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Optimizing Chronic Kidney Disease Diagnosis Using the C4.5 Algorithm and Missing Value Imputation Strategies

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Abstract: The occurrence of missing values in data mining is a significant challenge that can hinder the knowledge extraction process. Incomplete data not only reduces efficiency in data management and analysis, but also has the potential to bias decision-making. This study aims to improve the performance of the C4.5 algorithm in dealing with missing value problems through the application of imputation techniques and GridSearchCV optimization. In this study, we propose an approach to handling missing values by combining several imputation methods, including minimum, maximum, mean-mode, median, and k-Nearest Neighbors (k-NN). These methods are applied to the Chronic Kidney Disease dataset obtained from the UCI Repository. After the imputation process, we performed hyperparameter optimization using GridSearchCV to find the best parameter combination for the C4.5 algorithm. Experimental results show that the application of imputation techniques and GridSearchCV optimization significantly improves the classification accuracy of the C4.5 algorithm. The comparison results show that the application of missing value handling, combined with GridSearchCV optimization, successfully improves the accuracy of the model by 2.25% compared to without using missing values. This proves that handling missing values along with proper GridSearchCV optimization can improve the prediction quality of the model.

Keywords: C4.5 Algorithm; GridSearchCV; Imputation; Missing value

Introduction

Chronic Kidney Disease (CKD) has become a pressing public health concern globally due to its increasing prevalence and severe clinical implications (Chen et al., 2019; Ma et al., 2020). According to Ogunleye & Wang (2020), approximately one in ten adults in the United States is expected to develop CKD, with the highest incidence among individuals over the age of 65. CKD is characterized by a gradual and irreversible decline in kidney function, commonly defined by a glomerular filtration rate (GFR) below 60 ml/min per 1.73 m² for at least three months. This condition significantly increases the risk of mortality and morbidity, particularly during the perioperative period, surpassing even other chronic conditions like diabetes and hypertension. Given its silent progression and late symptom onset, early and accurate diagnosis of CKD is essential to improve patient outcomes (Ogunleye & Wang, 2020). Traditionally, the diagnostic process for CKD relies heavily on physicians' clinical judgment, guided by symptoms and diagnostic test results (Chung et al., 2023). However, with the increasing number of patients and the complexity of medical data, there is a growing need for computational tools to support decision-making (Fay & Cohen, 2021). The integration of data mining techniques in healthcare, particularly classification algorithms, offers promising solutions for disease diagnosis (Simões e Silva et al., 2020; Surís et al., 2022). One such algorithm is C4.5, a decision tree

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method known for its ability to handle continuous attributes and datasets containing missing values. It has been successfully applied in diverse domains, including medical diagnostics, due to its interpretability and high accuracy.

Chronic kidney disease (Chronic Kidney Disease/CKD) is now increasingly considered one of the significant health problems worldwide. In the United States, an estimated one in ten adults will develop CKD, with the highest incidence found in the age group over 65 (Kalamas & Niemann, 2013). Patients with chronic kidney disease (CKD) have a high risk of experiencing significant morbidity and mortality during the perioperative period, even greater than other conditions such as hypertension and diabetes. CKD is characterized by a progressive and persistent decline in kidney function, with a glomerular filtration rate (LFG) of less than 60 ml/min per 1.73 m^2 of body surface area, and this condition must last for at least three months (Wati et al., 2019).

In general, a medical professional will collect information based on the symptoms experienced by the patient and the results of the diagnosis. The diagnosis process is generally carried out by analyzing the results of tests performed on patients or by referring to decisions that have been made previously for other patients who have similar test results. The accuracy of diagnosis for conditions such as diabetes, breast cancer, and others is highly dependent on the experience and expertise of the medical personnel (Meesad & Yen, 2003). As the number of patients rapidly increases, the process of making diagnostic decisions is becoming increasingly complex. However, advances in the development of new computing tools and methods allow for easier decision-making by utilizing patient electronic databases. To illustrate, various classification systems have been created to help diagnose diseases such as diabetes, cancer, and liver disorders. (Shanmugarajeshwari & Ilayaraja, 2023).

