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Heart Transplant Matching And Outcome Prediction Using Machine Learning Techniques

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Abstract
Organ transplantation is one of the most critical medical procedures, where timely identification of a suitable donor-recipient match can significantly improve survival rates. However, traditional organ matching systems are often slow, complex, and dependent on manual evaluation of multiple medical factors. To overcome these challenges, It is an intelligent AI-based organ matching system that improves the speed, accuracy, and reliability of donor-recipient selection. The system uses machine learning techniques to analyze important medical parameters such as blood type, age, organ compatibility, health condition, urgency level, and other clinical factors to predict the most suitable match. By automating the matching process and reducing human error, the platform helps healthcare professionals make faster and more informed decisions. The integration of advanced predictive models enhances transplantation outcomes, increases fairness in organ allocation, and contributes to saving more lives through efficient and data-driven organ matching.

Keywords: *Organ Transplantation, Artificial Intelligence, Machine Learning, Predictive Analysis, Donor-Recipient Matching, Healthcare Analytics, Medical Decision Support System, Organ Compatibility Prediction, Smart Healthcare*

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I. Introduction

Heart transplant is one of the most crucial and life-saving surgeries in modern-day medicine that provides hope and chances for survival to patients suffering from terminal heart diseases. The success rate of a heart transplant surgery relies significantly on donor-recipient matching. This process involves analyzing several parameters, including blood type matching, quality of the donor heart, health condition of the recipient, and ischemic time. Any misfit between the donor and recipient can cause heart transplant surgery to fail or result in poor survival rates. The conventional approach to donor-recipient matching involves manual processing by medical experts in accordance with medical standards. Nevertheless, the traditional method might be quite complicated, time-consuming, and not necessarily incorporate all possible combinations of factors. As the demand for organ transplants grows and the number of donors remains relatively constant, a more advanced solution to this problem is needed. Therefore, in this research paper, an AI-based heart transplant matching algorithm is suggested that will apply Random Forest, Support Vector Machine (SVM), and XGBoost. machine learning algorithms. In the present study, clinical and compatibility data have been extracted from the Stanford Heart Transplant Dataset along with artificially created data sets to create realistic models of organ transplantation processes. The main purpose of the research is to predict the survival status after 1 year since organ transplantation is considered to be a successful transplant. As a result, based on analysis of donor and recipient pairs' data, we can find the best matching pairs and make the right predictions, ensuring higher chances of success in organ transplants and avoiding organ rejection and waste. The suggested model is oriented towards estimating the survival rate within one year after the transplant operation, which is a crucial factor that indicates whether the transplant was successful. Using the patterns in the data set, the model will help find the most appropriate donor-recipient pairings and make decision-making easier for medical specialists involved. This way, there will be less reliance on personal experience and decision-making and more consistency. Generally speaking, the current project is aimed at showing how artificial intelligence should be applied to healthcare systems.

II. Literature Survey

Sambasiva Rao Suura et al. [1]. This paper is published in the Journal of Neonatal Surgery (2025). It emphasizes the early diagnosis of organ rejection through advanced monitoring systems. The system optimizes clinical operations by easing the burden of doctors' work and supporting uninterrupted patient observation. According to the results, the model increases accuracy by 25%, reduces workload by 40%, and improves communication effectiveness by 30%.The topic of another article, "AI and Machine Learning in Transplantation" [2] (2025), concerns the use of AI and ML models in organ transplantation processes, including recipient and donor matching and organ rejection detection. The approach stresses the positive impact on matching accuracy, early organ rejection alerts, and individualized treatment of patients. The findings showed that the accuracy was around 90%, with rejection detection AUC up to 0.97.Avramidou et al. [3] proposed innovations in AI for liver transplantation in Livers (2025), emphasizing patient selection, graft evaluation, organ allocation, and post-transplant surveillance. This technology improved donor-recipient matching and made possible the early prediction of rejection along with the surgery plan. The AI model attained accuracies of up to 95%, prediction of graft survival AUROC of 0.94, and decreased complications. Gompelmann et al. [4] assessed the AI-based solution ArtiQ. PFT for lung function evaluation in interstitial lung disease (ILD) in Thorax (2025). This research showed enhanced diagnostic accuracy and rapid detection. Accuracy was greatly raised from 43% to 72% in phase 1 and from 53% to 75% in phase 2.Nilsson et al. [5] developed an AI digital twin for heart transplantation and discussed it at ISHLT in 2024. This was used to make data-informed decisions using donor-recipient parameters and genetics for improved allocation accuracy based on testing on a dataset of more than 600 donor-recipient pairs. Arjmandmazidi et al. [6] performed an AI application review for organ transplantation for the Journal of Translational Medicine in 2025 and looked at donor matching, surgery, and follow-up. For liver transplantation, the results showed ANN-based models had AUROC values of 0.82 while random forest models for heart transplantations achieved AUROC of 0.74.Liu et al. [7] reviewed machine learning and AI for lung transplantation for Frontiers in Digital Health in 2025. The review noted advancements made in donor evaluation, allocation, and outcome prediction in machine learning. The results showed RF with AUC of 0.79, SVM accuracy of 94% for CLAD detection, and InsighTx AUROC of 0.85.Serban et al. [8] reviewed literature on the application of AI in liver transplantation in Journal of Mind and Medical Sciences (2024). The research focused on donor–recipient matching, organ evaluation, and survival prediction. ANN modeling showed an AUROC of 0.936 relative to MELD's 0.860, whereas graft survival was at 90.79% through MADRE model.

