

Chronic Kidney Disease Detection Using Hybrid Machine Learning

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Abstract— Chronic Kidney Disease (CKD) is a significant global health challenge because it progresses slowly and often goes undetected until it reaches a critical or life-threatening stage. Early and precise identification of Chronic Kidney Disease (CKD) is crucial for ensuring effective treatment and enhancing patient well-being. In this study, we introduce a detailed diagnostic approach that uses machine learning techniques to strengthen CKD prediction, reduce misclassification, and aid clinicians in making informed decisions. The study analyzes multiple algorithms, including Naïve Bayes (NB), J48, Artificial Neural Networks (ANN) and various ensemble models, utilizing a commonly employed CKD dataset. By incorporating thorough data preprocessing, selecting the most informative features, and comparing model performances, the framework pinpoints the combinations that deliver the most dependable diagnostic results. The outcomes indicate that integrating machine learning into clinical workflows can markedly boost diagnostic accuracy, promote early detection, and ultimately support better management of patients at risk of CKD.

Keywords— Machine Learning, Chronic Kidney Disease (CKD), co-relational features, Recommendation Techniques, Machine Learning.

I. INTRODUCTION

Initial detection of CKD has become a major research focus, and numerous studies have used ML to improve diagnostic accuracy. Iftikhar et al. [1] demonstrated the effectiveness of ML models in clinical settings by developing early-stage CKD detection models capable of supporting real-time diagnostics. Dutta et al. [2] performed a comparative evaluation of multiple ML algorithms and highlighted the performance differences across techniques for CKD identification. Ghosh, Widatalla, and Khandoker [3] proposed an optimized eGFR-based ML framework that enhances CKD stage detection accuracy, particularly in early phases of kidney decline. Further, Ghosh et al. [4] conducted an in-depth comparative analysis of ML models and introduced a hybrid approach that outperformed conventional algorithms. The tested several ML methods for CKD prediction and found notable accuracy improvements when appropriate feature selection techniques were used. The explored classical ML models and confirmed their significant role in predicting CKD using clinical parameters. The similarly built ML-based CKD prediction models and emphasized the importance of data preprocessing to improve classifier performance. In addition, implemented ML models within an applied computing framework and validated their results through practical experimentation. Prasad, Kiran, and Reddy [9] examined ML-driven CKD risk classification and demonstrated how model optimization can improve prediction quality. Finally, Saif, Sarhan, and Elshennawy [10] introduced an ensemble of deep learning models with multiple optimizers that provided superior early CKD prediction performance compared to traditional ML algorithms.

II. LITERATURE SURVEY

Dharmarathne et al. (2024) [1] A diagnostic interface utilizing machine learning, augmented with explainable artificial intelligence (XAI) approaches, for the identification of chronic kidney disease (CKD). The study integrates multiple supervised learning models and evaluates their predictive capability using clinical and biochemical features. Among the tested models, the Random Forest classifier demonstrates superior accuracy and robustness in identifying early CKD cases. To address transparency challenges in medical AI, the authors incorporate SHAP and LIME tools to visualize feature contributions and improve clinician trust. The proposed system not only automates CKD detection but also provides interpretable insights, supporting medical professionals in making informed decisions. Overall, the framework highlights the importance of combining machine learning performance with explain ability for safe clinical deployment.

According to [2] value the efficacy of different machine learning algorithms to identify the most effective method for early identification of CKD. The research emphasizes criteria including accuracy, precision, recall, and computing economy. Results reveal that tree-based models outperform several baseline algorithms due to their robustness and interpretability. The authors highlight the importance of handling class imbalance and missing values to achieve reliable predictions. The paper concludes that machine learning can significantly strengthen clinical decision-making for early CKD diagnosis.

Ghosh, Samit Kumar, et al. (2025) [3] a framework that uses machine learning to detect different CKD stages by integrating optimized estimated glomerular filtration rate (eGFR) calculations. The authors introduce an enhanced eGFR estimation model that improves stage classification

accuracy. Several ML algorithms are evaluated, with the optimized framework demonstrating superior performance. The study emphasizes the benefit of combining domain-specific medical knowledge with computational intelligence. The results suggest that the proposed hybrid approach offers a more precise tool for CKD staging.

