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Health Chain: Kidney Liver Disease Diagnosis with Secure Organ Donation Using Blockchain

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Abstract- —This paper presents an integrated framework that leverages blockchain techniques and machine learning for the diagnosis of Kidney Disease and liver diseases. Combining blockchain-based decentralized organ donation systems with advanced machine learning models ensures accurate predictions, secure health record management, and efficient organ donation. We employ statistical feature extraction techniques such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) to improve disease classification, while blockchain ensures the security and transparency of the organ donation process. In this model we will be using an ILPD dataset for liver and the UC Irvine Machine Learning Repository for kidney, using attributes from ILPD for liver disease detection. We will integrate both liver and kidney detection and suitable approach for donations as well.

Index Terms: chronic kidney disease (CKD), Chronic liver Disease (CLD) Organ transplantation, Early detection, Blockchain technology, Decentralized platform.

I. Introduction

Advancement in medical science and technology has led to the creation of advanced diagnostic tools and treatment methods, significantly improving patient outcomes. In particular, the application of machine learning and deep learning techniques in healthcare has shown promising results in various domains, including disease prediction, diagnosis, and treatment planning. This paper presents a holistic approach using deep learning and machine learning algorithms to predict both kidney disease and liver disease based on various attributes. Undergoing datasets collected from multiple sources, our study aims to identify significant predictors of CKD and CLD and develop robust predictive models to assist user in the diagnosis.

Furthermore, to address the issue of class imbalance prevalent in medical datasets, particularly in datasets, we employ techniques like class weighting and ensemble methods using the Extreme Gradient Boosting classifier. Additionally, we can go further into the use of advanced deep learning architectures, incorporating techniques such as batch normalization, dropout, and multiple hidden layers, to enhance model performance and generalization. In addition to the predictive modelling aspect, this research introduces a blockchain-based organ donation system integrated with the predictive model. Leveraging the transparency, security, and decentralized nature of blockchain technology, our proposed system aims to streamline the organ donation process, ensuring fairness and traceability. By employing smart contracts on the Ethereum blockchain, the platform facilitates a secure and transparent organ matching between donors and recipients, thereby potentially increasing the efficiency and accessibility of organ transplantation procedures. The combined approach of predictive modelling and blockchain technology in healthcare showcases the potential of integrating advanced technologies to address critical healthcare challenges and gives rise to future research that can be made in the healthcare field. Kidney disease signifies that the kidneys are impaired and are not effectively filtering blood as they should. The main function of the kidneys is to eliminate excess water and waste from the blood by producing urine. When a person suffers from kidney disfunction, these waste materials accumulate in the body over time. This condition is termed "chronic" because the damage occurs gradually over an extended period. is becoming increasingly prevalent worldwide, posing significant health challenges. Liver disease represents a spectrum of liver conditions that cause long-term damage, inflammation, and scarring of the liver. These activities progress silently, often showing no symptoms until considerable damage has occurred. Numerous factors can lead to both kidney and liver disease such as diabetes, high blood pressure, obesity, and lifestyle choices.

Additionally, age and gender can influence the risk of developing both conditions. If the kidneys or liver are not functioning properly, individuals may experience symptoms such as abdominal pain, back pain, fever, jaundice, fatigue, or gastrointestinal issues. Kidney disease can be caused by diabetes and high blood pressure, while hepatitis and alcohol abuse are key contributors to liver disease. Therefore, managing and controlling these conditions is crucial for preventing both kidney and liver disease. Generally, both of these diseases do not exhibit noticeable symptoms until the organs are severely damaged. Studies have shown that hospitalization rates due to these diseases have been increasing annually. However, the global mortality rate associated with and remains consistent. There are limited diagnostic tests available to assess the status of these diseases. Existing tests are: eGFR, Urine Test, Blood Pressure, Complete Blood Count, Urinalysis, Blood Glucose Test, Liver Function Test, Renal Function Test, Hemoglobin Test, Urine Sodium Potassium, Glycated Haemoglobin Test, Electrolyte Panel.

II. DIAGNOSTIC TESTS FOR CHRONIC KIDNEY DISEASE (CKD) AND CHRONIC LIVER DISEASE (CLD)

A. eGFR (Estimated Glomerular Filtration Rate): • Purpose: Measures kidney function by estimating the rate at which blood is filtered by the glomeruli (tiny filters in the kidneys). • Relevance: An eGFR of less than 60 mL/min/1.73 m² for three months or more indicates kidney disease. It helps stage the severity of the disease of kidney.

