Artificial intelligence

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CHRONIC KIDNEY DISEASE DETECTION

Abstract:

Kidney plays an extremely important role in human health, and one of its important tasks is to purify the blood from toxic substances. Chronic Kidney Disease (CKD) means that kidney begins to lose its function gradually and show some symptoms, such as fatigue, weakness, nausea, vomiting, and frequent urination. Early diagnosis and treatment increase the likelihood of recovery from the disease. Due to high classification performance, artificial intelligence techniques have been widely used to classify disease data in the last ten years. In this study, a hybrid model based on Convolutional Neural Network (CNN) was proposed using data set that contains a CSV files, which automatically classified CKD. This data set consisted of foremost important features that were selected by Recursive Feature Elimination (RFE). Hemoglobin, Specific Gravity, Serum Creatinine, Red Blood Cell Count, Albumin, Packed Cell Volume, and Hypertension were found as key features in the RFE. Selected features were passed to machine learning models for classification purposes. and one output. If the features showed, CKD was diagnosed. Compared with many well-known machine learning methods, the proposed CNN based model obtained a classification accuracy of 99.17%.

Introduction:

Chronic kidney disease poses a significant public health challenge globally. Chronic kidney disease (CKD) means your kidneys are damaged and can't filter blood the way they should. The disease is called “chronic” because the damage to your kidneys happens slowly over a long period of time. This damage can cause waste to build up in your body. CKD can also cause other health problems. Chronic kidney disease, also called chronic kidney failure, involves a gradual loss of kidney function. Your kidneys filter wastes and excess fluids from your blood, which are then removed in your urine. Advanced chronic kidney disease can cause dangerous levels of fluid, electrolytes and wastes to build up in your body. In the early stages of chronic kidney disease, you might have few signs or symptoms. You might not realize that you have kidney disease until the condition is advanced.

The kidneys’ main job is to filter extra water and waste out of your blood to make urine. To keep your body working properly, the kidneys balance the salts and minerals such as calcium, phosphorus, sodium, and potassium that circulate in the blood. Your kidneys also make hormones that help control blood pressure, make red blood cells, and keep your bones strong. Kidney disease often can get worse over time and may lead to kidney failure. If your kidneys fail, you will need dialysis or a kidney transplant to maintain your health. Chronic kidney disease is a progressive disease with no cure and high morbidity and mortality that occurs commonly in the general adult population, especially in people with diabetes and hypertension.

Preservation of kidney function can improve outcomes and can be achieved through non-pharmacological strategies (e.g., dietary and lifestyle adjustments) and chronic kidney disease-targeted and kidney disease-specific pharmacological interventions. Managing chronic kidney

disease-associated cardiovascular risk, minimizing the risk of infection, and preventing acute kidney injury are crucial interventions for these patients, given the high burden of complications, associated morbidity and mortality, and the role of non-conventional risk factors in chronic kidney disease.

When renal replacement therapy becomes inevitable, an incremental transition to dialysis can be considered and has been proposed to possibly preserve residual kidney function longer. There are similarities and distinctions between kidney-preserving care and supportive care. Additional studies of dietary and pharmacological interventions and development of innovative strategies are necessary to ensure optimal kidney-preserving care and to achieve greater longevity and better health-related quality of life for these patients. Chronic kidney disease (CKD) affects how kidneys work and their structure. If not treated for a long time, it can cause problems like weak bones, high blood pressure, anemia, nerve damage, and issues with blood vessels or the heart. CKD happens in different stages, depending on how well the kidneys filter blood.

CKD has been increasing quickly and is strongly linked to a high risk of heart and kidney failure, which can be prevented by finding and treating it early. Doctors now commonly use machine learning to diagnose disease. CKD is considered a major health risk, especially in developing countries, as symptoms may not appear until the kidneys are badly damaged. Treating CKD focuses on reducing the risk to the kidneys by controlling the underlying causes of the disease in its early stages.

CKD's development and various clinical features are studied in epidemiology. Doctors usually use two tests to check for CKD: blood and urine tests. Factors like genetics, diabetes, obesity, and aging can affect CKD. Blood tests measure how well the kidneys filter blood by checking creatinine levels, a waste product from muscle breakdown. Urine tests detect if protein, particularly albumin, is present, which should normally not be found in urine if the kidneys are healthy. If albumin is found in urine, it indicates kidney damage and potential chronic kidney disease.

Chronic kidney disease (CKD) presents a significant public health challenge due to its often-asymptomatic progression, leading to late diagnoses and increased morbidity and mortality rates. Traditional diagnostic methods relying on symptoms and expert judgment are subjective and prone to error, highlighting the need for more efficient and accurate diagnostic tools. Utilizing artificial neural networks (ANN) offers a promising approach to enhance CKD detection by analyzing complex datasets and identifying patterns imperceptible to human observers. By developing automated diagnostic systems using ANN, early CKD detection can be facilitated, enabling timely interventions and improved patient outcomes.

In this report section II includes Literature Review, Section III includes materials and methods, section IV includes results and discussions.

Literature review:

CKD is a fatal disease if left undetected as it leads to renal failure, in the worst cases. However, the early diagnosis of CDK can significantly reduce the mortality rate. There are numerous studies available that utilize CKD data and built prediction models depending on the type of data analyzed. But in [1], The processed dataset was trained using different prediction models such as KNN, SVM, RF, and bagging. But the model we have applied for prediction is KNN. The models' performance was estimated to show higher reliability and significance in terms of accuracy, sensitivity, F-measure, specificity, and AUC score. KNN outperformed with an accuracy of 99.50%, sensitivity of 99.2%, precision of 100%, specificity of 98.7%, and F-measure and AUC score of 99.6%. Although the dataset contains all possible attributes that are enough to detect CKD.

In this work [2], new methodology is used which was compared with other machine learning techniques, namely, the K Nearest Neighbor (KNN), SVM, logistic regression, naive Bayes, random forest, and AdaBoost. This study discussed the diagnosis of CKD in accordance with the response of human body. The dataset used for CKD detection in the experiments was obtained from the Kaggle platform and was publicly available. A hybrid model based on Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) was proposed using a two-class data set, which automatically classified CKD. This dataset consisted of thirteen features and one output. If the features showed, CKD was diagnosed. Compared with many well-known machine learning methods, the proposed CNN-LSTM based model obtained a classification accuracy of 99.17%.

