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Identification of Diabetes Mellitus Risk Factors With a Data Mining Classification Approach

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ABSTRACT

Diabetes mellitus is a chronic disease characterized by an increase in the frequency of eating, drinking and urinating due to the failure of the process of sugar entering the body to be converted into energy due to the pancreas function not being able to produce enough insulin or not producing insulin at all. The purpose of writing this paper is to test the accuracy of the decision tree and rules generated by the ID3 algorithm and correlate it with literature studies from research that has been carried out by researchers in the health sector related to diabetes and the results of this classification are expected to be used as a reference. For everyone to be able to change their lifestyle to avoid the risk of developing diabetes mellitus by looking at the attributes of the dataset. In this study, the application of data mining with the classification method with the ID3 algorithm using datasets from the BRFSS survey results was carried out. The results of data testing can be obtained from the accuracy of the rules generated by the ID3 algorithm with an accuracy rate of 85.95%. The rules generated by the ID3 algorithm are also correlated with the literature from research that has been carried out by researchers in the health sector, and the results are that the rules generated from the attribute indicators of the dataset have relevance and suitability

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1. INTRODUCTION

Diabetes is a chronic disease that is characterized by the level of sugar (glucose) in the blood at a level above the threshold of normal. According to the official website of the World Health Organization (WHO), worldwide, there are 422 people listed as people with diabetes mellitus. Low and middle-income countries are the largest contributors to diabetes mellitus cases, which results in about 1.5 million deaths annually [1]. Referring to the databox site, Indonesia is in the 5th place with the highest diabetes mellitus cases after the United States [2]. just like any other infectious disease. Other diseases have risk factors or causative factors that contribute to the cause of other diseases. Risk factor control efforts will be very helpful to reduce the fatality rate and prevent the risk of diabetes mellitus. Both controllable and uncontrollable factors are risk factors for diabetes. Ethnicity, gender, age, race, and family history of diabetes mellitus are risk factors that can be controlled. Excessive body weight, lack of physical activity, obesity, dyslipidemia, hypertension, unhealthy and unbalanced diet (eating more calories), smoking, and conditions in which the body has prediabetes characterized by impaired glucose tolerance (TGT 140-199 mg/di) or impaired fasting blood sugar (GDPT 140 mg/d) are risk factors that can be controlled. Complications such as heart disease, vision loss, lower limb amputations, and diseases related to the level of sugar remaining in the bloodstream for people with diabetes. Although there is no cure for diabetes, strategies such as losing weight, eating healthy, being active, and receiving medical care can reduce the risk of the disease in many patients. Early diagnosis can lead to changes in lifestyle and better treatment, so models that predict diabetes risk are an important tool for public health officials and the public.

Several previous studies on diabetes mellitus have been carried out, both in terms of health itself and the use of algorithms based on data mining. Researchers [3] did a diabetes classification study using backward elimination to improve the performance of an algorithm studied by KNN (K-Nearest Neighbor), C4.5, and Nave Bayes. They did this by using a test data set with 16 attributes from the Early Stage Diabetes Prediction Dataset. The dataset has 520 records with the results of the KNN algorithm having an accuracy of 97.6%, while the best AUC algorithm is C4.5 with an AUC value of 0.988. Research [4] conducted a study of the correlation between the level of knowledge about diabetes and lifestyle, in addition to patients in the hospital, a total of 47 people, by conducting the Chi Square test, with the result that from the sampling taken, the level of patient knowledge was less about diabetes and an unhealthy lifestyle, indicating that there is a correlation between knowledge about diabetes and an unhealthy lifestyle that has an impact on diabetes. Research [5] conducted a study in terms of factors of adherence in the diet process in patients with type 2 diabetes mellitus at the hospital. In this study, using a cross-sectional study method with a population of 57 respondents with type 2 diabetes, The results of the study were factors related to diet management for type 2 diabetes, namely age, gender, and family role factors. Research [6] conducted research based on the experience of diabetics to prevent wounds that did not heal, and in the end, people with diabetes developed diabetic ulcers. The objects studied were 3 patients and obtained 6 aspects, namely aspects of knowledge, aspects of clinical manifestations, aspects of etiology, aspects of risk factors, aspects of prevention, and aspects of family care. From this study, it was concluded that to prevent diabetic ulcers in diabetics, namely the use of herbal medicines, diet programs, and always using footwear to prevent injuries, What is different from the 4 studies as previously described ([3], [4], [5], [6]) is to identify diabetes risk factors with a data mining classification approach using the ID3 algorithm with Rapid miner tools. The data used is survey data from BRFSS in the form of correspondence data from 253,680. In total, there are 21 attributes/indicators in the survey and 7 attributes will be taken, namely Diabetes_binary as the main attribute, HighBP, High Chol, Smoker, Stroke, PhysActivity, and Sex.