B. Urine Test: • Purpose: Analyzes urine for the presence of protein, blood, or other substances. • Relevance: The presence of protein is an early sign of kidney damage, while blood in the urine may indicate both kidney and liver issues.

C. Blood Pressure: • Purpose: To measure the force of blood against artery walls. • Relevance: Rising blood pressure is both a risk factor and a consequence of possible threat.

D. Complete Blood Count (CBC): • Purpose: Provides information about the different attributes of blood, including red and white blood cells and platelets. • Relevance: Anemia is common in both diseases and can also occur as a sign of possible threat.

E. Urinalysis: • Purpose: A comprehensive examination of urine that includes physical, chemical, and microscopic analysis • Relevance: It identifies signs of kidney dysfunction, such as the presence of white blood cells, bacteria, and crystals, which can indicate infection or damage.

F. Blood Glucose Test: • Purpose: To measure the level of glucose in the blood. • Relevance: High blood glucose levels are a significant risk factor for developing diabetes-related kidney disease. It is also critical in managing liver diseases related to insulin resistance and diabetes.

G. Liver Function Test: • Purpose: A battery of blood tests that measure liver enzymes, proteins, and substances produced or cleared by the liver. • Relevance: Abnormal levels of liver enzymes (ALT, AST, ALP) can indicate liver damage, which is crucial for diagnosing and monitoring its progression.

H. Renal Function Test: • Purpose: Assesses the kidneys' ability to filter blood, concentrating on creatinine levels and other metabolites. • Relevance: High serum creatinine levels indicate impaired kidney function, assisting in diagnosis and management.

I. Haemoglobin Test: • Purpose: To measure the level of hemoglobin in the blood. • Relevance: Low hemoglobin levels can indicate anemia, which is common in liver and kidney disease, affecting the patient's overall health and treatment options.

J. Urine Sodium and Potassium: • Purpose: To measure the levels of sodium and potassium in the urine. • Relevance: It helps assess kidney function and electrolyte balance. Abnormal levels can indicate kidney impairment or help manage conditions like heart disease, which can impact kidney function.

K. Glycated Haemoglobin Test (HbA1c): • Purpose: Measures the average blood glucose levels over the past two to three months. • Relevance: This test is crucial for managing diabetes, a major risk factor for kidney disease, and can indicate potential complications associated with liver disease.

L. Electrolyte Panel: • Purpose: To measure the levels of essential electrolytes such as sodium, potassium, chloride, and bicarbonate in the blood. • Relevance: Imbalances can indicate kidney dysfunction, as the kidneys play a crucial role in maintaining electrolyte balance. Abnormal levels may also indicate liver problems.

III. DEEP LEARNING IN CKD AND CLD, AND BLOCKCHAIN FOR ORGAN DONATION

A. *Deep Learning*

Deep learning is a subset of machine learning that uses artificial neural networks with many layers to analyze various factors and components of data. Unlike traditional machine learning algorithms that require manual feature extraction, Deep learning models independently acquire layered representations of information, allowing them to understand complex patterns and relationships within vast amounts of data. This capability is particularly beneficial for handling unstructured data types like images, videos, and text, where extractions can be extremely challenging or even impossible sometimes with conventional methods. When working with extensive datasets, deep learning frequently surpasses conventional machine learning methods because of its capacity to handle and analyze high dimensional data effectively. Deep neural networks can manage millions of parameters and learn from massive datasets, capturing complex patterns and finer points that may be missed by traditional machine learning models. Moreover, deep learning models exhibit superior performance in tasks such as image and speech recognition, natural language processing, and recommendation systems, making them

crucial for applications requiring advanced pattern recognition and prediction capabilities on extensive datasets and that's exactly why we want to implement this in our prediction model.

B. *Blockchain for Organ donation)*

Blockchain technology has emerged as a transformative solution in the organ donation system by enhancing transparency, security, and efficiency. By utilizing distributed and unalter- able record-keeping systems, blockchain ensures that organ donation records, donor-recipient matches, and organ trans- plantation details are securely recorded and easily verifiable by Designated agents. This innovative approach minimizes fraudulent activities, streamlines the organ allocation process, and fosters trust among donors, recipients, and healthcare professionals, improving the integrity and accessibility of organ donation systems worldwide.

