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Article

Type 2 Diabetes Mellitus Diagnosis Model Using the C4.5 Algorithm

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A B S T R A C T

Type 2 Diabetes Mellitus (DM) is a metabolic disorder characterized by elevated blood sugar resulting from decreased insulin secretion by pancreatic beta cells and/or impaired insulin function (insulin resistance). Over the last 50 years, there has been a rapid increase in the prevalence of diabetes, paralleling the rise in obesity rates. This study aims to develop a diagnostic model for type 2 DM using C4.5, incorporating feature selection and analyzing age and gender parameters of Type II DM patients. The research employs the Cross-Industry Standard Process for Data Mining (CRISP-DM). Based on the dataset used, the C4.5 model demonstrated superior performance compared to SVM and Random Forest, achieving an AUC value of 72.5%, indicating a reasonably good classification level. The predominant gender among Type II DM patients is female, comprising 210 patients or 54.8% in the age range of 18-94 years, while 173 male patients or 45.2% fall within the age range of 23-80 years.

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I. INTRODUCTION

Diabetes mellitus (DM) is defined as a chronic disease or metabolic disorder with multiple etiologies characterized by elevated blood sugar levels and disturbances in the metabolism of carbohydrates, lipids, and proteins, resulting from insufficient insulin function [1].

Type 2 diabetes is a condition in which blood sugar levels exceed the normal value due to insulin resistance. It is the most common type of diabetes, especially among adults. Under normal conditions, blood sugar levels are controlled within the range of 70-110 mg/dl, influenced by the insulin hormone produced by the pancreas. After eating, the absorption of food, particularly carbohydrates, in the intestines causes an increase in blood sugar levels. The elevated sugar levels stimulate the pancreas to produce insulin. Type 2 diabetes occurs as a consequence of insulin resistance, where the body's cells become immune or unresponsive to insulin. Insulin's function is to help cells absorb and convert sugar (glucose) into energy. As a result of insulin resistance, the pancreas must work harder to produce insulin, leading to potential damage over time. This condition causes a buildup of glucose in the blood, as insulin is the only hormone that can effectively lower blood sugar. Insufficient insulin is a key factor in the development of diabetes [2]. The hormone insulin is produced by the islet beta cells of the pancreas. The role of insulin is to ensure that cell tubules can utilize materials for burning. Insulin plays a role in opening the cell door so that materials for burning can enter the cells. When cells do not obtain materials for burning, the liver produces glucose (via glycogenesis or gluconeogenesis) and sends glucose into the bloodstream. This condition worsens hyperglycemia [3]. Several studies related to the diagnosis of diabetes mellitus have been conducted previously using the C4.5 method. Additionally, comparisons with other methods have also been carried out.

The C4.5 algorithm is a frequently used solution for solving technical problems in classification. The output from the C4.5 algorithm takes the form of a decision tree, similar to other classification techniques [4]. A decision tree is a structure that can be used to partition large datasets into smaller subsets by applying a series of decision rules. With each division in the series, the resulting subsets become more similar to one another [5].

For the solution case in the C4.5 algorithm, there are several known elements, namely: 1. Entropy, and 2. Gain. Entropy (S) is the estimated number of bits needed to extract a specific class (+ or -) from a random sample of data in space sample S. Entropy can be described as the number of bits required to represent a specific class. The smaller the Entropy value, the more it is used to extract a specific class. Entropy is used to measure the inauthenticity of S.

II. LITERATURES REVIEW

Data Mining

Data mining is an analytical process aimed at discovering patterns or significant information within large datasets. The main objective of data mining is to identify hidden relationships in the data, understand trends, and reveal knowledge that can be used for better decision-making. The data mining process involves the use of various techniques and methods to investigate and analyze data. Commonly used techniques in data mining include classification, clustering, regression, association, and anomaly detection. By applying these techniques, data mining can help identify patterns that may not be immediately apparent to humans.