In several studies regarding the use of algorithms for classification, the K-Nearest Neighbor and Nave Bayes algorithms have the highest accuracy. In research [7] on the classification of log firewall data, the results for decision trees are 100% accuracy value, K-Nearest Neighbor 99% accuracy value, and Nave Bayes 99%. In Research [8], in the study of classification on student performance, the results obtained a decision tree with an accuracy value of 78.85%, K-Nearest Neighbor accuracy value of 79.31%, and Nave Bayes 77.69%. Research [9] in a study to predict creditworthiness, obtained decision tree results with an accuracy value of 92.21%, K-Nearest Neighbor 81.82%, and Nave Bayes 81.83%. Research [10] in a study on the comparison of the 3 methods in the Jakarta water level report obtained the Decision Tree with an accuracy value of 96.56%, the K-Nearest Neighbor accuracy value of 95.98% and the Nave Bayes 94.32%. Referring to the 4 samples of the research results, the author's team decided the use of the Decision Tree should be applied in this study.

The purpose of this research is to generate decision trees and rules from the BRFSS survey dataset and to test the accuracy of the decision trees and rules generated by the ID3 algorithm and correlate them with literature studies from research conducted by researchers in the health sector. Everyone should be able to use the results of the dataset classification using the ID3 algorithm as a guide for making changes to their lives to avoid getting diabetes mellitus [11].

2. RESEARCH METHOD

2.1. Decision Tree

A decision tree is a specific decision rule organized into a tree structure (Gries & Schneider, 2010). A decision rule can be constructed from a decision tree by simply traversing any given path from the root node to any leaf. The complete set of decision rules generated The decision tree divides the document space into non-overlapping regions in its leaves, and predictions are made in each leaf (Gries & Schneider, 2010). The decision tree algorithm is formed based on the dataset. The divide and conquer approach is used to create a decision tree model using IG to select attributes from the dataset in the form of a tree (Lakshmi et al., 2016).

In the decision tree, there are two types of nodes: decision nodes and leaf nodes. Decision nodes represent features of the dataset and are used to make decisions. Leaf nodes are the output of the decision and contain no further branches [12].

The steps in the Decision Tree ID3 algorithm [13]:

1. Start by creating a root node or root.
2. If all samples are of class i, return a single root node tree with label = i
3. If the attribute set is empty, return a single root node tree with label = the most common target attribute value. A attribute, which is the best classifier (with the largest information gain), A decision attribute for the root for Vi (every A value). For example, add a branch under the root corresponding to the value of Vicreate a variable, for example, sample Vi as a subset of the sample set with the value Vi

on the attribute A. If sample Vi is empty, add a leaf node with label = value of the most common target attribute (which occurs most frequently) under this branch. Or else under this branch, add a subtree by calling function ID3 (Sample Vi, attribute target, Attribute-A).

