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Interpreting Chronic Kidney Disease Diagnosis: An AI Model Perspective

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Abstract

This research paper presents the development and evaluation of an artificial intelligence model specifically adapted for the diagnosis of early chronic kidney disease (CKD). Emphasis on explainability ensures transparent and understandable predictions, which are key to the adoption of AI in healthcare. CKD is a major global health problem that requires early diagnosis to stop kidney damage and reduce healthcare costs. The project aims to contribute to proactive solutions recognizing the borderline implications of CKD. Using an optimization framework balances classification accuracy and increases overall efficiency. This ML (Machine Learning) algorithm uses three key features for the diagnosis of CKD: Hb (hemoglobin), specific gravity, hypertension and required indicators for early detection of CKD. This model offers solutions and challenges, especially in developing countries, by emphasizing cost reduction and increasing the availability and affordability of health care. We also used methods to combine predictions from multiple models, including techniques such as a stacking classifier, yielding an impressive 100% accuracy.

Keywords: medical prediction model, early diagnosis, chronic kidney disease, feature selection, AI, Etiology.

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INTRODUCTION

A. Project Overview

Chronic kidney disease (CKD) is a prevalent and debilitating condition that affects millions of people worldwide. Accurate and timely diagnosis of CKD is essential for effective treatment and prevention of complications. Traditional diagnostic approaches rely heavily on clinical assessments and laboratory tests, often leading to delays in detection and misdiagnosis. Integrating artificial intelligence (AI) models into healthcare systems improves CKD diagnosis. Massive amounts of patient data AND AI algorithms can analyze complex patterns and identify indicators of CKD progression. Using machine learning techniques, these models can adapt and evolve, continuously improving their diagnostic accuracy. Our project aims to explore the potential of AI interpretation of CKD from a perspective. By developing and evaluating artificial intelligence diagnostic models, we aim to increase the accuracy and efficiency of CKD detection. In addition, we aim to explore the interpretability of these models and ensure that clinicians understand and trust the decisions made by AI algorithms. CKD is one of the few non-communicable diseases that have seen an increase in deaths in recent years,

health systems, especially in low-middle-income countries [1]. CKD is usually caused by diabetes, specific gravity, and hypertension, and is also a cardiovascular disease that is the leading cause of early mortality in patients with CKD [2]. CKD is the presence of kidney damage or an estimated glomerular filtration rate (eGFR) of less than 60 mL/min/1.73 mt2 for 3 months or longer. Globally, CKD accounted for 2,968,600 (1%) disability-adjusted life-years and 2,546,700 (1% to 3%) life-years lost in 2012[1]. The causes of CKD vary globally and the most common primary diseases causing CKD as Diabetes mellitus type 2, Diabetes mellitus type 1, Hypertension, Primary glomerulonephritis, vasculitis, neoplasm, etc. [6]. there are three categories: prerenal, intrinsic renal, or postrenal [6]. History of chronic hypertension, proteinuria, microhematuria and symptoms of prostate disease. Low serum calcium and high phosphorus levels have little discriminatory value, but normal parathyroid hormone levels are more suggestive of AKI than CKD. Patients who have very high blood urea nitrogen values greater than 140 mg/dL or serum creatinine greater than 13.5 mg/dL, who appear relatively well and yet pass normal volumes of urine, have CKD rather than acute kidney disease. "Nearly 750,000 patients annually in the United States and an estimated 2 million patients worldwide are affected by kidney failure. Those living with kidney failure make up 1% of the US Medicare population, but account for 7% of the Medicare budget." By combining artificial intelligence technologies with clinical knowledge, our project provides improved tools for early detection and intervention and improves the quality of life of affected individuals worldwide.

B. Objective

The aim of the project on the interpretation CKD of the diagnosis from the perspective of an AI model is that to Considering the limitations of conventional CKD diagnostic methods, particularly their lack of accuracy in detecting CKD at early stages.

