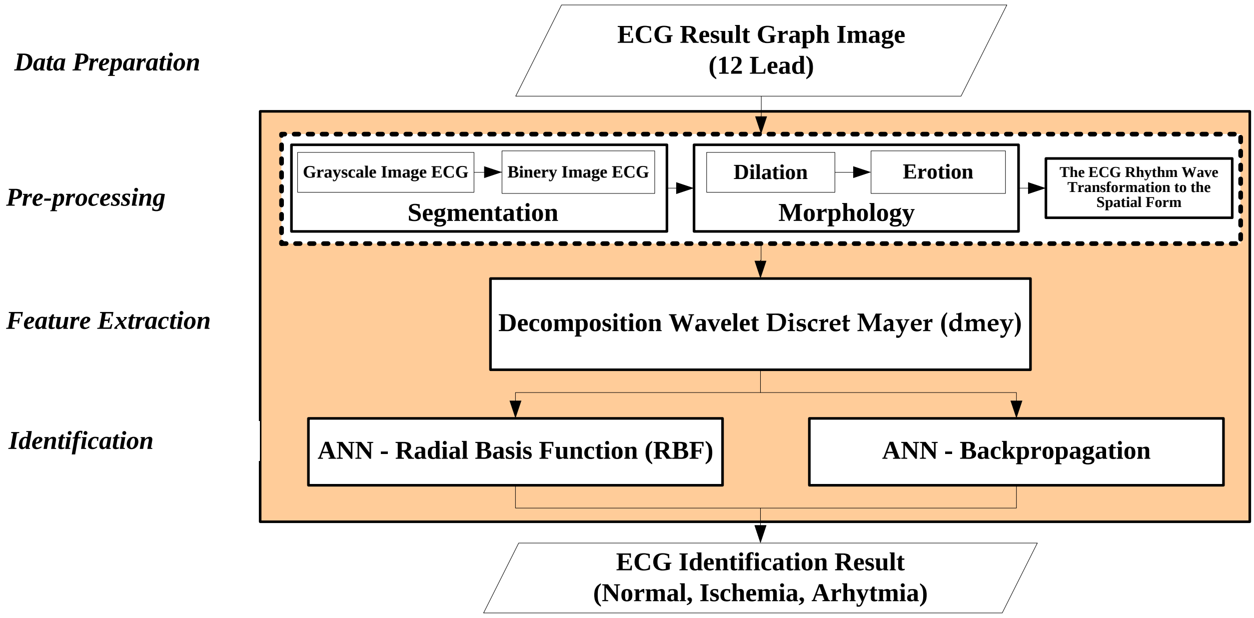


Figure: 3.1. Proposed Method

Table 1: Patient Data Distribution

No.	Condition	Patient	Lead	Number of Images
1.	Normal	15	12	180
2.	Ischemia	15	12	180
3.	Arrhythmias	15	12	180

From table 1, we can process a total of 540 image data ECG data (Figure 2).

Figure: 3.2. ECG Image Example on Lead V6

3.1. Pre-processing

The pre-processing stage is the same as that carried out by [31]. The pre-processing circuit consists of segmentation, morphology and transformation from ECG image to spatial shape. Segmentation in this study consists of a process of changing the color image to grayscale and changing grayscale to binary image. The morphology used to overcome the disconnected object becomes reconnected (close to its original shape). To improve the shape of the ECG graph, morphological operations are carried out, namely dilation and erosion [32].

3.2. Feature Extraction

The second stage in this research is to extract characteristics using Wavelet. Wavelet is a set of functions produced by a single function ψ with dilation and translation processes [33].

$$\Psi_{a,b}(t) = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right) \qquad (1)$$

With ψ (t) as the function of the parent wavelet. a is a dilation parameter a, and b is a translational parameter. This research uses wavelet decomposition transformation, which is a signal processing method where a signal is broken into several parts. Decomposition wavelet transformation as a depiction of a digital signal timescale is obtained using digital filtering techniques. A signal must be passed in two filters: a highpass filter and a lowpass filter in order for the frequency of the signal to be analyzed. This decomposition process can go through one or more levels. An example of single-level signal decomposition is like Figure 3.3.

