Journal of Theoretical and Applied Information Technology
15th January 2020. Vol.98. No 01
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

CARDIOVASCULAR DISEASE CLASSIFICATION BASED ON ECHOCARDIOGRAPHY AND ELECTROCARDIOGRAM DATA USING THE DECISION TREE CLASSIFICATION APPROACH

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ABSTRACT

For a doctor, diagnosing a patient's heart disease is not easy. It takes the ability and experience with high flying hours to be able to accurately diagnose the type of patient's heart disease based on the existing factors in the patient. Several studies have been carried out to develop tools to identify types of heart disease in patients. However, most only focus on the results of patient answers and lab results, the rest use only echocardiography data or electrocardiogram results. This research was conducted to test how accurate the results of the classification of heart disease by using two medical data, namely echocardiography and electrocardiogram. Initial research was conducted by comparing two classification methods, namely Naive Bayes and Decision Tree. The results of the comparison of classification models show that the decision tree approach has a better accuracy than Naive Bayes. Three treatments were applied to the two medical data and analyzed using the decision tree approach. The first treatment was to build a classification model for types of heart disease based on echocardiography and electrocardiogram data, the second treatment only used echocardiography data and the third treatment only used electrocardiogram data. The results showed that the classification of types of heart disease in the first treatment had a higher level of accuracy than the second and third treatments. The accuracy level for the first, second and third treatment were 78.95%, 73.69% and 50%, respectively. This shows that in order to diagnose the type of patient's heart disease, it is advisable to look at the records of both the patient's medical data (echocardiography and electrocardiogram) to get an accurate level of diagnosis results that can be accounted for.

Keywords: *heart disease, echocardiography, electrocardiogram, classification, decision tree*

1. INTRODUCTION

Heart disease is the leading cause of death in the world [1] and it is difficult to predict because to be able to diagnose someone indicated with this type of heart disease requires a specialist who has very good experience and knowledge [2], [3]. It is difficult to distinguish the boundary between a healthy hearts and not because many factors must be analyzed before the doctor issues the diagnosis [4]. Most specialists diagnose a person suffering from certain types of heart disease based on the patient's answers through observations and lab results [5].

On the other hand, the use of information technology, especially in the field of data mining and soft computing has been widely used to contribute to the world of health [6]. Some research in the field of data mining specifically for the classification of heart disease has been done. Researchers usually use symptoms observed by patients by looking at physical conditions and indicators such as cholesterol levels, smoking habits, alcohol consumption habits, obesity [7], family history, blood sugar, and others [8], [9] to classify (diagnose) type of heart disease suffered by a person. Several other studies have also developed a tool for diagnosing heart disease with an information technology approach, especially in the fields of artificial intelligence, machine learning, and data mining using data echocardiography [10], [11] and patient electrocardiogram [12],[13].

This research is not intended to compare several classification methods using decision trees. There

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

have been many studies that have made comparisons to determine the decision tree model as conducted [14], [15], [16], and [17]. And we believe that every researcher in the field of data mining believes that the accuracy of the decision tree model for the diagnosis of heart disease has a level of accuracy that can be accounted for according to their respective cases. Therefore, in this study a decision tree approach was re-implemented to find out the results of a patient's heart disease diagnosis by applying three treatments to the patient's echocardiography and electrocardiogram data. The three treatments of the data is the formation of classification models and testing using echocardiography checking results alone, electrocardiogram results alone, and a combination of both. This research is certainly expected to make a positive contribution to strengthening a doctor's confidence when diagnosing a type of heart disease using the right symptoms in the future. In addition, the results of this study will show whether heart disease can be diagnosed using only the results of echocardiography alone, or the results of an electrocardiogram alone or instead have to look at both indicators. This study ruled out the results of physical observations or complaints submitted by patients.

