

ARTIFICIAL INTELLIGENCE IN CHRONIC KIDNEY DISEASE USING DEEP LEARNING

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ABSTRACT

Chronic Kidney Disease (CKD) is a long-term medical condition that affects the kidneys' ability to filter blood. Early detection is essential because CKD often shows symptoms only in the later stages. In this project, Artificial Intelligence (AI) and Deep Learning techniques are used to predict CKD from medical data and reports. A deep learning model is trained using patient laboratory parameters such as blood pressure, serum creatinine, albumin level, hemoglobin, and other clinical features. The model identifies hidden patterns in the data and classifies whether a patient is CKD positive or negative. The proposed system aims to support medical professionals by providing fast and accurate predictions. The results show that the model provides high accuracy, making it a useful tool for early CKD detection.

Keyword : - Chronic Kidney Disease, Deep Learning, Artificial Intelligence, Medical Diagnosis, Prediction Model

1. INTRODUCTION

Chronic Kidney Disease (CKD) is a major global health issue that affects millions of people. Due to lifestyle changes, diabetes, hypertension, and other risk factors, CKD cases have increased rapidly. Traditional diagnosis requires clinical tests and manual analysis by experts, which may be time-consuming and prone to human error.

Artificial Intelligence, specifically Deep Learning, has gained importance in medical diagnosis because it can analyze large datasets and detect complex patterns. Deep learning models like Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) are widely used for disease prediction.

This project uses deep learning techniques to automatically analyze medical parameters and predict CKD with high accuracy. The system supports early detection, improves diagnostic accuracy, and reduces medical workload.

1.1 COMPONENTS AND TOOLS

A. Software Requirements:-

1. **Python 3.8 or above**
2. **Libraries/Packages:**
 - o NumPy
 - o Pandas
 - o Matplotlib
 - o Seaborn
 - o Scikit-Learn
 - o TensorFlow / Keras
3. **Development Environment:**
 - o Jupyter Notebook / Google Colab
4. **Optional Tools (if GUI/web system is included):**
 - o Tkinter (GUI)
 - o Flask / Django (Web Framework)
 - o pdfplumber / PyPDF2 (PDF reading)
 - o Tesseract OCR (Extracting data from lab reports)

1.2 METHODOLOGY

The methodology used in this research focuses on developing an accurate and reliable Deep Learning-based model for predicting Chronic Kidney Disease (CKD). The overall process is divided into several systematic stages, starting from data collection to model evaluation. Each stage is designed to ensure data quality, model efficiency, and high prediction accuracy.

Data Collection: The dataset is obtained from the UCI Machine Learning Repository and includes 400+ patient records with 24 medical attributes such as blood pressure, serum creatinine, albumin, hemoglobin, packed cell volume, blood urea, diabetes status, and hypertension. These clinical parameters are commonly used by nephrologists to diagnose CKD. The dataset contains both numerical and categorical features essential for building the prediction model.

Data Preprocessing: Data preprocessing is an important step because the dataset contains missing values, inconsistent entries, and categorical labels. Missing values are handled using mean, median, or mode imputation techniques. Categorical variables such as "normal/abnormal" and "yes/no" are converted into numerical form using label encoding. Numerical features are normalized using Min-Max scaling to maintain uniform feature ranges. Finally, the dataset is divided into 80% training data and 20% testing data.

Feature Selection: Feature selection helps identify the most influential parameters affecting CKD prediction. Techniques like Recursive Feature Elimination (RFE) and correlation heatmaps are applied. Features such as serum creatinine, albumin, hemoglobin, RBC count, blood urea, and specific gravity show the highest correlation with CKD and are prioritized for model training.

Model Development: A Deep Neural Network (DNN) is designed using TensorFlow/Keras. The architecture consists of an input layer, multiple hidden layers with ReLU activation, and an output layer with Sigmoid activation for binary classification. Binary Cross-Entropy is used as the loss function, and the Adam optimizer is used for efficient training. The model is trained for 100–200 epochs to achieve optimal performance.