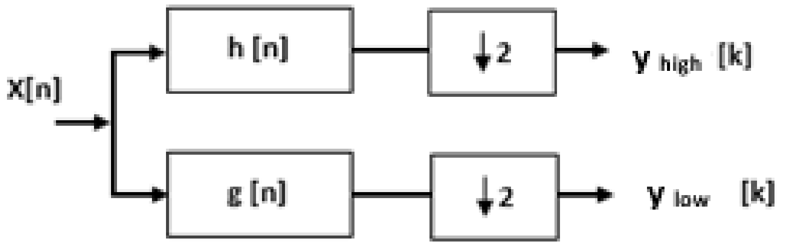


Figure: 3.3. Signal Decomposition Example

In figure 3, the result of the highpass filter, yhigh [k] is referred to as the detail signal and in the result of the lowpass filter, ylow [k] is referred to as approximation signal, x[n] is the origin signal. One-level signal decomposition is written with mathematical expressions on equations 2 and 3 [34].

Y_{high} [k]=$\sum_n [n]h[2k-n]$ (2)

Y_{low}[k]=$\sum_n [n]g[2k-n]$ (3)

yhigh [k] and *ylow* [k] are the results of highpass filter and lowpass filter, h[n] is the highpass filter and g[n] is the lowpass filter, n and k are integer variables. This deep current signal serves as the main signal or mother wavelet. When the decomposition process is carried out, the approximation coefficient signal will become a mother wavelet and decomposed based on the highpass and lowpass filters, and so on according to the level we want. In wavelet decomposition, signals are divided into approximation and detail components. The approximation component is then further divided into approximation and detail components, and so on until the desired level [35].

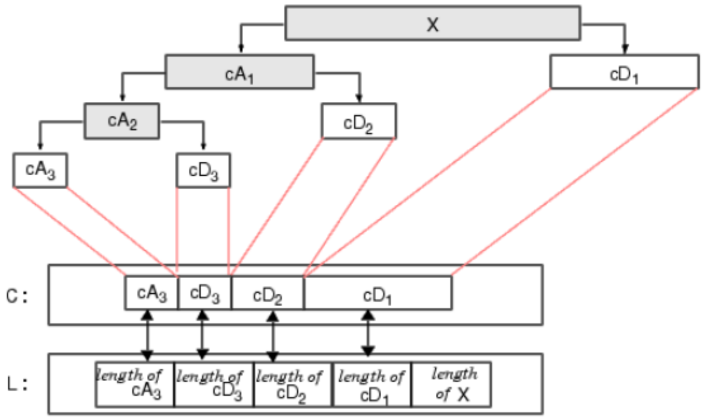


Figure: 3.4. Wavelet Decomposition

Mathematically the decomposition of level 3 wavelets can be written [36]:

$$\begin{aligned} X &= cA_1 + cD_1 \\ &= cA_2 + cD_2 + cD_1 \\ &= cA_3 + cD_3 + cD_2 + cD_1 \qquad (4) \end{aligned}$$

Where X decomposes a signal, where A is called the approximation coefficient of the ith level, and D is called the detail coefficient at level i. This study used Decomposition Wavelet Transformation. The mother wavelet used is Discret Meyer with the final result obtaining the value of the approximation coefficient and detail coefficient respectively.

3.3. Identification

Identification in this study using artificial neural networks by comparing radial basis function and backpropagation methods. In general, neural networks are machines designed to model the way the brain performs certain tasks or functions, where networks are usually implemented using electronic components or simulated in software on computers [37]. Radial Basis Function is a development of feed-forward neural network. The RBF network consists of three layers, namely the input layer, hidden layer and output layer [38]. Each node in the hidden layer activates a non-linear activation function on the input vector with a base radial function. The hidden layer transforms the input non-linearly and then the output layer receives an output signal from the hidden layer and is processed linearly [39]. RBFNN has an easy network structure but very fast convergence capabilities as well as very high non-linear approach capabilities [40].

