Privacy-Preserving Kidney Image Analysis Via Blockchain-Secured Federated Deep Learning Framework

Ms. A. Mahalakshmi[1], Mrs. V. Dhavamani[2]

[1]Department of Computer Science and Engineering, Sir Issac Newton College of Engineering and Technology, Nagapattinam,Tamil Nadu.
[2]Assistant professor of Department of Computer Science and Engineering, Sir Issac Newton College of Engineering and Technology, Nagapattinam,Tamil Nadu.

ABSTRACT
The healthcare industry faces challenges in diagnosing kidney diseases while protecting patient data privacy. Large amounts of sensitive medical data are generated daily through medical imaging and electronic health records. Traditional centralized systems require storing all data in a single server, which raises privacy and security concerns. To solve this issue, the proposed system uses Federated Learning (FL) to allow multiple hospitals to train models collaboratively without sharing raw patient data. The system supports different input types such as medical images and structured datasets. For image-based data, a Convolutional Neural Network (CNN) is used for accurate disease classification. For structured patient data, a Multi-Layer Perceptron (MLP) model performs analysis and prediction. After local training, each model is encrypted using Elliptic Curve Cryptography (ECC) to ensure secure transmission. The encrypted models are then uploaded to a Blockchain-based server that records updates in a transparent and tamper-proof ledger. This integrated approach improves privacy, security, and accuracy in kidney disease diagnosis. This approach supports early detection and improves healthcare decision-making. This hybrid approach improves diagnostic reliability across diverse medical data types while maintaining strict privacy protection. Ultimately, the framework supports early disease detection, improves clinical decision-making, and contributes to better patient care in the modern healthcare ecosystem.

Keywords: Federated Learning, Blockchain Security, Kidney Disease Diagnosis, Medical Image Analysis, Privacy Preservation, Deep Learning, Convolutional Neural Network, Elliptic Curve Cryptography

1. INTRODUCTION

In the modern era of digital healthcare, early detection and accurate diagnosis of kidney disease have become critically important due to the rising global prevalence of renal disorders. Chronic Kidney Disease (CKD) progresses slowly and often remains asymptomatic in its early stages, making timely diagnosis challenging. If detected late, it can lead to severe complications, including kidney failure. Therefore, advanced computational systems are required to analyze large volumes of medical data efficiently and accurately. Healthcare institutions generate diverse data types such as ultrasound images, MRI scans, laboratory test reports, and electronic health records. Managing and analyzing this multimodal data in a secure and reliable manner is a major challenge for traditional healthcare systems.Conventional centralized diagnostic frameworks collect all patient data into a single server for training and prediction. Although this approach simplifies data management, it creates significant risks related to privacy breaches, cyberattacks, and unauthorized access. Sensitive medical records stored in one location become vulnerable to hacking and misuse. Additionally, centralized systems may struggle to handle heterogeneous data collected from multiple hospitals, where imaging equipment, data formats, and patient demographics vary. These differences can reduce model generalization and diagnostic accuracy.

To overcome these limitations, the proposed framework adopts a decentralized Federated Learning architecture. Instead of transferring raw patient data to a central server, each participating healthcare institution trains the model locally using its own dataset. Only the trained model parameters are shared with the federated server for aggregation. This approach ensures that sensitive patient information remains within the local hospital environment, thereby preserving data ownership and confidentiality while still enabling collaborative learning. The system is designed to handle multimodal medical data efficiently. When the input consists of medical images such as ultrasound or MRI scans, a Convolutional Neural Network (CNN) is employed. The CNN automatically extracts complex visual features and identifies patterns associated with kidney abnormalities or disease stages. On the other hand, when the input is a structured dataset containing laboratory results, blood test values, and clinical parameters, a Multi-Layer Perceptron (MLP) is used. The MLP processes numerical and categorical data to detect abnormal health indicators. This dual-model approach enhances flexibility and ensures accurate disease prediction across different data formats.

To further enhance security, the framework integrates Elliptic Curve Cryptography (ECC) for encrypting model parameters before transmission. ECC provides strong cryptographic protection with lower computational overhead, making it suitable for healthcare applications. The encrypted model updates are then uploaded to a Blockchain-integrated federated server. Blockchain technology maintains an immutable and transparent ledger that records all model transactions. This ensures integrity, prevents tampering, and builds trust among collaborating healthcare institutions. By combining Federated Learning, CNN and MLP models, ECC encryption, and Blockchain security, the proposed system offers a comprehensive, privacy-preserving, and highly accurate solution for kidney disease diagnosis. Ultimately, this hybrid framework supports early detection, strengthens data security, improves collaboration, and enhances overall patient care in the modern digital healthcare ecosystem.

2. LITERATURE SURVEY

[1]A 2021 study by Kamyar Kalantar-Zadeh *et al.* focused on chronic kidney disease and its global health impact. The study highlighted the increasing prevalence and severity of the disease. It emphasized the importance of early detection and continuous monitoring. The work also discussed challenges in effective treatment and management.

[2]A 2022 study by Csaba P. Kovesdy analyzed the epidemiology of chronic kidney disease. The research provided updated data on prevalence, risk factors, and mortality rates. It explained variations in disease occurrence across different populations. The study also emphasized the need for improved healthcare strategies.