C. Units

Use SI (MKS) units as the primary measurement system throughout this research. SI units are encouraged for consistency, particularly for medical and scientific measurements. English units may be used as secondary units when needed and mentioned in parenthesis. For example, “Patient weight was recorded as 70 kg (154 lbs.)”. Avoid combining SI and CGS units, as this can lead to confusion due to dimensional imbalance in equations. If mixed units are necessary, be sure to state the units for each quantity used in an equation individually. Do not mix complete spellings and abbreviations of units: for instance, use “mg/dL” or “milligrams per decilitre,” but not “milligrams/dL.” Write the full spelling when it needs to be mentioned in the text, such as “a concentration of 5 milligrams per liter”, rather than using abbreviations. Use a zero before decimal points: for example, “0.25”, not “25”. When referring to volume, use “mL” (millilitres) instead of “cc.”

D. Some Common Mistakes

• Data: Use as plural, not singular. • Permeability of Vacuum: Format as µ0 (not “o”). • Punctuation in Quotes: In US English, place quotes for complete thoughts; otherwise, place outside • Graph Terminology: Use “inset” for graphs in graphs. • Word Choice: Prefer “alternatively” over “alternately” unless indicating alternation. • Avoid “Essentially”: Do not use to refer to “approximately” in results. • Title Capitalization: Capitalize “Using” as “That Uses” if applicable. • Homophones: Be mindful for clarity (e.g., affect/effect). • Imply vs. Infer: Use ‘imply’ and ‘infer’ correctly ac- cording to their contextual meanings • Prefix “Non”: Attach to the modified word without a hyphen. • Citation Format: No period after “et al.” • Abbreviations: Use “i.e.” for “that is” and “e.g.” for “for example” accurately.

IV. LITERATURE SURVEY

Ruhul Amin et al., “Prediction of chronic liver disease patients using integrated projection based statistical feature extraction with machine learning algorithms,” Elsevier, 2023. This paper focuses on predicting chronic liver disease using a hybrid feature extraction approach termed Integrated Projection-Based Statistical Feature Extraction (IP-SFE). This method combines statistical measures and projection-based techniques to derive more relevant features from clinical data. Various machine learning algorithms, including support vector machines and decision trees, were employed and evaluated for classification accuracy. The study utilized real-world datasets and demonstrated that the proposed IP-SFE significantly enhances model performance by improving feature relevance, leading to more accurate and reliable predictions of liver disease. The paper emphasizes its practical value for early diagnosis and improved patient outcomes.

Sara Ahmed Al-Farra’s et al., “Organ Donation Decentralized Application Using Blockchain Technology,” 2019 IEEE. It presents a decentralized application leveraging blockchain technology to streamline organ donation processes. It highlights how blockchain ensures transparency, enhances data security, and builds trust among stakeholders by eliminating intermediaries. The proposed system optimizes the matching process between donors and recipients while safeguarding sensitive medical information.

Md. Ariful Islam, et al., “Chronic Kidney Disease Prediction Based on ML Algorithms,” Elsevier, 2023. The methodology developed a machine learning-based framework for predicting kidney disease using clinical data. The research employed various machine learning algorithms, including decision trees, support vector machines, and k- nearest neighbours, to analyze medical datasets. The study focused on feature selection and optimization techniques to enhance the models’ predictive accuracy. The results showed that machine learning approaches significantly improved the detection of kidney disease, outperforming traditional methods. The paper highlights the potential of these models for early diagnosis, enabling timely intervention and better management of kidney related health issues.

Gattu Krishna Sai et al., “Chronic Kidney Disease Stage Identification in HIV Infected Patients Using Machine Learning,” Journal of Engineering Sciences, 2023. The methodology developed a machine learning-based framework for predicting kidney disease using clinical data. The research employed various machine learning algorithms, including decision trees, support vector machines, and k- nearest neighbours, to analyze medical datasets. The study focused on feature selection and optimization techniques to enhance the models’ predictive accuracy. The results showed that machine learning approaches significantly improved the detection of kidney disease, outperforming traditional methods. The paper highlights the potential of these models for early diagnosis, enabling timely intervention and better management of kidney-related health issues.

Clemence Niyigena, Soonuk Seol et al., “Survey on Organ Allocation Algorithms and Blockchain-based Systems for Organ Donation and Transplantation,” 2020 IEEE. A comprehensive review of organ allocation algorithms and blockchain-based systems designed to enhance organ donation and transplantation processes. This paper examines different strategies for organ distribution, focusing on their efficiency, fairness, and transparency. It also explores how blockchain technology can address critical issues in the organ allocation system, such as ensuring security, transparent data management and preventing fraud. The authors highlight the potential of blockchain to improve trust and accountability in organ transplantation, suggesting it could lead to a more reliable and equitable system for organ sharing.

