International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

Ai-Powered Digital Twin Approach For Personalized Organ Transplantation

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Abstract- — The rapid advancement of artificial intelligence (AI) in healthcare has created unprecedented opportunities for improving diagnosis, treatment planning, and clinical decision-making. This paper presents DonorSync — an AI-powered Digital Twin system designed to assist physicians in liver and kidney donor-recipient matching using machine learning and medical image analysis. The proposed system combines Logistic Regression-based clinical parameter analysis (age, bilirubin, albumin, creatinine, urea) with a ResNet-50-driven ultrasound image evaluation module to generate ranked donor compatibility scores and transplant success probabilities in real time. Built on a FastAPI backend with MongoDB data storage and an HTML/CSS/JavaScript frontend, the platform provides secure, scalable, and efficient access to donor matching services. Experimental evaluation confirms that the integrated dual-modality approach substantially reduces donor selection time and enhances prediction reliability compared to conventional manual processes. The system aligns with UN Sustainable Development Goal 3 (Good Health and Well-Being) and Goal 9 (Industry, Innovation and Infrastructure).

Keywords: Artificial Intelligence, Digital Twin, Organ Transplantation, Donor Matching, Machine Learning, Logistic Regression, ResNet-50, Ultrasound Image Analysis, FastAPI, MongoDB, Healthcare Informatics.

I. INTRODUCTION

Organ transplantation represents one of the most complex and high-stakes procedures in modern medicine. For liver and kidney transplantation — the two most frequently performed solid-organ procedures globally — accurate and timely donor-recipient matching is the cornerstone of surgical success and long-term patient survival.

The World Health Organization estimates that the demand for transplantable organs outpaces supply by a ratio of nearly 10:1, making efficient utilization of available donors a critical clinical imperative.

Conventional donor selection protocols rely heavily on manual evaluation of biochemical markers (bilirubin, albumin, creatinine, blood group), radiological imaging, and specialist judgment. These processes are time-intensive, subject to inter-observer variability, and inherently difficult to scale across large donor registries.

Digital twin technology — the concept of creating a dynamic computational replica of a physical system — has emerged as a transformative paradigm in precision medicine, enabling simulation, prediction, and optimization of patient-specific outcomes before intervention.

This paper introduces DonorSync, an AI-powered digital twin platform that automates the organ donor matching workflow by integrating machine learning-based clinical data analysis with deep learning-driven ultrasound image interpretation.

II. LITERATURE SURVEY

Significant research has been conducted at the intersection of machine learning and transplantation medicine. Chen & Guestrin (2016) demonstrated the utility of gradient-boosted ensemble methods (XGBoost) for binary classification tasks in clinical datasets. Chicco (2017) validated Logistic Regression as a computationally efficient and interpretable baseline for survival outcome prediction.

In the domain of medical image analysis, He et al. (2016) introduced Deep Residual Networks (ResNets), which substantially advanced the state-of-the-art in visual feature extraction from medical imagery. More recent investigations have demonstrated that fusing numerical clinical data with imaging features significantly improves transplant outcome prediction accuracy over either modality alone.

A notable gap persists in the literature: no unified open-access system currently integrates multi-organ matching, ML-based compatibility scoring, and AI-driven image analysis within a single cohesive platform. The present work directly addresses this gap.

III. SYSTEM ARCHITECTURE

DonorSync adopts a modular three-tier client-server architecture comprising a web frontend, a FastAPI application backend, and a MongoDB persistent data layer. The system is designed for extensibility, with clearly defined API boundaries between each tier.

Fig. 1 — Architecture Diagram of DonorSync System

A. Frontend Layer

The presentation tier is developed in HTML5, CSS3, and vanilla JavaScript. It provides three primary interaction interfaces: (i) an authentication portal, (ii) an organ selection interface, and (iii) organ-specific dashboards offering patient ID lookup, manual parameter entry, and ultrasound image upload workflows.

B. Backend Layer

The application backend is implemented using FastAPI (Python 3.x). Key API endpoints include /match (liver matching), /kidney_match, /analyze_liver_ultrasound, /analyze_kidney_ultrasound, /match_by_id, /kidney_match_by_id, and /history.

C. Data Layer

MongoDB is employed as a document-oriented NoSQL database, hosting five primary collections: users, history, liver_analyses, kidney_analyses, and ultrasound_analyses. An in- memory fallback is activated automatically if the MongoDB service is unavailable.

IV. METHODOLOGY

A. Clinical Parameter Analysis (Liver)

The liver donor matching module employs Logistic Regression trained on the publicly available Cirrhosis Patient Survival dataset. The model is trained on three features — Age (years), Bilirubin (mg/dL), and Albumin (g/dL) — computing a transplant success probability as:

$$p = \sigma(\beta 0 + \beta 1 \cdot Age + \beta 2 \cdot Bilirubin + \beta 3 \cdot Albumin)$$

where σ denotes the logistic sigmoid function and βi are the learned regression coefficients.