Data from echocardiography and electrocardiogram so far have been used together to determine the type of patient's heart disease. Some doctors then add the results of physical observation of the patient to make sure the diagnosis is generated. The question that arises then is, is it possible to diagnose heart disease using only echocardiography data, or only using an electrocardiogram, or indeed both must still be used. Assuming, both data must be used to diagnose heart disease, should all parameters be used to diagnose heart disease? Or rather, all the parameters of the two data, only a few can be used to diagnose heart disease based on existing data patterns. This then becomes the main basis for the research conducted. By not ignoring other opinions that the more indicators are used as a diagnostic amplifier, of course the diagnosis results will be more accurate, this research takes the other side that, if a type of disease can be identified properly based on the pattern of data formed without having to look at all indicators, why not?

The development of science, especially in the field of computing provides the possibility to be able to diagnose types of diseases more quickly and better, especially heart disease. Pattern recognition and data classification techniques allow extracted data to produce certain rules and choose certain parameters that are more dominant in the process of diagnosing heart disease. Thus, the activity of diagnosing heart disease can be done by looking at certain parameters.

2. ECHOCARDIOGRAPHY AND ELECTROCARDIOGRAM

In the world of health, especially heart disease, in addition to diagnosing the disease by considering the results of medical records and patient complaints, also carried out by considering the medical record information from Echocardiography and Electrocardiogram. Echocardiography utilizes the nature of sound waves to distinguish levels of variation in tissue density in the human body [18]. Another name for echocardiography is cardiac ultrasound. This test took a moving image of the heart based on the sound waves emitted [19]. Echocardiography test results are usually in the form and size of the heart, heart function, problems with heart valves, blood clotting levels, and information on heart muscle function. Electrocardiogram (ECG) is the result of examining the condition of a person's body against the heart organ based on the recording of electrical signals [20]. ECG signals usually consist of six main labels that make up peaks and valleys. The six main labels are P, Q, R, S, T, and U. In the implementation, some of the serial labels are then combined into an interval that is read at once, for example PR interval is a combination of the distance between the signals P to Q and then to R, QRS is a combination signal distance from the top of Q to R then to S. Likewise with other combined signals such as QT, ST and RR. Fig 1 shows the graph form of an electrocardiogram (ECG) signal.

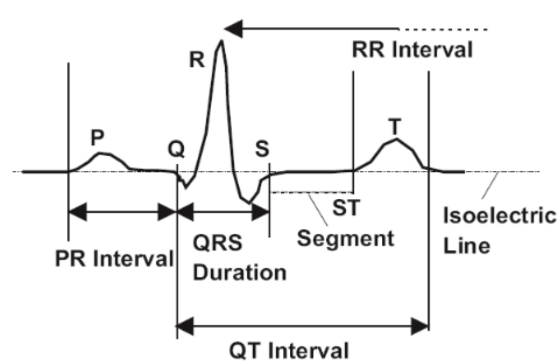

Figure 1: Graph of ECG Signals

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3. NAIVE BAYES

Naive Bayes is an approach commonly used for pattern recognition and classification of objects. This method works based on the probabilistic value possessed by an object naturally. The Naive Bayes method starts from the concept of conditional probability where two events occur simultaneously, for example X and Y where the probability of occurrence of both are expressed by P (X) and P (Y), respectively. A conditional probability applies if event X occurs after Y occurred first (or vice versa) and is expressed as P (X | Y) or P (Y | X) as shown in equations 1 and 2.

$$P(X|Y) = \frac{P(X \cap Y)}{P(Y)} \quad (1)$$

$$P(Y|X) = \frac{P(Y \cap X)}{P(X)} \quad (2)$$

In the event of conditional probabilities where X and Y occur together, it can be stated that P(X∩Y) = P(Y∩X), so that a new equation is obtained as shown in equation 3 and 4.

$$P(X \cap Y) = P(X|Y) \times P(Y) \quad (3)$$

and

$$P(Y \cap X) = P(Y|X) \times P(X) \quad (4)$$

Based on equations 3 and 4 a new equation is obtained as follows:

$$P(X \cap Y) = P(Y \cap X)$$

$$P(X|Y) \times P(Y) = P(Y|X) \times P(X)$$

$$P(X|Y) = \frac{P(Y|X) \times P(X)}{P(Y)} \quad (5)$$

or

$$P(Y|X) = \frac{P(X|Y) \times P(Y)}{P(X)} \quad (6)$$

Equations 5 and 6 are the basis for naive bayes. Further elaboration of the Bayess equation is done by describing the condition of the data Y with a certain number of samples and does not yet have class X, so that it can be described as shown in equation 7.

$$P(X_i|Y_1, Y_2, \dots Y_n) = \frac{P(Y_1, Y_2, \dots Y_n|X_i) \times P(X_i)}{\sum_{k=1}^{m} P(Y_1, Y_2, \dots Y_k|X_k) \times P(X_k)} \quad (7)$$

Where *Xi* is the i-specific class and *Yn* or *Yk* is the amount of data that does not yet have a class.

