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Computational Intelligence Approaches for Prediction of Chronic Kidney Disease

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Abstract. Over the past few decades, it has been observed that there is a growing interest in the area of intelligence systems, such as Machine Learning. Machine learning has been extensively used in order to support medical specialists and clinicians in the help of forecast and diagnosis of various diseases. The aim of this study is to compare the performance of six supervision-based Machine Learning techniques, which are used in the prediction and detection of the chronic kidney disease outbreak. Machine learning techniques are used to solve clinical problems and medical diagnosis' which have recently been developed. Hence, it is essential to have a framework that can instantly recognize the prevalence of kidney disease in thousands of samples. This research uses the chronic kidney disease dataset that contains 400 Kidney patient's data including 25 parameters. Moreover, we evaluated the performance of six supervision-based machine learning classification techniques, which are: KNN, Support Vector Machine, Decision Tree, Random Forest, Naïve Bayes and Logistics Regression. The performance of the supervised machine learning classification techniques was validated with sensitivity, specificity, f1 measure and accuracy. In this experiment, NB and RF outperformed, they were found to be at 100% accuracy, whereas the DT achieved 98% accuracy. Moreover, the KNN, SVM, LR classification techniques achieved 96% accuracy. Our findings showed that both the Random Forest and Naïve Bayes classification techniques outperformed as compared to other classification techniques used to predict kidney disease of the patients tested. In summary, our study has emphasized the research trends and scope in relation to Chronic Kidney Disease and as well as clinical research areas by machine learning techniques, which have had an effective impact in biomedical fields.

Keywords: Classification, Kidney Disease, Machine Learning, Computational Intelligence, Prediction

1 Introduction

The term "chronic kidney disease" is a disease that occurs slowly and has an impact on the Kidney functions over a long period of time. Generally, Chronic Kidney Disease (CKD) is defined as the damage of the kidney and it happens when the kidney cannot efficiently purify the blood. Thus, the impairment of kidney is a very unhealthy condition where the organ stops its daily processes inside the human body. In this stage, it is clinically considered to be end stage renal disease (ESRD) [1]. As a matter of fact, this chronic disease is getting widespread and comprehensively, CKD is a cause of death globally [2]. This damage usually occurs by the kidney's failure. A report published by American Kidney Fund, mentions that people are mostly in danger from kidney disease which is often the cause of other existing medical conditions such as (i) diabetes, (ii) hypertension, (iii) cardiovascular heart disease, (iv) having a family member affected with kidney disease, (v) more than 60 years of age, (vi) obesity [1]. As a result, kidney disease can increase the risk of malfunction and sabotage of different organs.

In terms of risk, there are 5 phases of kidney damage in CKD for example i) eGFR > 90 [phase 1], ii) eGFR between 60 and 89 [phase 2], iii) eGFR between 30 and 59 [phase 3], iv) eGFR between 15 and 30 [phase 4], v) eGFR < 15, end stage of kidney damage [phase 5] [3]. In the above 5 phases, phase 5 is the last stage of the kidney disease which occurs when the kidney(s) are getting close to completely stop functioning in the human body. Generally, in phase 4, prior to last stage of kidneys failure, the kidney(s) are not functioning properly and are close to injured in Phase 3. The minor problem happens for kidney disease in phase 2 and typically there are no symptoms of kidneys damage in phase 1.

Generally, kidney failure is recovered by dialysis or a kidney transplant. In terms of medication, dialysis care is a particularly complicated task and different factors may manipulate patient survival [4]. Moreover, the cost of kidney dialysis and diagnosis is very high and may be a financial burden on the patient because kidney disease is chronic in nature and takes a long time for recovery [5]. Due to this, most of the patients cannot afford the cost of the cure for kidney disease. Furthermore, chronic disease prediction is the most prominent matter for clinical practitioners and medical service centers in order to make accurate decisions about such a disease. The focus of this study is primarily concerned with the performance analysis of disease prediction methods using various variants of supervised machine learning algorithms. Prediction of disease in a wider sense, that medical field has recently allocated considerable attention from the data science research community in current years. It is mainly because computer-based technologies have been widely adapted in numerous health sectors and a large database for researchers have subsequently been available.