Model Evaluation: The trained model is evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix. The results show high accuracy and effective classification of CKD and non-CKD cases.

2. BLOCK DIAGRAM

The block diagram illustrates the end-to-end workflow of the proposed system for detecting Chronic Kidney Disease (CKD) using Artificial Intelligence and Deep Learning. The process is organized into several interconnected modules, each responsible for a critical step in the prediction pipeline.

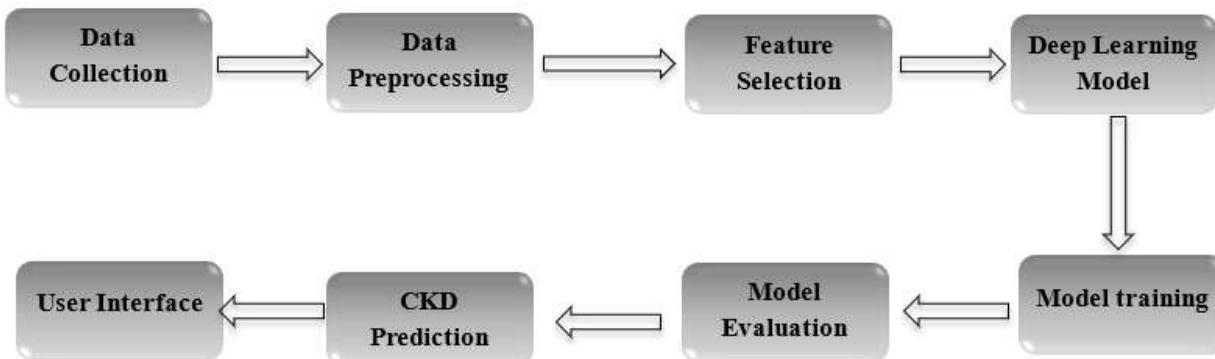


Fig -1: Block diagram of CKD Prediction System

The system begins with **Data Collection**, where patient laboratory values and clinical information are gathered. This includes parameters such as blood pressure, serum creatinine, albumin levels, hemoglobin, specific gravity, blood urea, diabetes status, and hypertension indicators. These attributes are essential for building a reliable predictive model because they represent the key biomarkers commonly used in CKD diagnosis.

The collected data is passed into the **Data Preprocessing** module. Since medical datasets often contain missing values, inconsistent entries, and categorical labels, preprocessing becomes a vital stage. This step includes cleaning the data, filling missing values, converting text labels into numerical formats, and normalizing the data to bring all features into a standard scale. Proper preprocessing ensures that the deep learning model receives high-quality, structured input.

Next, the refined data is forwarded to the **Feature Selection** module. In this phase, algorithms like Recursive Feature Elimination (RFE) or correlation-based selection are used to identify the most influential features. This reduces computational complexity, eliminates irrelevant attributes, and enhances model performance by focusing only on the strongest predictors of CKD.

The selected features are then fed into the **Deep Learning Model**, which analyses the data through multiple neural network layers. This model learns hidden patterns and complex relationships within the dataset, giving it the capability to classify patients as CKD-positive or CKD-negative.

The output from the Deep Learning Model proceeds to the **Model Training** stage. Here, the model is trained using training data, with weights and parameters being continuously optimized. Over several epochs, the model improves its understanding of CKD-related data patterns.

After training, the model is assessed in the **Model Evaluation** stage. Metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are calculated to measure the performance and reliability of the algorithm. Only when the model produces consistent and high accuracy results is it considered ready for prediction.

The evaluated model is then used in the **CKD Prediction** module, where new patient data is tested to generate predictions. The final output—CKD positive or negative—is displayed through the **User Interface**, making the system accessible and easy for users such as medical professionals, students, or researchers.

