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PREDICTION OF CHRONIC KIDNEY DISEASE USING MACHINE LEARNING ALGORITHMS

BY

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Abstract
Chronic Kidney Disease (CKD) is a progressive condition that affects millions worldwide and poses a major public health challenge due to its high morbidity and mortality rates. Early detection and accurate prediction are critical for effective intervention and improved patient outcomes. In recent years, machine learning (ML) algorithms have emerged as powerful tools for CKD prediction, offering enhanced diagnostic accuracy compared to traditional statistical methods. This review synthesizes current research on ML-based CKD prediction, highlighting commonly used datasets, feature selection techniques, and algorithms such as decision trees, support vector machines, random forests, logistic regression, and deep learning models. Studies demonstrate that ML approaches can effectively identify key risk factors including blood pressure, serum creatinine, and glucose levels while achieving high predictive performance across diverse populations. However, challenges remain in terms of data imbalance, model interpretability, and generalizability across clinical settings. Future directions emphasize the integration of explainable AI, federated learning, and multimodal data sources to improve transparency and robustness. Overall, ML-driven CKD prediction holds significant promise for advancing precision medicine and supporting early clinical decision-making.

Keywords: Chronic Kidney Disease (CKD), Machine Learning (ML), Artificial Intelligence (AI), Early Diagnosis, Risk Factors, Feature Selection

Introduction

Chronic kidney disease (CKD) is a persistent and progressive condition characterized by a gradual decline in kidney function over time, often remaining asymptomatic until advanced stages. Globally, CKD affects an estimated 10–15 % of the population and contributes significantly to morbidity, mortality, and healthcare costs due to complications such as cardiovascular disease and end-stage kidney disease (ESKD) requiring renal replacement therapy. Early and accurate detection of CKD is therefore critical for timely intervention and improved patient outcomes. Traditional diagnostic approaches, however, depend heavily on routine clinical assessments and conventional risk equations, which may not fully exploit complex patterns present in high-dimensional clinical data. In recent years, machine learning (ML) has emerged as a promising approach to improve CKD prediction and prognosis by identifying nonlinear relationships within diverse clinical features and electronic health record (EHR) variables. ML models have been applied to predict various CKD outcomes, such as progression to ESKD, initiation of renal replacement therapy, or short-term progression in advanced CKD stages, frequently demonstrating superior performance compared to traditional methods. For example, deep learning architectures combining convolutional and recurrent neural network layers achieved higher ROC-AUC values than established risk equations in predicting renal replacement therapy initiation in CKD cohorts. Similarly, recent multi-center studies have shown that ensemble algorithms like XGBoost can accurately forecast short-term progression to ESKD, with robust performance in both internal and external validation datasets. Beyond predictive performance, current research also emphasizes model interpretability, integration of multimodal and administrative claims data, and the use of explainable AI (XAI) techniques to improve clinical trust and application. Despite these advances, challenges such as data quality, class imbalance, limited generalizability across populations, and ethical considerations in data use remain critical areas for further investigation. The rapid evolution of ML approaches—from traditional classifiers to deep learning and ensemble frameworks—underscores their potential to transform CKD prediction and support precision healthcare delivery.

Literature Review

Chronic Kidney Disease is a progressive condition in which the kidneys gradually lose their ability to filter waste and excess fluids from the blood. This decline in renal function often develops silently over years, making early detection difficult but crucial for preventing severe complications. CKD is recognized as a major global health burden, affecting millions of people worldwide and contributing significantly to morbidity and mortality rates (National Kidney Foundation, 2023). The primary causes of CKD are diabetes mellitus and hypertension, which together account for most cases globally. Other contributing factors include glomerulonephritis, polycystic kidney disease, recurrent urinary tract obstructions, and prolonged use of nephrotoxic medications. These conditions damage the nephrons—the functional units of the kidney—leading to scarring and reduced filtration capacity (Mayo Clinic, 2023). Symptoms of CKD are often absent in the early stages, which is why the disease is frequently referred to as a “silent killer.” As kidney function declines, patients may experience fatigue, swelling in the extremities, changes in urination, muscle cramps, and difficulty concentrating. In advanced stages, fluid retention can cause shortness of breath, while toxin buildup may lead to nausea and vomiting (Cleveland Clinic, 2023). Diagnosis relies on laboratory and imaging tests. Blood tests measuring serum creatinine and calculating the estimated glomerular filtration rate (eGFR) are central to identifying CKD. Urine tests detecting proteinuria provide additional evidence of kidney damage. Imaging studies and, in some cases, a kidney biopsy may be used to confirm the diagnosis and assess structural abnormalities (National Kidney Foundation, 2023).