4. DECISION TREE

Decision tree is a classification technique that is widely used in the concept of data mining [21], [22], [23]. Usually, decision trees use if-then rules so that they are easier to use and implement [24]. Decision trees learn from a collection of data structures that already have a class label, which is then called data training [25]. The decision tree generally begins with the formation of one node and then has many branches as a result of training data extraction [26]. The decision tree is constructed by dividing the training data recursively into specific nodes so that it forms the same decision class label. The stage of forming a decision tree takes time and a complex computational process because the process of forming a decision tree is carried out repeatedly. The decision tree formation algorithm starts with selecting the attribute as root, then creating a branch for each value of the root formed. Divide cases into branches that have already been formed. Repeat the process until each case is attached to the branch with the class that it should be. Root and branch determination is done by calculating the gain information value, then the highest gain information is selected. To calculate the gain information previously calculated entropy values for each attribute based on their respective cases. Entropy calculation can be done with equation (1) while gain information is done with equation (2).

$$Entropy(S) = -\sum_{i=1}^{n} P_i \log_2 P_i \quad (8)$$

$$Gain(S,A) = Entropy(S) - \sum_{v \in Values_A} \frac{|S_v|}{|S|} \cdot Entropy(S_v) \quad (9)$$

where *i* is the number of classes of the attribute target, *Pi* is the number of occurrences of the i-th class to the total number of data instances, n is the number of partitions *S*, *S* is the case set, *A* is the attribute, |*Sv*| is the number of cases on partitions v and |*S*| is the number of cases in *S*.

5. RESEARCH METHOD

This research started with an analysis of the problem to be solved. Data collection was the next step in this research. Research data in the form of heart disease patient data obtained from one of the government hospitals in Indonesia. The results of data collection produced 150 patient data that had been carried out in the cleaning process and were

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ready to be analyzed. There are fifteen parameters used in this study based on medical records of echocardiography and electrocardiogram. The fifteen parameters are electrical signals from each patient's medical examination consisting of AORTA, Left Atrium, Heart Function, EDD, ESD, IVS Diastole, IVS Systole, PW Diastole, PW Systole, HR, PR- [PQ], QRS, QD , QTC and P. The selection of the fifteen parameters is based on the tendency of doctors to diagnose heart disease based on medical data from echocardiography and electrocardiogram. The data then divided into two parts, 70% as training data and 30% as testing data. The next stage was the formation of a classification model for disease types using the decision tree approach. There were three treatments that carried out when forming a classification model with a decision tree. The decision tree results from the three treatments then used to classify the types of heart disease based on existing testing data. The last step was to interpret the results of the classification.

6. RESULTS AND DISCUSSION

Before determining the appropriate classification model to use, this study tested two classification approaches namely naive bayes (NB) and decision tree (DT). The results of the model testing show that the accuracy of the decision tree classification model is better than Naive Bayess. The accuracy of the classification results with Naive Bayes based on modeling was 58.54% with a kappa value of 0.4852, while for the decision tree approach, the accuracy rate was 70.73% with a kappa size of 0.6298. The accuracy results between NB and DT as shown in Table 1. Statistical analysis in the form of sensitivity, specificity, negative and positive predictive values and the balance of accuracy of each class of disease as shown in Table 2.

Statistical analysis in the form of sensitivity, specificity, negative and positive predictive values and the balance of accuracy of each class of disease as shown in Table 2.