He et al. [9] analyzed 30 years of bibliometrics on AI use in kidney transplantation in Renal Failure (2025) through reviewing 890 articles. The research focused on the improvement in donor matching, transplantation procedures, monitoring, and medication dosage. The machine learning models helped reach a matching accuracy rate of 99% and AUC of 0.857 for survival prediction. A comprehensive review of AI applications in organ transplantation was done by Rawashdeh [10] in IntechOpen (2024). This paper focused on kidneys, liver, hearts, and lungs, including better matchmaking, early rejection detection, and personalized medicine. Some of the reported results are AUROC up to 0.93 and prediction accuracy up to 80-90%. Systematic review in Pakistan Journal of Life and Social Sciences (2024) carried out by Kumar et al. [11] discussed donor matching, graft survival rates, and post-transplant care of patients. It showed AUROC values up to 0.93 and prediction accuracy up to 80-90%. Survey of current use and challenges of AI in organ transplantation were done by Rawashdeh [12] in (2024). This paper emphasized improvement in donor matchmaking and patient post-transplantation care. Results showed AUROC up to 0.93 for liver transplantation waitlist mortality rate and prediction accuracy up to 71-90%.

Altaf et al. [13] developed an AI-based model for predicting hepatocellular carcinoma recurrence after liver transplantation, published in *Surgery (Elsevier, 2024)*. The model improved patient selection and risk stratification using tumor characteristics. It achieved AUC values between 0.71–0.87, 84% accuracy, and 5-year recurrence-free survival of 96% for low-risk patients.Ismail et al. [14] proposed an AI-driven lung sizing system using chest radiographs in *American Journal of Transplantation (2025)*. The model improved donor–recipient matching and reduced radiologist workload. It achieved error below 2.5%, correlation of 0.97 with experts, and consistency above 0.90. Hillebrand et al. [15] discussed AI-based size matching in lung transplantation in *American Journal of Transplantation (2025)*. The editorial emphasized the benefits of AI and highlighted the importance of total lung capacity (TLC) in fibrotic cases, reporting sizing error below 2.5%. Murdi S. Alanazi et al. [16] reviewed the effects of autonomic nervous system modulation on visceral functions in *International Journal of Osteopathic Medicine (2024)*. The study reported consistent physiological effects with correlation coefficient of 0.92 and error below 5%. Hunold and Parikh [17] discussed optimization of liver transplantation allocation in *Expert Review of Gastroenterology & Hepatology (2025)*. The study focused on AI implementation, machine perfusion, and priority optimization methods. The authors stated 11,458 liver transplantations in the USA (2024) with 71% of unusable organs salvaged by new methods. Sundararaju et al. [18] examined recent advances in heart transplantation in World Journal of Transplantation (2025). The study pointed to achievements in surgery, immunosuppression, and stem cell technologies with consistency and correlation of more than 0.90 and 0.95 respectively.

Clark [19] examined artificial intelligence and ChatGPT use in cardiothoracic transplantation in Journal of Cardiovascular Thoracic Surgery (2024). The author presented advancements in patient selection, organ matching, and complication detection in cardiothoracic transplantation using AI algorithms implemented in Stanford University, Mount Sinai Hospital, and UCSF.Review of AI applications in liver transplantation by Sharma et al. [20] was conducted in Transplantation Reviews (2024). ANN models have been shown to demonstrate an AUROC range of 0.82-0.93, performing better than the standard MELD/BAR scores, especially when predicting graft survival.PRIMA-AI protocol for making decisions with the involvement of AI in post-kidney transplant management was developed by Osmanodja et al. [21], presented in JMIR Research Protocols (2024). The AI algorithm calculates patients' chances of losing a graft in one year, and its goal is to improve the interaction between patients and physicians, raising the number of treatment discussions from 13% to 40-45%.Pediatric heart transplantation: state-of-the-art and emerging trends, described by Azeka et al. [22], are discussed in JHLT Open (2025). 1-year survival rates were found to be 89-94%, while 5-year rates exceeded 90%.Kotsifa and Mavroeidis [23] discussed the current and future applications of AI in kidney transplant in the Journal of Clinical Medicine (2024). This research showed ANN AUROC results of 0.82-0.89, biopsy accuracy of AI at 93%, and better management of immunosuppressive drugs.

