Revolutionizing Kidney Organ Post Transplantation Care through AI, ML and Blockchain

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ABSTRACT
Kidney transplantation stands as the most effective treatment for end-stage kidney disease, yet the success of such procedures relies heavily on post-transplantation care and monitoring. This paper presents a comprehensive framework for enhancing post-transplantation care using a combination of artificial intelligence (AI), machine learning (ML), and blockchain technologies. The proposed system incorporates two novel modules: the Kidney Evaluation Module and the Cox Model Prediction, alongside traditional post-transplant monitoring. The Kidney Evaluation Module utilizes deep learning techniques to assess kidney health from medical images, employing data augmentation, SMOTE for class balancing, and a Deep Feature Fusion Network (DFFN) to categorize kidney conditions accurately. The Cox Model Prediction module employs Cox linear regression to predict patients' waiting times for transplantation based on various predictors such as age, gender, dialysis duration, and cPRA, offering personalized estimations to aid informed decision-making for patients and physicians. Leveraging ensemble methods and custom neural networks, the system predicts early kidney rejection and categorizes patients based on depression severity using the Hamiltonian Depression Scale. Furthermore, blockchain based smart contracts ensure secure storage and traceability of transplant records, while appointment scheduling and a chatbot utilizing TF-IDF address post-transplant queries and provide timely support. Through these integrated modules, the project endeavours to revolutionize kidney transplantation care, offering comprehensive support to patients and facilitating improved clinical outcomes.

Keywords
Kidney transplantation, post-transplantation care, Artificial intelligence (AI), Machine learning (ML), Blockchain technologies, Ensemble methods, Hamiltonian Depression Scale, Cox Regression

1. INTRODUCTION
Kidney transplantation stands as the gold standard treatment for end-stage renal disease (ESRD), offering patients a chance at improved quality of life and longevity. However, the success of kidney transplantation hinges on meticulous pre-transplant evaluation, precise donor-recipient matching, and vigilant post-transplant care. Despite advancements in medical science, challenges persist in optimizing transplantation processes, including timely rejection detection and comprehensive patient support post-transplantation. To address these challenges, this project proposes an innovative framework that harnesses emerging technologies—namely, artificial intelligence (AI), machine learning (ML), and blockchain—to enhance the efficiency and efficacy of kidney transplantation ecosystems. In addition to traditional post-transplant care measures, this paper introduces two novel modules: the Kidney Evaluation Module and the Cox Model Prediction. The Kidney Evaluation Module leverages deep learning techniques to assess kidney health from medical images, employing data augmentation, SMOTE for class balancing, and a Deep Feature Fusion Network (DFFN) to categorize kidney conditions accurately. On the other hand, the Cox Model [7] Prediction module employs Cox linear regression to predict patients' waiting times for transplantation based on various predictors such as age, gender, dialysis duration, and cPRA, offering personalized estimations to aid informed decision-making for patients and physicians. By integrating AI-driven tools for mental health assessment, custom neural networks for rejection detection, and blockchain for secure record-keeping [3], the project aims to revolutionize post-transplantation care. Additionally, chatbots utilizing natural language processing (NLP) techniques will provide comprehensive support and information to patients and healthcare providers [1]. Through these advancements, the project seeks to optimize patient outcomes, streamline transplantation processes, and ultimately improve the overall quality of care in kidney transplantation.

2. RELATED WORKS
1) Sanabria, Gabriella et al. "“A Great Way to Start the Conversation”: Evidence for the Use of an Adolescent Mental Health Chatbot Navigator for Youth at Risk of HIV and Other STIs." Springer, 2023. This study explores the effectiveness of using the SmartBot360 chatbot for adolescent mental health support, incorporating features such as anti-drop-out technology. However, the sample size was limited to individuals local to the Tampa Bay Region, and only a small portion fell within the 16-17 age group. [1]

2) Sarkar, Siddharth, and Sandeep Grover. "Psychiatric Assessment of Persons for Solid Organ Transplant." IEEE ICTC Journal, 2022. This work utilizes the Confusion Assessment Method and Hamiltonian Depression Scale to assess psychiatric conditions in potential organ transplant

recipients. While comprehensive, the focus on post-transplantation care was limited. [2]

3) Choudary, Navjeevan et al. "Organ Bank Based on Blockchain." IEEE CONECCT Journal, 2022. This paper presents a blockchain-based organ bank system using Ethereum smart contracts. Despite its potential, operational costs and scalability issues pose challenges to widespread adoption. [3]

4) Shehata, Mohamed, and Fatma Taher. "Early Assessment of Acute Renal Rejection Post transplantation: A Combined Imaging and Clinical Biomarkers Protocol." IEEE ICSES Journal, 2018. This study proposes a protocol combining imaging techniques and clinical biomarkers to detect acute renal rejection post-transplantation with high accuracy. However, the authors suggest further research to include more diverse data sources, such as genomic markers and histopathology images. [4]

