RESEARCH PAPER

An Intelligent Iot-Driven Explainable Machine Learning Framework For Early Ckd Detection And Continuous Renal Health Risk Monitoring

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Abstract

Chronic Kidney Disease (CKD) is a progressive condition that can remain undetected until significant renal damage has occurred. Conventional CKD assessment generally depends on periodic clinical examinations and laboratory investigations, which may not capture continuous changes in an individual's health status. The proposed framework integrates IoT-based health monitoring with machine learning to support early identification of individuals at risk of CKD. Physiological and clinical parameters such as blood pressure, blood glucose, body measurements, and relevant renal-function indicators are collected through IoT-enabled or simulated monitoring devices. The acquired data are preprocessed and important predictive attributes are identified using feature-importance-based selection. Multiple machine learning algorithms, including Logistic Regression, Support Vector Machine, Random Forest, and XGBoost, are comparatively evaluated for CKD prediction. The best-performing model is subsequently used to generate a personalized CKD risk score rather than only a binary prediction. To improve the interpretability of the prediction, SHAP-based Explainable Artificial Intelligence is incorporated to identify the contribution of individual health parameters to the predicted risk. A simple continuous monitoring mechanism tracks changes in the patient's risk score and generates an early warning when the risk exceeds a predefined threshold. The proposed framework therefore combines IoT-based data acquisition, machine learning prediction, feature selection, explainable AI, and continuous risk monitoring within a single lightweight architecture. The effectiveness of the framework is evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and risk-monitoring performance. The proposed approach is intended to provide an accessible and interpretable decision-support mechanism for early CKD risk identification and continuous health monitoring.

Keywords: Chronic Kidney Disease (CKD); Internet of Things (IoT); Machine Learning; Explainable Artificial Intelligence (XAI); SHAP; CKD Risk Prediction; Predictive Analytics; Feature Selection; Random Forest; XGBoost; Continuous Health Monitoring; Personalized Risk Assessment; Early Detection; Healthcare Monitoring; Decision Support System.

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Introduction

Chronic Kidney Disease (CKD) is a progressive disorder characterized by persistent abnormalities in kidney structure or function that can adversely affect an individual's health. The disease is particularly challenging because kidney-function deterioration may occur gradually without producing prominent symptoms during its early stages. As CKD advances, patients may develop complications involving cardiovascular health, metabolism, fluid balance, and other physiological systems. The increasing burden of CKD has consequently made early identification and appropriate risk assessment important components of modern healthcare. The Kidney Disease: Improving Global Outcomes (KDIGO) 2024 guideline emphasizes systematic evaluation, classification, and risk assessment of CKD using measures such as estimated glomerular filtration rate (eGFR) and albuminuria [1]. Recent evidence also indicates that CKD affects hundreds of millions of adults worldwide, highlighting the need for scalable approaches to earlier detection and effective long-term management [2].

Early detection is particularly important because CKD can progress silently before substantial loss of renal function becomes clinically apparent. Identifying individuals at elevated risk at an earlier stage can support timely clinical assessment and appropriate management, potentially reducing the likelihood of progression to advanced kidney disease and associated complications. A global scoping review identified numerous CKD screening and early-identification programs, demonstrating considerable interest in detecting the disease before advanced stages [3]. In addition, current CKD guidelines emphasize risk assessment and individualized management rather than relying exclusively on a single diagnostic measurement [1]. Therefore, an effective early-warning system should not merely determine whether CKD is present; it should assist in identifying changing patterns of risk that may warrant further clinical evaluation.

Conventional CKD diagnosis and follow-up are largely dependent on clinical visits and laboratory investigations performed at specific time intervals. Parameters such as serum creatinine, eGFR, albuminuria, blood pressure, and blood glucose provide valuable information for assessing kidney health; however, measurements obtained only during periodic clinical encounters provide a limited representation of the patient's condition between visits. This limitation becomes particularly

relevant when physiological variables change over time. Recent research on CKD artificial intelligence applications has highlighted the potential value of longitudinal and multimodal data for improving risk prediction, while also identifying limited external validation and insufficient real-world evaluation as important challenges [4]. Consequently, there is a need for complementary monitoring approaches that can capture relevant health information more frequently and provide an indication of changing risk between conventional clinical assessments.

