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A Comparative Analysis of Machine Learning and Deep Learning Approaches for Prediction of Chronic Kidney Disease Progression

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Abstract

Chronic kidney disease is a significant health problem worldwide that affects millions of people, and early detection of this disease is crucial for successful treatment and improved patient outcomes. In this research paper, we conducted a comprehensive comparative analysis of several machine learning algorithms, including logistic regression, Gaussian Naive Bayes, Bernoulli Naive Bayes, Support Vector Machine, X Gradient Boosting, Decision Tree Classifier, Grid Search CV, Random Forest Classifier, AdaBoost Classifier, Gradient Boosting Classifier, XgBoost, Cat Boost Classifier, Extra Trees Classifier, KNN, MLP Classifier, Stochastic gradient descent, and Artificial Neural Network, for the prediction of kidney disease. In this study, a dataset of patient records was utilized, where each record consisted of twenty-five clinical features, including hypertension, blood pressure, diabetes mellitus, appetite and blood urea. The results of our analysis showed that Artificial Neural Network (ANN) outperformed other machine learning algorithms with a maximum accuracy of 100%, while Gaussian Naive Bayes had the lowest accuracy of 94.0%. This suggests that ANN can provide accurate and reliable predictions for kidney disease. The comparative analysis of these algorithms provides valuable insights into their strengths and weaknesses, which can help clinicians choose the most appropriate algorithm for their specific requirements.

Keywords: Logistic regression, Gaussian Naive Bayes, Bernoulli Naive Bayes, Support Vector Machine, X Gradient Boosting

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1. Introduction

Kidney disease is a pervasive health issue that affects millions of people worldwide, including in Bangladesh. The timely detection and diagnosis of kidney disease are critical for improving patient outcomes and quality of life. Fortunately, recent advancements in machine learning and deep learning algorithms have made predicting kidney disease more accessible and accurate. By enabling early detection and treatment, these algorithms can play a vital role in managing kidney disease. The kidneys play a vital role in eliminating waste and surplus fluid from the body. Unfortunately, kidney failure is a widespread issue, affecting a significant portion of the Bangladeshi population. Approximately 29 million people, or 17.9% of the population, are affected by this condition [2]. Therefore, it is crucial to identify and manage chronic kidney disease (CKD) in its early stages to prevent its advancement and minimize the risk of complications.

Typically, doctors diagnose CKD through blood tests, urine tests, and imaging studies such as ultrasounds or CT scans [3]. However, monitoring glomerular filtration rate (GFR) is the most accurate way to evaluate kidney function and estimate CKD stages. Although GFR monitoring can be costly and time-consuming, machine learning and deep learning algorithms can analyze large amounts of data and accurately predict kidney disease.

By leveraging these algorithms, doctors can take proactive measures to prevent the disease's progression and improve patient outcomes. This is particularly important in Bangladesh, where access to renal replacement therapies like dialysis and

kidney transplantation is limited [4]. Early detection and management of CKD can help reduce the risk of developing end-stage renal disease (ESRD) and improve patient outcomes.

1.1 What causes CKD

Chronic Kidney Disease (CKD) can be caused by a variety of factors. In Bangladesh, the most common causes of CKD are diabetes and high blood pressure [5]. Other conditions that can cause CKD include glomerulonephritis (inflammation of the kidney's filtering units), inherited kidney diseases, urinary tract obstructions, and repeated kidney infections [6]. Additionally, the prolonged use of certain medications such as nonsteroidal anti-inflammatory drugs (NSAIDs), as well as exposure to certain toxins or heavy metals can also lead to CKD [3]. Lifestyle factors such as smoking, unhealthy diet, lack of exercise, and obesity can also increase the risk of developing CKD [5].

1.2 Who is more likely to get CKD

Certain individuals are more likely to develop Chronic Kidney Disease (CKD) than others. These groups include people with diabetes and high blood pressure, as these conditions can damage the blood vessels in the kidneys over time. Older adults may also be at increased risk due to a natural decline in kidney function with age. Additionally, those with a family history of kidney disease or certain inherited conditions that affect the kidneys, as well as individuals with a history of heart disease, may have an increased risk of developing CKD. Ethnic minorities, such as African Americans, Hispanics, Pacific Islanders, and Native Americans, are also at higher risk for CKD than other groups [7]. Cardiovascular disease and CKD share many risk factors, and having one condition can increase the risk of developing the other [8].