In proposed work [3], the author carried out feature optimization, wherein three different feature selection algorithms were applied to find the algorithm most beneficial to extract the important feature for the prediction of Chronic Kidney Disease. As many datasets have imbalanced class, class balancing is needed for increasing the performance of classifier model. In this research SMOTE was used as a class balancer. The highest accuracy of 99.6% was achieved. This dataset is being provided by the UC Irvine Machine Learning Repository and it is available on the UCI website. This dataset contains 400 instances and 24 attributes with 1 target attribute. The target attribute has been labelled in two-class to represent CKD or non-CKD. The dataset was collected from various hospitals. Seven classifier algorithms have been applied in this research such as artificial neural network, C5.0, Chi-square Automatic interaction detector, logistic regression, linear support vector machine with penalty L1 & with penalty L2 and random tree. Although this technique has become reliable for medical treatment.

[4] proposed that, the author use the SVM and RF technique to achieve the lowest false-negative rates and test accuracy. A statistical technique, namely, the chi-squared test, is used for the extraction of the least-required set of adequate and highly correlated features to the output. For the model training, a stack of supervised-learning techniques is used for the development of a robust machine-learning model. Out of all the applied learning techniques, support vector machine (SVM) and random forest (RF) achieved the lowest false-negative rates and test accuracy, equal to 99.33%99.33% and 98.67%98.67%, respectively. However, SVM achieved better results than RF did when validated with 10-fold cross-validation.

In this work [5], In this section, the focus is on CKD attributed to diabetes (diabetic kidney disease) in adults, which occurs in 20–40% of people with diabetes (1–4). Diabetic kidney disease typically develops after a diabetes duration of 10 years in type 1 diabetes (the most common presentation is 5–15 years after the diagnosis of type 1 diabetes) but may be present at diagnosis of type 2 diabetes. CKD can progress to end-stage kidney disease (ESKD) requiring dialysis or kidney transplantation and is the leading cause of ESKD in the U.S. (5). In addition, among people with type 1 or type 2 diabetes, the presence of CKD markedly increases cardiovascular risk and health care costs (6). For details on the management of diabetic kidney disease in children. The only proven primary prevention interventions for CKD in people with diabetes are blood glucose (A1C goal of 7%) and blood pressure control (blood pressure.

[6] proposed that, chronic kidney disease is one of the deadly diseases spreading all over the world and manually diagnosis of this disease is very difficult since most of its symptoms are common to other diseases. Several medical and computer science scholars have developed computer based intelligent system or medical diagnosis system for chronic kidney disease diagnosis. In this paper a survey is made for chronic kidney disease diagnosis expert system developed by the persons, the methodology they adapted, the dataset they used, accuracy of the system and their contribution to the real world. This survey explores that a lot of work is yet to be done in the field of developing expert system for chronic kidney disease diagnosis using authorized dataset like UCI dataset machine learning repository and a powerful logic like fuzzy logic. In our future work we are about to implement the work left by the previous researchers.

In proposed work [7], In this paper, a deep learning-based Heterogeneous Modified Artificial Neural Network (HMANN) method has been proposed for the early detection, segmentation, and diagnosis of chronic renal disease. In the proposed HMANN system, the noise must be reduced after acquiring a raw image. To find a good solution to this problem tested three classifiers: support vector machine, artificial neural networks, and Multilayer perceptron. In this paper, the performed feature reduction with the help of significant results from this study, both to reduce excess fitness and to identify the most significant predictive attributes for CKD. Besides, the new factors have found that classifiers are used for more accurate detection of CKD than modern formulation.

In this work [8], If the important attributes that could help to detect CKD is known then even people who are not diagnosed CKD also may get a clue of the condition of their kidney from the medical test that they took for some other purposes. Then they may proceed to properly check for CKD. A weighting vector based on CSP filter and LDA analysis and then classification analysis using LDA and KNN classifiers were used to identify the dominant attributes. It is found that hemoglobin, albumin, specific gravity, serum creatinine, hypertension and diabetes mellitus are the most important attributes in detecting CKD. Further, these analyses suggest that when hypertension and diabetes mellitus are not available, blood glucose random and blood pressure can be used.

Chronic kidney disease is a worldwide public health problem with an increasing incidence, prevalence, and high cost. Approximately 2.5-11.2% of the adult population across Europe, Asia, North America, and Australia are reported to have chronic kidney disease. In [9], Early stage of Chronic Kidney Disease. This dataset includes 400 patients with 24 attributes collected from each

of these patients; 250 of them have CKD. The ages of these patients vary from 2 to 90 with a mean of 51.48 and a standard deviation of 17.17. Most of the 24 collected attributes shown in Table II have not been used by previous state of art approaches for CKD detection, e.g., most approaches use only age, serum creatinine, albumin, and urea. This work was supported, in part, by DGIST via funding from the Ministry of Education, Science and Technology of the Republic of Korea. two methods: the wrapper method and LASSO regularization. Through our evaluation we find that, the random forest algorithm with a reduced attribute set of 12 members can detect CKD with highest accuracy of .998 using the F1-measure and with a 0.107 root mean square error, which is a 57% RMSE reduction compared to the state-of-the-art solutions.

[10] proposed that, the foremost important features were selected by Recursive Feature Elimination (RFE). Hemoglobin, Specific Gravity, Serum Creatinine, Red Blood Cell Count, Albumin, Packed Cell Volume, and Hypertension were found as key features in the RFE. Selected features were passed to machine learning models for classification purposes. The proposed Deep neural model outperformed the other four classifiers (Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Logistic regression, Random Forest, and Naive Bayes classifier) by achieving 100% accuracy. The proposed approach could be a useful tool for nephrologists in detecting CKD. Different metrics, including classification accuracy, recall, precision, and f-measure, are used to estimate the comparative analysis. The proposed deep neural model outperformed the other five classifiers (Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Logistic regression, Random Forest, and Naive Bayes classifier) by achieving 100% accuracy. The accuracy of KNN, SVM, Naïve Bayes, Decision tree, Random Forest, logistic regression is 92%, 92%, 95%, 97%, and 99%, respectively.

The author of[11] developed a decision-making tool for doctors to forecast the occurrence of CRF in patients. The authors employed *K*NN, Naive Bayes, LDA, random subspace, and tree-based classification techniques on the CRF data set from the UCI repository. The random subspace with the *K*NN classifier has a 94% accuracy rate, according to the researchers.

The author of[12] presented a hierarchical multiclass classification technique for detecting chronic renal disease in an unbalanced data set. As a baseline, the authors used naive Bayes, logistic regression, decision trees, and random forests classifiers. Within each patient, the proposed classification approach discovered severe cases.

Z. Chen, X.et al. proved the reliability of multivariate models in clinical practice risk assessment for patients with CKD[13]. The Chronic Renal Failure (CFR) data bank at UC Irvine was used in this investigation. In their comparison investigation, they used the *K*NN, SVM, and Soft independent modeling of class analogy. In comparison to the other two models, the SVM model processed noise within the data set better. In this comparison, the SVM accuracy was 99%.