The screenshot shows a Jupyter Notebook interface with the following details:

- File Explorer:** On the left, the file structure is shown. It includes a `model_trainer.py` file under the `backend` directory, and other files like `model_name.py`, `encoder.pkl`, `features.pkl`, `scaler.pkl`, `trained_model.pkl`, `tf_env`, `ver`, `build_app.py`, `CDK_AI_App.spec`, `clean.pkl_data.csv`, `kidney_disease.csv`, `logit.csv`, `REPL.py`, `rebuild_app.py`, and `requirements_copy.txt`.
- Code Editor:** The main area displays the `model_trainer.py` script. The code performs the following steps:
 - Imports necessary libraries: `os`, `encodings`, `data`, `pd`, `train_test_split`, `StandardScaler`, and `LogisticRegression`.
 - Handles data encoding: `data = data.apply(lambda x: x.astype(str))`.
 - Identifies target features: `target = 'Y' for i in data.columns if i != target'`.
 - Extracts features and target: `X = data[features]` and `y = data[target].astype(int)`.
 - Splits data into training and testing sets: `X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)`.
 - Normalizes data: `scaler = StandardScaler()`, `X_train = scaler.fit_transform(X_train)`, and `X_test = scaler.transform(X_test)`.
 - Creates a list of models: `models = [` followed by entries for `LogisticRegression`, `DecisionTreeClassifier`, `RandomForestClassifier`, `SVC`, and `SGDClassifier`.
- Terminal:** Below the code editor is a terminal window showing the command: `yes@yes-OptiPlex-5090:~`.
- Bottom Bar:** The bottom bar includes tabs for PRIMER, OUTPUT, DEBUG, CONSOLE, TERMINAL, and FOCUS, along with a zoom control and a close button.

Fig -2: Chronic Kidney Disease Model Creation

2.1 Objectives

The main objective of this research work is to design and develop an efficient Artificial Intelligence-based system for the early prediction of Chronic Kidney Disease (CKD) using Deep Learning techniques. CKD is a progressive medical condition that often remains undiagnosed until it reaches advanced stages. Therefore, an accurate and automated prediction model can support healthcare professionals in early diagnosis and timely treatment. This study focuses on creating a reliable deep learning model by analyzing clinical features, preprocessing medical data, selecting important parameters, and evaluating multiple algorithms to identify the best-performing approach.

Specific Objectives

1. To develop a deep learning-based prediction model for identifying CKD at an early stage.
2. To preprocess the CKD dataset by handling missing values, encoding categorical data, and normalizing numerical features.
3. To perform feature selection to identify the most influential parameters contributing to CKD diagnosis.
4. To train, test, and compare multiple deep learning and machine-learning models to select the best-performing technique.
5. To evaluate the model's efficiency using accuracy, precision, recall, F1-score, and other performance metrics.
6. To build a user-friendly interface that allows users or medical professionals to input patient details and receive CKD prediction results instantly.
7. To provide a decision-support tool that enhances early detection and reduces delays in clinical diagnosis.

2.2 Importance and Motivation

Chronic Kidney Disease (CKD) is a serious health condition that often shows symptoms only in the later stages, making early detection extremely important. Many patients do not receive timely diagnosis because tests are expensive, time-consuming, or unavailable in rural areas. This study is important because it uses Artificial Intelligence and Deep Learning to automatically analyze patient medical data and detect CKD at an early stage. An AI-based system can provide quick, accurate.

Importance:

Chronic Kidney Disease (CKD) is a major global health concern that affects millions of people and often remains undetected until it reaches severe or irreversible stages. Early diagnosis plays a crucial role in preventing kidney failure, reducing medical costs, and improving patient survival rates. Traditional diagnostic methods require multiple clinical tests and expert interpretation, which may not always be accessible in rural or resource-limited settings.