Table 1: Accuracy Results between NB and DT

Overall Statistics of NB	Overall Statistics DT
Accuracy : 0.5854	Accuracy : 0.7073
95% CI : (0.4211, 0.7368)	95% CI : (0.5446, 0.8387)
No Information Rate : 0.2683	No Information Rate : 0.2683
P-Value [Acc > NIR] : 1.912e-05	P-Value [Acc > NIR] : 5.845e-09
Kappa : 0.4852	Kappa : 0.6298

Table 2: Statistical Value of Each Target Class

Statistics by Class of DT:

	Class: ASD	Class: CAD	Class:Cardial Class:	Disfunction Diastolic	Class: HHD
Sensitivity	NA	0.8000	NA	0.00000	0.9091
Specificity	1	0.9355	1	0.95000	0.9667
Pos Pred Value	NA	0.8000	NA	0.00000	0.9091
Neg Pred Value	NA	0.9355	NA	0.97436	0.9667
Prevalence	0	0.2439	0	0.02439	0.2683
Detection Rate	0	0.1951	0	0.00000	0.2439
Detection Prevalence	0	0.2439	0	0.04878	0.2683
Balanced Accuracy	NA	0.8677	NA	0.47500	0.9379

	Class: LVH Suspect HHD	Class: NR-Echocardiography	Class: RHD
Sensitivity	0.7500	0.50000	0.40000
Specificity	0.8182	1.00000	0.97222
Pos Pred Value	0.5000	1.00000	0.66667
Neg Pred Value	0.9310	0.92105	0.92105
Prevalence	0.1951	0.14634	0.12195
Detection Rate	0.1463	0.07317	0.04878
Detection Prevalence	0.2927	0.07317	0.07317
Balanced Accuracy	0.7841	0.75000	0.68611

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The obtained data consisted of 15 variables (symptoms) that used to diagnose the type of heart disease of a patient using the rules of the decision tree. Those thirteen symptoms divided into three parts of the variable, first in the form of the patient's Echo values, the second value of the patient's ECG measurement results, and finally the variable in the form of complaints and also the findings of the nurse when checking the patient's condition.

Echo or echocardiography is the result of examinations carried out by specialist doctors who give a picture of the heart when beating so that it can be used to evaluate a person's heart health. While the ECG or electrocardiogram is the result of a general diagnostic test to evaluate the function of the heart that is able to record the electrical activity of the heart to a certain extent and to identify if there is indication of abnormal blood circulation. In this study, the third type variable was not used for the purpose of determining whether a person's heart disease could be identified using the combined values of the Echo and ECG, Echo alone or the results of the ECG measurement alone. From thirteen variables, only eleven variables were used in this study, namely sub-variables of Echo and ECG types. In this study also, data analysis for the formation of rules for the classification of types of heart disease was divided into three treatments. The first treatment, the formation of classification rules was carried out on eleven combined variables of Echo and ECG. The second treatment, the formation of classification rules was carried out only on the types of Echo variables and the third treatment, the formation of classification rules was carried out on the types of ECG variables. The results of the three treatments then tested against the testing data that had been prepared.

In the first treatment, the results of the study showed that there were three out of eight types of diseases that were not affected by the decision tree approach. The three types of diseases are Atrial Septal Defect (ASD), Cardial Repair, and Diastolic Dysfunction. While five other types of diseases that can be extracted are Coronary Artery Disease (CAD), Hypertensive Heart Disease (HHD), Left Ventricular Hypertrophy Suspect Hypertensive Heart Disease (LVH Suspect HHD), Normal Resting Echocardiography (NR-Echocardiography), and Rheumatic Heart Disease RHD). The decision tree formed for the first treatment as shown in Figure 2.

While the classification rules for extracting results from the decision tree obtained as follows:

IF ESD >= 40 Then CAD

IF ESD < 40 AND PW Systole >=18 AND LEFT_ATRIUM < 42 Then HHD

IF ESD < 40 AND PW Systole >=18 AND LEFT_ATRIUM >= 42 Then RHD

IF ESD < 40 AND PW Systole <18 AND PW Diastole < 10 Then NR-Echocardiography

IF ESD < 40 AND PW Systole <18 AND PW Diastole >= 10 AND HEART_FUNCTION <54 Then CAD