LITERATURE SURVEY

A. Existing System

A project to interpret chronic kidney disease (CKD) diagnosis from the perspective of cognitive models, designed to improve diagnostic procedures using advanced machine learning. Currently available methods are based on traditional methods such as clinical trials, observational studies, and clinical trials but suffer from limitations such as lack of definition, delays in detection and intervention, dependence on invasive procedures, poor data processing, and limited availability. The project explores the use of cutting-edge techniques such as ExtraTree Classifier, Random Forest, AdaBoost Classifier, XGBoost and Extension Stacking Classifier to solve these problems. The ExtraTree classifier is a different type of forest algorithm that creates decision trees by separating them from each other to increase diversity and reduce overfitting. Random Forest is a learning method that involves estimation of multiple decision trees, increasing accuracy and robustness. AdaBoost Classifier combines multiple weak classifiers to create a strong classifier that focuses on difficult-to-sort examples. XGBoost is an optimized gradient boosting algorithm that uses a new tree learning algorithm to increase efficiency and performance. The next generation combines the advantages of Random Forest, ExtraTree, and AdaBoost by leveraging differences between multiple base classifiers to improve prediction performance. The project aims to improve the accuracy, efficiency and interpretation of CKD diagnosis by integrating these advanced techniques into the CKD diagnostic framework, ultimately improving patient outcomes and

reducing treatment burden. range of CKD data to provide clinical assistance to physicians. Moreover, the continuous classifier provides the best value and interpretation model by combining the results of various base classifiers, ensuring the reliability and informativeness of the information taken into account in the diagnosis of CKD. Together, the integration of these advanced learning systems into a CKD diagnostic framework represents an important step towards improving the accuracy, efficiency, and interpretation of CKD diagnosis. By leveraging the power of artificial intelligence and machine learning, the program aims to change the framework of CKD diagnosis, ultimately improving patient outcomes and reducing treatment burden.

B. Related Work

In Order to identify the patient's risk of kidney function, researchers have been developing several disease prediction models. They present an uncertain capability due to the use of non-public datasets, such as like medical images or clinical which helps in making the models. The use of the CKD dataset from the UCI-ML repository and implementing feature selection for the preprocessing step in their CKD data analysis. Although the related works always consider the reduction of the original number of features to get the best results. Thus, Our research provides a novel approach by analyzing the prediction model developed by the influence of selected features in the classification of CKD. In the diagnosis of chronic kidney disease (CKD), recent advances in artificial intelligence (AI) and machine learning (ML) have led to significant advances in early diagnosis and treatment control strategies. Some related projects are investigating various cognitive models to improve accuracy and efficiency.

TABLE I

"Distribution results of relevant tasks and their machine learning classifiers (best classifier written in *underlined italics*)"

Article	Acc	Sen	Spe	F1	Pre	#F	Machine Learning Classifier
Ekanayake [13]	100	100	-	100	100	7	*DT, RF*, XGB, *Ada*, ET (*)
Alaoui [14]	100	-	-	-	-	23	*XGB Lin*, Lin SVM, DT, RF
Ogunleye [15]	100	100	100	-	100	12	*XGB* (*)
Abdel-Fattah [11]	100	100	100	100	100	12	SVM, RF, DT, *GBT*, LR, NB(*)
Ebiaredoh-Mienye [10]	99.9	100	99.8	-	-	18	LR, DT, XGB, RF, SVM, *Ada*
Zeynu [16]	99.5	99.5	-	99.5	99.5	8	KNN, DT, *ANN*, NB, SVM.
Raju [17]	99.3	99	-	99	100	5	XGB, *RF*, LR, SVM, NB(*)
Imran Ali[18]	99,1	100	97.5	99.4	98.8	6	NB, *LG*, ANN, DT, RF, GBT, SVM
Khan [19]	99.1	99.7	-	99.3	98.7	23	*NB*, LR, SVM, DT, RF
Hasan [20]	99	-	-	99	-	13	*Ada*, RF, GB, ET(*)
Antony [21]	99	100	-	99,2	98.4	10	*KMeans*, DBScan, Autoencoder, IForest
Chaudhuri [22]	99	96	100	-	-	13	LR, NB, SVM, DT, RF, *EDT*(*)
Abdullah [23]	98.8	98.0	100	98.8	98.0	10	*RF*, SVM, NB, LR
Poonia [24]	98.75	98	-	99	100	14	*LR*, NB, SVM, KNN, ANN
Siddhartha [25]	98.75	100	96.67	99	98.03	5	*RF*, Ada, XGB
Alaiad [26]	98.5	99.6	96.8	-	98	12	NB, DT, SVM, *KNN*, Jrip
Kadhum [27]	98.1	98	-	98	98	10	SVM, *ELM*
Akter [28]	97	98	-	96	97	10	*ANN*, LSTM, Bi LSTM, GRU, Bi GRU, Simple RNN, ML
Theerthagiri [29]	96	97	99	94.9	95.8	6	LR, SVM, KNN, NB, *RF*
Ali [30]	91.25	91.89	97.37	94.81	97.81	5	NB, LG, DL, *ANN*, RF, GBT, SVM

