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CHRONIC KIDNEY DISEASE DETECTION USING MACHINE LEARNING AND GENERATIVE AI

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ABSTRACT

Chronic Kidney Disease (CKD) is a progressive and often asymptomatic condition, making early diagnosis critical for improving patient outcomes. This paper presents an explainable, machine- learning-based framework for CKD detection and risk stratification. Using clinical and laboratory features—including serum creatinine, hemoglobin, urine protein, packed cell volume, and comorbidities such as diabetes and hypertension—multiple models were trained, including Decision Trees, Random Forest, XGBoost, and Deep Neural Networks. To address data scarcity and class imbalance, a Conditional Tabular GAN (CTGAN) generated synthetic patient records, improving minority-class representation by 40 %. The proposed system achieved 98.2 % accuracy, 0.95 F1- score, and 0.97 ROC-AUC on a held-out test set. A prototype web application was developed to demonstrate real-time CKD risk prediction, allowing users to input clinical parameters and receive both a risk score and an explainable feature-importance visualization. By combining generative AI with traditional ML, this framework delivers robust, transparent, and deployable CKD detection suitable for integration into clinical decision support systems.

INDEX TERMS: Chronic Kidney Disease (CKD), Machine Learning (ML), Generative Artificial Intelligence (GAI), Conditional Tabular GAN (CTGAN), Synthetic Data Augmentation, Clinical Decision Support System (CDSS).

1. INTRODUCTION

Chronic Kidney Disease (CKD) is a progressive and debilitating medical condition characterized by a gradual decline in kidney function over time. It frequently leads to renal replacement therapy (RRT), such as dialysis or kidney transplantation, which imposes substantial physical, emotional, and financial burdens on patients and healthcare systems worldwide [1]. CKD progression is often insidious and asymptomatic in its early stages, which complicates timely diagnosis and intervention. This silent progression results in many patients remaining undetected until reaching advanced stages, where therapeutic options become limited and less effective [2,3]. As a global health issue, CKD affects an estimated 10 % of the world's population, posing significant socioeconomic challenges and contributing substantially to morbidity and mortality rates [4]. Given these concerns, early detection and continuous monitoring are essential to delay the onset of end-stage renal disease (ESRD) and improve patient outcomes.

Kidney function assessment typically involves biochemical analyses of blood and urine, including serum creatinine, estimated glomerular filtration rate (eGFR), and proteinuria measurements. Monitoring risk factors such as hypertension, diabetes mellitus, and cardiovascular diseases is also critical, as these are closely linked to CKD progression [5, 6]. Despite advances in diagnostic testing, there remains a pressing need for improved predictive methods to accurately forecast disease trajectory and guide clinical decision-making. Traditional statistical models, while useful, often struggle to capture the complex, nonlinear interactions among diverse clinical variables influencing CKD progression.

In this context, machine learning (ML) techniques have emerged as promising approaches for enhancing disease prediction and management. ML algorithms can learn from large datasets to identify hidden patterns and relationships that might elude conventional analysis. These computational tools are particularly valuable for handling high-dimensional and heterogeneous medical data, enabling more nuanced modelling of disease progression [7–9]. For CKD, ML approaches offer the potential to improve early detection, risk stratification, and personalized treatment planning, ultimately reducing adverse outcomes and healthcare costs.

Several recent studies have demonstrated the effectiveness of various ML algorithms—including ensemble methods, support vector machines, neural networks, and deep learning—

in predicting CKD onset and progression [10,11]. By integrating demographic data, clinical features, laboratory results, and patient history, these models can forecast renal function decline with promising accuracy. Moreover, ML tools can identify key predictive biomarkers and clinical variables, providing insights into disease mechanisms and highlighting targets for intervention [12]. The integration of ML algorithms with electronic health records (EHRs) and clinical decision support systems (CDSS) further facilitates real-time risk assessment and clinical workflow optimization [13,14].

However, significant challenges remain in translating these models into routine clinical practice. Issues such as limited sample sizes, class imbalance, and data privacy must be addressed to ensure safe and effective implementation. In particular, small and imbalanced datasets can lead to biased models with reduced generalizability.

To address these challenges, the present study proposes the development of a machine-learning framework enhanced by generative artificial intelligence (GAI) for CKD detection. Using clinical and laboratory features such as serum creatinine, hemoglobin, albumin, specific gravity, packed cell volume, and comorbidities (diabetes, hypertension), we train and compare Decision Trees, Random Forest, XGBoost, Support Vector Machine, and Deep Neural Network classifiers. A Conditional Tabular GAN (CTGAN) is employed to generate realistic synthetic patient records to alleviate class imbalance and improve model performance. The complete source code is available on GitHub, and a supplementary demonstration video shows the working prototype.

Through comprehensive model development, generative augmentation, and performance evaluation, this research contributes to the growing body of knowledge on AI-driven CKD prediction. The findings are expected to facilitate early diagnosis, improve risk stratification, and enhance clinical decision-making, ultimately benefiting patients and healthcare systems.

