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Intelligent Organ Transplantation Channel Using Machine Learning

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Abstract: Efficient donor–recipient matching is a critical step in organ transplantation, yet most hospitals still depend on manual comparison of clinical factors such as age, blood group, comorbidities, and organ-specific health indicators. This manual process is slow, prone to inconsistency, and unsuitable for handling the rapid inflow of medical data in real-world environments. To overcome these challenges, this study introduces an intelligent, machine-learning–enabled matching system designed to provide fast, reliable, and data-driven compatibility predictions. The proposed web-based framework incorporates Random Forest and K-Nearest Neighbours models along with computed clinical metrics—including a compatibility score, an organ function score, and a consolidated match score—to evaluate donor–recipient pairs for heart, kidney, liver, and lung transplants. The platform integrates role-based interfaces for administrators, doctors, receptionists, and patients, ensuring streamlined data entry, treatment management, and prediction access. Experimental analysis shows that the system delivers accurate compatibility assessments with efficient real-time execution, demonstrating the potential of machine learning to minimize mismatches, shorten waiting periods, and enhance clinical decision support in transplant workflows. The modular architecture also supports future expansion to additional organs and evolving hospital datasets.

Keywords: Organ Transplantation, Donor–Recipient Matching, Machine Learning, Random Forest Classifier, K-Nearest Neighbours (KNN), Compatibility Prediction, Clinical Decision Support System, Medical Data Processing.

I. INTRODUCTION

Organ transplantation remains a life-saving medical procedure, yet its success depends heavily on finding a donor whose medical profile aligns closely with that of the recipient. In most hospitals, the compatibility assessment is still carried out manually, where clinicians individually compare factors such as blood group, age, pre-existing diseases, infections, and organ-specific clinical values. While this traditional process is medically informed, it becomes difficult to manage when patient loads increase or when decisions must be made quickly. Manual decision-making can introduce delays, inconsistencies, and the risk of overlooking important compatibility parameters, which may negatively affect transplant outcomes.

Advancements in digital health technologies and the availability of structured clinical datasets have created opportunities for applying machine learning (ML) to support medical decision-making. Numerous research studies have reported the potential of ML models in predicting transplant success or estimating donor–recipient suitability. However, most existing approaches remain limited to controlled datasets, specific organ types, or offline experimental settings. These systems rarely consider real-time data entry, dynamic datasets that evolve in hospital environments, or integration into full hospital workflows. As a result, there is still a significant gap between theoretical ML models and practical clinical tools that can be deployed in healthcare institutions.

In response to these limitations, this study introduces an intelligent, machine-learning–driven system designed to automate donor–recipient matching across multiple organ types. The proposed framework utilizes Random Forest and K-Nearest Neighbours models, along with clinically meaningful computed metrics such as compatibility score, organ function score, and a consolidated match score. A web-based platform built using Python (Flask) and MySQL enables different hospital users—including doctors, administrators, receptionists, and patients—to interact with the system through dedicated dashboards. The system processes critical medical attributes, applies automated preprocessing, and generates compatibility predictions in real time, offering a faster and more consistent alternative to manual assessment.
The overarching aim of this work is to create a deployable, scalable, and clinically relevant tool that enhances transplant decision-making. By combining machine learning with a structured hospital workflow system, the study demonstrates

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how intelligent automation can reduce waiting time, improve matching accuracy, and support better clinical outcomes in organ transplantation.

II. LITERATURE REVIEW

Machine learning has increasingly been explored as a transformative tool in organ transplantation, particularly for improving donor–recipient matching and predicting post-transplant outcomes. Numerous studies across different organ types highlight the potential of data-driven decision support systems to enhance clinical judgment while addressing the limitations of traditional manual evaluation.

Deep learning and advanced predictive models have demonstrated substantial improvements in liver and kidney transplant outcome prediction. Börner et al. developed a deep-learning model that analysed donor, recipient, and perioperative factors to estimate survival following liver transplantation, achieving higher predictive performance than classical clinical scoring systems but suffering from limited generalizability due to single-centre training data [1]. Similar advancements were reported in solid-organ transplantation reviews, where machine learning techniques consistently outperformed traditional heuristics, though challenges such as data heterogeneity, lack of external validation, and limited interpretability remained prominent barriers to clinical adoption [2].