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Literature summary:

Authors	Year	Model	Dataset	Accuracy	Problem	Limitations
Ullah Z. et al.	2022	KNN	UCI among 24 features	99.50%	Prediction-Based Approach for Rapid and Cost-Effective Decision-Making	Overfitting and generalize
Yildiz et al.	2023	CNN-LSTM	UCI Machine Learning Repository	99.17%	Extract Accurate Diagnosis Using Feature-Rich Data	Feature Selection Bias
Chittora, P, et al	2021	Seven classifiers algorithms	UC Irvine Machine	99.6%.	integration of models into clinical practice, with extensive validation	Clinical Workflow Integration
Swain, D. et al.	2023	SVM and RF	UCI Machine Learning Repository	99.33% an d 98.67%	Approaches for Accurate Diagnosis using Publicly Available Data	Lack of Standardization
ElSayed, N.A, et al.		CNN	UCI data	88.78%	primary prevention interventions for CKD	Diabetes Management
Madhur Bhatt et al.	2019	Fuzzy logic using MATLAB	Birdum hospital Dhaka	86.7%	Disease and reports about condition of kidney functions	Guiding treatment decisions, monitoring disease progression etc.

Fuzz he ma. et al	2020	HMANN, MLP and BP	UCI Repository	90%	Analysis of patients using algo instead of use of ultrasounds images	Model Development and Validation
Nishant et al.	2018	LDA and KNN	UCI among 24 attributes 13 nominal and 11 numerical	98.09% and 71.65%	Identifying important attributes for early detection of CKD	understanding the key risk factors, biomarkers, and clinical indicators
A.Salekin et al.	2016	k-nearest neighbors, random forest, and neural network	UCI contains datasets of 400 patients	92.45%	Detection of CKD and Selecting Important Predictive Attributes	understanding the key risk factors.
Singh et al.	2022	four classifiers SVM, KNN, Linear	UCI CKD data	92%, 92%, 95%, 97%, and 99%, respectivel y.	Selection of different classifiers	It's essential to consider factors such as performance etc.
A1-HAYARI et al.	2013	Classificatio n techniques	UCI repository	94%	Occurrence of CRF in patients	Random subspace according to researchers
Bhattacha rya et al.	2018	hierarchical multiclass classificatio n	UCI repository	92%	Detect disease in an unbalanced dataset	classification approach discovered severe cases
Z. Chen et al.	2016	KNN, SVM and soft independent of class analogy	UC Irvine dataset	99%	clinical practice risk assessment for patients	Proved reliability of multivariate models

Methodology:

In the scope of this study, we introduce a meticulously designed system aimed at accurately identifying chronic kidney disease, employing a robust model as its cornerstone. The development of an effective and precise prediction model was realized through the strategic utilization of a machine learning-based approach. We developed a precise prediction model by using a machine learning approach. Additionally, Figure 1 visually explains the different stages of our system, making it easier to understand.

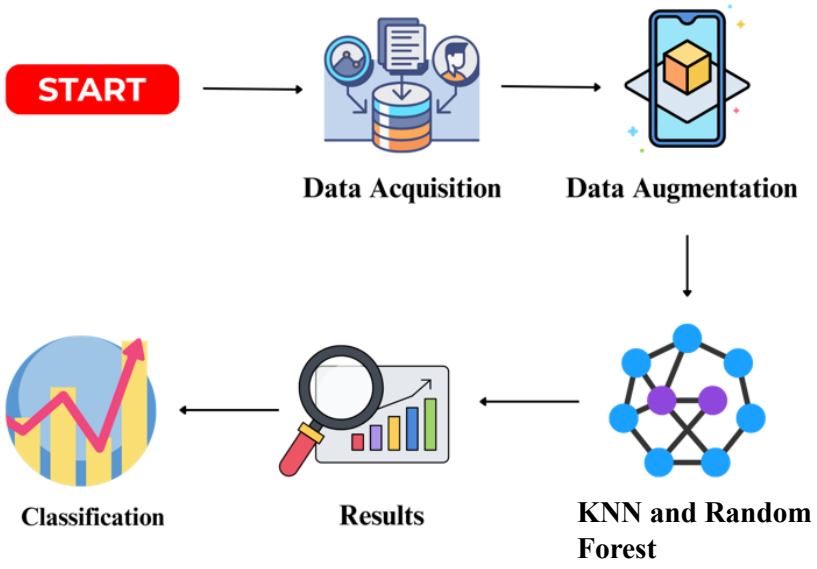
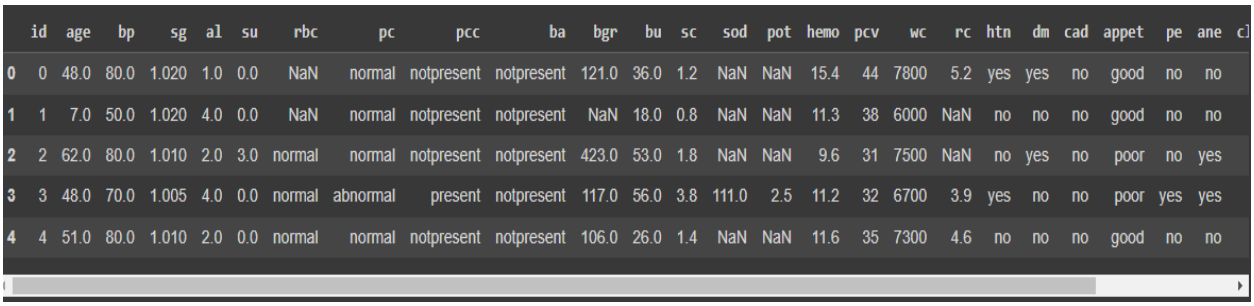


Figure 1. Block diagram of methodology

Data Acquisition:

The dataset utilized for detecting chronic kidney disease (CKD) in the experiments was sourced from the Kaggle platform and can be accessed publicly at Kaggle/input/chronic-kidney-disease/new_model.csv [10]. It comprised 400 samples with 14 features, and experts labeled this two-class dataset based on whether patients had CKD or not. Figure 2 displays five randomly chosen samples from this dataset. Figure 3 shows the several medical values that are used in our data set.



