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Application of Machine Learning to Determine the Factors Affecting Deterioration in Patients with Chronic Kidney Disease

Herwanto [a], Ali Khumaidi [a,*]

[a] *Faculty of Engineering, Universitas Krisnadwipayana, Jakarta, 17411, Indonesia*
Corresponding author: [*]alikhumaidi@unkris.ac.id

***Abstract*— Hospital databases generally contain large amounts of data and various, but it has not been used optimally. It needs a technique that can utilize mountains of data into strategically valuable information. This paper will investigate ways to use hospital data to help determine the factors that influence the deterioration in patients with chronic kidney disease. The criteria for the selected patients were patients with a diagnosis of chronic kidney disease and chemotherapy treatment at least once. Three hundred seventy-six patients met these criteria. Subsequently, observation the patient's treatment course for three years. Ninety patients died in the hospital during that period. All the results of patients' blood tests were collected for further analysis. In forming the classification model, there are three stages carried out. The first stage deals with diverse, incomplete, and inconsistent data. Then through the process of changing continuous data into categorical data, each variable is classified into several categories. The next stage is to create a predictive model to determine the factors that influence the deterioration in patients with kidney failure using the Random Forest, Logistic Regression, and Decision Tree algorithms. Information of the classification model, 12 variables were selected, namely age, sex, and the results of clinical pathology laboratory examinations-Ureum, Thrombocyte, Natrium, Creatinine, Chloride, Kalium, Hemoglobin, Hematocrit, and Leukocytes. The three algorithms can classify training data with an accuracy of 98% (Random Forest), 83% (Logistic Regression), 98% (ID3).**

***Keywords*— Chronic kidney disease; machine learning; classification; discretization; decision tree.**

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I. INTRODUCTION

Hospital databases generally contain large amounts of data and various, but it has not been used optimally. It needs a technique that can utilize mountains of data into strategically valuable information. This paper will investigate ways to use hospital data to help determine the factors that Kidney disease is a condition in which the kidneys experience a decrease in their normal kidney function. Disorders of the kidneys will affect the body's performance in washing the blood, namely filtering body waste and excess fluid that will become urine [1]. Kidney disease consists of acute and chronic. Acute kidney disease is a condition that occurs when the kidneys suddenly stop working. Chronic conditions refer to a condition in which the disease progresses and worsens over a long time. There are two stages in treating chronic kidney disease: conservative therapy and replacement therapy. Kidney conventional therapy includes inhibiting the progression of kidney disease, stabilizing the patient's condition, and treating reversible factors. Replacement is Kidney therapy with chronic kidney disease in dialysis or kidney transplantation [2].

In determining diagnosis and treatment, a doctor will conduct an examination based on symptoms, laboratory results, and other supporting tests before deciding the type of disease. The wrong diagnosis impacts incorrect treatment and can also lead to death [3]. Many studies have been carried out to develop predictive models to help diagnose diseases using machine learning. The Objective of machine learning is to learn about algorithms that can recognize patterns in data, turning various kinds of data into actions with as little human intervention as possible. Machine Learning can be a catalyst for the health system to improve the efficiency and effectiveness of patient care [4]. In order to solve a medical diagnostic task, a Machine learning system needs the following features: good performance, the ability to appropriately deal with missing data and with noisy data (errors in data), the transparency of diagnostic knowledge, the ability to explain decisions, and the ability of the algorithm to reduce the number of tests necessary to obtain reliable diagnosis [5].

There are many machine learning algorithms, but they all follow the same principle, which is to imitate the way humans learn through (a) data collection; (b) abstraction process, namely the process of translating data into a more general model; (c) generalization, namely the process of using the abstraction result model as the basis for making decisions or conclusions [6]. In machine learning, the model can be in the form of mathematical rules, logical rules (if-then rules), or in the form of tree-shaped flowcharts. Furthermore, the model must adapt to new data that has never been received before [7].

Several studies have conducted implementation machine learning using various machine learning algorithms to predict those related to kidney disease. The results prediction of transplantation of kidney transplant patients and assess their usefulness for decision making [8], detection of chronic kidney disease based on medical images such as retinal images that can add to existing chronic kidney disease screening strategies and use risk factors including age, gender, ethnicity, diabetes, and hypertension [9], machine learning to guide the evaluation of kidney function from segmentation to disease prediction [10]. Prediction of kidney outcome after surgery uses logistic regression, support vector machine, and random forest methods [11]. Prediction of risk for chronic kidney disease with low incidence and simple clinical predictors resulted in well-performing logistic regression [12] and machine learning applied to emergency room data for patients' identification at high risk of kidney injury [13]. Detection of factors that influence chronic kidney disease [14] and prediction of kidney disease patient's estimator uses fuzzy function [15].