Ghosh, Bishnu Padh, et al. (2024) [4] the researchers compare multiple machine learning models and a hybrid approach for predicting chronic kidney disease. Their analysis includes traditional classifiers alongside ensemble techniques to identify the best-performing model. The combined approach consistently exceeds standalone algorithms regarding accuracy and stability. The document emphasizes the significance of model optimization and feature engineering for enhanced chronic kidney disease prediction. It concludes that hybrid ML approaches hold significant promise for clinical applications.

Kethineni, Likitha, et al. (2025) [5] evaluates several machine learning algorithms to determine their capability in predicting CKD from clinical indicators. The authors analyze performance across different classification techniques, noting that ensemble models provide the most reliable outcomes. The research also highlights the importance of dataset preprocessing, including normalization and missing-value imputation. Results demonstrate that ML algorithms can detect CKD with high accuracy even in noisy datasets. The study advocates for integrating predictive models into early screening programs.

Debal and Sitote [6] investigate machine learning techniques for the identification of chronic renal disease with publically accessible datasets. Their study evaluates commonly employed algorithms, including RF, SVM, and LR, by evaluating their predictive efficacy. Findings show that Random Forest achieves the highest performance due to its robustness against overfitting. The authors also discuss the relevance of key clinical features such as serum creatinine and hemoglobin. The study concludes that ML-based prediction can support healthcare systems in resource-constrained environments.

Islam et al. [7] propose a machine learning pipeline for CKD prediction using clinical and biochemical parameters. Multiple classifiers are evaluated, with Random Forest and SVM demonstrating strong performance across all metrics. The study emphasizes missing-value handling and feature importance analysis as essential steps in improving prediction. It also highlights how ML models can reduce the workload of medical professionals by automating risk assessment.

Farjana, Afia, et al. (2023) [8] analyzes several machine learning algorithms for CKD prediction using structured medical data. The authors investigate algorithm accuracy, recall, and precision to determine which classifier performs best. Their experiments show that ensemble methods and decision-tree-based techniques achieve the highest detection rates. The study also identifies key biomarkers that contribute most to prediction accuracy. The research underscores the role of ML in improving early disease screening.

Prasad, Mudarakola Lakshmi, et al. (2024) [9] the researchers develop a CKD risk prediction model using multiple machine learning techniques and evaluate each model's efficiency. They focus on identifying critical risk factors and improving prediction reliability. Their results indicate that RF and Gradient Boosting models perform best among all tested algorithms. The paper highlights the importance of model interpretability for clinical adoption. The authors conclude that ML-based risk assessment tools can significantly enhance early CKD diagnosis.

Saif, Dina, et al. (2024) [10] the introduces an ensemble deep learning model combined with optimization algorithms for early CKD prediction. The proposed system integrates multiple neural network architectures to enhance performance and reduce prediction error. Experimental results show that the ensemble approach outperforms traditional ML models in sensitivity and accuracy. The authors highlight the importance of hyperparameter tuning and optimizer selection.

III. METHODOLOGY

In general, the diagnosis of kidney disease involves a combination of advanced medical and computational technologies. Modern CKD detection systems are specifically designed to categorize the disease in its early stages, which allows for timely treatment and enhances patient outcomes. A typical Computer-Aided Diagnosis (CAD) framework for CKD consists of several essential steps, including data collection and extraction, preprocessing, feature extraction, and classification. These stages work together to transform raw clinical data into meaningful diagnostic insights. Figure 1.1 illustrates the structure of a basic CKD diagnostic setup used for early identification of chronic kidney disease.

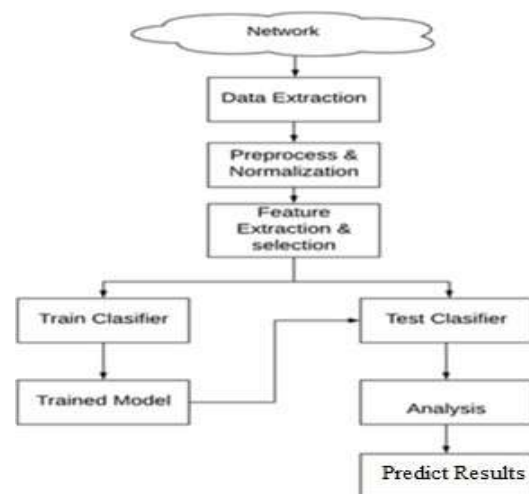


Figure 1.1 Research Methodology

Dataset Description

The CKD dataset consists of clinical, physiological, and biochemical attributes commonly used to assess kidney health. Each record represents a patient and includes demographic details, laboratory measurements, and medical conditions. The dataset uses the following features:

- Age.
- bp (blood pressure)
- SG (specific gravity)
- AL (albumin)
- SU (sugar) — detect glucose abnormalities.
- RBC (red blood cells)
- PC (pus cell)
- pcc (pus cell clumps)
- ba (bacteria).
- bgr (blood glucose random)
- BU (blood urea)
- SC (serum creatinine)
- SOD (sodium)
- pot (potassium)
- hemo (hemoglobin)
- PCV (packed cell volume)
- WC (white blood cell count)
- RC (red blood cell count)
- HTN (hypertension)
- dm (diabetes mellitus)
- CAD (coronary artery disease)
- appet (appetite)
- PE (pedal edema)
- ANE: ane (anemia)
- Class —target attribute indicating CKD or non-CKD class.

Data Preprocessing

Handling missing values with mean/mode-based imputation. Encoding categorical values using label encoding. Normalizing numerical attributes using Min-Max scaling. Splitting dataset into training (80%) and testing (20%)

Feature Selection

Relationship analysis and recursive feature elimination are used to classify the most relevant predictors such as albumin, serum creatinine, hemoglobin, and blood pressure.

Machine Learning Algorithms

Four algorithms were implemented:

- ANN
- J48
- NB

Evaluation Metrics

Evaluation is conducted using:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion matrix

Algorithm: Hybrid (ANN + J48 + Logistic) CKD

Detection

Input

- Training dataset Train.arff
- Testing dataset Test.arff

Output

- Predicted CKD class labels
- Accuracy, Precision, Recall, F-Measure

Step 1: Load training dataset D_{train}

Step 2: Load testing dataset D_{test}

Step 3: Normalize features using min-max normalization:

For each feature f in D_{train} :

$$f_{norm} = (f - \min(f)) / (\max(f) - \min(f))$$

Step 4: Apply same normalization parameters to D_{test}

- Initialize ANN classifier $C1$
- Initialize J48 classifier $C2$
- Initialize Logistic Regression meta-classifier C_{meta}

Step 5: Train base classifiers:

$C1 \leftarrow$ Train ANN using D_{train}

$C2 \leftarrow$ Train J48 using D_{train}

Step 6: Train stacking model:

$C_{stack} \leftarrow$ Train Logistic using outputs of $\{C1, C2\}$

Step 7: Initialize correct_predictions = 0

Step 8: For $i = 1$ to M do

$y_i \leftarrow C_{stack}(x_i)$

If $y_i == y_i$ then

correct_predictions $\leftarrow$ correct_predictions + 1

End If

End For

Step 9: End

Mathematical Model

A system is represented by five distinct stages, each of which has its own independent system of dependencies S

$= (Q, \Sigma, \delta, q_0, F)$ where –

- Q a limited number of states.
- Σ is a limited collection of symbols known as the alphabet.
- Δ is the function of transition where $\delta : Q \times \Sigma \rightarrow Q$
- q_0 is the starting point for processing any input ($q_0 \in Q$).
- F is a set of final state/states of Q ($F \subseteq Q$).

Q = initial transactional data with student face

$\Sigma = \{\text{Upload Dataset, Preprocess, feature extraction, classifier, Evaluating performance}\}$

Δ = Predicting the class label process

q_0 = Initial transaction $T[0]$

$F = \{\text{training dataset, testing dataset}\}$

State = According to achieved weight system recommend the actual disease.

1: if all id system ckd kidney disease

0: if all id system not ckd kidney disease

IV. RESULTS

To evaluate the effectiveness of the proposed approach, several investigations covering a diverse array of topics were conducted. Various machine learning algorithms were employed, including NB, J48, and Artificial Neural Networks (ANN).