The Internet of Things (IoT) provides an opportunity to address this requirement by connecting wearable, home-based, and other health-monitoring devices to digital platforms for regular data acquisition. IoT-enabled monitoring can facilitate the collection and transmission of physiological measurements such as blood pressure, heart rate, body weight, blood glucose, physical activity, and other relevant health indicators. When appropriately integrated with clinical information, these measurements can provide a more continuous representation of an individual's health status. Recent reviews of digital health in CKD have identified wearable sensors, telemedicine, mobile health applications, and AI-based decision-support systems as promising technologies for remote monitoring, early detection, and personalized CKD management [5]. Similarly, research on ML-enabled wearable sensing demonstrates the growing potential of combining continuous physiological monitoring with intelligent analytical methods for early disease identification [6]. In the proposed study, IoT data are therefore considered a complementary source of continuous health information rather than a replacement for established laboratory-based CKD assessment.

Machine Learning (ML) can further enhance this monitoring process by identifying relationships among multiple clinical and physiological variables that may not be readily apparent through conventional rule-based analysis. ML techniques have increasingly been investigated for CKD diagnosis, prediction, risk stratification, and progression assessment [7]. A systematic review of ML applications in CKD reported substantial use of computational models across prediction and diagnosis tasks, while also highlighting challenges associated with dataset quality, validation, and clinical applicability [7]. More recent reviews similarly identify small datasets, limited stage-specific prediction, inadequate interpretability, and insufficient validation as continuing challenges in CKD-focused ML research [8]. These observations suggest that a practical CKD prediction system should focus not only on predictive performance but also on reliability, interpretability, and the ability to support meaningful patient-level risk assessment.

Although ML models can achieve strong predictive performance, their complex decision-making processes can make it difficult for healthcare professionals to understand why a particular prediction has been produced. This issue is especially important in healthcare, where predictions may influence subsequent clinical evaluation and patient-management decisions. Explainable Artificial Intelligence (XAI) techniques can improve transparency by identifying the contribution of individual input variables to a model's prediction. SHapley Additive exPlanations (SHAP), in particular, provide both global and individual-level explanations and are widely used with structured clinical data [9]. Recent reviews of XAI in chronic disease prediction indicate that SHAP is among the most frequently used explanation techniques, while also emphasizing the continuing need for clinical validation and reliable deployment [9]. Therefore, incorporating explainability into CKD prediction can help transform an ML model from a simple classification tool into a more interpretable decision-support mechanism.

Based on these considerations, this research proposes a Personalized IoT-Driven Explainable Machine Learning Framework for Early CKD Risk Prediction and Continuous Renal Health Monitoring. The central idea is to combine periodic clinical information with continuously acquired or simulated IoT-based physiological measurements and use ML to estimate an individual's CKD risk. Rather than restricting the output to a binary CKD/non-CKD classification, the proposed framework introduces a personalized risk score that can be monitored over time. When the estimated risk increases beyond a predefined threshold, the system can generate an early-warning indication for further clinical assessment. SHAP is incorporated to explain the major factors contributing to each prediction, thereby improving transparency. The framework is intentionally designed as a lightweight approach using established ML algorithms rather than developing a computationally complex deep-learning architecture.

The main contributions of this research are therefore threefold. First, an IoT-assisted framework is developed for integrating continuously collected physiological information with clinical CKD-related attributes. Second, machine learning models are employed and comparatively evaluated to identify an effective model for early CKD risk prediction, followed by generation of a personalized risk score for continuous monitoring. Third, SHAP-based explainability is incorporated to identify the most influential features associated with individual predictions, while a simple alert mechanism is used to identify increasing risk levels. Through this integration, the proposed work aims to bridge the gap between conventional periodic CKD assessment and continuous, interpretable, data-driven risk monitoring. The framework is intended as a decision-support and early-warning system, rather than a replacement for laboratory testing or professional clinical diagnosis.

