CHRONIC KIDNEY DISEASE DETECTION USING MACHINE LEARNING AND DATA SCIENCE

Submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology

in

Computer Science and Engineering

by

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VIT, Vellore.

May, 2024

DECLARATION

We hereby declare that the thesis entitled "Chronic Kidney Disease Detection Using Machine Learning and Data Science" submitted by us, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering* to VIT is a record of bonafide work carried out by me under the supervision of Prof. S M Farooq.

We further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place : Vellore

Date : 09-05-2024

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CERTIFICATE

This is to certify that the thesis entitled "Chronic Kidney Disease Detection Using Machine Learning and Data Science" submitted by SALONI JATIN VYAS (20BCB0064), ANUSHKA GARG (20BCE0427) and MUSKAAN (20BCE2243), **School of Computer Science and Engineering**, VIT, for the award of the degree of *Bachelor of Technology Computer Science and Engineering*, is a record of bonafide work carried out by him / her under my supervision during the period, 01. 12. 2023 to 30.04.2024, as per the VIT code of academic and research ethics.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The thesis fulfills the requirements and regulations of the University and in my opinion meets the necessary standards for submission.

Place : Vellore

Date : 09-05-2024

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Signature of the Guide

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Internal Examiner

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External Examiner

Head of the Department

Programme

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I am also indebted to the library staff for their tireless efforts in providing access to a plethora of resources, which proved indispensable in my research and learning endeavors. Additionally, I am thankful to the research foundations that extended their permissions, enabling me to utilize essential equipment and facilities. Furthermore, I would like to acknowledge the contributions of my peers and colleagues who provided a conducive learning environment through stimulating discussions and collaborative projects.
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Place : Vellore
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Executive Summary

Chronic Kidney Disease (CKD) poses a significant global health challenge, often progressing undetected until advanced stages. Early detection is crucial for effective management, but traditional diagnostics are frequently inadequate. This project leverages machine learning and data science to enhance CKD detection, employing a structured methodology that includes data collection, preprocessing, feature selection, model training, evaluation, and application development. The system utilizes various machine learning algorithms, such as K-Nearest Neighbor, and various classifiers like Decision Tree, Random Forest, LGBM, etc., optimizing performance through cross-validation and model validation on independent datasets. The project also emphasizes creating user-friendly interfaces for clinicians and patients, facilitating accurate diagnosis and monitoring. Future developments focus on enhancing model interpretability, integrating novel biomarkers, and developing real-time monitoring tools. By addressing key gaps and integrating advanced technologies, this system aims to enhance early detection, contributing to improved healthcare management and reducing the burden of CKD globally.

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1. INTRODUCTION

1.1 OBJECTIVE

- Early CKD Detection: Develop a system leveraging machine learning algorithms to detect Chronic Kidney Disease (CKD) in its early stages which aims to improve patient outcomes through timely interventions.
- User-Friendly Interface: Design an instinctive and accessible interface for both clinicians and patients, facilitating easy access to the system’s diagnostic capabilities and improving user engagement.
- Performance Analysis and Evaluation: Implement robust performance analysis and evaluation modules to monitor and improve the accuracy, recall, and precision of the machine learning models used for CKD detection.
- Data Management and Processing: Establish efficient data collection, preprocessing, and feature engineering workflows to ensure high-quality inputs for the machine learning algorithms, enhancing the system’s overall reliability.
- System Validation and Deployment: Validate the system’s performance on independent datasets and deploy the validated models for real-world testing and adaptability, ensuring the system’s effectiveness across diverse populations and healthcare settings.

1.2 MOTIVATION

The motivation for this study lies in the pressing need for early detection of Chronic Kidney Disease (CKD) to improve patient outcomes and reduce healthcare burdens. Traditional diagnostic methods often fail to identify CKD in its early stages, where interventions can be most effective. Leveraging machine learning and data science offers a promising avenue for enhancing early detection, enabling timely interventions and potentially reducing the progression of this debilitating condition. The goal is to explore innovative methodologies and address existing gaps to ultimately improve CKD diagnostics and patient care.

1.3 BACKGROUND

Chronic Kidney Disease (CKD) is a progressive condition affecting millions worldwide, characterized by a gradual decline in kidney function. It's often discussed to as a "silent killer" because symptoms may not manifest until the disease has advanced. Early detection is crucial for effective intervention, as untreated CKD can lead to end-stage renal disease (ESRD), requiring dialysis or transplantation. Traditional diagnostic methods, relying on clinical evaluations and laboratory tests, often miss early stages of CKD. In recent years, the application of machine learning and data science has emerged as a promising approach to improve early detection and management. By analyzing vast datasets encompassing patient demographics, medical histories, and laboratory results, these technologies can identify at-risk individuals more accurately and earlier than conventional methods, potentially revolutionizing CKD diagnostics and patient care.

2. PROJECT DESCRIPTION AND GOALS

2.1 Survey on Existing System

2.2 Research Gap

[1] Debal and Sitote (2022) investigated CKD prediction using ML techniques on data from St. Paulo's Hospital in Ethiopia, testing RF, SVM, and DT algorithms. RF, enhanced by feature selection methods, showed superior performance.

Drawbacks: Limited by a single dataset's use, reducing generalizability, and the complexity of ML models may hinder practical application. Future directions include exploring advanced ML models and developing mobile tools for CKD monitoring.

[2] Bai et al. (2022) explored the use of ML models to predict ESKD risk in CKD patients, comparing five ML algorithms against the KFRE. Logistic regression, naïve Bayes, and random forest showed high sensitivity, highlighting ML's potential in early CKD risk identification.

Drawbacks: The study's reliance on a single dataset may limit findings' generalizability, lacked urine-based variables, and its retrospective design could reduce predictive accuracy. Future directions involve external model validation and including more predictors to enhance performance.

[3] Pal (2023) examines CKD prediction using ML, employing SVM, RF, and ANN models with majority voting, achieving a 3% accuracy increase over prior models, showcasing ML's capability in early detection.

Drawbacks: The study's use of a singular UCI dataset may affect its broad applicability, suggesting future exploration of unsupervised learning and the addition of more patient records for enhanced accuracy.

[4] Abdel-Fattah, Othman, and Goher (2022) utilize hybrid ML techniques on Apache Spark for CKD prediction, integrating feature selection with multiple algorithms to achieve up to 100% accuracy.

Drawbacks: The reliance on a single dataset may limit the findings' generalizability, and Apache Spark's complexity might challenge healthcare professionals' practical use. Future directions include using more varied datasets and creating user-friendly applications for clinical settings.

[5] Chen et al. (2023) outline a protocol for a systematic review and meta-analysis to evaluate ML in CKD prediction and diagnosis, following PRISMA-P guidelines to compare ML models' performance with traditional methods and assess their reporting quality.

Drawbacks: The protocol sets the stage for future research, highlighting the challenges in synthesizing diverse studies and the need for standardization in ML model performance reporting.

[6] Ghelichi-Ghojogh et al. (2022) examine how behavioral and health factors impact CKD in an Iranian cohort of 700, finding significant risk associations with low birth weight, diabetes, kidney diseases, and chemotherapy.

Drawbacks: The study might face recall bias due to self-reported data, limited generalizability from hospital-based controls, and its cross-sectional nature doesn't allow causality establishment. Its focus on a specific demographic could also restrict broader applicability.

[7] Kunnath, Sack, and Wilkins (2024) analyzed the "All of Us" Research Program data to assess sociodemographic impacts on chronic diseases, finding age as a consistent predictor while other factors varied by condition.

Drawbacks: The study might be biased due to self-reported data and its cross-sectional design limits causal conclusions. The selected sample might not fully represent the broader population, and the analysis omitted potential influential covariates and structural health determinants.

[8] Mathai and Thirunavukkarasu (2023) assessed machine learning techniques for CKD detection and classification, emphasizing data preprocessing and feature selection. They reviewed peer- reviewed papers, highlighting machine learning's role in enhancing CKD diagnostic accuracy.

Drawbacks: The study's limitations include a focus on technical aspects over clinical applicability, limited dataset diversity, and the challenge of applying findings in clinical practice. Further research is suggested to bridge these gaps and improve machine learning's integration into CKD management.

[9] Islam, Ziaul Hasan Majumder, and Alomgeer Husseinc (2023) explored ML algorithms for CKD prediction, showcasing the XgBoost classifier's high performance.

Drawbacks: The study's limited dataset diversity and size might affect generalizability and risk overfitting. It suggests further research on model interpretability and real-world application.

[10] Sanmarchi et al. (2023) systematically reviewed AI and ML techniques for CKD care, highlighting machine learning's potential in patient management.

Drawbacks: The review's single-database focus and language restrictions may have omitted relevant studies, and heterogeneous metrics complicated direct comparisons. Additionally, the lack of extensive model generalizability and clinical evaluation studies indicates a research-practice gap in healthcare applications.

[11] Arif, Mukheimer, and Asif (2023) developed a ML model for early CKD detection, achieving 90% accuracy with the UCI CKD dataset using Boruta algorithm and k-nearest neighbors.

Drawbacks: The model's reliance on a single dataset and its method for handling missing data could limit applicability across diverse populations, with its real-world effectiveness yet to be validated.

[12] Khalid et al.'s study introduces a hybrid ML model for CKD prediction, integrating various classifiers for enhanced accuracy.

Drawbacks: Limited generalizability due to dataset specificity and concerns over the model's complexity impacting interpretability and computational efficiency. Further validation in diverse settings is needed.

[13] Ghuse et al. (2022) explored ML algorithms for CKD prediction to enhance early detection. They assessed various classification techniques for their effectiveness in diagnosing CKD accurately.

Drawbacks: The study's limitations include a lack of dataset diversity and size, affecting generalizability, and a call for broader validation to confirm the ML models' robustness and clinical applicability.

[14] Sruthi et al. (2023) investigated the use of ML algorithms like Random Forest, SVM, and Naïve Bayes for early CKD detection, showing significant potential for improving diagnosis.

Drawbacks: The study's limited dataset size and diversity could impact generalizability. A focus on traditional algorithms without considering newer deep learning techniques may restrict performance enhancements. Additionally, challenges in integrating these models into clinical workflows and their real-world application were not addressed.

[15] Mozumder et al. (2023) evaluated ML algorithms for CKD prediction, highlighting ANN's superior accuracy using the UCI repository data.

Drawbacks: Sole reliance on the UCI dataset may affect the findings' broad applicability, and ANN's high performance could suggest overfitting, necessitating independent dataset validation for real-world clinical relevance.

2.3 Problem Statement

Current diagnostic approaches for CKD are limited by their inability to effectively detect the disease in its early stages, mainly due to the asymptomatic nature of early CKD and the need for more sensitivity and specificity in traditional diagnostic tests. There is an urgent need for innovative diagnostic solutions that can leverage the vast amounts of data available in the healthcare domain to improve early detection rates, thereby facilitating timely intervention and better disease management.

3. TECHNICAL SPECIFICATION

3.1 Requirements

3.1.1 Functional

Data Collection and Integration: Comprehensive data collection has been conducted, encompassing genetic, clinical, and laboratory data pertinent to chronic kidney disease. The integration of these diverse datasets ensures a holistic understanding of the disease.

Data Preprocessing: Rigorous data preprocessing techniques have been employed to ensure data quality and reliability. This includes handling missing values, outlier detection, and normalization or scaling of features as necessary.

Feature Encoding: Categorical features have been meticulously encoded into numerical representations suitable for machine learning algorithms. This transformation facilitates the utilization of categorical data in predictive modeling effectively.

Model Building: Advanced machine learning models have been developed utilizing various algorithms tailored to predict chronic kidney disease accurately. The selection of appropriate algorithms is based on extensive experimentation and evaluation to ensure optimal performance.

Model Evaluation: The performance of the developed models has been rigorously evaluated using a comprehensive set of evaluation metrics, including accuracy, precision, recall, and F1-score. This thorough evaluation process ensures the reliability and effectiveness of the predictive models.

Model Deployment: The finalized models have been seamlessly integrated into a user-friendly interface specifically designed for healthcare professionals. This interface empowers clinicians with intuitive tools for leveraging predictive analytics in real-world healthcare settings.

3.1.2 Non-Functional

Accuracy: A paramount objective has been to achieve high accuracy in predicting chronic kidney disease. Extensive efforts have been dedicated to refining the models to ensure they deliver reliable and precise predictions.

Interpretability: Emphasis has been placed on designing models that are interpretable, enabling clinicians to comprehend the underlying rationale behind the predictions. This interpretability fosters trust and facilitates informed decision-making in clinical practice.

Scalability: The system architecture has been engineered to accommodate large volumes of data efficiently, ensuring scalability as the dataset grows over time. This scalability is essential for handling the ever-expanding datasets in healthcare environments.

Robustness: The developed models exhibit robustness to variations in input data and demonstrate generalizability to unseen samples. This robustness is vital for ensuring consistent performance across diverse patient populations and clinical scenarios.

Ethical Considerations: Ethical concerns, including privacy protection, mitigation of bias, and promotion of fairness, have been meticulously addressed throughout the model development and deployment processes. Ethical guidelines for AI and machine learning in healthcare have been strictly adhered to.

User Interface: A user-centric interface has been meticulously designed to facilitate seamless interaction with the predictive models. The interface prioritizes usability and accessibility, empowering healthcare professionals to leverage advanced analytics effortlessly.

3.2 Feasibility Study

3.2.1 Technical Feasibility

Hardware and Software: The technical feasibility of the project has been meticulously evaluated, considering the availability of resources and the capabilities of the selected tools and technologies. The utilization of cutting-edge Python libraries for machine learning and data processing, coupled with robust web development technologies, ensures the technical feasibility of the project.

3.2.2 Economic Feasibility

Cost Considerations: Economic feasibility has been carefully assessed, taking into account the costs associated with hardware, software, and human resources. The project's minimal hardware requirements and the utilization of open-source software tools have contributed to cost reduction. Additionally, the expertise of skilled personnel proficient in the selected technologies has ensured economic viability.

3.2.3 Social Feasibility

Impact Assessment: The social feasibility of the project has been evaluated by assessing its potential impact on society and stakeholders. Early detection of chronic kidney disease holds immense potential to improve patient outcomes and alleviate healthcare costs. By providing a scalable and accessible solution, the project contributes significantly to addressing a critical healthcare challenge, thereby enhancing social welfare.

3.3 System Specification

3.3.1 Hardware Specification

● Processor: Any modern processor capable of handling data processing tasks efficiently.

● RAM: Minimum 4 GB RAM to accommodate data processing and machine learning tasks.

● Hard Disk: Minimum 100 GB of storage space to store datasets and model files.

3.3.2 Software Specification

● Operating System: Windows family for development and deployment.

● Technology: Python 3.6 for machine learning algorithms and data processing.

● Front-end Technology: HTML, CSS, JS for building the user interface, Flask for WebApp.

● Back-end Technology: MySQL and PHP for database management and server-side processing.