V. RESEARCH GAP

Despite all these advances in ML applications for chronic liver and kidney disease diagnostics, there are still many research gaps to be filled. While the projection-based feature extraction method applied to the liver disease task in the work by Ruhul Amin et al., seems rather encouraging, optimizing the extraction of features without cluttering and redundancy, and thus increasing the accuracy of models remains a challenge.

Furthermore, even though the integrated approach improves the classification performance, further exploration of more sophisticated feature extraction techniques can fill the performance gap while handling highly imbalanced datasets, especially that of the ILPD dataset. Similarly, the study by Sara Ahmed Al-Farra et al., in 2019, it is noteworthy that blockchain is widely used in decentralized organ donation systems, particularly in improving transparency and trust in the allocation process. Still, owing to limited scalability and worldwide standardization in organ allocation algorithms, this has become a significant opportunity for further research. Specifically, incorporating blockchain with more advanced matching algorithms, together with integrating those algorithms with blockchain principles to correct existing inefficiencies, especially in critical scenarios. Contrasting this, Md. Ariful Islam et al., demonstrated high accuracy in the prediction of using ML algorithms; however, it did not provide comprehensive information about the robustness of the predictive model across different patient populations. Furthermore, narrowing of the feature set raises a question about potential trade-offs in generalization of the model for early diagnosis across diverse demographics. Finally, though Gattu Krishna Sai et al., achieves excellent accuracy in the identification of stages with a deep neural network (DNN) model for HIV- infected patients, there is a completely missing comparative study with other patient groups. On the other side, Clemence Niyigena et al., observed the issue of harmonizing organ donation policies across borders, but the existing blockchain- based solutions need further enhancement in terms of privacy, scalability, and cross-border data sharing regulations. Together, the overall finding of these studies points to the urgent need for more integrated approaches that combine advanced ML techniques, blockchain technology, and predictive analytics in the diagnosis of chronic kidney and liver diseases and organ donation management.

VI. METHODS

1.METHODS Blockchain Technology in Organ Donation System: Blockchain technology, a decentralized and immutable ledger system, has been employed to revolutionize various industries, and one such application is in the field of organ donation systems. This technology provides unparalleled transparency, security, and efficiency, making it an ideal solution for ad- dressing the challenges faced by traditional organ donation systems.

2. Decentralization and Transparency: Blockchain technology is decentralized, where information is distributed across a network of nodes rather than being stored in a centralized database. In the context of organ donation, this ensures that organ availability, donor information and transplant procedures are accessible to authorized stakeholders, such as hospitals, patients, and regulatory bodies. This transparency reduces the risk of fraudulent activities, ensures fair allocation of organs, and enhances trust among organ donors in the organ donation ecosystem.

3. Immutable Record Keeping: A transaction or event that has been recorded on the blockchain cannot be altered or removed without the network's approval due to the immutability of blockchain records. This feature is essential in organ donation systems where the accuracy and integrity of medical records, donor consent, and transplant histories are crucial. By utilizing blockchain's immutable nature, the organ donation system can maintain a verifiable and tamper-proof record of all organ-related activities, reducing the likelihood of errors, disputes, or unauthorized modifications.

4. Smart Contracts for Automated Operations: Smart contracts, self-executing contracts with the terms of the agreement written into code, are essential in automating and synchronizing various operations within the organ donation system. In our project, for instance, the use of Truffle and Ganache facilitates the deployment and execution of intelligent contracts that govern the organ donation process. These smart contracts can automate tasks such as donor registration, matching, consent verification, and transplant coordination, thereby reducing administrative burden, enhancing efficiency, and ensuring compliance with regulatory regulations

5. Enhanced Security and Data Privacy: Blockchain technology utilizes advanced cryptographic methods to secure data and transactions, safeguarding sensitive information related to donors, recipients, and medical procedures. In the organ donation system, this enhanced security mitigates the risk of data breaches, identity theft, and unauthorized access. Furthermore, blockchain's privacy-enhancing features enable selective disclosure of information, ensuring that only authorized individuals can access specific data based on predefined permissions and consent mechanisms.