MATERIAL AND METHODS

A. Chronic kidney disease (CKD) Dataset

The CKD dataset from collected from the Apollo Hospital, Karaikudi, India during a 2-month period in the year 2015 that also includes the 400 patients where some given missing values in their features. Each dataset instance is composed of 11 numeric features, 3 ordinal features, 10 nominal features and 1 target feature which determines whether the person is having CKD or not. It is given two 2 values they are not CKD and CKD. The features in dataset given are age, blood pressure[bp], specific gravity to compare the density of urine to the density of water [sg], the presence of albumin in urine[al], level of sugar present in the urine[su], red blood cells in the urine[rbc],pus cells ,major or minor infection, growth of bacteria, the level of creatinine in the blood, percentage of cells in blood, amount of red blood cells present in the blood, whether the patient has diabetes[dm], coronary artery disease[cad], lossof appetite[appet], level of leg swelling and whether the patient has CKD or not [target class] etc.

B. Framework for Model Selection Optimization

The framework named feature selection and classification for improving explainable AI (SCI- XAI) and it is published and employed to develop the CKD prediction model (Figure 1). It is implemented by the Python scikit-learn package, allows obtaining detection model in terms of accuracy and number of features selected by considering different parameters. The dataset is split respectively into training and test sets in an ratio of (70/30). So, the model's performance is calculated over new data from the test set that is applied tot selected parameters by the framework in the preprocessing and training phases.

TABLE II

"Statistics for dataset properties: type (number, count, or number), percent of non-values, mean, standard deviation (for properties of numbers), categories, and samples per category (for attributes ames)"

Features (units) [legend]	Type of feature (% of non-null values) [classes in ordinal or nominal features]	Average (std) for numerical features / number of values for ordinal or nominal features
Age (year) [age]	Num (97,75 %)	51.48 (17.17)
Blood pressure (mm/Hg) [bp]	Num (97 %)	76.46 (13.68)
Specific gravity [sg]	Ord (88,25 %) [1.005,1.010,1.015, 1.020, 1.025]	7, 84, 75, 106, 81
Albumin [al]	Ord (88,5 %) [0,1,2,3,4,5]	199,44,43,43,24,1
Sugar [su]	Ord (87,75 %) [0,1,2,3,4,5]	290,13,18,14,13,3
Red blood cells [rbc]	Nom (62 %) [normal/abnormal]	47 abnormal
Pus cell [pc]	Nom (83,75 %) [normal/abnormal]	76 abnormal
Pus cell clumps [pcc]	Nom (99 %) [not present/ present]	42 present
Bacteria [ba]	Nom (99 %) [not present/ present]	22 present
Blood glucose random (mgs/dl) [bgr]	Num (89 %)	148.04 (79.28)
Blood urea (mgs/dl) [bu]	Num (95,25 %)	57.43 (50.50)
Serum creatinine (mgs/dl) [sc]	Num (95,75 %)	3.07 (5.74)
Sodium (mEq/l) [sod]	Num (78,25 %)	137.53 (10.41)
Potassium (mEq/l) [pot]	Num (78 %)	4.63 (3.19)
Hemoglobin (gms) [hemo]	Num (87 %)	12.53 (2.91)
Packed cell volume [pcv]	Num (82,50 %)	38.88 (8.99)
White blood cell count (cells/cumm) [wc]	Num (73,75 %)	8406.12 (2944.47)
Red blood cell count (cells/ cumm) [rc]	Num (67,5 %)	4.71 (1.03)
Hypertension [htn]	Nom (99,5 %) [no/yes]	147 yes
Diabetes mellitus [dm]	Nom (99,5 %) [no/yes]	137 yes
Coronary artery disease [cad]	Nom (99,5 %) [no/yes]	34 yes
Appetite [appet]	Nom (99,75 %) [good/poor]	82 poor
Pedal edema [pe]	Nom (99,75 %) [no/yes]	76 yes
Anemia [ane]	Nom (99,75 %) [no/yes]	60 yes
Target class	Nom (100%) notCKD/CKD	250 CKD