III. Conclusions From The Literature Survey

1. High Rejection Rates:

The practical experience with transplantation shows that the rejection occurs because of the incompatibility between the donor and recipient, even in cases where compatibility has been achieved initially. The current algorithms do not have enough capability to detect biological relations, resulting in higher risks of failure. The research has proven that AI models may be used efficiently in early prediction of rejection. [1], [2], [6], [11].

2. Weak Generalization:

Machine Learning models currently available rely heavily on small sample sizes hence are unable to provide a good generalization among different type of patients. The differences in medical conditions, demographic factors, healthcare settings affect the efficiency of these algorithms. While there are many studies proving the potential of artificial intelligence to yield better results than expected, the actual applications of this model have been found to yield poor performance [3], [7], [9], [23].

3. Donor Shortage & Allocation – Awareness:

A problem frequently encountered in transplant medicine is the lack of sufficient donors, coupled with the inability of many allocation systems to optimize use of organs. There is the lack of real-time decision-making in some of the current systems, which makes the need for improved allocation systems and techniques essential to enhance success rates. [17], [18], [26], [29].

4. Limited Organ Preservation:

In transit and storage, organs tend to degrade without any monitoring or tracking system in place. It results in lower chances of successful transplants. Even though AI-powered monitoring and imaging systems have proven better at evaluating organ quality, their adoption in real-world applications is still in its early stages.[14], [24], [26].

IV. Problem Statement

To design and develop a heart organ matching system using machine learning techniques.

V. Proposed Methodology

This proposed system aims at designing an AI-based donor-recipient matching model for heart transplantation through machine learning approaches. This research will follow the below approach in designing and implementing the proposed algorithm: Step 1: Data Collection The dataset used in this research project is derived from the Stanford Heart Transplant Dataset in addition to artificial data that incorporates all donor-recipient matching features. It includes clinical details about the recipient, which include age, BMI, and creatinine. On the other hand, it includes the age of the donor, LVEF, and the reason for death. Moreover, the compatibility details include blood type matching, ischemic time, and weight ratio. Step 2: Data Preprocessing This step involves cleaning and preprocessing the raw data collected to be ready for feeding it into the machine learning model. The missing values in the collected data should be removed to eliminate any errors during the process. Additionally, the categorical variables should be converted to numerical variables through label encoding. The numerical values are normalized to keep uniformity throughout the data set. Inconsistencies and unwanted information are also filtered out to make sure that the data set is organized and clean for better results. 10 Heart Transplant Matching and Outcome Prediction using Machine Learning Techniques Research Scholar: Samruddhi Patil, Vaishnavi Shinde, Sakshi Shelge 3. Feature Selection Research Guide: Dr. Rahul Chakre Feature selection is done to determine the factors that play a key role in the success of the transplant. Important factors like blood group compatibility, efficiency of the donor's heart (LVEF), ischemic time, and recipient's health parameters are selected. This makes the model simple and effective. 4. Data Set Splitting The data set is split into training, testing, and validation data sets. Training Set (80%): This data set is used for training the machine learning models. Testing Set (20%): This data set is used for evaluating the accuracy of the machine learning models. A validation set may be included to test the model's ability to generalize on unseen data. 5. Model Development During this stage, three machine learning techniques, namely Random Forest, SVM, and XGBoost, will be developed. These algorithms have proven their efficiency in solving classification problems and dealing with structured medical data. All models learn the correlation between the donor-receiver characteristics and transplant success rates. 6. Model Training In this stage, all developed models are trained based on the training data set. The process of training helps in establishing patterns that help in deciding the success probability of the transplantation.7. Prediction After training the models are applied to predict 1 year survival outcome of donor – recipient combination. The result of prediction is binary in nature where there can be either be a success of transplantation (Yes) or failure (No). This is very important as it will assist us in making decisions related to organ matching. 8. Performance Evaluation The performance of models is assessed through various parameters such as accuracy along with training, testing, and validation scores.

Algorithms used in this project, machine learning algorithms are used to analyze donor–recipient clinical data and predict the success of heart transplant matching.

