Heart Disease Classification using Gain Ratio Feature Selection with Hidden Layer Modification in Extreme Learning Machine

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***Abstract* – Heart disease is a non-communicable disease that causes a high mortality rate and is still a problem both in developed and developing countries. This disease often occurs because of the narrowing of blood vessels which causes the functioning of the heart is disturbed. The number of cases of heart disease in Indonesia is still quite high, making medical staff require a fairly in diagnosing the patient's conditional. The research proposed to implement Gain Ratio in selecting the most important feature that influences heart disease and building the classification models based on the modification of hidden layer weight on Extreme Learning Machine. The research collected the heart disease dataset which was obtained from *Kaggle UCI* Machine Learning consist of 1.025 samples, 14 attributes, and 2 labels. The data preprocessing include using data cleaning and normalization to find out dirty data or *missing values*. The experiment reported that Gain Ratio succeeds to generate the attribute ranking of heart disease dataset, then Gain Ratio score was added to the weighting of the hidden layer input on learning methods. The research used various validation sampling using the splitting test between training data and testing such as 70:30, 80:20, 90:10%, and set up 1500 hidden layers. The accuracy average performance of Extreme Learning Machine with modification using Gain Ratio reached 100% for the training phase and 97.67% for the testing phase.**

***Keyword*: Heart Disease, Gain Ratio, Modification, Classification, Extreme Learning Machine**

I. INTRODUCTION

Heart Disease is caused by blood deficiency disease due to the narrowing of the coronary arteries. According to WHO data in 2015 showed that 70% of deaths in the world were caused by non-communicable diseases (39.5 million of 56.4 deaths). All deaths due to non-communicable diseases, 45% were caused by heart and blood vessel disease with 17.7 million of 39.5 million deaths[1]. According to the age group demographic, coronary heart disease mostly occurs in the age group of 65 - 74 years (3.6%) followed by the age group 75 years and over (3.2%), the age group 55 - 64 years (2.1%) and the group age 35-44 years (1.3%)[2]. With increasingly sophisticated technology and digitization 4.0 being a good adaptation to change what was originally manual or traditional now has to switch to automatic. One of the current technology which it can be adopted is Data Mining, which is the set of the process to finding and recognizing the patterns of features that are large, varied models through multidisciplinary science include Statistical Science, Machine Learning, Artificial Neural Network to gain information valuable[3]. Data Mining is also included in the *Knowledge*, *Discovery* in *Database* (KDD).

The first step that can be done to find out how the quality of the dataset patterns that are owned before creating a classification model is through preprocessing starting from Data Cleansing, Data Integration, Data Transformation, and Data Normalization[4]. Many studies use Data Mining in the medical field which is to help in establishing an initial diagnosis based on the patient's medical history. One of them is to predict coronary heart disease based on clinical data medical records to make early prediction through classification algorithm system, the system can help provide information quickly and have good accuracy in decision making [5]. The related works by the other researcher were conducted by Ivan Fadilla et al [6] using Extreme Learning Machine (ELM) method to classify the conditions of patients with chronic kidney disease which was the model reached the accuracy of 96,7% with 50 the number of *hidden layers*. The comparison of training and testing data was 70:30, the research has also implemented the feature selection to determine the most important features in the chronic kidney disease dataset.

The feature selection technique[7]in the classification is a very important role because not all features have the same weighting score based on the level of relevance to a dataset. On the other hand, we need a feature selection approach to select important features that are useful for the process of making learning models and improve the accuracy. Several algorithms that include a single evaluation-based feature selection include Information Gain, Chi-square, Fisher's Discriminant Ratio (FDR), and many more. We use Gain Ratio as the feature selection approach which is an improvement of Information Gain that reduces the bias based on the entropy value [8]. The feature selection can help to find out the ranking results from each attribute. We used Heart Disease dataset which was obtained from *Kaggle UCI* Machine Learning consists of 14 features and 2 labels[9]. The research obtains the improvement of accuracy by combining the *hidden layers* modification in Extreme Learning Machine with Gain Ratio score[7]. The great expectation of this research is to be able to develop a system to predict the status of heart disease patients using Machine Learning algorithms by providing quick and precise decision making.