Num= numerical. Ord= ordinal. Nom= nominal

C. *Data Preprocessing*

The SCI-XAI framework adopts a method of a priori data generation and has three main stages: missing data processing, data coding, and feature selection. To handle missing data, the framework uses a data types-based rendering strategy. Properties of the number include the use of instruments, while the standard and nominal type (or active value) are used to fill in the blanks. During the encoding phase, numerical attributes are subjected to a min-max scaling process to standardize their values, while ordinal and nominal attributes are converted to numerical codes. Especially sequential attributes encoded with integers (e.g. 0-5 with step size 1). A character is said to be binary encoded (0 or 1). This first step to handle missing data and encodings is set outside the modification algorithm parameter. Additionally, this framework highlights the role of feature selection in improving model interpretation by removing redundant features during classification. It uses filtering techniques to select features and uses statistical tests such as analysis of variance, chi-square, or shared data to evaluate the reliability or significance of data, identifying features and different targets. This will help you determine which features should be kept or excluded. Additionally, wrapper methods such as Recursive feature Elimination (RFE) are used, where a classifier (such as logistic regression) helps identify the most important features by well evaluating their relationships with a different objective. This excellent choice not only simplifies the model but also improves its interpretation. Tree classifiers have become a top choice in the machine learning community due to their excellent stability and performance on multivariate datasets as well as their goodness at prediction. These classifiers are good at combining multiple decision tree models by weighting them or combining them to create a composite model that exceeds the performance of a single predictor. This combination not only improves the accuracy of prediction but also reduces the class mismatch problem, making the tree unique in different applications.

D. Classification Performance and evaluation metrics

Given the inconsistency of the data used, it is not sufficient to rely on accuracy to evaluate the performance of the model when comparing 250 CKD to 150 non-CKD data. Additional metrics such as sensitivity, specificity, accuracy, and F1 score are important to better understand the performance of the model. These parameters roughly estimate the model's ability to identify CKD cases (sensitivity) while including non-CKD cases (specificity), as well as the accuracy of prediction quality such as F1 score and the balance between accuracy and sensitivity. Also, in order to confirm that the material used in this study was well interpreted, Tagaris The formulas of these metrics are shown Table3.