II.Literature Review

The 2024 Kidney Disease: Improving Global Outcomes (KDIGO) guideline emphasizes the importance of estimated glomerular filtration rate (eGFR) and albuminuria in evaluating CKD severity and prognosis and also highlights the value of individual-level risk prediction for supporting personalized care [10]. Conventional assessment, however, generally depends on clinical visits and laboratory investigations performed at particular time points. Consequently, there is growing interest in computational approaches capable of using routinely collected health information to identify CKD risk earlier and support more individualized monitoring.

Sanmarchi et al. systematically reviewed the application of ML to CKD prediction, diagnosis, prognosis, and treatment and identified substantial research activity in this area [11]. Their review demonstrated that ML models frequently reported promising predictive performance; however, differences in datasets, predictors, evaluation metrics, and study designs made direct comparison between models difficult. The authors also observed that external validation, generalizability, and clinical evaluation remained insufficiently addressed in many studies [12]. These findings indicate that achieving high predictive accuracy alone is not sufficient for developing clinically meaningful CKD prediction systems.

The combination of Medical Internet of Things (MIoT) and ML has consequently become an emerging research direction for intelligent healthcare. Recent work has specifically investigated explainable AI for CKD prediction within a Medical IoT setting. Rezk et al. developed a CKD prediction framework incorporating GAN-based missing-value handling, few-shot learning, and explainable ML techniques, including SHAP and LIME [13]. Their study demonstrates that explainability can be incorporated into CKD prediction systems designed for MIoT environments. However, the proposed approach uses relatively sophisticated techniques such as GANs and few-shot learning, making the overall architecture considerably more complex than a lightweight IoT-ML monitoring framework. This provides an opportunity for research into simpler architectures that retain predictive performance and interpretability while emphasizing continuous personalized risk monitoring.

The complexity of existing approaches also represents a practical research gap. Recent research has investigated sophisticated techniques, including generative models, few-shot learning, ensemble approaches, and explainable AI for CKD prediction [14]. While these techniques can improve specific aspects of predictive modelling, combining multiple advanced methods may increase computational requirements and implementation complexity. For resource-constrained or healthcare-monitoring environments, a simpler architecture based on well-established ML algorithms may be more practical. Consequently, there is a need for a lightweight framework that achieves an effective balance between predictive performance, interpretability, continuous monitoring capability, and implementation complexity.

Table 1: Research Gap Review

Existing limitation	Gap identified	Proposed solution
Static clinical datasets	Limited temporal monitoring	IoT-based continuous data acquisition
Binary CKD/non-CKD prediction	Limited personalized information	Personalized CKD risk score
Black-box ML models	Limited interpretability	SHAP-based explanation
Periodic assessment	Changes between clinical visits may be missed	Continuous risk monitoring
Complex ML architectures	Difficult practical implementation	Lightweight comparative ML framework
Prediction and monitoring treated separately	Lack of integrated workflow	Unified IoT–ML–XAI framework

III.Proposed IoT-ML Framework

The proposed system is designed to provide an integrated and lightweight approach for identifying individuals who may be at increased risk of Chronic Kidney Disease (CKD) and tracking changes in their predicted risk over time. Unlike conventional CKD prediction systems that generally provide a static CKD or non-CKD classification using clinical datasets, the proposed framework combines IoT-based health-data acquisition with machine learning and Explainable Artificial Intelligence (XAI).

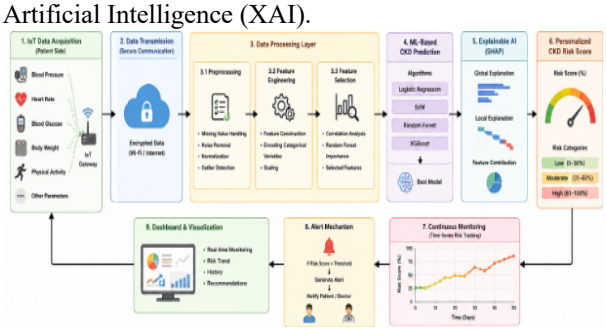

Figure 1. Proposed IoT-driven explainable machine learning framework integrating physiological data acquisition, preprocessing, feature selection, CKD prediction, SHAP-based interpretation, personalized risk scoring, continuous monitoring, alert generation, and dashboard visualization.