In the domain of kidney transplantation, several studies have focused on improving donor-offer acceptance decisions using registry datasets and ML-based risk models. Paquette et al. built decision-support models to assist clinicians in evaluating kidney donor offers, demonstrating improved individual-level risk predictions compared to global scoring methods, while noting the constraints of retrospective datasets [3]. Further, Alowidi et al. introduced a machine-learning pipeline for donor–recipient matching in kidney transplantation, showing accuracy improvements but emphasizing the need for real-time integration and multi-centre validation [4]. Comparative research has also assessed classical statistical methods against ML algorithms; for example, Guijo-Rubio et al. found that in some liver transplant scenarios, statistical models performed comparably or even better than ML approaches, underscoring the importance of dataset quality and feature engineering [5].
Recent work has emphasised interpretability and long-term patient outcome prediction. Salaün et al. employed transparent survival analysis models to predict graft and patient outcomes following kidney transplant offers, highlighting the trade-off between model interpretability and performance [6]. In pediatric transplantation, Liu et al. proposed an integrated ML framework to predict delayed graft function, demonstrating promising results but acknowledging the limitations posed by small cohort sizes [7].

Earlier explorations into personalized organ allocation frameworks also revealed the potential of ML for improving matching decisions. Yoon et al. introduced one of the first personalized donor–recipient matching systems, though constrained by the computational limitations and dataset availability of the time [8]. Broader reviews have documented increasing ML adoption in transplantation, outlining challenges such as inconsistent feature sets, lack of standardized evaluation, and limited real-world applicability [9, 12, 13, 14].

Hybrid machine-learning decision support systems have also been proposed to aid organ allocation, integrating multiple models to generate clinically actionable insights [10]. Large-scale datasets such as those provided by UNOS remain central to developing such systems, enabling long-term analyses of transplant trends and model performance benchmarking [11]. More recent research emphasizes AI-driven transplant decision support systems across multiple organs, signalling an emerging shift toward scalable, multi-organ prediction frameworks that align with evolving hospital needs [15].

Overall, the literature highlights significant progress in applying machine learning to transplantation medicine, yet major challenges persist, including limited real-time deployment, the absence of multi-organ prediction capabilities, and restricted integration with hospital workflows. These gaps reinforce the necessity for intelligent, scalable, and clinically deployable systems—such as the donor–recipient matching frame
work proposed in this study.

III. SYSTEM ARCHITECTURE AND WORKFLOW

3.1 SYSTEM ARCHITECTURE

The proposed system is designed as a **browser-based medical decision-support platform** that integrates machine learning models with a user-friendly interface to predict organ donor–recipient compatibility. At its core, the architecture

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consists of four primary components: the **medical data storage**, the **machine learning model training environment**, the **trained prediction models**, and the **Flask-based web application**.

The data storage component maintains structured donor and recipient medical records, including age, blood group, comorbidities, infection status, and organ-specific diagnostic values. These datasets are used during the training phase to develop compatibility prediction models for heart, kidney, liver, and lungs. The training environment—implemented in Python using scikit-learn—handles data preprocessing, feature encoding, score computation, and training of the Random Forest and K-Nearest Neighbours classifiers.

Once training is completed for each organ dataset, the best-performing model pipelines are saved in serialized form (e.g., rf_pipeline_heart.pkl, knn_pipeline_kidney.pkl). These pipelines include both the preprocessing transformer and the trained classifier, allowing the system to load models instantly during prediction without requiring retraining.

On the deployment side, the **Flask web application** provides an interactive interface with separate dashboards for administrators, doctors, receptionists, and patients. Doctors can navigate to the prediction module, enter donor and recipient clinical parameters, and receive real-time compatibility results. The backend loads the corresponding trained model pipeline, processes the inputs, computes derived scores (compatibility score, organ function score, final match score), and returns the prediction. This enables clinicians to access ML-powered insights directly through a browser without interacting with the underlying algorithms.

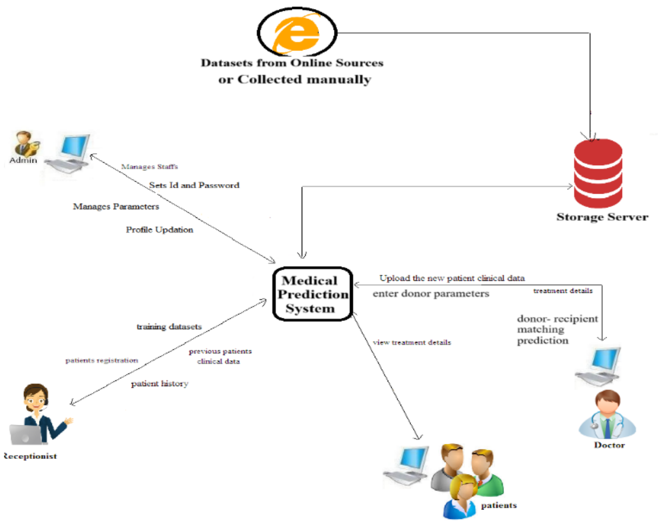

Figure.1 Architectural Workflow of the Medical Prediction System with user interactions and data flow.