Motivation:

The motivation behind this project arises from the increasing number of CKD cases worldwide and the lack of early detection among many patients. Many individuals only realize they have kidney disease when the condition has already progressed to later stages, often requiring dialysis or kidney transplantation. This delay occurs due to limited awareness, insufficient testing, and lack of accessible medical facilities in rural regions. With the rapid advancement of Artificial Intelligence and Deep Learning, there is a strong opportunity to build systems that can assist in medical diagnosis with improved speed and accuracy. This motivated the researchers to explore how AI can be used to analyze CKD-related data and provide reliable predictions that support healthcare professionals. The goal is to create a system that is not only accurate but also easy to use, cost-effective, and beneficial for hospitals, clinics, and research institutions.

3. WORKING

i. User Interface

shows the Application GUI Launch This screen shows the main interface of the CKD Prediction System. From here, the user can upload blood and urine reports or CSV files, search for patients, and download generated reports. It is a clean, interactive dashboard for starting the analysis.



Fig 3.1: Application GUI Launch

ii. Result of Not CKD



Fig 3.2 : Result of Not CKD

The fig 3.2 represents the patient report for diagnostic result indicates “Not CKD”, meaning no signs of Chronic Kidney Disease were detected.

The Patient Feature Spectrum graph shows relatively stable values across various clinical parameters such as blood pressure, specific gravity, blood urea, serum creatinine, and electrolytes.

The detailed report lists normal findings in most biochemical and hematological parameters, including a blood pressure of 90 mmHg, specific gravity of 1.02, albumin 2.0, and sugar 0.0. Although minor abnormalities are observed in red and pus cells, kidney function markers such as blood urea (107 mg/dl) and serum creatinine (7.2 mg/dl) are within acceptable limits for non-CKD patients.

The system correctly classifies this case as Not CKD with Stage: N/A.