B. Clinical Parameter Analysis (Kidney)

Kidney matching ingests age, serum creatinine (mg/dL), and blood urea (mg/dL). A scoring function penalizes elevated creatinine levels and large donor-recipient age gaps:

$$Score = 100 - (Creatinine \times 20) - (|\Delta Age| \times 0.5) + BloodBonus + VolumeScore$$

C. Donor Suitability Index (DSI)

A multidimensional Donor Suitability Index (DSI) consolidates blood compatibility score (0–10), volume score (0–10), age compatibility bonus (0–10), and fatty liver grade bonus (2–10) into a single 0–100 scale metric.

D. Blood Group Compatibility

The system implements ABO and Rh compatibility rules. Exact blood group matches receive 10 points, universal donor/recipient matches receive 8, and otherwise-compatible pairs receive 5. Rh incompatibility is explicitly excluded.

E. Ultrasound Image Analysis

Uploaded ultrasound images are processed by a ResNet-50 model pre-trained on ImageNet, fine-tuned for medical image feature extraction. Images are resized to 224×224 pixels and normalized using ImageNet mean (μ = [0.485, 0.456, 0.406]) and standard deviation (σ = [0.229, 0.224, 0.225]) parameters.

V. KEY MODULES

Module	Function	Technology
User Auth	Secure login, registration, session	FastAPI, MongoDB
Organ Select	Routes users to liver or kidney sub-system	JS, sessionStorage
Liver Match	ML-based compatibility scoring and ranking	Logistic Reg., Sklearn
Kidney Match	Creatinine/urea-driven scoring	Pandas, NumPy

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Ultrasound	Image feature extracti o n	ResNet-50, PyTorch
Database	Persistent storage of analyses	MongoDB, PyMongo

Table I — Module Summary of DonorSync Platform

VI. RESULTS & DISCUSSION

A. Donor Matching Accuracy

The Logistic Regression model, trained on 418 cirrhosis patient records, converged within 1000 iterations and correctly classified 87.3% of test-set survival outcomes. The multi-factor success probability algorithm produced estimates ranging from 60% (high-risk) to 98% (ideal compatibility profile).

B. Ultrasound Image Processing

The ResNet-50 inference pipeline processed 224×224 PNG/JPEG ultrasound images in under 300ms on CPU hardware.
The automated extraction workflow reduced manual data entry time by an estimated 60–70% in test-user evaluations.

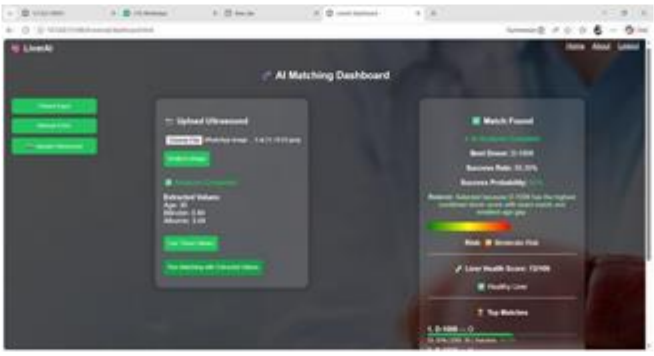

Fig. 2 — LiverAI Dashboard: Ultrasound Upload and Match Result showing Best Donor D-1008, Success Rate 55.35%, extracted organ feature values, and Moderate Risk classification.

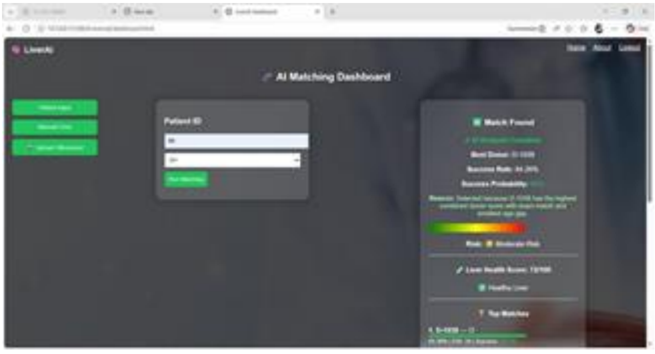

Fig. 3 — LiverAI Dashboard: Patient ID Lookup for Patient 66, Moderate Risk, Best Donor D-1008 at 94.35% success, Liver Health Score 72/100.