3.2 WORKFLOW

The overall workflow of the system is divided into two major phases: the **Model Development Phase** and the **Runtime Prediction Phase**.

3.2.1 Model Development Phase

1. Dataset Preparation

The process begins by collecting organ-specific donor–recipient datasets for heart, kidney, liver, and lungs. Each dataset includes medically relevant features required for compatibility evaluation. Columns such as IDs or precomputed scores are removed, and the final dataset is divided into training and test sets. These datasets serve as the foundation for developing predictive models.

2. Data Preprocessing

Feature preprocessing is performed using a combined transformer consisting of StandardScaler for numerical attributes and OneHotEncoder for categorical attributes. This ensures uniform scaling and categorical consistency. Additional derived fields—such as compatibility score and organ function score—may be calculated depending on the organ type.

3. Model Design and Training

Two different machine learning models, **Random Forest** and **K-Nearest Neighbours**, are independently trained for each organ. Pipelines are constructed to integrate preprocessing and classification into a unified flow. Training performance

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is monitored using metrics such as accuracy, confusion matrix, and classification reports. The model that provides the most reliable classification performance is selected for deployment.

4. Model Saving

After satisfactory performance is achieved, each model pipeline (including preprocessing steps) is saved in serialized form (.pkl files). Additionally, a JSON file is generated to store the model's feature order and evaluation metrics. These artifacts enable the system to reload models instantly during real-time prediction.

3.2.2 Runtime Prediction Phase

1. User Data Entry

In the deployed Flask web application, the doctor navigates to the prediction module and enters donor and recipient parameters such as age, blood group, organ type, comorbid conditions, and organ-specific metrics (e.g., GFR for kidney, EF for heart).

2. Preprocessing for Inference

The backend converts all input values into the expected numerical or categorical format, aligns them to the exact feature order required by the selected organ model, and computes additional derived compatibility scores if necessary. This ensures full compatibility with the pipeline used during training.

3. Model Inference

The prepared input vector is fed into the loaded ML pipeline (RF or KNN). The model computes the compatibility classification and may produce an internal match probability or decision path depending on the algorithm. The final predicted label—*Compatible* or *Not Compatible*—is generated based on the model output.

4. Result Display

The predicted compatibility result, along with computed scores such as compatibility score, organ function score, and final match score, is displayed on the doctor's dashboard. These outputs help clinicians interpret the prediction quickly and support informed medical decision-making. The prediction result is also saved in the database for future reference and audit tracking.

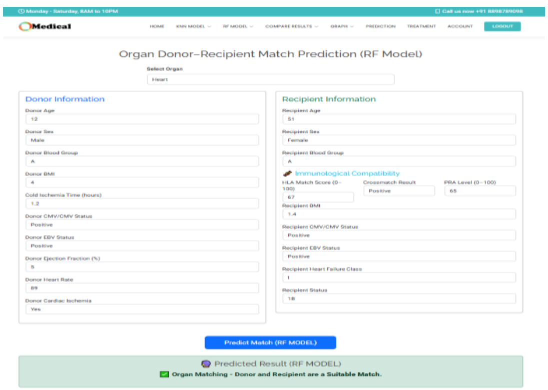

Figure 1: Prediction output indicating that the donor–recipient.

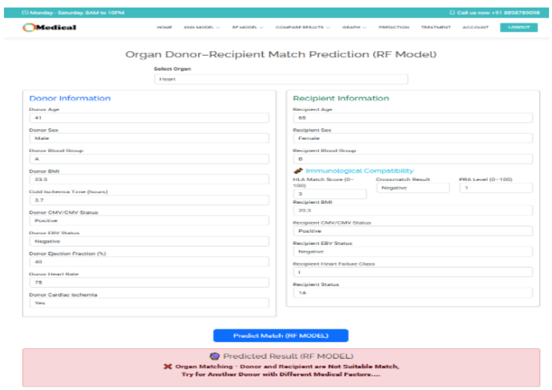

Figure 2: Prediction output indicating that the donor–recipient pair is not compatible