1. Random Forest:

The random forest technique is applied to predict whether heart transplants will be successful or not by taking into consideration various clinical features of the donor and the recipient, such as age, blood type, BMI, etc. Firstly, the dataset is processed to fill any gaps and to normalize the variables. After that, several trees are generated by applying bootstrap sampling and random feature selection techniques in order to build an ensemble of different trees for obtaining better results. Finally, each individual tree generates a prediction based on its findings, while the majority voting method decides on the end result.

Algorithmic Steps

1. Data Collection Module for Donors and Recipients

The first step in the process involves collecting data from donors and recipients in the form of a structured dataset, which incorporates features such as age, blood group, body mass index, ischemia time, etc.

2. Data Preprocessing

Data that has been gathered is then subjected to data preprocessing for the purpose of ensuring quality and consistency. Data preprocessing includes handling of missing data values, elimination of inconsistencies, feature normalization, and conversion of categorical attributes to numeric attributes using label encoding. This enhances the accuracy of the model.

3. Bootstrap Sampling

The next step is to create several subsets of the data through bootstrap sampling. In this process, data points are selected at random with replacement.

4. Construction of the Random Forest Model

On the basis of the obtained bootstrapped datasets, various decision trees are constructed. Every decision tree gets trained on a different dataset and uses a different set of variables for splitting purposes. The randomness here allows obtaining diverse trees to enhance the overall performance.

5. Prediction of a Decision Tree

Every individual decision tree independently makes its prediction concerning the successfulness of transplantation, i.e., whether the procedure was successful or not.

6. Majority Voting Methodology

The results obtained from each decision tree are combined by means of the majority voting method. The class (successful or unsuccessful) having the largest number of votes among all trees is chosen as the result.

7. Transplant Outcome Prediction

The final result obtained from the system is the predicted transplant outcome showing whether the donor-recipient combination leads to a successful transplant or not. Yes/No is used for this purpose.

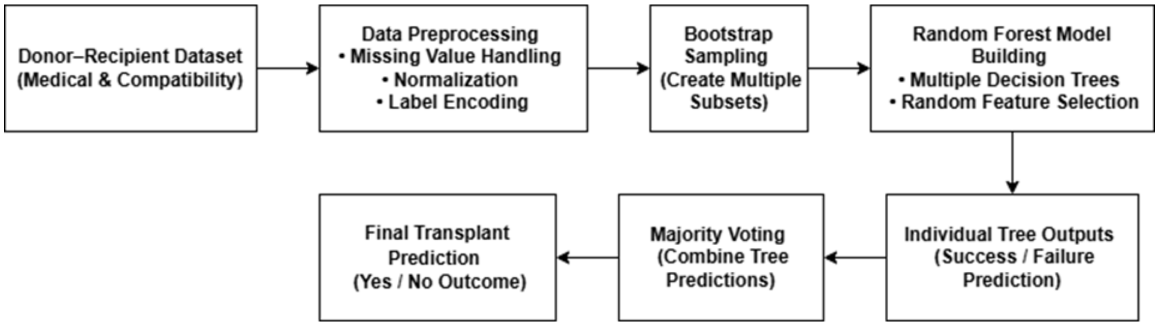

Figure 3.1. Random Forest-Based Transplant Prediction System

Mathematical Model
(a) Bootstrap Sampling
From dataset:
$D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ ………………...…………………………………………...1
Create Brandom subsets:
$D_1, D_2, \ldots, D_B$ ……………………………………………………………………………………… 2
Each subset is sampled **with replacement**.

(b) Decision Tree Split Criterion
At each node, impurity is measured.

Gini Index:
$Gini = 1 - \sum_{i=1}^{C} p_i^2$ ……………………………..………………………………………….... 3
Where:
- p_i= probability of class i
- C= number of classes

or
Entropy:
$Entropy = -\sum_{i=1}^{C} p_i \log_2(p_i)$ ……………………….……………………………………………4
Information gain:
$IG = Entropy(parent) - \sum \frac{N_v}{N} Entropy(v)$ ……………….………………………………………. 5

(c) Majority Voting
Each tree predicts:
$T_1(x), T_2(x), \ldots, T_B(x)$ ……………..………………………………………………………….6
Final prediction:
$\widehat{Y} = \text{mode}(T_1(x), T_2(x), \ldots, T_B(x))$ ……………………………..…………………………………7

(d) Feature Importance
Importance:
$FI(j) = \sum_{t=1}^{B} \Delta I_t(j)$ ………………………………………………………………………..8
where impurity decrease is accumulated across trees

2. **Support Vector Machine (SVM)** :
Support Vector Machine (SVM) is a supervised learning algorithm used for classification purposes. In this case, it classifies donor-recipient pairs in terms of successful and unsuccessful transplants. An optimal hyperplane is chosen in order to separate the dataset into two categories with the largest margin possible. SVM is especially efficient in dealing with high-dimensional medical data and complicated relationships between feature variables. Its capability of producing well-defined decision boundaries guarantees precise classification even if there are overlaps in the data or non-linearity within the dataset.