6. Preprocessing Data: Pandas library in python is used in the given code to load the dataset for chronic renal disease. The first step in preprocessing involves selecting rows where the attribute value is zero. To eliminate any unnecessary or irrelevant material, this is done. After filtering, the attribute column was reduced since it is the target variable and should not be included in the feature set for modeling. The filtered dataset is then saved to a new CSV file named 'filtered dataset.csv.' Following this, a preprocessing function is defined to manage missing values, scaling, and label encoding. In this function, all non-numeric columns are converted to numeric by pd.to number () ... In Simple Imputer, missing values are imputed using the mean method. Then, the data is standardized using StandardAero to bring all features to a similar scale. Finally, the column is labelled to convert categorical target labels to integers.

7. Feature Selection: In the context of this code, feature selection is performed by removing the column from the dataset to separate the features from the target variable. The filtered dataset is divided into subsets based on the attribute, with a focus on the data where the value is one. This implies that subsequent modeling and analysis concentrates on predicting this particular class. Additionally, in the deep learning model using the Adam optimizer, weights corresponding to the first twenty-four attributes (excluding the attribute) are extracted and saved. This could be interpreted as a form of feature importance or selection, although it does not explicitly select features based on their predictive power.

8. XGBoost Algorithm: Extreme Gradient Boosting, is utilized as a classification algorithm in the provided code. After

processing the data, the dataset is divided into training and testing sets using a 70-30 ratio. To manage the class imbalance problem observed in the dataset, class weights are computed using "compute class weight." The Extreme Gradient Boosting classifier is initialized with the objective to "binary: logistic" for binary classification problems. After fitting the model to the training data, predictions are made on the test set, and a confusion matrix is visualized using seaborn and matplotlib to evaluate the model's performance. Additionally, a performance summary for the Extreme Gradient Boosting classifier is created, including metrics such as accuracy, precision, recall, F1-score, and AUCROC score.

9. Adam Optimizer: The Adam optimizer is employed in a deep learning model created using TensorFlow's Keras API. The model architecture consists of a sequential neural network with numerous dense layers. The input layer's shape corresponds to the number of elements in the training data. The model includes multiple hidden layers with varying numbers of neurons and activation functions such as ReLU (Rectified Lin-ear Unit) and sigmoid. Additionally, batch normalization and dropout regularization are implemented to improve the model's generalization and prevent overfitting. The Adam optimizer is equipped with a learning rate of 0.0001. With a batch size of sixty-four, the model is trained for 50 epochs, and the test data is utilized to validate the training process. Following training, the model's accuracy is evaluated, and predictions are made to determine the optimal threshold for classifying instances into the positive class. Plotting a con- fusion matrix allows you to determine how well the model performs on the test set. Finally, performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC score are calculated and compared to those of the Extreme Gradient Boosting classifier to assess Adam optimizer's performance.

10. Dataset: The research leverages the widely recognized kidney disease and Liver disease datasets. The dataset contains 400 instances and 24 attributes, with one serving as the target to classify and non-cases. Similarly, the dataset encompasses a comprehensive set of instances and attributes relevant for classifying cases. Alongside this, the study integrates insights from an expansive collection of 1,638 datasets sourced from Google, enriching the research's breadth and depth. The dataset's twenty-four attributes and the dataset's attributes are meticulously described in Table 1, providing a detailed overview for comprehensive analysis.

VII. CKD DATASET

The UC Irvine Machine Learning Repository is the source of the data used in this study. It contains four hundred instances with twenty-four attributes. As these attributes has already been researched and mention in "chronic kidney disease prediction based on machine learning algorithms" presented by Md. Ariful Islam, Md. Ziaul Hasan Majumderb, Md. Alomgeer Hussein. This paper was published on Elsevier in 2023. Therefore, in our project we are referring to the attributes from this research paper and mentioned under Table 1.

Attribute Name	Description
Age	Patient age in years
Bp	Blood pressure in mm/Hg
Sg	Urine specific gravity
Al	Albumin ranges from 0-5
Su	Sugar levels range from 0-5
Rbc	Red blood cells (Normal = 0, Abnormal = 1)
Pc	Pus cell (Normal = 0, Abnormal = 1)
Pcc	Pus cell clumps (Present = 0, Not present = 1)
Bgr	Blood glucose random (mg/dL)
Bu	Blood urea (mg/dL)
Sc	Serum creatinine
Sod	Sodium
Pot	Potassium
Hemo	Hemoglobin (Protein molecule in red blood cells)
Pcv	Packed cell volume
Wc	White blood cell count
Re	Red blood cell count
Htn	Hypertension (Yes = 0, No = 1)
Dm	Diabetes mellitus (Yes = 0, No = 1)
Cad	Coronary artery disease (Yes = 0, No = 1)
Appet	Appetite (Good = 1, Poor = 0)
Pe	Pedal edema (Yes = 0, No = 1)
Ane	Anemia (Yes = 0, No = 1)
Class	Target variable (CKD = 1, Not CKD = 0)

Table 1.