5) Flynn, Dennis, and Haklin Kimmr. "Geofencing Implementation for Self-Monitoring Wandering Behavior and Sharing Location in Real Time with Firebase." IEEE Cloud Summit, 2023. This work presents a geofencing system using the Android location API and Google Maps SDK to monitor wandering behavior of individuals. While effective, the system exhibits latency issues, averaging around 6 minutes. [5]

6) Ali Elmhamudi, Colin Wilson et al. "Deep Learning Assisted Kidney Organ Image Analysis for Assessing the Viability of Transplantation" presented at the IEEE Conference 2022. This study explores the utilization of deep learning techniques for the analysis of kidney organ images to assess transplantation viability. By leveraging deep learning algorithms, the authors aim to enhance the accuracy and efficiency of transplantation assessments. [6]

7) Xudong Zhou, Qiewn Liu. "Mechanistic study and analysis of Cox regression model for colon cancer based on SEER database" presented at the IEEE Conference 2021. This research delves into the mechanistic study and analysis of Cox regression models in the context of colon cancer, utilizing data from the Surveillance, Epidemiology, and End Results (SEER) database. The study seeks to elucidate the underlying mechanisms of colon cancer progression and prognosis using Cox regression analysis. [7]

8) Clemence Niyigena, Artem Lenskiy et al. "Survey on Organ Allocation Algorithms and Blockchain-based Systems for Organ Donation and Transplantation" presented at the IEEE Conference 2020. This survey paper provides an overview of organ allocation algorithms and blockchain-based systems for organ donation and transplantation. By examining existing literature and technologies, the authors aim to identify trends, challenges, and opportunities in the field of organ transplantation. [8]

9) Kübra Eroğlu, Tuğba Palabaş. "The Impact on the Classification Performance of the Combined Use of Different Classification Methods and Different Ensemble Algorithms in Chronic Kidney Disease Detection" presented at the IEEE Conference 2020. This study investigates the impact of combining different classification methods and ensemble algorithms for chronic kidney disease detection. By analyzing classification performance metrics, the authors aim to identify optimal approaches for disease detection and diagnosis. [9]

10) Baddam Madhu, Saraf Sai Vivek Rao et al. "Automated Data Management for HealthCare using Machine Learning" presented at the IEEE Conference 2022. This research focuses on automated data management solutions for healthcare using machine learning techniques. By leveraging machine learning algorithms, the authors aim to streamline data management processes in healthcare settings, improving efficiency and accuracy. [10]

3. PROPOSED MODEL

The proposed work presents a comprehensive system aimed at transforming post-transplant kidney transplantation processes using cutting-edge technologies. It incorporates various techniques tailored to different aspects of the transplantation journey. For mental health assessment pre-transplantation, the system utilizes the Hamiltonian Depression Scale [2] to evaluate recipients' psychological wellbeing. Additionally, the framework integrates the Kidney Evaluation Module, employing deep learning techniques to assess kidney health from medical images, thus enhancing the pre-transplant evaluation process.

In the realm of blockchain technology, the system employs smart contracts to securely store transplantation records, ensuring transparency and immutability. This facilitates seamless data management and traceability, mitigating risks associated with data tampering and unauthorized access. To address post-transplantation queries, a chatbot is implemented using TF-IDF and cosine similarity algorithms, providing personalized assistance to recipients [8]. By analysing patient queries and retrieving relevant information from a knowledge base, the chatbot offers timely and accurate support, enhancing patient satisfaction and engagement.

Moreover, the system utilizes a stacking ensemble method as mentioned in Fig 2, with custom convolutional neural networks (CNN) for early detection of kidney rejection. By aggregating predictions from multiple models and leveraging the capabilities of custom CNN architectures, the system enhances the accuracy and reliability of rejection detection [4], leading to timely intervention and improved patient outcomes. These components collectively streamline transplantation processes, optimize patient care, and bolster the efficiency of kidney transplantation ecosystems, ultimately contributing to enhanced clinical outcomes and patient well-being. The overall architecture related to post transplantation module is shown in Fig.1. The proposed system's multi-faceted approach ensures a comprehensive solution that addresses both pre- and post-transplantation needs. By integrating advanced technologies such as deep learning and blockchain, the framework not only enhances diagnostic accuracy but also fortifies data security and patient privacy. Additionally, the inclusion of intelligent support systems like chatbots ensures continuous patient engagement and support, making the transplantation journey more manageable and less stressful for recipients.