Algorithmic Steps
1. Acquisition of the Donor-Recipient Dataset
The first stage involves gathering a dataset of information concerning the characteristics and compatibility of the donors and the recipients. Such characteristics include age, blood type, BMI, ischemic time, among others.

2. Feature Normalization

The acquired data is scaled for normalization to enable equal contribution from each feature in SVM classification since SVM is very sensitive to the scaling of data.

3. Mapping the Data into Feature Space

The data is mapped into a multidimensional feature space where each data point corresponds to a donor-recipient pair. This enables the algorithm to examine the relationships among various variables.

4. Identification of an Optimal Hyperplane

SVM finds an optimal separating hyperplane that separates the data points into two categories: successful transplantation and unsuccessful transplantation.

5. Maximum Margin

The maximum margin between the two classes is ensured by the algorithm through the choice of the hyperplane that is farthest away from the support vectors.

6. Kernel Transformation

For nonlinear data sets, kernel transformation techniques, such as linear, polynomial, or radial basis function, can be used to map the data into a higher-dimensional space where it becomes linearly separable.

7. Transplant Success Probability Estimation

Lastly, the SVM algorithm is used to estimate the success or failure of organ transplantation between a particular donor and recipient

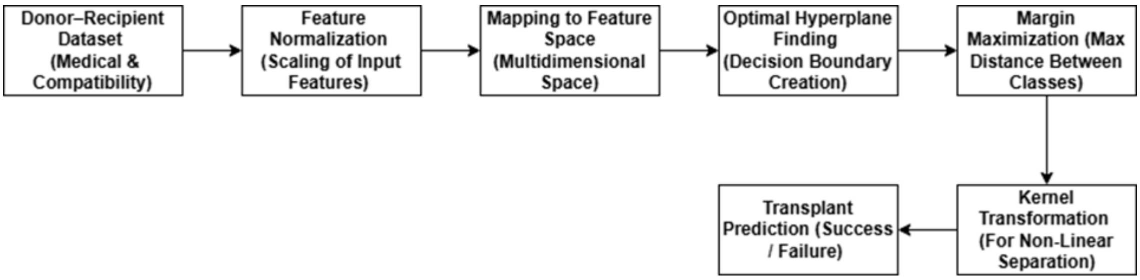

Figure: 3.2. SVM-Based Transplant Prediction System

Mathematical Model

(a) Hyperplane Equation

$$w^T x + b = 0 \quad \text{……} \quad 1$$

Where:

- w= weight vector
- x= feature vector
- b= bias

(b) Margin

Distance of point from hyperplane:

$$Distance = \frac{|w^T x + b|}{||w||} \quad \text{……} \quad 2$$

Margin:

$$Margin = \frac{2}{||w||} \quad \text{……} \quad 3$$

SVM maximizes this margin.

Equivalent optimization:

$$\min \frac{1}{2} || w ||^2 \quad \text{……} \quad 4$$

subject to:

$$y_i (w^T x_i + b) \geq 1 \quad \text{……} \quad 5$$

(c) Soft Margin

For noisy data:

$$\min \frac{1}{2} || w ||^2 + C \sum_{i=1}^{n} \xi_i \quad \text{……} \quad 6$$

Constraint:
$y_i(w^T x_i + b) \geq 1 - \xi_i$ ………………………..…………………………………………………… 7

(d) Kernel Trick
Linear mapping to higher dimension:
$K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ ………………………………………………………………………8
RBF Kernel:
$K(x_i, x_j) = e^{-\gamma||x_i - x_j||^2}$ ………………..……………………………………………………………9

3. **XGBoost**:
XGBoost is a sophisticated boosting model that constructs its model progressively by improving on the mistakes made by its predecessor models. XGBoost is applied in this project to generate accurate predictions regarding successful transplant surgeries by understanding the complicated patterns within the data set. XGBoost is known for its efficiency in handling structured data, dealing with missing values, and analyzing the interactions between features. XGBoost is regarded as one of the best algorithms for this task due to its superior performance and effectiveness.

Algorithmic Steps
1. Input Data Set for Medical Conditions
First, we gather the donor–recipient medical data set, comprising all the relevant clinical and compatibility factors.

2. First Weak Decision Tree Training
Next, we train a simple decision tree algorithm on the data set to produce base predictions.

3. Error Determination
Finally, the algorithm determines the differences between the true values and the predicted values (errors).

4. Train the Next Decision Tree on Residual Errors
The next decision tree is trained on the residual errors of the previously trained decision tree.