TABLE III

METRICS OF CLASSIFICATION PERFORMANCE AND EXPLAINABILITY EVALUATION

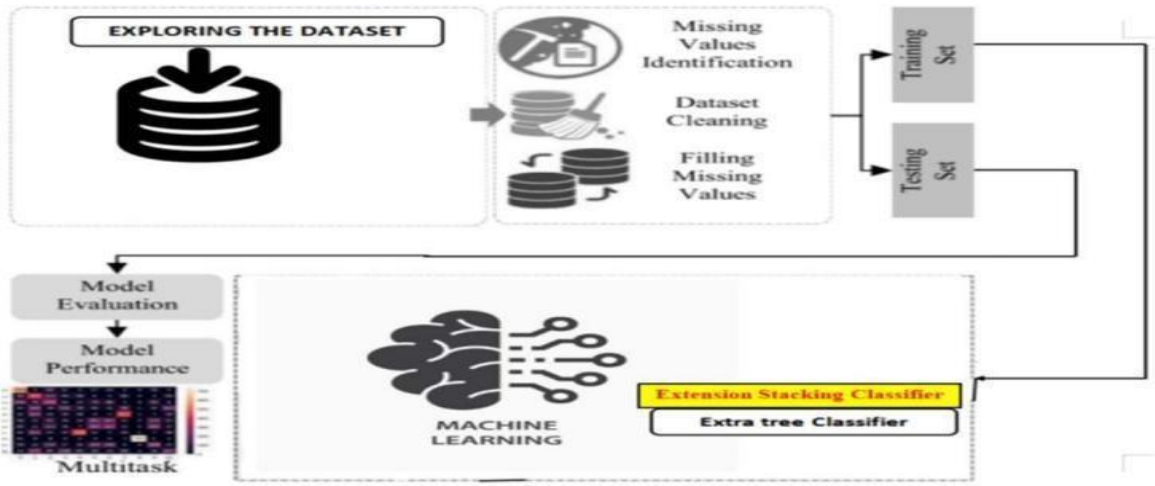
Metric	Equation
Accuracy (Acc)	$Acc = \frac{TP + TN}{TP + TN + FP + FN}$
Sensitivity/Recall (Sen)	$Sen = \frac{TP}{TP + FN}$
Specificity (Spe)	$Spe = \frac{TN}{TN + FP}$
Precision (Pre)	$Pre = \frac{TP}{TP + FP}$
F1-Score (F1)	$F1 = 2 * \frac{Pre*Sen}{Pre+Sen}$
Interpretability (I)	$I = \frac{Masked\ features}{Total\ features}$
Fidelity (F)	$F = \frac{Acc.equivalent\ interpretable\ model}{Acc.\ original\ model}$
Fidelity-Interpretability Index (FII)	$FII = F * I$
Fidelity-Accuracy Index (FAI)	$FAI = F * Acc$

PROPOSED SYSTEM

The proposed system describes a new artificialintelligence (XAI) model developed for the earlydiagnosis of chronic kidney disease (CKD) and covers a new improvement approach that makes it better to know the truth by collaborating with the transparent model. Combining advanced machine learning techniques with a unique gradient boosting technique, the system guides the path to accurate and timely CKD detection. This integration of cutting-edge techniques not only increases the accuracy of diagnosis, but also informs the logicbehind decision-making, which is important in supporting trust and acceptance of AI-driven solutions in healthcare. In this context, we strive to leverage the power of collaboration to increase the accuracy and reliability of data-driven approaches to early diagnosis of CKD. Our model achieves the opposite by demonstrating the power of the combination of many predictive models, using the concept of common ideas, specifically discrete parts. We also created an interface for intermediate users using Flask to improve accessibility and user interaction. The interface is designed with a secure authentication mechanism to ensure a seamless and secure user experience; This allows us to define the AI model not only as a measure for the early detection of CKD, but also as an easy-to-use anduser-friendly solution.

A. System Architecture

The System architecture for the project, the journey begins with a close examination of the dataset, where preliminary data is required to clean, model and optimize ideas for later