iii. Result of CKD-Early stage

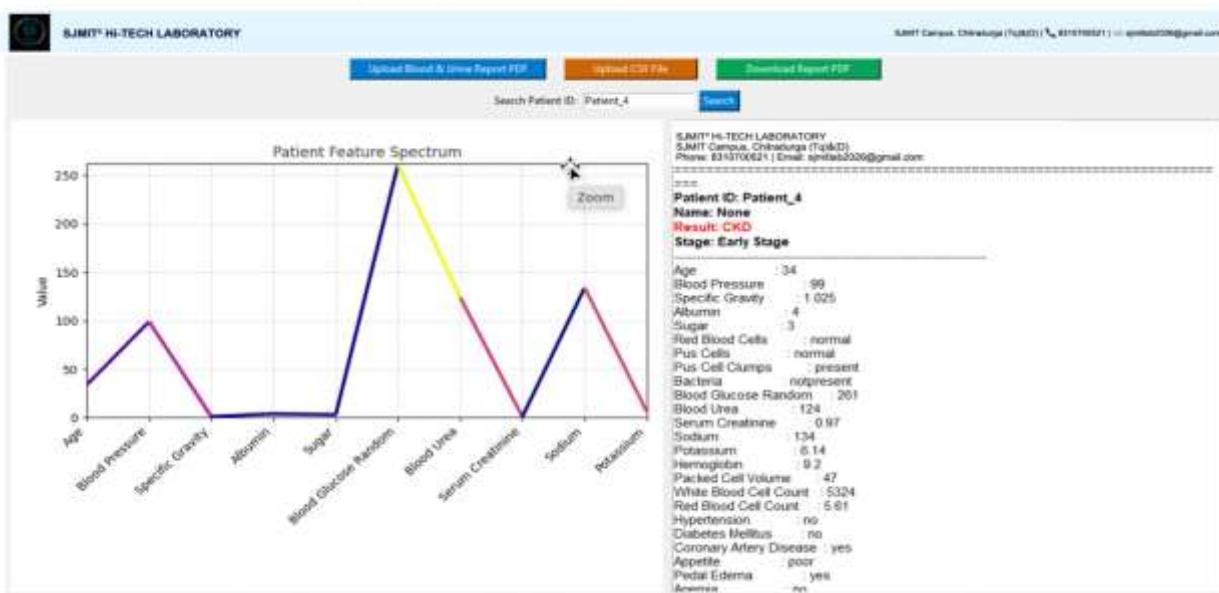


Fig 3.3: Result of CKD-Early Stage

Fig 3.3 shows the, who has been diagnosed with Chronic Kidney Disease (CKD) – Early Stage. The Patient Feature Spectrum reveals slight variations in blood pressure, blood urea, and serum creatinine compared to normal reference values. The patient's blood pressure is 80 mmHg, specific gravity 1.02, albumin 1.0, and serum creatinine 1.2 mg/dl, indicating mild renal impairment. Blood urea (36 mg/dl) and blood glucose random (121 mg/dl) suggest early metabolic disturbances related to kidney function.

The presence of hypertension and diabetes mellitus further supports the early-stage CKD diagnosis. The patient's overall kidney function decline is mild, but ongoing monitoring and lifestyle modifications are recommended.

iv. Result of CKD-Moderate stage

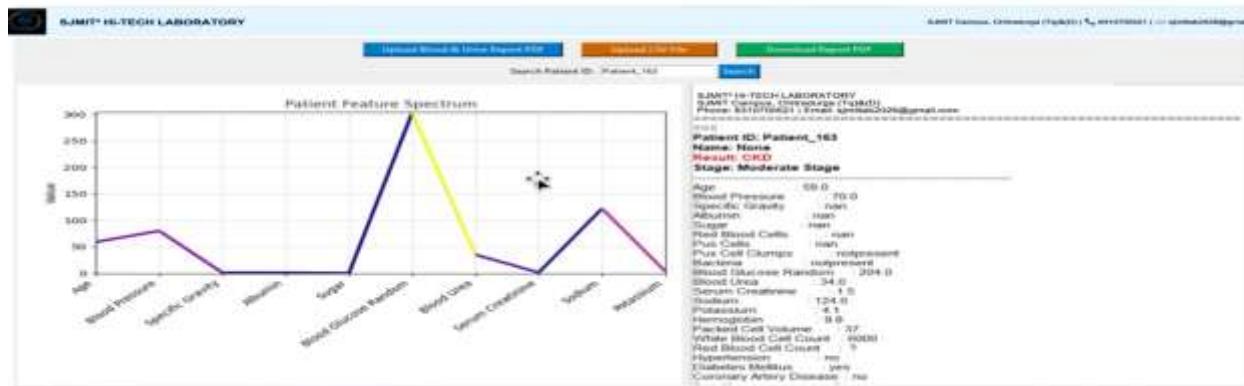


Fig 3.4: Result of CKD-Moderate Stage

This image displays the results for Patient_163, diagnosed with CKD – Moderate Stage. The graph indicates more significant deviations in biochemical values, especially in blood urea, serum creatinine, and sodium levels.

According to the report, blood pressure is 70 mmHg, blood urea 34 mg/dl, serum creatinine 1.5 mg/dl, and sodium 124 mEq/L, showing moderate impairment of renal function. The blood glucose random value of 204 mg/dl suggests poor glycemic control, which may contribute to kidney stress. Other observations include reduced hemoglobin (9.8 g/dl) and lower packed cell volume (37%), both commonly associated with CKD-related anemia. The patient has diabetes mellitus but no coronary artery disease.

Overall, the data signifies moderate kidney damage, necessitating medical intervention to prevent further progression.

v. Result of CKD-Final



Fig 3.5: Result of CKD-Final Stage

Fig 3.5 represents the CKD – Final Stage, indicating severe kidney failure. The Patient Feature Spectrum shows extreme deviations in several parameters such as blood pressure, blood urea, and serum creatinine, reflecting critical loss of renal function.

