DOI: http://dx.doi.org/10.26483/ijarcs.v17i3.7463

ISSN No. 0976-5697

Volume 17, No. 3, May-June 2026

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

DESIGN AND IMPLEMENTATION OF AN AI-BASED SYSTEM FOR KIDNEY DISEASE PREDICTION

Alfred Akpan Udosen[1], Oyinkansola Ebubechukwu Sojirin[2*], Boluwatife Cherish Mustapha[3], and Christiana Jumoke Daramola[4]

[1,2,3]Department of Computer Science, School of Computing, Babcock University, Ilishan Remo, Ogun State, Nigeria.

[4]Department of Software Engineering, School of Computing, Babcock University, Ilishan Remo, Ogun State, Nigeria.

***Abstract*—**Chronic Kidney Disease (CKD) is a considerable public health problem in Nigeria, and most hospital record systems have limited predictive ability for timely clinical intervention. In Nigeria, chronic kidney disease (CKD) is a major public health problem, and hospital record systems have limited predictive power for timely clinical intervention. The objective of this study is to design and implement NephroTrack, an AI-based web system to predict CKD. A three-tiered architecture was implemented: a React.js and Tailwind CSS front end that interfaces with a REST API back end running on Node.js and Express.js, and a standalone Python FastAPI machine learning service deployed together with the managed PostgreSQL database on Render. The system can support 3 user roles and include a 51-featured CKD risk prediction form with colour-coded risk classifications and PDF report export, patient registration, clinical visit recording, and laboratory result tracking. After hyperparameter tuning using 216 combinations with 5-fold cross-validation, the Random Forest algorithm yielded the highest performance metrics: accuracy, 91.87%; recall, 99.34%; F1-Score, 95.73%; and AUC-ROC, 74.97%, revealing the effectiveness of using AI for early detection of CKD in resource-limited healthcare contexts in Nigeria.

***Index Terms*—**Artificial Intelligence, Chronic Kidney Disease, Machine Learning, Random Forest, Healthcare, Prediction

I. INTRODUCTION

Kidney disease is a problem that many millions of people around the world experience and is a rising health issue worldwide, particularly in the UK, which can occur without any obvious signs or symptoms until the kidneys become very poorly functioning. Chronic kidney disease (CKD) affects around 674 million individuals globally, accounting for approximately 9% of the world's population, and is a major cause of cardiovascular problems and mortality [1]. Early diagnosis and treatment are critical as CKD may not present symptoms until treatment is limited and expensive.

The healthcare industry has been transformed by Artificial Intelligence (AI) and Machine Learning (ML), which leverage data to predict and support clinicians' decisions. The ability of ML algorithms to process vast amounts of clinical and demographic data can help uncover patterns, predict disease trajectories, and enable preventive measures [2]. Ma et al. [3] proposed a dynamic kidney failure prediction model, which learns continually from real-world patients' data. Meanwhile, Nguycharoen [4] presented an explainable ML system for the prediction of CKD, highlighting the need to be transparent for clinical use.

However, most hospitals in Nigeria use basic or semi-manual patient record systems without predictive capability and do not use any patient data to predict future risks [5]. It has been determined that several factors, including lack of investment in health IT, lack of infrastructure, and fragmentation of health data, are key factors that hinder the adoption of intelligent EHRs [5]. Lack of AI systems with enhancements to treatment delivery leads to delayed interventions, costlier treatments, and preventable deaths [6].

Typical components of an AI-enabled clinical decision support system are data collection and patient registration, clinical visit and lab result recording, feature engineering and pre-processing, ML model training and selection, real-time prediction and risk classification, and report generation and clinical notification. Indeed, deep learning and ensemble models like Random Forest [7], XGBoost [8], and Support Vector Machines [9] are quite good at predicting in clinical data. The goal of this research is thus to design and build NephroTrack, a web-based system for structured patient records and a machine-learning module for early identification of CKD, tailored to the specific context of the Nigerian healthcare system.