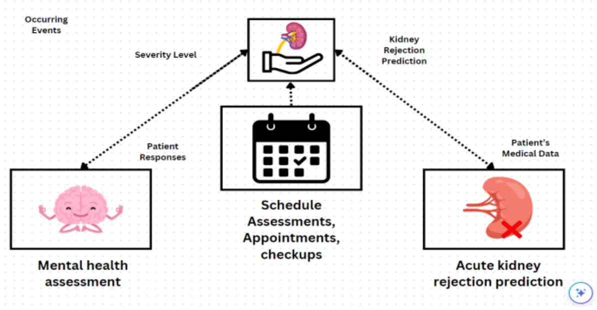


Fig 1: Kidney Post transplant Architecture

4. IMPLEMENTATION

4.1 Kidney Post Transplant Rejection Prediction

The submodule designed for detecting kidney rejection post-transplantation is built upon a sophisticated ensemble method known as stacking, complemented by a custom neural network architecture. This submodule is pivotal in ensuring the timely identification of rejection instances, facilitating prompt intervention and personalized patient care.

```
Input: Patient's medical data comprising 25 features including blood
pressure (bp), hemoglobin (hemo), age, and red blood cell count (rbc).
Output: Prediction of Post transplant kidney rejection (PTKR).

Algorithm:

Split the dataset into train and test sets.
Initialize base models:
CNN1 - Custom neural network 1
CNN2 - Custom neural network 2
CNN3  - Custom neural network 3
CNN4  - Custom neural network 4

Initialize the meta-learner as Extra Trees Classifier (ETC).

For each base model:

a. Train the model on the training set.
b. Predict the PTKR status for the test set.
c. Store the predictions.

Aggregate the predictions from all base models.
Train the meta-learner on the aggregated predictions.
Compare the actual PTKR status with the predictions from the
meta-learner to evaluate accuracy.
Return the final predictions from the meta-learner as the output.
```

Fig 2: Algorithm for Kidney Post Transplant Rejection Prediction

4.2 Mental health Assessment

Employing the Hamiltonian Depression Scaling, an opensource LLAMA model is fine-tuned to assess the mental wellbeing of post-transplantation patients for our scale as mentioned in Fig 3. Through this, patients are categorized into depression severity levels, aiding doctors in tailored care. Additionally, doctors can prescribe specific assessments via the chatbot, ensuring patients complete them timely for comprehensive evaluation (e.g., PHQ-9, GAD-7).

```
Input: Patients responses to the 17 questions in the Hamiltonian Depression
Scaling.
Output: Severity level of depression

Initialize  total_score -> 0, LLaMA_model.
Load LLaMA_model fine-tuned for Hamiltonian Depression Scaling
for each question in questions do:
    embeddings = embed(question_response) using LLaMA_model
    hidden_states = encode(embeddings) using LLaMA_model
    attention_weights = embed(hidden_states) using LLaMA_model
    scale  = classify(attention_weights) using LLaMA_model
end for

if total_score>=0 and total_score <=7 then:
  severity_level = "Normal"
else if total_score>=8 and total_score <=17 then:
  severity_level = "Mild"
else if total_score>=18 and total_score <=24 then:
  severity_level = "Moderate"
else if total_score>=25 and total_score <=52 then:
  severity_level = "Severe"
else:
  severity_level = "Very severe depression"
end if
return severity_level
```

Fig 3: Algorithm for Mental health Assessment

4.3 Post transplant Schedule Module

The Post Transplant Schedule Module is designed to streamline the scheduling of appointments for patients following kidney transplantation, facilitating efficient access to medical tests and consultations with consulting physicians. This module works as mentioned in Fig 4 and 5 offering a user-friendly interface for patients to book appointments, ensuring convenience and timely access to essential healthcare services.

Key features of the Post Transplant Schedule Module include:

Appointment Booking: Patients can conveniently schedule appointments for medical tests and routine check-ups with their consulting doctors through the module's intuitive interface.

Appointment Reminders: The module sends timely notifications to patients via mobile phone alerts, reminding them of upcoming appointments with doctors. This proactive approach helps patients stay informed and prepared for their scheduled medical consultations.

Alarming Situation Alerts: In the event of any alarming medical situations or urgent concerns, the module is equipped to send real-time alerts to patients, prompting them to seek immediate medical attention or contact their healthcare providers.

Statistical Medical Data: The module provides patients with access to statistical medical data, offering insights into their health status and treatment progress. This feature empowers patients to monitor their health metrics and track their recovery journey post-transplantation.

```
function get_user_appointments(username):
   Input: username
   Output: appointments for the given username or False if database
connection is invalid

   if database_connection is valid:
      return appointments[].get(username)
   else:
      return False
   end if
```

Fig 4: Algorithm for Post Transplant Schedule Module - get user appointments

```
function modify_schedule(action, username, event_details=None):
  Input: action (add/delete), username, event_details (optional)
  Output: Modify the schedule

  if action == 'add':
    Generate unique ID for new event using .generate()
    Convert start and end times to required format
    if database_connection is valid:
      return appointments[].add(event_details)
    else:
      return False
    end if
  else if action == 'delete':
    if database_connection is valid:
      return appointments[].delete(event_details)
    else:
      return False
    end if
  end if
```

Fig 5: Algorithm for Post Transplant Schedule Module - modify user appointments.