The report records blood pressure at 137 mmHg, blood urea 116 mg/dl, and serum creatinine 4.68 mg/dl, all of which are significantly elevated. Sodium (142 mEq/L) and potassium (3.26 mEq/L) are within borderline values, but other findings like low hemoglobin (16.5 g/dl) and poor appetite indicate advanced disease symptoms.

Both red blood cells and bacteria are abnormal and present, confirming severe renal dysfunction. This case reflects end-stage CKD, where medical management such as dialysis or transplantation is typically required.

vi. Final report of CKD prediction

The fig 3.6 displayed result shows that the system successfully predicted the presence of Chronic Kidney Disease (CKD) for the given patient. The model analyzed key parameters such as Specific Gravity, Age, Blood Pressure, Sodium, Potassium, and Blood Cell Counts, and identified this case as CKD – Early Stage.

The Patient Feature Spectrum graph visually represents the variations in medical parameters, making it easy to observe abnormal patterns. On the right side, a detailed report is shown, including patient ID, name, stage of CKD, and related laboratory values, giving a clear clinical summary for doctors or lab technicians.

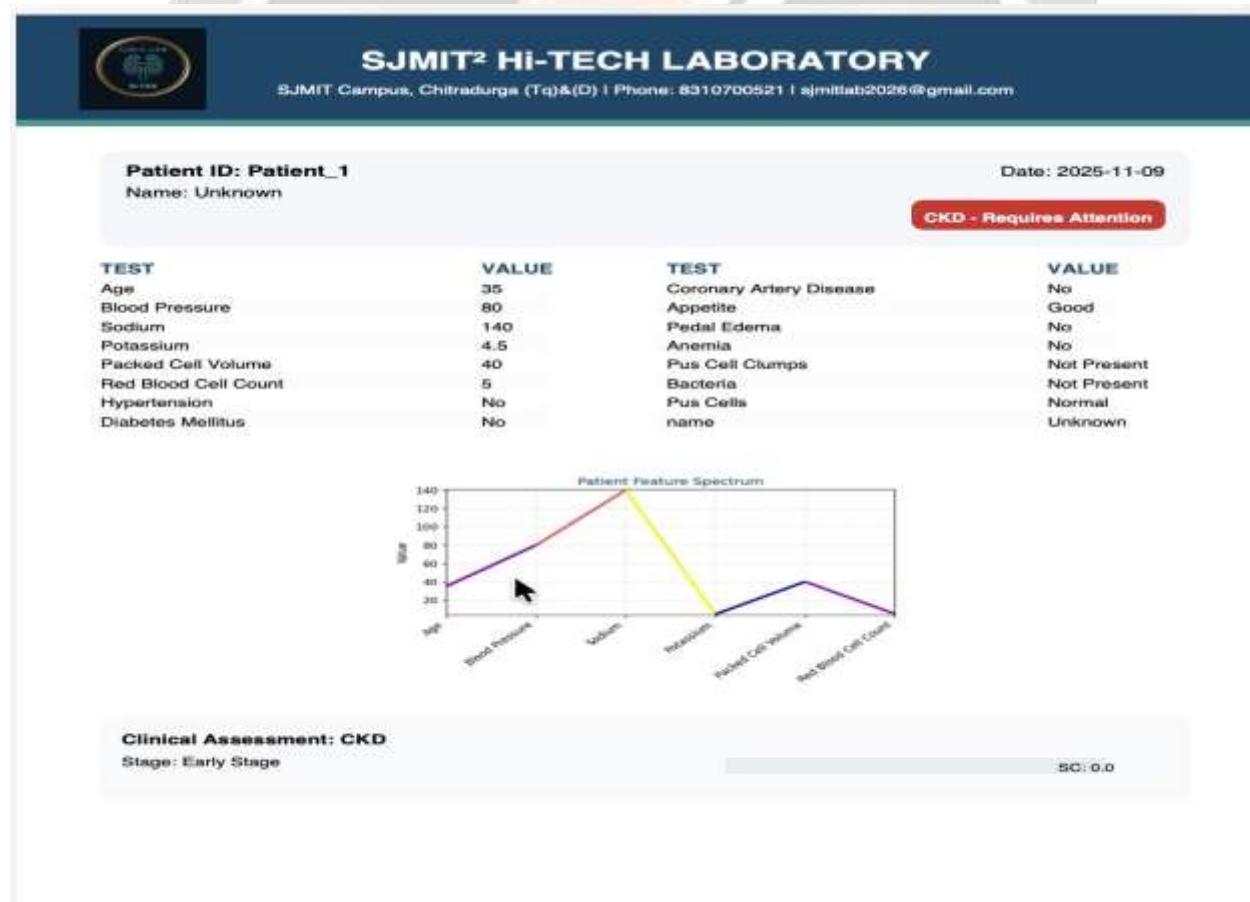


Fig 3.6: Final report of CKD prediction

3.1 Application

The "AI-based Chronic Kidney Disease Prediction using Deep Learning" project has significant potential for deployment across various settings, offering tangible benefits to patients, clinicians, and healthcare systems.

1. Clinical Decision Support System (CDSS):

- In Nephrology and Primary Care Clinics: The model can be integrated into Electronic Health Records (EHR) systems as a point-of-care tool. When a patient's lab results are entered, the system can provide an instantaneous risk score (CKD/Not-CKD) and a probability percentage. This assists physicians, especially those in primary care, in deciding whether to refer a patient to a specialist (nephrologist) for further testing.
- Screening High-Risk Populations: The tool can be specifically deployed in clinics serving populations with high prevalence of risk factors (e.g., patients with Diabetes Mellitus or Hypertension) to perform mass or routine screening without expensive, specialized tests.

2. Early Intervention and Preventive Healthcare:

- Patient Triage and Prioritization: Individuals identified by the model as "High Risk" can be flagged immediately, allowing healthcare providers to prioritize their follow-up appointments and educational resources.