One method of classification is to use an algorithm Decision Tree that have been applied in various fields, for example in the field of medicine (Setsirichok et al., 2012), business field (Duchessi & Lauría, 2013) and failure detection (Sahin et al., 2013). In the health sector, one example of the application of Decision Tree is to predict the likelihood of breast cancer in patients (Cahyani & Muslim, 2020; Shanmugarajeshwari & Ilayaraja, 2023). C4.5 algorithm (Decision Tree) is a development of the Iterative Dichotomizer 3 (ID3) which is designed to address continuous variables as well as data that have value missing values (Ahmed & Salah, 2023; Ariyanti & Alamsyah, 2023). In a real-world database, missing values often arises as a result of unfilled attributes. The causes can vary, ranging from errors in the manual data entry process to tool errors or inaccurate measurements. Presence missing values Data mining can cause various problems in the knowledge extraction process, such as decreased efficiency and difficulties in data management and analysis. In addition, this can also lead to biased decisions due to differences between missing value and complete data (Purwar & Singh, 2015; Prabowo et al., 2024).

Chronic Kidney Disease (CKD) is increasingly recognized as one of the most critical global health concerns, affecting millions of individuals worldwide. According to Kalamas & Niemann (2013), one in ten adults in the United States is expected to develop CKD, with the highest prevalence among those aged over 65. The serious implications of CKD, which include high rates of perioperative morbidity and mortality often greater than those seen in conditions such as hypertension and diabetes highlight the urgent need for accurate and timely diagnosis. CKD is marked by a progressive and persistent loss of kidney function, and early detection is vital to slow its progression and reduce complications. However, the diagnostic process is often complex, relying heavily on the subjective expertise of medical professionals, which can lead to inconsistent or delayed diagnoses, especially as patient volumes continue to grow. The use of data-driven decision-making tools such as machine learning offers a promising solution to this challenge. By leveraging clinical data and intelligent algorithms, medical practitioners can improve diagnostic accuracy and efficiency. Moreover, the prevalence of missing values in medical datasets further complicates analysis and model performance, necessitating robust preprocessing strategies. Hence, addressing missing data and optimizing diagnostic models like C4.5 is not only a technical necessity but a clinical imperative to support reliable decision-making in CKD diagnosis. The results of this study can be used to develop a decision support system that helps in the decision-making process and the first step in the treatment of patients with chronic kidney disease. In addition, this research is expected to contribute to the development of science related to decision-making methods in the health sector (Wati et al., 2019).

Based on the research background and problem identification that has been described, the formulation of the problem (Research Question) in this study is to find out the extent to which the accuracy of the prediction produced by the C4.5 algorithm when applied to the dataset containing missing values, after preprocessing the data using various methods of handling missing value, namely imputation with the value Minimum, Maximum, Mean-Mode, Median, and k-NN imputation. In addition, this study will also explore the potential of GridSearchCV optimization in improving the performance of the C4.5 model on the imputed dataset.

The purpose of this study (Research Objective) is to evaluate the effectiveness of various missing value data imputation techniques in improving the prediction accuracy of the C4.5 algorithm in the diagnosis of chronic kidney disease. The imputation method applied includes replacement with Minimum, Maximum, Mean-Mode, Median, and k-NN imputation. By optimizing the data pre-processing process using the GridSearchCV technique, it is hoped that a more accurate and reliable prediction model can be obtained.

Method

Dataset Collection

The dataset used in this study comes from the UCI Repository, namely Chronic Kidney Disease / CKD which can be accessed at http://archive.ics.uci.edu/dataset/336/chronic+kidney+disease. The CKD dataset became available on July 03, 2015 and was retrieved by the researchers on December 11, 2024. This dataset was chosen because there are still few researchers who have conducted further research on CKD and the dataset also contains missing values which can be a problem during the classification process.

In Table 1, information about the dataset used in this study can be seen.The Chronic Kidney Disease (CKD) dataset consists of 400 entries. There is a total of 25 attributes, consisting of 14 categorical attributes and 11 numerical attributes. The number of missing values in this dataset reaches 1,012, which is classified as a significant number and has the potential to affect the classification results if not handled properly. This CKD dataset has two classes: the "ckd" class, which includes 250 entries of people with CKD, and the "nockd" class, with 150 entries indicating individuals do not have CKD. The distribution of classes in this dataset is shown in Table 2.