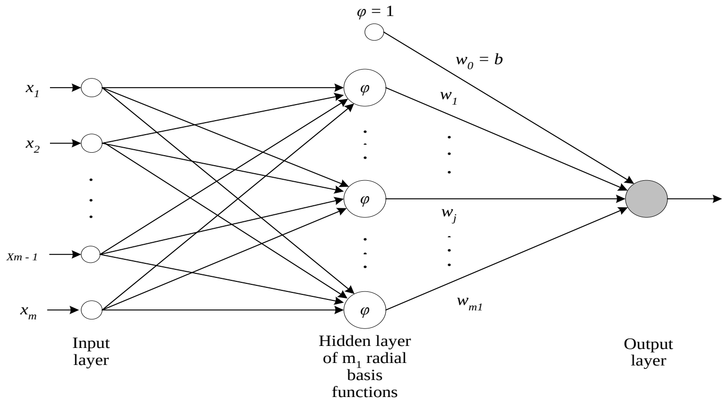


Figure: 3.5.RBF Neural Network Architecture [37]

The parameters used in RBFNN are the center value, the base function spread on the hidden layer and the weight value on the output layer [41]. To produce a good function approximation, the spread value must be larger. Large spread values mean that there are many neurons needed to adjust rapidly changing functions [42]. The output of the RBFNN learning model can be formulated as follows [39].

While Backpropagation has been widely applied to various research applications. Early studies such as [43] have resulted in NETtalk. Served as classification engines for sonar signals [44]. The latest developments are widely used for various disciplinary case studies, one of which is related to health. Backpropagation can train the network to obtain a balance between the ability to recognize patterns used during the training process and the ability to respond correctly to input patterns similar to the patterns used during training [45]. A very general nature of backpropagation training methods can be used to solve problems in many cases [46].

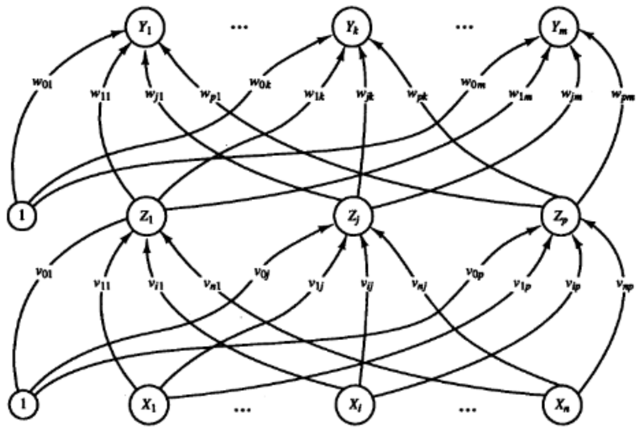


Figure: 3.6. Backpropagation Architecture with One Hidden Layer [46]

3.4. K-fold Cross Validation

The last method is used to find the level of validity of a system. The method used in this study is K-Fold Cross validation. K-Fold Cross Validation where k will repeat k-times to divide a set, random examples into k mutually independent subsets, each repetition leaving one subset for testing and the other subset for training [47]. In general, K-Fold Cross Validation all data used will be treated equally, namely as training and testing data. For example, we will divide the data used into 3-Fold Cross Validation, meaning that the data set will be divided into three parts. In the first experiment, the first two-thirds of the data will be treated as training data and the other third will be treated as testing data, and this will continue to be tried according to the K division.