IF ESD < 40 AND PW Systole <18 AND PW Diastole >= 10 AND HEART_FUNCTION >=54 AND QTC >=435 Then LVH Suspect HHD

IF ESD < 40 AND PW Systole <18 AND PW Diastole >= 10 AND HEART_FUNCTION >=54 AND QTC <435 AND PR.PQ. >=131 Then LVH Suspect HHD

IF ESD < 40 AND PW Systole <18 AND PW Diastole >= 10 AND HEART_FUNCTION >=54 AND QTC <435 AND PR.PQ. < 131 Then NR-Echocardiography

The results of the decision tree which were formed then tested against testing data. Thirty-eight patient data were tested to determine the classification of heart disease based on the first treatment. The test results showed the accuracy of the classification rules formed by 78.95% with an error rate of 21.05%.

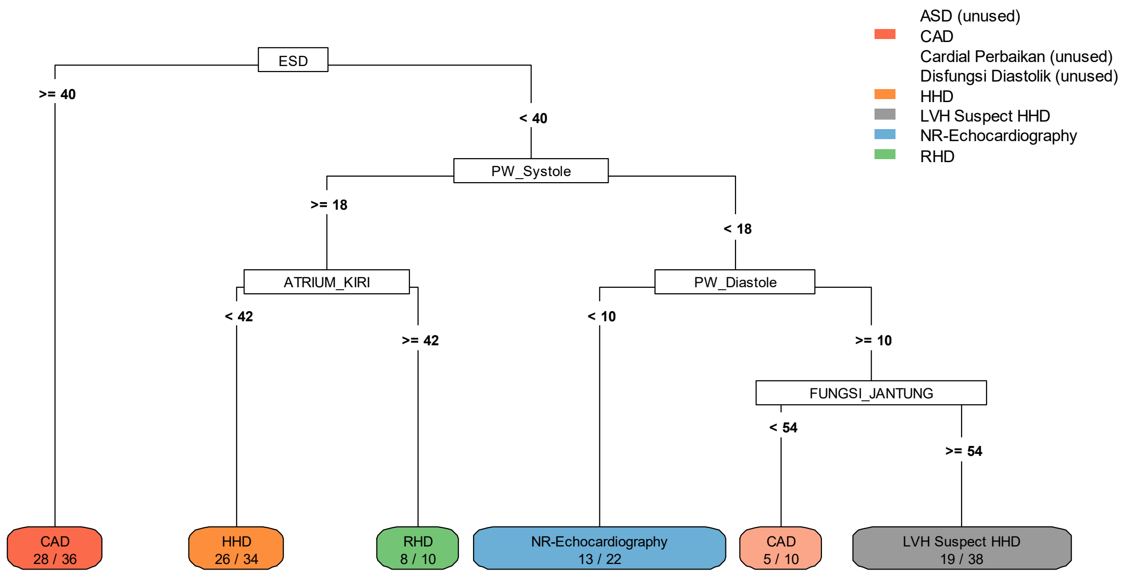

Figure 2: The First Treatment of Decision Tree

In the second treatment, the classification rules formed show that there are three types of diseases that cannot be identified by the decision tree. This is not much different from the results of the first treatment. Similar to the first treatment, data testing was carried out on thirty-eight heart disease data. The test results show the accuracy of the classification rules formed by 73.69% with an error rate of 26.31%. Figure 3 shows the decision tree formed.

The third treatment was performed on training data where the data contained all ECG values variables. The results of the formation of classification rules showed that there were very significant differences in the third treatment. The level of accuracy of the classification results in the third treatment dropped dramatically by 50%. This also indicates that the type of heart disease can not only be determined based on the patient's ECG value. Table of differences in classification results between real patient data, first, second, and third treatment results as shown in Table 1, where Id_P is the serial number of patient data, Class_DataTesting is a classification of pure testing data according to the diagnosis data from the doctor, ClassWith_ECHO_ECG is the result of classification of testing data using the first treatment training data (a combination of echocardiography and electrocardiogram medical data), ClassWith_ECHO is the result of testing data classification using the second treatment training data (only based on medical echocardiography data), and ClassWhit_ECG is the result of classification of testing data using third treatment training data (only based on data medical electrocardiogram).