Table 1. Dataset used in experiments

Dataset	Number of Records	Number of Attributes	Number of Nominal Attributes	Number of Numeric Attributes	Missing Value	Sum Class
Chronic Kidney Disease	400	25	14	11	1012	2

Table 2. Class distribution on a dataset

Yes	Class	Number of Records	Information
1	ckd	250	Number of samples declared as people with chronic kidney disease
2	nockd	150	Number of samples declared not to have chronic kidney disease
Total Record		400	

After the dataset is obtained, it is then observed and calculated how many missing values in each attribute are displayed in Table 2. Table 2 describes the details of the attributes in the dataset including the unit, data type and number of missing values in each attribute. Then the dataset is divided into 2, namely 90% as training data and 10% as testing data.

Preprocessing

Sample Bootstrapping

Before applying various approaches to deal with missing values, the first step is to conduct sample bootstrapping, which is sampling from the original data using the sampling with replacement method. In this sampling technique, each element has an equal chance of being selected at every step. After the sample selection, the element can be re-selected in the next steps. Therefore, samples taken with replacement can include the same element more than once. Furthermore, this method allows for the creation of samples that are larger in size compared to the original dataset. The number of samples in the dataset can be determined either absolutely or relatively, depending on the settings of the sample parameters. In this study, the sample parameters used were relative to a ratio of 1.0.

Missing Value Approach

In this study, special handling is needed for datasets that have missing value. As already described, there are several strategies that can be applied to address this problem, including statistical methods that use data centering measures and machine learning-based approaches. This study uses the imputation method, which is to replace the missing value with the size of data concentration such as minimum, maximum, mean, mode (MC), median, and with the k-Nearest Neighbors (k-NN) technique.

Proposed Method

The methods proposed in this study are shown in Figure 3.1. The Chronic Kidney Disease (CKD) dataset obtained from the UCI Repository was then processed using the bootstrap technique, namely sampling with replacement, to produce bootstrap data. The number of datasets used is set by setting the relative parameters at a ratio of 1.0.

After completing the bootstrap stage, the dataset that still has missing values is then processed using the imputation method to populate these values. The first step is to implement imputation with a minimum value, where all missing values are replaced with the lowest value of each attribute, resulting in a complete new dataset. Next, the process continues by replacing all missing values using the maximum value of each attribute, resulting in a new dataset that is also complete. For numerical data, imputation is done with the mean, where the average value of each attribute is calculated and used to replace the missing value. Meanwhile, for nominal data, imputation with mode is applied to find the values that appear most often in place of missing values. Then, the median imputation is done by sorting all the values in the same class from smallest to largest and determining the middle value for each attribute. This middle value is used to replace the missing value in the data. In addition, the k-NN method with k = 3 is applied to fill in the missing value so as to produce a complete dataset. From these various imputation methods, after obtaining a new dataset that is ready for processing, the next step is to classify using the C4.5 algorithm. To optimize classification accuracy, the GridSearchCV technique will be applied by considering the gain ratio and average gain evaluation metrics. The final stage of this study is to comprehensively analyze and evaluate the classification results using a confusion matrix, focusing on the accuracy, precision, recall, and Area Under the Curve (AUC) metrics.