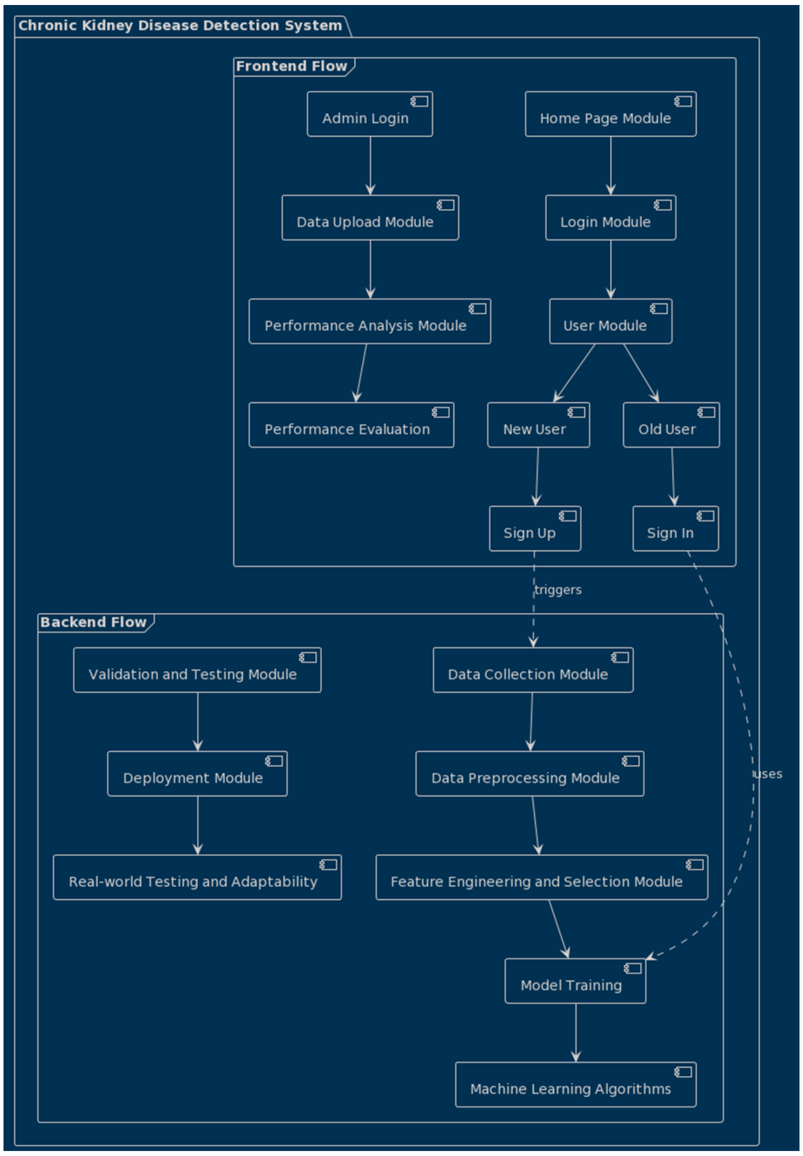
● IDE: Visual Studio Code and Google Collab for development and collaboration.

3.3.3 Standards and Policies

Regulatory Compliance: The project adheres to relevant standards and policies governing data privacy, security, and healthcare regulations, including HIPAA compliance. Ethical guidelines for AI and machine learning in healthcare are strictly followed to promote responsible technology usage.

4. DESIGN APPROACH AND DETAILS

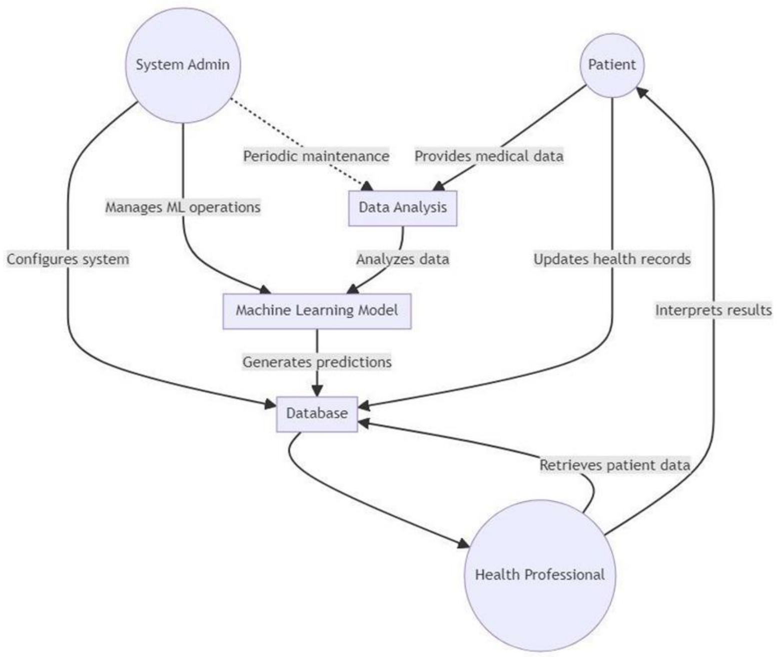
4.1 System Architecture


Chronic Kidney Disease Detection System
Frontend Flow
Admin Login
Home Page Module
Data Upload Module
Login Module
Performance Analysis Module
User Module
Performance Evaluation
New User
Old User
Sign Up
Sign In
triggers
uses
Backend Flow
Validation and Testing Module
Data Collection Module
Deployment Module
Data Preprocessing Module
Real-world Testing and Adaptability
Feature Engineering and Selection Module
Model Training
Machine Learning Algorithms

4.1 System Architecture

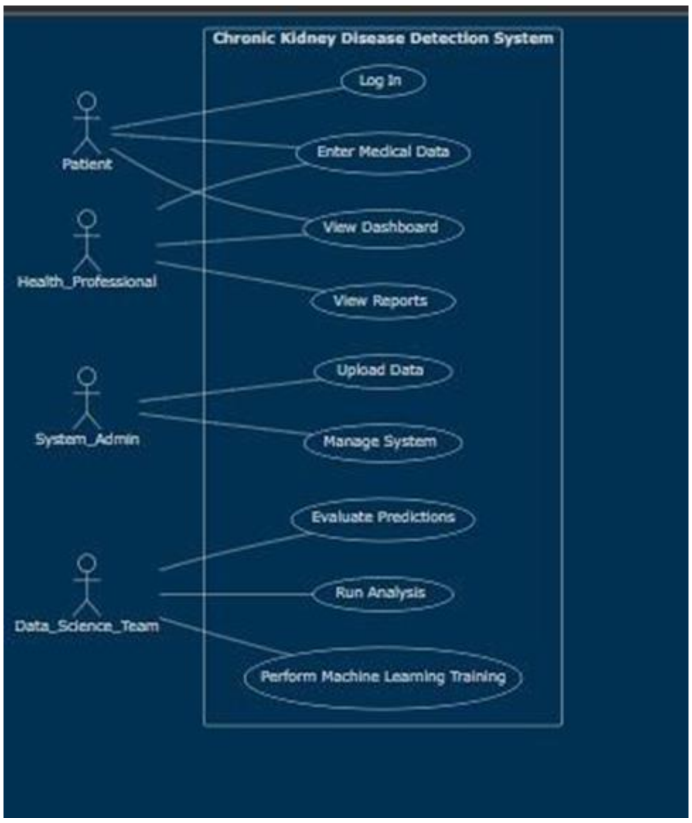
4.2 Design

4.2.1 Data Flow Diagram



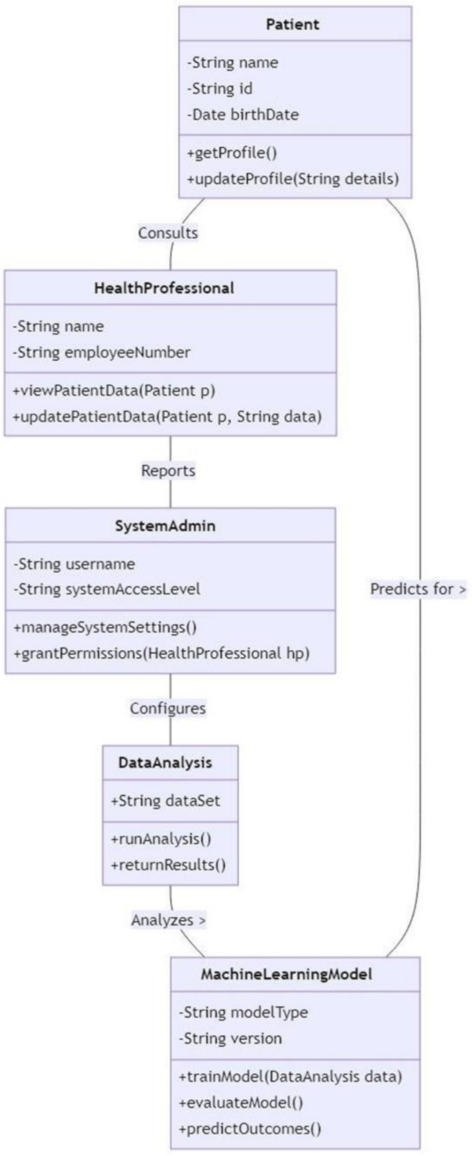
4.2.1 Data Flow Diagram

4.2.2 Use Case Diagram



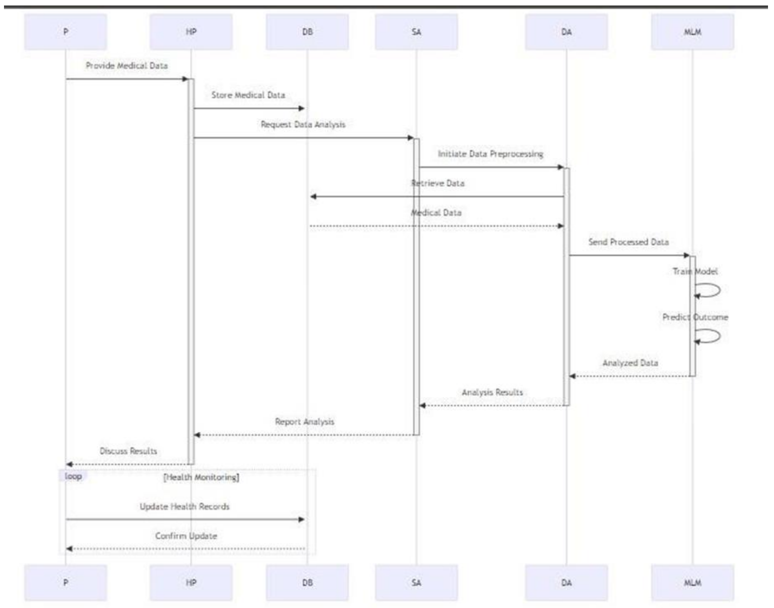
4.2.2 Use Case Diagram

4.2.3 Class Diagram



4.2.3 Class Diagram

4.2.4 Sequence Diagram



4.2.4 Sequence Diagram

4.3 Constraints, Alternatives and Tradeoffs

1. Constraints

Data Availability:

The quality and diversity of available datasets can limit the system’s generalizability and accuracy. Accessing comprehensive and representative data can be challenging due to privacy concerns and resource limitations.

Model Complexity:

Highly complex models might offer superior accuracy but can be challenging to interpret and implement in clinical settings. Balancing model performance with usability and transparency is crucial.

Computational Resources:

Machine learning models, particularly deep learning algorithms, can be computationally concentrated, requiring substantial processing power and memory, which might not be feasible for all institutions.

2. Alternatives

Simpler Models:

Using simpler models like Logistic Regression or Decision Trees can provide more interpretable results, albeit potentially at the cost of lower accuracy compared to more complex models like Random Forest or Neural Networks.

Synthetic Data Generation:

Employing synthetic data generation techniques can supplement existing datasets, enhancing diversity and helping to overcome data limitations. However, this approach requires careful validation to ensure the synthetic data accurately reflects real-world conditions.

Cloud-Based Processing:

Utilizing cloud computing services for model training and prediction can overcome local computational constraints, though it might introduce concerns related to data security and ongoing operational costs.

3. Tradeoffs

Accuracy vs. Interpretability:

Complex models like Neural Networks might offer higher accuracy but lack interpretability, while simpler models like Logistic Regression offer clearer insights but might compromise on predictive performance. The choice be subject to the specific needs of the healthcare application.

Speed vs. Robustness:

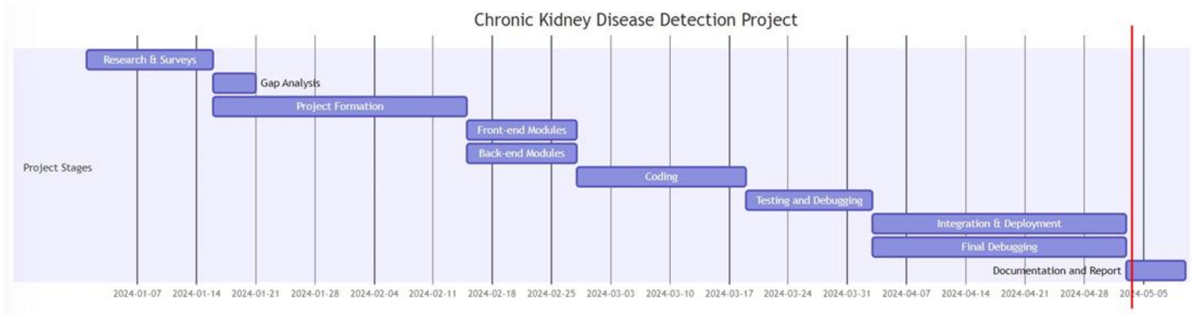
Faster, simpler models might provide quick results but may lack the robustness and accuracy of more computationally intensive models. The tradeoff here involves balancing the need for real-time predictions with the accuracy required for reliable diagnosis.

Cost vs. Performance:

Investing in high-end computational infrastructure can significantly enhance model performance but involves higher costs. Alternatively, utilizing cloud-based services can offer flexibility but might incur ongoing operational expenses. The tradeoff involves balancing budget constraints with the desired system performance.

5. SCHEDULE, TASKS AND MILESTONES

5.1 Gantt Chart



5.1 Gantt Chart

5.2 Module Description

5.2.1 Frontend

The flowchart outlines the frontend modules of an application designed to detect Chronic Kidney Disease (CKD) using machine learning and data science. Here is a description of each module and their functionality:

i. Home Page Module

- Serves as the entry point of the application.
- Provides access to the login module and displays general information about the application.

ii. Login Module

- Facilitates user identification and access control.
- Differentiates between new user registration and old user login.

  New User

  - Handles the registration process for new users.
  - Collects essential information such as name, age, gender, email, username, password, and mobile number.
  - Performs user authentication with valid details as part of the registration.