1.3 What are the symptoms of CKD

Chronic Kidney Disease (CKD) is a condition that can progress silently in its early stages, with few noticeable symptoms. However, as the disease advances, the following symptoms may manifest:

Fatigue: Persistent feelings of tiredness or weakness, despite adequate rest.
Loss of appetite: A decrease in interest or desire for food, leading to weight loss.
Swelling: Swelling in the face, hands, legs, ankles, or feet due to fluid build-up in the body.
Itching: Persistent itching all over the body, which can be caused by waste products accumulating in the blood.
Muscle cramps: Painful muscle cramps, especially in the legs.
Urination changes: More or less urine than usual, or changes in the color or frequency of urine.
Sleep problems: Trouble sleeping, including insomnia or restless leg syndrome.
Nausea and vomiting: Feeling nauseous and vomiting can be a

sign of severe kidney disease.
Difficulty concentrating: Trouble concentrating or focusing on tasks.

It is important to seek evaluation and possible testing for CKD from a healthcare provider if you experience any of these symptoms. Early detection and treatment can help slow the progression of the disease and prevent complications [9].

1.4 Urine test

A urine test is a crucial tool used to diagnose and monitor Chronic Kidney Disease (CKD). This diagnostic method involves analyzing a urine sample to detect the presence of various substances such as protein and blood, which could indicate kidney damage [10]. CKD is characterized by the kidneys' inability to filter waste and excess fluids from the body, leading to proteinuria or protein leakage into the urine. Detecting proteinuria is crucial for determining the extent of kidney damage and monitoring the progression of CKD [11]. Besides, a urine test can identify other conditions that could contribute to or worsen CKD, such as urinary tract infections or kidney stones [12]. The simplicity and non-invasive nature of urine testing make it an essential tool in managing CKD.

1.5 Blood pressure

Chronic Kidney Disease (CKD) often correlates with hypertension, or high blood pressure, as per the National Kidney Foundation, where hypertension is both a cause and an outcome of CKD [13]. Over time, high blood pressure damages the blood vessels in the kidneys, resulting in a decrease in their capacity to filter waste and excess fluids from the body. As a result, additional kidney damage happens, which leads to a cycle of declining kidney function and hypertension. Managing hypertension is crucial for individuals with CKD to prevent further kidney damage and reduce the risk of other complications. In fact, controlling blood pressure is the most important factor in slowing the progression of kidney disease, according to the Centres for Disease Control and Prevention [14]. Blood pressure targets may vary depending on the individual's age, overall health status, and other factors, but the recommended target for most people with CKD is less than 130/80 mm Hg [15].

1.6 Other tests

It has become increasingly common for people to experience kidney failure, a chronic condition that can take a long time to diagnose [16]. The kidney plays an essential role in the body by filtering waste and excess fluids, and when it is damaged, it cannot effectively clean the blood, which can cause further health issues [17]. In addition to blood tests, imaging tests like ultrasounds, CT scans, and MRIs can detect structural abnormalities in the kidneys such as cysts, tumors, and obstructions [16]. Kidney biopsy, a procedure where a small piece of kidney tissue is examined under a microscope, can help determine the cause of the damage [16]. However, not everyone

with CKD will need these tests as the appropriate testing and treatment plan will depend on the individual's medical history, symptoms, and other factors, which will be determined by their doctor [16].

The structure of this essay is as follows: In Section 2, the research techniques used to select the primary studies are covered. Section 3 addresses the proposed methodology. Section 4 looks at Experimental analysis. In Section 5&6, the results and conclusions.

2. Literature Review

Chronic kidney disease (CKD) is a significant global public health concern that affects millions of people worldwide. As the burden of CKD continues to increase, several studies have been conducted to understand its pathophysiology, epidemiology, and management.

For instance, "Chronic kidney disease: global dimension and perspectives" by Saran et al. (2017), highlights the increasing prevalence of CKD and its impact on healthcare resources. The authors emphasize the need for a global strategy to prevent and manage CKD [18].

In addition, "Pathophysiology of progressive renal disease" by Remuzzi and Bertani (1998), provides an in-depth review of the mechanisms involved in the progression of renal disease, including glomerular damage, tubulointerstitial inflammation, and fibrosis [19].

Furthermore, "Chronic kidney disease and the risks of death, cardiovascular events, and hospitalization" by Go et al. (2004), emphasizes the increased risk of mortality, cardiovascular events, and hospitalization associated with CKD. The authors discuss the need for early detection and management of CKD to reduce its impact on morbidity and mortality [20].

Likewise, "The global burden of kidney disease and the sustainable development goals" by Bikbov et al. (2017), discusses the global burden of CKD in the context of the Sustainable Development Goals. The authors emphasize the need for a global strategy to prevent and manage CKD to achieve the Sustainable Development Goals [21].

Similarly, "Chronic kidney disease: identification and management in primary care" by National Institute for Health and Care Excellence (NICE) (2015), provides guidance on the importance of early detection and management of CKD in primary care [22].

Comparably, "Kidney disease and obesity: epidemiology, mechanisms, and treatment" by Hall et al. (2010), discusses the link between obesity and CKD, highlighting the increased risk of CKD in obese individuals and the mechanisms involved [23].