II. METHODOLOGY

Figure 1 is illustrated the proposed system design of heart disease research begins from data collection, preprocessing data, attribute ranking using Gain Ratio, classification model using Extreme Learning Machine, and the last is the performance evaluation of accurate result using Confusion Matrix.

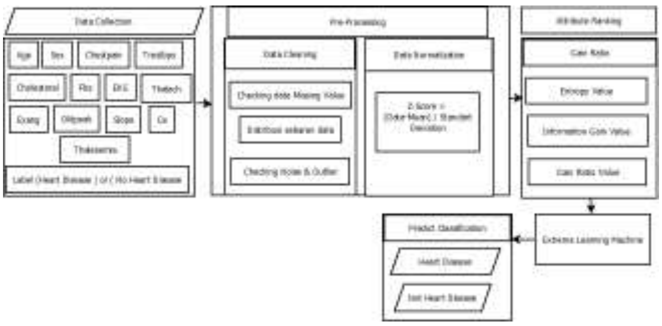

Figure 1. The proposed research system design

A. *Data Collection*

The first stage of the research is the data collection dataset which is obtained from *Kaggle UCI* ML. The heart disease dataset consists of 1.025 samples, 14 features, and 2 labels. Table 1 shows the detail of the heart disease dataset.

TABLEI. THE DETAIL INFORMATION OF HEART DISEASE DATASET

No	Information Dataset		
	Attribute	**Label**	**Description**
1	Age	Age	-
2	Sex	Sex	0= Female, 1=Male
3	Chest pain type	Cp	0= Typical angina 1= Atypical angina 2= Non-anginal pain 3= Asymptomatic
4	Resting blood pressure	Trestbps	-
5	Cholesterol	Chol	-
6	Fasting blood sugar	Fbs	0= False, 1= True
7	Resting electrocardio graphic result	EKG	0= Normal 1= Non-Normal 2= Left ventricular hypertrophy
8	Thalach	Thalach	-
9	Exang	Exang	0= No 1=Yes
10	Oldpeak	Oldpeak	-
11	Slope	Slope	0= Upsloping 1= Flat 2= Downsloping
12	Ca number of major vessels	Ca	-
13	Thalasemia	Thal	3= Normal 6= Fixed defect 7= Reversible defect
14	Label	Label	0= Heart disease 1= Not disease heart

B. *Preprocessing*

After collecting the heart disease dataset, the next step is data preprocessing. The data preprocessing in this research include data cleaning and data normalization.

1) *Data Cleaning*

Before entering into deeper stages, we need to know in advance about the data we have. Does not rule out the possibility of data that has dirty data or missing values and inconsistencies when inputting into *raw* data[10]. Then it is necessary to use preprocessing techniques in heart disease data to find out and identify *missing values, noise,* and *outlier* data. In this study Machine Learning that is used as a type of *supervised* learning which is to find out or group data based on dataset labels, it is important to do data cleaning if there is inconsistent labeling of heart disease data. This dataset consists of 526 patients with 'no heart disease' label while 499 were patients with 'heart disease' labels. Figure 2 shows a visualization of the case number of each label of heart disease in the bar chart.

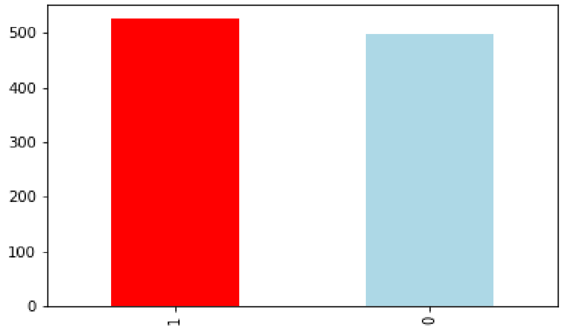

Figure 2. The case number of each label of heart disease

2) *Data Normalization*

The next step is Data Normalization, the values of the data attributes must have a range of values that differ according to the characteristics of the feature, it needs a scaling process to provide a balance of the actual minimum and maximum range of each data feature[10]. Z-score is one of the normalization methods that are appropriate and stable to provide it. By utilizing the average value and standard deviation. The formula of the Z-score follows equation (1).

$$new\ data = \frac{data - mean}{standard\ deviation} \tag{1}$$

C. *Feature Selection*

Feature Selection, one of the technical process in data mining that belongs to a subset of feature engineers and is often used by data mining practitioners in reducing or selecting the number of features, eliminating *noise*, and removing the *outlier* in the dataset[10][11][12]. The most fundamental problem and challenge for data mining practitioners are to analyze from big data with a high level of complexity with very diverse features, feature selection can be used in the selection of relevant feature to increase prediction accuracy. While in various the size of the dataset, feature selection is implemented to identify the most important feature. The research is proposed to use the Gain Ratio to identify it.