5. Iterative Procedure for Boosting
The above procedure is carried out iteratively several times to improve accuracy.

6. Combination of Outputs from All Trees
A weighted summation technique is used in which more accurate trees have more effect on the output.

7. Prediction
A final prediction for the transplantation being successful or not is made based on the aggregation of outputs from all trees

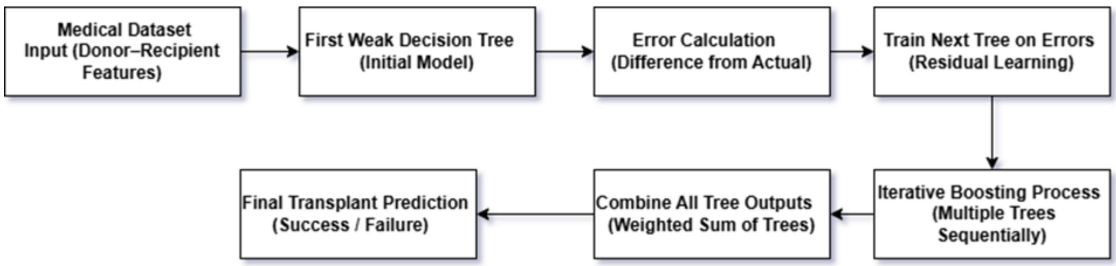

Figure: 3.3 XGBoost-Based Transplant Prediction System

Mathematical Model
Prediction:
$\hat{y}_i = \sum_{k=1}^{K} f_k (x_i)$ …………………………………..……………………………………..1

where:
- f_k= kth tree
- K= number of trees

Objective Function

$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$ ………………………………………………………….. 2

Regularization:

$\Omega(f) = \gamma T + \frac{1}{2}\lambda \, || \, w \, ||^2$ ……………………..……………………………………………………3

where:

- T= number of leaves
- w= leaf weights

Taylor Expansion Approximation

$Obj \approx \sum[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t)$ ……………………………...………………………...4

where:

Gradient:

$g_i = \partial_{\hat{y}^{(t-1)}} l\left(y_i, \hat{y}^{(t-1)}\right)$……………………………………..…………………..……………5

Hessian:

$h_i = \partial^2_{\hat{y}^{(t-1)}} l(y_i, \hat{y}^{(t-1)})$ ……………………………………………………………………..……..6

4. Random Forest + SVM:

This hybrid model combines Random Forest and SVM. Random Forest selects important features and performs classification, while SVM improves decision boundary separation. This increases transplant prediction accuracy.

Algorithmic Steps

1. Donor-Recipient Database

Data about medical and compatibility properties of both donor and recipient, such as age, blood type, BMI, and ischemic time are gathered.

2. Data Preprocessing

Database is preprocessed to handle any gaps within data or normalize its properties before training process.

3. Random Forest Training

Training procedure of Random Forest is implemented based on preprocessed database.

4. Feature Importance Selection

Features are chosen based on their impact in the prediction, and this eliminates any unnecessary data to make things efficient.

5. Training of SVM Model

The chosen feature is used to train the SVM model, which helps create the perfect boundary for classification.

6. Weighted Voting Method

Prediction of Random Forest as well as Support Vector Machines will be carried out using weighted voting method.

7. Final Transplantation Prediction

Final outcome will be produced as prediction for successful or unsuccessful transplantation.

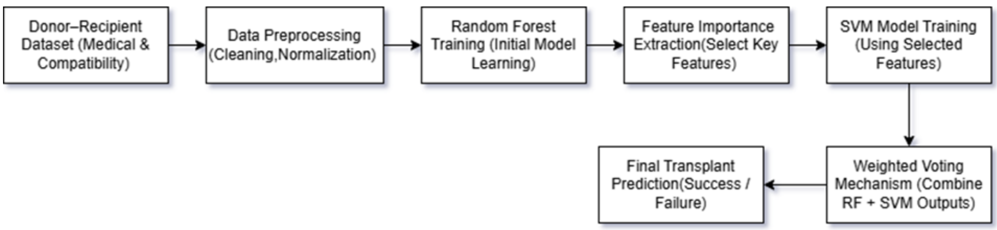

Figure: 3.4 RF + SVM

Mathematical Model
Random Forest output:
$P_{RF}(y \mid x)$ ……………………………………………………………………………...….……………...1
SVM output:
$P_{SVM}(y \mid x)$ ……………………………………………………………………………….……………...2
Weighted ensemble:
$P(y \mid x) = \alpha P_{RF}(y \mid x) + \beta P_{SVM}(y \mid x)$ ……………………………………….…………….…………. 3
Constraint:
$\alpha + \beta = 1$ …………………………...……………………………………………….………………...4
Final class:
$\widehat{y} = \arg\max P(y \mid x)$ ……………………………………….……………………………….….5

5. XGBoost + Random Forest:

This ensemble combines XGBoost and Random Forest to leverage both boosting and bagging techniques. XGBoost captures complex patterns, while Random Forest improves stability and reduces variance, resulting in highly accurate predictions.