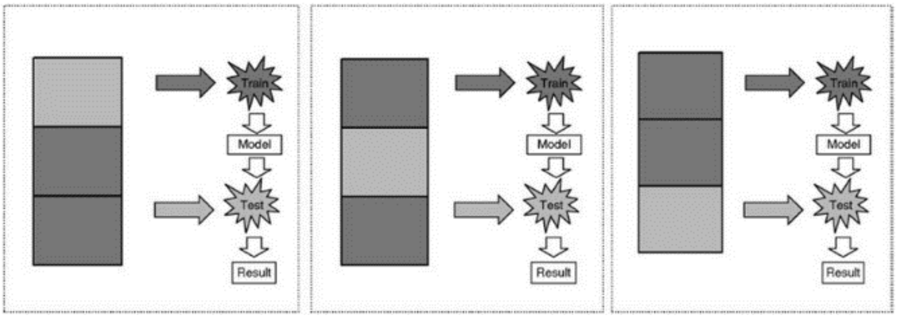


Figure: 3.7.3-Fold Cross Validation Procedure [48]

From K-Fold Cross Validation we can find the level of accuracy, sensitivity and specificity using the Confusion Matrix [49]. Matrix confusion is one of the methods used to obtain evaluation results based on matrix tables [50].

Table 2: Model Confusion Matrix

True classification	Classified as	
	+	-
+	TP	FN
-	FP	TN

Accuracy is obtained by equation (5), sensitivity is obtained by equation (6), and specificity by equation (7) [49]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} x\ 100\% \quad (5)$$

$$Sensitivity = \frac{TP}{TP+FN} x\ 100\% \quad (6)$$

$$Specificity = \frac{TN}{TN+FP} x\ 100\% \quad (7)$$

Where :

TP = *True Positive*,
TN = *True Negative*,
FP = *False Positive*, and
FN = *False Negative*.

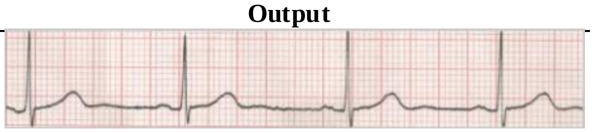
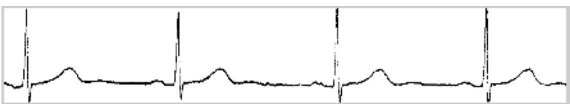
IV. RESULT & DISCUSSION

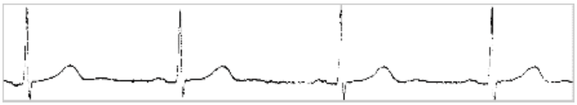
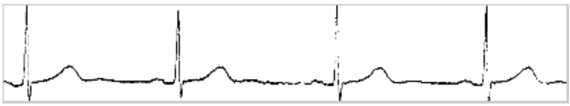
Based on the order of data processing, results can be presented according to the stages, namely pre-processing, extraction, characteristic, identification and accuracy.

4.1. Pre-Processing

The pre-processing stage follows the stages carried out by [31] (Table 3). Pre-processing includes reading 12-lead ECG images, segmentation (grayscale to binary), morphology (dilation and erosion), and image transformation to spatial form.

Table 3: Pre-Processing Stage Steps [31]

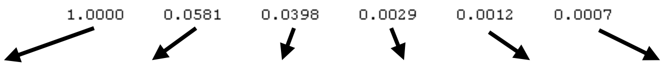
Methods	**Output**
ECG Image	
Grayscale	
Binary	

Dilation	
Erosion	
Graphs	

The results of the pre-processing stage will be input material at the feature extraction stage in the next step.