In conclusion, data mining is an analytical approach that applies specific techniques and methods to discover patterns or information that provide in-depth insights into the available data [6].

Algorithm C4.5

C4.5 is a widely used algorithm for generating decision trees, a type of predictive model employed in machine learning. Developed by Ross Quinlan, the C4.5 algorithm is an extension of his earlier ID3 (Iterative Dichotomiser 3) algorithm. C4.5 is notably recognized for its effectiveness in classification tasks, aiming to assign a label or category to input data based on its features [7][8].

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Diabetes Mellitus

Diabetes mellitus, often referred to as diabetes, is a persistent metabolic disorder marked by increased blood glucose levels (hyperglycemia) due to deficiencies in insulin secretion, insulin action, or both. Insulin, a hormone produced by the pancreas, plays a vital role in the regulation of blood sugar levels [9].

Novelty in the context of this literature review is introduced by the involvement of Primaya Hospital Bekasi Utara. The novelty lies in the utilization of data extracted from Primaya Hospital Bekasi Utara in this research. Subsequently, a prototype is developed from this data to enable the early detection of diabetes, presented in an easily understandable format for the general public. This approach contributes to the advancement of healthcare solutions and promotes proactive disease management.

III. FRAMEWORK

Table 1. Research Framework for Type 2 Diabetes Mellitus using C4.5

Stage	Activities	Objectives
Business Understanding	☙ Interview with the Hospital Director, Medical Manager, and the person in charge of medical records. ☙ Observation of the medical record system to understand the recording of patients with type II diabetes mellitus.	☙ Identification of factors influencing the diagnosis of type II diabetes mellitus. ☙ Literature review to find references related to methods and solutions used in previous research.
Understanding	☙ Interviews with the Hospital Director, Medical Manager, and the person in charge of medical records. ☙ Data collection from the Primaya Hospital Bekasi Utara Information System.	☙ Determination of attributes to be used in the study. ☙ Understanding the characteristics of patient data with a diagnosis of type 2 diabetes from January 2020 to December 2021.
Data Preparation	☙ Data reduction on the type attribute. ☙ Data cleansing on attributes with missing values. ☙ Data transformation process for ages below 1 year.	☙ Obtaining a dataset for modeling purposes. ☙ Transforming the age attribute from months to years for patients under 1 year old ☙ Stratified random sampling to determine training and testing data. ☙ Exploration of preprocessing techniques, feature selection, and dataset composition to enhance model
Modeling	☙ Exploration of modeling using classification methods such as C4.5, Random Forest, and Support Vector Machine. ☙ Implementation of C4.5, Random Forest, and Support Vector Machine methods.	☙ Building a learning model using Python and the Flask framework. ☙ Selection of the model with the best performance for predicting type II diabetes mellitus.
Evaluation	☙ Using test data and 10-fold cross-validation as evaluation techniques. ☙ Using the confusion matrix to measure accuracy, precision, and recall.	☙ Assessing whether the model aligns with Business Understanding and ensuring no processes are overlooked.
Deployment	☙ Development of a predictive prototype for use by Primaya Hospital Bekasi Utara. ☙ Model implementation if it aligns with the evaluation.	☙ Evaluation of whether the model and attributes align with the initial goals of Business Understanding.

Table 1 details the steps in a data analysis project to predict the diagnosis of type II diabetes at Primaya Hospital Bekasi Utara. The stages involve business understanding through interviews, factor identification, and literature review. Subsequently, data preparation includes reduction and cleansing of data, along with attribute transformation. Model exploration utilizes classification methods such as C4.5, Random Forest, and Support Vector Machine, with evaluation using test data and 10-fold cross-validation. The deployment stage involves developing a predictive prototype for hospital

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use, assessing the model's alignment with initial business goals before implementation.