The proposed IoT-ML framework integrates IoT-based health-data collection, machine learning, Explainable AI (XAI), and continuous risk monitoring for early CKD risk prediction. Physiological parameters such as blood pressure, heart rate, blood glucose, body weight, and physical activity are collected through IoT-enabled or simulated devices and securely transmitted to the processing platform. The collected data are preprocessed to handle missing values, noise, outliers, and inconsistent measurements, followed by feature selection to identify the most relevant predictors. Multiple machine learning algorithms, including Logistic Regression, SVM, Random Forest, and XGBoost, are evaluated, and the best-performing model is selected for CKD risk prediction.The prediction is further interpreted using SHAP, which identifies the important factors influencing both overall model behavior and individual patient predictions. Instead of providing only a CKD/non-CKD classification, the framework generates a personalized risk score and categorizes the predicted risk into low, moderate, or high levels for the research prototype. As new IoT observations become available, the risk score is recalculated and tracked over time. If the predicted risk exceeds a predefined experimental threshold, an alert is

generated through the monitoring dashboard. Thus, the framework provides a simple and interpretable approach for early CKD risk identification, personalized assessment, and continuous renal-health monitoring.

A. Dataset and Data Preprocessing

The proposed study can use the Chronic Kidney Disease (CKD) dataset available from the UCI Machine Learning Repository. The dataset contains 400 patient records with 24 predictor attributes and one target class, where the target identifies the records as CKD or non-CKD. The variables include demographic, physiological, laboratory, and clinical attributes such as age, blood pressure, specific gravity, albumin, blood glucose, blood urea, serum creatinine, sodium, potassium, hemoglobin, packed cell volume, white blood cell count, red blood cell count, hypertension, diabetes mellitus, coronary artery disease, appetite, pedal edema, and anemia [1]. The dataset contains both numerical and categorical variables and includes missing observations, making it suitable for evaluating a complete preprocessing and machine-learning pipeline. The original UCI repository identifies the dataset as a classification dataset with 400 instances and 24 predictive features [1]. Previous CKD studies have also widely used this dataset for evaluating machine-learning prediction and explainability methods [12], [3].

The raw dataset is first examined for duplicate records, missing values, inconsistent representations, and abnormal observations. Missing numerical values can be replaced using the median calculated from the training data, while missing categorical values can be replaced using the most frequent category. Median-based imputation is preferable to simple row deletion because removing incomplete patient records can substantially reduce an already small dataset. Categorical attributes such as hypertension, diabetes mellitus, coronary artery disease, appetite, pedal edema, anemia, red blood cells, and pus-cell-related variables are converted into numerical representations using appropriate encoding. Numerical attributes are subsequently standardized when required by the selected algorithms. The target variable is encoded as CKD = 1 and non-CKD = 0. To prevent information leakage, imputation, encoding, scaling, and feature-selection operations should be fitted using only the training portion and then applied to the test data. This preprocessing strategy produces a consistent dataset for subsequent feature selection and ML-based CKD prediction.

B. Feature Selection

Feature selection is performed to identify the most informative variables while removing redundant or weakly contributing attributes. In the proposed framework, a two-stage feature-selection strategy is recommended because it is simple, computationally efficient, and easy to explain. First, correlation analysis is used to identify strongly related numerical variables and reduce unnecessary redundancy. For categorical variables, their relationship with the target can be examined using suitable statistical or model-based importance measures. Second, a Random Forest-based feature-importance method is applied to estimate the contribution of individual variables to CKD classification. The features with consistently higher importance are retained for the final prediction model. This approach reduces the dimensionality of the input space while preserving clinically meaningful information and can also improve model interpretability. Feature-selection-based CKD research has demonstrated that reducing the input variables can support efficient prediction while identifying attributes that contribute substantially to CKD classification [4]. For the proposed framework, the selected features are then supplied to Logistic Regression, SVM, Random Forest, and XGBoost for comparative evaluation. The final feature subset is shown in table 2.