Overall based on the results of a study of 150 heart disease patient data in three different treatments, it can be seen that the determination of the type of heart disease should not only consider the ECG value alone. However, the Echo values can actually be used to identify early types of heart disease suffered by patients. This is with the accuracy of the classification results of patient data based on training data by only taking Echo variable samples which have a better accuracy rate than just using ECG values. The results of the classification model testing of the testing data with the Echo parameter show that there were only nine patients who had a different diagnosis from the real data. The rest have the same classification results with real data. However, to further ensure the accuracy of the classification of types of heart disease it is advisable to consider not only from one of the test results such as Echo alone or ECG alone. It is advisable to look at the two variables as a whole to diagnose the patient's heart disease.

In addition, there are interesting things from the results of studies conducted. From the eight types of diseases found in the data of one hundred and fifty patients, three of them were not identified by the classification rules pattern. The results of checking the data showed that the percentage of distribution of patients suffering from Atrial Septal Defect (ASD) was only 0.89% of the total amount of training data or only 0.67% of the total data. For types of Cardial Repair Disease, the percentage distribution was 1.78% of the total amount of training data or only 1.33% of the total data. As for the type of diastolic dysfunction, the distribution percentage of patients was 5.36% of the total amount of training data or only 4% of the total data. This is certainly far from being inversely proportional to the five other types of diseases that have more data distribution.

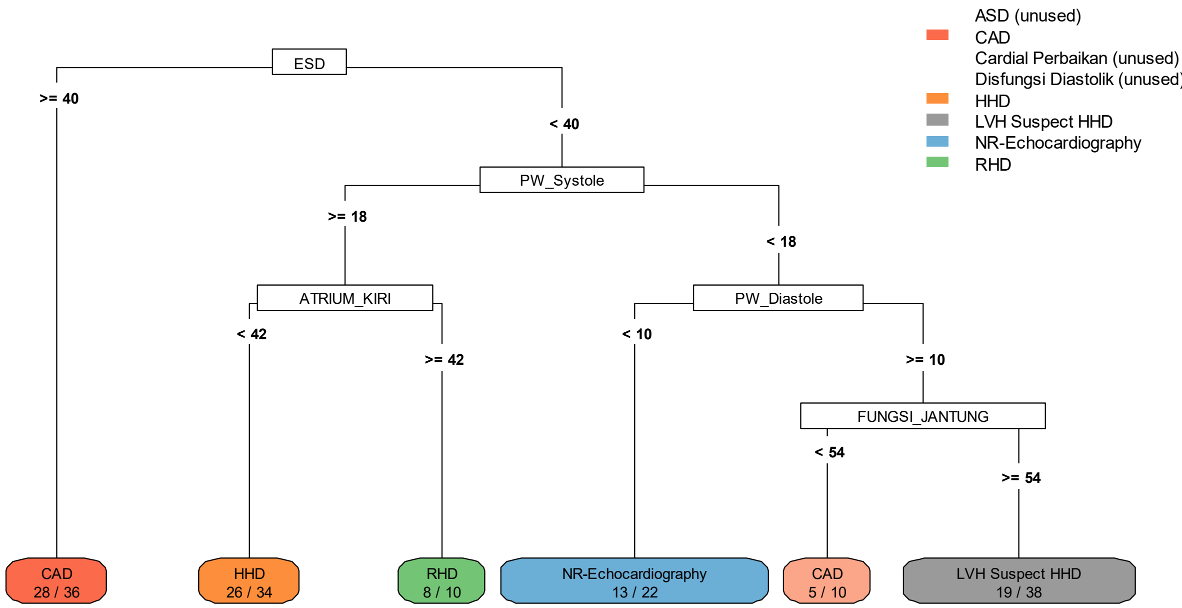

Figure 3. The Second Treatment of Decision Tree

Table 1: Comparison of Pure Testing Data Classification Results towards Three Data Treatments