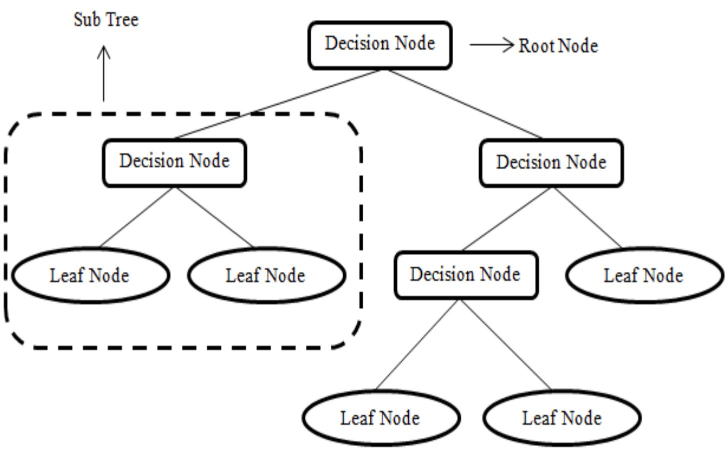

Figure 1. Decision Tree Concept

2.2. Dataset

The dataset used in this study is an open dataset from www.kaggle.com and contains survey results from the American Survey Institute's Behavioral Risk Factor Surveillance System (BRFSS), which contains data on diabetics and non-diabetics and their indicators [14]. This dataset contains more than 253,680 correspondences from 2015. The data is divided into several parts for training data and testing data. For train data, multiples of 5,000 records are made, starting from 5,000 records to 35,000 records, and the remainder will be used as test data. The initial data set is still in binary form, such as the sample data set in Table 1.

Table 1. Sample Dataset

Diabetes_binary	HighBP	HighChol	Smoker	Stroke	PhysActivity	Sex
0	10	0	10	0	0	0
0	10	10	10	0	10	0
10	10	10	10	0	0	0
0	0	0	0	0	0	10
10	0	0	10	0	10	10
0	10	10	10	0	0	0
0	0	0	10	0	0	0
10	10	10	0	0	0	0
0	0	10	10	10	10	0
0	10	0	0	0	10	0
0	10	10	0	0	10	0
10	0	0	10	0	10	10
0	0	0	0	0	0	0

2.3. Data Analysis

Data analysis is a process of collecting, selecting, processing, and converting data into useful information [15]. At this stage, using data mining techniques in processing data into information with the application of classification methods and the Decision Tree ID3 algorithm (Iterative Dechotomizer 3) [16] [15]. The stages carried out in data preprocessing include data cleaning to add the contents of empty or missing data attributes, changing inconsistent data and transforming data into the appropriate form or just what is needed for the data mining process. Then the next step is to reduce the data to eliminate any attributes that are not needed so that the dataset will be smaller in size and only the attributes that will be used in this study are included. Table 2 shows the data after preprocessing.

Table 2. Preprocessing Dataset

Diabetes_binary	HighBP	HighChol	Smoker	Stroke	PhysActivity	Sex
no diabetes	yes	no	yes	no	no	female
no diabetes	yes	yes	yes	no	yes	female
diabetes	yes	yes	yes	no	no	female
no diabetes	no	no	no	no	no	male
diabetes	no	no	yes	no	yes	male
no diabetes	yes	yes	yes	no	no	female

Diabetes_binary	HighBP	HighChol	Smoker	Stroke	PhysActivity	Sex
no diabetes	no	no	yes	no	no	female
diabetes	yes	yes	no	no	no	female
no diabetes	no	yes	yes	yes	yes	female
no diabetes	yes	no	no	no	yes	female
no diabetes	yes	yes	no	no	yes	female
diabetes	no	no	yes	no	yes	male
no diabetes	no	no	no	no	no	female

2.4. Research Stage

At this stage of research, the first step is to take the dataset from Kaggle that will be used, which is survey data from BRFSS in the form of correspondence data from more than 253,680 people and their attributes. Then, the data is cleaned up by choosing the attributes to use, figuring out how many data records to use for classification data mining with the ID3 algorithm, and testing the data. After the data is ready, the next step is to process it with the ID3 algorithm classification method to generate rules and decision trees. Then, the rule that was made will be tested with real data to see how accurate it is, and the results will be compared to research results from the health literature.