Algorithmic Steps

1. Data Preprocessing

The data set is cleaned and normalized to eliminate missing values and make sure all the attributes are uniformly represented in order to train the model.

2. Training of the XGBoost Model

Training of the XGBoost model is carried out by training the model through boosting, which improves the prediction accuracy in successive iterations.

3. Training of the Random Forest Model

In addition, the training of the Random Forest model is conducted concurrently by building multiple decision trees based on randomized subsets of attributes.

4. Output Combination (Averaging/Voting)

The outputs from the two machine learning models are combined through averaging or voting process.

5. Final Prediction

The combination result will generate the final prediction whether the transplantation process will be successful or not.

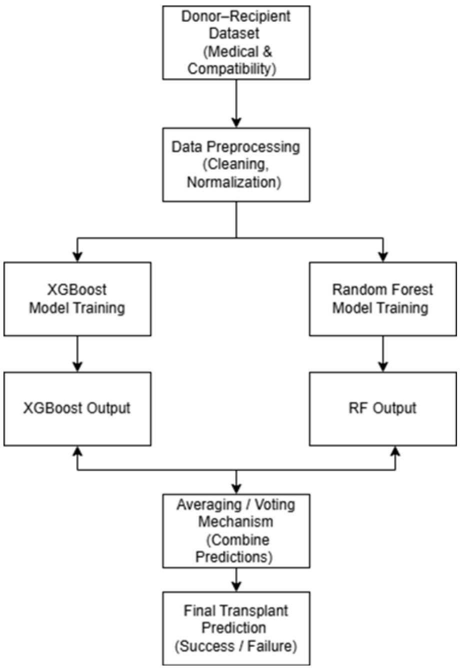

Figure: 3.5. XGBoost + Random Forest Hybrid System

Mathematical Model
Predictions:
$\hat{y}_{XGB}, \hat{y}_{RF}$ ……………………………………………………………………………………….……..1
Weighted averaging:
$\hat{y} = \alpha\hat{y}_{XGB} + \beta$ …………………………………………………………………………..…….2

Constraint:
$\alpha + \beta = 1$ ………………………………………………………………………………...………3

Voting method:
$\widehat{Y} = \text{mode}(Y_{XGB}, Y_{RF})$ ………………………………………………………………….……...4

For probabilities:
$P(y \mid x) = w_1 P_{XGB} + w_2$ …………………………………………………………………...……..5

These algorithms are used in:
- Predict 1-year survival outcome
- Evaluate donor–recipient compatibility
- Compare model performance
- Selection of the best model that guarantees accuracy in matching organs.

