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Diagnosing Chronic Kidney Disease using Decision Tree Classification model

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Machine Learning, Chronic kidney disease (CKD), University of California Irvine (UCI), renal failure, Accuracy, Precision and Recall.

ABSTRACT

Chronic kidney disease (CKD) is a health condition that happens when the kidneys can no longer filter toxins effectively from the blood. Also known as renal failure, CKD is a progressive and irreversible condition managed mainly through hemodialysis or kidney transplantation. Due to the several risk factors like food, environment and living standards many people get diseases suddenly without understanding of their condition. Diagnosing of chronic kidney diseases is generally invasive, costly, time-consuming and often risky. There is increasing interest in automated diagnostic systems powered by Machine Learning (ML). This paper presents Diagnosing Chronic Kidney Disease using Decision Tree Classification model. Dataset used for this study was collected from University of California Irvine (UCI) ML repository on early stage of CKD. This study focuses on developing a Decision Tree (DT) classifier for CKD diagnosis. Experimental results show that the described model achieved excellent performance, and obtains Accuracy as 97.5%, Precision as 97%, Recall as 97% and F1-Score as 96% parameters. These results demonstrate strong predictive capability and indicate that the model is highly promising for automated CKD detection

I. INTRODUCTION

The kidneys perform essential homeostatic functions, foremost among them the filtration of metabolic waste products and toxins from the bloodstream, concentrating them into urine for excretion. In addition to waste removal, the kidneys regulate fluid and electrolyte balance, maintain acid–base homeostasis, and produce hormones that regulate blood pressure and stimulate red blood cell production [1]. When kidney function is compromised, the loss of these functions may lead to accumulation of toxic metabolites, fluid overload, electrolyte imbalance, and other systemic disturbances ultimately jeopardizing health and survival.

Chronic Kidney Disease (CKD) is one of the types of kidney disease, which results in a gradual loss of kidney function. This phenomenon can be observed over a period of months or years due to several living conditions of patients [2]. Kidney disease has a symptoms of pain in abdominal only for normal person, but for sugar patients it is a silent killer, thus the symptoms and severity predominantly increases with time. Thus by detecting the abnormalities present in the kidney and to avoid a loss of life. The CKD is also called a chronic kidney failure where according current medical statistics the 10% of the population worldwide is affected by CKD. In recent times, the burden of CKD has increased dramatically, making it one of the fastest growing non-communicable diseases worldwide. According to the latest estimates from the global burden of disease study 2023 (GBD 2023), approximately 788 million adults (aged 20 years and older) globally were affected by CKD in 2023, more than double the ~378 million reported in 1990 (Mark et al., 2023).

According to the study of Renal disease, physiology study were conducted which is about the study of kidney functions and Nephrology is the specialties study about abnormalities of kidney and provide solution for the disease [3]. Kidney consists of various diseases such as kidney cysts, kidney tumor, acute kidney syndromes, nephritic syndromes, urinary tract infection, urinary tract obstruction and some other diseases are spreading widely. The glomerular filtration is used to measure the rate of kidney functioning and provide the solution for treatment options and also for kidney transplantation [4].

To deal with chronic kidney disease, it is important to carry the correct diagnostic process. Diagnosis plays an important role to perform a well-done treatment. Since patients with chronic kidney disease should obtain appropriate treatment according to the results of the diagnosis. If the diagnosis result is incorrect, the patient will obtain mismatch treatment. Hence, it is necessary to identify the causes and complications of chronic kidney disease in patients to improve the quality treatment [5].

The automated diagnosis of different diseases has attracted many researchers. ML algorithms can efficiently analyze large, multidimensional datasets, detect subtle patterns, and provide consistent, objective predictions. They enable risk stratification, early intervention, and optimization of healthcare resources. This study focuses on developing a Decision Tree (DT) classifier for CKD diagnosis. Finally it identifies the normal kidney and abnormal kidney of the patients by this automatic segmentation can save a loss of life. This paper achieves high diagnostic accuracy, much surpassing the performance of state-of-the-art models.