Therefore, machine learning is an extensive platform, which can solve these kidney disease problems through early prediction and detection. This kind of process is able to improve early diagnosis of kidney disease to patients. To date, machine learning classification techniques have created a significant impact and obligation in the chronic disease research society for early detection of kidney disease [6]. Moreover, machine learning algorithms are given more accurate results in chronic disease prediction as compared to others data classification techniques [7, 8, 9, 20, 21]. Previous studies have already shown that the supervision-based classification techniques have obtained excellent accuracies in the field of disease prediction including gait biomechanical patterns analysis [10, 11, 12, 13, 14, 23]. Motivated by these studies, the authors have used six popular machine learning techniques for early detection of CKD by prediction in order to provide proper treatment for CKD patients. Hence, our study can be a significant approach for predicting the kidney disease outbreak using machine learning algorithms. The findings of this study will assist scholars to better understand and formulate their research goals using supervised machine learning algorithms to better understand current trends and hotspots of disease prediction models. The remainders of this study are ordered as follows, the materials and methodology are described in section 2. The performance as a result is illustrated in section 3. Finally, the conclusions and viewpoints for future research are presented in Section 4.

2 Materials and Methods

2.1 Experimental Methodology

This section presents our designed workflow for machine learning application on the dataset of CKD, through different classification techniques. The outperform machine learning model will be approved for the predictive application. Details workflow for machine learning application is presented in figure 1.

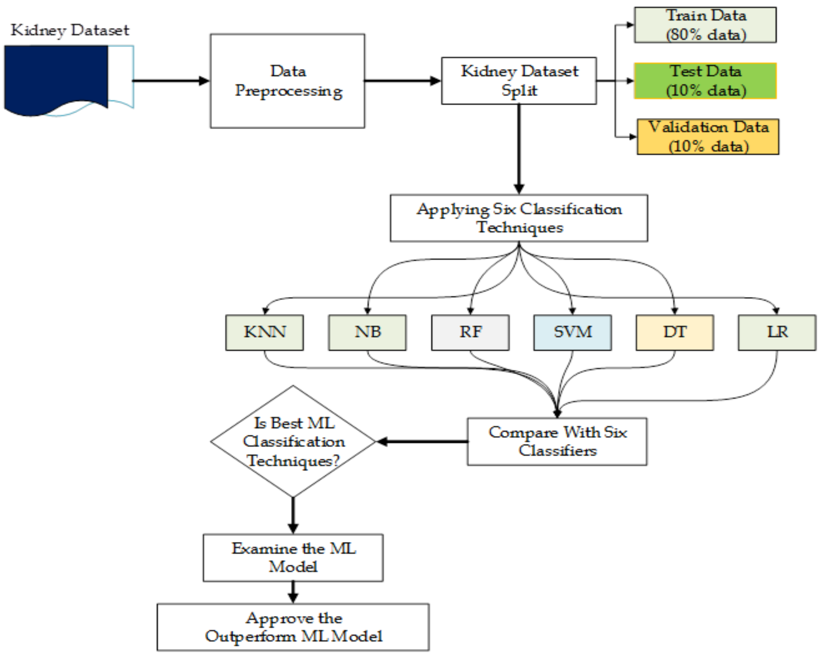

Figure 1. Workflow for Machine Learning predictive model.

2.2 Data Collection

In this study, we used 400 kidney patient's data as a dataset, which is provided by the University of California, Irvine (UCI Machine Learning Repository). In addition, this dataset was created originally by the Apollo Hospitals, Managiri, Madurai Main Road, Karaikudi, Tamilnadu, India [15]. The dataset consists of 26 parameters (11 parameters are numerical, 13 are nominal, 1 parameter removed and 1 as targeted class) which are presented in Table 1.

Table 1. Features and description about datasets

No	Attributes	Indication	Description
1	Age	Numerical	Years
2	Blood Pressure	Numerical	Mm/Hg
3	Specific Gravity	Nominal	1.005,1.010, 1.015, 1.020, 1.025
4	Albumin	Nominal	0, 1, 2, 3, 4, 5
5	Sugar	Nominal	0, 1, 2, 3 ,4, 5
6	Red Blood Cells	Nominal	Normal or Abnormal
7	Pus Cell	Nominal	Normal or Abnormal
8	Pus Cell Clumps	Nominal	Present or Not Present
9	Bacteria	Nominal	Present or Not Present
10	Blood Glucose Random	Numerical	Mgs/dl
11	Blood Urea	Numerical	Mgs/dl
12	Serum Creatinine	Numerical	Mgs/dl
13	Sodium	Numerical	mEq/L
14	Potassium	Numerical	mEq/L
15	Hemoglobin	Numerical	Gms
16	Packed Cell Volume	Numerical	Gms
17	White Blood Cell Count	Numerical	Cells/cmm
18	Red Blood Cell Count	Numerical	Millions/cmm
19	Hypertension	Nominal	Yes or No
20	Diabetes Mellitus	Nominal	Yes or No
21	Coronary Artery Disease	Nominal	Yes or No
22	Appetite	Nominal	Good or Poor
23	Pedal Edema	Nominal	Yes or No
24	Anemia	Nominal	Yes or No
25	Targeted class	Nominal	CKD or Not CKD