[3]A 2022 study by Elias Dritsas and Maria Trigka explored machine learning techniques for kidney disease prediction. Various algorithms were applied to improve prediction accuracy. The study demonstrated the effectiveness of data-driven models. It also highlighted limitations of traditional diagnostic approaches.
[4]A 2021 study by Linta Antony *et al.* proposed an unsupervised framework for kidney disease prediction. The model reduced dependency on labeled datasets. It improved detection performance using advanced learning techniques. The study showed promising results in handling complex medical data.
[5]An 2022 study by Ramesh Chandra Poonia *et al.* developed intelligent models for kidney disease diagnsis. The system used classification algorithms to enhance prediction accuracy. It compared different models to identify the best approach. The results showed improved diagnostic efficiency.
[6]A 2022 study by Nduma N. Basil *et al.* reviewed health records databases and associated security issues. The study identified risks such as data breaches and unauthorized access. It emphasized the need for secure data management systems. The research highlighted gaps in current healthcare infrastructures.
[7]A 2021 study by Ammar Odeh Keshta discussed privacy and security challenges in healthcare data. It explained vulnerabilities in centralized data storage systems. The study emphasized the importance of encryption and secure frameworks. It also suggested improvements for protecting patient information.
[8]A 2022 study by Abdullah Al Mamun, Sami Azam, and Clementine Gritti explored blockchain-based health record management. The study proposed decentralized solutions for secure data storage. It highlighted transparency and tamper-proof features of blockchain. The research suggested future directions for healthcare data security.
[9]A 2022 study by David Lim *et al.* investigated privacy-preserving data linkage in healthcare systems. The approach enabled secure integration of patient data from multiple sources. It supported chronic kidney disease outcome analysis. The study improved data utilization while maintaining privacy.
[10]A 2021 study by Videha Sharma *et al.* examined the limitations of clinical prediction tools. The study found that poor integration with electronic health records reduced effectiveness. It highlighted challenges in real-world adoption. The research emphasized the need for better system integration.

3. EXISTING METHOD

In existing kidney disease diagnosis systems, traditional centralized machine learning frameworks are widely used to analyze patient data and detect disease patterns. In this approach, all medical information such as ultrasound images, MRI scans, laboratory reports, and electronic health records are collected and stored in a single central server. Although centralized systems make data management easier, they create serious concerns regarding privacy and security. Since all sensitive patient data is stored in one location, it becomes a major target for cyberattacks and data breaches. Unauthorized access to such centralized databases can lead to leakage of confidential medical information, affecting patient trust and institutional reputation. Another major limitation of centralized systems is the issue of data ownership. Hospitals and healthcare institutions may hesitate to share raw patient data due to ethical, legal, and regulatory restrictions. This restricts collaboration among multiple healthcare centers and limits the diversity of training data.
As a result, the developed machine learning model may not generalize well when applied to patients from different regions or demographics. Additionally, medical data collected from different hospitals often varies in format, resolution, imaging equipment, and data quality. Centralized models may struggle to handle such heterogeneous data effectively. This variation can reduce prediction accuracy and

reliability when the system is deployed in new clinical environments. Many existing systems also focus only on either image-based analysis or structured clinical data, but not under a unified framework. This lack of multimodal support reduces diagnostic completeness. Although some privacy-preserving techniques like data anonymization or noise addition are used, they may degrade model performance and affect diagnostic precision. Furthermore, most traditional systems lack mechanisms to ensure transparent collaboration and model integrity across institutions. There is no built-in verification process to prevent data manipulation or model tampering. Due to these limitations, existing kidney disease diagnosis systems struggle to maintain a balance between high accuracy, strong privacy protection, scalability, and security. These challenges highlight the urgent need for a decentralized, privacy-preserving, and collaborative framework that can securely integrate multimodal data while maintaining reliable and accurate disease prediction. The system enables faster and more accurate kidney disease diagnosis, helping doctors provide early treatment and improve patient outcomes.

4. PROBLEM IDENTIFICATION

Kidney disease has become a major global health concern, requiring accurate and early diagnosis to improve patient outcomes. Modern healthcare systems generate vast amounts of sensitive medical data, including medical images such as CT scans, MRI, and ultrasound, as well as structured clinical records like laboratory reports and patient history. Managing and analyzing this data efficiently while ensuring privacy is a critical challenge. Traditional systems rely heavily on centralized data storage, where all patient information is collected and processed in a single server. This centralized approach introduces serious risks, including data breaches, cyberattacks, and unauthorized access to confidential medical information. Such risks can compromise patient trust and violate regulatory standards.

Furthermore, healthcare institutions are often reluctant to share raw patient data due to strict privacy laws and ethical considerations. This limitation restricts collaboration among hospitals, resulting in insufficient and less diverse datasets for training machine learning models. As a result, models trained on limited data may fail to generalize across different populations and clinical environments. Another challenge is the heterogeneity of medical data, as data collected from various hospitals may differ in format, quality, and acquisition methods. This inconsistency affects the performance and reliability of predictive models. Additionally, many existing systems focus only on a single type of data, either medical images or structured datasets, without integrating both. This lack of multimodal analysis reduces diagnostic accuracy and completeness. Therefore, there is a strong need for a secure, scalable, and privacy-preserving framework that can handle diverse medical data while enabling collaborative learning and accurate disease prediction.