IV. METHODS

In this research, the method used is the CRoss Industry Standard Process for Data Mining (CRISP-DM). The methodology consists of six stages: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. The CRISP-DM method is considered a neutral technology, industry-independent, and constitutes the de facto standard for data mining. According to an online poll on KDNuggets in 2014, 45% of respondents chose CRISP-DM as the main method in data analysis, data mining, or other data science projects [10].

Business Understanding

In this stage, activities involve conducting interviews with the Hospital Director, Medical Manager, and the person in charge of medical records. The aim is to gather insights into the factors that can influence the diagnosis of type II diabetes mellitus, along with observing the medical record system to understand how the recording process is specifically conducted for patients with type II diabetes mellitus. The objective is to identify any issues that may arise. Following this, a literature review is conducted to find references related to methods and solutions implemented in previous research. The outcome of these stages leads to the formulation of research problems and study goals [11][12].

Data Understanding

After formulating the research problems and goals, the data collection process is initiated at this stage. To achieve this, interviews were conducted with the Hospital Director, Medical Manager, and the individual responsible for medical records to determine the attributes to be used in the study. The data was obtained from the Information System of Primaya Hospital, North Bekasi. The data utilized includes patient information diagnosed with type 2 diabetes mellitus from January 2020 to December 2021.

Data Preparation

The aim of this data preparation phase is to obtain the dataset that will be used in the modeling process. In the study, data preprocessing activities include data reduction on attribute types. Since all the missing values are treated, the subsequent step involves data cleaning on attributes marked as blank, achieved by deleting records in the dataset. Additionally, the data transformation process in this study involves changing the age attribute from months to years, specifically for patients under the age of 1 year. In this research, stratified random sampling was employed to determine both training and testing data. Various techniques for preprocessing, feature selection, and dataset composition are explored to enhance model performance.

Modelling

The dataset has undergone various pre-processing activities, and in the modeling phase, various classification methods were explored to obtain the best-performing model. In this stage, a learning model was created using the Python programming language and Flask frameworks, implementing the C4.5 method, which was then compared with the Random Forest and Support Vector Machine methods. This comparison was based on a preliminary study that had been previously conducted to obtain the best-performing model for predicting type II diabetes mellitus.

Evaluation

The evaluation of existing models has already been conducted in alignment with Business Understanding, ensuring that no steps were overlooked in the process. In this phase, test data is utilized along with the 10-fold cross validation technique and the application of a confusion matrix for evaluation. The parameters tested include accuracy, precision, and recall.

Deployments

After obtaining the attributes and their corresponding models in the initial stages, they will be further developed into a prototype for making predictions that can be used by Primaya Hospital North Bekasi as an evaluation tool. If the model is created in alignment with the

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business objectives discussed initially, the next stage involves implementation.

V. DISCUSSION

Data collection

The determination of attributes used in this study resulted from interviews with the Hospital Director, Medical Manager, and the person responsible for medical records. The data utilized comprises patient data diagnosed with type 2 diabetes from January 2020 to December 2021. A total of 16 attributes were identified, including Type, Age, Gender, Polyuria, Polydipsia, Polyphagia, decreased body weight, itchy skin, slow-healing wounds, fungal infections, genital irritation, weakness, dizziness, tingling/numbness, additional illnesses, and the Class attribute indicating the diagnosis. [13][14].

The data collection process resulted in 1191 records, with 806 (67.90%) belonging to the No DM potential class and 382 (32.10%) indicating individuals with a high potential for type II DM.

Data Preprocessing

The data obtained from the existing medical information system cannot be used directly due to the presence of other attributes and data that do not meet the conditions for use in the data mining process. To address this, Microsoft Excel is utilized to assist in the process. Additionally, the modeling phase is conducted using the Python programming language. Preprocessing activities in this study involve data reduction, data cleaning, and data transformation.

During the stages, data reduction is carried out by subtracting a number of attributes (dimensionality reduction) that are not utilized in the classification process of DM disease, as they hold a singular value. Specifically, the attributes Type and Fungal Infection are excluded from the process, where Type has consistent values across all data points, indicating the uniformity of this attribute. Consequently, the total number of attributes employed is reduced to 14.