2.3 Data Preprocessing

Firstly, we removed the 'Id' parameter from the dataset because it is an impractical parameter for classification methods. Secondly, we found 'ckd\t' in a targeted parameter within this dataset. This 'ckd\t' value seems to show incorrect values so we replace it by 'ckd' value. Therefore, we set the target factor value 'ckd' as 1 and 'notckd' as 0 in order to get the good performance of machine learning algorithms.

Missing value (figure 2) in the dataset is another factor which was removed in order to get a better result. Hence, we used dropna () function to remove all rows with missing values. After cleaning the missing value, there are 158 samples for further analysis in this study. Though the number of samples is reduced but the consistency is increased for the classification model. Moreover, we checked and found a few wrong values for certain parameters in the dataset, and we input correct values accordingly. Then we checked the correlation among 25 parameters of the CKD dataset, in order to verify the similarities among them. Finally, we did not find any correlation among the 25 parameters of the CKD dataset which are presented in figure 3.

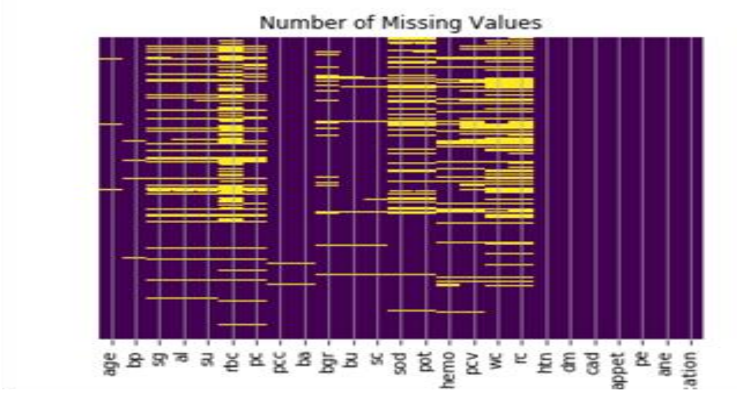

Figure 2. Number of missing values in CKD datasets

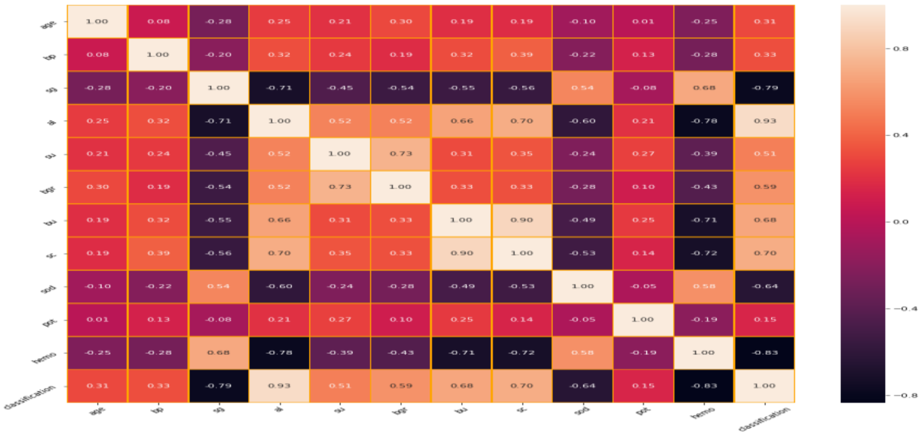

Figure 3. Heat map for checking correlated columns in CKD

2.4 Performance Measurement Benchmark

In this study, we used six machine learning techniques for the early detection of CKD. Therefore, the performance measurements of the classifiers are appraised by different statistical methods, such as confusion matrix (True Positive, False Positive, True Negative, and False Negative), Recall, Precision, f1- measure, and accuracy. These statistical methods are well known and are a reliable approach for the performance measurement of different classifiers [16]. Details of the statistical methods applied in this study are following:

True Positive (TP): Prediction results are true and the patient has CKD.
True Negative (TN): Prediction results are false and the patient does not have CKD.
False Positive (FP): Prediction results are true but the patient does not CKD.
False Negative (FN): Prediction results are false and the patient has CKD.
The computation method of the measurement considerations are as follows,

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

$$\text{Sensitivity or Recall} = \frac{TP}{TP+FN} \tag{2}$$

$$\text{Specificity or True Negative Rate} = \frac{TN}{TN+FP} \tag{3}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{4}$$

$$\text{f1} = \frac{2 * (Recall * Precision)}{(Recall + Precision)} \tag{5}$$

$$\text{False Positive Rate} = 1 - \text{Specificity} \tag{6}$$

2.5 Software and Tools

This work was implemented by Python version 3.7.0 and using Jupyter Notebook. We used several machine learning libraries to analysis this kidney dataset. For example- NumPy, scikit-learn, pandas, matplotlib, seaborn, and plotly.