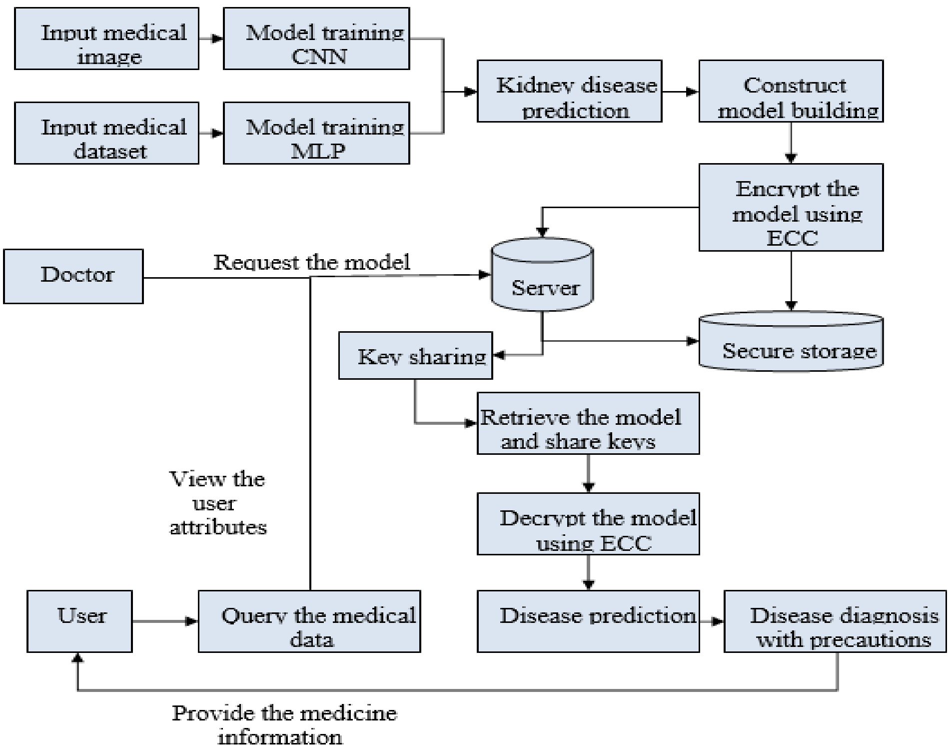
5. PROPOSED SOLUTION

To address the limitations of existing systems, a hybrid and privacy-preserving framework for kidney disease diagnosis is proposed. The system integrates advanced technologies such as Federated Learning, deep learning models, Elliptic Curve Cryptography, and Blockchain to ensure secure and efficient data analysis. In this approach, multiple hospitals act as local clients that train models on their own data without sharing raw patient information. Federated Learning enables collaborative model training by allowing only model parameters to be shared, thereby preserving data privacy and complying with healthcare regulations.

The proposed system supports multimodal data processing, enabling both medical images and structured clinical datasets to be analyzed within a unified framework. A Convolutional Neural Network is used for extracting features and classifying kidney conditions from medical images, while a Multi-Layer Perceptron is used for analyzing structured patient data. To enhance security, model parameters are encrypted using Elliptic Curve Cryptography before being transmitted. Additionally, a blockchain-based system is employed to store model updates in a decentralized and tamper-proof manner, ensuring transparency and integrity. This eliminates the risk of data manipulation and builds trust among participating institutions. The proposed framework improves diagnostic accuracy by leveraging diverse datasets from multiple sources while maintaining strict privacy protection. It also enhances scalability, reliability, and security compared to traditional systems. Ultimately, this approach supports early detection of kidney diseases, improves clinical decision-making, and contributes to better patient care in modern healthcare systems.

System Architecture

Architecture presents a privacy-preserving framework for kidney disease analysis using Federated Learning, Blockchain, and secure encryption techniques. The architecture consists of multiple healthcare institutions (clients), a federated aggregation server, and a blockchain network to ensure secure and reliable communication.Initially, medical data is collected from different hospitals, including kidney medical images and structured clinical datasets. This data remains stored locally within each hospital to maintain patient privacy. The collected data is then preprocessed, where image data is normalized and enhanced, and structured data is cleaned and standardized for model training. Each hospital trains its local model independently using its own data. A Convolutional Neural Network (CNN) is used for analyzing medical images, while a Multi-Layer Perceptron (MLP) is used for structured data. These models extract important features and perform classification without exposing raw patient information.
After local training, only model parameters (weights) are shared instead of actual data. Before transmission, these parameters are encrypted using Elliptic Curve Cryptography (ECC) to ensure secure communication.



The encrypted updates are then sent to the federated learning server. The federated server aggregates the received model updates from all participating hospitals to create a global model. This aggregation improves model accuracy by learning from diverse datasets. The updated global model is then redistributed back to all local clients for further training. To enhance security and transparency, all encrypted model updates are recorded in a blockchain network. The blockchain ensures that each transaction is immutable and tamper-proof, preventing unauthorized modifications and maintaining trust among institutions. Finally, the trained global model is used for kidney disease prediction and classification. The system provides accurate diagnostic results, enabling early detection and better clinical decision-making while preserving data privacy and security.