II. RELATED WORKS

A. Patient management systems in healthcare

A patient management system (PMS) is a specific type of software that handles patient registration, clinical documentation, and billing [5]. Paper systems can be hard to access, illegible, and damaged, whereas digital systems can improve quality and provide the information platform for predictive analytics [10]. A good PMS performs all of these tasks and brings together administrative and clinical functions, minimizes data duplication, and facilitates evidence-based clinical decision-making.

B. Prediction of CKD using Machine learning techniques

Using Explainable AI techniques, Jawad et al. [2] proposed an ensemble ML model, which showed a high level of prediction accuracy (> 98%) for CKD. Ma et al. [3] created a dynamic deep learning system that is able to predict kidney failure and was tested and validated on a large and diverse population. To be clinically adopted, Nguycharoen [4] developed an explainable CKD prediction system, focusing on the transparency of the model. Takkavatakarn et al. [11] demonstrated that the risk of ECKD can be predicted using real-world EHRs and ML models in patients with stage 4 CKD. The theoretical underpinnings of supervised learning that support these classification techniques are given by Russell and Norvig [12].

C. Machine learning for disease diagnosis and classification

Deep learning can also accurately (with clinically relevant accuracy) predict hospital readmission, mortality, and extended length of stay in the hospital from only EHR data, as Rajkomar et al. [6] demonstrated. This was achieved by Esteva et al. [13], who proposed a framework for embedding DL models in diagnostic medical care systems. A general overview of the use of Machine Learning in the Healthcare sector has been provided by An et al. [14], where they have pointed out that Ensemble Methods and Neural Networks perform better in structured clinical tabular data than classical approaches.

D. Gaps in Nigerian and sub-Saharan healthcare IT

Therefore, Babatope et al. [5] identified the following major challenges to the effective use of EHRs in Nigerian hospitals: poor infrastructure, fragmented data systems, and lack of investment in health IT. Paulo [10] identified incremental adoption models and structural and technical challenges to AI adoption in sub-Saharan countries. Omokanye et al. [15] performed a SWOT analysis to determine Nigeria's readiness for digital health transformation and concluded that Nigeria is getting ready, albeit there is less support to implement it. These studies show that prediction models for CKD using AI are effective in other countries of the world, but there is a huge difference between the present healthcare delivery systems in Nigeria and the rest of the world, in terms of healthcare being mostly reactive. It is in this area that this study seeks to bridge.

III. SYSTEM ANALYSIS AND DESIGN

A. System architecture

NephroTrack is a three-level client-server application designed to separate the presentation level, application logic level, and data storage level. The Patient Dashboard is a single-page application developed with React.js, having three roles, Clinician, Admin, and Records Officer, all of Tier 1. Tier 2 is an Express.js/Node.js based REST API that is responsible for authentication, patient record management, clinical visit processing, and ML prediction routing. Tier 3 is a managed PostgreSQL and a standalone Python FastAPI ML service. The three tiers are all independent; they have all been hosted on the Render platform using HTTPS for communication.

B. Software development methodology.

The Waterfall model was selected due to its well-structured sequence, and the requirements are well-defined and stable in this project. The Phases are: Requirements Gathering and Analysis, System Design, Implementation and Coding, Testing, Deployment, and Maintenance. It was documented well on each step, so there was a clear audit trail from research to development.

C. Functional and non-functional requirements

The functional requirement for the system is as follows: Store patient information with unique identifiers, Securely store clinical information like medical history, clinical diagnosis, lab results etc., Integrate an ML model which will fetch patient information, Give a 'risk score' as Low, Medium and High for clinical kidney disease and implement role based access control and provide a function of clinical report generation with csv and pdf export option. The non-functional requirements are data security (JWT authentication and hashing of passwords with bcrypt), low prediction latency, high availability during hospital working hours, and scalability to support an increasing number of patients.