  Old User

  - Allows returning users to log in using their username and password.
  - Links to the prediction module after successful authentication.

iii. User Module

- A comprehensive interface for both new and returning users.
- Provides an overview of the application, navigation, instructions, and announcements.
- Introduces the project and its objectives.

  Admin Login

  - A secured entry point for admin users to log in with their credentials.
  - Admin authentication process ensures that only authorized personnel can upload and manage data.
  - Access to system maintenance and configuration and Access to all interfaces and functionalities.

  Patient Dashboard:

  - Access to prediction, recommendation, and medication authorization modules.

  Doctor Dashboard:

  - Access to data upload, prediction, video upload, recommendation, and medication authorization modules.

iv. Data Upload Module

- Enables admins to upload datasets, typically in CSV format.
- Includes detailed instructions for uploading data and tools for reviewing the uploaded dataset.

v. Performance Analysis Module

- Allows admins to analyze the performance of the machine learning model.
- Includes metrics such as recall, F1 score, precision, confusion matrix, and static charts for evaluation.

  Performance Evaluation

  - Used by admins to evaluate the overall performance of the machine learning model.
  - Helps in assessing and improving the model's accuracy and reliability in detecting CKD.

vi. Prediction Module

- Users input health attributes and submit them for prediction.
- Displays the results of the CKD prediction based on the inputted health data.

  Prediction Process

  - The backend process that takes the user’s health attributes, applies the machine learning model, and returns the prediction.

vii. Recommendation Module

- Provides suggestions or health advice to the user based on the prediction results.
- Could include dietary, lifestyle, or medical recommendations depending on whether CKD is detected.

Each module works in conjunction to provide a seamless user experience, from registration to data analysis and prediction, for effective CKD detection and management.

5.2.2 Backend

Based on the flowchart, here's a detailed description of the backend modules for the Chronic Kidney Disease Detection system:

i. Data Collection Module

- Aggregates and compiles data from multiple sources relevant to patient health, such as Electronic Health Records (EHRs), genetic databases, wearable devices, and lab results.

ii. Data Preprocessing Module

- Conducts initial data cleaning which includes handling missing values, normalizing data, and preparing it for analysis. This step ensures data quality and consistency.

iii. Feature Engineering and Selection Module

- This process inputs the most relevant features for CKD prediction which are available with patients from their reports.

iv. Model Training

- Utilizes various machine learning algorithms for training models, including Classifiers(AdaBoost, XGB), Neural Networks (NNs), Decision Tree, Random Forest, and k- Nearest Neighbors (k-NN).

v. Validation and Testing Module

- Conducts rigorous validation and testing using methods such as cross-validation and external validation. This is crucial for assessing the model's performance and generalizability.

vi. Deployment Module

- After validation, the model is deployed for use in a clinical setting, where it can provide real- time predictions on CKD risk based on incoming patient data.

vii. Continuous Monitoring

- Involves ongoing surveillance of the model's performance in a real-world clinical environment, ensuring the reliability and accuracy of its predictions over time.

viii. Real-world Testing and Adaptability

- Assesses the model's adaptability and efficiency in actual clinical practice, allowing for further refinement and adjustment to improve its practical utility and performance.

The backend architecture of this system is designed to ensure that the data flows smoothly from collection to model deployment, with an emphasis on ensuring that the model is accurate, interpretable, and reliable for clinical use in detecting Chronic Kidney Disease.

5.3 Testing:

Unit and integration testing ensured the reliability, functionality, and seamless integration of all system components, guaranteeing the accuracy and effectiveness of the Chronic Kidney Disease Detection system.

5.3.1 Unit Testing

Unit testing was conducted to ensure that individual components or units of the system functioned as expected. Each module was tested independently to verify its functionality.

5.3.1.1 Frontend Unit Testing:

I. Home Page Module:

- The home page was tested to ensure it loaded correctly.
- The functionality of the login module link was verified.
- General information about the application was confirmed to be displayed as intended.

II. Login Module:

- New user registration was tested:
- Essential information such as name, age, gender, email, username, password, and mobile number was successfully collected.
- User authentication during registration was tested and confirmed.
- Old user login was tested:
  - ✓ Returning users were able to log in using their username and password.
  - ✓ Successful redirection to the prediction module after authentication was confirmed.

III. User Module:

- The user interface was tested to provide navigation, instructions, and announcements.

- Admin login functionality was tested:

        - ✓ Secured access for admin users using their credentials was confirmed.
        - ✓ Access to system maintenance, configuration, and all interfaces and functionalities was verified.
- Patient dashboard was tested:
    - ✓ Access to prediction, recommendation, and medication authorization modules was confirmed.
- Doctor dashboard was tested:
    - ✓ Access to data upload, prediction, recommendation, and medication authorization modules was confirmed.

5.3.1.2 Backend Unit Testing:

IV. Data Collection Module:

- Data aggregation from multiple sources, such as Electronic Health Records (EHRs), genetic databases, wearable devices, and lab results, was tested.

V. Data Preprocessing Module:

- Testing included handling missing values, normalizing data, and preparing it for analysis. Data cleaning was verified to ensure data quality and consistency.

VI. Feature Engineering and Selection Module:

- Identification of relevant features for CKD prediction was confirmed.

VII. Model Training:

- Testing involved training machine learning models using various algorithms including Classifiers(AdaBoost, XGB), Neural Networks (NNs), Decision Tree, Random Forest, and k- Nearest Neighbors (k-NN).

- Integration of machine learning algorithms was verified.

VIII. Validation and Testing Module:

- Rigorous validation and testing using methods such as cross-validation and external validation were conducted.
- Model's performance and generalizability were verified.

5.3.2 Integration Testing

Integration testing ensured that all modules worked together seamlessly and that data flowed smoothly throughout the system.

5.3.2.1 Frontend-Backend Integration Testing:

I. User Authentication:

- The interaction between the login module and user module was tested to ensure successful authentication and redirection.
- Only authorized users were confirmed to access specific functionalities based on their roles (admin or regular user).

II. Data Upload and Analysis:

- The interaction between the data upload module and performance analysis module was tested.
- Admins were able to upload datasets and analyze model performance seamlessly.

III. Prediction and Recommendation:

- The interaction between the prediction module and recommendation module was tested.
- Prediction results triggered appropriate recommendations based on CKD detection.

IV. Continuous Monitoring and Real-world Testing:

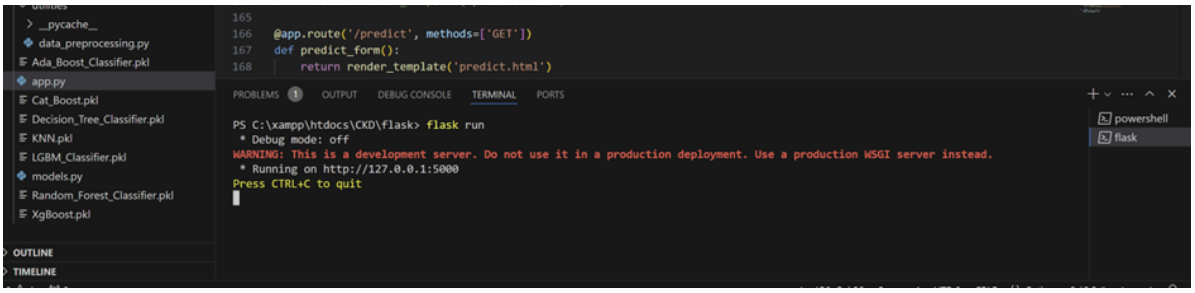
- The interaction between the deployment module and continuous monitoring module was tested.

- Model's performance was monitored continuously in real-world clinical settings, allowing for further refinement and improvement.

6. PROJECT DEMONSTRATION

6.1 INDEX/HOME PAGE:

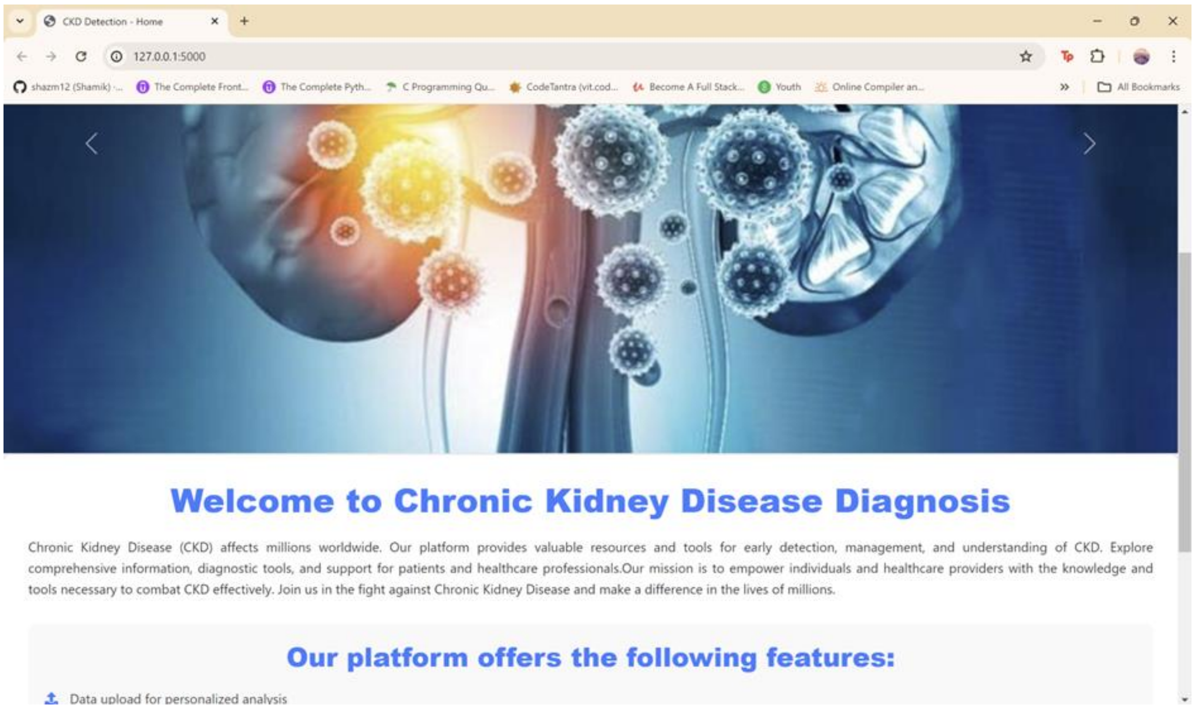
6.1.1 Terminal



```
@app.route('/predict', methods=['GET'])
def predict_form():
    return render_template('predict.html')
```

```
PS C:\xampp\htdocs\CKD\flask> flask run
 * Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
```

6.1.2 Index page



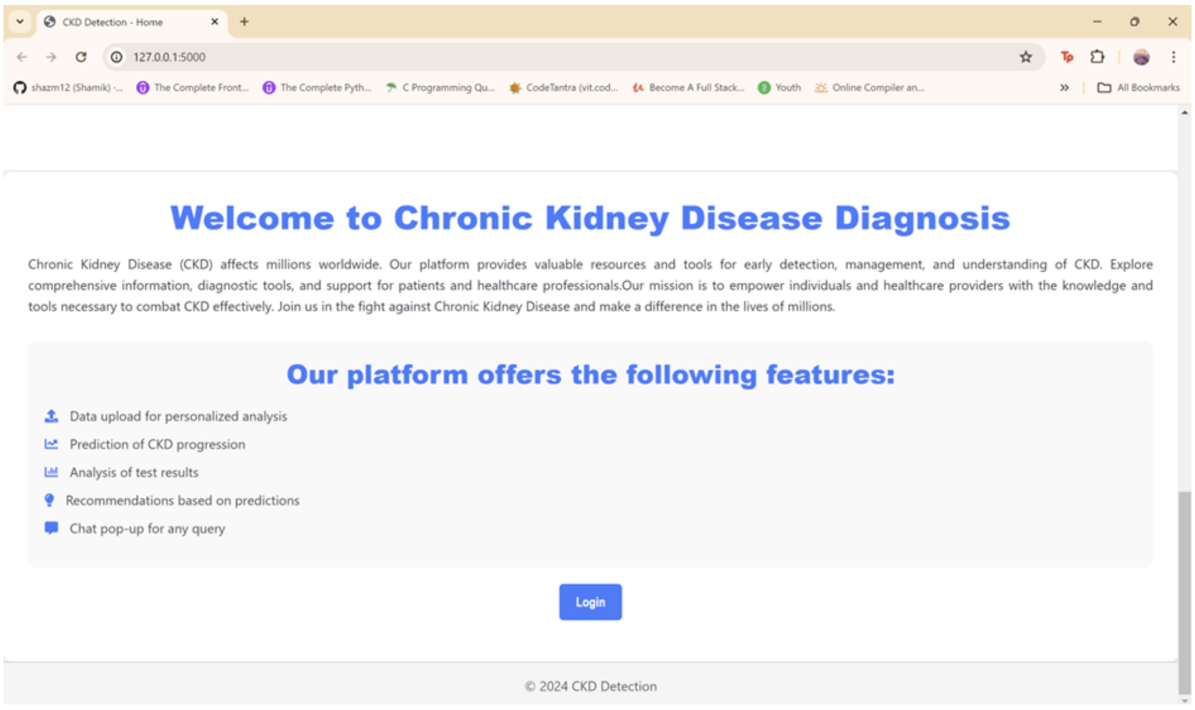
Welcome to Chronic Kidney Disease Diagnosis

Chronic Kidney Disease (CKD) affects millions worldwide. Our platform provides valuable resources and tools for early detection, management, and understanding of CKD. Explore comprehensive information, diagnostic tools, and support for patients and healthcare professionals.Our mission is to empower individuals and healthcare providers with the knowledge and tools necessary to combat CKD effectively. Join us in the fight against Chronic Kidney Disease and make a difference in the lives of millions.