	id	age	bp	sg	al	su	rbc	pc	pcc	ba	bgr	bu	sc	sod	pot	hemo	pcv	wc	rc	htn	dm	cad	appet	pe	ane	cl
0	0	48.0	80.0	1.020	1.0	0.0	NaN	normal	notpresent	notpresent	121.0	36.0	1.2	NaN	NaN	15.4	44	7800	5.2	yes	yes	no	good	no	no	
1	1	7.0	50.0	1.020	4.0	0.0	NaN	normal	notpresent	notpresent	NaN	18.0	0.8	NaN	NaN	11.3	38	6000	NaN	no	no	no	good	no	no	
2	2	62.0	80.0	1.010	2.0	3.0	normal	normal	notpresent	notpresent	423.0	53.0	1.8	NaN	NaN	9.6	31	7500	NaN	no	yes	no	poor	no	yes	
3	3	48.0	70.0	1.005	4.0	0.0	normal	abnormal	present	notpresent	117.0	56.0	3.8	111.0	2.5	11.2	32	6700	3.9	yes	no	no	poor	yes	yes	
4	4	51.0	80.0	1.010	2.0	0.0	normal	normal	notpresent	notpresent	106.0	26.0	1.4	NaN	NaN	11.6	35	7300	4.6	no	no	no	good	no	no	

Figure 2. Samples from the CKD data set

Sr. No	Attributes	Abbreviations
1	Bp	Blood Pressure
2	Sg	Specific Gravity
3	Al	Albumin
4	Su	Sugar
5	Rbc	Red Blood Cells
6	Bu	Blood Urea
7	Sc	Serum Creatinine
8	Sod	Sodium
9	Pot	Potassium
10	Hemo	Hemoglobin
11	Htn	Hypertension

Figure 3. Attributes and Abbreviations used in Dataset.

Data Preprocessing:

Data preprocessing in artificial neural networks (ANNs) involves preparing and transforming raw data into a format that is suitable for training the neural network model. This typically includes steps such as data cleaning, normalization, feature scaling, and feature engineering. Data preprocessing aims to enhance the quality of the input data, reduce noise, and improve the

efficiency and effectiveness of the neural network during training and inference. Figure 3 flowchart of data preprocessing for textual data (csv file).

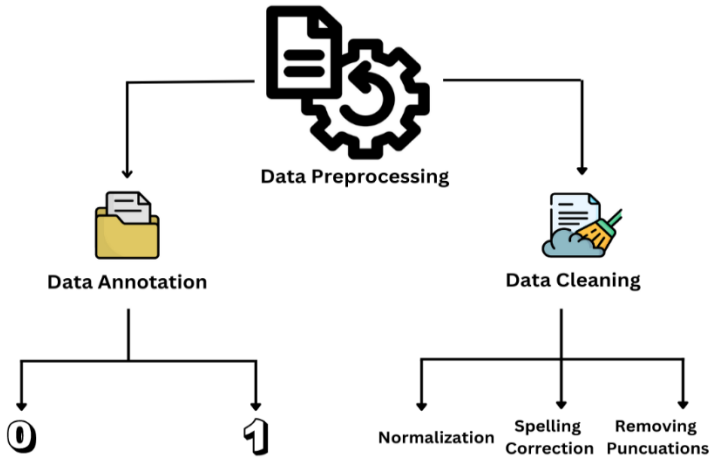


Figure 3. Data Preprocessing Diagram

- ***Data Annotation*:**

  Data annotation in ANN involves labeling data to provide the network with examples for training and learning associations between inputs and outputs.

- ***Data Cleaning:***
  - **Normalization:** Normalization scales data to a standard range (e.g., between 0 and 1), ensuring consistent input magnitudes for efficient ANN training.
  - **Spell Checking:** Spell checking corrects text errors to improve data quality, ensuring accurate inputs for the ANN's learning and prediction.
  - **Removing Punctuations**: Punctuation removal strips out symbols like commas and periods from text data, simplifying inputs for the ANN to focus on semantic content.

Machine Learning Models:

K-nearest neighbors (KNN):

The k-nearest neighbors (KNN) algorithm is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. It is one of the popular and simplest classification and regression classifiers used in machine learning today.

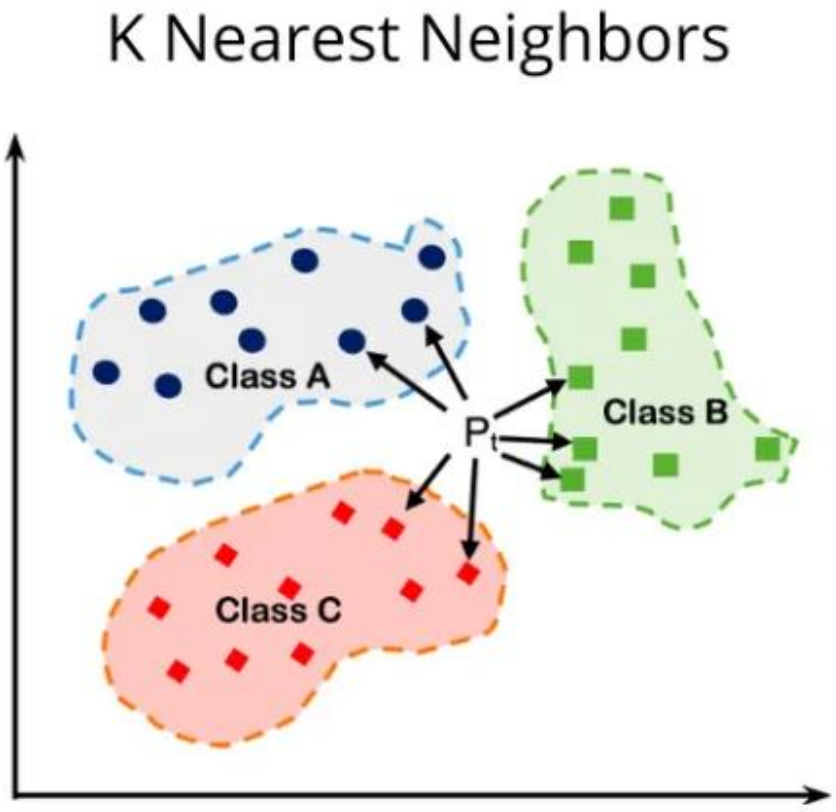
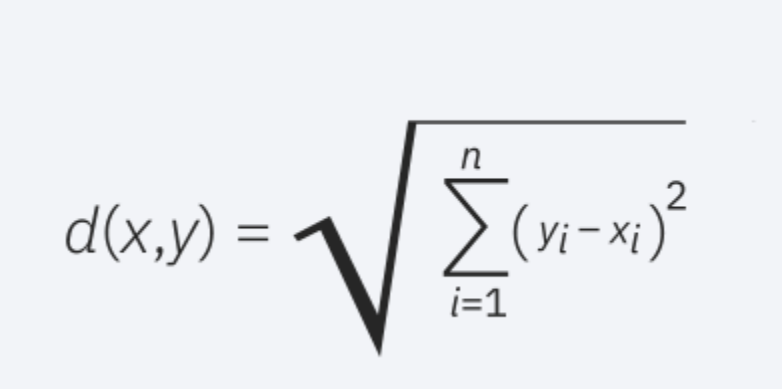