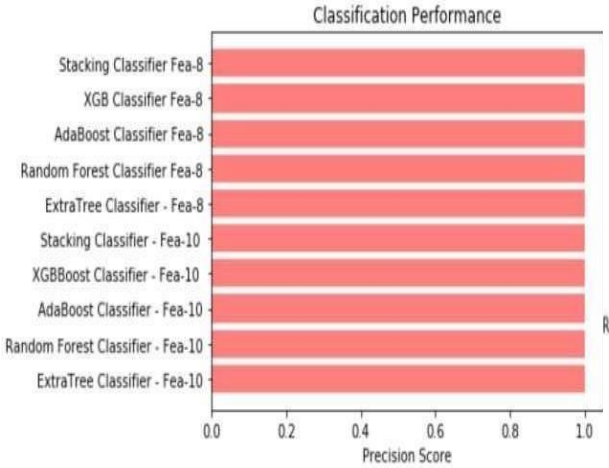


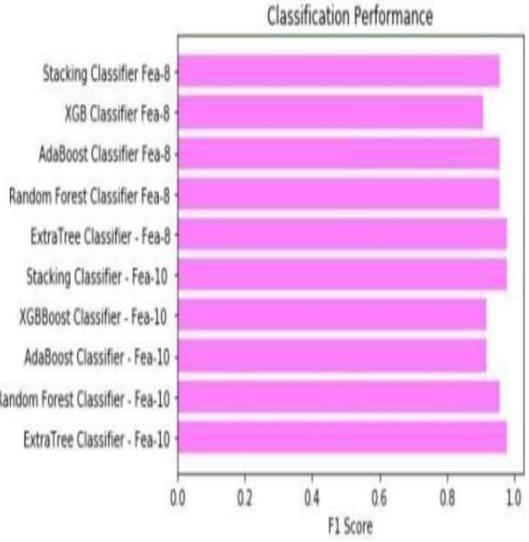
analysis. After this first step, the equipment is divided into training and testing, and the foundation of training models and effective use is laid. The basis of the model level is the integration of complex methods such as bulk classifiers and additive tree classifiers, allowing the analysis of the project to be extended.

Fig 1 Proposed Architecture

METHODOLOGY AND RESULTS

Dataset features include various clinical parameters: age [age], diastolic blood pressure [bp], urine density relative to water [sg], urine albumin level [al], urine glucose [water], presence of red blood cells in urine [rbc], pus in the urine indicates an infection [pc], cysts in the brain indicate a serious infection [pcc], bacterial growth in the urine [ba], blood glucose concentration [bgr], blood urea nitrogen [bu], blood creatinine [sc], blood sodium [sod], blood potassium [pot], hemoglobin in red blood cells [hemo], hematocrit [pcv], white blood cell count [wc], red blood cell count [rc], presence of hypertension [htn], diabetes [dm], coronary arterial disease [cad], appetite [appetite], pedal edema [pedal] and anemia [ane], and CKD status [objective category]. A detailed compilation of these clinical indicators provides a comprehensive framework for CKD diagnosis and greatly contributes to the advancement of clinical research and treatment.