4.2. Feature Extraction

The extraction of the characteristics of this study used the wavelet method, with mother wavelet Discret Meyer. The method used is level 5 Decomposition Wavelet Transformation. Inputs from the 12-lead ECG image will be extracted to obtain approximation data and energy details at level 5. So that the ECG data that comes out of each lead is the approximation coefficient, detail 1, detail 2, detail 3, detail 4, and detail 5. The results of extracting characteristics from table 2 using equation (4) in lead V6 after normalization can be written for each approximation coefficient and the details are as follows:



cA_5	**cD_5**	**cD_4**	**cD_3**	**cD_2**	**cD_1**
1.0000	0.0581	0.0398	0.0029	0.0012	0.0007

Figure:4.1. Illustration of Approximation Coefficient and Detail on V6 Leads

From one lead (Table 3) we can get 6 pieces of data so that from 12 leads (one patient) we can get 72 data. All patient data used will be extracted using the same method. The result of the trait extraction stage will be the input for the neural network.

4.3. Identification

In the third stage, we will use the Radial Basis Function &Backpropagation Neural Network by inputting the data from the extraction of characteristics for input into the neuron. The input data entered is 72 data and the output is a network target in the form of one of three targets (Table 4). The data to be entered into the network has been calcified as normal data, ischemia and arrhythmia with each data of 15 patient data, so that the total training data is 45 patient data that have been classified.

Table 4: Neural Network Output and Target

Network Output	**Network Target**
Normal	1
Ischemia	2
Arrhythmias	3

After all the data and targets are determined we can build network training according to what we have set. The results of network training using the radial basis function method are obtained as figure 4.2.

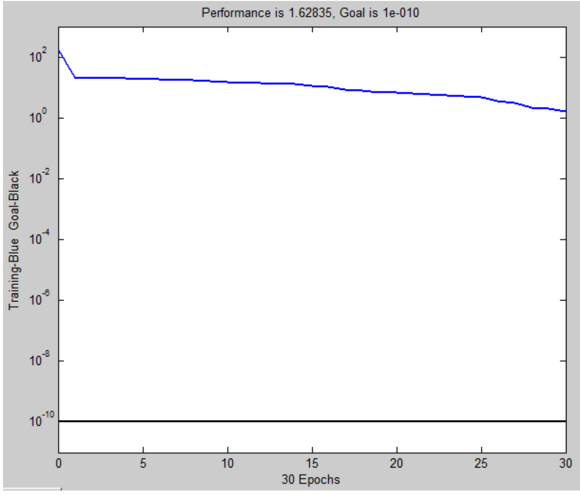


Figure: 4.2.: Network Training

The results of the training can be seen in figure 4.3.

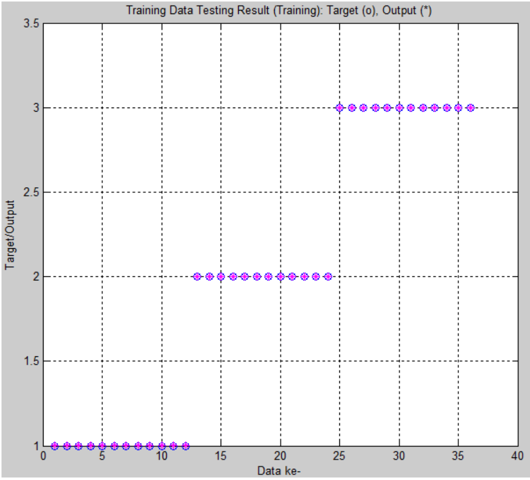


Figure: 4.3. Test and Training Results

Our training results can be evaluated by looking at training data and targets (figure 4.4).

```
m1 =

    1.0000


c1 =

  7.8158e-013


r1 =

    1.0000
```