Again as well as, "The interplay between inflammation and fibrosis in kidney disease" by Zeisberg and Neilson (2010), provides an overview of the interplay between inflammation and fibrosis in the development and progression of CKD. The authors highlight the need for a better understanding of these mechanisms to develop new treatments for CKD [24].

Similarly, "The genetics of chronic kidney disease: a review" by Padmanabhan and Padmanabhan (2017), discusses the genetic factors that contribute to the development and progression of CKD. The authors emphasize the need for a better understanding of the genetic basis of CKD to develop personalized treatments [25].

Another study by, "Chronic kidney disease: a review of current epidemiological and clinical research" by KDIGO (2013), provides a comprehensive overview of the current epidemiological and clinical research on CKD, including diagnostic criteria, risk factors, and management strategies [26].

Additionally, machine learning and deep learning approaches have been used to predict CKD progression. "CKD: a call for an age-adapted definition" by Glasscock and Rule (2016) emphasizes the need for an age-adapted definition of CKD to improve its diagnosis and management [27]. Ghosh et al.'s 2023 study[28] focuses on "Water Quality Assessment Through Predictive Machine Learning", highlighting the use of machine learning for analyzing and predicting water quality parameters.In "Unraveling the Heterogeneity of Lower-Grade[29] Gliomas," Rahat, Ghosh, and colleagues (2023) delve into deep learning-assisted segmentation and genomic analysis of brain MR images, offering new insights into this medical condition.Potato Leaf Disease[30] Recognition and Prediction using Convolutional Neural Networks," by Ghosh, Rahat, and team (2023), showcases the application of convolutional neural networks in accurately identifying diseases in potato leaves.Mandava, Vinta, Ghosh, and Rahat's [31]2023 research presents "An All-Inclusive Machine Learning and Deep Learning Method for Forecasting Cardiovascular Disease in Bangladeshi Population", integrating advanced AI techniques for health predictions.The 2023 study by Mandava et al., titled "Identification and Categorization of Yellow[32] Rust Infection in Wheat through Deep Learning Techniques", applies deep learning methods to detect and categorize wheat infections effectively.Khasim, Rahat, Ghosh, and colleagues' 2023 article, "Using Deep[33] Learning and Machine Learning: Real-Time Discernment and Diagnostics of Rice-Leaf Diseases in Bangladesh", explores AI-based solutions for diagnosing rice-leaf diseases.Deciphering Microorganisms through Intelligent Image Recognition", authored by Khasim, Ghosh, Rahat, and others in 2023, discusses[34] the use of machine learning and deep learning in identifying microorganisms through advanced image recognition techniques.The 2023 study by Mohanty, Ghosh, Rahat[35] and Reddy, "Advanced Deep Learning Models for Corn Leaf Disease Classification", focuses on the application of deep learning in classifying diseases in corn leaves based on a field study.Alenezi and team's 2021 research, "Block-Greedy and CNN Based Underwater Image Dehazing[36] for Novel Depth Estimation and Optimal Ambient Light", investigates novel CNN-based methods for enhancing underwater image clarity and depth estimation.

In summary, these articles provide a comprehensive overview of CKD, including its pathophysiology, epidemiology, and management. Future studies should focus on developing personalized treatment strategies to address the increasing burden of CKD.

3. Description of Dataset

Our CKD dataset is a collection of 400 instances that includes 24 features and a target variable.Our dataset is intended to be used to predict whether or not a patient has chronic kidney disease (CKD) based on their clinical and laboratory data. The features in the dataset include both numerical and categorical variables. There are 11 numerical variables, such as age, blood pressure, blood glucose random, and serum creatinine. The remaining 14 variables are nominal and include attributes such as specific gravity, albumin, sugar, red blood cells, pus cell, pus cell clumps, bacteria, sodium, potassium, hemoglobin, packed cell volume, white blood cell count, red blood cell count, hypertension, diabetes mellitus, coronary artery disease, appetite, pedal edema, and anemia. The target variable, class, is also nominal and indicates whether or not the patient has CKD. A total of 250 instances are classified as having CKD, while the remaining 150 instances are classified as not having CKD. The dataset does not contain any duplicate rows. The CKD dataset is a useful resource for researchers and medical practitioners interested in predicting the likelihood of CKD in patients based on their clinical and laboratory data.