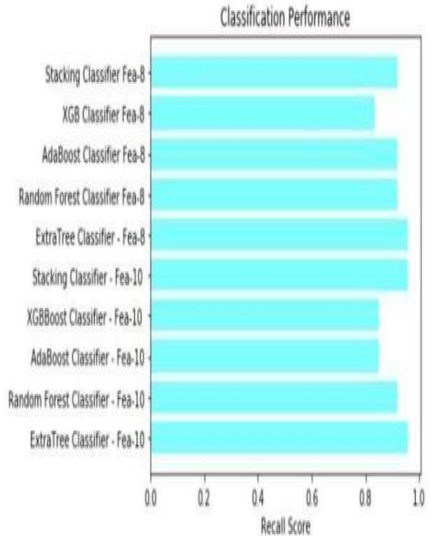


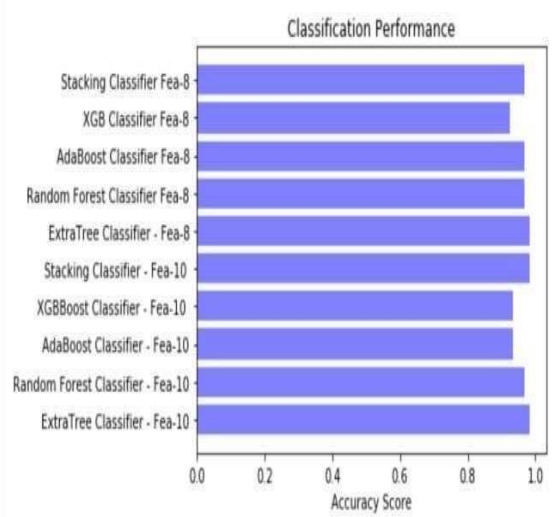


	Algorithms Used	Accuracy	Precision	Recall	F1-Score
0	ExtraTree Classifier - Fea-10	0.983	1.0	0.957	0.978
1	Random Forest Classifier - Fea-10	0.967	1.0	0.918	0.957
2	AdaBoost Classifier - Fea-10	0.933	1.0	0.849	0.918
3	XGBBoost Classifier - Fea-10	0.933	1.0	0.849	0.918
4	Extension Stacking Classifier - Fea-10	1.000	1.0	1.000	1.000
5	ExtraTree Classifier - Fea-8	0.983	1.0	0.957	0.978
6	Random Forest Classifier Fea-8	0.967	1.0	0.918	0.957
7	AdaBoost Classifier Fea-8	0.967	1.0	0.918	0.957
8	XGB Classifier Fea-8	0.925	1.0	0.833	0.909
9	Extension Stacking Classifier Fea-8	0.992	1.0	0.978	0.989

id	age	bp	sg	al	su	rbc	pc	pcc	ba	bgr	...	pcv	wc	rc	htn	dm	cad	appet	pe	ane	classification
0	48.0	80.0	1.020	1.0	0.0	NaN	normal	notpresent	notpresent	121.0	...	44	7800	5.2	yes	yes	no	good	no	no	ckd
1	7.0	50.0	1.020	4.0	0.0	NaN	normal	notpresent	notpresent	NaN	...	38	6000	NaN	no	no	no	good	no	no	ckd
2	62.0	80.0	1.010	2.0	3.0	normal	normal	notpresent	notpresent	423.0	...	31	7500	NaN	no	yes	no	poor	no	yes	ckd
3	48.0	70.0	1.005	4.0	0.0	normal	abnormal	present	notpresent	117.0	...	32	6700	3.9	yes	no	no	poor	yes	yes	ckd
4	51.0	80.0	1.010	2.0	0.0	normal	normal	notpresent	notpresent	106.0	...	35	7300	4.6	no	no	no	good	no	no	ckd

5 rows × 25 columns





CONCLUSION AND FUTURE SCOPE

The program represents a significant advance in the diagnosis of chronic kidney disease (CKD) by leveraging the power of machine learning algorithms and artificial intelligence (XAI) technology. By leveraging integrated methods such as Random Forest, ExtraTree, AdaBoost and XGBoost and a novel continuous group classifier, the system achieves unparalleled accuracy and robustness in early CKD detection. The integration of these advanced techniques not only improves forecasting performance but also provides clarity and clarification in the decision-making process; Meeting expectations has become important in medicine. Through careful review of preliminary data, sample selection and optimization, the project developed a comprehensive and reliable CKD diagnostic system. The model extracts the most important features and information by searching UCI-ML's CKD data and using best-in-class architectural techniques, thus reducing computational cost while increasing diagnostic accuracy.

A. *Future Scope*

External validation is an important step in evaluating the effectiveness of diagnostic criteria for early kidney disease (CKD) [4]. It involves evaluating the performance of the model on independent data not used during training to ensure that it is generalizable to

different patient populations. By creating a model for different materials with similar properties, researchers can determine its stability and reliability in real situations, thus providing confidence in its validity. Transparency and reliability are important in medical practice, the decision directly affects the health of patients. While the development of a transparent model improves understanding of doctors' decision-making process, trust must be established to have a good relationship with clinical information and emotions. Further progress in this area may require using machine learning models, improving descriptive models, or gathering feedback from practitioners to increase trust and acceptance in healthcare. Techniques such as Partial Belief Plot (PDP) and SHapley Additive Interpretation (SHAP) [51, 52] provide sophisticated methods for examining in more depth the individual consequences of the model's predictions. While PDP specifies

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