



Explainable AI and Machine Learning for Chronic Kidney Disease Detection: Integrating Clinical Decision Support, Telemedicine, and Personalized Healthcare Management

Manisha Mane¹, Rasika Kachore², Kashish Agrawal³, Shruti Bhosale⁴, Samruddhi Yeole⁵, Shruti Bendre⁶

^{1,2} Assistant Professor, Dept. of Artificial Intelligence and Data Science, Dr. D. Y. Patil Institute of Engineering, Management and Research, Akurdi, Pune, India and Research, Akurdi, Pune, India

^{3,4,5,6} UG Scholar, Dept. of Artificial Intelligence and Data Science, Dr. D. Y. Patil Institute of Engineering, Management and Research, Akurdi, Pune, India

Emails: manisha.mane35@gmail.com ¹, rasika.kachore@dypiemr.ac.in ², agrawalkashish111@gmail.com ³, bhosaeshruti1106@gmail.com ⁴, syeole2804@gmail.com ⁵, shrutibendre2004@gmail.com ⁶

Abstract

Chronic kidney disease impacts millions worldwide, and delayed diagnosis results in unfavorable outcomes and higher healthcare expenses. Recent advancements in machine learning present promising diagnostic features, but their “black box” nature restricts clinical uptake. This review surveys recent methods for CKD detection, emphasizing the urgent need to bridge the gap between predictive performance and clinical interpretability. We examine traditional machine learning models, deep learning algorithms, and emerging explainable AI approaches. The work synthesizes research on CKD prediction, telemedicine integration, and donor-matching platforms. Our analysis demonstrates that although many high-accuracy models exist, few provide transparent decision-making explanations essential for clinicians. We propose an integrated approach involving interpretable decision tree models and comprehensive patient-management features such as remote consultations and personalized lifestyle recommendations. This paradigm meets the dual challenge of balancing diagnostic accuracy with clinical transparency, potentially transforming early CKD detection and long-term disease management.

Keywords: Chronic Kidney Disease, Explainable AI, Machine Learning, Telemedicine, Clinical Decision Support, Predictive Modeling

1. Introduction

Chronic kidney disease (CKD) is one of the most significant public health concerns today, affecting millions of individuals globally and placing an enormous burden on healthcare systems. The disease progresses silently over several years, often remaining asymptomatic until it reaches advanced stages, at which point substantial and irreversible kidney damage has occurred. This delayed manifestation significantly limits treatment options and increases the likelihood of complications such as cardiovascular disorders, anemia, and renal failure. Traditional CKD diagnosis relies heavily on clinician-interpreted laboratory tests such as serum creatinine levels, glomerular filtration rate (GFR), urine albumin, and blood pressure measurements. While effective, these methods require repeated

assessments, specialist availability, and timely patient follow-ups—factors that create bottlenecks in early detection, especially in resource-constrained or rural settings. With the increasing digitization of healthcare, machine learning algorithms have emerged as powerful tools capable of analyzing large-scale patient datasets and identifying subtle, nonlinear patterns not easily detectable through conventional diagnostic techniques. These models offer the potential to automate preliminary screening, stratify patient risk, and support clinicians in making more informed decisions. Despite this technological promise, the healthcare sector has been slow to adopt machine learning systems due to several challenges, including limited interpretability, concerns regarding data bias, lack of standardized deployment frameworks, and the need for seamless integration into existing clinical work flows. This disconnects between the rapid advancement of

computational methods and their real-world clinical application underscores the core motivation for this review. To address these gaps, our work concentrates on four major areas essential for modern CKD management: (1) machine learning–based diagnostic prediction methods, (2) explainability frameworks that promote transparency and clinical trust, (3) telemedicine integration for continuous monitoring and remote specialist access, and (4) holistic patient-management systems that support long-term care through lifestyle modification, donor matching, and personalized disease monitoring. Together, these domains form the foundation for a comprehensive, technologically enabled CKD management ecosystem.