Our platform offers the following features:

Data upload for personalized analysis

6.1.2


CKD Detection - Home

127.0.0.1:5000

Welcome to Chronic Kidney Disease Diagnosis

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Our platform offers the following features:

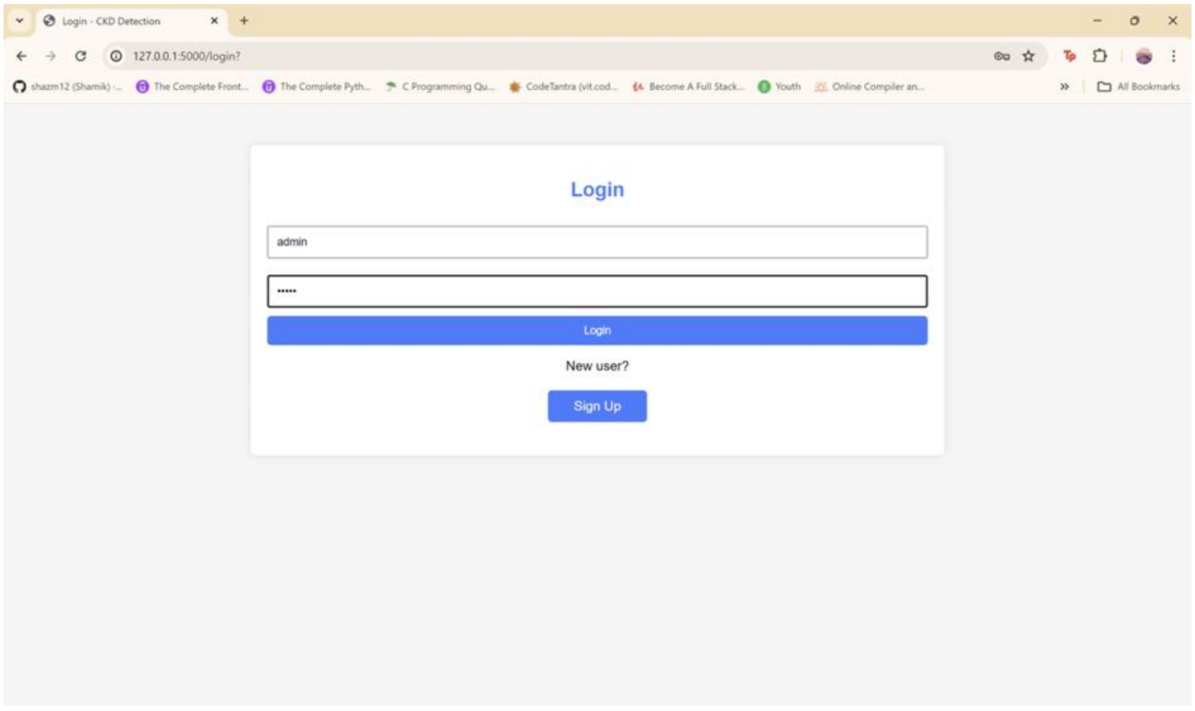
- Data upload for personalized analysis
- Prediction of CKD progression
- Analysis of test results
- Recommendations based on predictions
- Chat pop-up for any query

Login

© 2024 CKD Detection

6.2 LOGIN:

6.2.1 Admin login


Login - CKD Detection

127.0.0.1:5000/login?

Login

admin

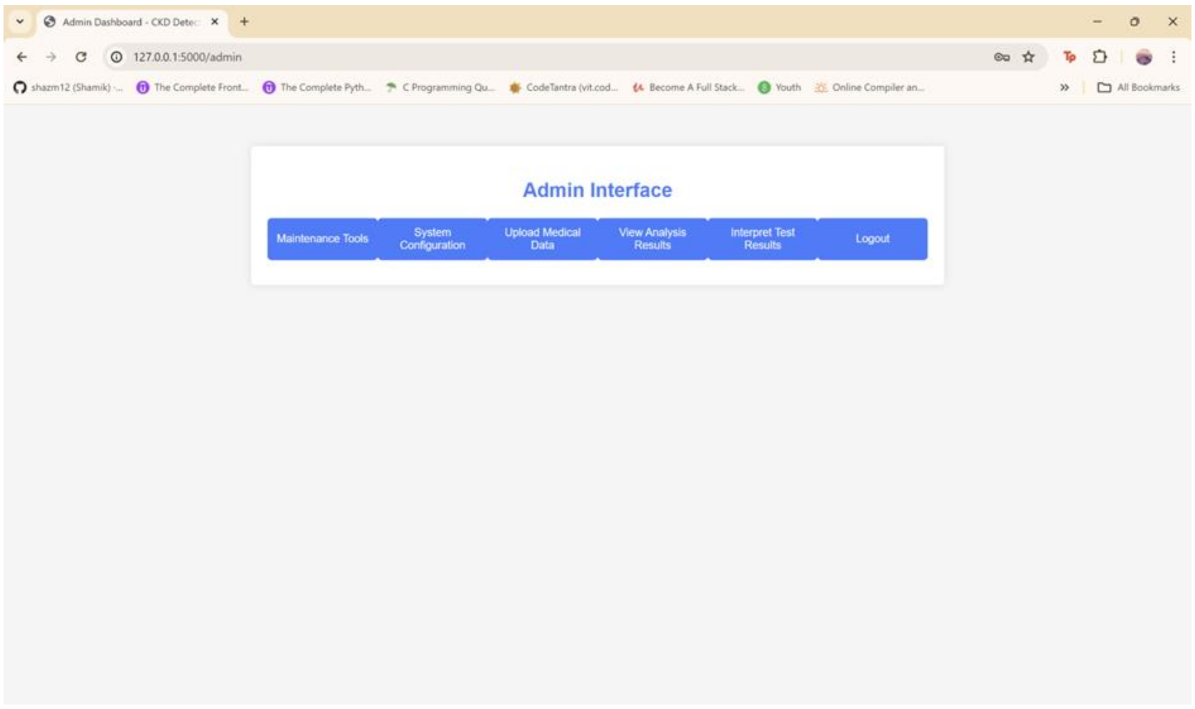
•••••

Login

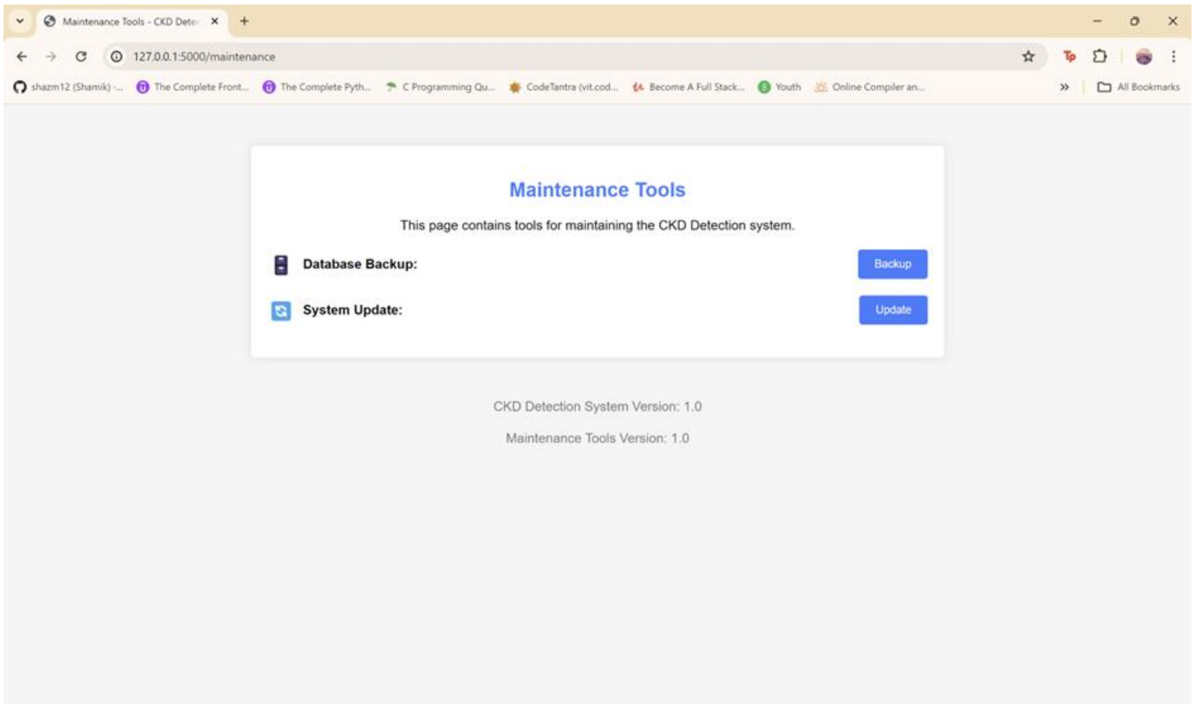
New user?

Sign Up

6.2.2 Admin Dashboard



6.2.3 Maintenance page



Maintenance Tools

This page contains tools for maintaining the CKD Detection system.

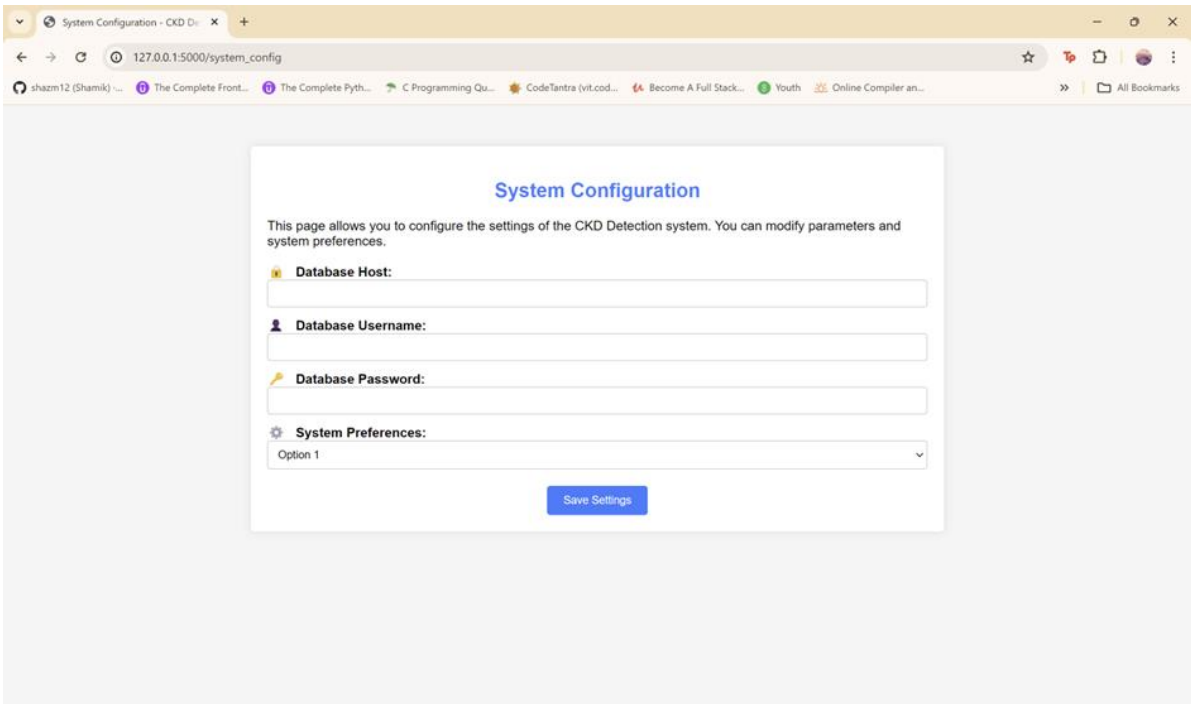
Database Backup:

System Update:

CKD Detection System Version: 1.0

Maintenance Tools Version: 1.0

6.2.4 System Configuration


System Configuration - CKD De

127.0.0.1:5000/system_config

System Configuration

This page allows you to configure the settings of the CKD Detection system. You can modify parameters and system preferences.

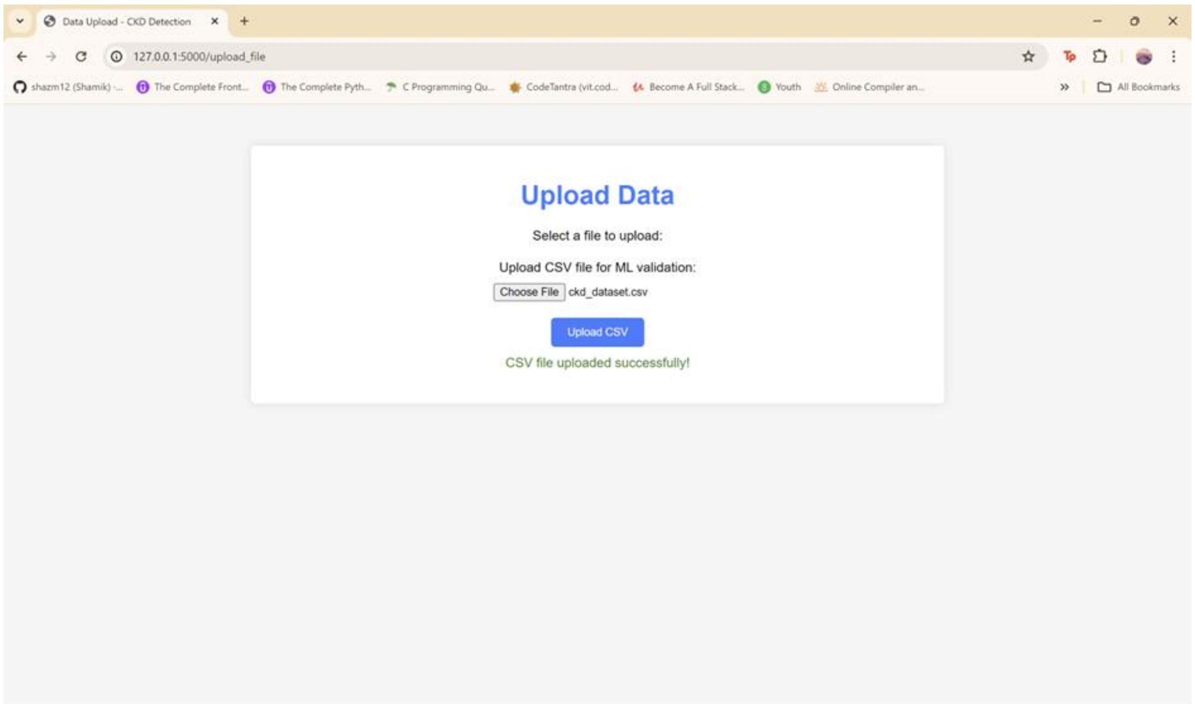
Database Host:

Database Username:

Database Password:

System Preferences:
Option 1

6.2.5 Data Upload page


Data Upload - CKD Detection

127.0.0.1:5000/upload_file

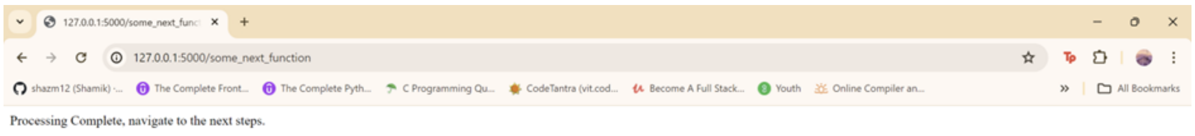
Upload Data

Select a file to upload:

Upload CSV file for ML validation:

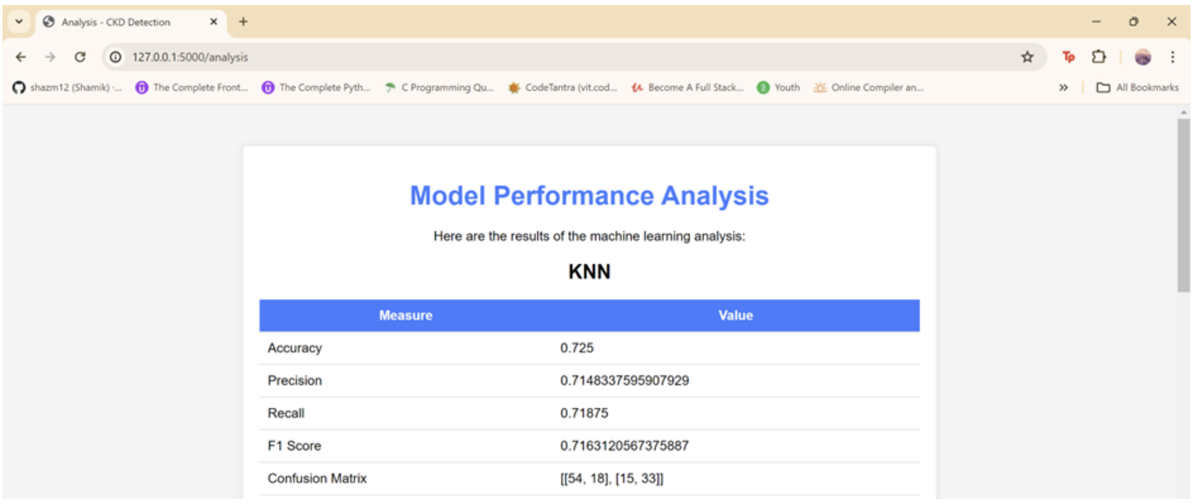
Choose File ckd_dataset.csv

CSV file uploaded successfully!