IV. RESULTS AND DISCUSSION

Results

The performance of the proposed Organ Donor–Recipient Matching System was evaluated using organ-specific datasets for the heart, kidney, liver, and lungs. Two machine learning models—Random Forest (RF) and K-Nearest Neighbours (KNN)—were trained and assessed for each dataset. The results showed a consistent trend across all organ types: **Random Forest outperformed KNN in terms of accuracy, precision, recall, and stability of predictions**. This can be attributed to RF's ability to handle complex non-linear relationships and mixed numerical–categorical clinical features more effectively than distance-based methods.

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The evaluation metrics derived from an 80:20 train–test split revealed strong model generalization, with RF models achieving the highest classification performance. Confusion matrix analysis indicated fewer false negatives and false positives compared to KNN, which is critical in medical decision contexts where incorrect compatibility assessment can adversely affect transplant outcomes. Additionally, the system's integration of **derived clinical scores**—Compatibility Score, Organ Function Score, and Final Match Score—offered complementary insights into model decisions and contributed to more interpretable outputs.

On the system side, real-time prediction tests were conducted through the Flask web interface. The backend successfully loaded organ-specific pipelines, processed user inputs, computed derived scores, and returned predictions with negligible latency. The output screens (refer to Figure 3) displayed clear compatibility results, score breakdowns, and essential clinical indicators, demonstrating the effectiveness of the UI in supporting fast comprehension and decision-making. Overall, the results confirm that the system delivers accurate, efficient, and clinically meaningful compatibility predictions suitable for practical deployment in hospital environments.

Discussion

The results highlight the significant potential of machine learning to improve organ donor–recipient matching, particularly in environments where manual evaluation is time-consuming and prone to inconsistencies. The superior performance of the Random Forest models reinforces the suitability of ensemble learning for medical data that contain diverse attribute types and non-linear interactions. RF's lower misclassification rates compared to KNN further underscore its appropriateness for high-stakes clinical applications where prediction reliability is essential.

A key strength of the system is its integration of **domain-informed scoring mechanisms** alongside ML predictions. The Compatibility Score and Organ Function Score synthesize relevant clinical factors such as age difference, HLA compatibility, PRA levels, and organ-health metrics, allowing clinicians to understand not only the final prediction but also the underlying contributors. This enhances transparency—an important requirement for medical decision-support systems.

Furthermore, real-time usability tests indicate that the system can seamlessly fit into existing hospital workflows. The multi-role interface ensures that doctors, receptionists, administrators, and patients interact with the system according to their responsibilities, maintaining data flow consistency and reducing operational friction. The instant prediction capability also reduces decision delays, which is critical when evaluating urgent transplantation cases.

Despite its strong performance, the discussion highlights areas that can be improved. Model accuracy is influenced by dataset size and diversity, meaning that multi-centre datasets and broader feature sets could further enhance generalizability. Additionally, integrating advanced models such as gradient boosting or deep neural networks may offer marginal performance improvements, though interpretability must remain a priority.

Overall, the discussion confirms that the proposed system provides a meaningful step toward intelligent, reliable, and scalable transplant decision support. Its combination of ML-driven compatibility prediction, interpretable scoring, and user-friendly workflow integration positions it as a promising tool for enhancing the accuracy and efficiency of organ allocation practices.

V. CONCLUSION

The work presented demonstrates an effective machine learning–based framework for predicting organ donor–recipient compatibility using clinically relevant features and organ-specific parameters. By combining structured medical data with Random Forest and K-Nearest Neighbours models, the system is able to generate reliable compatibility assessments supported by interpretive scoring metrics such as the Compatibility Score, Organ Function Score, and Final Match Score. Experimental results confirm that Random Forest offers more consistent and accurate predictions, making it well-suited for complex medical decision tasks.

Beyond algorithmic performance, the system's web-based interface enables practical integration into hospital workflows. Doctors can perform real-time compatibility checks, receptionists can manage patient records, and administrators can oversee user access, creating a cohesive environment for transplant-related activities. The rapid prediction capability and clear visual outputs significantly reduce reliance on manual evaluations and help streamline the decision-making process. Overall, the study illustrates the potential of machine learning to enhance transparency, speed, and accuracy in transplant matching. The proposed system provides a strong foundation for data-driven organ allocation and represents a meaningful step toward improving clinical efficiency and supporting better transplant outcomes.

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