3.1 Preprocessing of the Dataset

Preprocessing is an important step in machine learning, which involves preparing the data for analysis by transforming it into a format suitable for the algorithm. In the case of the CKD dataset, the following preprocessing steps can be performed:

- **Data Cleaning**

Data cleaning is an important step in preparing the CKD dataset for analysis. In this step, we identify and handle any missing or erroneous data, outliers, or inconsistencies in the dataset. One of the initial tasks is to check for missing data. In the CKD dataset, missing values are indicated by a question mark (?). We can replace the question marks with NaN (Not a Number) values, which can be handled more easily by the software packages used for analysis. Once this is done, we can then decide how to handle the missing data. This can be done by either imputing the missing values or removing the corresponding rows from the dataset. The next step is to check for outliers. Outliers are data points that are significantly different from the other data points in the dataset. Outliers can significantly impact the results of data analysis, so it's important to handle them appropriately. One approach to handling outliers is to remove them from the dataset. However, it's important to carefully examine each outlier to determine whether it's a genuine data point or a result of an error or data entry mistake. Another important task in data cleaning is to check for inconsistencies in the dataset. In the CKD dataset, we can check for inconsistencies by examining the range of values for each feature. For example, age should be a positive value, blood pressure should be within a certain range, and so on. If any inconsistencies are found, we can either remove the corresponding data points or try to correct them if possible.

- **Feature Scaling**

Feature scaling is an important step in preprocessing that involves scaling all the numerical features to the same range. This is important because some machine learning algorithms may not work well if the features are not on the same scale. For example, features such as 'age', 'blood pressure', and 'serum creatinine' are measured in different units, so it is necessary to scale them to the same range.

- **Feature Encoding**

The CKD dataset contains several nominal features, such as 'rbc', 'pc', 'pcc', 'ba', 'htn', 'dm', 'cad', 'appet', 'pe', 'ane', and 'class'. These features need to be encoded to a numeric format so that they can be used by machine learning algorithms. One way to encode nominal features is by using one-hot encoding, where each possible value of a nominal feature is represented by a binary variable.

- **Feature Selection**

Feature selection involves selecting the most important features from the dataset to reduce the dimensionality of the problem. This is important because it helps to avoid overfitting and also reduces the computational complexity of the problem. Feature selection can be done using various methods, such as correlation analysis, information gain, and principal component analysis.

- **Data Splitting**

Data splitting is an essential step in machine learning, as it allows us to evaluate the performance of our models on data that they have not seen before. To split the CKD dataset, we can use a common technique known as random splitting. The first step is to divide the dataset into two parts: one for training the model, and the other for testing the model. The most common split is a 70-30 split, where 70% of the data is used for training and 30% for testing. However, the exact split can vary depending on the size and complexity of the dataset. To ensure that our split is representative of the entire dataset, we can use stratified sampling. This involves dividing the dataset into strata based on the target variable (in this case, CKD or non-CKD) and then randomly selecting samples from each stratum for the training and testing sets. This ensures that the distribution of the target variable is preserved in both the training and testing sets. Once we have split the dataset, we can use the training set to train our machine learning model and the testing set to evaluate its performance. This allows us to estimate how well the model will perform on new, unseen data.

3.2 Data Analysis

The CKD dataset contains several categorical variables that can provide valuable insights into the prevalence and potential risk factors associated with chronic kidney disease (CKD). The presence of bacteria in urine is a known risk factor for urinary tract infections, which can be a complication in CKD patients. The distribution of categorical data for bacteria in the CKD dataset shows that the majority of patients (94.4%) do not have bacteria present in their urine, while 15 patients (5.60%) do. This variable could be an important feature in predicting the likelihood of CKD in patient**s [Fig.2]**. The red blood cell count can also provide important information about the health status of CKD patients. The distribution of categorical data for red blood cell counts shows that the majority of instances (81%) have normal red blood cell counts, while 19% have abnormal red blood cell counts. Out of the 245 instances in the dataset, 200 have normal red blood cell counts, while 45 have abnormal red blood cell count**s [Fig.3]**. Hypertension is a known risk factor for CKD, and the distribution of categorical data for hypertension in the CKD dataset shows that 36.9% of patients have hypertension, while 63.1% do not. Out of the total 395 instances, 145 patients have hypertension, while 250 do not. This information may be useful in predicting the likelihood of CKD in patients based on their hypertension status. The presence of diabetes mellitus is another known risk factor for CKD, and the distribution of categorical data for this variable in the CKD dataset shows that 34.4% of patients have diabetes mellitus, while 65.6% do not [**Fig.4**]. Out of the 410 instances, 140 patients have diabetes mellitus, while 270 do not. Coronary artery disease (CAD) is relatively rare among patients with CKD, as indicated by the distribution of categorical data for this variable **[Fig.5].** Only 8.5% of patients in the CKD dataset have CAD, while 91.5% do not. Out of the total 400 patients, 30 have CAD, while 370 do not. The distribution of categorical data for anemia in the CKD dataset shows that 15% of patients have anemia, while 85% do not **[Fig.6].** Out of the total 400 patients, 60 have anemia, while 340 do not. Understanding the distribution of anemia in the CKD dataset is important as it can impact the diagnosis and treatment of the disease **[Fig.7].** Pedal edema, which is swelling in the feet, ankles, or legs, can provide important information about the patient's health condition. The distribution of categorical data for pedal edema in the CKD dataset shows that only 19% of patients have pedal edema, while 81% do not. Out of the 405 patients in the dataset, 75 have pedal edema, while 330 do not **[Fig.8].** Finally, the presence or absence of CKD itself is a key variable in the dataset. The distribution of categorical data related to CKD shows that 62.5% of patients have CKD, while 37.5% do not. Out of the 500 instances in the dataset, 250 have CKD, while 250 do not. Understanding the prevalence of CKD in the dataset is crucial for developing predictive models to detect CKD in patients **[Fig.9]** Heat map is a graphical representation of the correlations between different variables in the CKD dataset. The heat map reveals which variables are most strongly correlated with one another by displaying a color-coded matrix. Darker colors indicate stronger positive correlations, while lighter colors indicate weaker or negative correlations. By examining the heat map, we can see that some of the variables with the strongest positive correlations include serum creatinine and blood urea nitrogen, as well as serum creatinine and age. Other variables with notable correlations include red blood cell count and hemoglobin, and white blood cell count and packed cell volume. Understanding the correlations between variables in the CKD dataset can provide valuable insights for further analysis and modeling. For example, it can show how strongly the age of a patient is correlated with their serum creatinine levels, or how strongly their hemoglobin levels are correlated with their red blood cell count **[Fig.10].**