3 Results and Discussion

This section deliberates the experimental performance results of our analysis of different classification techniques. We conducted different analyses to evaluate the six machine learning classification algorithms for diagnosis and prediction of CKD. The classification performance among six machine learning classifiers for kidney disease prediction is shown in Table 2 and figure 4.

Table 2. Performance analysis among six classification techniques

	KNN	NB	RF	SVM	DT	LR
Classification Accuracy	0.96	1	1	0.96	0.98	0.96
Precision	1	1	1	1	1	1
Sensitivity	0.95	1	1	0.95	0.97	0.95
f-1	0.97	1	1	0.97	0.98	0.97
Specificity	1	1	1	1	1	1

For predicting chronic kidney disease, six computational intelligence techniques were examined for classification using sample dataset of chronic kidney disease. Here, NB and RF outperformed than the other classification techniques in terms of accuracy by obtaining the highest accuracy as 100%. The DT performed better accuracy (98%) compare ton KNN, SVM and LR. The lowest accuracy (96%) is observed in the classification techniques of KNN, SVM and LR. Additionally, NB and RF performed better results in terms of precision, sensitivity, f-1, and specificity compared to other classification techniques. These results indicate that the NB and RF classification techniques are highly appropriate for early detection of kidney disease in patients.

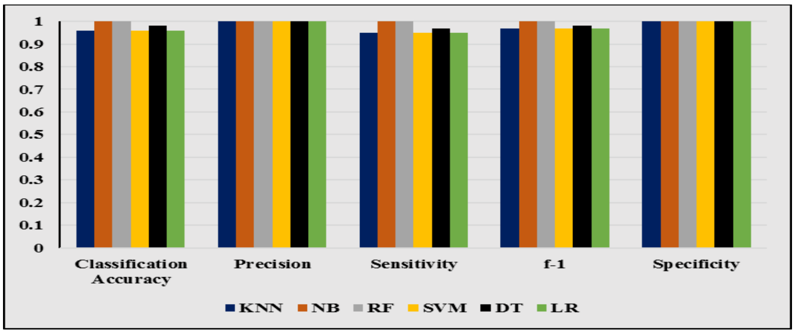

Figure 4. Performance of six supervised classification techniques

Moreover, the TP, FP, TN, and FN are calculated using confusion matrix in order to analyze the performance among six machine learning classifiers. The details result of the confusion matrix on TP, FP, TN, and FN are shown in figure 5. Results indicated that the TP as utmost (35) and FP as lowest (0) level were found among all measurement parameters of the confusion matrix, for our six classification techniques. Beside this, the FN is zero (0) and TN is thirteen (13) were found for the classification techniques of NB and RF. Hence that NB and RF classification techniques predicted the highest number of kidney patients.