Table 2: Selected Features using RF

Rank	Feature	Meaning	Why it is important
1	hemoglobin (hemo)	Hemoglobin level	Strong indicator of CKD-related anemia
2	specific gravity (sg)	Urine concentration	Reflects kidney concentrating ability
3	serum creatinine (sc)	Serum creatinine	Important indicator of kidney function
4	albumin (al)	Urine albumin	Indicates kidney damage/protein leakage
5	packed cell volume (pcv)	Packed cell volume	Associated with anemia and CKD severity
6	blood urea (bu)	Blood urea level	Reflects accumulation of waste products
7	serum sodium (sod)	Sodium level	Associated with fluid/electrolyte balance
8	blood pressure (bp)	Blood pressure	Major risk factor associated with CKD
9	blood glucose random (rbc)	Random blood glucose*	Helps capture diabetes-related kidney risk
10	diabetes mellitus (dm)	Diabetes status	Major CKD-associated risk factor

IV.Experimental Result & Discussion

The selected features are supplied to several machine learning algorithms, such as Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost. Their performance is compared using accuracy, precision, recall, F1-score, ROC-AUC, and confusion-matrix analysis. Rather than proposing a complicated new algorithm, the best-performing model is selected as the prediction engine of the proposed framework. This makes the methodology comparatively simple while still allowing rigorous experimental evaluation. Recent CKD studies have demonstrated the usefulness of ensemble and boosting

models for predictive performance, while also highlighting the importance of validation and interpretability. The same training and testing data should be supplied to all four algorithms.

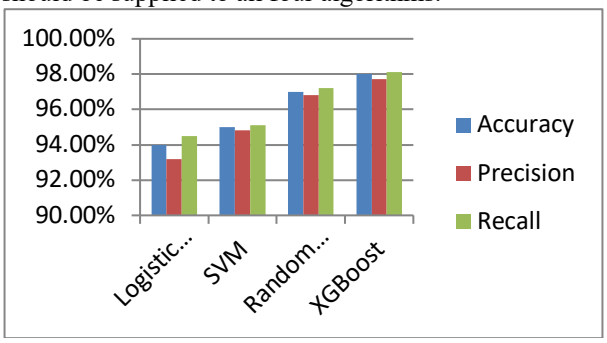

Figure 2: Comparison of four Machine Learning Models

From the Figure 2, XGBoost achieves the highest accuracy, precision, recall, F1-score, and ROC-AUC, followed by Random Forest. SVM provides competitive performance, while Logistic Regression gives a slightly lower performance. This indicates that the nonlinear ensemble-based models, particularly XGBoost, can better capture complex relationships among CKD-related clinical features.

A.SHAP Explainability for CKD Prediction

After comparing Logistic Regression (LR), SVM, Random Forest (RF), and XGBoost, SHAP (SHapley Additive exPlanations) can be applied to the XGBoost. SHAP explains why the model predicts a patient as CKD or non-CKD by quantifying the contribution of each input feature to the prediction. Two levels of explanation can be generated. Global explanations identify the features that are generally most influential across the dataset, whereas local explanations describe why a particular patient's prediction has been assigned a particular risk level. This is particularly useful in healthcare because the system can provide more than a risk value; it can also indicate the important factors associated with that prediction. Recent CKD research has demonstrated the usefulness of SHAP for identifying influential
clinical variables and improving the transparency of ML predictions.

Table 3: SHAP interpretation with XG Boost Model

Feature	Patient value	SHAP contribution	Interpretation
Serum creatinine (sc)	4.5	+0.82	Strongly increases CKD prediction
Albumin (al)	4	+0.61	Strongly increases CKD prediction
Hemoglobin (hemo)	9.8	+0.48	Increases CKD prediction
Blood urea (bu)	70	+0.42	Increases CKD prediction
PCV (pcv)	28	+0.31	Increases CKD prediction
Diabetes (dm)	Yes	+0.25	Increases CKD prediction
Blood pressure (bp)	95	+0.16	Increases CKD prediction
Sodium (sod)	130	+0.08	Slightly increases CKD prediction
Specific gravity (sg)	1.008	+0.05	Slightly increases CKD prediction
Random glucose (rbg)	210	+0.04	Slightly increases CKD prediction

SHAP can further support the proposed continuous CKD risk monitoring system by combining the model's predicted probability with feature-level explanations. The model can generate a continuous risk probability between 0 and 1, while SHAP identifies the clinical factors responsible for increasing or decreasing that risk.