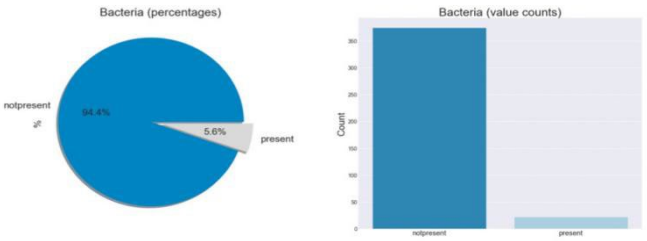


Fig.2 Percentage of Bacteria

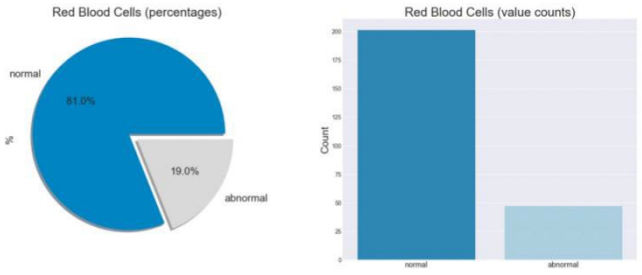


Fig.3 Percentage of Red Blood Cells

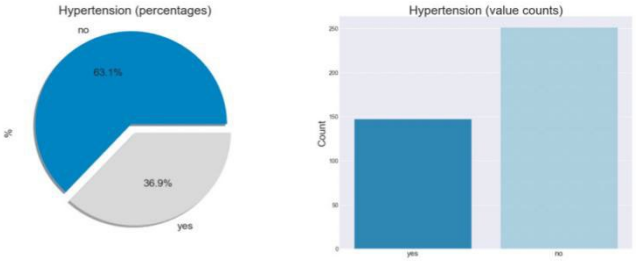


Fig.4 Percentage of Hypertension

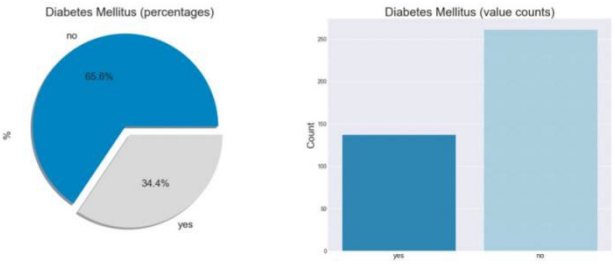


Fig.5 Percentage of Diabetes Mellitus

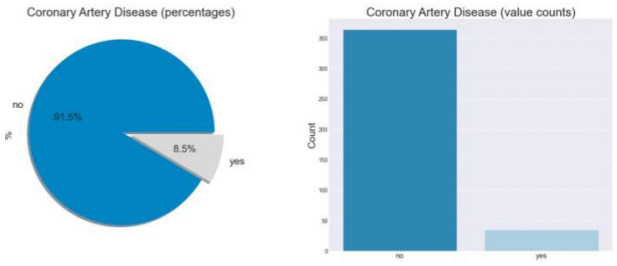


Fig.6 Percentage of Coronary Artery Disease

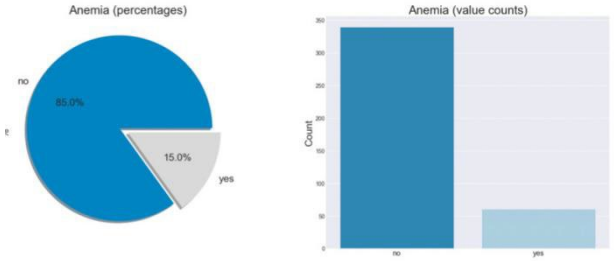


Fig.7 Percentage of Anemia

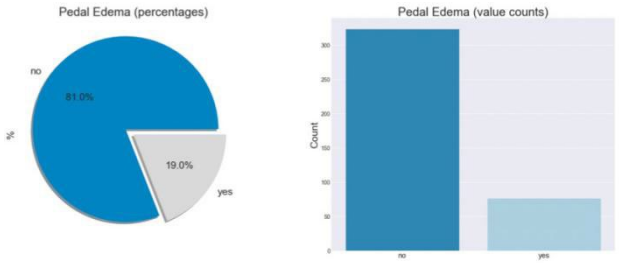


Fig.8 Percentage of Pedal Edema

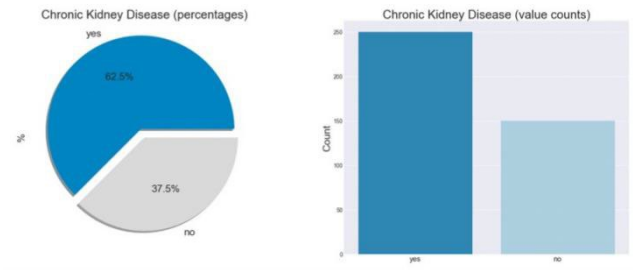
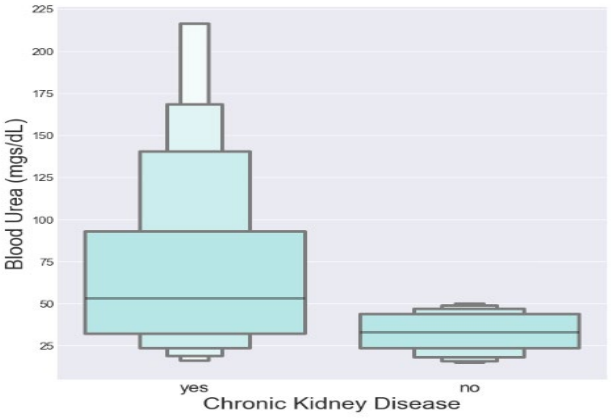


Fig. 9 Percentage of CKD

Fig. 10 Heatmap

4. Experimental Analysis

The boxplot depicts the distribution of Blood Urea levels (measured in mg/dL) in two groups: patients with Chronic Kidney Disease (CKD) and those without CKD. The box for the CKD group is noticeably higher, indicating a higher median level of Blood Urea in this group compared to the non-CKD group. The whiskers of the CKD box are also longer, indicating a wider range of values. There are some outliers in both groups, but the CKD group has more extreme values. This suggests that Blood Urea is a potential biomarker for CKD, and its levels may be useful in diagnosing and monitoring the disease **[Fig.11]** varied depending on the specific architecture and training parameters employed. By comparing and analyzing the performance of these models, researchers can gain a deeper understanding of their capabilities and make informed decisions about the most suitable models for further development and deployment in real-world agricultural settings.