CKD is associated with numerous complications, including cardiovascular disease, anemia, bone disorders, and electrolyte imbalances. If left untreated, it can progress to end-stage renal disease (ESRD), at which point patients require dialysis or kidney transplantation to survive (Mayo Clinic, 2023). Although CKD has no cure, management strategies aim to slow disease progression and alleviate complications. These include strict control of blood pressure and blood sugar, the use of medications such as ACE inhibitors or ARBs, dietary modifications to reduce sodium and protein intake, and lifestyle changes like regular exercise and smoking cessation. In advanced stages, renal replacement therapies such as dialysis or transplantation become necessary (Cleveland Clinic, 2023). Preventive measures are vital, especially for individuals at high risk. Maintaining a healthy lifestyle, monitoring blood pressure and blood sugar regularly, avoiding excessive use of nephrotoxic drugs, and undergoing routine kidney function tests can significantly reduce the likelihood of developing CKD (National Kidney Foundation, 2023).

Machine learning has become an increasingly valuable tool in the prediction, diagnosis, and management of Chronic Kidney Disease (CKD). Traditional diagnostic methods often rely on laboratory tests and clinical expertise, which can delay early detection. ML algorithms, however, can process large volumes of patient data—including demographic information, laboratory results, and imaging reports—to identify subtle patterns and risk factors that may not be immediately evident to clinicians (Pal, 2022). Several algorithms have been applied to CKD prediction tasks. Decision trees and random forests are widely used due to their ability to handle categorical and numerical data while providing interpretable results. Support vector machines (SVMs) have shown strong performance in classifying CKD stages, particularly when datasets are well-structured. Logistic regression remains a baseline model for many studies, offering simplicity and transparency. More recently, deep learning approaches, including neural networks, have demonstrated superior accuracy by capturing complex nonlinear relationships in patient data (Dritsas & Trigka, 2022). Applications of ML in CKD extend beyond prediction. Algorithms are used for risk stratification, identifying patients at high risk of progression to end-stage renal disease (ESRD). They also support clinical decision-making by recommending personalized treatment strategies based on patient profiles. Furthermore, ML models can assist in resource allocation, helping healthcare systems prioritize patients who require urgent intervention (Dritsas & Trigka, 2022).

Despite these advances, challenges remain. Data imbalance, where healthy patient records outnumber CKD cases, can bias models and reduce predictive accuracy. Model interpretability is another concern, as clinicians require transparent reasoning behind predictions to trust and adopt ML tools. Generalizability across diverse populations is also limited, since many models are trained on region-specific datasets. Future directions emphasize the integration of explainable AI (XAI), federated learning to preserve patient privacy, and multimodal data sources combining laboratory, imaging, and genetic information to enhance robustness (Pal, 2022). ML algorithms hold significant promise for transforming CKD care by enabling earlier diagnosis, personalized treatment, and improved patient outcomes. However, careful attention to data quality, model transparency, and clinical integration is essential for realizing their full potential. Mhamd (2026) carried out a systematic review of machine learning methods for CKD diagnosis and prediction covering studies published between 2020 and 2025. The methodology focused on evaluating data preprocessing strategies, feature engineering techniques, algorithm selection, and validation approaches across a broad range of studies. Particular attention was given to hybrid and ensemble models as well as deep learning architectures. The results showed that ensemble and hybrid models consistently outperformed traditional single classifiers in terms of accuracy and AUROC, while deep learning approaches achieved high predictive performance but suffered from limited interpretability. Across the reviewed literature, most studies reported AUROC values greater than 0.80, indicating reliable prediction of CKD presence and progression. The author concluded that future research should prioritize explainable models, external validation on multi-center datasets, and integration into clinical decision-support systems.