1.1. Proposed System Architecture:

The Explainable Diagnosis Engine utilizes interpretable machine learning models, particularly decision-tree-based approaches, trained on clinical datasets. It identifies key features influencing predictions and presents them in an understandable format, ensuring transparency and building trust among healthcare professionals. This module supports early-stage detection and risk stratification. The Telemedicine Integration Module connects high-risk patients with nephrologists through virtual consultations. It enables continuous monitoring, follow-ups, and timely medical intervention, especially benefiting patients in remote or underserved areas. Integration with mobile applications further enhances accessibility and ease of use. The Donor Matching System maintains a structured database of donors and recipients. It applies compatibility criteria such as blood group, medical history, and immunological factors, along with geographic proximity, to ensure faster and efficient matching. This reduces delays in transplantation and improves patient outcomes. The Personalized Lifestyle Recommendation Module provides customized guidance based on patient health data, medical history, and predicted risk levels. It includes diet plans, exercise routines, medication reminders, and preventive measures, empowering patients to manage their condition proactively.

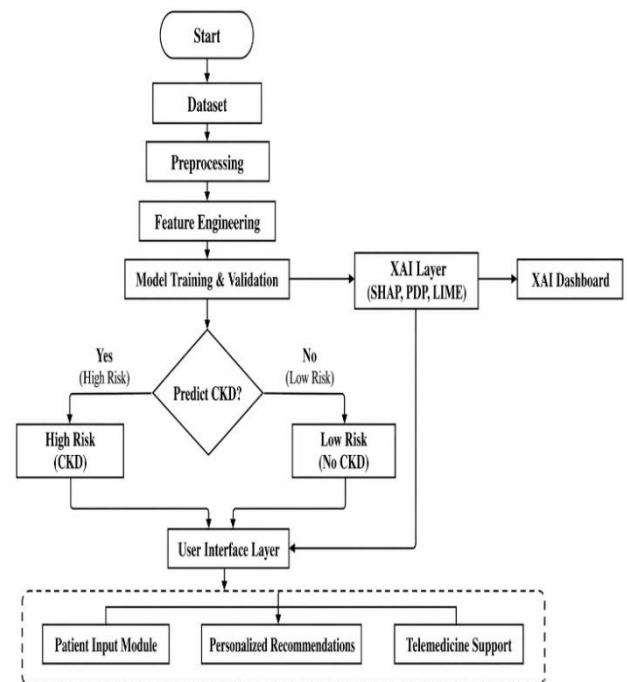


Figure 1 Architecture of the proposed CKD prediction system with explainable AI

1.2 Critical Analysis and Synthesis

- **Current Trends in CKD Prediction:** CKD prediction is moving toward hybrid models that balance accuracy and interpretability. While deep learning models achieve high performance, their lack of transparency limits clinical use. Explainability methods like LIME and SHAP are used, but they may not always provide consistent or reliable interpretations, highlighting the need for inherently interpretable models.
- **Methodological Strengths and Weaknesses:** Current approaches show strong predictive accuracy, use of diverse ML algorithms, and multimodal clinical data. However, explainability is often limited, and many models lack real-world clinical validation. Issues like poor user interface design, limited follow-up care, and concerns about accessibility and equity remain underexplored.
- **Comparative Perspectives:** Two main approaches exist: accuracy-focused models that prioritize performance and

transparency-focused models that emphasize interpretability. Despite progress, gaps remain in patient empowerment and solutions for resource-constrained healthcare settings, indicating a need for more practical and inclusive systems.

- Comparative Analysis of Existing Methods

Table 1 Comparative Analysis of Existing Methods

Approach	Accuracy Range	Interpretability	Clinical Integration	Scalability
Traditional ML	85–95%	Moderate	Limited	High
Deep Learning	90–98%	Very Low	Poor	Moderate
Decision Trees	80–90%	High	Good	High
Ensemble Methods	92–96%	Low	Limited	Moderate
Hybrid Approaches	88–94%	Moderate	Fair	Moderate

1.3 Confusion Matrix Analysis of Hybrid Ensemble Model

The confusion matrix illustrates the classification performance of the proposed hybrid ensemble model for CKD prediction. Out of the total samples, 148 instances were correctly classified as Not CKD (True Negatives) and 249 instances were correctly identified as CKD (True Positives). The model shows very low misclassification, with only 2 False Positives (healthy individuals predicted as CKD) and 1 False Negative (CKD case predicted as healthy).