4.4 Blockchain Implementation

The Blockchain Module serves as a foundational element in the kidney transplantation ecosystem, providing a decentralized and secure platform for managing critical transplant records. Through blockchain technology, users can seamlessly register as donors as shown in Fig 6 and patients, or pledges as shown in Fig 7, enabling transparent and immutable data storage. By leveraging blockchain's distributed ledger architecture, the module ensures enhanced data integrity and security, mitigating risks associated with fraud or manipulation.

Furthermore, the module facilitates seamless transactional processes, allowing for the efficient recording of transplant related activities such as donor-recipient matches and organ transplantation details. By standardizing data recording procedures and eliminating centralized intermediaries, the blockchain module streamlines the transplantation process (Fig. 9), fostering trust and transparency among all stakeholders involved. This innovative approach not only enhances the efficiency of kidney transplantation operations because of the validation process (Fig. 8, 10) but also lays the groundwork for future advancements in healthcare data management and patient care.

```
Input: newDonorDetails:Initialize donor details - full name, age, gender,
medical_id, blood_type, organ, weight, height
Output: Add donor to the registry)

Initialize an empty list ->  donorMap[]

for each donor D in registry:
  if D.medical_id == medical_id:
        return error -> "Donor already exists"
  end if
end for

donorMap[].add(newDonorDetails)
registry.add(donorMap)
```

Fig 6: Algorithm for Adding donor records to blockchain

```
Input: newPatientDetails[] - full name, age, gender, medical_id, blood_type,
organ, weight, height
Output: Add patient to registry

Initialize an empty list -> patientMap=[]

for each patient P in registry:
  if P.medical_id == medical_id:
        return error -> "Patient already exists"
  end if
end for

patientMap.add(newPatientDetails)
registry.add(patientMap)
```

Fig 7: Algorithm for Adding patient records to blockchain

```
Input: donorMedicalId
Output: Boolean (true if the donor is valid, false otherwise)

if donorMap[donorMedicalId].medical_id == donorMedicalId &&
  donorMap[donorMedicalId].transplant_status != 1:
  return true
else:
  return false
end if
```

Fig 8: Algorithm for validating donor in blockchain

```
Input: newTransplantRecord[] - donorMedicalId, patientMedicalId, organ,
donorType
Output: Add transplant record to blockchain

if !validateDonor(donorMedicalId):
  return error -> "Invalid donor medical ID"
end if
if !validatePatient(patientMedicalId):
  return error -> "Invalid patient medical ID"
end if

timestamp = current_timestamp
transplantRecord[].add(newTransplantRecord)

donorMap[donorMedicalId].transplant_status=1
patientMap[patientMedicalId].transplant_status=1

transplant_record_cnt+=1
return
```

Fig 9: Algorithm for Adding transplant records to blockchain

```
Input: patientMedicalId
Output: Boolean (true if the patient is valid, false otherwise)

if patientMap[patientMedicalId].medical_id == patientMedicalId &&
  patientMap[patientMedicalId].transplant_status != 1:
  return true
else:
  return false
end if
```

Fig 10: Algorithm for validating patient in blockchain

4.5 Chatbot Module

The Chatbot Module defined as mentioned in Fig 11, tailored for addressing posttransplant queries, harnesses TF-IDF and Cosine Similarity techniques to provide specialized support to transplant recipients. Leveraging TF-IDF, the module efficiently captures the context of user inquiries, facilitating precise retrieval of relevant information from extensive datasets.

Through cosine similarity computation, the chatbot identifies semantic correlations between user queries and existing knowledge repositories, ensuring personalized and pertinent responses to post-transplant concerns. This specialized approach not only enhances the accessibility of information but also fosters an interactive platform for addressing the unique needs of transplant recipients. By leveraging TF-IDF and cosine similarity, the chatbot module (Fig. 21) serves as a dependable virtual assistant, empowering patients with timely and accurate insights tailored to their post-transplantation journey.

```
Input: Get the user query regarding kidney donation.
Output: Return chatbot_response

Initialize chatbot_response -> default_response, max_similarity ->
min_threshold

Preprocess the user query using spaCy to remove stopwords and
lemmatize the text
Initialize and fit TF-IDF vectorizer with preprocessed user queries from
the dataset
Transform the user query into a TF-IDF vector
Compute cosine similarity between the TF-IDF vector of the user query
and the TF-IDF matrix of preprocessed queries in the dataset


for each query in the dataset do
   Calculate cosine similarity score between the user query and the
current query
   If cosine similarity score > max_similarity then
      max_similarity = cosine similarity score
      chatbot_response = corresponding response
   End If
end for

If max_similarity > threshold then
   Return chatbot_response
Else
   Return default_response
End If
```