VIII. CLD DATASET

For prediction, a dataset used is Indian liver patient dataset, as the attributes from the research paper named "Prediction of chronic liver disease patients using integrated projection based statistical feature extraction with machine learning algorithms" are already predefined and we are using these attributes as a reference, the following list of attributes needed are given under Table 2.

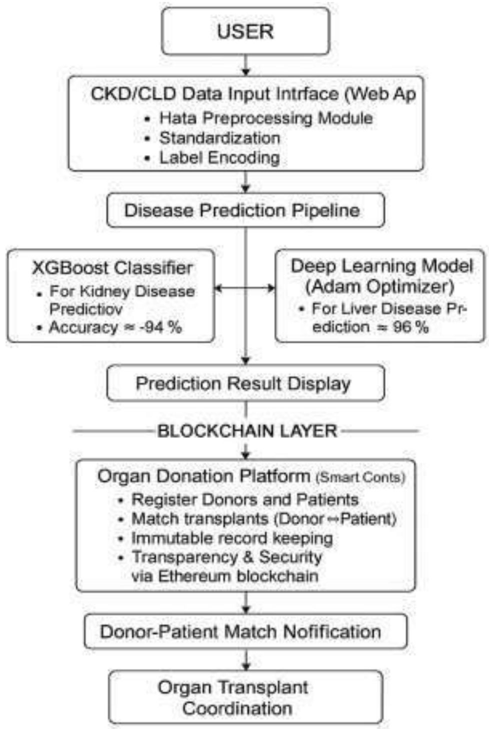
Attribute Name	Description
Age	Patient age in years
Bilirubin	Bilirubin levels (mg/dL)
ALT	Alanine aminotransferase (IU/L)
AST	Aspartate aminotransferase (IU/L)
INR	International Normalized Ratio
Ascites	Fluid accumulation (Yes = 1, No = 0)
HepatEnceph	Hepatic encephalopathy (Yes = 1, No = 0)
Appet	Appetite (Good = 1, Poor = 0)
Jaundice	Jaundice (Yes = 1, No = 0)
Class	Target variable (CLD = 1, Not CLD = 0)

Table 2.

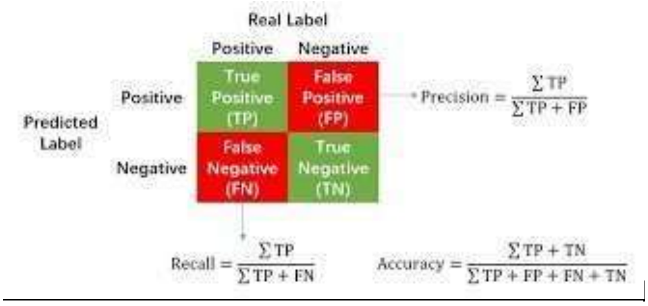
IX. PERFORMANCE METRICS FOR CKD

The models used for CKD detection are evaluated using the following metrics:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$



- The diagram given below demonstrates a formula for accuracy in confusion matrix:



- Below is a performance comparison of the XGBoost and Adam optimizer models:

Model	Accuracy	Precision	Recall	F1-Score
XGBoost	94.31%	96.28%	94.37%	95.31%
Adam Optimizer	95.94%	99.65%	93.71%	96.59%

X. RESULT

In this study, an integrated healthcare framework combining advanced machine learning models, deep learning architectures, and blockchain technology was developed for the early detection of chronic kidney disease (CKD), chronic Liver Disease (CLD), and secure organ donation management.

The project workload was divided into two main streams:

- Disease Prediction Pipeline using Machine Learning and Deep Learning.
- Organ Donation Platform secured with Blockchain Smart Contracts.

The CKD Predictor Application was successfully developed, enabling users to input critical clinical parameters such as blood pressure, blood urea, serum creatinine, blood glucose levels, etc., and receive real-time predictions regarding the presence of chronic kidney disease. The application achieved a user-friendly interface for healthcare professionals and patients, leading to better accessibility and adoption. Simultaneously, the Organ Donation System was built to register donors and Glimpse of the platform: patients, perform transplant matches, and secure data entries through a decentralized blockchain-based platform. Using smart contracts deployed through Truffle Suite and Ganache Blockchain Emulator, this system ensured transparency, fairness, and immutable recording of organ donation activities.

