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Evaluation of Machine Learning Models in the Prediction of Chronic Kidney Disease

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Abstract

Chronic Kidney Disease is a progressive condition that affects millions of people worldwide, often leading to kidney failure if not detected early. The early prediction of chronic kidney disease using machine learning models can significantly improve patient outcomes through timely intervention. This study evaluates the performance of various machine learning models, including Logistic Regression, Decision Tree, and Random Forest in predicting the presence of chronic kidney disease based on patient data. A dataset consisting of clinical features indicators was used for training and evaluation. The models were assessed based on accuracy, precision, recall, and F1-score. The results of this study showed that Random Forest outperformed the other models, although all models employed in the prediction demonstrated great accuracy in predicting the disease. This study demonstrates the potential of machine learning models in healthcare to aid in the early diagnosis of chronic kidney disease, thereby improving patient management and reducing the burden on healthcare systems. Further research should focus on integrating these models into clinical workflows for real-time prediction.

Keywords: kidney, diagnosis, models, healthcare, prediction, failure

1. Introduction

Chronic kidney disease (CKD) is a condition that occurs when the kidneys become damaged and can no longer filter blood effectively (Chittora *et al.*, 2021). Primary job of the kidneys include filtering out extra fluid and waste from the blood to create urine (Caon, 2016). Invariably, individuals with chronic kidney disease (CKD) have excess of waste products clogging their body. Chronic kidney disease represents a significant public health challenge, impacting millions globally and leading to increased morbidity and mortality (Schoolwerth, 2006). There are 177.4 million men and 210.1 million women living in low- and middle-income countries, among the 387.5 million individuals with this disease (Khalid *et al.*, 2023). Despite these alarming figures, the disease has continued to gain ground (Tuttle *et al.*, 2022). Due to the illness's obscure patterns in the early stages and patient abnormalities, it is imperative to concentrate on early detection to give patients the right treatment and prevent further deterioration (Levin & Stevens, 2011). Addressing the challenges in predicting chronic kidney disease is critical for improving early diagnosis and treatment outcomes, thereby enhancing the quality of healthcare delivery and supporting better health outcomes for affected populations. Integrating machine learning models serve as a potential solution for improving the accuracy of chronic kidney disease prediction and diagnosis (Padmanaban & Parthiban, 2016; Shon *et al*., 2020; Supriya & Deepa, 2020; Chandra & Kapil, 2022). With its ability to evaluate large quantity of data, as well as identify patterns difficult for human healthcare practitioners to discern, machine learning algorithms appear to have wide applicability even in the field of medicine. It operates in different phases, ranging from the stage of data collection to the stage of model comparison (Alowais *et al*., 2023). For accurate classification and prediction, datasets are employed for training or learning mathematical functions or rules (Rabby *et al*., 2019). Individuals suffering from chronic kidney disease experience an accumulation of waste products in their bodies due to impaired kidney function, which can precipitate serious complications, including cardiovascular diseases and strokes (Ubaid *et al*., 2022). Symptoms often manifest as nosebleeds, vomiting, nausea, a lack of appetite, and difficulty sleeping (Sanyaolu *et al*., 2018). As this disease does not usually show symptoms until the kidneys are severely damaged, early detection and treatment are pertinent to its control (Locatelli *et al*., 2002). Early detection will allow timely and prompt treatment for kidney disease to prevent the occurrence and improve treatment (Nordheim & Jenssen, 2021). This chronic ailment has a steady death rate due to its progressive nature over an extended period, it is frequently believed to be a worldwide illness (Roca *et al.*, 2015). People with chronic kidney disease have gone without effective therapy for generations. Currently, the only treatments available for the chronic renal disease are kidney dialysis and transplants (Ibitoba *et al.*, 2024). Therefore, as new technologies are progressively incorporated into CKD research, cutting-edge solutions are needed to reduce fatalities in CKD patients in the present era (Luyckx *et al*., 2019). An important use of the modern-day intelligent systems has been seen in the processing of data using machine learning (Alowais *et al*., 2023). This is crucial towards acquiring comprehension of symptom data and revealing details concealed in copious patient medical records, which physicians frequently acquire from patients to execute precise therapy regimens (Aslinda *et al*., 2020). Recent studies, such as the hybrid model presented by Khalid *et. al.* (2023), have reported striking results, achieving 100% accuracy in forecasting renal illness. However, the model's lack of correlation analysis between input variables raises critical questions about its findings' interpretability and practical applicability. Without a thorough examination of the relationships between the variables, the accuracy of the results may be misleading, limiting the model's utility in clinical settings (Sen *et. al*., 2017). Existing literature emphasizes the importance of feature selection based on CKD biomarkers to optimize model performance. For instance, Luyckx *et al*. (2019) examined this concept's application to chronic disease prognosis, utilizing sophisticated feature selection tools to extract disease data from databases. The study employed various techniques, including link-based feature selection, folder feature selection, and minimal collapse, ultimately achieving an impressive accuracy of 96.86% using an L2-regularized least squares support vector machine (LSVM). Halder *et al*. (2024) developed a smart web app to assist in predicting the status of the presence of chronic kidney disease. It is automated to accurately and quickly diagnose kidney illness at different stages and make predictions about the condition. Also, binary and multiclass classification has been used in chronic kidney disease predictions, where various algorithms were employed in conjunction with cross-validation and analysis of variance to select features (Debal & Sitote, 2020). Overall, existing literature provides valuable insights into the application of machine learning models in predicting chronic kidney disease. However, there are common limitations across these studies, such as the inadequate focus on the relationships between variables influencing CKD progression. This study aims to evaluate the application of machine learning algorithms in the prediction of kidney disease. Therefore, the objectives of this research include i) Assessing the performances of these algorithms in the prediction of chronic kidney disease, and ii) Comparing the performance of these machine learning algorithms in chronic kidney disease prediction.