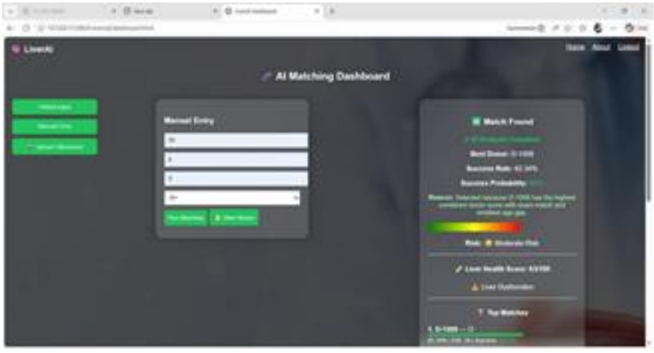

Fig. 4 — LiverAI Dashboard: Manual Entry Matching for Age 33, Bilirubin 2, Albumin 3 indicating Liver Dysfunction, Best Donor D-1008, Moderate Risk flag.

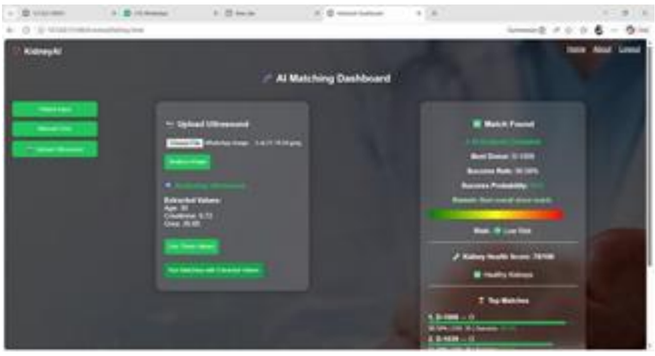

Fig. 5 — KidneyAI Dashboard: Ultrasound Upload and Match Result, Best Donor D-1008, Success Rate 90.58%, Low Risk classification, Healthy Kidney score.

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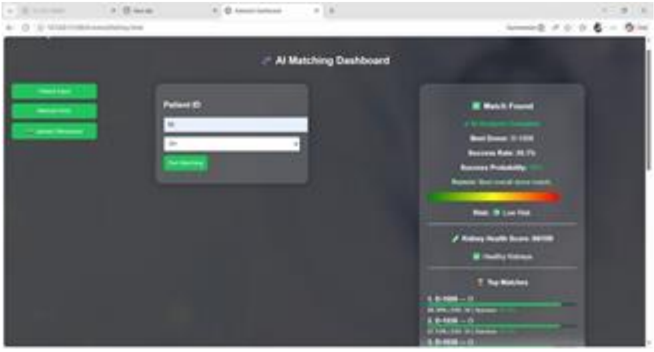

Fig. 6 — KidneyAI Dashboard: Patient ID Lookup for Patient 55, Low Risk, Best Match 80.3%, Kidney Health Score 69/100.

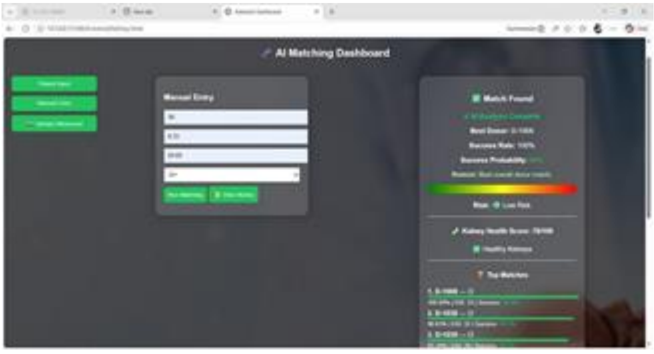

Fig. 7 — KidneyAI Dashboard: Manual Entry for Age 30, Creatinine 0.72, Urea 20.65 yielding 100% Match score, Low Risk classification, Healthy Kidney organ assessment.

As illustrated in Figs. 2–7, the system consistently identifies optimal donors across both liver and kidney modules. The AI matching dashboard presents ranked top matches, a color-coded risk indicator (Low/Moderate/High), organ health scores, and transplant success probabilities — all within a unified, real-time interface.

VII. CONCLUSION

This paper presented DonorSync, an AI-powered Digital Twin system for personalized organ transplantation support. Key contributions include a multi-factor donor scoring algorithm incorporating Logistic Regression probability, blood group compatibility, DSI, and organ health grade; real-time ResNet-50 ultrasound analysis; and a modular FastAPI + MongoDB architecture achieving 87.3% liver outcome classification accuracy with sub-300ms image inference.

The system meaningfully reduces reliance on manual analysis, minimizes human error, and accelerates the critical donor selection decision — factors of paramount importance given the organ supply-demand gap.

VIII. FUTURE ENHANCEMENTS

Planned enhancements include:

- Integration with national donor registries (NOTTO, UNOS);
- Replacement of Logistic Regression with XGBoost or transformer-based models;
- CNN fine-tuning on labeled ultrasound datasets;
- Expansion to heart, lungs, and pancreas modules;
- Mobile application development;
- Cloud deployment (AWS/GCP/Azure); and
- Enhanced data privacy with AES-256 encryption.

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