The next stage involves data cleansing, specifically addressing data cleaning to address the presence of empty data in certain attributes, such as Dizziness, weakness, wounds that take a long time to heal, tingling, illness Supplements, and Diagnosis. Within the Diagnosis attribute, there were six patient records without known diagnosis results. Consequently, these six records were removed.

There are two missing values in the Dizzy attribute, one missing value in Weak, one in Old Wounds Heal, and one in Tingling. After consulting with the primary data source, the decision was made to fill these missing values with the value T, which is equivalent to No.

In the case of the Disease Addition attribute, there are 327 missing values. According to information from the source, an empty value in this attribute can be interpreted as the patient not having an additional disease. Consequently, the 327 missing values in the Disease Addition attribute were replaced with the value None.

Moving on to the next stage, which is data transformation. This involves transforming attributes such as Disease Addition, Age and transforming categorical attributes using the One Hot Encoding function.

The dataset attributes to be used are obtained through the process of data transformation:

Table 2. Dataset attributes used

Attribute	Type
Age	Numerical
Gender	Categorical
Polyuria	Categorical
Polydipsia	Categorical
Polyphagy	Categorical
BB Decreased	Categorical
Itchy Skin	Categorical
Old Wounds Heal	Categorical
Genital Irritation	Categorical
Weak	Categorical
Dizzy	Categorical
Tingling/Numbness	Categorical
Disease Addition	Categorical
Diagnosis	Categorical

The data obtained from the dataset, as shown in Table 2 below, involves the selection of attributes or data in stages to ensure the relevance of the data used in the classification process. Not all data is utilized, as the selected attributes serve as decisive information processed through data mining. Following the data selection, 13 attributes were identified, with 12 serving as predictors and 1 as the result

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used in this research. The method employed for data selection is Chi-Square, which is a statistical method used for feature selection involving independence tests and purposeful estimation to identify the dependency of a class on a feature.

Table 3. Selection Results Attribute

Attribute	Type
Age	Numerical
Gender	Categorical
Polyuria	Categorical
Polydipsia	Categorical
Polyphagy	Categorical
BB Decreased	Categorical
Itchy Skin	Categorical
Old Wounds Heal	Categorical
Genital Irritation	Categorical
Weak	Categorical
Tingling/Numbness	Categorical
Disease Addition	Categorical
Diagnosis	Categorical

After completing the data preprocessing, the subsequent step involves the identification of training and testing datasets. The available datasets were subjected to stratified random sampling to establish the distribution of the training dataset, which comprises 70% or 833 records, and the testing dataset, which accounts for the remaining 30% or approximately 357 records. The determination of the 70-30 split was based on experimental results from testing three algorithms. The accuracy results, as shown in Table 3, were used to determine the composition of the training and test data, selecting the combination that yielded the highest accuracy.

Table 4. Experiment Results Data Proportion 3 Algorithm

Data Proportion	C.45	Random Forest	SVM
60/40	73%	75%	68%
70/30	76%	74%	68%
80/20	72%	72%	68%

The proportions of training data and testing data are derived from the data presented in Table 4 as follows:

Table 5. Proportion of Training Data and Testing Data

Information	Training	Testing	Amount
Proportion	70	30	100
Amount	833	357	1191

Modelling

After completing the retrieval of testing and training data, a simple random method was employed for further modeling using the C4.5 algorithm implemented in the Python programming language. The general data was divided into training and testing datasets. The training data comprises existing data based on previously observed facts, utilized by the classification algorithm to generate new classes for predicting diagnoses. This model represents knowledge used for predicting new data classes, particularly the prediction of type II diabetes mellitus. The testing data is crucial for evaluating the success of the classification model in accurately classifying the data. It is essential that the testing data does not overlap with the training data to ensure the classifier model has performed well in classification. Overfitting, where a model performs well on training data but poorly on new data, is a common challenge. The obtained results from this model include label classes or diagnosis classes, with the diagnosis level categorized into two labels: potential DM II and no potential DM II.