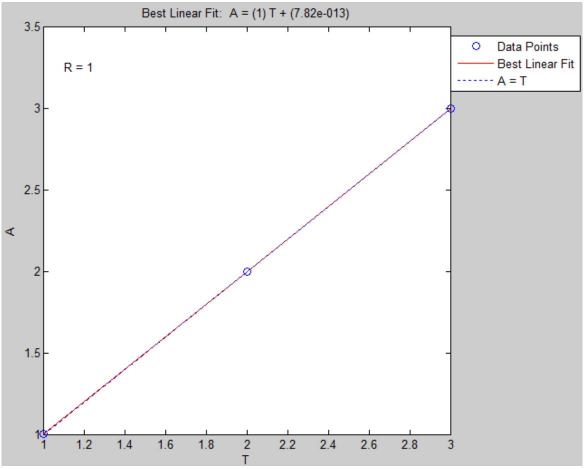


Figure: 4.4. Evaluation Results Between Training Data and Target

After the training, testing is carried out by entering test data (testing). Data testing is used to test whether the system that has been trained can recognize new data or not. Test results when new data is entered with normal data, the system recognizes as normal data.

```
Risk =

      1


Result =

Normal
```

For the use of the backpropagation method the sequence of training and testing can be carried out in almost the same way of steps, so that for its test results when new data is entered with normal data, the system recognizes as normal data.

4.4. Accuracy

Systems that have been trained and tested run well, we need to test for the level of validation. For validation here (RBF &Backpropagation) using K-Fold Cross Validation, that is, every data used will get the same treatment as training and testing data. This study used K-Fold with K = 5, and the division of each training and testing data was 80% training data and 20% testing data. Table 5 is the evaluation result to obtain the value of accuracy, sensitivity and specificity using equations 5, 6 and 7 in the base function radial neural network. While table 6 is the evaluation result for neural network backpropagation using the same method as table 5.

Table 5: Validation Results For Accuracy, Sensitivity and Specificity in ANN-Radial Basis Function

K = 1		K = 2		K = 3		K = 4		K = 5	
Condition	**Result**	**Condition**	**Result**	**Condition**	**Result**	**Condition**	**Result**	**Condition**	**Result**
Normal-13	Normal	**Normal-10**	Normal	**Normal-07**	Normal	**Normal-04**	Normal	**Normal-01**	Normal
Normal-14	Normal	**Normal-11**	Normal	**Normal-08**	Normal	**Normal-05**	Normal	**Normal-02**	Normal
Normal-15	Normal	**Normal-12**	Normal	**Normal-09**	Normal	**Normal-06**	Normal	**Normal-03**	Ischemia
Ischemia-13	Ischemia	**Ischemia-10**	Ischemia	**Ischemia-07**	Ischemia	**Ischemia-04**	Ischemia	**Ischemia-01**	Ischemia
Ischemia-14	Ischemia	**Ischemia-11**	Ischemia	**Ischemia-08**	Ischemia	**Ischemia-05**	Ischemia	**Ischemia-02**	Ischemia
Ischemia-15	Ischemia	**Ischemia-12**	Ischemia	**Ischemia-09**	Ischemia	**Ischemia-06**	Ischemia	**Ischemia-03**	Ischemia
Arrhythmia-13	Ischemia	**Arrhythmia-10**	Arrhythmia	**Arrhythmia-07**	Arrhythmia	**Arrhythmia-04**	Arrhythmia	**Arrhythmia-01**	Arrhythmia
Arrhythmia-14	Arrhythmia	**Arrhythmia-11**	Arrhythmia	**Arrhythmia-08**	Arrhythmia	**Arrhythmia-05**	Arrhythmia	**Arrhythmia-02**	Arrhythmia
Arrhythmia-15	Arrhythmia	**Arrhythmia-12**	Arrhythmia	**Arrhythmia-09**	Arrhythmia	**Arrhythmia-06**	Arrhythmia	**Arrhythmia-03**	Normal
Accuracy (%)	92,31	**Accuracy (%)**	100,00	**Accuracy (%)**	100,00	**Accuracy (%)**	100,00	**Accuracy (%)**	84,00
Sensitivity (%)	88,89	**Sensitivity (%)**	100,00	**Sensitivity (%)**	100,00	**Sensitivity (%)**	100,00	**Sensitivity (%)**	77,78
Specificity (%)	94,12	**Specificity (%)**	100,00	**Specificity (%)**	100,00	**Specificity (%)**	100,00	**Specificity (%)**	87,50