Fig 11: Algorithm for Chatbot Module

4.6 Cox Module

The Cox Model Prediction submodule (Fig. 12, 13) is meticulously crafted to forecast the waiting time for patients awaiting kidney transplantation. Utilizing Cox linear regression, the submodule calculates the partial hazard based on encoded input predictors such as age, gender, and dialysis duration (more on Fig. 23). By iteratively assessing the significance of each predictor through p-values, the submodule computes the partial hazard, which serves as a crucial indicator for predicting transplant wait time. This submodule plays a pivotal role in aiding patients and physicians in making informed decisions regarding transplantation, thereby optimizing resource allocation and patient management strategies.

```
Method Signature: predict_partial_hazard(input_parameters)
Input: Get the encoded input predictors like age, gender etc., input_parameters = [age, gender,
dialysis_duration,...., cPRA]
Output: Return partial_hazard.
Initialize hazard_ratio, and all the coefficients of each predictor to 0.
for each predictor in input_parameters do

    p = getPValue(predictor)

    if p > 0.005 then

        partial_hazard+= (covariate of predictor * coefficient of predictor)

    end if

end for
```

Fig 12: Algorithm for COX Module - Partial Hazard prediction

```
Method Signature: predict_wait_time( input_parameters )
Input: Get the input predictors like age, gender etc., input_parameters = [age, gender,
dialysis_duration,...., cPRA]
Output: Return the wait_time.
Initialize wait_time, partial_hazard, transplant_probability to 0.

for each predictor in input_parameters do

    predictor = encode( predictor )

end for

partial_hazard = predict_partial_hazard( input_parameters )

predicted_transplant_time = e ^ -( partial_hazard )

wait_time = -1 * log( predicted_transplant_time )
```

Fig 13: Algorithm for COX Module - Wait-time prediction

4.7 Kidney Evaluation Module

The Kidney Evaluation Module, an integral component of the proposed framework, harnesses advanced deep learning techniques to assess kidney health from medical images. Employing data augmentation and class balancing methods, the submodule prepares the dataset for training, ensuring robust model performance. Through the utilization of a Deep Feature Fusion Network (DFFN), tailored specifically for kidney disease diagnosis as mentioned in Fig. 14, the submodule extracts intricate features from MRI images, surpassing the limitations of traditional CNN architectures. By training the model on a comprehensive kidney disease dataset and evaluating its performance metrics, including loss and accuracy, the submodule demonstrates its efficacy in aiding pre-transplant evaluation processes and enhancing clinical decision-making in kidney transplantation.

```
Input: Initialize the scan image of Donor's kidney as tensor T
Output: Viability label - "Normal", "Cyst", "Tumor", "Stone"
Initialize an empty list features = [ ]
for each row R in range(1, ROW_LENGTH(T) + 1) do
   for each column C in range(1, COLUMN_LENGTH(T) + 1) do
      features.append(EXTRACT_FEATURE(T[R][C]))
   end for
end for
features_array = CONVERT_TO_NDARRAY(features)
features_array = RESHAPE(features_array, (1, -1, 1))
prediction = PREDICT_VIABILITY(model, features_array)
viability_labels = ["Normal", "Cyst", "Tumor", "Stone"]
predicted_viability = viability_labels[prediction]
return predicted_viability
```

Fig 14: Algorithm for Kidney Evaluation Module

4.8 Reports - for both Patient and Donor

The patient/donor report has the following features:

● Patient/Donor Details

The patient/donor details (Fig, 21, 22) section encompasses basic medical and personal information essential for post-transplantation care as mentioned in Fig. 14. This includes demographic data, blood type, medical history, contact information, and any relevant medical conditions. A comprehensive database ensures quick access to critical donor information during follow-up consultations and emergencies.

● Patient/Donor History

The patient/donor history records significant events such as surgery dates, transplant dates, and any complications encountered during or after the transplant procedure. This historical data aids healthcare providers in assessing the longterm impact of transplantation on patient/donor health and identifying potential areas for intervention or support.

● Mental Health Assessment

A key aspect of post-transplant care is the assessment of patient/donor mental health. Our system incorporates a standardized assessment tool that quantifies mental health parameters pre-transplantation and post-transplantation. The results are graphically represented to illustrate changes in severity levels over time, enabling healthcare providers to track emotional well-being and intervene when necessary.

● Appointment Schedule

Efficient coordination of post-transplant appointments is critical for ongoing monitoring and management. Our system integrates an appointment scheduler (Fig. 22) that facilitates seamless scheduling, reminders, and follow-ups for patient/donor consultations, lab tests, medication reviews, and other necessary interventions. This feature aims to reduce missed appointments and improve continuity of care.

