***Review Article***

**A Comprehensive Analysis to Detect Chronic Kidney Disease and Stage Prediction: Using Machine Learning**

**Abstract:** Chronic Kidney Disease (CKD) is worldwide health concern that causes other diseases and has a high rate of morbidity and mortality. Patients hardly ever notice chronic kidney disease (CKD) because there aren't visible signs in the early stages. Patients can obtain appropriate treatment to control the progression of chronic kidney disease (CKD) if the condition is detected early. This article investigates the applications of ensemble learning methods, such as AdaBoost, Random Forest, Gradient Boosting, and Voting Classifiers, for CKD prediction. These models address significant problems with CKD datasets, including missing values, unbalanced classes, and excessive complexity, by utilizing the benefits of several base learners. The ensemble models provide a tool for the early detection of CKD and tailored treatment by effectively representing the different patterns and interactions observed in the data.

**Keywords:** Machine learning, chronic kidney disease (CKD), GFR, Prisma, Ensemble Learning, deep learning

**1. Introduction**

**1.1 Background and Motivation**

Damage to the kidneys resulting from improper blood filtering is known as chronic kidney disease (CKD). The kidney's primary function is to filter extra water and waste from human blood and expel it through urine. That is, waste products build in the body of a person with CKD, leading to symptoms like fever, rash, vomiting, back pain, diarrhoea, nosebleeds, and abdominal pain. Since the damage occurs gradually, it will impact the rest of the body and cause a variety of ailments. The condition may cause mortality as it progresses and reaches its last stages.

Due to the fact that these diseases are not diagnosed early, the mortality rate due to infection with several diseases is currently going up. Numerous studies have been carried out to solve this issue, support medical professionals, and fewer fatality rates with the use of advanced computer-based detecting techniques [1]. Chronic kidney disease (CKD) affects millions of people worldwide; it's only worsened over time. Kidney disease is currently the only NCD with a persistent increase in age-adjusted mortality and the third fastest-growing cause of death worldwide. CKD by 2040 is predicted to be the fifth most common cause of the world’s year of life lost (YLL) [2].

|  |  |  |  |
| --- | --- | --- | --- |
| **Stage** | **Description** | **GFR (mL/min/1.73****m2 )** | **Symptoms/Indicators** |
| **1** | Damaged kidneys with normal GFR | ≥90 | Normal / slightly reduced kidney function. Usually no symptoms. Proteinuria may be present. |
| **2** | Mild decline in renal function | 60 – 89 | Mild decline in GFR. Generally no symptoms. May detect protein or blood in urine. |
| **3a** | Mild to moderate reduction | 45–59 | Early signs of kidney dysfunction: fatigue, fluid retention, mild bone disease risk. |
| **3b** | Moderate reduction | 30–44 | Noticeable symptoms such as fatigue, swelling, and back pain. Anemia may develop. |
| **4** | Severe reduction | 15–29 | Severe symptoms like fatigue, nausea, and swelling. Preparation for dialysis or transplant. |
| **5** | Kidney failure (End-Stage) | < 15 | Requires dialysis or transplant. Severe symptoms include appetite loss, muscle cramps, and itching. |

**Table 1. CKD Stages**



 **Fig. 1 shows GFR filtration rate values [23]**

The Glomerular Filtration Rate (GFR) blood test evaluates the capacity of kidney to remove waste from the blood. An undesirable by-product of the body's normal muscle breakdown is creatinine. Creatinine is eliminated from the blood by the kidneys. GFR can be ascertained by medical professionals by examining blood creatinine levels. Blood creatinine levels will increase as renal disease worsens. The GFR reading of 60 or higher is regarded as normal. A GFR number below 15 indicates kidney failure, but a value between 15 and 60 indicates renal disease.