Figure 4. K-nearest neighbors

To determine which data points are closest to a given query point, the distance between the query point and the other data points will need to be calculated. These distance metrics help to form decision boundaries, which partitions query points into different regions. While there are several distance measures that you can choose from, this article will only cover the following:

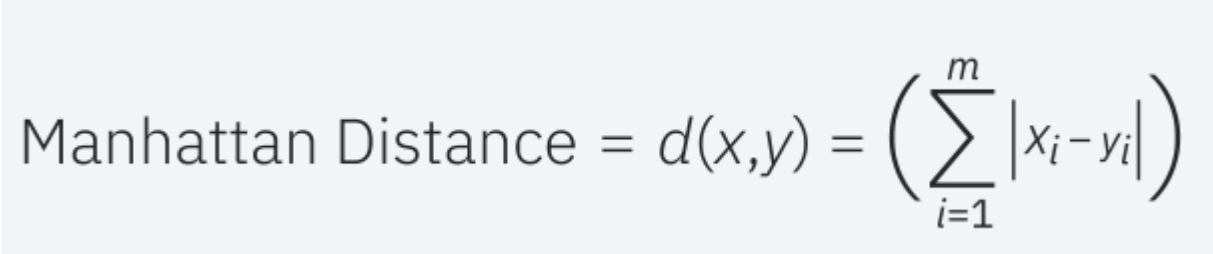
Euclidean distance (p=2): This is the most used distance measure, and it is limited to real-valued vectors. Using the below formula, it measures a straight line between the query point and the other point being measured.



$$d(x,y) = \sqrt{\sum_{i=1}^{n} (y_i - x_i)^2}$$

Eq 1. Formula for Euclidean distance

Manhattan distance (p=1): This is also another popular distance metric, which measures the absolute value between two points. It is also referred to as taxicab distance or city block distance as it is commonly visualized with a grid, illustrating how one might navigate from one address to another via city streets.



$$\text{Manhattan Distance} = d(x,y) = \left(\sum_{i=1}^{m} \left| x_i - y_i \right| \right)$$

Eq 2. Formula for Manhattan distance

Hamming distance: This technique is used typically used with Boolean or string vectors, identifying the points where the vectors do not match. As a result, it has also been referred to as the overlap metric. This can be represented with the following formula:

$$\text{Hamming Distance} = D_H = \left(\sum_{i=1}^{k} |x_i - y_i| \right)$$

$$x = y \quad D = 0$$
$$x \neq y \quad D \neq 1$$

Eq 3: Formula for Hamming distance

Minkowski distance: This distance measure is the generalized form of Euclidean and Manhattan distance metrics. The parameter, p, in the formula below, allows for the creation of other distance metrics. Euclidean distance is represented by this formula when p is equal to two, and Manhattan distance is denoted with p equal to one.

$$\text{Minkowski Distance} = \left(\sum_{i=1}^{n} |x_i - y_i| \right)^{1/p}$$

Eq 4: Formula for Minkowski distance

Results:

To evaluate the effectiveness of a classification model, various performance metrics are commonly used, including accuracy, Mean Squared Error, Root Mean Squared Error, Mean Absolute Error, R-squared, and F1-score. Following are the equations with their explanation for these metrics.

Mean Square Error represents the average of the squares of the errors between true and predicted values. Here, it is applied in an atypical manner to classification outcomes.

$$\mathbf{MSE = \Sigma\ (Y_i - p_i)^2 n} \qquad \mathbf{(1)}$$

The square root of MSE, giving an idea of the magnitude of errors between the predictions and the actual values. Equation (3) tells the formula to calculate RMSD:

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{N}} \qquad \mathbf{(2)}$$

F1-score is a consolidation of precision and recall admitting the fundamental concept on how this system works. Equation (3) tells the formula to calculate F1-Score:

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \qquad (3)$$

Mean Absolute Error calculates the average of the absolute differences between predictions and actual values, providing an understanding of the error magnitude. Equation (4) tells how to find Mean Absolute Error:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \qquad (4)$$

R-squared is a statistical measure representing the proportion of the variance for the dependent variable that's predicted from the independent variables. It is used here to quantify the goodness of fit for the model predictions in a regression sense, though its application to classification results is unconventional. Following is the equation to find r-squared:

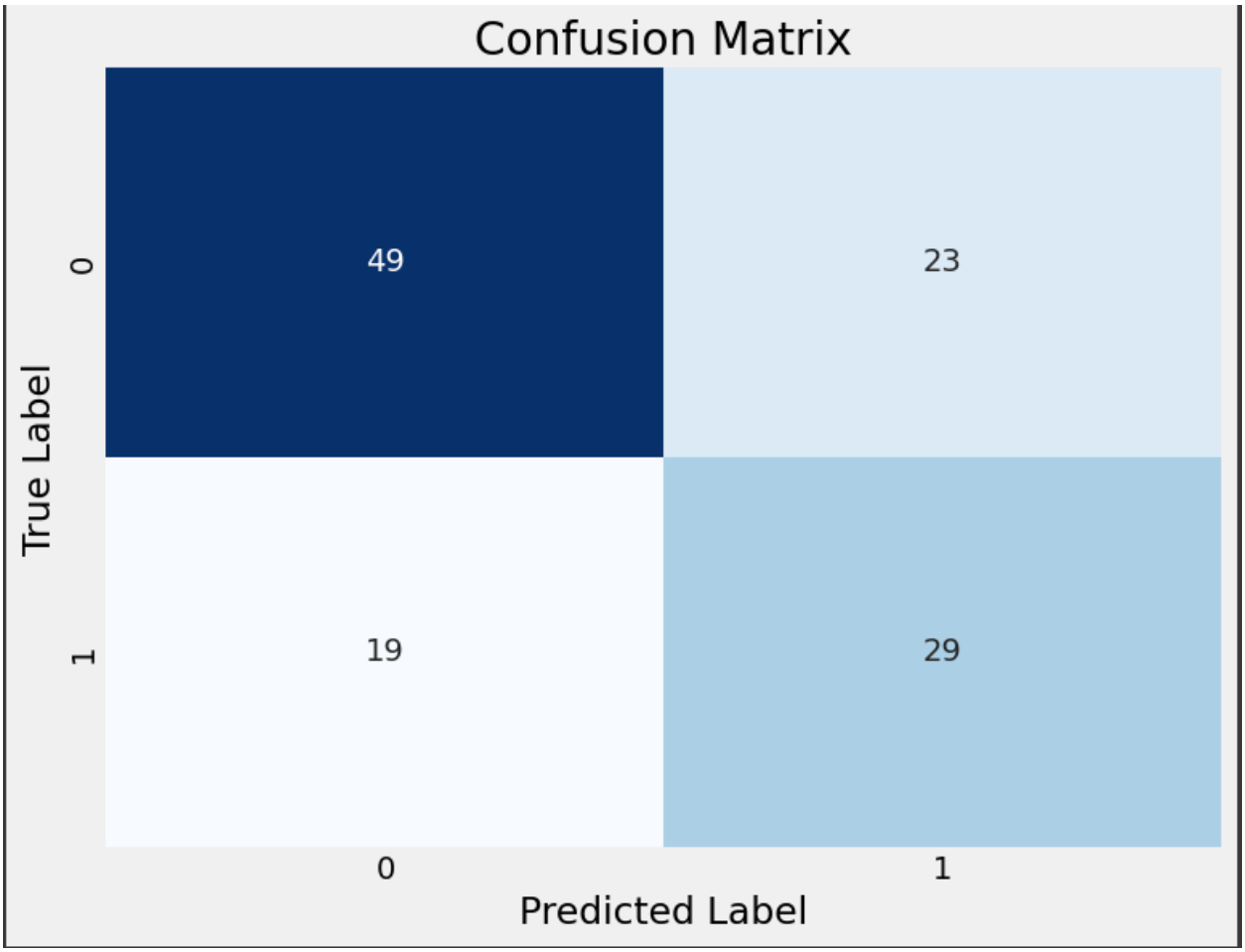
$$R^2 = 1 - \frac{RSS}{TSS} \qquad \mathbf{(5)}$$