This paper study how to use machine learning to help determine the factors that influence the deterioration in patients with chronic kidney disease. The test result clinical pathology laboratory for three years of patients undergoing hemodialysis therapy was collected. There were four stages of processes that carried they were (1) compiling the data in a format that is appropriate to a specific algorithm; (2) carrying out the model formation process; (3) interpreting and evaluating models; (4) applying the selected model, to build a classification model, the quality of discretization impacts speed and accuracy. This study aims to classify data from the test results clinical pathology laboratory in patients with kidney disease into an appropriate category to detect kidney disease, which causes deterioration of the patient's condition. For this purpose, there were three algorithms chosen, the Random Forest, Logistic Regression, and ID3 algorithms.

II. Material and Method

The research method consists of three main stages: the data preparation process, the formation of a classification model, and the selection of the appropriate model, as shown in Figure 1a. The process begins with collecting patient data and then the data preparation process. In making machine learning models, the quality of the training dataset dramatically affects the quality of the model. Therefore, it needs a mechanism for data collection and preparation for machine learning purposes.

Operations related to data preprocessing activities include collecting, filtering, processing, and combining relevant data from various sources into training data tables. The result of data preprocessing is the production of data that meets the criteria for the analysis process.

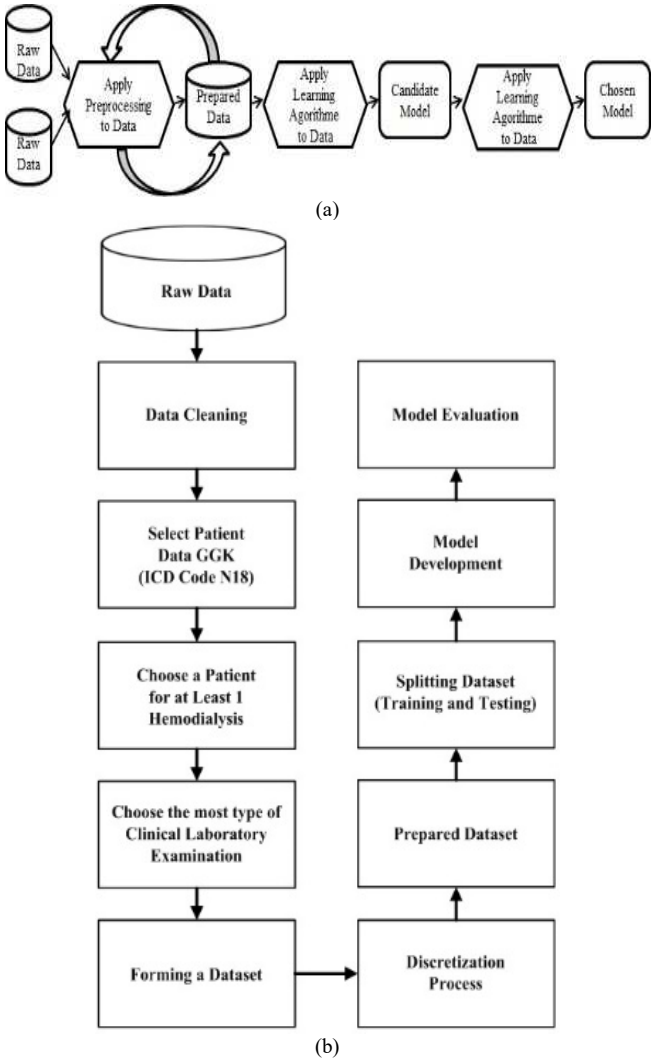

Fig. 1 (a) Research method; (b) research stages

This paper uses a classification model for model formation. Classification is the process of finding a model or function that explains or distinguishes a concept or class of data to estimate the class of an object whose label is unknown. The model can be an "if-then" rule, a decision tree, a mathematical formula, or a neural network. The classification process consists of two phases: Learning and testing. In the learning phase, model building using data whose class has known. Then in the test phase, the model is tested using other data to determine the accuracy. If the accuracy is sufficient, this model can be used to predict unknown data classes.