1) *Gain Ratio*

Gain Ratio is a modification of the Information Gain reduces usually[8]. This process will find out which features have the lowest to highest contribution value. Gain Ratio formula follows the equation (4), while the equation (2) and (3) is entropy and Information Gain formula respectively.

The entropy formula follows equation(2).

$$entropy(S) = -\sum_i^c p_i Log_2 p_i \tag{2}$$

Where:
$p_{i=}$ sample probability of class *i*

Information Gain formula follows the equation (3).

$$Gain\ (S, A) = Entropy(S) - \sum_v \left(\frac{S_v}{s}\right) entropy(S_{v)} \tag{3}$$

Where:
V = the variation values on feature *A*
$|S_v|$ = the number of samples that exist at value *v*
S = the value of the sample data
Entropy(S) = entropy for samples with values *v*

Gain Ratio formula follows the equation(4).

$$gain\ ratio\ (A) = Gain(A)/SplitInfo(S) \tag{4}$$

The split information follows equation (5).

$$split\ info = -\sum_{i=1}^{v} \left(\frac{S_i}{S}\right) Log_2\left(\frac{S_i}{S}\right) \tag{5}$$

Where :
S_i value is a subset of *C* that is formed from split *S* using feature *A* and the variance of value *V*

To facilitate the reader in understanding this research, it will be illustrated in Figure 3 which is a Gain Ratio flowchart.

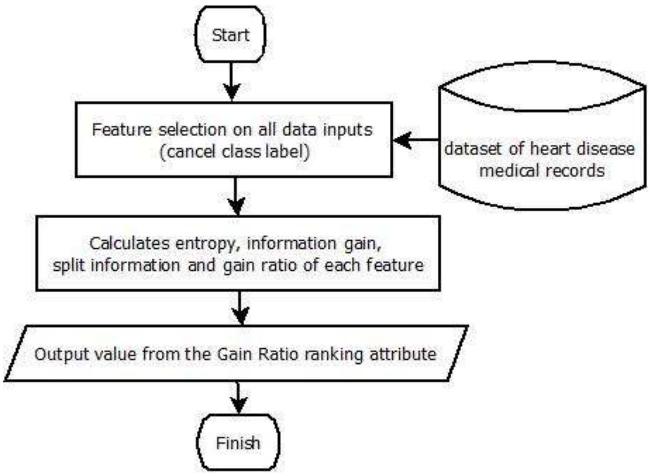

Figure 3. Gain Ratio *flowchart*

D. *Extreme Learning Machine*

Extreme Learning Machine[7][13][14][15]is one method of *pattern recognition* and regularities in data that adopts the concepts of *feedforward neural network* learning structure with one *hidden layer* or can be known as the theory of the *single hidden layer feedforward neural network*(SLFn). Huang[13] first discovered in 2014. The ELM method was created based on the deadline with weaknesses in Artificial Neural Network with backpropagation learning methods such as backpropagation[7][13] which are still slow, especially in learning speed. The existing features in the dataset used will initialize as input layer nodes connecting to the *hidden layer* will be processed using the random activation function. After obtained the Gain Ratio score in each attribute, then it will take a role as additional weight in the learning method. This value will take as a duplication of the Extreme Learning Machine in the input random neural network structure. The additional weight features formula in Extreme Learning Machine follows the equation(10) and (11). While the output layer nodes will classifier output according to the class label. The formula follows the equation (6), (7), (8), and (9).