The metrics obtained by both models are given below:

Metric	Value
MSE	0.035
RMSE	0.5916
MAE	0.035
R2 Score	-0.458
Accuracy	0.65
F1 Score	0.57999

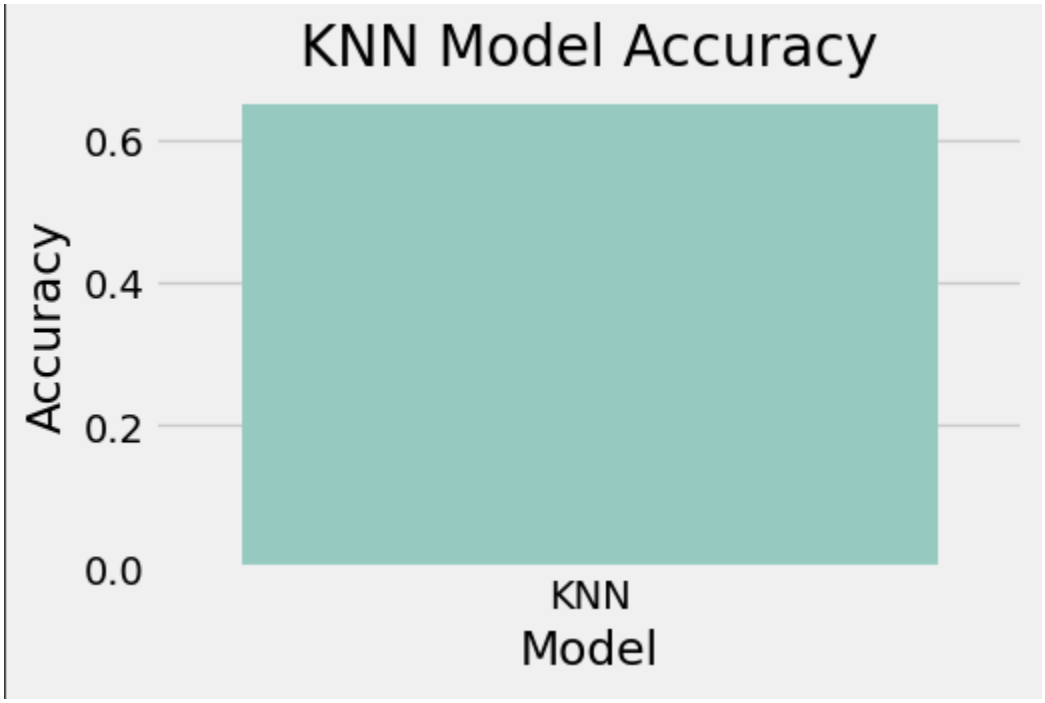
Metrics For KNN

Confusion Matrix:



Graphs:

The following figures shows the graph of the proposed models:



Graph of KNN Model

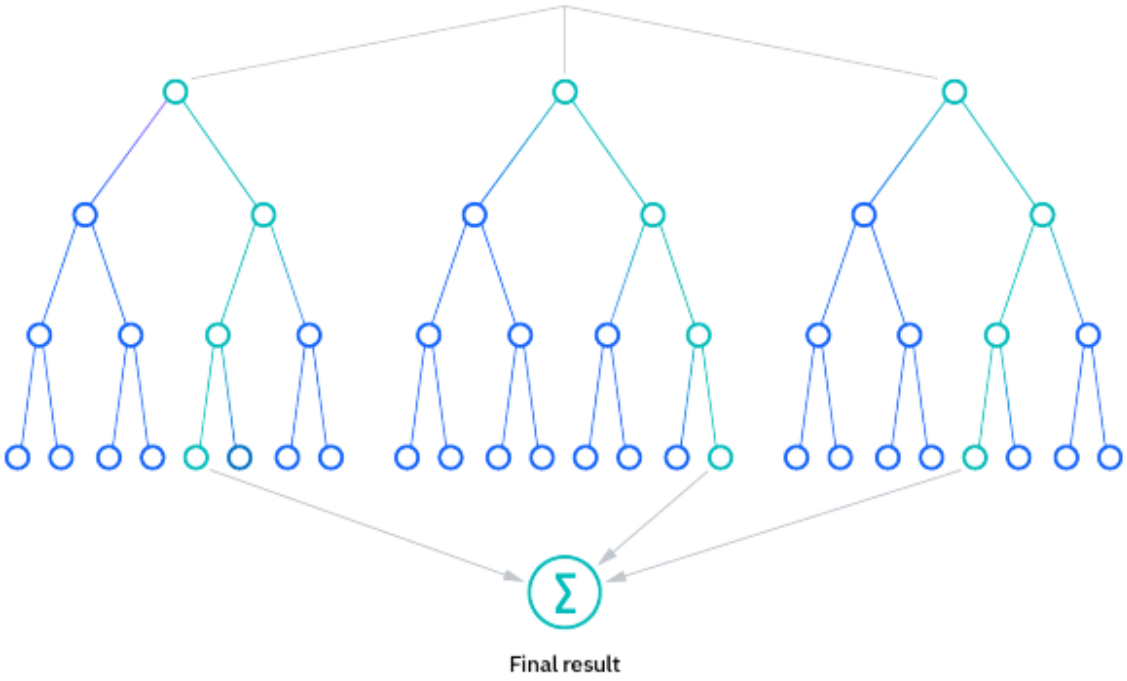
Random Forest:

Random forest is a commonly used machine learning algorithm, trademarked by Leo Bierman and Adele Cutler, that combines the output of multiple decision trees to reach a single result. Its ease of use and flexibility have fueled its adoption, as it handles both classification and regression problems.