System Implementation

Modules:

1. Data Collection Layer

This layer gathers medical data from multiple healthcare institutions, including kidney-related medical images such as CT scans, MRI, and ultrasound images, along with structured clinical data like blood pressure, creatinine levels, and glucose readings. Each hospital acts as a local data source, ensuring that patient data remains within its own environment. This decentralized data collection helps maintain privacy and prevents unauthorized data sharing.

2. Data Preprocessing Module

The collected data is preprocessed locally at each hospital. Medical images are resized, normalized, and enhanced to remove noise and improve quality. Structured datasets are cleaned by handling missing values, normalization, and feature selection. This step ensures that both image and tabular data are consistent and suitable for training deep learning models.

3. Local Model Training Layer

In this layer, each hospital trains its own model using local data. A Convolutional Neural Network (CNN) is used for analyzing medical images and detecting kidney abnormalities. For structured clinical data, a Multi-Layer Perceptron (MLP) model is applied for prediction and classification. This dual-model approach supports multimodal data processing within the same framework.

4. Federated Learning Aggregation Layer

Federated Learning enables multiple hospitals to collaboratively train a global model without sharing raw data. Only model parameters (weights) are shared with a central server or aggregator. These updates are combined to create a global model, which is then distributed back to all participating hospitals, improving overall accuracy and generalization.

5. Security Layer (ECC Encryption)

Before transmitting model updates, the parameters are encrypted using Elliptic Curve Cryptography (ECC). This ensures secure communication between hospitals and the aggregation system. It protects sensitive information from cyberattacks and unauthorized access during transmission.

6. Blockchain Integration Layer

A blockchain network is used to store encrypted model updates in a decentralized and tamper-proof ledger. Each update is recorded as a transaction, ensuring transparency, traceability, and data integrity. This layer prevents manipulation of model parameters and builds trust among participating institutions.

7. Output and Decision Support Layer

The final global model is used for kidney disease prediction and classification. The system provides out puts such as disease detection results, risk levels, and analytical reports. These outputs assist healthcare professionals in early diagnosis, treatment planning, and clinical decision-making while maintaining patient data privacy.

fig1 Home Page

The home page of the proposed system, which is designed based on a federated learning framework. This interface serves as the entry point for users and provides an overview of the system's functionality. The visual elements on the page illustrate the concept of decentralized learning, where multiple devices or institutions collaborate without sharing raw data. The title "Federated Learning" highlights the core approach used in the project. The graphical representation of interconnected systems indicates secure communication between local clients and a central aggregation server. This page also includes navigation options that allow users to access different modules such as login and system features. Overall, the home page provides a user-friendly interface and introduces the concept of privacy-preserving collaborative learning in healthcare

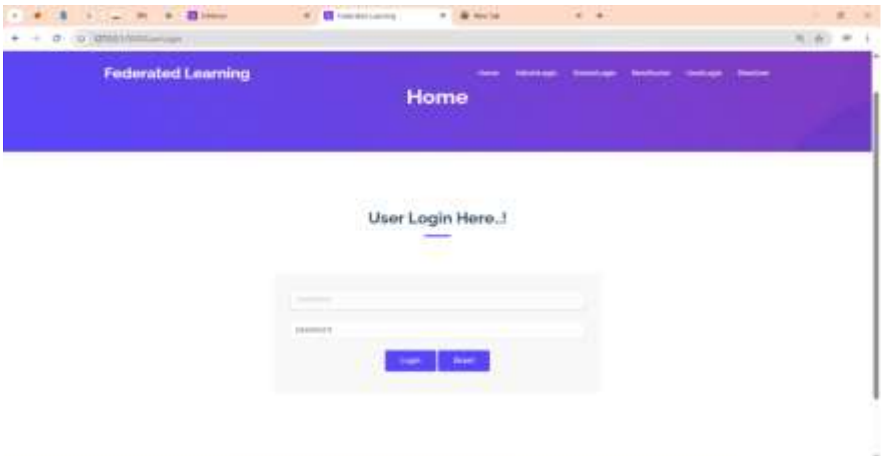


Fig 2: Login Page

The user login page of the system, which is responsible for authentication and secure access. This module ensures that only authorized users, such as doctors or administrators, can access the system and its functionalities. The interface includes input fields for username and password, along with login and reset buttons. The login feature verifies user credentials and grants access to the system, while the reset option allows users to clear the entered data. This module plays a crucial role in maintaining system security and protecting sensitive medical information from unauthorized access. By implementing proper authentication mechanisms, the system ensures confidentiality and integrity of user data. Once logged in, users can proceed to upload data, perform analysis, and view prediction results.