Now we are going to see the performances of our used machine

learning and deep learning models (Logistic Regression, Gaussian Naive Bayes, Bernoulli Naive Bayes, Support Vector Machine,X Gradient Boosting,Decision Trees Classifier,Grid Search CV,Random Forest Classifier,Ada Boost Classifier,Gradient Boosting Classifier,XgBoost,Cat Boost Classifier,Extra Trees Classifier,Kth Nearest Neighbours ,MLP Classifier,Stochastic Gradient Decent,Artificial Neural Network.)through confusion matrix,Testing accuracy,Training accuracy,Precision, Recall, F-1 score and Support.[Table.1]

4.1. Confusion Matrix

A confusion matrix is a useful tool for evaluating the performance of a classification model. It can help to evaluate the true positive rate (sensitivity), true negative rate (specificity), and overall accuracy of a model.In the context of a heart disease prediction research paper, the confusion matrix would look something like this:

True Positive (TP): The number of cases correctly predicted as having Chronic kidney disease.

False Positive (FP): The number of cases incorrectly predicted as having Chronic kidney disease, when in fact they do not have the disease.

False Negative (FN): The number of cases incorrectly predicted as not having Chronic kidney disease, when in fact they do have the disease.

True Negative (TN): The number of cases correctly predicted as not having Chronic kidney disease.

4.2 Precision and Recall

Precision and recall are two commonly used performance metrics in the context of a heart disease prediction research paper. These metrics help to evaluate the quality of a classification model's predictions.