$$\beta = H^{+}T, \qquad (6)$$

$$\boldsymbol{H}(w_1, \ldots, w_N, b_1, \ldots., b_N, x_1, \ldots, x_N) \qquad (7)$$

$$= \begin{bmatrix} g(w_1.x_1 + b_1) & \ldots & g(w_n.x_1 + b_N) \\ \vdots & \cdots & \vdots \\ g(w_1.x_n + b_1) & \ldots & g(w_N.x_N + b_N) \end{bmatrix} \qquad (8)$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix} \quad \text{and} \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix} \qquad (9)$$

Where:
H = *hidden layer* output matrix
β = calculate the output weight β
T = target

The explanation of the equation (6)-(9) is:
Step 1: Process of assigning *weight* w_i and b_i *biases* is done randomly $i = 1, \ldots., N$ as is the equations (7) and (8)
Step 2:Then calculate the H matrix *output*
Step 3: Calculate the *weight output* β as in equation (6) and (9)

The additional weight of Gain Ratio in Extreme Learning Machine follows the equation (10) and (11).

$$h_i(x) = G\,(a_i, b_i, \mathrm{x}, f_j), a_i, \epsilon R^d, b_i, \epsilon^R \qquad (10)$$

$$G\,(a_i, b_i, x, f_i) = G\big(f_j.a_i.x_j + b_i\big) \qquad (11)$$

Where:
f_j= derived from the *weigh*t of the Gain Ratio feature.

III. Result and Discussion

A. *Preprocessing*

The results of this preprocessing will explain the process of *exploratory data analysis* (EDA) starting from the data cleansing and normalization data before entering into the feature selection.

1) *The Descriptive Statistical Analysis*

The descriptive statistical analysis of the heart disease dataset proposed to show statistical summaries such *as count*, *min*, *max*, and *mean* which is illustrated in Figure 4.

	Age	Sex	Cp	Trestbps	Chol	Fbs	EKG	Thalach	Exang	oldpeak	slope	Ca	thal	label
count	1025.00	1025.00	1025.00	1025.00	1025.00	1025.00	1025.00	1025.00	1025.00	1025.00	1025.00	1025.00	1025.00	1025.00
mean	54.43	0.70	0.94	131.61	246.00	0.15	0.53	149.11	0.34	1.07	1.39	0.75	2.32	0.51
std	9.07	0.46	1.03	17.52	51.59	0.36	0.53	23.01	0.47	1.18	0.62	1.03	0.62	0.50
min	29.00	0.00	0.00	94.00	126.00	0.00	0.00	71.00	0.00	0.00	0.00	0.00	0.00	0.00
25%	48.00	0.00	0.00	120.00	211.00	0.00	0.00	132.00	0.00	0.00	1.00	0.00	2.00	0.00
50%	56.00	1.00	1.00	130.00	240.00	0.00	1.00	152.00	0.00	0.80	1.00	0.00	2.00	1.00
75%	61.00	1.00	2.00	140.00	275.00	0.00	1.00	166.00	1.00	1.80	2.00	1.00	3.00	1.00
max	77.00	1.00	3.00	200.00	564.00	1.00	2.00	202.00	1.00	6.20	2.00	4.00	3.00	1.00

Figure 4. The descriptive statistical analysis of the heart disease dataset

2) *The Percentage of Heart Disease Patient Based on Gender Attribute*

Figure 5 shows the total percentage of heart disease patients in which they are (30.4%) female and (69.6%) male. The percentage showed that male sex has more dominant.

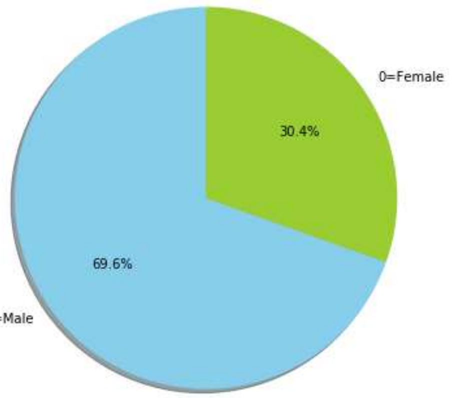

Figure 5.The percentage of heart disease patient based on gender attribute

3) *Z-score Normalization Result*

Figure 8 shows the Z-score normalization results in the line chart by processing the mean and standard deviation of the attribute values. The Z-score formula follows equation(1).