Pranjal and Valan (2025) provided a comprehensive review of machine learning approaches used for predicting and diagnosing chronic kidney disease. The study involved categorizing existing studies based on algorithm type, including traditional machine learning, ensemble methods, and deep learning models, while also analyzing data preprocessing techniques such as feature selection, normalization, and missing-value handling. The review emphasized methodological challenges, including class imbalance, small sample sizes, and lack of explainability. The reported results showed that ensemble learning models, such as random forests and XGBoost, frequently achieved higher accuracy and robustness than single classifiers, while deep learning models demonstrated strong performance in modeling complex nonlinear relationships. However, it was noted that many studies reported accuracies above 90% on limited or local datasets, raising concerns about overfitting. Ilyas et al. (2025) presented a systematic literature review analyzing recent work on CKD prediction using different machine learning learning approaches—classical ML (CML), deep learning (DL), and ensemble learning. Focused on strengths, limitations, and evolving trends. The conventional ML remains widely used; ensemble and DL models increasingly provide superior performance in complex pattern recognition. Deep learning especially showed potential for pattern capture,e but challenges in interpretability remain.

Pranjal and Valan (2025) published a comprehensive review examining machine learning approaches for predicting and diagnosing chronic kidney disease. The work involved an extensive survey of peer-reviewed literature, where studies were grouped according to algorithmic approach, including conventional machine learning models, ensemble techniques, and deep learning architectures. The review also analyzed data preprocessing strategies such as feature selection, normalization, and missing-value imputation, as well as common evaluation metrics like accuracy and AUROC. The results showed that ensemble models, particularly random forests and gradient boosting methods, consistently achieved higher predictive performance compared to single classifiers. Deep learning models demonstrated strong capability in modeling complex nonlinear relationships within clinical data, but often lacked interpretability. The study concluded that although predictive accuracy in many studies exceeded 90%, limited dataset diversity and lack of external validation restrict clinical deployment, emphasizing the need for explainable and standardized machine learning frameworks. Sheng et al. (2025) reviewed the application of artificial intelligence in nephrology with a particular focus on CKD progression prediction and personalized treatment. The methodology centered on synthesizing studies that applied machine learning and deep learning to longitudinal electronic health records, laboratory trends, and multimodal clinical data. The review highlighted the growing use of recurrent neural networks and attention-based models for the temporal prediction of kidney function decline. The reported results showed that AI-driven models consistently outperformed traditional regression-based risk models in predicting CKD progression and adverse renal outcomes. The mode concluded that machine learning holds strong promise for personalized CKD management, though they stressed that issues such as data heterogeneity, algorithm transparency, and regulatory validation remain unresolved.

Khilji et al (2024) conducted a systematic review of 13 studies that employed ML and AI techniques to predict progression of CKD, including progression to ESRD and need for renal replacement therapy. Reviewed models like logistic regression, SVM, random forests, neural networks, and DL methods, with metrics such as accuracy, sensitivity, specificity, and AUC.AI/ML models showed promising performance across studies, highlighting high predictive accuracy and efficiency, though methodologies and performance measures varied. The review showed strong potential but also calls for more standardized evaluation and validation. Fahad et al. (2024) conducted a systematic review on the prediction of chronic kidney disease progression using machine learning. Their methodology followed PRISMA guidelines and involved searching major scientific databases, including PubMed, Embase, and Web of Science, to identify studies applying machine learning or artificial intelligence to CKD prognosis. The reviewed studies predominantly used structured clinical data from electronic health records, incorporating laboratory indicators such as estimated glomerular filtration rate, serum creatinine, proteinuria, and demographic variables. Classical machine learning algorithms such as logistic regression, support vector machines, random forests, and gradient boosting were most frequently reported, with fewer studies employing deep learning models. The results indicated that machine learning models generally achieved strong predictive performance, with most studies reporting AUROC values above 0.80 for CKD progression or end-stage renal disease prediction.

Ramah et al.(2024) did survey of machine learning models for predicting CKD, covering supervised and unsupervised methods and referencing performance analysis studies such as feature selection and classification approaches. Reviewed notable models such as logistic regression, SVM, RF, ANN, and others,s demonstrating predictive ability across different datasets and tasks. The review highlighted trends in predictive performance and common features used.