**1.2 Role of Technology and Advancements**

Early detection is essential for effective intervention, therapy, and patient outcomes in chronic kidney disease (CKD). In recent years, algorithms using deep learning have been identified as a potentially helpful technique for the detection of conditions like chronic kidney disease (CKD). The CNN architecture works well for complex medical data analysis when used in a deep learning-based system. The CNN design depends on how the visual information has been processed by the human brain, and CNN may automatically use this to extract features and patterns from data. The algorithm for CKD detection uses the clinical and laboratory parameters from the CKD dataset [3]. To identify CKD early on, some research employed SVM (Support Vector Machines), ANN (Artificial Neural Network), DNN (Deep Neural Network), Extra tree, Ensemble method, Logistic Regression models and Random Forest. Additionally, for the CKD classification, the density-based feature selection (DFS) with ant colony based optimization algorithm (D-ACO) was created. CNN, Light GBM, Logistic Regression, Decision Tree, and Random Forest models have been developed to forecast CKD between a period of six to twelve months ahead of time.

Numerous studies have used a range of datasets and approaches to investigate the way various machine learning algorithms predict chronic kidney disease. For instance, using the "chronic kidney disease" database on WEKA, Boukenze et al. examined the use of SVM, Multilayer Perceptrons C4.5, (MLP), Bayesian Networks (BN), and K-Nearest Neighbours (K-NN) in Chronic Kidney Disease prediction. Their findings demonstrated the potential of both MLP and C4.5, with ROC analysis indicating that C4.5 had the maximum efficiency. The limitations of the study, including its lack of clinical validation and dependence on a single dataset, emphasized the need for more study to validate these results across other datasets and demographics [4].

Two algorithms presently rule the machine learning field, according to a vast quantity of research: Ensemble and Deep Learning algorithms [5]. Deep Learning is the study standard for machine learning algorithms and methods that combine several deep learning classifiers to reach a conclusion are collectively referred to as deep ensemble algorithms. Therefore, in the present study, we combine ensemble and deep learning methods with an ensemble algorithm. In contrast, deep learning approaches are thought to be the most potent and dominant force in a range of machine learning problems. Its main function is to find hidden information in the vast amount of data that physicians routinely collect from patients in order to make a final forecast. The objective of the deep learning model is to learn features that can’t be extracted with traditional techniques. By overcoming the shortcomings of traditional learning techniques, our algorithm improves the accuracy of prediction and detection [6].

Nowadays, deep learning methods perform better than conventional classification methods. Deep learning algorithms use long short-term memory, convolutional neural networks, and numerous more methods to address machine learning problems. In an effort to enhance predictive performance, numerous methods that combine deep learning models with ensemble methods have been developed recently. For create a final model that performs the best in terms of generalization, the deep ensemble learning method combines the advantages of ensemble learning with deep learning.

In this complicated situation, our goal was to thoroughly examine the published research that used machine learning to diagnose, forecast, prognosticate, and treat patients with chronic kidney disease. In doing so, the main goal is to present the outcomes that have been realized in this area as well as how ML variables and models have been applied to CKD diagnosis, treatment and prediction.

**1.3 Methodology**

We employed the Preferred Reporting Items for Systematic Reviews (PRISMA) technique [7] to perform a systematic literature review, which included research that used machine learning (ML) algorithms for CKD diagnosis, prognosis, treatment, and forecasting. The results of this study that are of interesting include ML models, characteristics, performances, and applications related to CKD diagnosis, prognosis, and treatment.

**Records identified by searching database (PubMed)**

**n = 648**

**Identification**

**Records Excluded**

**N = 421**

**Records screened**

**n= 648**

**Fig 2: Prisma Flowchart**

**Full text papers are evaluated for eligibility**

**N =68**

**Included**

**Studies included for examination**

**N = 31**

n

**Eligibility**

**Records Excluded**

**N=19**

**Records Excluded**

**n = 140**

**Records Excluded**

**N = 0**

**Record screened by full text n=87**

**Records screened by Abstract n = 227**

**Screening**

Papers that published original data, used AI and ML techniques to evaluate the diagnosis, prognosis, or treatment of CKD patients, and were in vivo (human-based) investigations were included for review. Since being as inclusive as possible and collecting all accessible data from any research design and any outcomes of interest was our main goal, we didn't limit our requirements for inclusion to any specific research design or outcomes of interest. Research that wasn’t in English, Reviews, systematic reviews, editorials, comments, case reports, and those that dealt with animals were all excluded. In order to compile the available data about the use of ML models on people, we chose to omit studies that were carried out in vitro (on cellular substrates) and studies that were animal-centred.