The research stage began with collecting all master patient data, then selecting data on patients who have been diagnosed with kidney failure and performing hemodialysis at least once. Then proceed with the selected nine of the type of clinical laboratory examination that is most often performed. After the dataset is formed, the discretization process is carried out. The dataset is then split and then developed a model using the selected algorithm, and the last step is to evaluate the model by measuring its performance. The stages of this research seem in Figure 1b.

A. Data Source

The research sample is from the Pertamina Central Hospital database. The data collection period was from January 2016 to December 2018. The first stage carried out data collection by selecting all patients diagnosed with kidney disease and undergoing hemodialysis therapy. In determining the classification of disease types, compiled based on a category system and grouped into a disease according to predetermined criteria known as the International Statistical Classification of Disease and Related Health Problems Tenth Revision (ICD-10). ICD-10 contains a diagnostic classification of diseases with international standards, arranged based on a category system and grouped into a disease according to predetermined criteria. The ICD aims to uniformly record and collect data on diseases and health-related problems to create statistical information on morbidity and mortality relevant, accurate, timely, effective, efficient at local, national, and international levels. Patients with kidney disease have the ICD code N18[16].

In this study, patients with kidney disease diagnosed and at least once undergoing hemodialysis were selected. Three hundred seventy-six patients met the criteria, 156 female patients, 220 male patients, average age 60 years, 95 patients of whom the last visit was declared dead in the hospital.

The process continued by selecting the attributes of age, death status (DEA), and the type of clinical pathology test often performed. There are nine types of tests, namely Ureum (UR), Thrombocyte (TR), Natrium (NA), Creatinine (CR), Chloride (CH), Kalium (KL), Hemoglobin (HE), Hematocrit (HM), and Leukocyte (LE). Figure 2 summarizes laboratory tests performed in patients with kidney disease. Table 1 shows some samples of patient data. General characteristics of patient data, range of normal values [17], and the average variables test seem in Table 2.

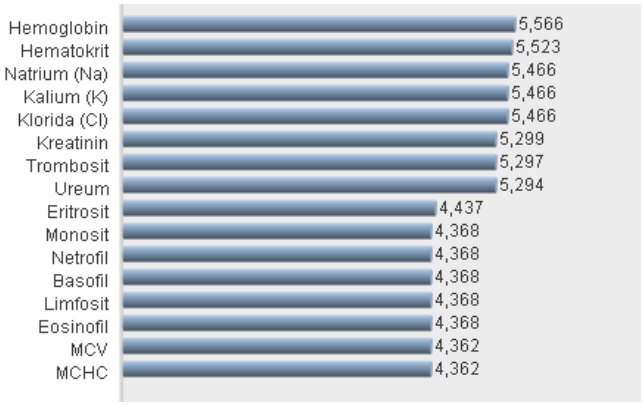

Fig. 2 Type of clinical pathology test

Before proceeding with modeling, it is necessary to see whether there is a proper relationship between the variables in the training dataset. The correlation matrix is helpful to measure how closely the relationship between two variables follows a straight line. This correlation value is between -1 and 1. Figure 3 shows a relationship between death status and creatinine; creatinine has a strong relationship with urea; hemoglobin has a strong relationship with the hematocrit; sodium has a fragile relationship with death status.

Attributes	Age	Death_Status	Clorida	Creatinine	Hemoglobin	Hematocrit	Kalium	Leukocytes	Natrium	Trombocyt	Ureum
Age	1	-0.157	0.076	-0.021	0.006	0.001	0.004	-0.043	0.136	-0.018	0.018
Death_Status	-0.157	1	0.022	0.153	0.139	0.129	-0.106	-0.255	0.004	0.055	0.011
Clorida	0.076	0.022	1	-0.046	0.260	0.290	0.015	-0.075	0.642	-0.070	-0.134
Creatinine	-0.021	0.153	-0.046	1	-0.124	-0.087	0.012	-0.104	0.062	0.059	0.563
Hemoglobin	0.006	0.139	0.260	-0.124	1	0.984	-0.262	0.012	0.266	0.036	-0.187
Hematocrit	0.001	0.129	0.290	-0.087	0.984	1	-0.283	-0.002	0.291	0.046	-0.179
Kalium	0.004	-0.106	0.015	0.012	-0.262	-0.283	1	-0.078	-0.203	-0.169	-0.113
Leukocytes	-0.043	-0.255	-0.075	-0.104	0.012	-0.002	-0.078	1	0.007	0.244	0.147
Natrium	0.136	0.004	0.642	0.062	0.266	0.291	-0.203	0.007	1	0.096	0.143
Trombocyt	-0.018	0.055	-0.070	0.059	0.036	0.046	-0.169	0.244	0.096	1	-0.095
Ureum	0.018	0.011	-0.134	0.563	-0.187	-0.179	-0.113	0.147	0.143	-0.095	1