The rest of the article is sectioned as follows: Section II deals with literature survey, Section III explains the described methodology. Results and discussions are represented in Section IV and finally paper concludes with Section V.

II. Literature Survey

In [6] applied machine learning to medical records of patients with CKD and cardiovascular disease (CVD). First, we predicted if patients develop severe CKD, both including and excluding information about the year it occurred or date of the last visit. Our results show that our computational intelligence approach can provide insights about diagnosis and relative important of different clinical variables that otherwise would be impossible to observe.

In [7] explore the use of image registration methods for detecting renal morphologic changes in patients with CKD. From real and simulated dynamic time series, kidney deformation fields were estimated using a poroelastic deformation model. We found that the absolute deformation, normalized volume changes, as well as pressure gradients correlated significantly with arteriosclerosis from biopsy assessments. Image registration applied to dynamic time series correlated with structural renal changes and should be further explored as a tool for invasive measurements of arteriosclerosis.

In [8] presents an advanced methodology for early prediction of chronic diseases, including heart attack, diabetes, breast cancer, and kidney disease, leveraging a synergistic combination of cutting-edge techniques. We introduce a novel approach that begins with Feature Engineering using Recursive Feature Elimination (RFE) in conjunction with a Support Vector Machine (SVM). The proposed approach showcases a substantial improvement in the early prediction of chronic diseases, demonstrating the effectiveness of the proposed approach. In [9] describes a groundbreaking study of early CKD detection and progression tracking utilizing machine learning approaches applied to real-time clinical datasets. Predictive models are developed using a varied range of clinical tests and patient data to provide reliable insights into CKD development and progression. The proposed method effectively evaluates longitudinally gathered data by combining test findings with medical histories. This study improves machine learning algorithms' effectiveness for early CKD detection and progression monitoring by incorporating ensemble approaches.

In [10] presents early CKD recognition using the XGBoost algorithm, confirmed by cross-valuation and recursive feature reduction. Our work involves the integration of ML approaches-especially XGBoost-into CKD diagnosis and prognosis by means of enhanced accuracy in prediction and early intervention, therefore enhancing patient outcomes. In [11] introduces the idea of detecting the presence of kidney disease through machine learning based classification modelling, by processing the patient's ECG signal. Recent studies and ongoing researches have showed that patients undergoing kidney problems start developing cardiac problems- scientifically known as the Cardio Renal Syndrome (CRS) which can lead to a sudden cardiac arrest in the last stages of their disease. In our study, we found an accuracy level of 97.6% which was the highest using both features QT and RR interval, in comparison to the accuracy that was found when either one of the features was used.

III. Diagnosing Chronic Kidney Disease using DT

The workflow of described model of Diagnosing Chronic Kidney Disease using Decision Tree Classification model is shown in Figure 1.

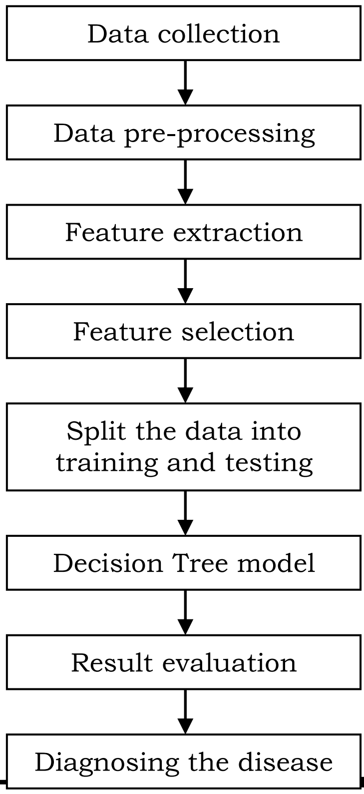

Figure 1. Workflow of Diagnosing Chronic Kidney Disease using DT

Dataset used for this study was collected from University of California Irvine ML repository on early stage of CKD. The dataset contains 24 features which include demographic, clinical and laboratory information. A total of 400 subjects were included where 250 were cases of CKD and 150 were the controls. The features include age, sugar, hypertension, diabetes mellitus, coronary artery diseases, blood pressure, appetite, pus cell, red blood cell, specific gravity, red blood cell count, hemoglobin, sodium, pedal edema, anemia, pus cell clumps, bacterial, packed cell volume, potassium, white blood cell count, serum creatinine, albumin, blood urea and blood glucose random

Preprocessing the data before it is fed into classifiers is vital part of developing machine-learning model. Similarly, the dataset for this study contains missing values that needs to be handled appropriately. It has to also be in a suitable format for modeling. Removing outlier and smoothening noisy data is an important part of preprocessing.