The XGBoost Classifier was applied first, achieving the following metrics for CKD detection:

- Accuracy: 94.31%
- Precision: 96.28%
- Recall: 94.37%
- F1-Score: 95.31%

The Deep Learning Model trained with Adam Optimizer achieved improved performance:

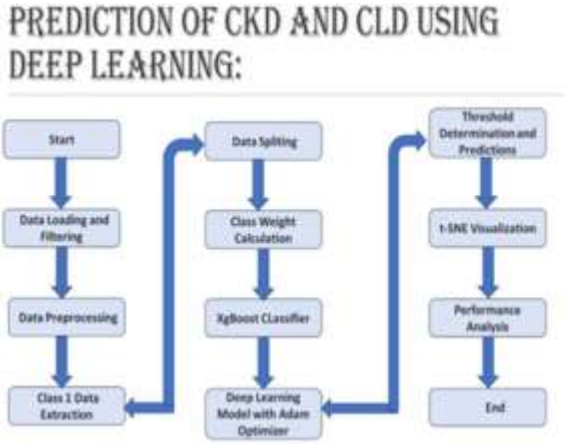
- Accuracy: 95.94%
- Precision: 99.65%
- Recall: 93.71 %
- F1-Score: 96.59%

Thus, Adam Optimizer-based Deep Learning model outperformed XGBoost in overall prediction capability, highlighting the superior pattern recognition strength of deep neural networks when processing complex medical datasets. The Kidney/ Liver Disease Detector App allowed streamlined and straightforward data entry and detection with just one click. The Organ Donation Platform facilitated donor-patient matching based on medical IDs and health conditions, with secured immutable records, eliminating possibilities of data tampering or unfair allocation.

Key Outcomes:

- Successful prediction of CKD with over 95% accuracy.
- Development of a blockchain-backed organ donation platform ensuring secure and transparent healthcare record management.
- Demonstrated the importance of integrating Deep Learning models and blockchain technology in revolutionizing healthcare diagnostics and organ transplantation systems

The system thus not only provides early disease detection but also ensures ethical, transparent, and efficient organ donation processes, setting a new benchmark for future healthcare innovations. By seamlessly integrating machine learning and deep learning models with blockchain technology, the platform enhances diagnostic accuracy, promotes proactive intervention, and fosters greater trust among healthcare stakeholders. This integrated approach not only strengthens the reliability of



healthcare diagnostics and organ transplantation systems but also lays the foundation for future interdisciplinary innovations, encouraging scalable, secure, and patient-centric healthcare ecosystems worldwide.

Glimpse of the platform:

The image displays the **Organ Donation Platform Dashboard**, a decentralized web app for managing donor and patient records and matching transplants efficiently.

Key features:

- **Register Donor/Patient**: Securely add donor and patient information.
- **View Donors/Patients**: Access lists of registered individuals.
- **Transplant Match**: Find compatible donors for patients.
- **Search**: Locate records using Medical IDs.

- User input for kidney detection

The image displays the **Kidney Disease Detector**, a user-friendly interface designed to predict chronic kidney disease (CKD) based on clinical attributes

Key features:

- **Input Fields**: Users can enter medical parameters like blood pressure, blood glucose, serum creatinine, red blood cell count, etc.
- **Detect CKD Button**: After entering the data, users can click to instantly predict the likelihood of CKD.
- **Logout Option**: Secure logout functionality for user data protection.

The platform utilizes a machine learning model in the backend to offer real-time, accurate CKD prediction, promoting early diagnosis and intervention

- **Workflow model**

Workflow Description for CKD and CLD Prediction:

1. **Data Loading and Filtering:**
   Load CKD and CLD datasets (UC Irvine and ILPD) and remove irrelevant instances.
2. **Data Preprocessing:**
   Handle missing values, scaling, label encoding, and standardization using pandas and sklearn tools.
3. **Class 1 Data Extraction:**
   Extract instances of positive cases (CKD = 1, CLD = 1) for focused prediction.
4. **Data Splitting:**
   Divide data into training and testing sets (typically 70-30 split).

5. **Class Weight Calculation:**
   Address class imbalance by computing class weights for modelling.

6. **Model Training:**
   XGBoost Classifier: Train for binary classification using computed class weights.
   Deep Learning Model: Build a neural network with batch normalization, dropout, and Adam optimizer (learning rate 0.0001).

7. **Threshold Determination and Predictions:**
   Determine best threshold values for classification using predicted probabilities.