Table 6: Validation Results For Accuracy, Sensitivity and Specificity in ANN-Backpropagation

K = 1		K = 2		K = 3		K = 4		K = 5	
Condition	**Result**	**Condition**	**Result**	**Condition**	**Result**	**Condition**	**Result**	**Condition**	**Result**
Normal-13	Normal	**Normal-10**	Normal	**Normal-07**	Normal	**Normal-04**	Normal	**Normal-01**	Normal
Normal-14	Normal	**Normal-11**	Normal	**Normal-08**	Normal	**Normal-05**	Normal	**Normal-02**	Normal
Normal-15	Normal	**Normal-12**	Normal	**Normal-09**	Normal	**Normal-06**	Normal	**Normal-03**	Normal
Ischemia-13	Ischemia	**Ischemia-10**	Normal	**Ischemia-07**	Ischemia	**Ischemia-04**	Arrhythmia	**Ischemia-01**	Ischemia
Ischemia-14	Normal	**Ischemia-11**	Ischemia	**Ischemia-08**	Ischemia	**Ischemia-05**	Ischemia	**Ischemia-02**	Ischemia
Ischemia-15	Ischemia	**Ischemia-12**	Ischemia	**Ischemia-09**	Ischemia	**Ischemia-06**	Ischemia	**Ischemia-03**	Ischemia
Arrhythmia-13	Arrhythmia	**Arrhythmia-10**	Arrhythmia	**Arrhythmia-07**	Ischemia	**Arrhythmia-04**	Arrhythmia	**Arrhythmia-01**	Arrhythmia
Arrhythmia-14	Arrhythmia	**Arrhythmia-11**	Arrhythmia	**Arrhythmia-08**	Arrhythmia	**Arrhythmia-05**	Arrhythmia	**Arrhythmia-02**	Arrhythmia
Arrhythmia-15	Arrhythmia	**Arrhythmia-12**	Arrhythmia	**Arrhythmia-09**	Arrhythmia	**Arrhythmia-06**	Arrhythmia	**Arrhythmia-03**	Ischemia
Accuracy (%)	92,31	**Accuracy (%)**	92,31	**Accuracy (%)**	92,31	**Accuracy (%)**	92,31	**Accuracy (%)**	92,31
Sensitivity (%)	88,89	**Sensitivity (%)**	88,89	**Sensitivity (%)**	88,89	**Sensitivity (%)**	88,89	**Sensitivity (%)**	88,89
Specificity (%)	94,12	**Specificity (%)**	94,12	**Specificity (%)**	94,12	**Specificity (%)**	94,12	**Specificity (%)**	94,12

From table 5 (ANN-RBF) it can be seen that the average percentage for accuracy is 95.26%, sensitivity is 93.33% and specificity is 96.32%. As for table 6 (ANN-Backpropagation) obtained an average percentage for accuracy of 92.31%, sensitivity of 88.89% and specificity of 94.12%.

V. CONCLUSION

Based on a series of 12-lead ECG image studies from the beginning and characteristic extraction using the level 5 Wavelet Transformation Decomposition method on Meyer Discret Wavelet (dmey), approximation coefficient data and details were obtained. Extraction data obtained as input material for neural networks by comparing the level of accuracy using Radial Basis Function and Backpropagation. The level of system validation that has been tested using K-Fold Cross Validation, obtained by ANN-RBF with an accuracy rate of 95.26%, Sensitivity of 93.33% and Specificity of 96.32%. Furthermore, for ANN-Backpropagation, accuracy was obtained at 92.31%, sensitivity of 88.89% and specificity of 94.12%. The results of the study are still lacking and may be far from ideal results, and the scope of computer-assisted medical research is very broad and needs different approaches, so the development or follow-up of future research related to ECG still needs to be improved, both by adding research data and by comparing the methods used.

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