5. COMPARISON WITH EXISTING WORK

Using Custom NN’s, the Stacking ensemble method is used and an accuracy of 99.99 is achieved in prediction of the early kidney rejection post-transplant which can help make informed decisions. The proposed project represents a significant advancement in the field of kidney transplantation care, leveraging cutting-edge technologies to address key challenges and improve patient outcomes. A comparative analysis with existing works highlights the novel contributions and advantages of the proposed system.

Advantages Over Existing Solutions:

Enhanced Post-Transplantation Care: Unlike traditional approaches, which primarily focus on pre-transplant evaluation and surgery, the proposed system emphasizes continuous post transplantation care. Sanabria et al. (2023) demonstrated the use of a chatbot navigator for adolescent mental health support, whereas Sarkar and Grover (2022) focused on psychiatric assessment for solid-organ transplant candidates. In contrast, our system integrates advanced AI-driven tools for mental health assessment and kidney rejection detection, ensuring proactive monitoring and timely intervention.

Comprehensive Support and Personalization: Existing solutions often lack personalized support for transplant recipients, leading to suboptimal care experiences. Choudary et al. (2022) introduced an organ bank based on blockchain for transparent organ allocation, while Flynn and Kimmr (2023) implemented

geofencing for self-monitoring of wandering behavior post-transplantation [5]. In contrast, our system offers tailored interventions and support mechanisms, such as personalized mental health assessments and appointment scheduling functionalities, enhancing patient engagement and satisfaction. Blockchain-Enabled

Transparency and Traceability: While some existing platforms utilize electronic health records (EHRs) for data management, Shehata and Taher (2018) proposed an imaging and clinical biomarkers protocol for early assessment of acute renal rejection post-transplantation. In contrast, our system integrates blockchain technology to ensure transparent and immutable record-keeping of transplant-related data. By leveraging smart contracts and decentralized ledger technology, the system enhances data security, interoperability, and auditability, fostering trust among stakeholders.

Advanced AI-Powered Chatbot: While conventional chatbots may provide basic information, our system incorporates advanced AI techniques, such as TF-IDF and cosine similarity, to deliver more accurate and contextually relevant responses to post-transplant queries. This AI-powered chatbot enables better decision-making and promotes self-management among transplant recipients, as compared to existing solutions

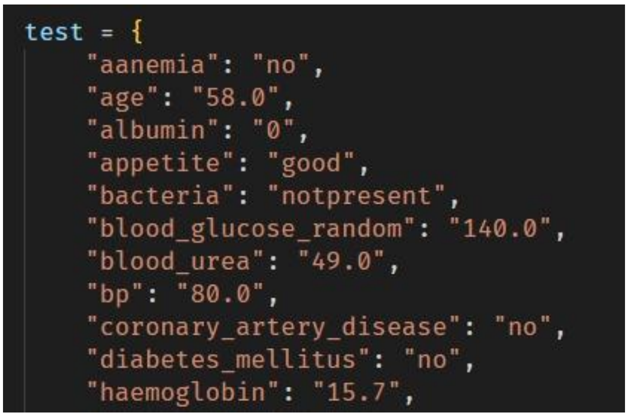
6. RESULT AND DISCUSSION

6.1 Kidney Rejection Module

6.1.1 Dataset:

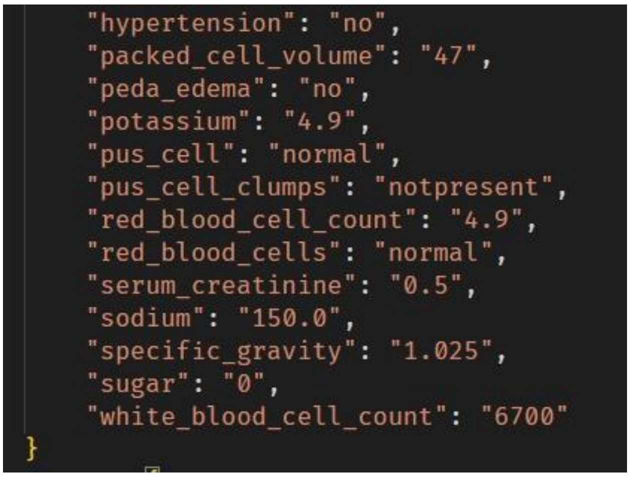
Various Parameters such as anime, age, bp, blood sugar level, hypertension, sugar, sodium etc (more attributes are mentioned in Fig. 15, and 16) are analysed which play an important role in deciding whether the kidney is being rejected by the body.