Qiang Pan and Ming Tong (2024) presented a review on meta-analysis examination on artificial intelligence models for predicting CKD prognosis. Their methodology involved aggregating results from multiple eligible studies and statistically pooling diagnostic and prognostic performance metrics, including sensitivity, specificity, and AUROC. The analysis focused on machine learning models applied to CKD progression and adverse renal outcomes. The results demonstrated that AI-based models achieved consistently high predictive accuracy, with pooled AUROC values around or exceeding 0.80, indicating good discriminative ability. The ensemble and advanced machine learning techniques generally outperformed conventional models. It was concluded that artificial intelligence has clear potential to enhance CKD prognosis prediction, although heterogeneity among datasets and model designs poses challenges for clinical generalization. Francesco et al. (2023) conducted one of the most comprehensive systematic literature reviews assessing how artificial intelligence and machine learning techniques have been employed to predict, diagnose, and even guide treatment in chronic kidney disease. Their methodology involved a systematic search of PubMed and application of the Preferred Reporting Items for Systematic Reviews (PRISMA) approach to identify and analyze a broad set of studies that utilized machine learning for CKD clinical tasks. The review extracted key study variables, including data sources, problem types, predictors, and performance metrics. Sanmarchi and colleagues found that while many models demonstrated high reported metrics, direct comparison across studies was challenging due to heterogeneous evaluation protocols. Importantly, it was noted that model generalizability and validation on diverse populations were limited, and only a small fraction of models had been evaluated in actual clinical contexts, emphasizing the need for future work on interpretability and external validation.

Francescoet al. (2023) focused on artificial intelligence and machine learning (ML) techniques forthe prediction, diagnosis, and treatment of CKD. The collected evidence from multiple databaseswasd comparedin study designs. The results indicate that ML methods (e.g., random forests, neural networks, logistic regression) consistently outperform traditional statistical approaches, offering enhanced early prediction and risk profiling for CKD patients.
Hira Khalid et al.(2023) proposed and evaluated a hybrid machine learning model that combined various algorithms (gradient boosting, random forest, decision tree, and others) on the UCI CKD dataset. The study assessed both individual and combined models, reporting that their hybrid approach attained perfect classification accuracy under the dataset conditions, while individual methods such as gradient boosting and random forests also achieved high performance (around 99% and 98%, respectively). This comparative evaluation underscored the utility of hybrid and ensemble methods in elevating predictive performance for CKD classification tasks. Ariful Islam et al. (2023) investigated the performance of multiple supervised learning classifiers, ultimately demonstrating that the XGBoost algorithm achieved high performance indicators, including accuracy above 98%, precision of 0.98, recall of 0.98, and an F1-score of 0.98 when identifying CKD cases. This work used a feature selection process to narrow predictive variables and compared twelve different classifiers in a supervised learning context, highlighting the potential of ensemble and tree-based approaches for early CKD detection.

Francesco et al.(2022) published a major systematic review on the use of artificial intelligence and machine learning algorithms to predict chronic kidney disease and its progression. The review searched multiple scientific databases, including PubMed, Medline, Scopus, Web of Science, and IEEE Xplore, to identify studies in which machine learning models were used for early CKD detection and prognosis. Across 55 selected articles, they observed that machine learning algorithms are capable of combining a large number of predictors in nonlinear and interactive ways, improving the diagnostic and prognostic capability over traditional approaches. The review highlighted limitations such as a lack of physician-verified datasets, the absence of patient ethnicity information, the inclusion of irrelevant predictive variables, and limited external validation of models. Overall, however, the analysis suggested that machine learning has the potential to support clinicians in predicting CKD onset and progression, though improved interdisciplinary development and validation practices are needed. Nuo et al. (2022) conducted a systematic review and meta-analysis evaluating the diagnostic accuracy of machine learning algorithms in predicting kidney disease progression. Data were retrieved from multiple bibliographic databases, including PubMed, EMBASE, Cochrane Central, and Chinese national databases up to October 2020. They extracted data from studies where machine learning models were used to predict kidney disease outcomes, including progression of CKD and other conditions like IgA nephropathy. Meta-analytic pooling revealed that machine learning algorithms had an overall area under the hierarchical summary receiver operating characteristic curve (HSROC) of approximately 0.87, with particularly strong specificity but variable sensitivity. For CKD prognosis specifically, the pooled AUROC was about 0.82, indicating that machine learning-based models can provide moderately accurate prediction of CKD progression, though heterogeneous model performance and study methodology remain challenges. Dibaba and Tilahun (2022) presented an empirical study on chronic kidney disease prediction using machine learning techniques. A larger, multi-class CKD dataset was collected from St. Paulo's Hospital in Ethiopia, encompassing five CKD stages and binary classification of CKD vs non-CKD. Methodologically, they applied classical machine learning models, including random forest, support vector machine, decision tree, and extreme gradient boosting, combined with two feature selection strategies (recursive feature elimination with cross-validation and univariate feature selection). Using ten-fold cross-validation, random forest and support vector machine models—particularly when combined with feature selection—achieved very high accuracy (up to nearly 99.8%) for the binary task, while XGBoost performed best for the multiclass stage prediction task. The study underscored how feature selection and algorithm choice can significantly influence predictive accuracy in CKD risk stratification