Subsequently, an exploration was conducted using the Python programming language, comparing three algorithms: Random Forest, Support Vector Machine (SVM), and C4.5. This involved dividing the data into training and testing sets. The selected algorithms for comparison were chosen based on the top ten algorithms [15]. The results are presented in Table 5 below.

Table 6. Classifier Performance Comparison

Classifier	Accuracy	Precision	Recall	AUC
C4.5	76%	82%	82%	72.5%
SVM	63.3%	68%	68%	68.4%
Random Forest	71.7%	69%	69%	69.2%

Model Evaluation

The evaluation of the model, specifically the ROC measurement for the C4.5 algorithm, involves visualizing the calculation results through an ROC curve implemented in the Python programming language. The comparison of labels can be observed in Figure 1, which

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represents the ROC curve for the C4.5 algorithm. The curve, as depicted in Figure 1, illustrates the results of the ROC curve with an AUC value of 72%. The model, formed and tested based on these measurement results using the ROC Curve, indicates a performance exceeding 72%. This value signifies that the calculation results on the dataset fall within the very good category.

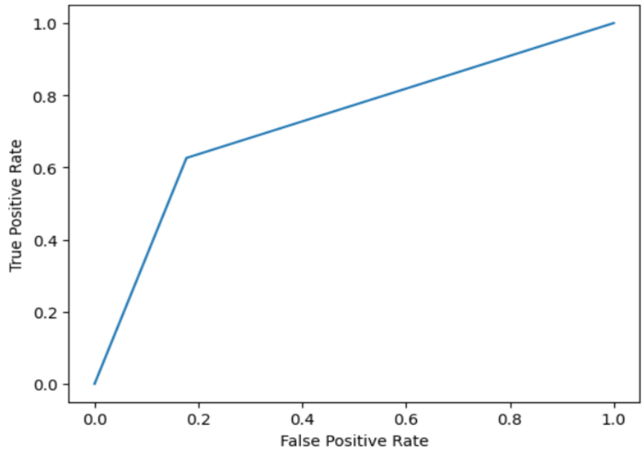

Figure 1. AUC values on Model C4.5

Figure 1 indicates that the classification results are deemed to be sufficiently good. Moreover, it measures the interest variable independently for patients based on the importance of marked features. The determination of feature importances is derived from calculating the information gain for each variable, with the information gain value being computed using entropy or a similar method from the resulting tree. The values for feature importance are elaborated in Table 7.

Table 7. Feature Importance

Variables	Value Feature Importance
Age	0.39354627
Disease Addition	0.30369030
Tingling/Numbness	0.08483967
BB Decreased	0.08101318
Gender	0.06710708
Weak	0.02962639
Old Wounds Heal	0.02879244
Polydipsia	0.00699509
Polyuria	0.00438958
Polyphagy	0.00100000
Itchy Skin	0.00100000
Genital Irritation	0.00100000

Based on the prediction results using the C4.5 algorithm, Table 8 presents the confusion matrix results to assess the accuracy, precision, and recall, which are found to be satisfactory. Therefore, further testing with a confusion matrix is conducted to validate the accuracy of the obtained results.

Table 8. Confusion Matrix

		Classified as	
		Type II DM	No potential DM
Label	Type II DM	200	43
	No potential DM	43	72

By manually calculating the confusion matrix results, including accuracy, precision, recall, and AUC, we obtained consistent results that align with the system's values.

Deployments

Based on the dataset used in this study, several insights have been gathered that can be valuable for internal hospital management in formulating policies related to Type II diabetes mellitus (DM) patients. Among the 383 patients with Type II DM, it was observed that the age range of patients varied from 18 to 94 years. The dominant gender among patients with Type II DM was female, accounting for 210 patients or 54.8%, while male patients totaled 173, constituting 45.2%.