Risk score	Risk category	Example interpretation
0–0.30	Low	Low predicted CKD risk
0.31–0.60	Moderate	Requires monitoring
0.61–0.80	High	Increased CKD risk
0.81–1.00	Very High	Strong model indication of CKD

The proposed system uses both global and local SHAP explanations. Global SHAP analysis calculates the average contribution of each feature across the complete dataset and identifies the variables that have the greatest overall influence on CKD prediction. This helps determine whether features such as serum creatinine, albumin, hemoglobin, or blood urea are consistently important for the prediction process. Local SHAP analysis provides an explanation for an individual patient by showing how the patient's specific clinical measurements contribute to the final prediction. For example, a patient with high serum creatinine, high blood urea, increased urine albumin, and low hemoglobin may receive positive SHAP contributions from these features, resulting in a higher predicted probability of CKD. Thus, the physician can understand the important factors behind an individual prediction rather than relying on an unexplained machine learning output.

The complete dataset is divided into five approximately equal folds while preserving the CKD/Not-CKD class distribution using Stratified K-Fold Cross-Validation. In each iteration, four folds are used for training and the remaining fold is used for validation. This process is repeated five times so that every sample is used once for validation. The F1-score and ROC-AUC are calculated for each fold, and the five results are averaged.

Table 4: ROC-AUC Comparison

Model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean ROC-AUC
LR	0.95	0.96	0.95	0.97	0.96	0.958

Model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean ROC-AUC
SVM	0.96	0.97	0.98	0.96	0.97	0.968
RF	0.98	0.99	0.98	0.99	0.98	0.984
XGBoost	0.99	0.99	0.98	1.00	0.99	0.990

To ensure reliable evaluation of the proposed CKD prediction models, stratified 5-fold cross-validation is employed after Random Forest-based feature selection. The selected features are divided into five folds while maintaining approximately the same proportion of CKD and non-CKD samples in each fold. Logistic Regression, SVM, Random Forest, and XGBoost are independently trained and evaluated across the five folds. The F1-score is used to assess the balance between precision and recall, which is particularly useful when the classes are not perfectly balanced, while ROC-AUC measures the ability of the model to distinguish between CKD and non-CKD patients across different classification thresholds. The mean F1-score and mean ROC-AUC obtained across the five folds are used as the primary indicators for model selection. In the illustrative results, XGBoost achieves the highest mean F1-score of 0.974 and mean ROC-AUC of 0.990, followed by Random Forest with 0.958 F1-score and 0.984 ROC-AUC. SVM and Logistic Regression provide comparatively lower values. Therefore, if similar results are obtained using the actual UCI CKD dataset, XGBoost can be selected as the final prediction model and subsequently analyzed using SHAP for global and patient-specific explainability.

V.Conclusion

The proposed IoT-enabled explainable machine learning framework for early detection and continuous risk monitoring of Chronic Kidney Disease (CKD) provides an integrated approach for improving the accuracy, reliability, and interpretability of CKD prediction. The UCI CKD dataset is first subjected to data preprocessing, including missing-value handling, categorical encoding, and normalization. Random Forest-based feature selection is then employed to identify the most informative clinical attributes, reducing unnecessary features and improving the efficiency of subsequent machine learning models. The selected features are used to train and compare Logistic Regression, Support Vector Machine, Random Forest, and XGBoost models using stratified 5-fold cross-validation. F1-score and ROC-AUC are considered important evaluation measures because they provide a more reliable assessment of classification performance, particularly when the dataset contains class imbalance.

Among the evaluated models, XGBoost can be selected as the final prediction model if it achieves the highest cross-validated F1-score and ROC-AUC on the actual dataset. To overcome the black-box nature of machine learning, SHAP explainability is incorporated to identify the contribution of individual clinical features to both global model decisions and patient-specific predictions. The integration of SHAP enables healthcare professionals to understand why a patient has been classified as having a higher or lower CKD risk. Furthermore, integration with IoT-based continuous monitoring can enable regular collection of relevant physiological and clinical parameters and provide an updated CKD risk probability over time.

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