Fig. 3 Correlation matrix training dataset

TABLE I
PATIENT DATA SAMPLE

Age	Death Status	Ureum	Thrombocyte	Natrium	Creatinine	Chloride	Kalium	Hemoglobin	Hematocrit	Leukocytes
46	Yes	99	167	137	8,9	99	5,6	3	9	21,8
54	No	97	146	144	7,9	107	4	10,1	32	6,88
68	No	146	#N/A	140	2,4	105	4,1	#N/A	#N/A	#N/A
65	No	69	218	143	6,8	101	4	10,5	31	4,97
57	No	125	199	136	2,8	101	4	8,8	26	10,96
57	Yes	56	222	134	2,7	97	2,6	7,1	20	17,3
61	Yes	93	#N/A	125	2	88	4,8	#N/A	#N/A	#N/A
85	No	125	287	132	4,9	95	3,7	9,5	28	16,04
73	Yes	105	144	136	6,9	101	4,1	9,8	31	7,54
76	Yes	57	168	138	7	102	3,5	11,5	35	5,58

Table 2 shows that the average values for creatinine and ureum examinations are more than the normal range of values-kidney function assessment necessary testing of ureum and creatinine [18]. A high creatinine test indicates kidney function that is not working as expected, which is caused, among other things, due to kidney disease [19].

TABLE II
GENERAL CHARACTERISTICS OF PATIENT

Examination Type	Normal value	Min	Max	Average
Ureum	10 ~ 50	8,1	432	136,6
Trombocyt	170 ~ 380	21	581	229,3
Natrium	135 ~ 144	6,8	150	135,8
Creatinine	0,6 ~ 1,3	0,6	20	9,42
Chloride	97 ~ 106	8	113	99,3
Kalium	3,6 ~ 4,8	1,8	96	4,96
Hemoglobin	8,1 ~ 11,2	3	61,6	10,45
Hemotocrit	35 ~ 45	9	61	31,38
Leukocytes	3,2 ~ 10,0	2,1	74,6	10,06
Age		20	88	60

B. Preprocessing

The data preparation process is carried out through two stages, namely a) handling incomplete data by filling in empty data values with average values b) changing data with continuous value into discrete data. The discretization process use supervised and unsupervised discretization. Before carrying out the learning process, it is necessary to re-code each continuous-valued attribute into a discrete-valued attribute by setting a specific interval. This process is known as discretization [20].

There are many ways to carry out the discretization process. One way involves dividing the range of possible values into sub-ranges called bins. In this way, select the appropriate number of intervals. Substitute continuous attributes into intervals of the same width or frequency [21]. The Equal Width Interval Binning process is conducted by observing the data values to determine the minimum and maximum values and dividing the range into N sub-ranges of the same size. Equal frequency binning divides the range of values into N bins, each holding the same amount of data.

$$\text{Bin width} = (\text{max\_value} - \text{min\_value}) / N$$

Both methods in Figure 4a and Figure 4b shows unsupervised methods. The discretization method ignores a significant source of information, namely class values of the training data. Figure 4c shows the supervised method, which is more efficient by only determining two intervals than three intervals, so the quality of supervised or unsupervised in the discretization method is essential for consideration [22].

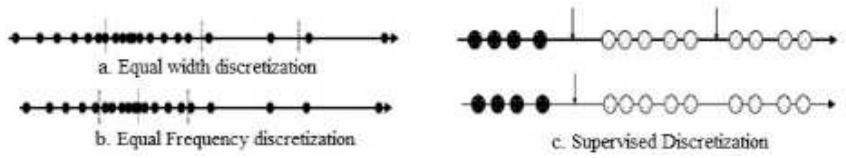

Fig.4 Discretization Method

In this study, the discretization process uses discretization based on the normal value range and equal frequency binning by dividing the range of values into several bins. The selection of this discretization method is appropriate for the characteristics of the data. The results of the data discretization process seem in table 3.