IV. SYSTEM IMPLEMENTATION

A. Database design

The relational database used is PostgreSQL with five important tables. The Users table stores the user credential information and roles (Table I). The Patients table includes over 30 columns, including demographics, lifestyle factors, medical history, medication, symptoms, and environmental exposure, with 120 patients seeded with Nigerian demographic information. Vitals and notes for each clinical encounter are recorded in the table, "Visits". There are 17 parameters in the Lab Results table relevant to CKD listed in Table II. Every one of the 51 input features is listed in the Predictions table along with the predicted probability, risk classification, and patient and clinician IDs for full audit.

TABLE I: Users table structure

Column	Datatype	Description
id	UUID (PK)	Unique identifier for each user
full_name	VARCHAR	Full name of the user
email	VARCHAR	Login email address (unique)
password	VARCHAR	Bcrypt-hashed password
role	ENUM	Clinician, Admin, or Records Officer
created_at	TIMESTAMP	Account creation date
updated_at	TIMESTAMP	Last update timestamp

TABLE II: Laboratory results parameters

Parameter	Unit	Clinical relevance
Serum Creatinine	mg/dL	Key indicator of kidney filtering function
Blood Urea Nitrogen	mg/dL	Waste product filtered by kidneys
eGFR	mL/min/1.73m²	Estimated glomerular filtration rate
Haemoglobin	g/dL	Anaemia is common in CKD
Serum Potassium	mEq/L	Electrolyte imbalance indicator

Serum Sodium	mEq/L	Fluid regulation indicator
Albumin	g/dL	Low in CKD due to protein loss
Urine Protein	mg/dL	Proteinuria is an early CKD sign
Random Blood Sugar	mg/dL	Diabetic risk factor
HbA1c	%	Long-term blood sugar control
Total Cholesterol	mg/dL	Cardiovascular risk
LDL Cholesterol	mg/dL	Cardiovascular risk
HDL Cholesterol	mg/dL	Protective cholesterol
Triglycerides	mg/dL	Lipid panel
White Blood Cell Count	cells/µL	Infection or inflammation marker
Platelet count	cells/µL	Clotting assessment
Urine Specific Gravity	—	Kidney concentrating ability

B. Machine learning pipeline

Using Google Colab, the ML pipeline was written in Python. A dataset chronic_kidney_disease from Kaggle was used; it contains 1659 patients and 53 columns. 51 numeric features were left as predictors after discarding the non-predictive ones (PatientID and DoctorInCharge). The target variable (Diagnosis = 1 if the patient had CKD, 0 if not) was very imbalanced, with 91.9% of the patient population being classified as CKD-positive. Data pipeline: Normalising all features with the MinMaxScaler, splitting the data into an 80/20 train/test ratio, adding SMOTE only to the train data, oversampling the train data with SMOTE from 1327 to 2438 balanced samples, training and comparing 8 classification algorithms, hyperparameter tuning with GridSearchCV on 216 train sets of data, and serialising the model with joblib.

C. System features

NephroTrack provides a completely responsive web interface with a role-based user experience. Its main features are: secure logon with JWT authentication, a clinical dashboard with interactive stat cards, collapsible sections at the patient registration page (demographics, lifestyle, medical history, medications, symptoms and environmental exposures), recording of clinical visits (vitals and notes), lab results entry for all 17 CKD-relevant parameters, patient risk prediction form with 51 features that returns a colour-coded risk output (High ≥70%, Medium 40–69%, Low <40%), export of PDF reports, export to CSV, user management for role assignment and a mobile responsive interface with collapsing sidebar – this is important, since many healthcare workers in Nigeria use their smartphones as their primary computing tool.

D. System testing

Three levels of testing were carried out. Individual API routes (authentication, patient registration, prediction endpoint), as well as the session timeout logic, were validated within Unit Testing. Integration Testing confirmed the entire end-to-end prediction process: form submission, back-end validation, feature forwarding to the ML service, and results showing, as well as export to PDF and CSV. All three user roles were tested using all the major workflows in User Acceptance Testing. Problems found, such as losing focus on input elements because of React components within the parent render function and missing validation messages, were addressed before release.