Id_P	Class_DataTesting	ClassWith_ECHO_ECG	ClassWith_ECHO	ClassWith_ECG
5	NR-Echocardiography	NR-Echocardiography	NR-Echocardiography	CAD
14	LVH Suspect HHD	LVH Suspect HHD	LVH Suspect HHD	HHD
16	NR-Echocardiography	NR-Echocardiography	NR-Echocardiography	NR-Echocardiography
26	NR-Echocardiography	NR-Echocardiography	LVH Suspect HHD	HHD
28	ASD	NR-Echocardiography	NR-Echocardiography	HHD
29	NR-Echocardiography	NR-Echocardiography	NR-Echocardiography	NR-Echocardiography
36	LVH Suspect HHD	LVH Suspect HHD	LVH Suspect HHD	HHD
39	Disfunction of Diastolic	NR-Echocardiography	LVH Suspect HHD	NR-Echocardiography
40	LVH Suspect HHD	HHD	HHD	CAD
50	NR-Echocardiography	NR-Echocardiography	LVH Suspect HHD	NR-Echocardiography
53	Disfunction of Diastolic	LVH Suspect HHD	LVH Suspect HHD	CAD
58	NR-Echocardiography	NR-Echocardiography	NR-Echocardiography	CAD
60	CAD	CAD	CAD	CAD
61	CAD	CAD	CAD	CAD
66	CAD	CAD	CAD	CAD
72	CAD	CAD	CAD	CAD
74	CAD	CAD	CAD	CAD
81	LVH Suspect HHD	CAD	CAD	CAD
86	CAD	LVH Suspect HHD	LVH Suspect HHD	HHD
90	CAD	CAD	CAD	CAD
92	HHD	NR-Echocardiography	NR-Echocardiography	HHD
100	CAD	CAD	CAD	CAD
111	CAD	CAD	CAD	CAD
113	HHD	HHD	HHD	HHD
116	CAD	CAD	CAD	HHD
117	CAD	CAD	CAD	CAD

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

120	RHD	RHD	RHD	HHD
121	CAD	CAD	CAD	CAD
122	HHD	HHD	HHD	HHD
123	CAD	CAD	CAD	HHD
124	HHD	HHD	HHD	HHD
131	LVH Suspect HHD	LVH Suspect HHD	LVH Suspect HHD	HHD
135	LVH Suspect HHD	LVH Suspect HHD	LVH Suspect HHD	NR-Echocardiography
137	NR-Echocardiography	LVH Suspect HHD	LVH Suspect HHD	HHD
140	HHD	HHD	HHD	NR-Echocardiography
142	HHD	HHD	HHD	CAD
147	HHD	HHD	HHD	HHD
149	CAD	CAD	CAD	HHD

The results of the classification of heart disease with Echo parameters appear to have better accuracy than using only ECG. This is not surprising because Echo medical records produce heart size and shape, heart function, problems with heart valves, blood clotting levels and heart muscle function information. While the ECG results are more indicative of medical data in the form of electrical signals from the human heartbeat. Thus it is very reasonable if the Echo parameters have more recommended results than using ECG. In addition, the combination of heart conditions (Echo) with ECG data also has results that also have a better level of recommendations than just using ECG.

7. CONCLUSION

Based on the results of research conducted, it can be seen that determining the type of heart disease is recommended to look at two important indicators, namely the results of checking the Echo value and also the patient's ECG. The level of accuracy of the classification of types of heart disease by considering both Echo and ECG indicators is much better than just considering the value of Echo or ECG alone. The pattern of classification rules formed from a training data is also influenced by the distribution of data that refers to certain disease hypotheses. The more data distribution of a type of disease, the classification rule pattern extraction will be formed properly, while the less data distribution of a type of disease in the training data, the worse the classification rule pattern that is extracted, may even be undetected.

Test results on testing data can be seen that the diagnosis of heart disease can be done using Echo medical data of patients or by looking at a combination of Echo and ECG data. The results of the study of the three treatment data showed that either by using Echo alone, or a combination of Echo and ECG, the difference in the classification results of real data was only 23.68% for the combined Echo and ECG and 26.3% for the classification results that only used Echo.

ACKNOWLEDGEMENT

Thank you to the Ministry of Research, Technology and Higher Education of Republic of Indonesia for funding this basic research scheme through the Directorate General of Research and Development Strengthening of RISTEK DIKTI.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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