**1.4 Data Extraction**

The information was retrieved by two impartial reviewers (AC and FC). (DGoI), an unbiased arbiter, was consulted on disagreements regarding the retrieved data.

From every article that was included, the following information was taken:

(primary text and/or supporting information): objective of the main study, category of objective (diagnosis, prognosis, risk, and treatment), category of prognosis, study population, data source, problem type (classification, regression), sample size, machine learning (ML) algorithms to analyse the predictor categories, predictor list, study, number of predictors used, performance matrices, conclusion, utilize in the five most significant model features and the clinical context. Only the model that the authors thought was best was taken out of the study when multiple models were taken into consideration. Performance indicators are always used to characterize the models' behaviour on test sets.

**1.5 Quality and risk assessment**

PROBAST [8] and the Rules for creating along with publishing ML predictive models in the field of biomedical research [9] created by Luo and associates were both used to evaluate the included studies.

**2. Literature Survey**

Scientists and academics are currently captivated by the development of instruments and techniques for monitoring and predicting a wide range of illnesses, particularly those that are common in human life. In this, we will review a few of the most current research on utilizing machine learning approaches to predict CKD risk and some methods for working with extremely tiny datasets. In (Saif et al.,2024)create and evaluate deep learning models such as CNN, LSTM, and LSTM-BLSTM for 6–12 month CKD prediction; addressing data imbalance, feature selection, and optimizer optimization; and constructing an ensemble model that combines the best individual models (CNN-Adamax, LSTM-Adam, and LSTM-BLSTM-Adamax), they close the gap between current detection techniques and preventive interventions.[1]

The authors of (Kumar et al., 2023) built a self-learning knowledge-based system for analysis and treatment using machine learning. Out of all the methods they investigated, they discovered that (SVM) Support vector machine had the best classification accuracy 98.3% and sensitivity 0.99. A 400-sample dataset was used to test classifiers such as K-NN, RF, and ANN (Wang et al., 2022). The study's use of a wrapper feature picker led to the selection of five characteristics for model building. [10]

With RF, we obtain a 98% classification precision and an RMSE of 0.11. The study "Prediction of Chronic Kidney Disease Using Machine Learning Algorithm" (Mondol et al., 2022) employed a dataset of 400 patients and 14 characteristics. They have used SVMs and decision trees. The dataset has undergone pre-processing, resulting in the reduction of the initial (25) features to (14). (SVM) Support vector machine are praised as the best model because their 96.75 percent accuracy [11].

Naïve Bayes was used to predict chronic renal illness (Barua et al., 2020) [12]. They classified proteinuria into mild, moderate, and severe categories using 18 criteria after reviewing the medical records of 551 individuals with the ailment. They came to the conclusion showed logistic regression's AUC of 0.863 made it superior., se of 83%Sp of 82%, Although Mohammed and this study only uses a small quantity of data for the first three stages of chronic renal disease, A prototype created by the researchers enables patients to ask KBS in order to monitor the advice dissemination process.. A decision tree was used to create the rules. According to reports, the prototype's current version is 91% effective (Rao et al., 2023) [13].

Based on a limited set of variables, the study by Lambert et al. (2022) aimed to quantify the effectiveness of machine learning algorithms in the prediction of chronic renal illness. To do some modelling, predictive features were selected using statistical and machine learning techniques. Out of all the methods they evaluated, they discovered that Gradient Boosting had the highest F-measure, at 99.1. They use machine learning techniques to forecast the risk of CKD by analysing the data of CKD patients [14]. Both an ANN and Random Forest have been used to some extent. RF and ANN have been used to retrieve twenty of the twenty-five features that could be found (Aswathy et al., 2022). 97.12% is the highest percentage of accurate RF identifications to date. (PNNs) Probabilistic neural networks, (MLPs) Multilayer perceptron, (SVMs) Support vector machines, and (RBFs) Radial basis functions were used to assess algorithms for predicting the stages of renal illness [15]. A small dataset with few attributes was used in the investigation. To determine which supervised machine learning strategy would be most effective for BCD anticipation, Baskar et al. (2023) investigated a number of different ML-strategies. In summary, the findings showed that on the BCD dataset, k-NN obtains the maximum accuracy (97%) [16].