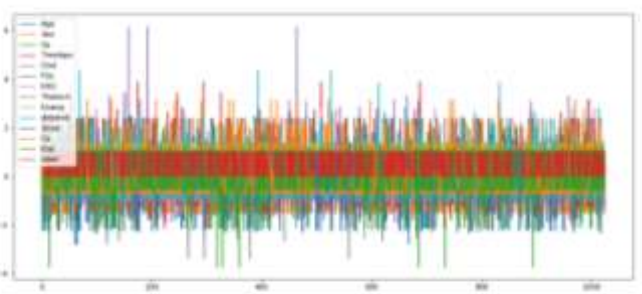

Figure 8. Z-score Normalization Result

B) Gain Ratio Attribute Ranking Result

Figure 9 shows the attribute ranking score using Gain Ratio, which highest score is Chest pain(Cp) attribute (0.2047) and the lowest score is Fasting blood sugar(Fbs) attribute (0). Then the Gain Ratio score will be used to double the weighing input in Extreme Learning Machine.

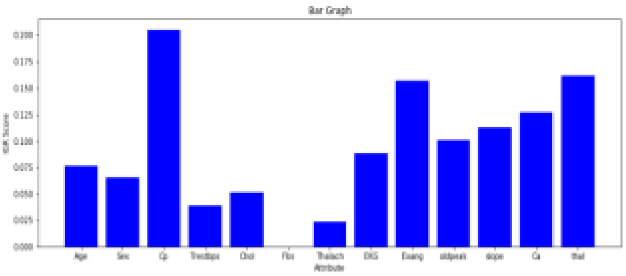

Figure 9. Gain Ratio attribute ranking

C) Extreme Learning Machine with Hidden Layer Modification Performance

The heart disease dataset consists of 1.025 samples, 14 attributes and 2 labels, the set of steps begins from preprocessing, and attribute ranking was done before. The next step is adding values from the Gain Ratio score to the *hidden layer* input. The validation sampling of this research used the various comparison of training and testing data. We used the ratio of training and testing data such as 70: 30, 80:20, and 90:10 respectively. We set up the number of *hidden layers* is 1500 nodes. Table II shows the comparison of the accuracy of the Extreme Learning Machine with *hidden layer* modification using Gain Ratio. The experiment shows Extreme Learning Machine + Gain Ratio given the best accuracy performance in various validation sampling using a splitting test. The splitting test 70:30, the training, and testing accuracy reached 100%:95% respectively. The splitting test 80:20, the training and testing accuracy reached 100%:98% respectively. The splitting test 90:10, the training and testing accuracy reached 100%:100% respectively. Logically, if the testing data is slightly accurate, the higher of bigger it is, but if the test size is bigger, the size of the testing data will result in smaller training sizes, resulting in less information from the data. And from the third experiment of the separation test, that we also need to know based on the three separation tests that we made an increase in testing data by 2-3%, but from the three separation tests with different numbers respectively-each ratio provides a value for data accuracy consistent and stable training. So that it provides the separation test information that has the highest accuracy value of the three tests. The average accuracy of Extreme Learning Machine + Gain Ratio given the best performance of 100% for the training phase and 97.67% for the testing phase. For the process of analyzing data, we use the *anaconda navigator tools*. Table III shows the sample data with labels and features that correspond to heart disease, then will be discussed in the Machine Learning model. And Table IV shows the testing results will display results of the actual label match experiment with prediction labels that have been processed. To measure the evaluation of the accuracy results from the testing phase process by comparing the actual label data, the Extreme Learning Machine method has been carried out using Confusion Matrix on dataset used. In Table V is the result of Confusion Matrix. So that the following values can be generated.

TABLE II. EXTREME LEARNING MACHINE WITH HIDDEN LAYER MODIFICATION PERFORMANCE RESULTS

Splitting Test	**Extreme Learning Machine + Gain Ratio**	
	Training accuracy	**Testing accuracy**
70:30	100%	95%
80:20	100%	98%
90:10	100%	100%
Average	100%	97.67%