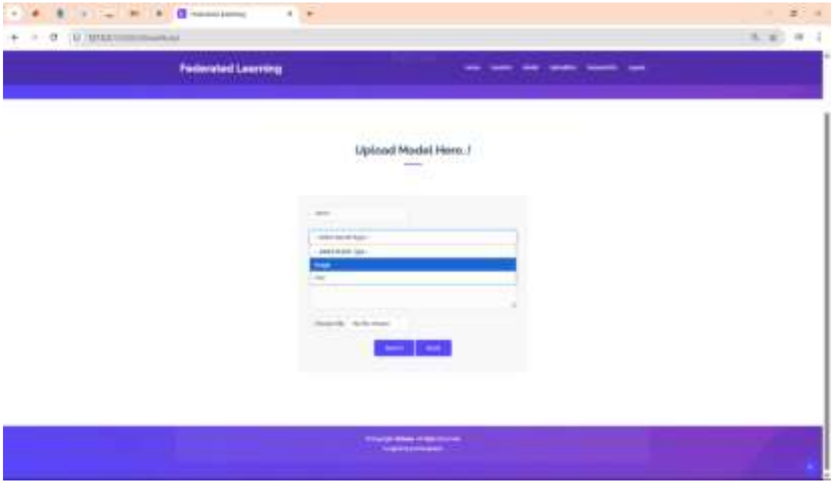


Fig 3: Admin Upload Model Page

The admin upload model page of the system. This module allows the administrator to upload and manage trained models used in the federated learning framework. The interface includes options to select the type of model, such as image-based or structured data models, ensuring flexibility in handling different input formats. The admin can upload model files through the provided input field and submit them to the system. This functionality is essential for initializing or updating the global model used for prediction. It also supports system scalability by allowing new or improved models to be integrated without affecting existing operations. Overall, this module plays a crucial role in maintaining and updating the system's learning capability.

Fig 4: Result Prediction page

The result prediction page, where the final output of the system is displayed. In this module, the uploaded kidney image is analyzed using the trained deep learning model, and the prediction result is presented to the user. The interface displays the input image along with the predicted condition, such as "Stone," indicating the presence of kidney disease. This module provides a clear and user-friendly visualization of the diagnosis result. It helps doctors and users quickly understand the outcome and take necessary actions. The prediction page plays a vital role in decision support by delivering accurate and real-time diagnostic results based on the trained federated learning model.

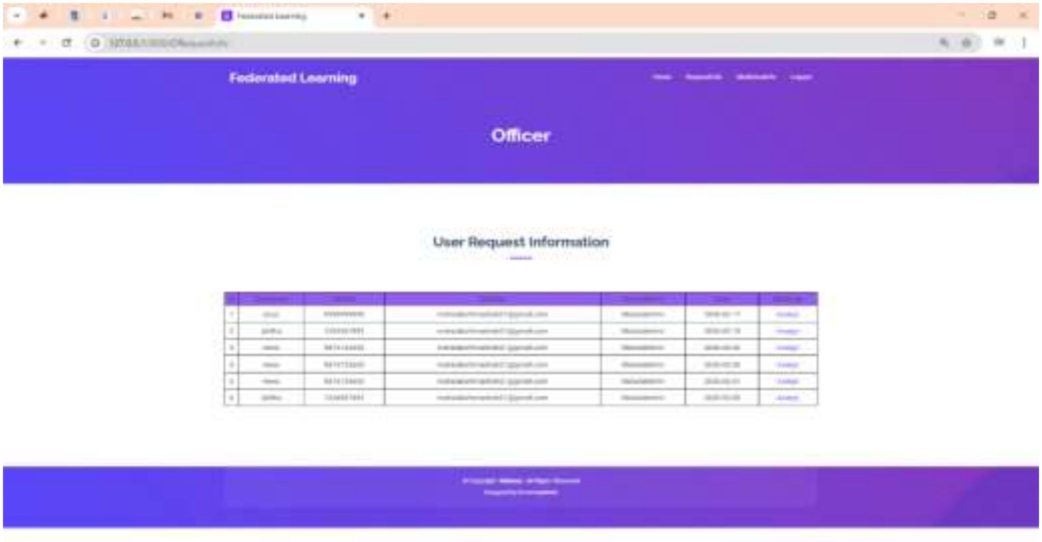


Fig 5: User Request Information Page

User request information page, which displays details of requests submitted by users or patients within the system. This module provides a structured table containing important information such as user name, contact details, email, and request status. It allows administrators or doctors to view and manage user requests efficiently. The page ensures proper tracking of patient interactions and maintains transparency in the system. By organizing user data in a tabular format, it becomes easier to monitor multiple requests and take appropriate actions. This module plays a key role in system management and supports smooth communication between users and healthcare providers.