C. Modeling

The methods used in this classification modeling are decision tree and logistic regression. A decision tree is a popular classification algorithm in data mining studies and is easily interpreted by humans. The decision tree concept is to change the data in the form of a decision tree and decision rules [23]. To determine the shape of the decision tree, it can select several parameters. Classification prediction modeling attempts to develop a model in the form of a function that can mathematically map as closely as possible an input variable (x) to an output variable (y) [24]. Logistic Regression Algorithm is used to predict binary category (0 or 1). This prediction is made based on one or more features that become predictors where each feature will weight to generate predictions [25]. Logistic regression is a classification algorithm to find the relationship between discrete/continuous features (input) and the probability of certain discrete output results. Logistic regression is a special form of regression that is formulated to classify data into two groups (prediction group) and explain the dependent variable binary (categorical/non-metric). Logistic regression does not require the assumption of normality of the dependent variable. When the dependent variable is categorically binary, the distribution is binomial. Logistic regression does not require the assumption of normality of the independent variables [26]. In addition, the independent variables can be of metric or non-metric type. Unlike discriminant analysis, which can also be used to predict the binary dependent variable, logistic regression does not require checking the balance of the variance-covariance matrix between the two groups; logistic regression is preferred. In some classification methods with known group membership, multiple discriminant analysis and logistic regression are two statistical methods, different from algorithmic methods such as decision trees or support vector machines.

Random Forest and The Iterative Dichotomiser 3 (ID3) are decision tree-based classification methods. The basic concept of a decision tree is to create a rule model in the form of a tree from existing training data. Then the former model can be used to classify the new object. The ID3 algorithm splits the data into two groups based on the data attributes by measuring a number called entropy [27]. The lower entropy value indicates that the data group is getting more homogeneous. ID3 algorithm is the most basic decision tree learning algorithm. This algorithm performs a thorough search on all possible decision trees. Forming a classification tree with the ID3 algorithm goes through two steps: calculating the entropy value and calculating the information gain value of each variable. ID3 algorithm ID3 is the predecessor of the C4.5

algorithm. In simple terms, ID3 builds a decision tree from a fixed set of examples. The resulting decision tree is used to classify the sample to be used as a guide in the future. The leaf node of the decision tree contains the class name, while the non-leaf nodes are the decision nodes. A decision node is an attribute with each branch (to another decision tree) being a possible attribute value [28]. ID3 uses a feature selection heuristic to help it decide which attributes go into the decision node. The required heuristics can be selected by the criteria parameters. The ID3 algorithm attempts to generate a decision tree in top-down order.

The Decision tree that uses the ID3 method only generates one tree, while the Random Forest method produces many trees. Random forest is a classification method consisting of mutually independent classification trees (CART). The classification prediction is obtained through a voting process (the highest number) of the classification trees formed [29]. Random forests are the ensemble method's development used to improve classification accuracy. If in the bagging process bootstrap resampling is used to generate a classification tree with many versions and then combine them to obtain the final prediction, in random forests, the randomization process to form a classification tree is not only carried out for sample data but also for taking predictor variables. Thus, this process will produce a collection of classification trees with different sizes and shapes [30]. The expected result is a collection of classification trees with a small correlation between trees. A small correlation will reduce the prediction error of Random Forests [31].

D. Evaluation Model

After modeling, it is necessary to carry out the process of evaluating or validating the model. This process is needed to choose the best model. In this paper, the technique used to measure the model's performance uses a confusion matrix. The confusion matrix is in the form of a matrix table that describes the performance of the classification model on a series of test data whose actual values are known [32]. The confusion matrix has four different combinations of predicted and actual values. There are four terms representing the results of the classification process in the confusion matrix. The four terms are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The confusion matrix formed measures the model's performance, namely accuracy, precision, and recall.

Accuracy is the ratio of correct predictions (positive and negative) to the overall data. This figure illustrates how accurately the model can classify correctly. The precision value can be obtained by equation (1). Precision is the ratio of positive correct predictions to the overall positive predicted results. This figure describes the level of accuracy between the requested data and the prediction results provided by the model. The precision value can be obtained by equation (2). Recall is the ratio of true positive predictions compared to the total number of true positive data. This figure illustrates the success of the model in retrieving information. So, the recall value can be obtained by equation (3).