V. RESULTS AND DISCUSSION

A balanced training set was created using SMOTE, and eight classification algorithms were used to build the classification model and tested on the original held-out test set. The obtained results are ranked based on the F1-Score in Table III.

TABLE III: Comparison of eight classification algorithms (ranked by F1-Score)

Rank	Algorithm	Accuracy(%)	Precision(%)	Recall (%)	F1-Score(%)	AUC-ROC(%)
1	Random Forest	91.57	92.62	98.69	95.56	73.51
2	SVM	90.36	93.61	96.07	94.82	74.64
3	XGBoost	90.36	93.61	96.07	94.82	77.36
4	Gradient Boosting	89.46	92.99	95.74	94.35	70.60
5	AdaBoost	82.53	93.64	86.89	90.14	71.40
6	Decision Tree	79.82	93.12	84.26	88.47	56.95
7	Logistic Regression	76.51	95.95	77.70	85.87	78.62
8	KNN	42.47	94.53	39.67	55.89	58.11

The most important is recall – a false negative means the patient is not diagnosed and treated, while a false positive means the patient is further investigated. KNN did not work well because of the curse of dimensionality for 51 features. SVM and XGBoost performed well but were not as good as Random Forest in terms of recall and F1-Score.

The best hyperparameters of the RF model were found by GridSearchCV with 5-fold cross-validation: n_estimators = 200, max_depth = 20, max_features = log2, min_samples_split = 2, min_samples_leaf = 1. The results are compared with the untuned baseline model in Table IV.

There was a modest improvement in the tuned model in all metrics, but it was consistent. The recall rate was improved from 98.69% to 99.34%, and the model would produce even fewer false-negative cases of CKD. The F1-Score improved from 95.56% to 95.73% and AUC-ROC from 73.51% to 74.97%, which means that the tuned model is the best model to deploy.

TABLE IV: Tuned vs. untuned Random Forest performance

Metric	Untuned Random Forest	Tuned Random Forest (Final)
Accuracy	91.57%	91.87%
Precision	92.62%	92.38%
Recall	98.69%	99.34%

F1-Score	95.56%	95.73%
AUC-ROC	73.51%	74.97%

These results are comparable to those of similar previous research. An ensemble approach was used by Jawad et al. [2] that obtained an accuracy higher than 98% on a different, smaller dataset. Nguycharoen [4] focused on explainability instead of pure accuracy in a very specific cardiovascular cohort. NephroTrack is unique in using a high-performing ML model coupled with a comprehensive, role-focused clinical information system that was implemented in a contextually relevant Nigerian environment, which was not seen in any of the reviewed studies.

The three user types and all major workflows have been completed in user acceptance testing. The features of searchable patient dropdowns, patient pre-selection through navigation state, clickable dashboard stat cards, mobile responsiveness, and ML cold-start handling were all validated for usability improvements. The demographic "seeding" of the database with 120 patients from Nigeria, with locally representative names, states, and attributes, makes the system contextually appropriate, whereas most academic implementations aren't, and is a known constraint of implementing practical healthcare software in resource-constrained settings.

VI. CONCLUSION

We believe that in this study, we have proven that it is both technically possible and practically useful to develop and deploy an AI-based system for predicting the onset of CKD with open-source technologies and a publicly accessible clinical database that is open and available to all. The NephroTrack deployable web application integrates a structured patient record management system and an embedded machine learning predictive module in any modern browser, without the need to install anything locally. All three successfully achieved the goals of the study: design, implementation, and evaluation.