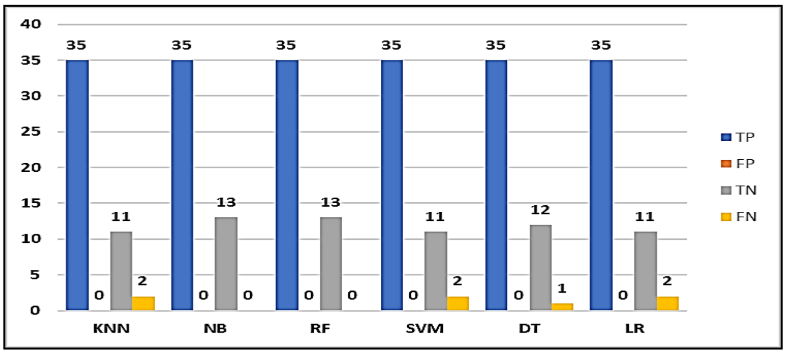

Figure 5. Confusion matrix of six ML classifiers

Many researches have been applied to different machine learning techniques with CKD datasets for early prediction of kidney disease. For example, studies [17-22] used the CKD dataset which is also used in our present study. The study [17] has used DT and NB machine learning techniques for kidney disease prediction. In their study, they found accuracy 91% and 86% for DT and NB, respectively and concluded that the DT has achieved the best performance as compared to NB, for predicting kidney disease. The other study [18] has used WEKA data mining tool to examine accuracy for prediction of CKD. The authors have compared the six machine learning algorithms, i.e. DT, NB, Multilayer Perceptron, SVM, J48, Conjunctive Rule. In their experiment, Multilayer Perceptron (99.75%) have achieved the best performance among the other classifiers. In addition, the accuracy of DT, NB, J48, Conjunctive Rule are mostly similar (i.e. 99%, 95%, 99%, 94.5%, respectively), whereas SVM (i.e. 62%) performed poorly. The study [19] observed the performance between KNN (i.e. 99.3%), RF (i.e. 99%) and NN (i.e. 0.985), according to the F1 measure. As per their investigation, performance of the all classification techniques are remarkably brilliant. In another study [6], they have used four machine learning techniques for their predictive analysis and found in respect to the accuracy, LOGR (98.1%) and MLP (98.1%) achieved the best performance whereas the performance is quite good in RPART and SVM (i.e. 95.6% for RPART and 95% for SVM). Moreover, Abdelaziz A et al. [22] have analyzed kidney disease using a hybrid machine learning model and they have shown the accuracy of machine learning model in forecasting CKD as

97.8%.

All the above studies mentioned, have used CKD datasets in their experiment to evaluate the performance of various machine learning algorithms. In their work, they have used different techniques and tools for data preprocessing that's why performance sometimes shows different results in the same datasets. Here, we have considered six supervised based classifiers to our study. Thus, the performance of classifiers shows the accuracy level above 95% for kidney disease prediction. With respect to the accuracy and F1 measure, NB and RF achieved the highest accuracy among the other classifiers. Our findings indicated that the performance of these classification techniques is excellent for kidney disease prediction. Thus, it is very important to know about the receiver operating characteristics (ROC) curve in order to find the best classification technique among six classification techniques that have been used in this study. Usually, the ROC is generated based on true positive rate (TPR) and false positive rate (FPR) [6]. The ROC curve, as a result of this study, is presented in figure 6. According to the ROC curve result, SVM, RF and LR outperform than other classification techniques in Kidney Disease for prediction.

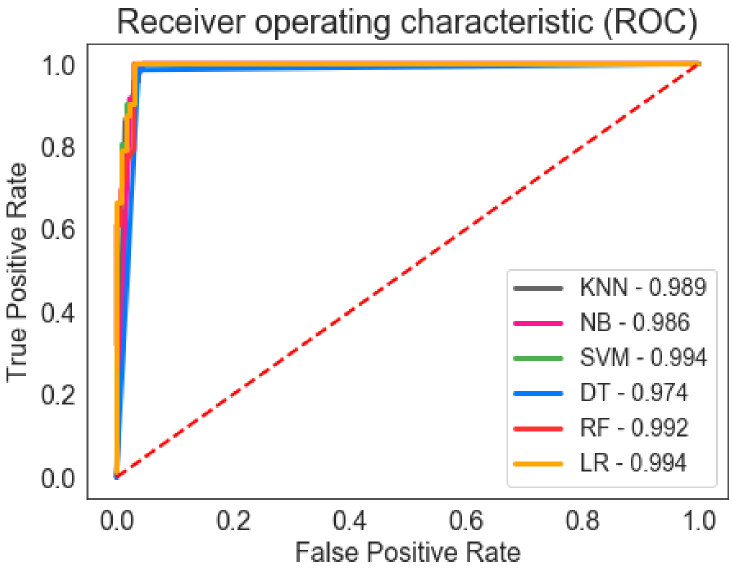

Figure 6. Receiver Operating Characteristics curve for kidney datasets.

4 Conclusion

A Chronic kidney disease prediction, in its early stages, is important for diagnosis and treatment. This investigation has provided a workflow on machine learning based decision support systems for the early prediction of CKD disease. First, we compared the performance of the six classifiers which are used in the prediction of chronic kidney diseases based on different parameters. Secondly, we used the statistical test to investigate the performance of the difference classification techniques. Then, we proposed a predictive model that has the purpose to develop a computerized tool to give more precise treatment to normal events and make a superior decision to complex situations. This application tool can be able to detect the kidney damage in its any stages with extreme likelihood of having kidney disease. Future work will be used to evaluate the reliability of our application by different diseases of the proposed model in health care system applications.

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