These results indicate that the model achieves high accuracy, sensitivity, and specificity, making it highly reliable for CKD detection. The extremely low number of false negatives is particularly important in medical diagnosis, as it minimizes the risk of missing critical CKD cases in Figure 2.

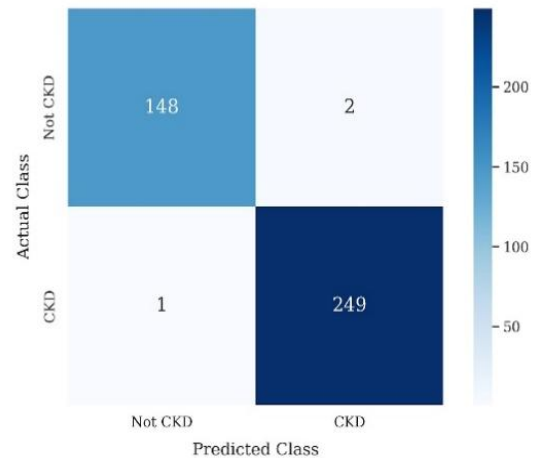


Figure 2 Confusion Matrix of the Hybrid Ensemble Model

2. Results and Discussion

2.1 Results

Current CKD prediction models achieve high accuracy using hybrid and ensemble techniques trained on diverse clinical datasets. The hybrid ensemble model demonstrates strong performance in terms of sensitivity and specificity, as reflected in the confusion matrix. Many approaches incorporate multimodal data such as laboratory reports, patient history, and real-time monitoring to improve prediction reliability. Explainability techniques like LIME and SHAP are increasingly used to interpret model decisions, enhancing transparency to some extent. Additionally, modern systems integrate telemedicine and mobile-based monitoring for improved patient care. The proposed CuraKidney framework combines diagnosis, donor matching, and lifestyle management into a unified system, improving efficiency and usability.

2.2 Discussion

Although current models show strong predictive performance, their clinical adoption is limited due to lack of interpretability and real-world validation. Deep learning models often act as black boxes, reducing trust among healthcare professionals. While LIME and SHAP improve explainability, their inconsistency highlights the need for inherently interpretable models. There is a clear need for hybrid approaches that balance accuracy and transparency. Existing systems also lack focus on user experience,



accessibility, and follow-up care, especially in resource-constrained settings. Future research should emphasize real-time adaptive systems, clinician collaboration, and practical deployment strategies. Incorporating features like wearable integration, multilingual support, and offline functionality can further enhance system effectiveness. The CuraKidney framework addresses these gaps by providing a scalable, patient-centered solution that bridges the gap between research and real-world healthcare applications.

Conclusion

This review highlights the strengths and limitations of current AI and machine learning approaches for CKD detection. While high-performing models exist, lack of interpretability and real-world integration limits their clinical adoption. Explainable AI, particularly decision tree approaches, provides a promising path forward. The proposed CuraKidney framework integrates diagnosis, telemedicine, donor matching, and lifestyle management into a unified, patient-centered system. Prioritizing transparency and usability can help bridge the gap between machine learning research and clinical practice, enabling scalable and equitable CKD management. The proposed CuraKidney framework addresses these challenges by integrating diagnosis, telemedicine, donor matching, and lifestyle management into a unified, patient-centered system. This comprehensive approach not only streamlines the care continuum but also ensures consistent data flow and coordinated interventions across all stages of CKD management. By embedding explainability into the diagnostic engine and maintaining user-friendly interfaces for both patients and providers, the framework aims to foster trust and encourage adoption.

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