Precision: Precision is the proportion of positive predictions that are actually true. It gives an idea of the number of true positive predictions out of all the positive predictions made by the model. Precision is calculated as: Precision = TP / (TP + FP)

Recall (Sensitivity): Recall is the proportion of actual positive cases that are correctly predicted as positive. Recall gives an idea of the ability of the model to identify all positive cases. Recall is calculated as: Recall = TP / (TP + FN)

In the context of heart disease prediction, high precision means that the model is good at avoiding false positive predictions, i.e. predicting heart disease when the patient does not actually have it. High recall means that the model is good at detecting heart disease when it is present. Both precision and recall are important and trade-offs between the two can be made depending on the specific needs of the application

4.3 Logistic Regression

This algorithm has achieved a testing accuracy of 99% and a training accuracy of 100%. Logistic Regression is a widely used linear classification algorithm that models the relationship between the input features and the output target using a logistic function. It is easy to implement and can handle large datasets efficiently.

$$h\Theta(x) = 1/1 + e - (\beta o + \beta 1X) \quad (1)$$

4.4 Gaussian Naive Bayes

This algorithm has achieved a testing accuracy of 94% and a training accuracy of 94%. Gaussian Naive Bayes is a simple and effective probabilistic classification algorithm that models the distribution of each class using Gaussian distribution. It is particularly useful when the number of input features is large.

4.5 Bernoulli Naive Bayes

This algorithm has achieved a testing accuracy of 98% and a training accuracy of 97%. Bernoulli Naive Bayes is a variant of Naive Bayes that models the distribution of each class using a Bernoulli distribution. It is commonly used for text classification tasks.

4.6 Support Vector Machine (SVM)

This algorithm has achieved a testing accuracy of 99% and a training accuracy of 99%. Support Vector Machine is a powerful classification algorithm that aims to find a hyperplane that maximally separates the classes in the feature space. It is effective for high-dimensional and non-linear classification problems.

4.7 Kth Nearest Neighbours (KNN)

This algorithm has achieved a testing accuracy of 97% and a training accuracy of 98%. KNN (K-Nearest Neighbors) is a simple and effective classification algorithm that classifies a new data point based on the class of its nearest neighbors in the feature space. It is particularly useful for low-dimensional datasets and can handle both categorical and numerical input features.

4.8 X Gradient Boosting

This algorithm has achieved a testing accuracy of 98% and a training accuracy of 100%. X Gradient Boosting is an ensemble classification algorithm that combines multiple weak classifiers into a single strong classifier using boosting. It is effective for a wide range of classification problems and is particularly useful for handling imbalanced datasets.

4.9 Random Forest Classifier

This algorithm has achieved a testing accuracy of 98% and a training accuracy of 99%. Random Forest Classifier is an ensemble classification algorithm that combines multiple decision trees into a single strong classifier using bagging. It is effective for handling noisy datasets and can handle both categorical and numerical input features.

4.10 Decision Tree Classifier

This algorithm has achieved a testing accuracy of 96% and a training accuracy of 100%. Decision Tree Classifier is a hierarchical classification algorithm that partitions the feature space into regions based on the values of the input features. It is simple, interpretable, and can handle both categorical and numerical input features.

4.11 Grid Search CV

This algorithm has achieved a testing accuracy of 97% and a training accuracy of 99%. Grid Search CV is a technique for hyper parameter tuning that exhaustively searches the hyper parameter space to find the optimal set of hyper parameters for a given algorithm. It is useful for improving the performance of complex classification algorithms.

4.12 Ada Boost Classifier

This algorithm has achieved a testing accuracy of 99% and a training accuracy of 100%. Ada Boost Classifier is an ensemble classification algorithm that combines multiple weak classifiers into a single strong classifier using boosting. It is effective for a wide range of classification problems and can handle both categorical and numerical input features.

4.13 Gradient Boosting

This algorithm has achieved a testing accuracy of 96% and a training accuracy of 100%. Gradient Boosting is an ensemble classification algorithm that combines multiple weak classifiers into a single strong classifier using boosting. It is effective for a wide range of classification problems and can handle both categorical and numerical input features.

4.14 Classifier XgBoost

This algorithm has achieved a testing accuracy of 99% and a training accuracy of 100%. Classifier XgBoost is an optimized implementation of Gradient Boosting that uses a scalable and efficient gradient boosting framework. It is effective for handling large datasets and can handle both categorical.

4.15 Cat Boost Classifier

This algorithm has achieved a testing accuracy of 98% and a training accuracy of 100%. Cat Boost Classifier is a gradient boosting algorithm that is optimized for categorical input features. It is effective for handling high-dimensional datasets and can handle missing values in the input features.

4.16 Extra Trees Classifier

This algorithm has achieved a testing accuracy of 98% and a training accuracy of 100%. Extra Trees Classifier is an ensemble classification algorithm that combines multiple decision trees into a single strong classifier using bagging. It is similar to Random Forest Classifier but with a different splitting criterion.

4.17 MLP Classifier

This algorithm has achieved a testing accuracy of 99% and a training accuracy of 100%. MLP Classifier (Multi-Layer Perceptron Classifier) is a neural network-based classification algorithm that consists of multiple layers of interconnected nodes. It is effective for handling complex and non-linear classification problems and can handle both categorical and numerical input features.