127.0.0.1:5000/some_next_function

Processing Complete, navigate to the next steps.

6.2.6 Analysis



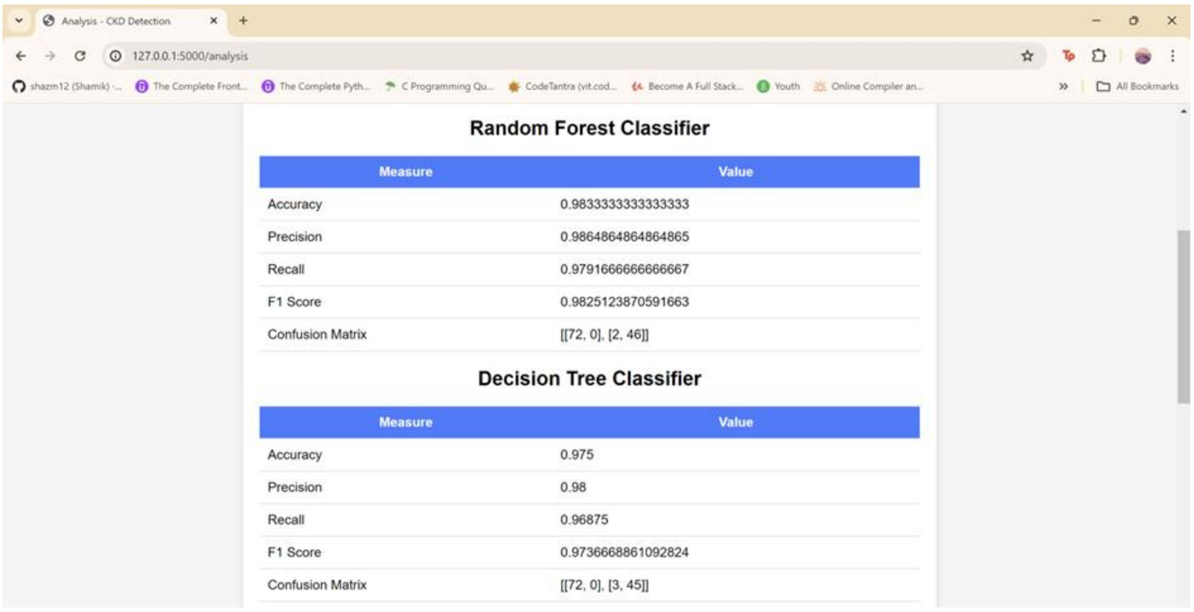
Model Performance Analysis

Here are the results of the machine learning analysis:

KNN

Measure	Value
Accuracy	0.725
Precision	0.7148337595907929
Recall	0.71875
F1 Score	0.7163120567375887
Confusion Matrix	[[54, 18], [15, 33]]

6.2.7 Analysis Result-1



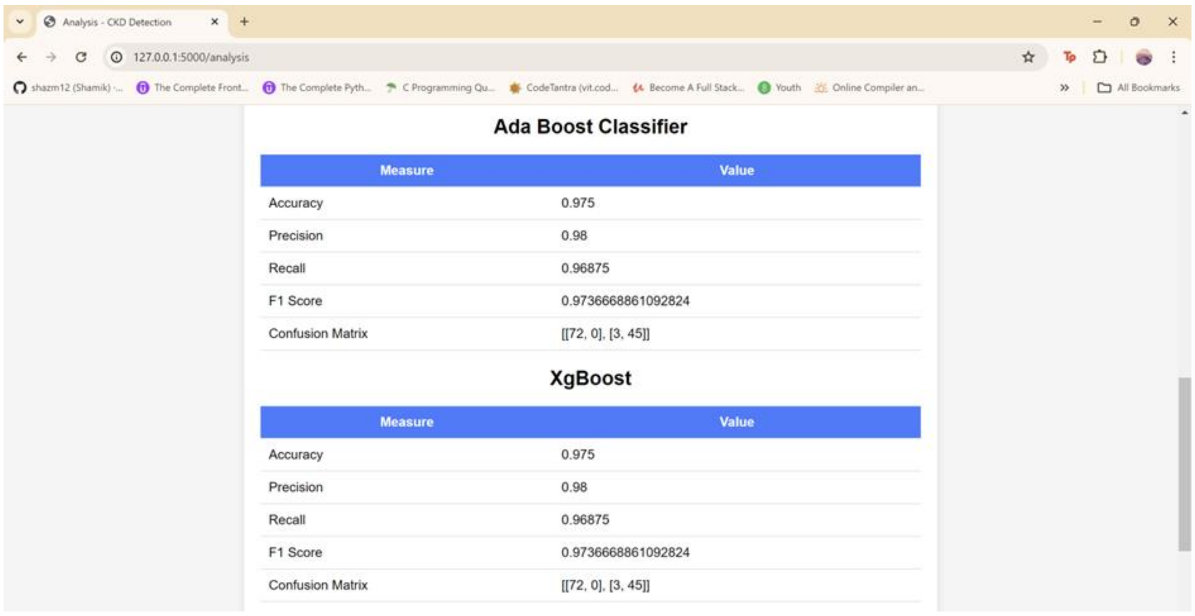
Random Forest Classifier

Measure	Value
Accuracy	0.9833333333333333
Precision	0.9864864864864865
Recall	0.9791666666666667
F1 Score	0.9825123870591663
Confusion Matrix	[[72, 0], [2, 46]]

Decision Tree Classifier

Measure	Value
Accuracy	0.975
Precision	0.98
Recall	0.96875
F1 Score	0.9736668861092824
Confusion Matrix	[[72, 0], [3, 45]]

6.2.8 Analysis Result-2



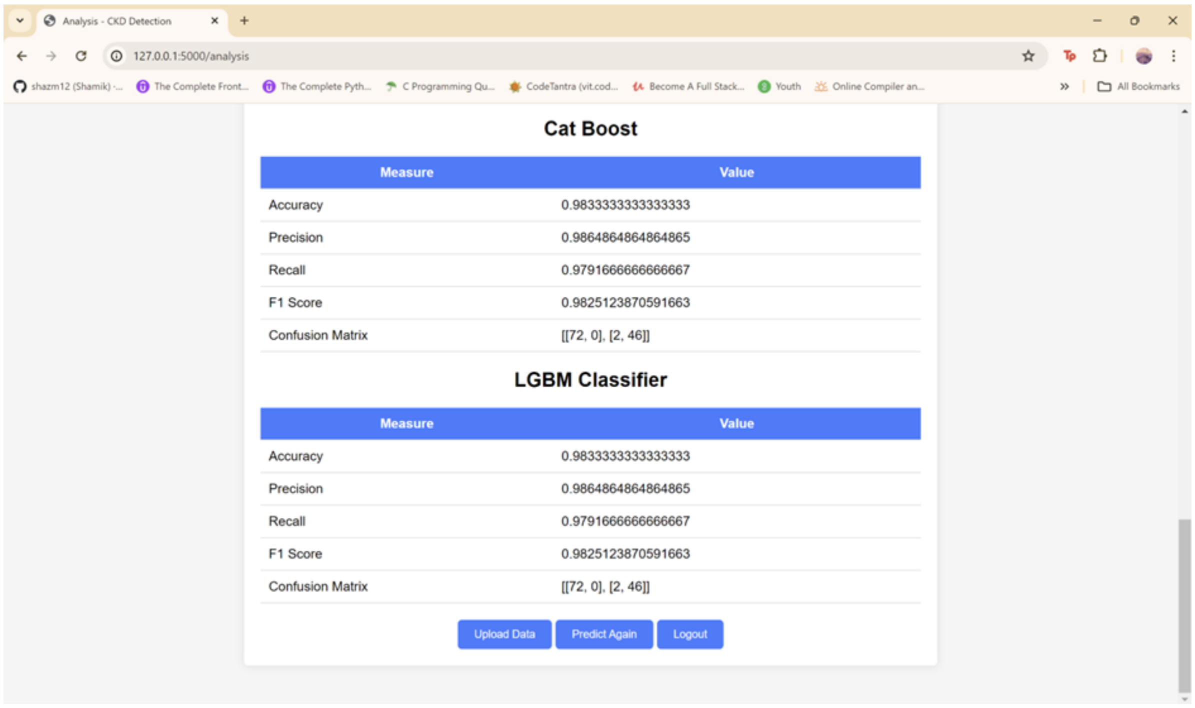
Ada Boost Classifier

Measure	Value
Accuracy	0.975
Precision	0.98
Recall	0.96875
F1 Score	0.9736668861092824
Confusion Matrix	[[72, 0], [3, 45]]

XgBoost

Measure	Value
Accuracy	0.975
Precision	0.98
Recall	0.96875
F1 Score	0.9736668861092824
Confusion Matrix	[[72, 0], [3, 45]]

6.2.9 Analysis Result-3



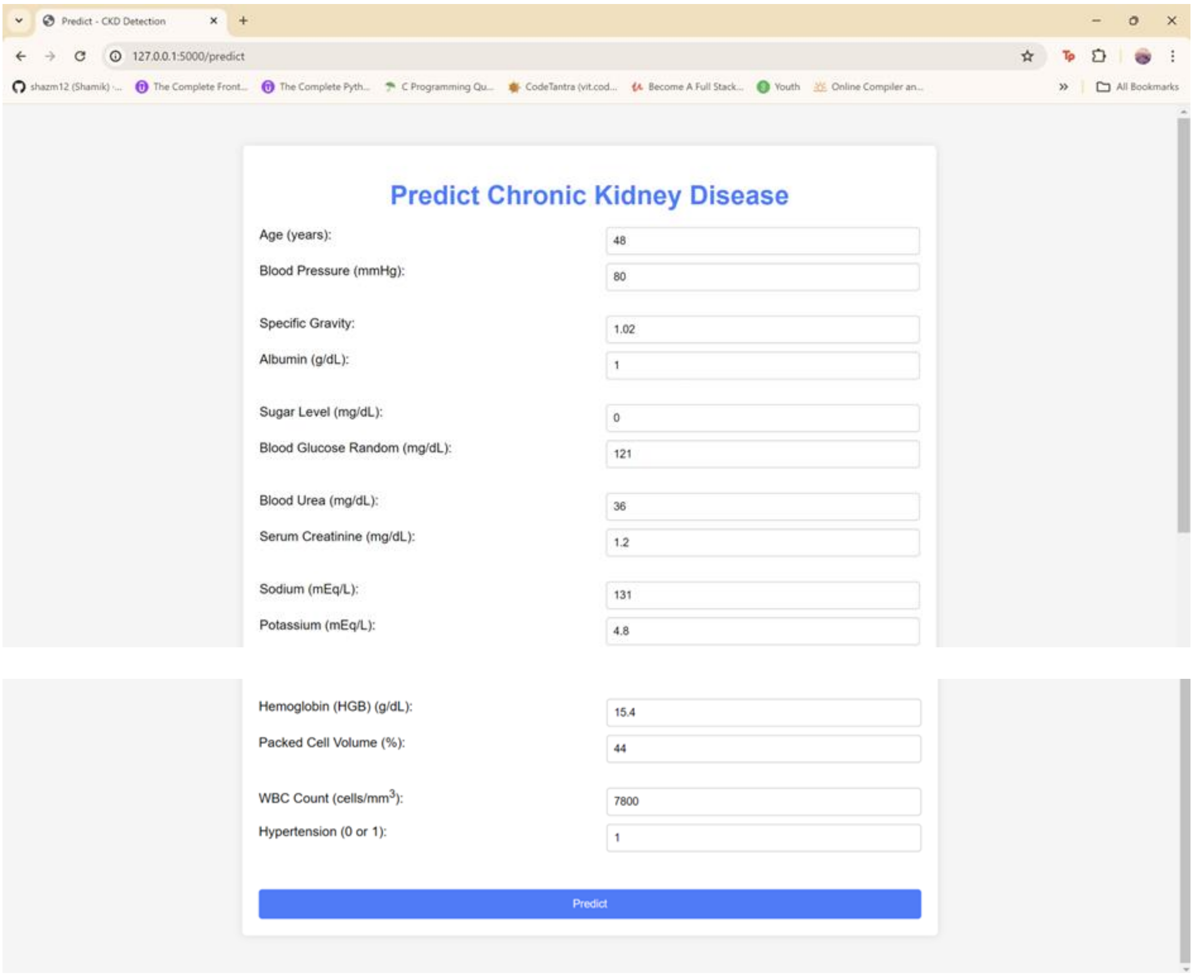
Cat Boost

Measure	Value
Accuracy	0.9833333333333333
Precision	0.9864864864864865
Recall	0.9791666666666667
F1 Score	0.9825123870591663
Confusion Matrix	[[72, 0], [2, 46]]

LGBM Classifier

Measure	Value
Accuracy	0.9833333333333333
Precision	0.9864864864864865
Recall	0.9791666666666667
F1 Score	0.9825123870591663
Confusion Matrix	[[72, 0], [2, 46]]