Using Custom NN’s, the Stacking ensemble method is used and an accuracy of 99.99 is achieved (Table 1 and the loss plot is depicted in Fig. 18) in prediction of the early kidney rejection post-transplant which can help make informed decisions [9].



```
test = {
    "aanemia": "no",
    "age": "58.0",
    "albumin": "0",
    "appetite": "good",
    "bacteria": "notpresent",
    "blood_glucose_random": "140.0",
    "blood_urea": "49.0",
    "bp": "80.0",
    "coronary_artery_disease": "no",
    "diabetes_mellitus": "no",
    "haemoglobin": "15.7",
```

Fig 15(i): Test data 1

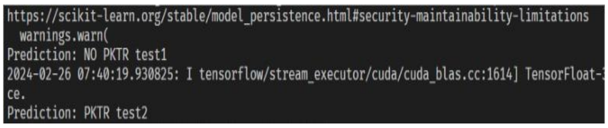


```
    "hypertension": "no",
    "packed_cell_volume": "47",
    "peda_edema": "no",
    "potassium": "4.9",
    "pus_cell": "normal",
    "pus_cell_clumps": "notpresent",
    "red_blood_cell_count": "4.9",
    "red_blood_cells": "normal",
    "serum_creatinine": "0.5",
    "sodium": "150.0",
    "specific_gravity": "1.025",
    "sugar": "0",
    "white_blood_cell_count": "6700"
}
```

Fig 15(ii): Test data 1

```
test2 = {
    "aanemia": "yes",
    "age": "55",
    "albumin": "1",
    "appetite": "poor",
    "bacteria": "notpresent",
    "blood_glucose_random": "140",
    "blood_urea": "49",
    "bp": "80",
    "coronary_artery_disease": "yes",
    "diabetes_mellitus": "yes",
    "haemoglobin": "15.7",
    "hypertension": "no",
    "packed_cell_volume": "44",
    "peda_edema": "no",
    "potassium": "4.9",
    "pus_cell": "abnormal",
    "pus_cell_clumps": "present",
    "red_blood_cell_count": "4.9",
    "red_blood_cells": "normal",
    "serum_creatinine": "0.5",
    "sodium": "150.0",
    "specific_gravity": "1.020",
    "sugar": "0",
    "white_blood_cell_count": "6700"
}
```

Fig 16: Test data 2



```
https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
  warnings.warn(
Prediction: NO PKTR test1
2024-02-26 07:40:19.930825: I tensorflow/stream_executor/cuda/cuda_blas.cc:1614] TensorFloat-
ce.
Prediction: PKTR test2
```

Fig 17: Prediction results of proposed stacking method

Using the Stacking method of the custom neural network, signs of rejection by kidney is predicted.

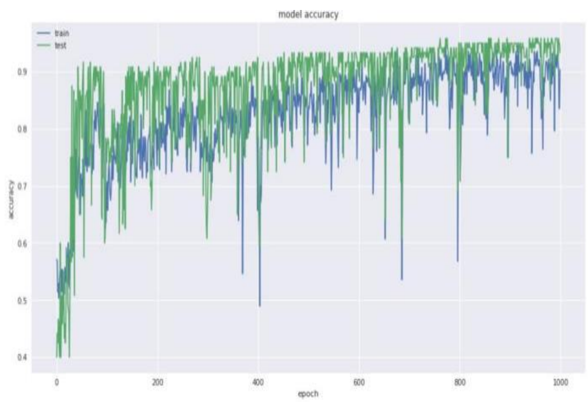
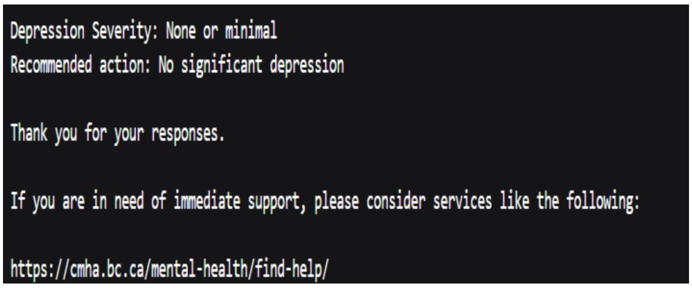


Fig 18: Accuracy and Loss plots of the proposed stacking method

Table 1. Accuracy score of stacked model and other models

Model	Score
Stacking Custom NNs	99.999995
Custom NN1	94.999999
Custom NN2	94.999999
Custom NN3	93.333334
Custom NN4	90.833336
KNN	64.166667

6.2 Mental Health Assessment Module



```
Depression Severity: None or minimal
Recommended action: No significant depression

Thank you for your responses.

If you are in need of immediate support, please consider services like the following:

https://cmha.bc.ca/mental-health/find-help/
```