Data pre-processing, collaborative filtering for missing values, and attribute selection were all part of the methods studied. Random forest and additional tree classifiers are the least biased and most accurate of the 11 machine learning methods. The study emphasizes the usefulness of data collection as well as the significance of domain expertise in enhancing CKD prediction [17].

In order to address the absence of values in the University of California dataset, author Jiongming Qin investigated the use of KNN imputation. Irvine applied machine learning algorithms for CKD diagnosis. Random forest generated the best accuracy out of six machine learning algorithms that were applied that gives an accuracy of 99.75%. The study also suggests an integrated model that combines random forest with logistic regression, with an average simulation accuracy of 99.83%. This approach seems to have promise for the use of complex clinical data in sickness identification [18].

Reshma S supports the prediction of CKD through ML algorithms, especially the Ant Colony Optimisation (ACO) algorithm and SVM classifier. The major objective is to maximize diagnostic accuracy and resource efficiency while using the least amount of information to determine whether a person has chronic kidney disease [19].

P. Ghosh tested four distinct approaches (SVM, AB, LDA, and GB) using a UCI machine learning dataset. Gradient boosting lead to an outstanding 99.80% accuracy rate. A range of performance metrics are included in the analysis to help determine which algorithm are most effective for chronic kidney disease prediction. In the field of medical, it handles the primary issue with delayed diagnosis [20].

By using a machine learning system to forecast CKD during the first six or twelve months, Krishnamurthy investigated the health issues caused by chronic kidney disease. It uses CNN with high AUROC values to analyse medication and comorbidity data from Taiwan's National Health Insurance Research Database. Significant predictors included age, gout, diabetes, and certain drugs. By enabling chronic kidney disease trend prediction, early detection, proactive monitoring, effective patient-centric management, and resource allocation, the algorithm is a useful tool for policymakers to counteract the healthcare impact of CKD [21].

Using predictive modelling to link data elements and target class features, Md. Ariful Islam studies several ML techniques for early CKD diagnosis. For CKD identification, it narrows the original collection of 25 variables to a 30% subset. In terms of F1-score, recall, accuracy, and precision, XgBoost performs better than the other machine learning-based classifiers. This study highlights how current developments in machine learning hold potential for increasing prediction accuracy in renal disease and other conditions [22].

Cloud platforms allow secure storage of large volumes of CKD-related data from hospitals, laboratories, wearable devices, and electronic health records (EHRs). [23]

**3. Results**

Incorporation of AI and ML techniques in CKD detection and prediction has led to significant improvements in early diagnosis and risk assessment. The emphasis on explain ability and integration with traditional statistical methods further enhances the clinical applicability of these models, paving the way for more personalized and effective CKD management strategies.

Recent studies have explored ensemble-based deep learning models for CKD diagnosis and achieved a remarkable accuracy in early CKD detection. This advancement holds promise for improving clinical outcomes and underscores the critical role of machine learning in addressing complex medical challenges. Some remarkable resent studies in this field are represented in the table below.