TABLE III. SAMPLE DATA

Class	***Sample 10 Data***
	Attribute
Class : 0	Features / attribute : [52. 1. 0. 125. 212. 0. 1. 168. 0. 1. 2. 2. 3.]
Class : 0	Features / attribute : [53. 1. 0. 140. 203. 1. 0. 155. 1. 3.1 0. 0. 3.]
Class : 0	Features / attribute : [70. 1. 0. 145. 174. 0. 1. 125. 1. 2.6 0. 0. 3.]
Class : 0	Features / attribute : [61. 1. 0. 148. 203. 0. 1. 161. 0. 0. 2. 1. 3.]
Class : 0	Features / attribute : [62. 0. 0. 138. 294. 1. 1. 106. 0. 1.9 1. 3. 2.]
Class : 1	Features / attribute : [58. 0. 0. 100. 248. 0. 0. 122. 0. 1. 1. 0. 2.]
Class : 0	Features / attribute : [58. 1. 0. 114. 318. 0. 2. 140. 0. 4.4 0. 3. 1.]
Class : 0	Features / attribute : [55. 1. 0. 160. 289. 0. 0. 145. 1. 0.8 1. 1. 3.]
Class : 0	Features / attribute : [46. 1. 0. 120. 249. 0. 0. 144. 0. 0.8 2. 0. 3.]
Class : 0	Features / attribute : [54. 1. 0. 122. 286. 0. 0. 116. 1. 3.2 1. 2. 2.]
Class : 0	Features / attribute : [52. 1. 0. 125. 212. 0. 1. 168. 0. 1. 2. 2. 3.]

TABLE IV. RESULT TESTING OF THE ACTUAL AND PREDICTIVE LABELS

Sample 103 Data		
Target	**Predictions**	**Features / attribute**
Target : 1	Predictions : 1	Features / atrribute : [61. 1. 0. 138. 166. 0. 0. 125. 1. 3.6 1. 1. 2.]
Target : 1	Predictions : 1	Features / atrribute : [57. 1. 0. 152. 274. 0. 1. 88. 1. 1.2 1. 1. 3.]
Target : 0	Predictions : 0	Features / atrribute : [44. 0. 2. 118. 242. 0. 1. 149. 0. 0.3 1. 1. 2.]
Target : 1	Predictions : 1	Features / atrribute : [66. 1. 1. 160. 246. 0. 1. 120. 1. 0. 1. 3. 1.]
Target : 0	Predictions : 0	Features / atrribute : [45. 0. 1. 112. 160. 0. 1. 138. 0. 0. 1. 0. 2.]

Target : 1	Predictions : 1	Features / atrribute : [61. 1. 0. 120. 260. 0. 1. 140. 1. 3.6 1. 1. 3.]
Target : 1	Predictions : 1	Features / atrribute : [53. 1. 0. 140. 203. 1. 0. 155. 1. 3.1 0. 0. 3.]
Target : 0	Predictions : 0	Features / atrribute : [60. 0. 3. 150. 240. 0. 1. 171. 0. 0.9 2. 0. 2.]
Target : 1	Predictions : 1	Features / atrribute : [59. 1. 0. 170. 326. 0. 0. 140. 1. 3.4 0. 0. 3.]
Target : 0	Predictions : 0	Features / atrribute : [54. 0. 2. 108. 267. 0. 0. 167. 0. 0. 2. 0. 2.]

TABLE V. RESULT OF CONFUSION MATRIX

Type of labels	Frequency calculation	Precision(%)	Recall(%)	Accuracy(%)
TN	51	96,56%	95,87%	98,65%
FN	0			
FN	0			
TP	52			

IV. CONCLUSION

The experiment results show that Extreme Learning Machine with modification of the added weight of Gain ratio score on the input *hidden layer* given high classification accuracy. The research was the medical field in diagnosing early on the condition of heart disease patients. Extreme Learning Machine can be used as an alternative to the development of an Artificial Neural Network algorithm. The results of the feature selection using Gain Ratio showed the most important features which have the highest score that was reached by Chest Pain (Cp) 0.2047 while the lowest score was reached by Fasting blood sugar (Fbs) 0. The input hidden layer in Extreme Learning Machine was modified by using the Gain Ratio score as weighting. The experiment result reported the accuracy average results of Extreme Learning Machine modification with Gain Ratio given the best performance of 100% for the training phase and 97,67% for the testing phase. The suggestion for further works is how to determine the number of optimal nodes in the *hidden layer* to get the best accuracy performance.

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