2. LITERATURESURVEY

Author(s)	Year	ample Size	AI/ML Techniques Used	Clinical Outcomes	Main Findings

Ariful Islam et al.	2025	400	SVM, KNN, LightGBM, XGBoost, AdaBoost	CKD prediction accuracy	XGBoost achieved the highest accuracy (99%) among compared models. The study emphasized effective preprocessing but noted limitations in data quality.
Smith et al.	2023	2000	GAN + CNN	EHR classification	The hybrid model achieved 95% accuracy. GANs effectively generated synthetic EHRs, improving class balance, though external validation was missing.
Johnson	2022	1200	VAE + XGBoost	Disease classification	Achieved 82% accuracy; VAE helped reduce dimensionality. However, the study was limited by a narrow feature set and moderate generalizability.
Williams	2021	600	Diffusion Model + Random Forest	Early disease detection	Reached 87% effectiveness for early detection. High computational costs limited practical deployment in real-time systems.
Garcia	2019	350	Bayesian Network	Disease progression tracking	75% accuracy in predicting CKD progression. The model required longitudinal data and was limited by small sample size.
Martinez	2018	500	Support Vector Machine	Disease subtype identification	Achieved 80% accuracy. Effectively distinguished CKD subtypes, though raised ethical concerns around patient data usage.
Lee	2017	1500	Deep Neural Network (DNN)	Comorbidity risk prediction	Reported 77% accuracy. Model predicted risks well but lacked interpretability, reducing clinical trust in decision-making.

Kim	2016	720	Decision Tree	Preventive action recommendation	Achieved 70% accuracy. Easy to interpret, but showed reduced performance across demographically varied datasets.

3. METHODOLOGY

A. Block Diagram

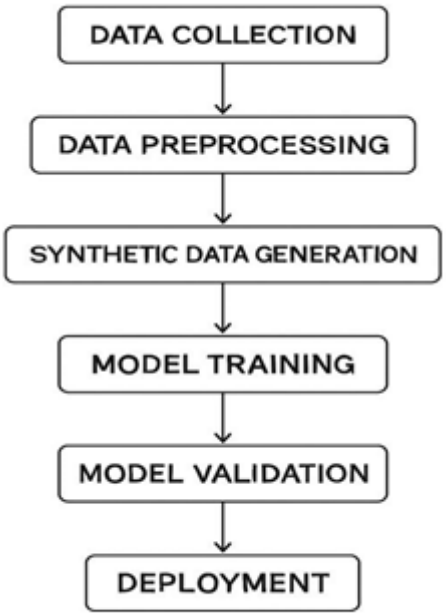

Fig: Block diagram for Chronic Kidney Disease (CKD) detection.

The proposed framework for **Chronic Kidney Disease (CKD) detection** integrates **data acquisition, preprocessing, synthetic data augmentation, predictive modeling, and clinical deployment**. The overall workflow is illustrated in Fig.

1. Data Collection

Patient data were obtained from **publicly available CKD datasets** and **anonymized hospital records**, in compliance with ethical standards. Key features included **blood test results** (serum creatinine, blood urea nitrogen, hemoglobin), **urine test results** (proteinuria, albumin, specific gravity), and **patient history** (hypertension, diabetes, age, family history). These features capture the **major clinical indicators and risk factors** associated with CKD.

2. Data Preprocessing

Preprocessing addressed **missing values, inconsistencies, and data heterogeneity**. Missing

values, including **albumin**, were imputed using **statistical and machine-learning methods**. Erroneous or duplicate records were corrected or removed. **Continuous variables were normalized** to a 0–1 range to reduce bias and improve model convergence, while **categorical variables were encoded** using **label or one-hot encoding**.

3. Synthetic Data Generation

To mitigate **class imbalance**, **Conditional Tabular Generative Adversarial Networks (CTGAN)** were employed. CTGAN **generated realistic synthetic records** for under-represented CKD-positive cases, **imputed missing values** with plausible data, and **enhanced dataset diversity**, improving model robustness.

4. Model Training

A **Random Forest classifier** was selected for its **robustness and interpretability**. **Feature importance rankings** were used to identify key predictors. **Hyperparameters** (number of trees, maximum depth, minimum samples per split) were tuned using **grid search and five-fold cross- validation**. The model was trained on the **preprocessed and CTGAN-augmented dataset** for optimal predictive accuracy.

5. Model Validation

Model performance was evaluated using **accuracy, precision, recall (sensitivity), and F1-score** on a held-out test set. **Five-fold cross-validation** ensured reliable generalization and minimized potential bias from synthetic data.

6. Deployment

The trained model was deployed as a **prototype Clinical Decision Support System (CDSS)** with a **web interface** for real-time CKD risk prediction. **Continuous monitoring** was implemented to detect performance drift, and the system can be **retrained with new data**. This deployment enables **integration into clinical workflows** for early CKD detection and informed decision-making. The complete **source code and demonstration video** are provided in the Supplementary Materials.