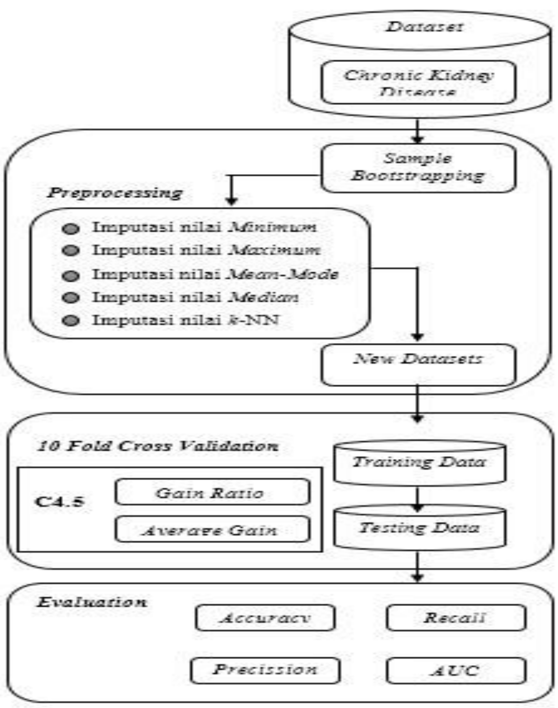

Figure 1. Proposed method framework

Result and Discussion

Experiments and Testing Methods

In the proposed method, the first step is to preprocess the Chronic Kidney Disease (CKD) dataset using the bootstrap technique. The bootstrap technique applied is sampling with replacement, which means that sampling the original data is done by returning it. In this way, the amount of data remains the same, but there are variations in the data due to sampling and return, which aims to estimate the standard error value in the dataset. For example, the calculation of the standard error value can be done using the formula 2.10, as will be explained below.

In the age attribute, a standard error value is obtained:

$$\text{ONE} = \frac{17.1691}{20} == 0.8584$$

In the blood pressure attribute, a standard error value is obtained:

$$SE = \frac{13.68364}{20} == 0.6841$$

The results of the standard error calculation in the CKD dataset are shown in Table 3 as follows.

Table 3. Standard error values in the CKD dataset

Attribute	Standard Error	
	Before Bootstrap	After Bootstrap
Age	0.858486	0.829621
Blood Pressure	0.684182	0.686361
Specific Gravity	0.000286	0.000280
Albumin	0.067634	0.065592
Sugar	0.054960	0.052190

Table 3 shows a comparison of the standard error values in the CKD dataset before and after the implementation of the bootstrap method. From this analysis, it can be concluded that the average standard value of error after implementing the bootstrap method is lower than before implementation, which indicates that the bootstrap method can be used as an effective alternative to estimate the standard value of errors in a dataset.

Table 4. C4.5 classifier measurement results on the CKD dataset

Imputation Method	TP	FP	FN	MR	Accuracy (%)	Precision (%)	Recall (%)
Minimum + Gridsearch CV	243	4	3	150	98.75	98.54	98.83
Maximum + Gridsearch CV	245	1	0	154	100	100	100
Mean-Mode + Gridsearch CV	246	0	1	153	99.00	99.00	98.50
Median + Gridsearch CV	244	6	2	148	98.44	98.48	98.98
k-NN + Gridsearch CV	245	1	0	154	100	100	100
Without Missing Value	246	1	0	153	97.50	97.50	97.50

Performance Measurement Results Method

After all stages of decision tree formation in each method are carried out, then the results of the method measurement based on the results of the confusion matrix, accuracy, precision and recall, and AUC curve are recorded. Table 4.2 shows a recap of the measurement results of each method against the C4.5 algorithm based on training and testing data as shown in Table 4.

Discussion

Comparison of Method Performance

This study examines the application of Decision tree in chronic kidney disease with a focus on handling missing value and parameter optimization using GridSearchCV. Data preprocessing is carried out using Minimum, Mean-Mode, and Median imputation techniques to overcome missing values. GridSearchCV optimization aims to find the best Decision tree parameters. This approach is expected to improve the prediction accuracy compared to the previous Bootstrap method which reached 97.50%, by optimizing preprocessing and model parameters.

This study evaluated the Decision Tree for the diagnosis of Chronic Kidney Disease (CKD) with a focus on handling missing value using GridSearchCV. Accuracy comparisons were performed against various imputation strategies: Minimum, Maximum, Mean-Mode, Median, k-NN, and no missing value. Maximum and k-NN achieve the highest accuracy (100%), better than other strategies (above 98%). These findings highlight the importance of choosing the right imputation method. Interestingly, the scenario without missing value actually shows an accuracy of 97.5%, indicating that proper imputation can improve model performance.

Figure 2 shows the accuracy comparison. The accuracy comparison diagram in Figure 2 shows that the GridsearchCV optimization method shows better accuracy compared to using only the Minimum, Maximum, Median and k-NN imputation methods.