Challenges of CKD Predictive Models

Machine learning techniques for chronic kidney disease (CKD) prediction face several well-documented challenges that limit their accuracy, generalizability, and clinical adoption. One of the most significant problems is data quality and availability. Publicly available CKD datasets are often small, contain missing laboratory values, and are cross-sectional rather than longitudinal, even though CKD is a slowly progressive disease. These limitations make it difficult for models to learn true disease trajectories and often lead to biased or unstable predictions (UCI ML Repository, 2019; Almansour et al., 2019). In addition, class imbalance is common, with early-stage CKD cases underrepresented, causing models to prioritize accuracy over sensitivity and reducing their usefulness for early detection (Kora & Kalva, 2015). The clinical complexity of CKD further complicates prediction. CKD is influenced by multiple interacting risk factors such as diabetes, hypertension, age, and lifestyle, which exhibit nonlinear and heterogeneous effects across patients. Machine learning models may struggle to capture these interactions when important biomarkers are unavailable or inconsistently measured across healthcare institutions (Chen et al., 2019). Variability in laboratory standards and clinical practices also reduces the robustness of trained models when applied outside their original training environment. Model-related challenges also play a critical role. Many studies report high predictive accuracy, but these results are often due to overfitting, especially when complex algorithms are trained on limited datasets (Xiao et al., 2018). Moreover, highly accurate models such as ensemble methods and neural networks tend to lack interpretability, making it difficult for clinicians to understand, trust, and act upon their predictions in real clinical settings (Ribeiro et al., 2016). Poor generalization across populations remains another major issue, as models trained on data from specific regions or ethnic groups may perform poorly elsewhere (Beam & Kohane, 2018).

In conclusion, real-world implementation presents ethical, operational, and regulatory challenges. Integrating machine learning systems into clinical workflows is often difficult, and many proposed models lack external validation or prospective clinical trials. Bias in training data can lead to unequal performance across patient groups, raising concerns about fairness, transparency, and patient safety (Obermeyer et al., 2019). As a result, despite promising research results, machine learning models for CKD prediction are still far from routine clinical use.

Solution to Challenges of CKD Predictive Models

Addressing the challenges of machine learning techniques for chronic kidney disease (CKD) prediction requires a combination of data, methodological, clinical, and policy-level solutions. Improving data quality is a foundational step. This can be achieved through the use of larger, multi-center datasets that better represent diverse populations and disease stages. Standardizing data collection protocols and laboratory measurements across healthcare institutions can reduce variability and improve model robustness. Advanced data preprocessing methods such as robust imputation, noise reduction, and outlier handling can also mitigate the impact of missing or low-quality clinical data (Xiao et al., 2018). In addition, incorporating longitudinal patient records rather than relying solely on cross-sectional data enables models to capture disease progression and temporal patterns, which is critical for CKD prediction and monitoring (Beam & Kohane, 2018). The issue of class imbalance, particularly the underrepresentation of early-stage CKD, can be addressed through both data-level and algorithm-level strategies. Techniques such as synthetic minority oversampling, cost-sensitive learning, and balanced loss functions help models focus more effectively on minority classes without sacrificing overall performance (Kora & Kalva, 2015). Clinically informed feature engineering also plays an important role. Collaborating with nephrologists to select meaningful biomarkers and combining clinical knowledge with automated feature selection methods can improve predictive relevance while reducing noise from irrelevant variables (Almansour et al., 2019).

Model-related challenges can be mitigated by prioritizing generalization and interpretability over sheer predictive accuracy. Simpler models or regularized algorithms often perform comparably to complex methods while reducing the risk of overfitting, especially in limited datasets. When complex models are necessary, explainable artificial intelligence techniques such as feature attribution and local explanation methods can help clinicians understand how predictions are made, thereby increasing trust and adoption in clinical practice (Ribeiro et al., 2016). External validation on independent datasets and prospective evaluation in real clinical environments are essential to ensure that models generalize well across populations and healthcare settings (Chen et al., 2019). Successful real-world deployment also depends on seamless integration into clinical workflows. Machine learning tools should be embedded with in electronic health record systems and designed to support, rather than disrupt, clinical decision-making. From an ethical and regulatory perspective, fairness-aware modeling techniques and routine bias audits can reduce disparities in prediction performance across demographic groups. Transparent reporting, adherence to data privacy regulations, and continuous model monitoring after deployment further enhance safety and reliability (Obermeyer et al., 2019). Overall, overcoming the challenges of machine learning for CKD prediction requires a shift from isolated, accuracy-focused models toward clinically grounded, interpretable, and well-validated systems. By combining high-quality data, appropriate modeling techniques, explainability, and strong clinical integration, machine learning can become a reliable tool for early detection and management of chronic kidney disease.