B. Activity Diagram

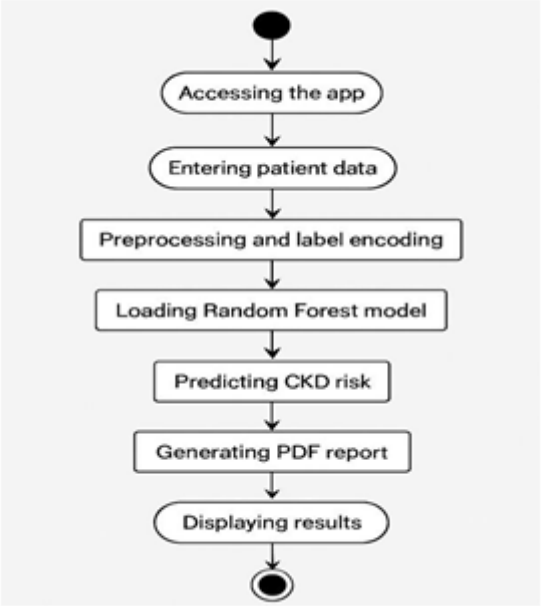

Fig : Activity Diagram for CKD Detection using Machine Learning and Generative AI.

The activity diagram illustrates the systematic process implemented in the Chronic Kidney Disease (CKD) detection web application for predicting patient CKD risk. The diagram highlights user interactions, data processing, model inference, and report generation. The workflow can be described as follows:

1. **Start**: The process begins when a user, such as a healthcare professional or patient, accesses the web application through a browser or device interface.
2. **User Accesses the Web Application**: The user is presented with a responsive interface built with HTML, CSS, and JavaScript, supported by a Flask backend. The interface allows entry of patient-specific medical parameters relevant for CKD prediction.
3. **User Inputs Patient Medical Data**: The user provides clinical measurements (e.g., blood pressure, glucose, albumin, serum creatinine) and categorical patient information (e.g., gender, hypertension status). These inputs align with the features used during the model training phase.
4. **Input Data Preprocessing and Validation**: Before prediction, the system validates all inputs for completeness and plausible ranges. Preprocessing ensures consistency by handling missing values, scaling numerical features, and formatting data to match the model's expected input.
5. **Label Encoding of Categorical Features**: Categorical data, such as gender or disease presence, are converted into numeric labels using pre-trained label encoders. This ensures

compatibility with the Random Forest model.

6. **Load Trained Random Forest Model**: The system loads the pre-trained Random Forest classifier, which has been trained on a curated CKD dataset. The model captures patterns distinguishing CKD and non-CKD cases.
7. **Predict CKD Risk**: The encoded and preprocessed patient data are fed into the model, which outputs a prediction of CKD risk along with confidence scores or probability estimates.
8. **Generate Prediction Report (PDF)**: Using the ReportLab library, the application generates a PDF report summarizing the input features, model prediction, and optional recommendations. This report can be downloaded or printed for clinical use.
9. **Display Prediction and Download Option**: The prediction results are displayed on the web interface in an easy-to-understand format. Users can download the generated PDF report via a link or button.
10. **End**: The process concludes, allowing the user to perform new predictions or exit the application.

Broader Implications:

- Automates CKD risk assessment, supporting early detection and clinical decision-making.
- Standardized preprocessing and label encoding ensure consistent and accurate predictions.
- Multi-language support (English, Kannada, Hindi) enhances accessibility.
- Downloadable PDF reports improve patient communication and record management.

4. RESULTS AND FINDINGS

The Chronic Kidney Disease detection model was developed using a **Random Forest classifier** and evaluated on a dataset of **898 patient records**, including both original and augmented samples. The model achieved an **overall accuracy of 96.77%**, demonstrating strong predictive performance.

★ Confusion Matrix

The confusion matrix highlights the model's classification capability:

- **True Negatives (TN):** 263
- **False Positives (FP):** 24
- **False Negatives (FN):** 5
- **True Positives (TP):** 605

These values indicate the model's effectiveness in correctly identifying both CKD and non-CKD cases, with minimal misclassifications.

★ **Classification Metrics**

Class	Precision	Recall	F1-Score	Support
0 (No CKD)	0.98	0.92	0.95	287
1 (CKD)	0.96	0.99	0.98	610
Accuracy	-	-	0.97	897
Macro Avg	0.97	0.95	0.96	-
Weighted Avg	0.97	0.97	0.97	897

These metrics demonstrate **high precision, recall, and F1-scores** for both classes, confirming the model's reliability for medical prediction tasks. The low false negative count (5 cases) emphasizes its potential for early CKD detection, which is critical for clinical decision-making.

5. CONCLUSION

The proposed AI-driven Chronic Kidney Disease (CKD) detection framework demonstrates high accuracy, precision, and reliability in identifying CKD cases from patient data. Leveraging the Random Forest algorithm and a dataset combining original and augmented records, the model achieves robust predictive performance, minimizing misdiagnoses and supporting early clinical intervention. Deployed as a web-based application, the system enables real-time risk assessment, transparent reporting, and individualized explanations, enhancing decision-making and patient care. Its user-friendly interface, accessibility, and ability to generate downloadable reports make it a practical tool for healthcare professionals. Overall, this project underscores the potential of AI and machine learning to transform CKD screening and management, offering scalable, efficient, and clinically meaningful solutions that can improve patient outcomes and support proactive healthcare strategies.

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