Fig 19: Sample output of Mental Health Assessment Module

6.3 Blockchain Module

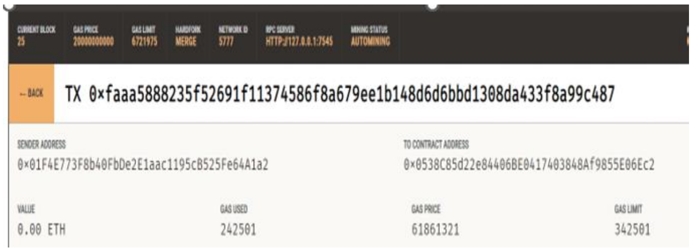


Fig 20: Blockchain Module - contract deployment and execution

6.4 Report generation Module:

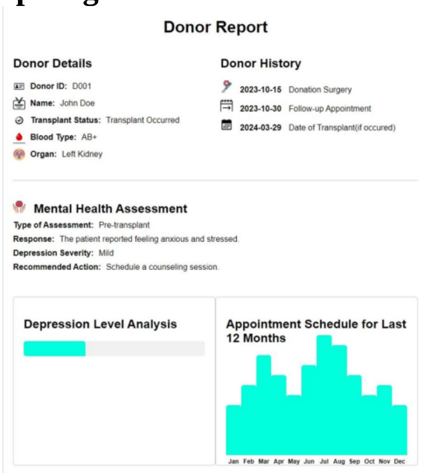


Fig 21: Sample donor report generation

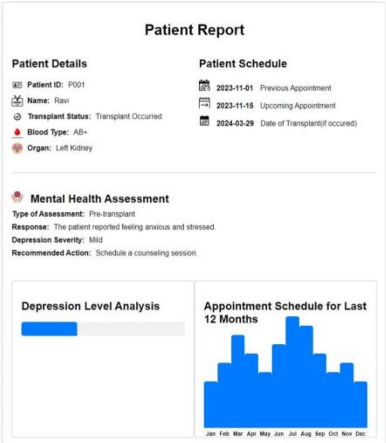


Fig 22: Sample donor report generation

6.5 Kidney Evaluation Implementation

Evaluation metrics, including accuracy, precision, recall, and F1-score, were computed for the Kidney Evaluation Module, demonstrating its high performance in detecting abnormalities such as cysts, tumors, and stones in kidney images. The accuracy plot depicted the module's performance across different thresholds, illustrating its robustness and consistency in accurately identifying organ viability, thereby facilitating informed transplantation decisions. The accuracy of the evaluation model is depicted in Fig. 23.

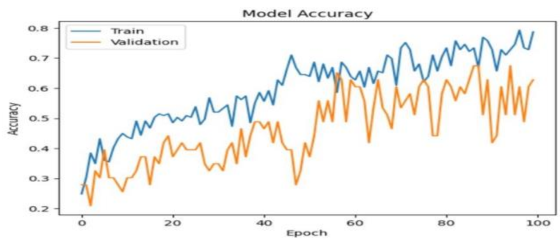


Fig 23: Kidney Evaluation model accuracy

7. CONCULSION

In conclusion, this project signifies a remarkable leap forward in kidney transplantation care, harnessing the latest advancements in artificial intelligence (AI), machine learning (ML), and blockchain technologies. By prioritizing the post transplantation phase, the project effectively addresses pivotal challenges and elevates patient outcomes to new heights. Through the deployment of cutting-edge deep learning methodologies, the project significantly enhances the accuracy of organ viability predictions, thereby ensuring the success of transplantation and fostering improved patient care.

Moreover, the establishment of a robust blockchain infrastructure serves as a cornerstone in guaranteeing secure and transparent record-keeping within the transplantation ecosystem. This innovative approach not only enhances data security but also instills trust and accountability among stakeholders, ultimately bolstering the integrity of transplant related processes.

Furthermore, the integration of frequently asked questions (FAQs) and AI-powered chatbots provides invaluable support and guidance to transplant recipients, enhancing their overall experience and facilitating seamless navigation through the transplantation journey. By combining these technological innovations, the project sets a new standard for kidney transplantation care, promising a future marked by enhanced efficiency, efficacy, and patient satisfaction.

8. FUTURE WORK

As the project looks towards the future, several avenues for further enhancement and expansion emerge. One key area for future exploration is the integration of IoT sensors to enable real-time monitoring of transplant recipients' health parameters. By collecting and analyzing continuous data streams, early signs of complications can be detected, allowing for timely interventions and improved patient outcomes. Additionally, efforts will focus on refining and expanding chatbot functionalities to offer more personalized and context-aware support to transplant recipients. Furthermore, ongoing research and development will optimize the performance and scalability of the blockchain infrastructure, facilitating broader adoption and interoperability within the healthcare ecosystem. Overall, the project lays the foundation for a more efficient, transparent, and patient-centric approach to kidney transplantation care, with the potential to transform the field of organ transplantation in the years to come.

9. REFERENCES

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