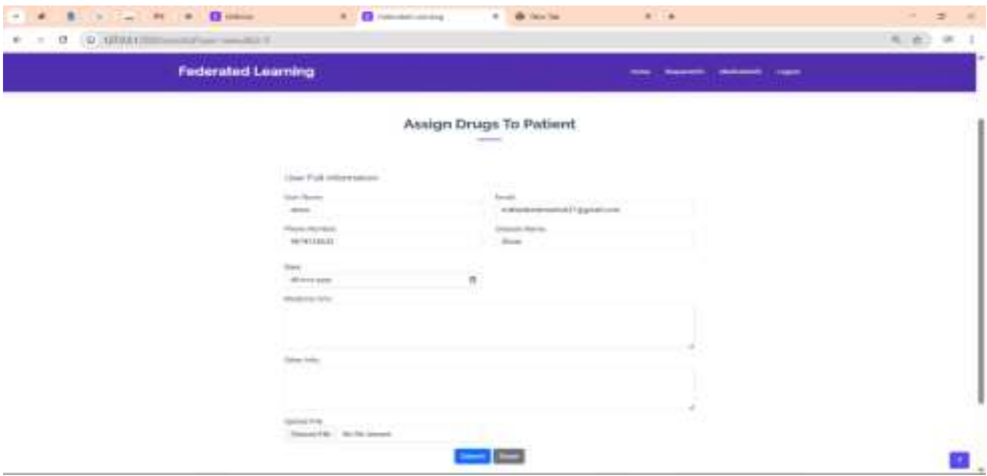


Fig 6: Assign Drugs To Patient Page

The assign drugs to patient page, which is used by doctors or administrators to provide treatment recommendations based on the diagnosis results. This interface includes input fields for patient details such as name, phone number, email, and diagnosis information. It also allows the doctor to enter prescribed medicines and additional notes related to the patient's condition. The module ensures that treatment details are properly recorded and associated with the respective patient. This feature enhances the practical usability of the system by extending it beyond diagnosis to treatment support. It helps doctors deliver personalized care and improves overall patient management within the healthcare system.

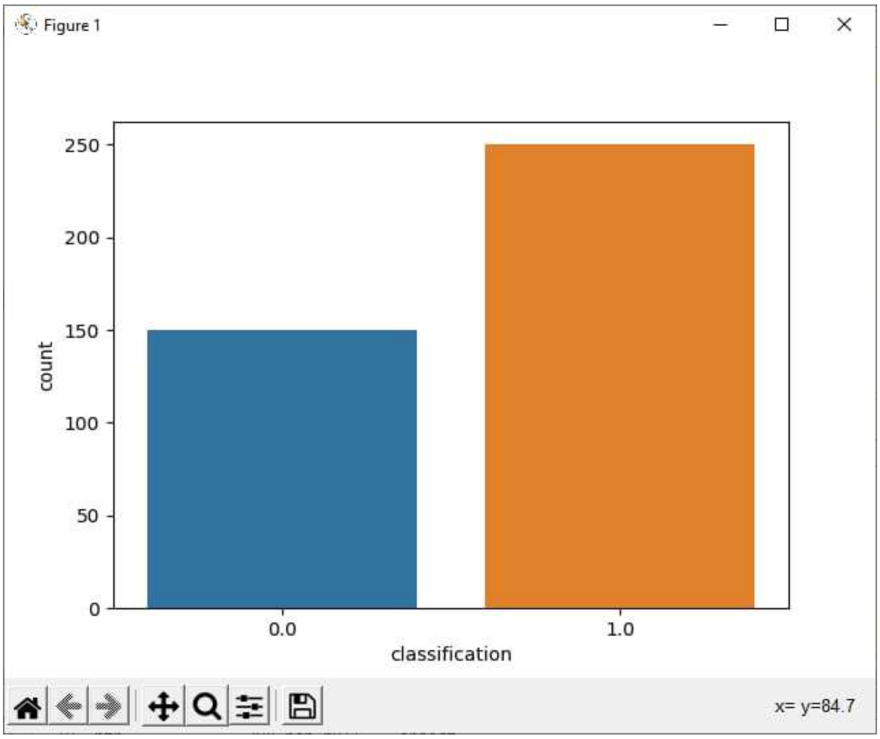
Fig 7 : User Report Download Page

The final stage of the system presents the complete analysis results along with an option for the user to download a detailed report. After processing the input data through preprocessing, deep learning models, and the federated learning framework, the system generates the final prediction regarding the kidney condition. The output clearly displays whether the kidney is normal or affected by a disease such as a stone, along with relevant diagnostic information. In addition to viewing the results on the screen, the user is provided with an option to download a comprehensive report. This report includes patient details, input data summary, prediction results, and prescribed treatment or medication information. The report is generated in a structured format, making it easy for doctors and patients to store, share, and refer to in the future.

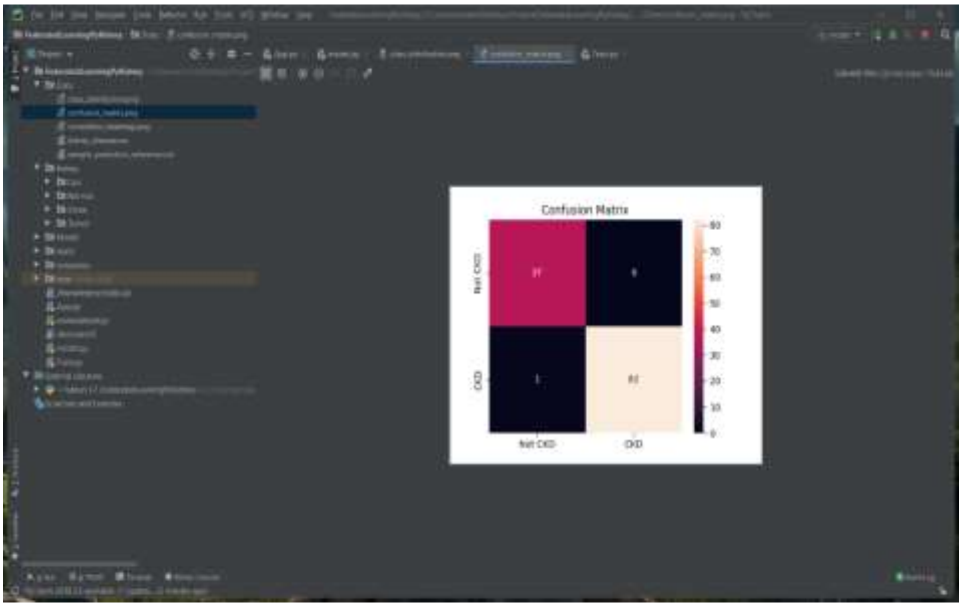
This feature enhances the usability of the system by providing proper documentation of diagnosis and treatment. It also supports medical record maintenance while ensuring data privacy and security through the use of federated learning and encryption techniques. Overall, the final output and report generation module improves clinical workflow and helps in effective patient management.