Summary of Findings and Discussion

Recent literature on the application of machine learning techniques for the prediction and diagnosis of chronic kidney disease (CKD) demonstrates that these models consistently outperform traditional statistical and rule-based diagnostic approaches. A wide range of algorithms—including logistic regression, support vector machines, decision trees, random forests, gradient boosting models, and deep learning architectures—have been employed to detect CKD and predict its progression. Ensemble learning methods, particularly random forests and boosting-based models, were repeatedly reported to achieve higher accuracy and stronger generalization capability, often recording AUROC values above 0.80. Deep learning approaches further enhanced the ability to capture nonlinear relationships and temporal disease patterns, especially when longitudinal electronic health record data were available. However, their application was frequently constrained by limited interpretability and high computational demands. Across studies, strong agreement emerged on the importance of key clinical variables such as serum creatinine, estimated glomerular filtration rate, blood pressure, glucose level, proteinuria, and age as dominant predictors of CKD. Ensemble learning approaches provided a practical balance between accuracy and interpretability, making them more suitable for clinical decision-support applications than highly complex black-box models. In contrast, while deep learning demonstrated superior modeling capacity for temporal and high-dimensional data, its lack of transparency remains a critical challenge to clinical trust and adoption. This highlights the need for integrating explainable artificial intelligence techniques that can provide meaningful clinical insight alongside accurate predictions. Despite promising results, several methodological limitations persist. Common challenges include class imbalance, reliance on small or region-specific datasets, insufficient external validation, and limited consideration of ethical and fairness issues. The underrepresentation of early-stage CKD cases further reduces model sensitivity at the stage where early intervention would be most beneficial. Addressing these limitations will require larger, multi-center, and longitudinal datasets, particularly from underrepresented regions, to ensure the broader applicability of predictive models. Beyond technical performance, ethical and operational considerations—such as bias, fairness, transparency, and integration into existing clinical workflows—remain central to real-world implementation. Overall, the findings reinforce the growing consensus that machine learning has significant potential to transform the early detection and management of CKD. By moving beyond accuracy-driven experimentation toward clinically grounded, interpretable, and externally validated systems, machine learning can evolve into a reliable and effective tool for improving early detection, monitoring, and management of chronic kidney disease. Aligning methodological rigor with clinical relevance will be essential to achieving widespread adoption and realizing the full promise of these technologies in healthcare.

Conclusion

This review highlights the transformative potential of machine learning in the prediction and management of chronic kidney disease (CKD). Across recent studies, algorithms such as logistic regression, support vector machines, decision trees, random forests, gradient boosting, and deep learning consistently demonstrated superior predictive performance compared to traditional diagnostic approaches. Ensemble methods, in particular, achieved robust accuracy and generalization, while deep learning models showed promise in capturing complex nonlinear and temporal disease patterns. Key clinical variables—including serum creatinine, estimated glomerular filtration rate, blood pressure, glucose levels, proteinuria, and age—were repeatedly identified as dominant predictors of CKD progression. Despite these advances, several challenges remain. Data limitations, including small and imbalanced datasets, hinder generalizability and reduce sensitivity for early-stage CKD detection. Model interpretability continues to be a barrier to clinical trust, particularly with deep learning approaches, while ethical concerns related to bias, fairness, and transparency restrict widespread adoption. Addressing these issues will require larger, multi-center, and longitudinal datasets, integration of explainable AI techniques, and rigorous external validation to ensure clinical reliability. Overall, machine learning offers substantial promise for advancing precision medicine in CKD care. By aligning methodological rigor with clinical relevance and embedding fairness and transparency into predictive systems, ML-driven approaches can evolve into reliable tools for early detection, risk stratification, and personalized treatment. The future of CKD prediction lies in developing clinically grounded, interpretable, and ethically responsible models that can be seamlessly integrated into healthcare workflows to improve patient outcomes.

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