In this paper, feature extraction using principle component analysis. Principal Component Analysis (PCA) is an unsupervised statistical technique used to reduce the dimensionality of large datasets, increasing interpretability while minimizing information loss. It transforms potentially correlated variables into a smaller set of uncorrelated variables, called principal components, which capture the maximum variance in the data.

Feature selection is crucial to develop chronic kidney disease predictive model. This reduces the dimensionality and complexity of the data and makes the model be faster, more effective and accurate. Hence, feature selection algorithm have been used to select relevant features after the construction of the dataset. With wrapper method, relevant features are selected using the classification algorithm.

In the next step image data is divided into two sets as Training set and Testing set. Splitting dataset into 80%

for training set and 20% for testing set. In the next stage, classification task is performed using decision tree model.

A decision tree is a supervised algorithm for learning in classification problems that works both for specific and continuous variables. It uses a tree-like graph or model of decisions alongside the possible consequences based from it. It is an algorithm that shows conditional control statements. Its nodes contain a “test” on a certain feature, and the branches are the test outcome. Then the exact output or results are evaluated by using performance metrics such as Accuracy, Precision, Recall and F1-Score.

IV. Result Analysis

This section presents the performance of Diagnosing Chronic Kidney Disease using Decision Tree Classification model. For evaluation of our model, we have used several evaluation metrics such as Accuracy, Precision, Recall and F1-Score and these are described as follows:

Accuracy: It refers to the proportion of correct guesses to total predictions. Equation 1 represents the Accuracy parameter.

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

Precision: It’s a fraction of closely predicted positive observations and total predicted positive values observed. Precision parameter is represented in below equation 2.

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

Recall: It is also known as sensitivity and is a fraction of correct predicted positive values to total actual values (positives). Representation of Recall parameter is shown below equation 3.

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

F1-Score: It is a measure for finding the test’s accuracy. F1 score is function (i.e., weighted average) of recall and precision. Equation 4 shows F1-Score parameter.

$$\text{F1} - \text{Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Where, True positive (TP) is the where the model correctly predicts the positive instance. False negative (FN) is the outcome that appears negative when it is supposed to be not. It can be reiterated as the number of incorrect predictions for negative situations. False positive (FP) is the outcome that produces positive result when it should be negative. True negative (TN) is the total number of correct predictions given a number of negative instances.

Comparative Performance of described Diagnosing Chronic Kidney Disease using Decision Tree Classification model is represented in below Table 1. In comparative analysis, we considered Chronic kidney disease detection using described Decision Tree (DT), Random Forest (RF) and K-Nearest Neighbor (KNN) in terms of Accuracy, Precision, Recall and F1-Score.

Table 1: Comparative performance analysis

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RF	91	90	91	90
KNN	88	87	89	89
DT	97.5	97	97	96

Figure 2 represents the Accuracy parameter comparative analysis for described Diagnosing Chronic Kidney Disease using DT, RF and KNN. X-axis represents the classification models and Y-axis represents percentage of parameter value. From figure 2 it is clear that accuracy of described model is high compared to other models.

Comparative performance analysis of Precision parameter for described Diagnosing Chronic Kidney Disease using DT, RF and KNN is represented in below Figure 3, in which Y-axis shows the percentage value and X-axis denotes classification models. Precision parameter of DT model is high than RF and KNN models.