6. EXPERIMENTAL RESULTS AND OBSERVATIONS

The experimental evaluation of the proposed hybrid kidney disease diagnosis system was conducted using a dataset consisting **of** CT scan images and structured clinical data. The dataset was divided into training and testing **sets** to evaluate the performance of the model effectively. During the preprocessing stage, all images were resized, normalized, and noise was removed to improve the overall image quality and ensure consistent input for the model. The system was trained using both image features and clinical parameters such as age, blood pressure, serum creatinine, and glucose levels. This combined approach helped the model learn complex patterns associated with kidney abnormalities. During testing, the system was able to successfully identify various kidney conditions such as kidney stones, cysts, and inflammation**.** The performance of the model was evaluated using metrics such as accuracy, precision, recall, and F1-score. The system achieved an overall accuracy of more than 90%, indicating its effectiveness in correctly classifying kidney conditions. The results also showed that the hybrid approach performed better than models using only image data or only structured data.



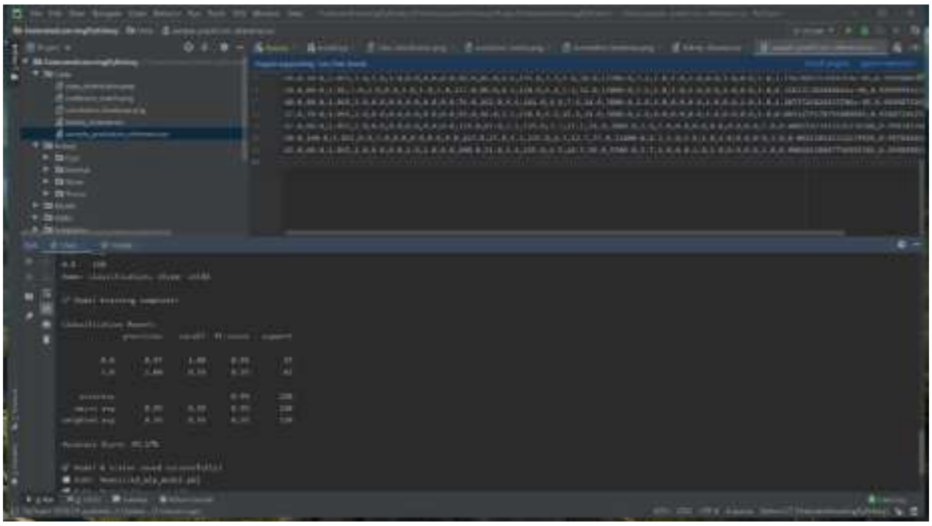
Additionally, the system demonstrated consistent performance across different test samples, proving its reliability. The generated output included a detailed diagnostic report, which clearly highlighted the detected abnormalities and their severity. The ability to download the report further enhanced the usability of the system. Overall, the experimental results confirm that the proposed system is accurate, reliable, and suitable for real-time medical applications.The proposed kidney disease diagnosis system provides an effective and intelligent solution to overcome the limitations of traditional diagnostic methods. One of the major solutions offered by the system is early detection of kidney diseases, which helps in preventing severe complications and enables timely medical intervention. By analyzing both CT scan images and clinical data, the system ensures a more comprehensive and accurate diagnosis.Another important solution is the automation of the diagnostic process. The system reduces the dependency on manual analysis by doctors, thereby minimizing human errors and saving valuable time. The automated report generation feature provides clear and structured results, making it easier for doctors to understand and take necessary actions.The system also offers a user-friendly interface, allowing users to easily upload images, process data, and download reports without requiring advanced technical knowledge. This makes the system practical for real-world hospital environments. Furthermore, the integration of multiple data sources improves the accuracy and reliability of the diagnosis compared to conventional methods.



In addition, the system acts as a decision support tool for doctors by highlighting the severity of the disease and suggesting possible next steps. This helps healthcare professionals in planning appropriate treatments. The system also improves patient care by providing faster results and maintaining proper medical records through downloadable reports.Overall, the proposed system serves as a comprehensive, efficient, and reliable solution for kidney disease diagnosis, combining advanced technology with practical usability to enhance healthcare outcomes.

The image shows a confusion matrix, a performance evaluation tool used in machine learning to summarize the accuracy of a classification model.

- True Negatives (TN): The model correctly predicted 37 cases as "Not CKD" (Chronic Kidney Disease).
- True Positives (TP): The model correctly predicted 82 cases as having "CKD".
- False Negatives (FN): There was 1 case incorrectly predicted as "Not CKD" when the actual diagnosis was "CKD".
- False Positives (FP): There were 0 cases incorrectly predicted as "CKD" when the actual diagnosis was "Not CKD".