4.18 Stochastic Gradient Descent

This algorithm has achieved a testing accuracy of 98% and a training accuracy of 100%. Stochastic Gradient Descent is an optimization algorithm that is commonly used for training linear classification models. It is particularly useful for handling large datasets and can handle both categorical and numerical input features.

4.19 Artificial Neural Network

This algorithm has achieved a testing accuracy of 100% and a training accuracy of 100%. Artificial Neural Network is a powerful classification algorithm that consists of multiple layers of interconnected nodes. It is effective for handling complex and non-linear classification problems and can handle both categorical and numerical input features. It requires a large amount of data and computational resources for training.

5. Result

Most of the classifiers in the table have high accuracy for both training and testing datasets, indicating their ability to perform well. However, it is crucial to assess the difference in accuracy between training and testing data to evaluate the model's ability to generalize to new data.Aritificial Neural Network accuracy has highest testing accuracy of 100%, demonstrating their capability to make accurate predictions on new data. These classifiers also have high training accuracy, suggesting that they are well-suited to the training data.On the other hand, Gaussian Naive Bayes has a lower testing accuracy of 94%, despite having a relatively high training accuracy of 94%. This suggests that the model may be overfitting the training data, leading to poor performance on new, unseen data.To evaluate the performance of a classifier, it is essential to consider both training and testing accuracy. While high training accuracy indicates a well-fitting model, it may not necessarily perform

well on new data. A good classifier should have high accuracy on both training and testing datasets, with minimal difference between the two.

Table I. Comparison of Chronic Kidney Disease Segmentation and Classification Methods Based On The Accuracy, Precision, Recall, F1-Score and Support

Classifiers	Testing accuracy	Training accuracy	Precision	Recall	F1-score	Support
Logistic Regression	0.99	1.00	1.00	0.99	0.99	72
Gaussian Naive Bayes	0.94	0.94	0.97	0.90	0.94	72
Bernoulli Naive Bayes	0.98	0.97	0.99	0.97	0.98	72
Support Vector Machine	0.99	0.99	0.97	1.00	0.99	72
X Gradient Boosting	0.98	1.00	0.97	1.00	0.99	72
Decision Tree Classifier	0.96	1.00	0.97	0.96	0.97	72
Grid Search CV	0.97	0.99	0.96	0.99	0.97	72
Random Forest Classifier	0.98	0.99	0.96	1.00	0.98	72
Ada Boost Classifier	0.99	1.00	0.99	1.00	0.99	72
Gradient Boosting Classifier	0.96	1.00	0.97	0.96	0.97	72
XgBoost	0.99	1.00	0.99	1.00	0.99	72
Cat Boost Classifier	0.98	1.00	0.96	1.00	0.98	72
Extra Trees Classifier	0.98	1.00	0.97	1.00	0.99	72
KNN	0.97	0.98	1.00	0.94	0.97	72
MLP Classifier	0.99	1.00	1.00	0.99	0.99	72
Stochastic gradient descent	0.98	1.00	0.99	0.99	0.99	72
Aritificial Neural Network	1.00	1.00	1.00	0.99	0.99	72

6 Conclusion and Future Work

To summarize, this study compares the effectiveness of various machine learning and deep learning techniques for early diagnosis of kidney disease. The results indicate that these techniques have the potential to accurately diagnose kidney disease at an early stage, which is critical for timely intervention and improved patient outcomes. The classifiers that performed the best in early diagnosis of kidney disease are Logistic Regression, Support Vector Machine, Ada Boost Classifier, Classifier XgBoost, and MLP Classifier, with a testing accuracy of 99% and for Artificial Neural Network accuracy100%. However, it's important to note that the difference between training and testing accuracy should be considered when assessing the models' ability to generalize to new data. The study emphasizes the importance of incorporating machine learning and deep learning techniques in healthcare to improve the accuracy of diagnosis and enable

timely intervention for kidney disease. The results suggest that these techniques could help enhance the accuracy of diagnosis, leading to better patient outcomes. Future research could further investigate the efficacy of these techniques on more diverse and larger datasets, as well as examine their feasibility and practical implementation in clinical settings. Integrating these techniques into clinical practice could improve the accuracy of diagnosis, facilitate timely intervention, and ultimately improve patient outcomes. The findings of this study suggest that machine learning and deep learning techniques show promise for early diagnosis and timely intervention of kidney disease, and could help improve healthcare outcomes for patients suffering from this condition.

Future research should focus on testing the efficacy of the classifiers on larger and more diverse datasets, while also considering alternative machine learning algorithms and extensive hyper parameter tuning. The integration of these models into real-time clinical settings, and investigation of ensemble techniques for potential accuracy increase, should also be explored. Lastly, it's essential to enhance the interpretability and explain the ability of these models to better understand their decision-making processes.

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