The stages of research carried out in the application of the Iterative Dichotomiser 3 (ID3) algorithm for the classification of diabetics and non-diabetics are as shown in Figure 2. [17]

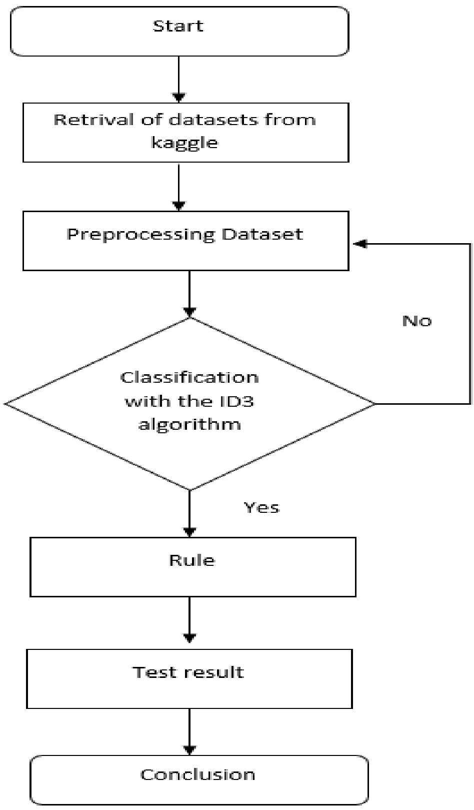

Figure 2. Research Stage

3. RESULTS AND ANALYSIS

This data will be processed by loading 7 main attributes that will have an impact on a person having diabetes or not. The 7 (six) attributes include Diabetes_binary as the main attribute, HighBP, High Chol, Smoker, Stroke, PhysActivity, and Sex. The dataset contains seven attributes that affect whether a person has diabetes or not.

Variable descriptions are given as follows:

1. Diabetes_binary : As a label that provides information on the condition of the respondent when the survey is carried out, whether he has diabetes or not.
2. HighBP: Is the respondent's condition high blood pressure or not?
3. High Chol: Is the respondent's condition high in cholesterol or not?
4. Smoker: Is the respondent a smoker or not?

5. Stroke: Has the respondent ever had a stroke or not?
6. PhysActivity: Did the respondent do any physical activity in the last month?
7. Sex: Indicates whether the respondent is male or female.

The results of testing the data set using 7 attributes and breaking the data set into seven data trains and 1 test data can be seen in the table 3

Table 3. Result accuracy data train and data test

Parameter Decision Tree	Parameter Value Decision Tree	Number of Dataset Train	Train Accuracy	Number of Dataset Testing	Test Accuracy
criterion, max depth	accuracy, 6	35000	64.40%	113680	64.60%
criterion, max depth	accuracy, 6	30000	63.54%	113680	64.60%
criterion, max depth	accuracy, 6	25000	64.40%	113680	67.50%
criterion, max depth	accuracy, 6	20000	67.32%	113680	67.50%
criterion, max depth	accuracy, 6	15000	67.32%	113680	68.30%
criterion, max depth	accuracy, 6	10000	68.09%	113680	70.13%
criterion, max depth	accuracy, 6	5000	69.92%	113680	85.95%

The results of the data set test can be concluded that the higher the train dataset that is submitted to the test data, the lower the accuracy and vice versa, the fewer train datasets, the higher the accuracy value. The highest accuracy value of 85.95% was obtained by using train data of 5000 records and test data of 113680 records, which were used as a reference for analysis.