Table 2 : Model selected by different studies

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  **Serial No.** | **Author** | **Year** | **Main aim** | **Model task** | **Selected model** | **Performance****metrics** |
| **1.** | Sarah A. Ebiaredoh Mienye , Theo G.Swart Ebenezer Esenogho and Ibomoiye Domor Mienye [24] | 2022 | Prediction | Classification | cost-sensitive adaptive boosting (AdaBoost) classifier |  |
| **2.** | Qiong Bai, Chunyan Su & Wen Tang,Yike Li[25] | 2022 | Prediction | Classification | naïve Bayes,K-nearest neighbors, decision tree,logistic regression and random forest | AUC:0.81 |
| **3.** |  B. Yamini, J. Aswini,K. Sankara Nayaki, Rajaram Jatothu, M. Nalini[26**]** | 2022 | Prediction  | Classification | boosted support vector machine |  |
| 4. | Md. Ariful Islam ,Md. Ziaul Hasan Majumder ,Md. Alomgeer Hussein c[27] | 2023 | diagnosis | Classification | XgBoost classifier | F1-score = 0.98, recall = 0.98, precision = 0.98, and accuracy = 0.983 |
| **5.** | Rahul Sawhney, Aabha Malik ,Shilpi Sharma, Vipul Narayan [28] | 2023 | diagnose  | Classification | deep neural network, ANN | accuracy score of 1.0 |
| 6. | Ajab Khan, Hira Khalid, Gulzar Mehmood, Muhammad Zahid Khan Muhammad Shuaib Qureshi [29] | 2023 | diagnose | Classification  | Hybrid model | 100% accuracy |
| 7. | Sultana Umme Habiba, Farzana Tasnim,Mohammad Saeed Hasan Chowdhury [30] | 2023 | Prediction | Classification  | machine learning-based prediction system | 100% accuracy |
| 8. | Debabrata Swain , Utsav Mehta , Ayush Bhatt , Hardeep Patel [31] | 2023 |  diagnosis | Classification | machine-learning model | SVM=99.33% random forest= 98.67% |
| 9. | Francesco Sanmarchi,Claudio Fanconi,Davide Golinelli, Davide Gori[32] | 2023 | predict, diagnose, and treat |  | Machine learning and AI | Review |
| 10. | Bishnu Padh Ghosh, Touhid Imam,Nishat Anjum[33] | 2024 | Prediction | Classification | Hybrid Model | 94.99% accuracy, 95.21% precision, 95.11% recall, 95.32% F-1 Score, and 95.56% AUROC |
| 11. | Ziliang Ye; Yuanyuan Zhang; Yanjun Zhang; Sisi Yang[34] | 2024 | Prediction | Classification |  |  |
| 12. | S Phani Praveen, Veerapaneni Esther Jyothi, Chokka [35] | 2024 | Prediction | Classification | Neuro-Fuzzy model | 97% accuracy |
| 13. | M. S. Jayaprabha; V. Vishwa Priya[36] | 2024 | Prediction | classification |  | survey |
| 14. | K Hema,K. Meena Ramaraj Pandian[37] | 2024 | Prediction | Classification | XGBoost, Gradient Boost (GB), Random Forest (RF),Decision Tree (DT) and KNN (k-nearest neighbours) | KNN has improved its accuracy from 77% to 83% |
| 15. | Hirotaka Saito, Hiroki Yoshimura, Kenichi Tanaka[38] | 2024 | Prediction | Classification | A light gradient boosting machine and time-series cluster analysis and | Accuracy=0.675 |
| 16. | Jin-Xin Zheng, Xin Li, Jiang Zhu2, Shi-Yang Guan[39] | 2024 | Prediction | Classification | Randomforests, logistic regression, neural networks, and eXtreme Gradient Boosting (XGBoost) | AUC-ROC of 0.867 |

These reviews indicate that some attempts have been made to use machine learning techniques to predict chronic renal illness. A model's efficacy can be greatly impacted by a wide range of factors, including dataset size, quality, and collecting time. In this work, we use a sizable, newly gathered dataset to apply machine learning techniques to the CKD anticipation problem. It is challenging to create therapy recommendations based on the stages involved because the majority of previous studies have only examined two groups.

**Conclusion**

This review paper focused on different detection and prediction techniques of Chronic Kidney Disease. The ensemble approach is the most effective machine learning method for disease prediction since it lowers bias and variance, increasing the accuracy of the model. The four main ensemble approaches are bagging, boosting, stacking, and voting, which are commonly employed in disease prediction or illness prediction. The literature review indicates that using an ensemble technique to other ML or machine learning algorithms increases the underlying classifier’s accuracy. Ensemble learning is found to be a robust method in handling complex datasets and achieving higher predictive performance. The integration of multiple models enhances the reliability in the diagnosis of CKD.

Future work in CKD detection should further investigate the integration of different ensemble learning techniques, such as bagging, boosting, and stacking, to improve prediction accuracy. The development of a web application for real-time CKD prediction could make these models more accessible and beneficial for healthcare providers. Moreover, efforts will be made on the generalisability of these models by working with diverse comprehensive datasets so the ensemble learning model will be more competent in real-time healthcare settings.

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