How it Works:

Random forest algorithms have three main hyperparameters, which need to be set before training. These include node size, the number of trees, and the number of features sampled. From there, the random forest classifier can be used to solve regression or classification problems.

The random forest algorithm is made up of a collection of decision trees, and each tree in the ensemble is comprised of a data sample drawn from a training set with replacement, called the bootstrap sample. Of that training sample, one-third of it is set aside as test data, known as the out-of-bag sample, which we'll come back to later. Another instance of randomness is then injected through feature bagging, adding more diversity to the dataset, and reducing the correlation among decision trees. Depending on the type of problem, the determination of the prediction will vary. For a regression task, the individual decision trees will be averaged, and for a classification task, a majority vote—i.e. the most frequent categorical variable—will yield the predicted class. Finally, the oob sample is then used for cross-validation, finalizing that prediction.



Eq 1: Diagram of Random Forest

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$$\mathbf{MSE = \Sigma\ (Y_i - p_i)^2 n} \qquad \mathbf{(1)}$$

The square root of MSE, giving an idea of the magnitude of errors between the predictions and the actual values. Equation (3) tells the formula to calculate RMSD:

$$\mathbf{RMSD} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{N}} \qquad \mathbf{(2)}$$

F1-score is a consolidation of precision and recall admitting the fundamental concept on how this system works. Equation (3) tells the formula to calculate F1-Score:

$$\boldsymbol{F1 - Score} = \frac{\mathbf{2} * \boldsymbol{Precision} * \boldsymbol{Recall}}{\boldsymbol{Precision} + \boldsymbol{Recall}} \qquad (\mathbf{3})$$

Mean Absolute Error calculates the average of the absolute differences between predictions and actual values, providing an understanding of the error magnitude. Equation (4) tells how to find Mean Absolute Error:

$$\mathbf{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \qquad (4)$$

R-squared is a statistical measure representing the proportion of the variance for the dependent variable that's predicted from the independent variables. It is used here to quantify the goodness of fit for the model predictions in a regression sense, though its application to classification results is unconventional. Following is the equation to find r-squared:

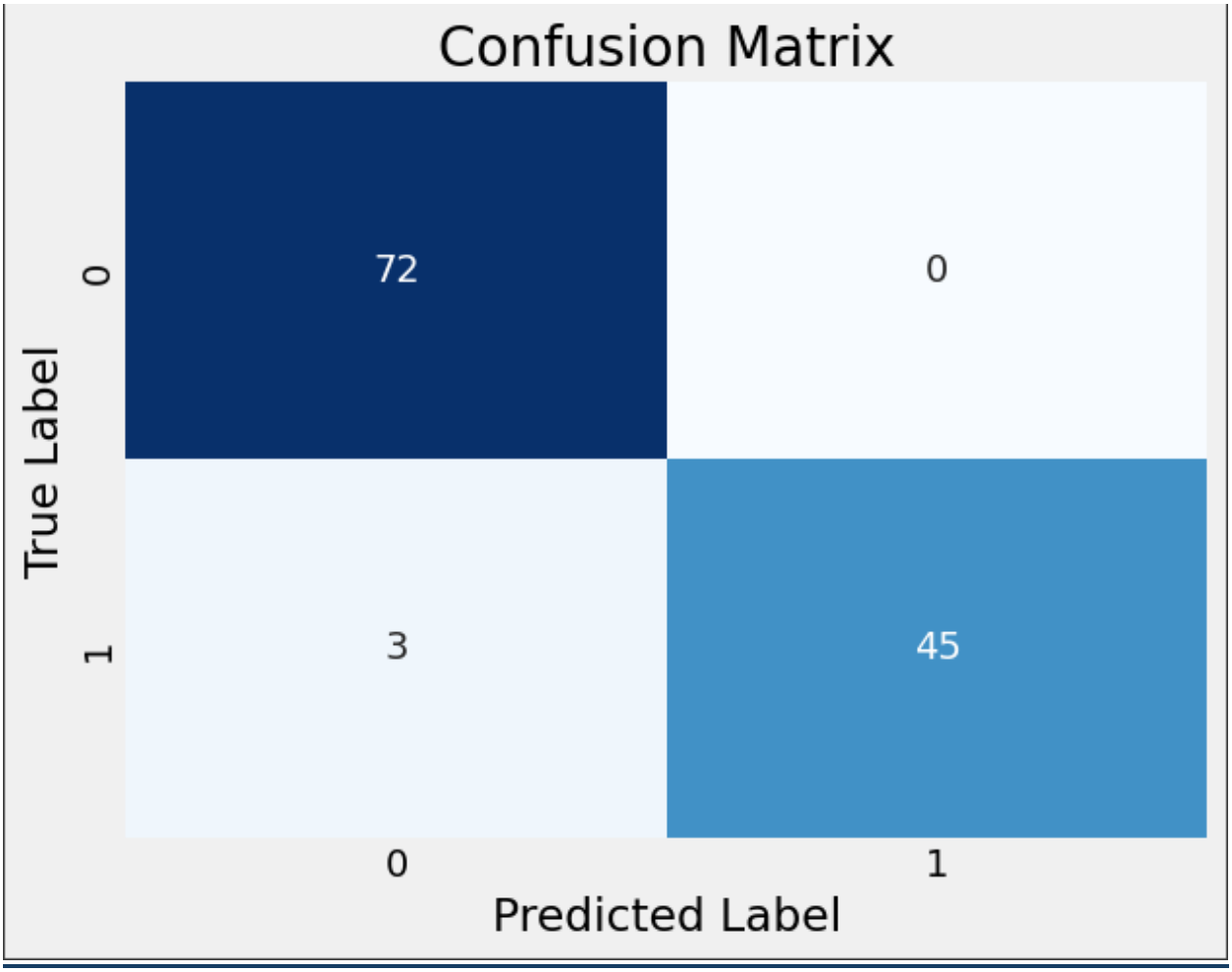
$$R^2 = 1 - \frac{RSS}{TSS} \qquad \mathbf{(5)}$$

The metrics obtained by both models are given below:

Metric	Value
MSE	0.035
RMSE	0.5916
MAE	0.035
R2 Score	-0.458
Accuracy	0.975
F1 Score	0.57999