Table 4. Highest Result Accuracy

Parameter Decision Tree	Parameter Value Decision Tree	Number of Dataset Train	Train Accuracy	Number of Dataset Testing	Test Accuracy
criterion, max depth	accuracy, 6	5000	69.92%	113680	85.95%

Based on the results of testing the ID3 decision tree algorithm on the dataset of diabetics and non-diabetics, the accuracy rate is 85.95%, and as a sample, the results of the ID3 algorithm are:

if HighBP = yes and HighChol = yes then diabetes (1370 / 681)
if HighBP = no and HighChol = no then no diabetes (272 / 885)

The rule obtained is that if a person has high blood pressure and high cholesterol, he is also likely to suffer from diabetes. quoting from halodoc, who said that the relationship between high blood pressure and diabetes may make sense because there are complications from diabetes that are already acute. In this case, it is not surprising that diabetics have a mortality rate from coronary heart attack of around 40%. These attacks are linked to a rise in blood lipids, which causes plaque to build up, and diabetes and high blood pressure may go together because their bodies work in similar ways [18].

According to Nita Garg's 2014 study, which found that average fasting blood sugar, cholesterol, triglycerides, and LDL cholesterol scores were higher in the diabetic group than in the non-diabetic group, and HDL cholesterol values were lower in the diabetic group. As compared to the non-diabetic group, there was a correlation between high cholesterol and diabetes. This research was conducted by Rahayu Anggraini. In fact, the cholesterol/HDL ratio and LDL/HDL ratio are substantially greater in diabetics than in non-diabetics [19].

if PhysActivity = yes and Sex = female then no diabetes (116 / 153)
if PhysActivity = no and HighBP = no then no diabetes (25 / 27)

Furthermore, the correlation between diabetes and physical activity refers to research conducted by Mala Azitha, Dinda Aprilia, and Yose Ramda Ilhami, stating that physical activity is one of the pillars in the management of diabetes mellitus because it helps maintain body fitness and increases insulin sensitivity. Physical activity can help glucose get into cells without the need for insulin. It can also help diabetics lose weight and slow the rate at which their glucose problem turns into diabetes mellitus.

if Smoker = yes and HighBP = yes then diabetes (263 / 194)

The link between smokers and diabetes mellitus comes from research done by Alya Azzahra Utomo, Andira Aulia R, Sayyidah Rahmah, and Rizki Amalia. They found that smoking can affect insulin sensitivity and that nicotine and other chemicals in cigarettes can make insulin less sensitive. Smoking can also raise hormone levels. Catecholamines in the body include adrenaline and noadrenaline [21]. The incidence of insulin resistance is also influenced by other possible pathways of exposure to tobacco, such as smoking during pregnancy or breastfeeding. Stopping smoking is one way to raise blood sugar and slow the start of type 2 diabetes.

if Sex = female and HighBP = yes then no diabetes (68 / 72)
if Sex = female and HighBP = no then no diabetes (82 / 113)

The correlation between gender and diabetes refers to the journal Journal of Health Kusuma Husada by Mildawati, Noor Diani, and Abdurrahman Wahid based on research results showing a relationship between gender and blood sugar levels (Allorerung, D.L., Sekeon, S.A., & Joseph, 2016). According to the findings in his research, female respondents were up to 2,777 times more likely to be affected than males by having type 2 diabetes mellitus. In this regard, pregnancy is a risk factor for the development of diabetes mellitus. Researchers have found that women are more likely than men to get type 2 diabetes mellitus. This is because hormonal processes like premenstrual syndrome, monthly cycle syndrome, and postmenopause make it easy for body fat to build up. This makes type 2 diabetes mellitus a problem for women [22].

4. CONCLUSION

The decision tree and rules generated from the classification method with the ID3 algorithm from the Behavioral Risk Factor Surveillance System (BRFSS) dataset, which contains data for diabetics and non-diabetics, by taking 7 attributes as indicators, have the highest accuracy rate of 85.95%. From these rules, it has been correlated with literature studies from research that has been carried out by researchers in the health sector that has conformity and relevance so that at least it can be used as a reference for attributing indicators as the cause of diabetes mellitus to change lifestyle and habits to avoid the risk of diabetes, such as doing physical activity and quitting smoking. The results of this study can still be developed with other methods and or using attributes that have been used in this study because a total of 21 indicators were used as indicators in this study, including aspects of health, aspects of physical activity, economic aspects, and aspects of daily food intake.

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