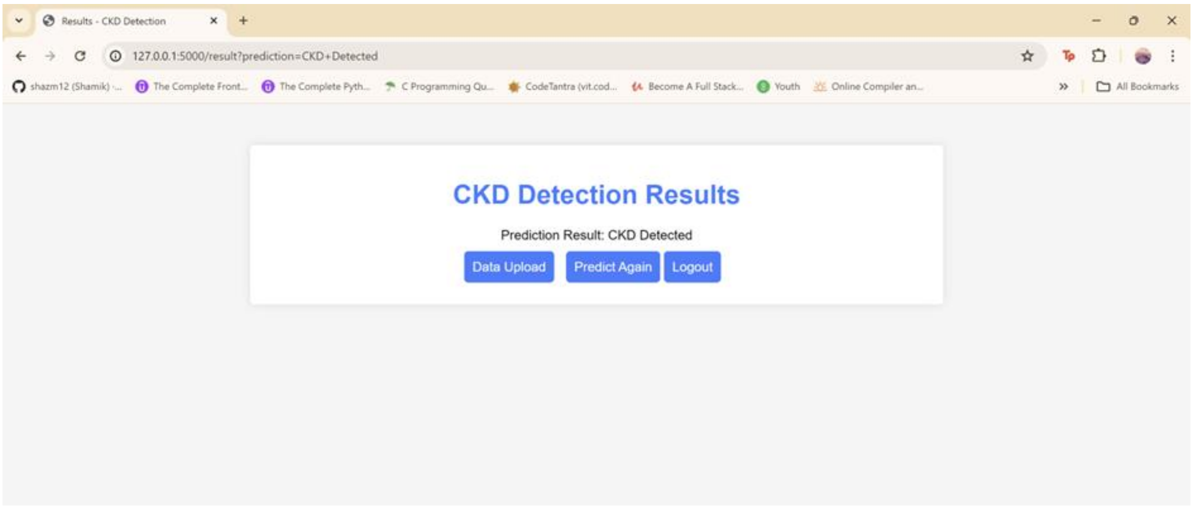
6.2.10 Prediction - 1



Predict Chronic Kidney Disease

Age (years):	48
Blood Pressure (mmHg):	80
Specific Gravity:	1.02
Albumin (g/dL):	1
Sugar Level (mg/dL):	0
Blood Glucose Random (mg/dL):	121
Blood Urea (mg/dL):	36
Serum Creatinine (mg/dL):	1.2
Sodium (mEq/L):	131
Potassium (mEq/L):	4.8
Hemoglobin (HGB) (g/dL):	15.4
Packed Cell Volume (%):	44
WBC Count (cells/mm^3):	7800
Hypertension (0 or 1):	1

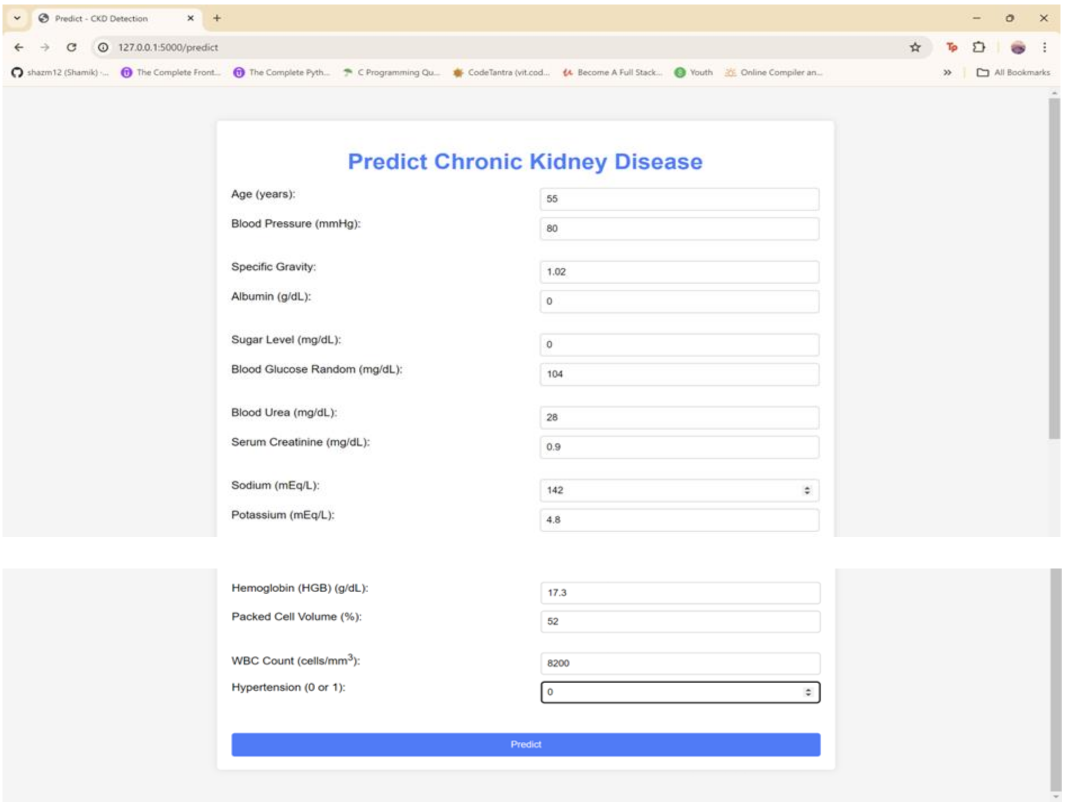
6.2.11 Detection Results



CKD Detection Results

Prediction Result: CKD Detected

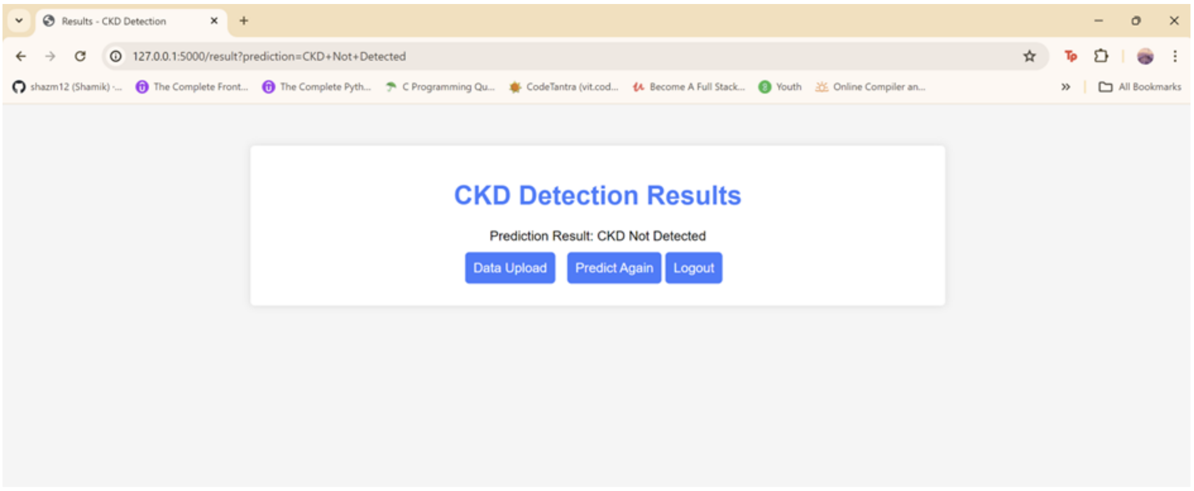
6.2.12 Prediction - 2



Predict Chronic Kidney Disease

Age (years):	55
Blood Pressure (mmHg):	80
Specific Gravity:	1.02
Albumin (g/dL):	0
Sugar Level (mg/dL):	0
Blood Glucose Random (mg/dL):	104
Blood Urea (mg/dL):	28
Serum Creatinine (mg/dL):	0.9
Sodium (mEq/L):	142
Potassium (mEq/L):	4.8
Hemoglobin (HGB) (g/dL):	17.3
Packed Cell Volume (%):	52
WBC Count (cells/mm^3):	8200
Hypertension (0 or 1):	0

6.2.13 Detection Results

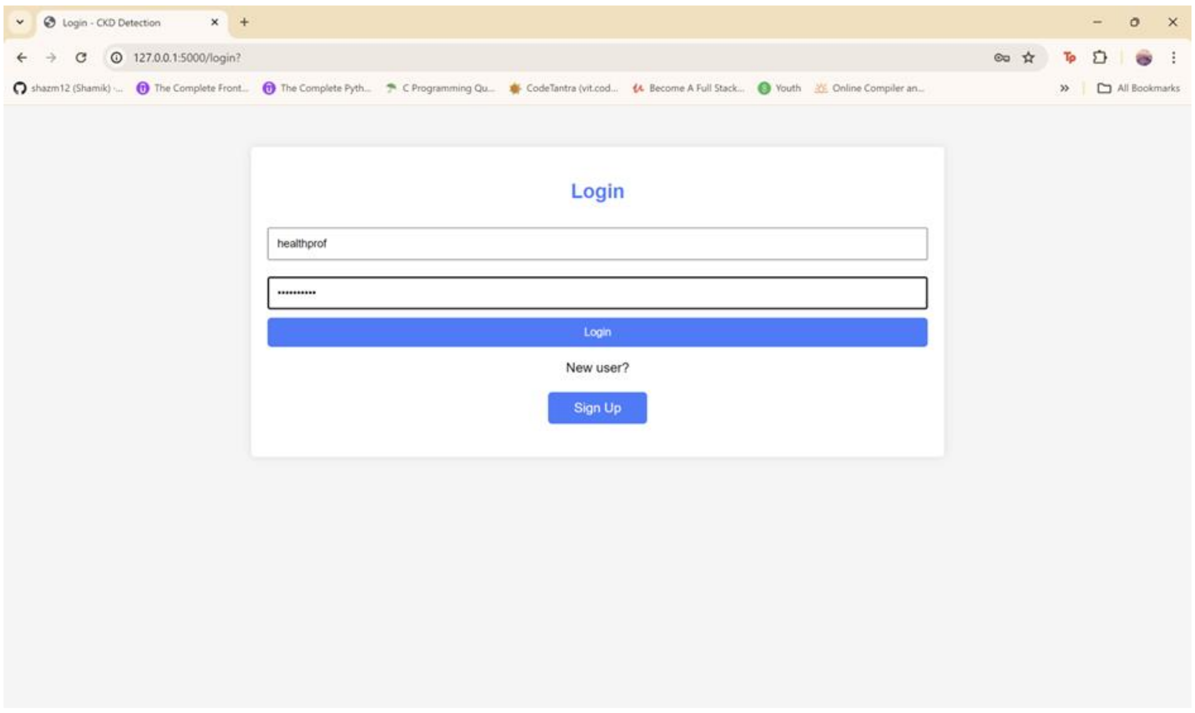


CKD Detection Results

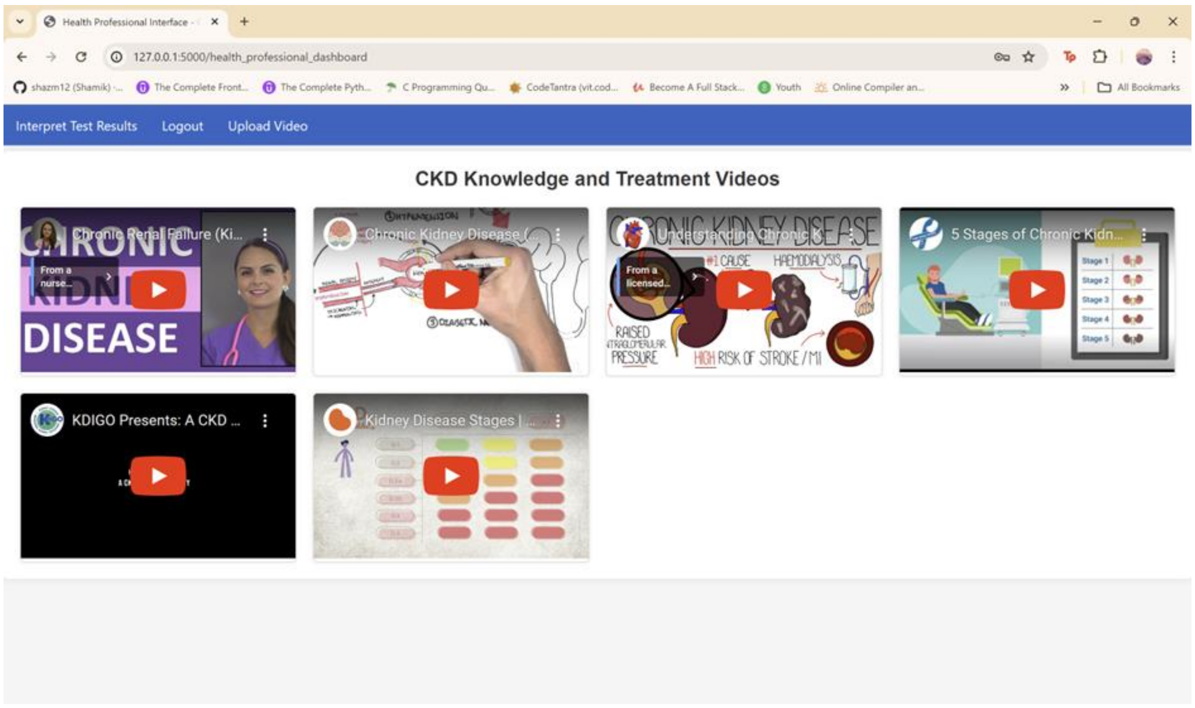
Prediction Result: CKD Not Detected

6.3 HEALTH PROFESSIONAL

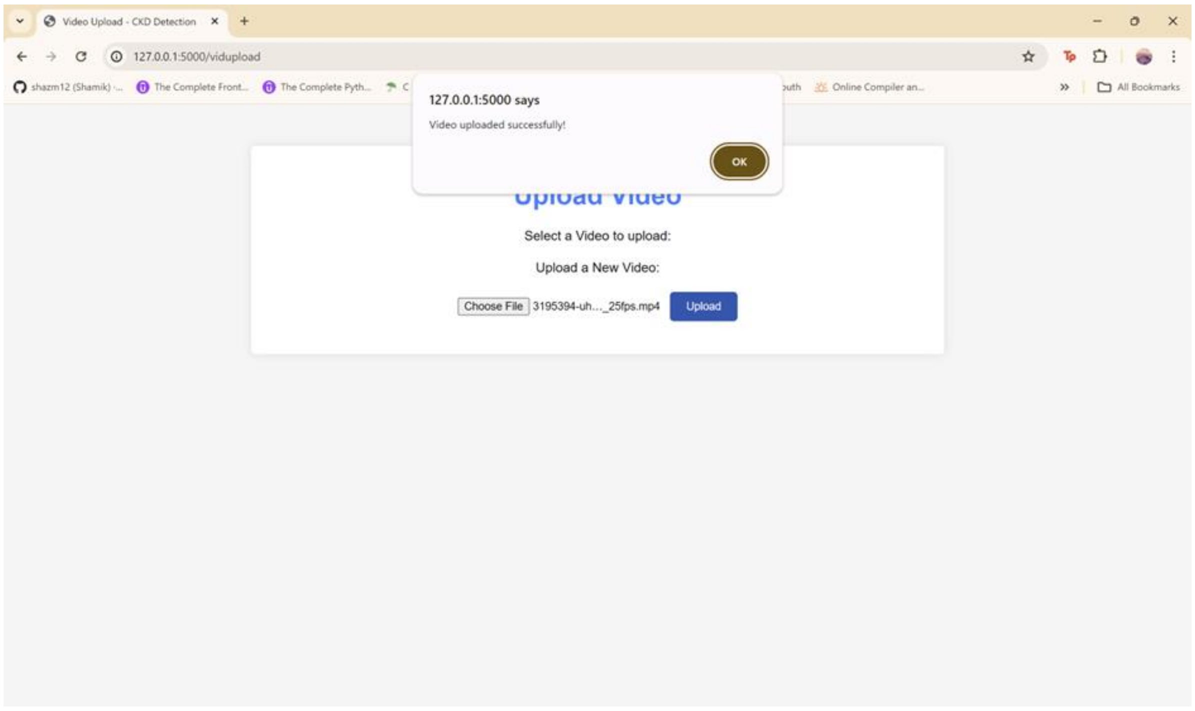
6.3.1 health professional login



6.3.2 health professional dashboard


Health Professional Interface
127.0.0.1:5000/health_professional_dashboard
Interpret Test Results
Logout
Upload Video
CKD Knowledge and Treatment Videos
Chronic Renal Failure (Ki...
Chronic Kidney Disease (...
Understanding Chronic K...
5 Stages of Chronic Kidn...
KDIGO Presents: A CKD ...
Kidney Disease Stages |