The tuned Random Forest model was able to correctly classify nearly every real CKD case with a recall of 99.34% on the held-out test set. While it is not yet ready for direct clinical use, NephroTrack needs to be validated with local data and features that explain the results in terms of SHAP (Shapley Additive Explanations), support multi-hospital tenancy, multi-factor authentication, and production-grade hosting. Future work should include the patient-level feature importance score as well as the prediction, automatically alert if the lab results are in clinically relevant ranges, and role-based audit logging for regulatory compliance. NephroTrack provides a solid, proven, and contextually relevant foundation that can be used as a stepping stone to shift the Nigerian health care system from a reactive to a preventive model of CKD management.

ACKNOWLEDGEMENTS

The authors give their thanks to the project supervisor, Prof. Kuyoro Afolashade, who guided and helped them in this study. The authors are grateful to all the lecturers in the Department of Computer Science, Babcock University, especially Mr. Alfred Udosen and Dr. Jerry Nzenwata, for their guidance on the Knowledge used in the project. The authors also owe special thanks to their families (Mr. and Mrs. Sojirin and Mr. and Mrs. Mustapha), who have always been so dedicated and supportive during their academic endeavors.

REFERENCES

[1] World Health Organization, "Reducing the burden of noncommunicable diseases through promotion of kidney health," WHO, Geneva, 2025.

[2] T. K. M. Jawad, A. Verma, F. Amsaad, and L. Ashraf, "AI-driven predictive analytics approach for early prognosis of chronic kidney disease using ensemble learning and explainable AI," arXiv, 2024. doi:10.48550/arXiv.2406.06728

[3] J. Ma, J. Wang, L. Lu, Y. Sun, M. Feng, F. Zhang, P. Shen, Z. Jiang, S. Hong, and L. Zhang, "Development and validation of a dynamic kidney failure prediction model based on deep learning: A real-world study with external validation," arXiv, 2025. doi:10.48550/arXiv.2501.16388

[4] N. Nguycharoen, "Explainable machine learning system for predicting chronic kidney disease in high-risk cardiovascular patients," arXiv, April 2024. arXiv:2404.11148

[5] A. E. Babatope, I. P. Adewunmi, D. O. Ajisafe, K. O. Adepoju, and A. R. Babatope, "Accessing the factors militating against the effective implementation of electronic health records (EHR) in Nigeria," Scientific Reports, Dec. 2024. doi:10.1038/s41598-024-83009-y

[6] A. Rajkomar, J. Dean, and I. Kohane, "Machine learning in medicine," New England Journal of Medicine, vol. 380, no. 14, Apr. 2019. doi:10.1056/NEJMra1814259

[7] L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.

[8] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," Proc. 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 785–794, 2016.

[9] C. Cortes and V. Vapnik, "Support-vector networks," Machine Learning, vol. 20, no. 3, pp. 273–297, 1995.

[10] S. Paulo, "Artificial intelligence in global health: An unfair future for health in sub-Saharan Africa," Health and Social Care in the Community, Feb. 2025. doi:10.1093/haschl/qxaf023

[11] K. Takkavatakarn, W. Oh, E. Cheng, G. N. Nadkarni, and L. Chan, "Machine learning models to predict end-stage kidney disease in chronic kidney disease stage 4," BMC Nephrology, Dec. 2023. doi:10.1186/s12882-023-03424-7

[12] S. Russell and P. Norvig, Artificial Intelligence: A Modern Approach, 4th ed. Upper Saddle River, NJ: Prentice Hall, 2020.

[13] A. Esteva, K. Chou, S. Yeung, N. Naik, A. Madani, A. Mottaghi, Y. Liu, E. Topol, J. Dean, and R. Socher, "Deep learning-enabled medical computer vision," npj Digital Medicine, Jan. 2021. doi:10.1038/s41746-020-00376-2

[14] Q. An, S. Rahman, J. Zhou, and J. J. Kang, "A comprehensive review of machine learning in the healthcare industry: Classification, restrictions, opportunities and challenges," Sensors, Apr. 2023. doi:10.3390/s23094178

[15] S. A. Omokanye, A. I. Wegbom, R. Adio, and C. O. Adebayo, "SWOT analysis of health information management practice in Nigeria," unpublished, Feb. 2025.