2. Methods

This section discusses the detailed procedure for the development of machine learning classifiers in the prediction of chronic kidney disease for the evaluation of their performance and comparison of their results.

2.1 Research Design

This study utilized a quantitative approach to analysis in carrying out the research. The steps followed are:

i. Data Collection
ii. Data Preprocessing
iii. Data Analysis
iv. Feature selection
v. Model development
vi. Model Evaluation and Comparison

2.2 Data Collection

The dataset utilized for this study was obtained from the publicly accessible Kaggle platform, ensuring credibility through its established licensing for open research use. This dataset contains key medical features relevant to predicting the likelihood of chronic kidney disease in patients. The data underwent standard pre-processing to maintain quality and reliability for this research.

2.3 Data Preprocessing

Before model development, the dataset underwent extensive preprocessing to ensure its quality and readiness for analysis. Missing values were handled through imputation techniques, and outliers were examined and treated to reduce their impact on model performance. Additionally, the data was normalized or standardized where necessary to bring all features onto a comparable scale. Categorical variables were encoded into numerical formats, allowing them to be used in machine learning algorithms. This preprocessing step was essential to prevent biases and inaccuracies during model development.

2.4 Data Analysis

The data was explored to understand its structure, distribution, and relationships among variables. Descriptive statistics, including means, medians, and standard deviations, were calculated for continuous variables, while frequency distributions were examined for categorical variables. Subsequently, correlation analysis was performed to identify relationships between medical features and the target variable (presence of chronic kidney disease). This step helped in assessing feature importance and potential multicollinearity among predictors. Data visualization techniques, such as histograms and box plots, were employed to identify outliers and understand the distribution of features.

These analytical processes laid the groundwork for effective feature selection and model development, ultimately enhancing the robustness and reliability of the machine learning classifiers used in this study.

2.5 Feature Selection

Feature selection is a critical step in enhancing model accuracy and reducing overfitting by identifying the most significant medical features relevant to chronic kidney disease prediction. In this study, correlation analysis and recursive feature elimination were applied to determine the most predictive variables. The selected features were found to have a strong correlation with chronic kidney disease and contributed significantly to the performance of the classifiers.

2.6 Model Development

The selected algorithms for this study are logistic regression, decision tree and random forest. These models were trained using the processed dataset, with parameters fine-tuned using techniques like cross-validation to ensure optimal performance. Each algorithm was selected for its ability to handle non-linear relationships, class imbalances, and its interpretability in clinical contexts. The data is split in the ratio 80:20 for training and testing purposes.

2.7 Model Evaluation and Comparison

The evaluation of machine learning models is crucial in understanding their effectiveness in predicting chronic kidney disease based on the selected medical features. In this study, several performance metrics were utilized to assess and compare the classifiers, specifically focusing on accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of model performance, especially in the context of medical diagnoses where false negatives and false positives can have significant implications.

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

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

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

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Where:

TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

3. Results and Discussion

Table 1 displays the distribution of patients with and without chronic kidney disease. The analysis reveals that 62.5% of the patients do not have chronic kidney disease, while 37.5% do. Specifically, this translates to 150 patients diagnosed with CKD and 250 without it. Understanding this distribution is crucial as it helps set expectations regarding model performance in predicting CKD.

Table 1. Analysis of Target Variable

Target Variable	**Percentage(%)**	**Number of people**
CKD (Present)	37.5	150
CKD (Absent)	62.5	250

From Table 2, it is evident that while the random forest model achieved a remarkable 100% accuracy across all metrics, both the logistic regression and decision tree models also demonstrated strong performance, with accuracies of 94% and 93%, respectively. The high performance of all models indicates that they are effective tools for predicting chronic kidney disease. The random forest's superiority, however, highlights its potential for clinical applications, as it can provide more reliable predictions, thereby supporting timely interventions for patients at risk of CKD.

Table 2. Evaluation and Comparison of Model Performance

Model	**Accuracy**	**Precision**	**Recall**	**Fi-score**
Logistic regression	0.941667	0.906170	0.916667	0.926316
Decision tree	0.925400	0.933333	0.875000	0.903226
Random forest	1.000000	1.000000	1.000000	1.00000

4. Conclusion

This study successfully developed and evaluated several machine learning models to predict chronic kidney disease (CKD). The analysis revealed that all models, including logistic regression, decision tree, and random forest, demonstrated strong predictive capabilities. Notably, the random forest model achieved perfect accuracy across all evaluation metrics, showing its effectiveness as a predictive tool in clinical settings. These findings highlight the potential for machine learning algorithms to enhance early detection and intervention strategies for CKD, ultimately improving patient outcomes.

5. Recommendations

To enhance research on the application of machine learning algorithms in predicting kidney disease, the following recommendations are proposed:

i. Data Collection: Ensure access to high-quality, diverse medical records that include patient demographics, medical history, and lab results. A large and representative dataset is essential for effectively training machine learning algorithms.

ii. Interpretability: Develop machine learning models that are interpretable and provide insights into the factors influencing kidney disease predictions. Validating these models on external datasets will confirm their performance and generalizability.

iii. Collaboration with Healthcare Professionals: Engage with nephrologists and other healthcare professionals to validate model predictions and ensure clinical relevance.

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