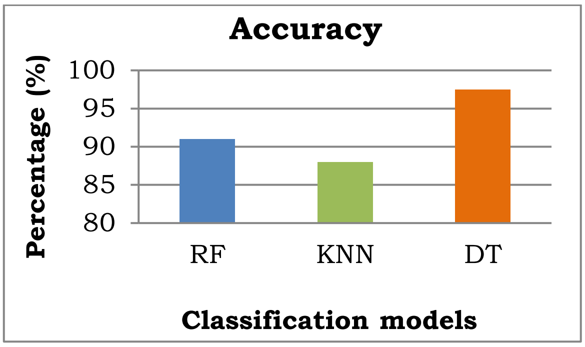

Figure 2. Comparative analysis for Accuracy parameter

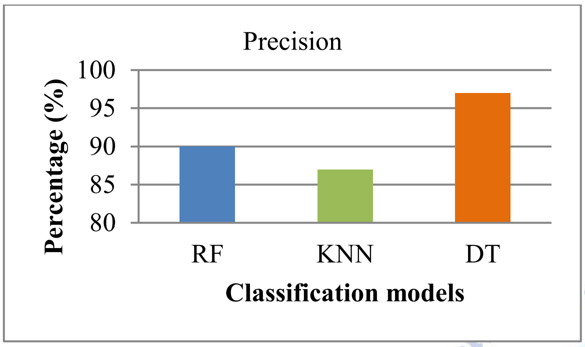

Figure 3. Comparative analysis in terms of Precision parameter

Recall parameter comparative analysis graphical representation is shown in Figure 4. X-axis represents the classification models and Y-axis represents percentage value. DT model achieves high recall value than other two models.

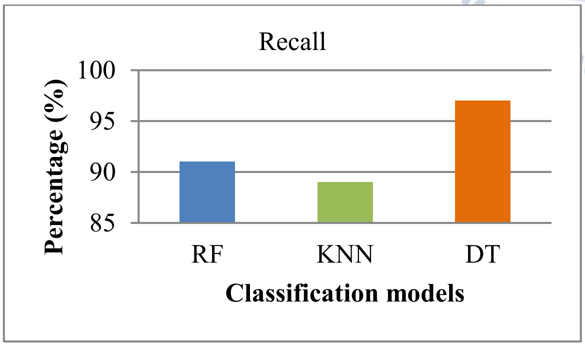

Figure 4. Recall parameter Comparative analysis

Figure 5 shows the graphical representation of F1-Score parameter in which models are declared in X-axis and Y-axis denotes the percentage of parameter value. F1-Score value of described DT is high compared to other models.

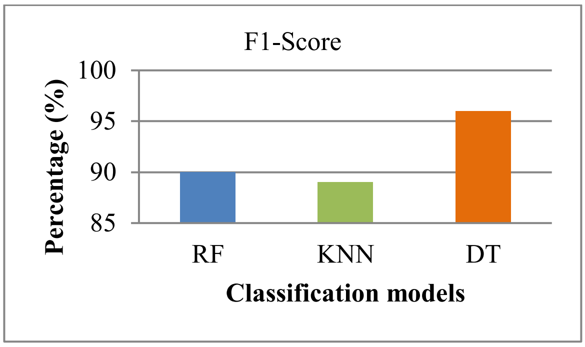

Figure 5. F1-Score parameter Comparative analysis

Therefore from overall results, described Diagnosing Chronic Kidney Disease using Decision Tree Classification model is efficient in terms of Accuracy (97.5%), Precision (97%), Recall (97%) and F1-score (96%) than other models.

V. Conclusion

In this paper, Diagnosing Chronic Kidney Disease using Decision Tree Classification model is described. Kidneys filter the wastes and excess blood fluids from the blood and then excreted in the urine. Diagnosis plays an important role to perform a well-done treatment. This study uses a Decision Tree (DT) classifier for CKD diagnosis. Dataset used for this study was collected from University of California Irvine ML repository on early stage of CKD. Splitting dataset into 80% for training set and 20% for testing set. We have used several evaluation metrics such as Accuracy, Precision, Recall and F1-Score. Therefore from overall results, described Diagnosing Chronic Kidney Disease using Decision Tree Classification model is efficient in terms of Accuracy (97.5%), Precision (97%), Recall (97%) and F1-score (96%) than other models.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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