Female patients with Type II Diabetes Mellitus are within the age range of 18-94 years, while male patients fall between the ages of 23-80 years. In the deployment stage, the research's simple model or prototype, developed using

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the Python programming language, was also elucidated. The subsequent section provides an explanation of the created prototype.

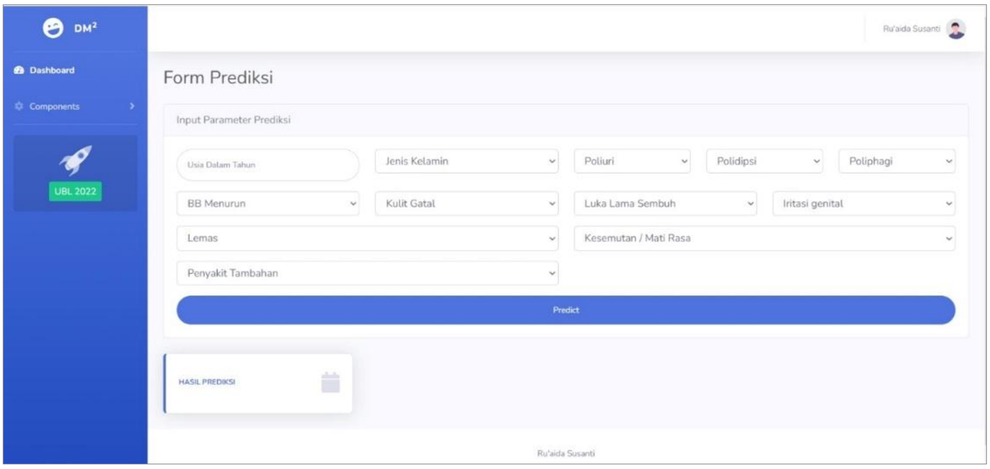

Figure 2. Display initial prototype

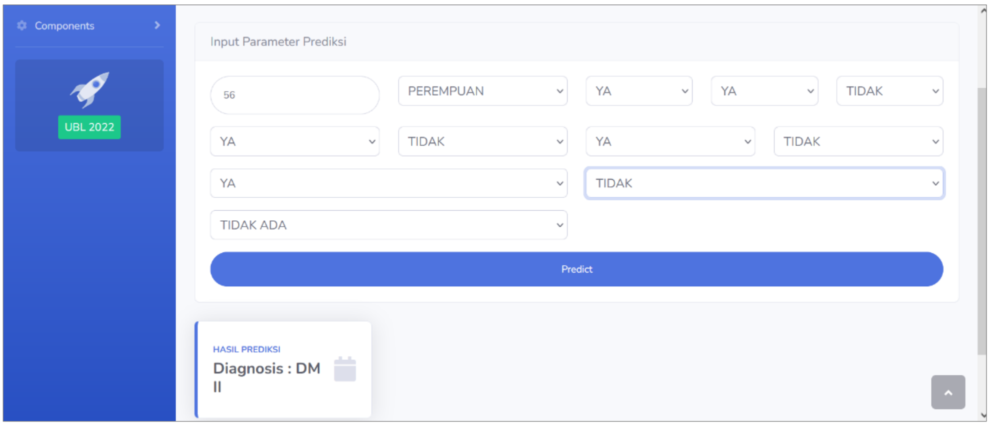

Figure 3. Example results classification of prototypes

VI. CONCLUSION

Based on the dataset used in this study, the C4.5 model demonstrates superior performance compared to SVM and Random Forest. With an AUC value of 72.5%, the model achieves a satisfactory level of classification accuracy.

In terms of the dominant gender, 210 out of 383 patients with Type II DM were women, accounting for 54.8%, and their ages ranged from 18 to 94 years. Meanwhile, male patients totaled 173, comprising 45.2%, with ages ranging from 23 to 80 years.

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