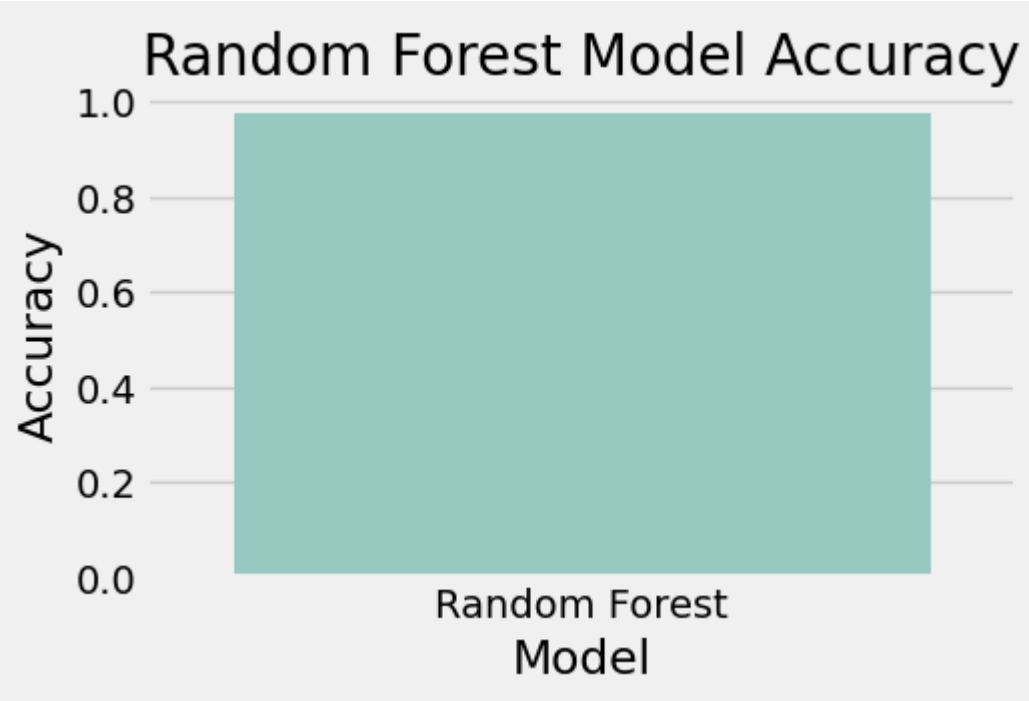
Metrics For Random Forest

Confusion matrix:



Graphs:

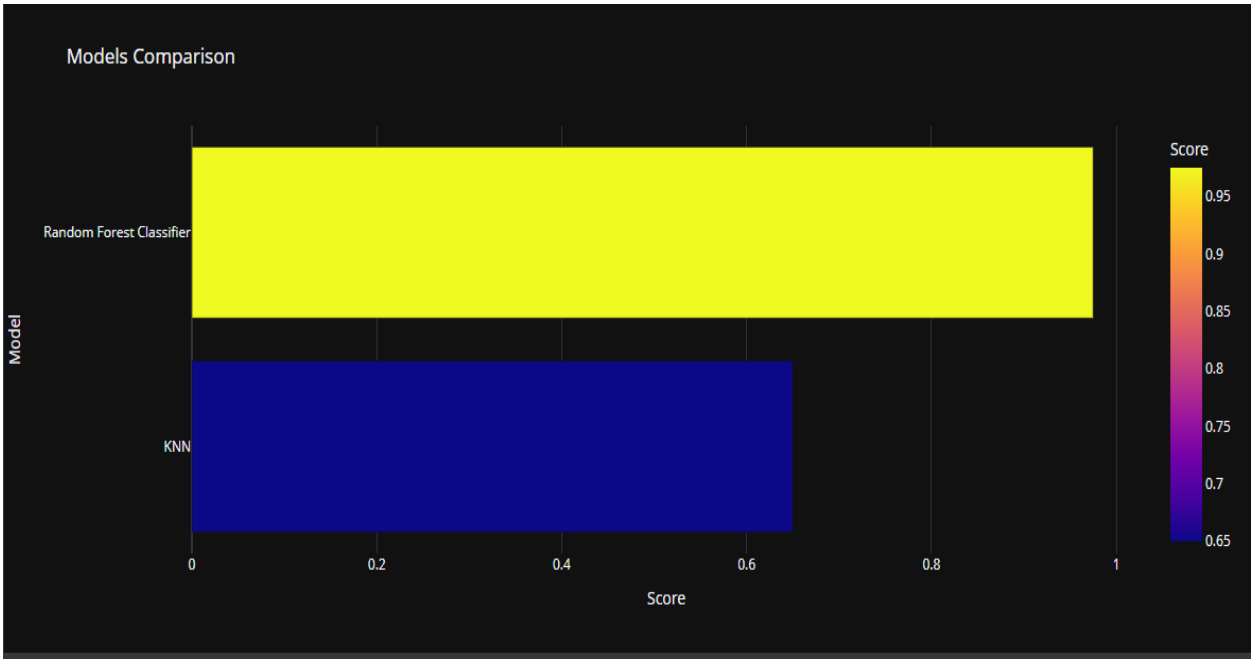
The following figures shows the graph of the proposed models:



Graph of Random Forest Model

Model comparison:

The figure shows the comparison of both models that we have implemented.



Conclusion:

In conclusion, our study has demonstrated significant progress in chronic kidney disease detection through the utilization of machine learning algorithms, including Convolutional Neural Networks (CNN), k-Nearest Neighbors (KNN), and Random Forest. The achieved accuracies underscore the effectiveness of these methods in analyzing complex medical data related to kidney health. While our results are promising, there remains potential for further refinement and enhancement. Future research could focus on optimizing the architectures and parameters of these models, potentially incorporating techniques such as transfer learning to leverage pre-trained models for improved performance. Additionally, exploring larger and more diverse datasets could enhance the models' ability to generalize to different populations and conditions, thereby increasing their clinical utility. By continually refining and advancing our approaches to using machine learning for chronic kidney disease detection, we can contribute to the development of more accurate and reliable diagnostic tools, ultimately improving patient outcomes and healthcare delivery.

Future Work:

For future work, involve investigating hybrid approaches that combine the strengths of multiple machine learning algorithms, such as ensembles of CNN, KNN, and Random Forest. Exploring such hybrid models could potentially lead to further improvements in accuracy and robustness by leveraging the complementary strengths of each algorithm. Additionally, incorporating domain knowledge and expert insights into the model development process could enhance its interpretability and clinical relevance. Furthermore, the deployment of these models in real-world clinical settings and evaluating their performance in diverse patient populations would be crucial steps towards their practical application and integration into healthcare systems. Lastly, continuous monitoring and updating of the models based on new data and emerging research findings would ensure their ongoing relevance and effectiveness in supporting clinical decision-making for chronic kidney disease diagnosis and management.

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