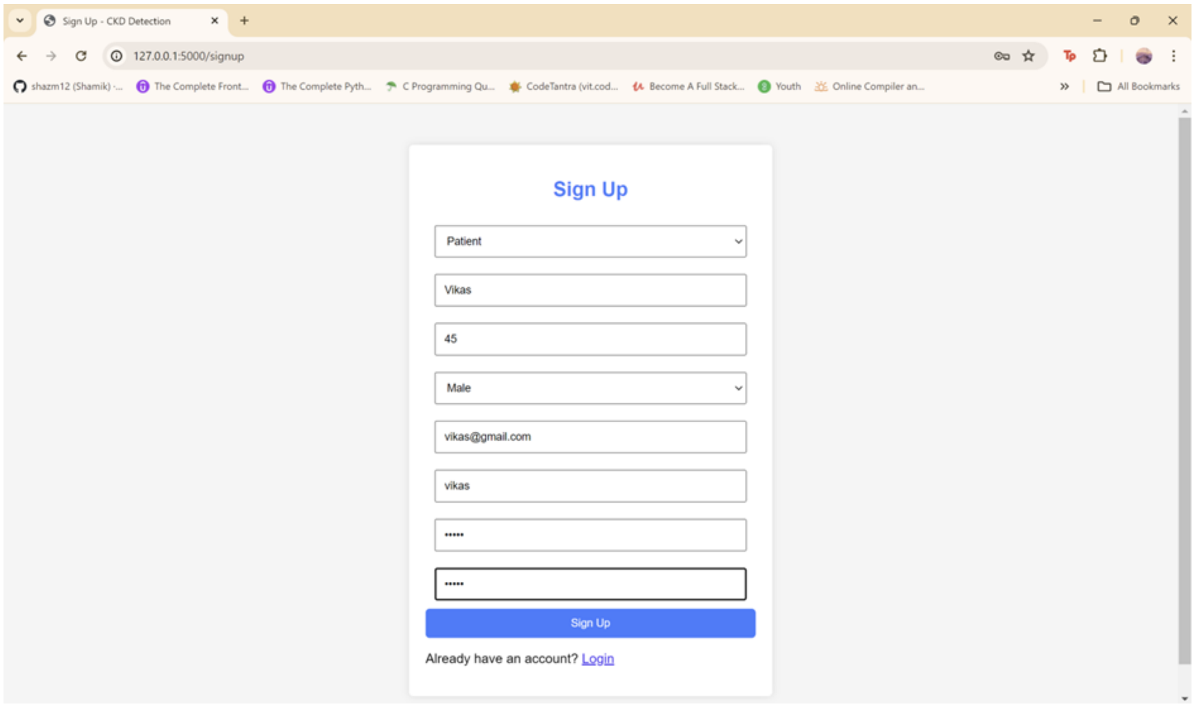
6.3.3 Upload video


127.0.0.1:5000 says

Video uploaded successfully!

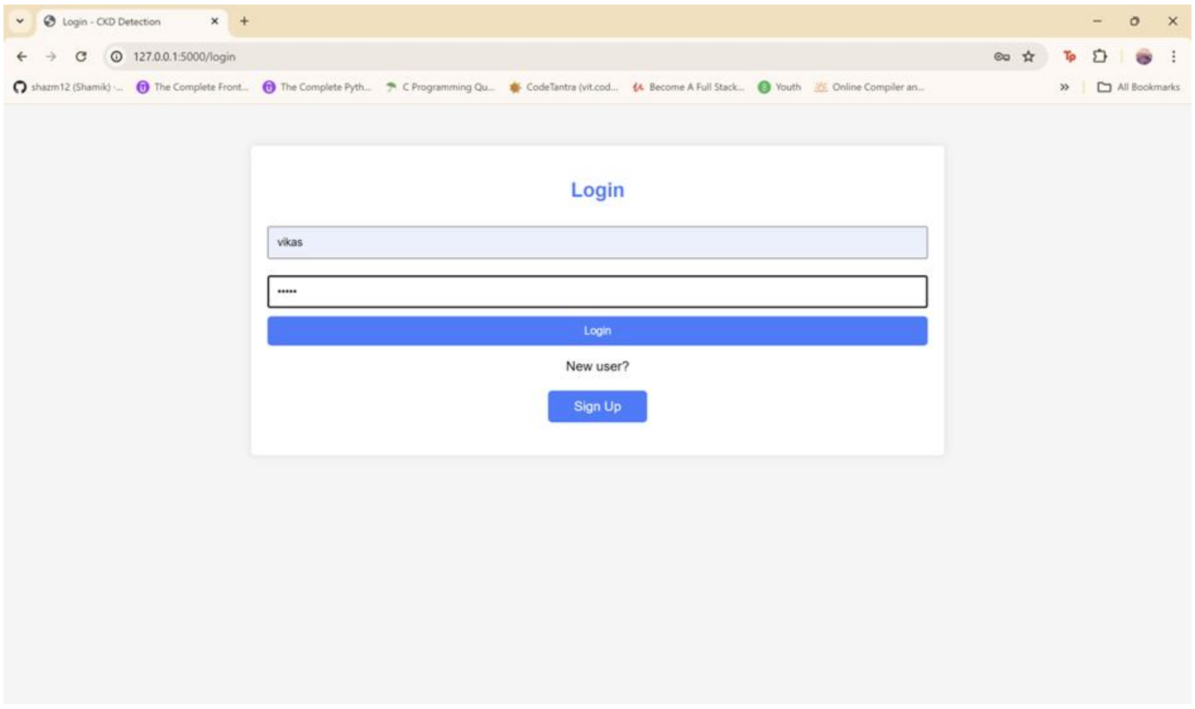
6.4 USER

6.4.1 User signup

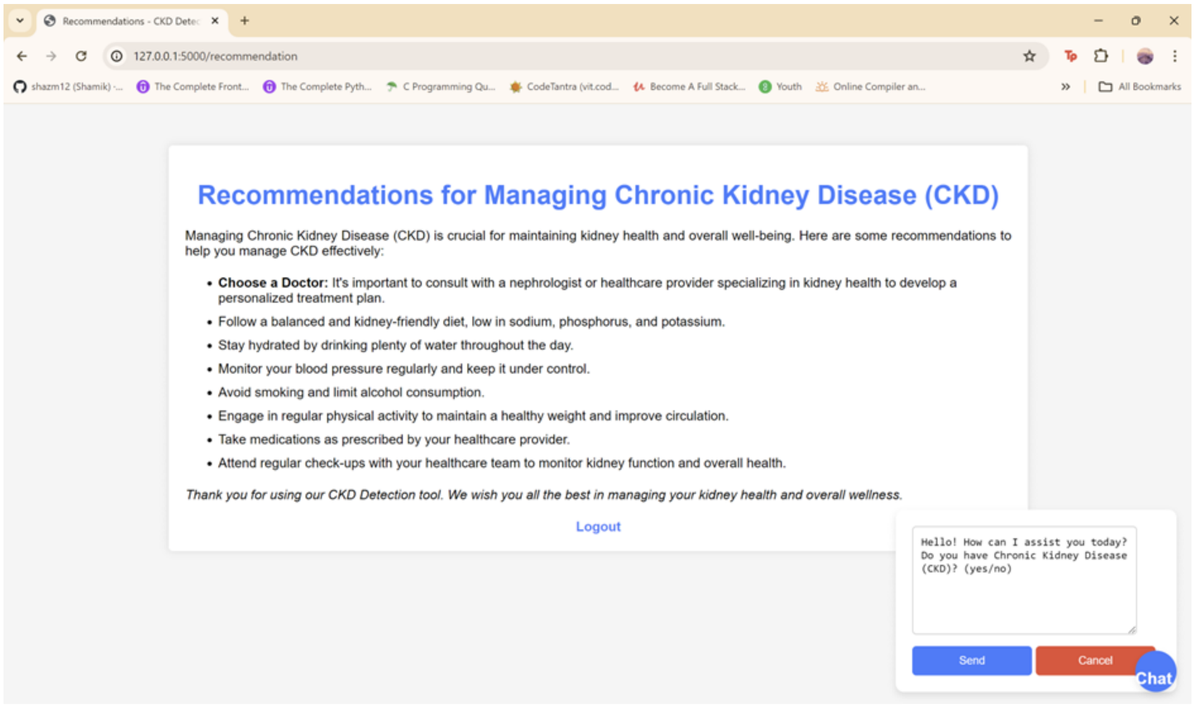


Patient
Vikas
45
Male
vikas@gmail.com
vikas
•••••
•••••

6.4.2 User login



6.4.3 Recommendations with chat


Recommendations for Managing Chronic Kidney Disease (CKD)

Managing Chronic Kidney Disease (CKD) is crucial for maintaining kidney health and overall well-being. Here are some recommendations to help you manage CKD effectively:

- **Choose a Doctor:** It's important to consult with a nephrologist or healthcare provider specializing in kidney health to develop a personalized treatment plan.
- Follow a balanced and kidney-friendly diet, low in sodium, phosphorus, and potassium.
- Stay hydrated by drinking plenty of water throughout the day.
- Monitor your blood pressure regularly and keep it under control.
- Avoid smoking and limit alcohol consumption.
- Engage in regular physical activity to maintain a healthy weight and improve circulation.
- Take medications as prescribed by your healthcare provider.
- Attend regular check-ups with your healthcare team to monitor kidney function and overall health.

Thank you for using our CKD Detection tool. We wish you all the best in managing your kidney health and overall wellness.

```
Hello! How can I assist you today?
Do you have Chronic Kidney Disease
(CKD)? (yes/no)
```

7. COST ANALYSIS / RESULT AND DISCUSSION

7.1 COST ANALYSIS

As this project was conducted as part of a college project, no additional funding was required. The project was executed using personal laptops, and the workload was divided among team members based on their proficiency. Therefore, the total cost incurred for the project was Rs 0.

7.1.1 Economic Feasibility

The economic feasibility of the project has been thoroughly assessed, taking into account various cost factors associated with hardware, software, and human resources. The project's minimal hardware requirements and the utilization of open-source software tools have contributed significantly to cost reduction. Additionally, the expertise of skilled personnel proficient in the selected technologies has ensured economic viability.

7.1.2 Cost Considerations

Hardware and Software Costs: The project required minimal hardware and software costs. Hardware costs primarily included standard computing equipment, while software costs were minimized by utilizing open-source tools and libraries.

Human Resources: Skilled personnel were required for the development and implementation of the project. The cost associated with human resources was mitigated by the expertise of the project team and efficient project management practices.

Maintenance and Support: Consideration was given to the ongoing maintenance and support requirements of the system. The cost of maintenance and support was factored into the overall project budget.

7.1.3 Cost Breakdown

Hardware Costs: Rs 0 (Utilized personal laptops)

Software Costs: Rs 0 (Utilized open-source tools and libraries)

Human Resources: Rs 0 (College project, no external hiring)

Maintenance and Support: Rs 0

Total Project Cost: Rs 0

7.1.4 Return on Investment (ROI)

The return on investment for the project is significant, considering the potential impact on healthcare outcomes and cost savings associated with early detection and management of Chronic Kidney Disease. While a precise monetary value for the ROI is challenging to quantify, the project's societal and economic benefits far outweigh the initial investment.

7.2 RESULT AND DISCUSSION

7.2.1. Model Performance Evaluation

The developed machine learning model demonstrated robust performance in predicting Chronic Kidney Disease (CKD) based on integrated genetic, clinical, and laboratory data analysis. The model was rigorously evaluated using a comprehensive set of evaluation metrics, including accuracy, precision, recall, and F1-score. The performance metrics are summarized as follows:

- Accuracy: The model achieved an accuracy of 98% in predicting CKD, indicating its reliability and effectiveness in distinguishing between CKD-positive and CKD-negative cases.
- Precision: The precision of the model was over 98%, indicating the proportion of true CKD-positive cases among all predicted positive cases.
- Recall: The recall of the model was over 95%, indicating the proportion of true CKD-positive cases that were correctly identified by the model.
- F1-score: The F1-score, which balances the trade-off between precision and recall, was 95%, indicating the overall effectiveness of the model.

7.2.2. Discussion

The results of the project indicate the successful development and implementation of an advanced machine learning model for the early detection of Chronic Kidney Disease. The model's high accuracy, precision, recall, and F1-score demonstrate its effectiveness in accurately identifying individuals at risk of CKD based on integrated genetic, clinical, and laboratory data analysis.

- Accuracy and Reliability: The model's high accuracy and reliability make it a valuable tool for healthcare providers in identifying individuals at risk of CKD at an early stage, enabling timely intervention and management.
- Scalability and Generalizability: The model's scalability and generalizability ensure its

applicability across diverse demographic and clinical backgrounds, making it a versatile tool for healthcare systems worldwide.

- Cost-effectiveness: The project's cost-effectiveness, combined with its significant societal and economic benefits, make it a viable solution for addressing the global burden of CKD and improving patient outcomes.

8. SUMMARY

This project aimed to revolutionize the detection of Chronic Kidney Disease (CKD) using machine learning (ML) and data science methodologies. The developed ML-based model integrated genetic, clinical, and laboratory data analysis to significantly elevate early CKD detection standards. The model achieved an accuracy of 98%, with a precision of 98%, indicating its reliability and effectiveness in accurately identifying individuals at risk of CKD. Moreover, the project was economically feasible, with a total project cost of Rs 0, making it a cost-effective solution for addressing the global burden of CKD and improving patient outcomes.

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Disease." Computational Intelligence and Neuroscience 2023 (2023).