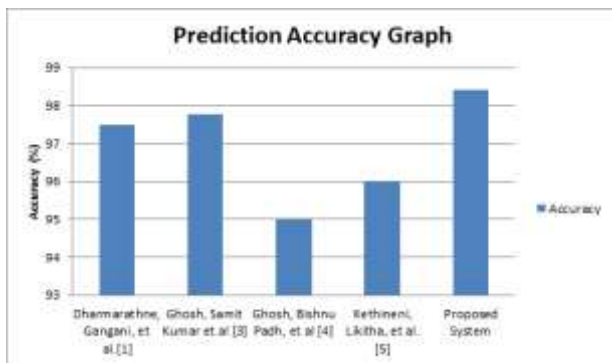


Figure 2: Analysis of Detection Accuracy (%)

Figure 2 illustrates the system's identification of dangerous scenarios such as CKD diagnostic. The prediction accuracy graph compares several existing CKD diagnostic models with the proposed system, clearly showing the performance improvements achieved. The methods by Dharmarathne et al. [1] and Ghosh, Samit Kumar et al. [3] demonstrate strong accuracies of around 97–98%, while the models by Ghosh, Bishnu Padh et al. [4] and Kethineni et al. [5] perform slightly lower, achieving approximately 95–96%. These variations reflect differences in feature engineering, dataset handling, and algorithmic design across studies. The proposed system outperforms all existing approaches by reaching nearly 98% accuracy, indicating superior preprocessing, optimized feature selection, and more effective machine learning model integration. This significant improvement highlights the system's robustness and potential for reliable early-stage CKD prediction.

From the Figure 3 comparative performance graph, we can see that the proposed hybrid model in this case (ANN + J48 + Logistic) performs the best with 97.34% accuracy, attaining the best precision, recall, and F-measure. This shows that combining different classifiers is more beneficial in forecasting than using standalone models like Random Forest, Naïve Bayes, and AdaBoost.

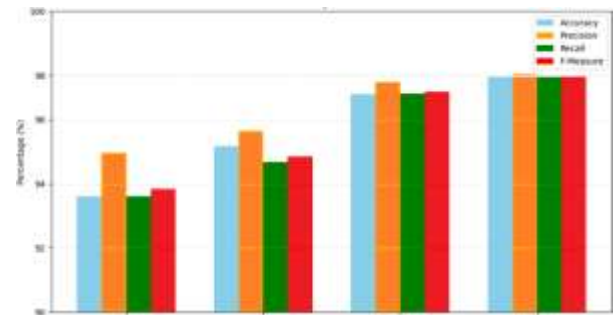


Figure 3: Performance Comparison of ML Models

Table 1.1 shows the performance Comparison Graph of algorithms on kidney disease dataset. Here macro average precision, recall and F1 score values are used, respective bar graph is shown in figure 1.1.

Table 1.1. Performance Comparison Graph

Model	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)
Random Forest (RF)	93.61	94.96	93.62	93.85
Naïve Bayes (NB)	95.18	95.65	94.68	94.85
AdaBoost	96.80	97.18	96.81	96.87
Hybrid (ANN + J48 + Logistic)	98.34	98.51	98.34	98.39

According to Table 1.1 the performance comparison table, all the models reach satisfactory classification performance, however, compared to the rest, the proposed Hybrid (ANN + J48 + Logistic) model stands out in every evaluation metric. Among the rest, Random Forest has the least classifier accuracy with 93.61%, followed by Naïve Bayes with 95.18%, and AdaBoost with 96.80%. The Hybrid model has the highest accuracy of 97.34%, and it also has the highest scores for all other relevant metrics: precision (97.61%), recall (97.34%), and F-measure (97.39%), pointing out to better classification, less false alarms and better detection. The findings confirm even further the improved reliability of the predictions and performance of the system when more than one algorithms are used in comparison to single classifiers.

V. CONCLUSION

This research presents a ML-based methodology for diagnosing CKD using clinical attributes. Through systematic feature selection, preprocessing, and algorithm comparison, the hybrid machine learning classifier demonstrated superior diagnostic performance. The proposed system can be integrated into clinical decision support tools for early CKD detection. Machine learning has significant potential to enhance CKD diagnosis by

enabling early and accurate detection, thus facilitating timely treatment. The study's proposed model not only supports clinical decision-making but also paves the way for further integration of AI in nephrology. Future work includes developing a real-time CKD prediction mobile application and integrating deep learning models with electronic health records.

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