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$precision = \frac{TP}{TP + FP} \quad (2)$$

$$recall = \frac{TP}{TP + FN} \quad (3)$$

TABLE II
DISCRETIZATION RESULT

Attribute	Continuous Value	Category	Attribute	Continuous Value	Category
Age	20<=Age<40	Mature	CR	13,05>=CR< 210	Very High
Age	40<=Age<60	Old	CH	CH<98	Low
Age	Age>=60	Senior	CH	98<=CH<= 109	Normal
UR	UR<99,5	Low	CH	CH > 109	High
UR	99,5<=UR<135,5	Normal	KL	KL<3,5	Low
UR	135,5<=UR<183	High	KL	3,5<=KL<=5,1	Normal
UR	183<=UR< 432	Very High	KL	KL> 5,1	High
TR	TR< 150	Low	HE	HE <12	Low
TR	150<=TR< 450	Normal	HE	12<=HE<=14	Normal
TR	TR>=450	High	HE	HE>14	High
NA	NA<135	Low	HM	HM<37	Low
NA	135<=NA<153	Normal	HM	37<=HM<=43	Normal
NA	NA>153	High	HM	HM>=43	High
CR	CR< 6,85	Normal	LE	LE< 5	Low
CR	6,85<=CR< 9,9	Enough High	LE	5<=LE<=10	Normal
CR	9,9<=CR< 13,05	High	LE	LE> 10	High

III. RESULT AND DISCUSSION

After preprocessing, the next step is to build a classification model using the Random Forest, Logistic Regression, and ID3 algorithms. The results of the three models are evaluated by measuring the success of the classification results based on the Accuracy, Precision, and Recall parameters.

The distribution of training data and testing data with proportions of 70 and 30 and the results of modeling the training data with the ID3 algorithm obtained TP = 50, FP = 22, FN = 4, TN = 133 so that the value of accuracy = 0,97, precision = 0,96 and recall = 0,93. The results of modeling the training data with Logistic Regression obtained the value of TP = 21, FP = 15, FN = 22, TN = 120 so that the value of accuracy = 0,75, precision = 0,58 and recall = 0,39. The results of modeling the training data with Random Forest obtained the value of TP = 49, FP = 1, FN = 5, TN = 134 so that the value of accuracy = 0,97, precision = 0,98 and recall

= 0,91. Comparison of the performance of the three algorithms can be seen in table 3. The performance of the model on training data built using Random Forest and ID3 algorithm is better than Logistic Regression.

TABLE IV
CONFUSION MATRIX RESULTS OF TRAINING DATA AND TESTING DATA

Algorithm	Class	Training Data					Testing Data				
		Actual Result		Accuracy	Precision	Recall	Actual Result		Accuracy	Precision	Recall
		D	ND				D	ND			
ID3	Death (D)	50	22	0,97	0,96	0,93	28	1	0,98	0,97	0,97
	Not Death (ND)	4	133				1	52			
Logistic Regression	Death (D)	21	15	0,75	0,58	0,39	22	7	0,83	0,76	0,76
	Not Death (ND)	33	120				7	46			
Random Forest	Death (D)	49	1	0,97	0,98	0,91	28	1	0,98	0,97	0,97
	Not Death (ND)	5	134				1	52			

The results of the modeling of data testing with the ID3 algorithm obtained the value of TP = 28, FP = 1, FN = 1, TN = 52 so that the value of accuracy = 0,98, precision = 0,97 and recall = 0,97. The results of the modeling of data testing with Logistic Regression obtained the value of TP = 22, FP = 7, FN = 7, TN = 46 so that the value of accuracy = 0,83, precision = 0,76 and recall = 0,76. The results of the modeling of data testing with Random Forest obtained the value of TP = 28, FP = 1, FN = 1, TN = 52 so that the value of accuracy = 0,98, precision = 0,97 and recall = 0,97. The performance comparison of the three algorithms can be seen in table 4. The model's performance built on data testing using Random Forest and ID3 algorithm has the same accuracy, precision, and recall values and is better than Logistic Regression. The model's performance with testing data has increased slightly compared to the training data.

IV. CONCLUSION

Based on the test results, machine learning can classify the results of clinical pathology laboratory examinations in kidney failure patients into the proper category for detecting kidney failure, which causes the deterioration patient's condition. The Random Forest and ID3 algorithms have accuracy, precision, and recall values and are better than logistic regression. The Random Forest and ID3 algorithms, decision tree-based classification methods, have better performance than logistic regression. However, the ID3 algorithm is easier to read the results.

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