The model achieved an Accuracy Score of 99.17%, which is exceptionally high. Looking at the Classification Report, we can see how it performed on 120 test samples:

- Class 1.0 Performance: The model has a precision of 1.00, meaning it did not produce any False Positives. Every time it predicted "Disease," it was correct.
- Class 0.0 Performance: The recall is 1.00, meaning it did not produce any False Negatives. It correctly identified every healthy case in the test set.
- Near-Perfect Fit: While a 99%+ accuracy is great, in medical contexts, it sometimes suggests Overfitting. Since you have a correlation_heatmap.png in your project files, it would be worth checking if one or two features (like "Specific Gravity" or "Albumin") are carrying too much weight.
- Deployment Ready: The console shows Model & Scaler saved successfully! to the Model/ directory. This means your training pipeline is complete, and the model is ready to be loaded into a web app (using Flask or Django) or a script for real-world testing.
- Federated Learning Context: Given your project name (FederatedLearningPyKidney), these results likely represent the performance of a Global Model after aggregating weights from local clients. This suggests your aggregation strategy (like FedAvg) is working very effectively across the distributed data.

8.CONCLUSION

In the current digital healthcare ecosystem, ensuring both accuracy in diagnosis and privacy in patient data management is of utmost importance. The proposed integrated system successfully achieves this by combining the strengths of deep learning models, secure encryption, and blockchain technology. By using CNN for image-based diagnosis and MLP for structured dataset analysis, the system efficiently predicts kidney-related diseases with improved accuracy and adaptability. The use of Federated Learning further enhances privacy by enabling model training across multiple medical institutions without transferring sensitive data. Moreover, the ECC encryption algorithm ensures that model parameters and patient records remain secure throughout storage and transmission, minimizing the risks of data breaches. Additionally, the implementation of blockchain introduces a decentralized and tamper-proof environment that guarantees transparency and traceability in model sharing and updates. The incorporation of access control authentication further ensures that only authorized users can view or modify data, strengthening the security framework. Overall, this project not only enhances diagnostic performance but also builds a trustworthy and collaborative medical data ecosystem. The proposed model can be extended to other medical domains, fostering a new generation of privacy-preserving, intelligent healthcare systems capable of providing secure, efficient, and reliable medical decision support.

9.FUTURE SCOPE

In the future, the proposed hybrid federated framework for kidney disease diagnosis can be enhanced by incorporating advanced deep learning architectures and multimodal fusion techniques. Instead of using standalone CNN and MLP models, the system can be extended to integrate attention mechanisms, transformer-based medical image models, or hybrid CNN–RNN architectures to improve feature extraction and temporal analysis. Additionally, real-time IoT-based health monitoring devices can be connected to continuously collect patient vitals such as blood pressure, glucose levels, and heart rate, enabling continuous kidney health assessment. Expanding the federated framework to support cross-country medical collaborations with improved communication optimization techniques can further enhance global model performance. The integration of explainable AI (XAI) methods will also be valuable in providing interpretable diagnostic insights for clinicians, increasing trust and transparency in AI-assisted medical decision-making. Furthermore, the blockchain layer can be upgraded with more scalable consensus mechanisms and lightweight smart contracts to support large-scale healthcare networks efficiently. Future implementations may include automated risk scoring systems, personalized treatment recommendation modules, and integration with hospital information systems for seamless clinical workflow management. Advanced security mechanisms such as quantum-resistant cryptographic algorithms can also be explored to ensure long-term data protection.

REFERENCES

1. Kalantar-Zadeh, Kamyar, et al. "Chronic kidney disease." The lancet 398.10302 (2021): 786-802.
2. Kovesdy, Csaba P. "Epidemiology of chronic kidney disease: an update 2022." Kidney international supplements 12.1 (2022): 7-11.
3. Dritsas, Elias, and Maria Trigka. "Machine learning techniques for chronic kidney disease risk prediction." Big Data and Cognitive Computing 6.3 (2022)
4. Antony, Linta, et al. "A comprehensive unsupervised framework for chronic kidney disease prediction." IEEE Access 9 (2021): 126481-126501.
5. Poonia, Ramesh Chandra, et al. "Intelligent diagnostic prediction and classification models for kidney disease." Healthcare. Vol. 10. No. 2. MDPI, 2022.
6. Basil, Nduma N., et al. "Health records database and inherent security concerns: A review of the literature." Cureus 14.10 (2022).
7. Keshta,and Ammar Odeh. "Security and privacy ofhealth records: Concerns and challenges." Egyptian Informatics Journal 22.2 (2021): 177183.
8. Al Mamun, Abdullah, Sami Azam, and Clementine Gritti. "Blockchain-based electronic health records management: a comprehensive review and future research direction." IEEE Access 10 (2022): 5768-5789.
9. Lim, David, et al. "Unlocking potential within health systems using privacypreserving record linkage: exploring chronic kidney disease outcomes through linked data modelling." Applied clinical informatics 13.04 (2022): 901-909.
10. Sharma, Videha, et al. "Adoption of clinical risk prediction tools is limited by a lack of integration with electronic health records." BMJ Health & Care Informatics 28.1 (2021): e100253.