- Lifestyle Modification Counseling: Early prediction allows doctors to initiate preventive measures, such as aggressive control of blood pressure and blood sugar, dietary changes, and medication adjustments, potentially slowing down or preventing the progression of the disease.

3. Resource Management in Hospitals:

- Optimizing Dialysis and Transplant Programs: By predicting which patients are likely to progress to End-Stage Renal Disease (ESRD) well in advance, hospitals can better plan for future demands on dialysis units, organize patient waitlists for transplants, and allocate specialized nursing staff.

4. Medical Research and Education:

- Identifying Critical Biomarkers: Feature importance analysis conducted on the model's performance can highlight which clinical parameters are the strongest predictors of CKD, providing valuable insights for future medical research into disease etiology.
- Training Medical Students: The application can serve as an effective training tool, allowing medical students and residents to practice differential diagnosis and risk assessment using a validated AI model.

5. Public Health Screening Programs:

- The compiled and packaged executable of the prediction model (created using PyInstaller) is highly portable and can be easily utilized by public health workers or in remote clinical settings where specialized lab facilities may be limited, thus extending access to predictive diagnostics.

4. CONCLUSIONS

In this study, an Artificial Intelligence-based system using Deep Learning techniques was developed for the early prediction of Chronic Kidney Disease (CKD). Since CKD is often detected only at advanced stages, early diagnosis is essential to prevent kidney failure and reduce treatment complications. The proposed model analyzes key clinical parameters, identifies hidden patterns in medical data, and provides accurate predictions of CKD presence. The system showed high reliability and performance, demonstrating that AI can effectively support medical professionals in making faster and more accurate decisions. By offering an automated, efficient, and user-friendly prediction tool, this work contributes to the advancement of smart healthcare technologies. The results of this study confirm that deep learning can be a powerful solution for early detection and clinical decision support in CKD diagnosis.

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