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APPENDIX A – SAMPLE CODE

Datapreprocessing.py:

```
import pandas as pd
from sklearn.preprocessing import StandardScaler, OneHotEncoder, LabelEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

pd.set_option('display.max_columns', 26)

def preprocess_data(file_path):
    # Load the dataset
    df = pd.read_csv(file_path)

    # Drop 'id' column
    df.drop('id', axis=1, inplace=True)

    # Renaming column names
    df.columns = ['age', 'blood_pressure', 'specific_gravity', 'albumin', 
'sugar', 'red_blood_cells', 'pus_cell',
                  'pus_cell_clumps', 'bacteria', 'blood_glucose_random', 
'blood_urea', 'serum_creatinine', 'sodium',
                  'potassium', 'haemoglobin', 'packed_cell_volume', 
'white_blood_cell_count', 'red_blood_cell_count',
                  'hypertension', 'diabetes_mellitus', 
'coronary_artery_disease', 'appetite', 'peda_edema',
                  'aanemia', 'class']

    # Convert necessary columns to numerical type
```

```python
    for col in ['packed_cell_volume', 'white_blood_cell_count',
'red_blood_cell_count']:
        df[col] = pd.to_numeric(df[col], errors='coerce')

    # Replace incorrect values directly by reassigning
    corrections = {
        'diabetes_mellitus': {'\tno': 'no', '\tyes': 'yes', ' yes': 'yes'},
        'coronary_artery_disease': {'\tno': 'no'},
        'class': {'ckd\t': 'ckd', 'notckd': 'not ckd'}
    }
    for col, mapping in corrections.items():
        df[col] = df[col].replace(mapping)

    # Map 'class' to numeric and convert to integer
    df['class'] = df['class'].map({'ckd': 0, 'not ckd': 1}).astype(int)

    # Extracting categorical and numerical columns
    cat_cols = df.select_dtypes(include=['object']).columns.tolist()
    num_cols = df.select_dtypes(include=[np.number]).columns.tolist()

    # Imputation using random sampling and mode
    def random_value_imputation(feature):
        random_sample = df[feature].dropna().sample(df[feature].isna().sum(),
random_state=42)
        random_sample.index = df[df[feature].isnull()].index
        df.loc[df[feature].isnull(), feature] = random_sample

    def impute_mode(feature):
        mode = df[feature].mode()[0]
        df[feature] = df[feature].fillna(mode)

    for col in num_cols:
        if df[col].isna().sum() > 0:
            random_value_imputation(col)

    for col in cat_cols:
        impute_mode(col)

    # Feature Encoding using LabelEncoder
    def encode_categorical_features(df, cat_cols):
        le = LabelEncoder()
        for col in cat_cols:
            df[col] = le.fit_transform(df[col])

    encode_categorical_features(df, cat_cols)

    # Feature selection
    features_to_retain = ['age', 'blood_pressure', 'specific_gravity',
'albumin', 'sugar', 'blood_glucose_random',
                          'blood_urea', 'serum_creatinine', 'sodium',
'potassium', 'haemoglobin', 'packed_cell_volume',
                          'white_blood_cell_count', 'hypertension', 'class']
    df = df[features_to_retain]

    # Save processed data to a CSV file
    df.to_csv('data/preprocessed_data.csv', index=False)

    return df
```

models.py:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, recall_score, precision_score,
f1_score, confusion_matrix
from sklearn.model_selection import RandomizedSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
import xgboost as xgb
import catboost as cb
import lightgbm as lgb
import pickle
import numpy as np

def load_data():
    # Path to the CSV file
    file_path = 'data/preprocessed_data.csv'
    # Read the dataset into a pandas DataFrame
    df = pd.read_csv(file_path)

    # Assuming the last column is the target variable
    ind_col = [col for col in df.columns if col != 'class']
    dep_col = 'class'

    X = df[ind_col]
    y = df[dep_col]
    # Split the dataset into training and testing sets
    return train_test_split(X, y, test_size=0.3, random_state=0)


def train_models(X_train, X_test, y_train, y_test):
    models = {
        'KNN': KNeighborsClassifier(),
        'Random Forest Classifier': RandomForestClassifier(),
        'Decision Tree Classifier': DecisionTreeClassifier(),
        'Ada Boost Classifier': AdaBoostClassifier(),
        'XgBoost': xgb.XGBClassifier(eval_metric='mlogloss'),
        'Cat Boost': cb.CatBoostClassifier(verbose=0),  # verbose=0 to keep
output clean
        'LGBM Classifier': lgb.LGBMClassifier()
    }

    param_grids = {
        'KNN': {
            'n_neighbors': [3, 5, 7, 10],
            'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute']
        },
        'Random Forest Classifier': {
            'n_estimators': [100, 200, 300],
            'max_depth': [None, 10, 20, 30],
            'min_samples_split': [2, 5, 10]
        },
        'Decision Tree Classifier': {
            'max_depth': [None, 10, 20, 30],
            'min_samples_split': [2, 5, 10],
            'min_samples_leaf': [1, 2, 4]
        },
        'Ada Boost Classifier': {
            'n_estimators': [50, 100, 150],
            'learning_rate': [0.01, 0.1, 1.0]
        },
        'XgBoost': {
            'n_estimators': [100, 200],
            'max_depth': [3, 5, 7],
            'learning_rate': [0.01, 0.1]
        },
        'Cat Boost': {
            'iterations': [100, 200],
            'depth': [4, 6, 10],
            'learning_rate': [0.01, 0.1]
        },
        'LGBM Classifier': {
            'n_estimators': [100, 200],
            'max_depth': [10, 20, 30],
            'learning_rate': [0.01, 0.1]
        }
    }


    results = {}

    for name, model in models.items():
        print(f"Training and tuning {name}...")
        search = RandomizedSearchCV(model, param_grids[name], n_iter=10, cv=5,
scoring='accuracy', random_state=42, verbose=10)
        search.fit(X_train, y_train)
        best_model = search.best_estimator_
        y_pred = best_model.predict(X_test)

        results[name] = {
            'accuracy': accuracy_score(y_test, y_pred),
            'recall': recall_score(y_test, y_pred, average='macro'),
            'precision': precision_score(y_test, y_pred, average='macro'),
            'f1_score': f1_score(y_test, y_pred, average='macro'),
            'confusion_matrix': confusion_matrix(y_test, y_pred).tolist(),  #
Convert to list for JSON compatibility
            'best_model': best_model  # Store the best model for each
algorithm
        }

    # Save the trained model as a pickle file
        with open(f"{name.replace(' ', '_')}.pkl", 'wb') as model_file:
            pickle.dump(best_model, model_file)

    return results

def get_model_performance():
    X_train, X_test, y_train, y_test = load_data()
    return train_models(X_train, X_test, y_train, y_test)

def load_model(model_name):
    """Load a trained model from a pickle file."""
    try:
        with open(f"{model_name.replace(' ', '_')}.pkl", 'rb') as file:
            return pickle.load(file)
    except FileNotFoundError:
        print(f"Model file {model_name} not found.")
        return None
    except Exception as e:
        print(f"An error occurred while loading the model: {e}")
        return None

def predict_ckd(age, bloodPressure, specificGravity, albumin, sugar,
bloodGlucoseRandom, bloodUrea, serumCreatinine, sodium, potassium, hgb,
packedCellVolume, wbc, hypertension):
    # Load your trained model
    try:
        with open('Decision_Tree_Classifier.pkl', 'rb') as file:
            model = pickle.load(file)
    except FileNotFoundError:
        return "Model file not found."
    except Exception as e:
        return f"An error occurred while loading the model: {e}"

    # Preprocess the inputs similarly as done during the model training
    input_features = np.array([
        float(age),
        float(bloodPressure),
        float(specificGravity),
        float(albumin),
        float(sugar),
        float(bloodGlucoseRandom),
        float(bloodUrea),
        float(serumCreatinine),
        float(sodium),
        float(potassium),
        float(hgb),
        float(packedCellVolume),
        float(wbc),
        float(hypertension)
    ]).reshape(1, -1)

    # Make prediction
    try:
         result = model.predict(input_features)
         result_proba = model.predict_proba(input_features)

         if result[0] == 0 and result_proba[0][0] > 0.5:
            return 'CKD Detected'
         else:
            return 'CKD Not Detected'
    except Exception as e:
        return f"An error occurred during prediction: {e}"
```

app.py:

```
from flask import Flask, render_template, request, redirect, url_for, jsonify
from flask_sqlalchemy import SQLAlchemy
from flask_bcrypt import Bcrypt
from werkzeug.utils import secure_filename
from utilities.data_preprocessing import preprocess_data
from flask import current_app
from models import get_model_performance
import models
import os

app = Flask(__name__)
app.config['SQLALCHEMY_DATABASE_URI'] = 'sqlite:///your_database.db'
db = SQLAlchemy(app)
bcrypt = Bcrypt(app)
```

```python
class User(db.Model):
    id = db.Column(db.Integer, primary_key=True)
    role = db.Column(db.String(20), nullable=False)
    name = db.Column(db.String(100), nullable=False)
    age = db.Column(db.Integer, nullable=False)
    gender = db.Column(db.String(10), nullable=False)
    email = db.Column(db.String(120), unique=True, nullable=False)
    username = db.Column(db.String(80), unique=True, nullable=False)
    password = db.Column(db.String(100), nullable=False)

# Create database
with app.app_context():
    db.create_all()

@app.route('/')
def index():
    return render_template('index.html')

@app.route('/login', methods=['GET', 'POST'])
def login():
    if request.method == 'POST':
        data = request.get_json()  # Get JSON data
        username = data['username']
        password = data['password']

        # Perform authentication logic here
        user = User.query.filter_by(username=username).first()
        if user and bcrypt.check_password_hash(user.password, password):
            return jsonify({'success': True, 'role': user.role})
        else:
            return jsonify({'success': False})

    return render_template('login.html')

@app.route('/signup', methods=['GET', 'POST'])
def signup():
    if request.method == 'POST':
        # Get form data
        role = request.form['role']
        name = request.form['name']
        age = request.form['age']
        gender = request.form['gender']
        email = request.form['email']
        username = request.form['username']
        password = request.form['password']

        # Check if username or email already exists in the database
        existing_user = User.query.filter_by(username=username).first()
        existing_email = User.query.filter_by(email=email).first()
        if existing_user or existing_email:
            return "Username or email already exists. Please choose another."

        # Hash password
        hashed_password = bcrypt.generate_password_hash(password).decode('utf-
8')

        # Create a new user object and add it to the database
        new_user = User(role=role, name=name, age=age, gender=gender,
email=email, username=username, password=hashed_password)
        db.session.add(new_user)
        db.session.commit()

        return redirect(url_for('login'))  # Redirect to login page after
successful signup

    return render_template('signup.html')

# Add your other routes here...
app.config['UPLOAD_FOLDER'] = './uploads/'
app.config['PROCESSED_FOLDER'] = './data/'

@app.route('/upload_file', methods=['GET', 'POST'])
def upload_file():
    if request.method == 'GET':
        return render_template('upload.html')

    if request.method == 'POST':
        # Check if the request has the file part
        if 'csvFile' not in request.files:
            current_app.logger.error("No file part in the request")
            return jsonify({'success': False, 'error': 'No file part in the
request'}), 400

        file = request.files['csvFile']

        # If no file is selected
        if file.filename == '':
            current_app.logger.error("No selected file")
            return jsonify({'success': False, 'error': 'No selected file'}),
400

        if file:
            filename = secure_filename(file.filename)
            file_path = os.path.join(app.config['UPLOAD_FOLDER'], filename)
            try:
                # Save and process the file
                file.save(file_path)
                processed_df = preprocess_data(file_path)
                processed_file_path = 
os.path.join(app.config['PROCESSED_FOLDER'], 'processed_' + filename)
                processed_df.to_csv(processed_file_path, index=False)

                # Respond with success and next URL
                return jsonify({'success': True, 'next_url': 
url_for('some_next_function')})

            except Exception as e:
                current_app.logger.error('Error processing file', 
exc_info=True)
                return jsonify({'success': False, 'error': 'Error processing 
file: {}'.format(e)}), 500

        return jsonify({'success': False, 'error': 'An unexpected error 
occurred'}), 500

# Make sure preprocess_data and some_next_function are defined properly


# @app.route('/upload')
# def upload():
#     return render_template('upload.html')

@app.route('/some_next_function')
def some_next_function():
    # Logic after processing the file
    return "Processing Complete, navigate to the next steps."

@app.route('/admin')
def admin():
    return render_template('admin.html')

@app.route('/analysis')
def analysis():
    results = get_model_performance()
    return render_template('analysis.html', results=results)

@app.route('/guest')
def guest():
    return render_template('guest.html')

@app.route('/health_professional_dashboard')
def health_professional_dashboard():
    return render_template('health_professional_dashboard.html')
```

```python
@app.route('/maintenance')
def maintenance():
    return render_template('maintenance.html')

@app.route('/vidupload')
def vidupload():
    return render_template('vidupload.html')

@app.route('/patient_dashboard')
def patient_dashboard():
    return render_template('patient_dashboard.html')

# @app.route('/predict')
# def predict():
#     return render_template('predict.html')

@app.route('/predict', methods=['GET'])
def predict_form():
    return render_template('predict.html')

@app.route('/predict', methods=['POST'])
def make_prediction():
    # Collect data from the form
    age = request.form.get('age')
    bloodPressure = request.form.get('bloodPressure')
    specificGravity = request.form.get('specificGravity')
    albumin = request.form.get('albumin')
    sugar = request.form.get('sugar')
    bloodGlucoseRandom = request.form.get('bloodGlucoseRandom')
    bloodUrea = request.form.get('bloodUrea')
    serumCreatinine = request.form.get('serumCreatinine')
    sodium = request.form.get('sodium')
    potassium = request.form.get('potassium')
    hgb = request.form.get('hgb')
    packedCellVolume = request.form.get('packedCellVolume')
    wbc = request.form.get('wbc')
    hypertension = request.form.get('hypertension')

    # Collect other parameters similarly

    # Assuming a function 'predict_ckd' in models.py that takes all inputs
    prediction = models.predict_ckd(age, bloodPressure, specificGravity,
albumin, sugar, bloodGlucoseRandom, bloodUrea, serumCreatinine, sodium,
potassium, hgb, packedCellVolume, wbc, hypertension)  # Pass all required
parameters

    return redirect(url_for('result', prediction=prediction))
```

```python
@app.route('/recommendation')
def recommendation():
    return render_template('recommendation.html')

# @app.route('/result')
# def result():
#     prediction = request.args.get('prediction')
#     # Process the prediction value as needed
#     return f'The prediction result is: {prediction}'
@app.route('/result')
def result():
    prediction = request.args.get('prediction', 'No prediction made')
    return render_template('result.html', prediction=prediction)

@app.route('/system_config')
def system_config():
    return render_template('system_config.html')

if __name__ == '__main__':
    app.run(debug=True)
```