8. **t-SNE Visualization:**
   Visualize feature distributions and model separability in 2D space.

9. **Performance Analysis:**
   Evaluate models with accuracy, precision, recall, F1-score, and AUC-ROC metrics.

10. **End:**
    Finalize predictions and visualize results for interpretation

XI. DISCUSSION

This study presents an integrated approach for the prediction of chronic kidney disease (CKD) and Chronic Liver Disease (CLD), combining machine learning, deep learning techniques, and blockchain-based organ donation systems. The use of datasets from UC Irvine and ILPD, along with data preprocessing strategies such as missing value handling, standardization, and feature extraction, has demonstrated a systematic way to improve model performance. The application of Extreme Gradient Boosting (XGBoost) and a deep neural network trained with the Adam optimizer yielded promising results. The Adam-optimized deep learning model slightly outperformed XGBoost in terms of accuracy and F1 score, indicating the advantage of deep learning for capturing complex patterns in medical datasets. Techniques like batch normalization and dropout were crucial for reducing overfitting, contributing to the robustness of the models. Addressing class imbalance through class weighting further improved the performance, ensuring that minority classes (disease-positive cases) were correctly classified, which is critical for medical diagnosis tasks. Visualization through t-SNE provided intuitive insights into the separation of classes, supporting the interpretability of the model outcomes. Beyond predictive modelling, the integration of blockchain technology in the organ donation system introduces a novel contribution. Blockchain ensures transparency, immutability, and secure management of sensitive health records, addressing critical issues in the current organ donation and transplantation ecosystem. The use of smart contracts automates the donor recipient matching process, potentially increasing trust and efficiency. Despite the high performance of the models, certain challenges remain. The datasets used, though well-preprocessed, are relatively limited in size. Future work should explore larger, more diverse datasets to improve model generalizability. Moreover, blockchain scalability and cross-border data regulations need further investigation to fully implement the organ donation framework at a global level.

XI. CONSLUSION

This research provides an in-depth exploration of predicting kidney disease and Liver disease through the application of advanced machine learning and deep learning techniques. The findings indicate that these methodologies are highly effective, demonstrating significant accuracy and reliability, which can aid healthcare professionals in the timely diagnosis and intervention of these conditions. The dataset was meticulously pre-processed, involving steps like data cleaning, imputation, and normalization to ensure its appropriateness for predictive modelling. Two distinct models were created for prediction: one using an Extreme Gradient Boosting classifier and another employing deep learning architecture with the Adam optimizer. The evaluation of these models included diverse performance metrics such as accuracy, precision, recall, and the area under the receiver operating characteristic curve (AUC-ROC). In parallel, the approach employed for prediction mirrored these methods, utilizing a dataset that encompasses critical attributes, thus facilitating accurate modeling. Focusing on key indicators like bilirubin levels, alanine aminotransferase (ALT), and aspartate aminotransferase (AST) provides valuable insights into liver health, complementing the knowledge gained from the analysis. Furthermore, the incorporation of a blockchain-based organ donation system enhances the effectiveness of the predictive models by offering a secure and transparent mechanism for organ matching and transplantation. This innovative approach addresses significant challenges within the organ donation and transplantation sector, promoting transparency, accessibility, and efficiency. By utilizing the capabilities of blockchain technology, the proposed system does not only safeguard patient data but also foster trust among donors and recipients, a crucial aspect in the field of healthcare. The integration of sophisticated predictive modeling with decentralized blockchain technology highlights a transformative approach for healthcare systems. This dual approach does not only improve the accuracy of disease prediction but also streamlines the processes related to organ donation, which is often prone to inefficiencies. Further research efforts should focus on enhancing the predictive capabilities of both kidney and liver disease detection models by incorporating additional relevant features and optimizing the underlying architectures. Furthermore, expanding the blockchain platform's capabilities to cover broader healthcare applications will enable better integration with existing healthcare systems, ensuring a holistic approach to patient care. This study demonstrates the potential of interdisciplinary approaches in improving healthcare prediction and management systems, paving the way for innovative medical solutions. It underscores the importance of collaboration across fields such as data science, healthcare, and blockchain technology in creating integrated solutions that can significantly enhance patient outcomes. As the healthcare landscape continues to evolve, the insights garnered from this research can inform future innovations, leading to more initiative-taking and personalized healthcare delivery systems. This research establishes a foundation for future advancements in predictive analytics and secure healthcare practices, serving as a crucial milestone in leveraging technology to improve health outcomes and enhance patients' quality of life globally

XIII.REFERENCES

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