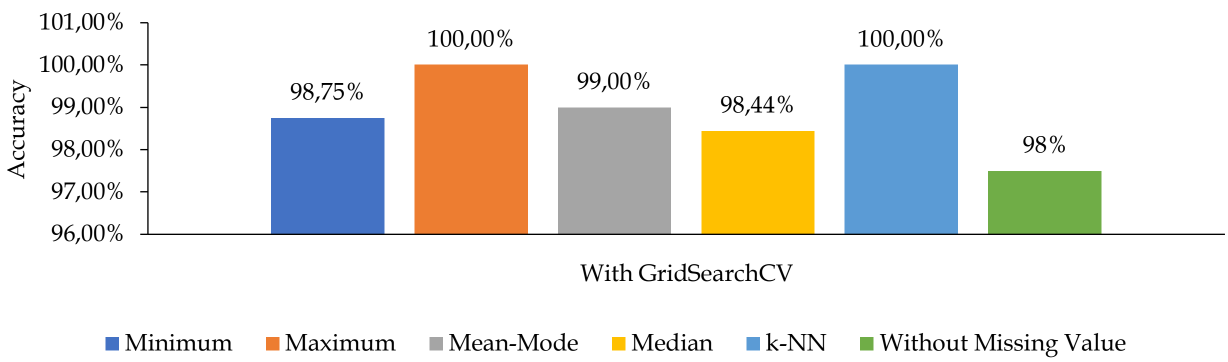

Figure 2. Accuracy comparison diagram

Improved Method Performance

Table 5 shows the performance improvement of the C4.5 classifier.

Table 5. Improved performance of the C4.5 classifier

Method	Increased Accuracy (%)
Minimum Imputation	1.25
Maximum Imputation	2.50
Mean-Mode Imputation	1.50
Median Imputation	0.94
K-NN imputation	2.50

Based on Table 5, the application of the imputation method improved the performance of the C4.5 classifier in chronic kidney disease (CKD) research. Imputation with maximum value and k-NN provided the highest increase (2.25%), followed by minimum value imputation (1.25%), mean-mode (1.50%), and median (0.94%). All of these imputation methods are better than without missing value handling, proving that imputation in data preprocessing is effective in improving C4.5 performance.

This study introduces a novel approach to enhancing the diagnosis of Chronic Kidney Disease by combining the strengths of the C4.5 decision tree algorithm with various missing value imputation strategies and optimization techniques. While the C4.5 algorithm has previously been applied in numerous domains, including medical diagnosis, its performance is often compromised by the presence of incomplete data—a common issue in real-world clinical datasets. What sets this research apart is its comprehensive evaluation of multiple imputation techniques, including Minimum, Maximum, Mean-Mode, Median, and k-Nearest Neighbors (k-NN) imputation, in conjunction with C4.5. Additionally, this study integrates GridSearchCV, a hyperparameter optimization method, to fine-tune the algorithm for maximum predictive accuracy after data imputation. Such a combined strategy has not been widely explored in the context of CKD diagnosis. Most prior research either focuses on algorithmic modeling without addressing the quality of the input data or applies limited imputation methods without optimization. By bridging this gap, the current study not only improves the diagnostic performance of the model but also offers a more generalized and robust approach to preprocessing incomplete medical data. This innovation has the potential to contribute meaningfully to the development of clinical decision support systems and advance the practical application of machine learning in healthcare (Prasad et al., 2019).

Conclusion

This study aims to evaluate the effectiveness of various imputation techniques in handling missing data in the C4.5 decision tree algorithm. Through the bootstrap approach, we impute missing values using the minimum, maximum, mean-mode, median, and k-Nearest Neighbors (k-NN) methods. By completing the dataset, we then applied the C4.5 algorithm to classify and compare the performance of each imputation method in producing an accurate and reliable model. The test results showed that in handling missing value, the best value was obtained by using the missing value imputation method using the maximum value and k-NN with GridSearchCV optimization. The performance of the C4.5 classifier increased by 2.25% compared to without the use of the missing value imputation method. Therefore, in this study, it can be concluded that the use of the missing value handling approach method with imputation techniques in data preprocessing accompanied by GridSearchCV optimization can improve the performance of the C4.5 classifier.

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The authors declare no conflict of interest.

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