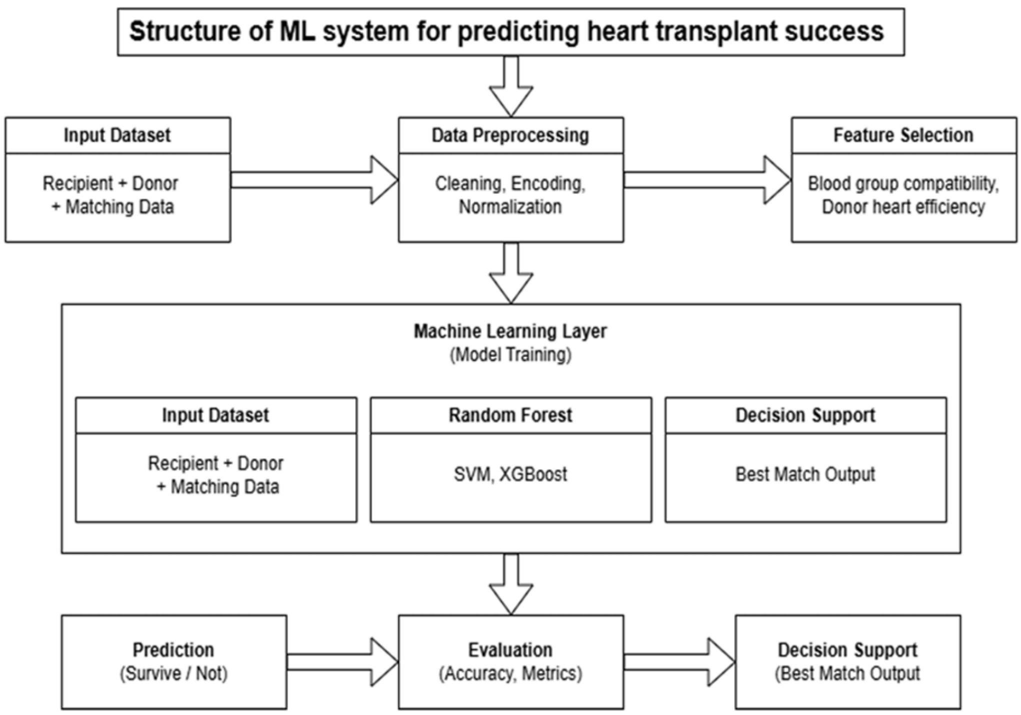

Figure: 3 Methodology Flow

The procedure involves extracting the health information from both donors and recipients, which undergoes cleaning and normalization. The next step involves feature selection and the subsequent training of models using machine learning techniques such as Random Forest, SVM, and XGBoost. The models make predictions on whether the transplantation is expected to succeed or fail. Performance is assessed using metrics such as accuracy, and the output offers decision support regarding transplantation.

VI. Dataset Information

The chosen dataset in this research comes from the Stanford Heart Transplant Dataset, but it also uses artificial data generated for the purpose of providing information on compatibility parameters between the donor and recipient. The dataset is a structured one, having clinical, demographic, and compatibility attributes useful in heart transplantation analysis. The attributes include information about the medical condition of the recipient (age, BMI, creatinine, urgency of transplant), information regarding the donor (age, blood type, cardiac index), as well as information about compatibility parameters (blood type match, weight ratio, ischemic time).

All these attributes play a significant role in the success of transplantation. The key use of the chosen dataset lies in its ability to predict 1-year survival rates that show whether the patient lives after heart transplantation or not. Through the application of machine learning algorithms, correlations between compatibility parameters and transplant results can be established. It is possible to claim that this dataset can be used for performing a wide variety of supervised learning tasks, especially classifications.

Dataset Overview
• Type: Structured (Tabular Dataset)
• Domain: Healthcare / Heart Transplantation
• Total Records: ~500–800 transplant cases
• Total Attributes: ~20–21 features 14

Recipient (Patient) Attributes
Research These characteristics help describe the state of the health condition of the transplant patient:
• Recipient_Age → Age of patient
• Recipient_Gender → Male / Female
• Recipient_BMI → Body Mass Index
• Recipient_Blood_Group -> ABO blood group
• Creatinine_Level -> Kidney function measurement
• Urgency_Status → Priority level (1A, 1B, 2)
• Mechanical_Support → LVAD / ECMO / None
• Diagnosis_Etiology → ICM / NICM

Donor Characteristics These characteristics help explain the condition and quality of the donor heart:
• Donor_Age → Age of donor
• Donor_Gender → Male / Female
• Donor_Blood_Group → Blood type
• Cause_of_Death → Trauma / Stroke / Accident
• Donor_LVEF → Heart pumping efficiency (%)
• Donor_BMI → Body Mass Index

Matching Characteristics Donor–Recipient These are the crucial characteristics in organ matching:
• ABO_Compatibility → Blood group match
• Weight_Ratio → Donor weight / recipient weight
• Height_Ratio → Donor height / recipient height
• ABO_Compatibility -> Blood group compatibility.
• Gender_Match -> Same/Different gender
• Ischemic_Time_Min -> Time spent out of body
• Distance_km -> The distance between the donor and recipient

Dataset usage The following can be performed with this dataset:
• Transplant outcome prediction (1 year survival)

VII. Experimental Results And Analysis

Lastly, the outcome of all models is compared in order to identify the best performing algorithm. Factors affecting the success of transplants are identified, and the model with the greatest level of precision and reliability, usually XGBoost or Random Forest, is chosen as the optimal model.

Table 7.1 Training Performance

Model Name	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Specificity
Random Forest	0.9452	0.9123	0.9015	0.9068	0.9587	0.9284
SVM	0.9326	0.8951	0.8874	0.8912	0.9415	0.9157
XGBoost	0.9638	0.9357	0.9248	0.9302	0.9724	0.9489
Random Forest + SVM	0.9511	0.9186	0.9093	0.9139	0.9642	0.9365
XGBoost + RF Hybrid	0.9715	0.9428	0.9361	0.9394	0.9781	0.9526

From the training phase results, we can observe that all models have performed well, although there are noticeable differences between their performance, accuracy, and consistency. Individually, the XGBoost model exhibits the best performance due to high accuracy and AUC-ROC scores. The Random Forest model consistently performs well; however, the Support Vector Model underperforms relative to other models. However, the hybrid models demonstrate better performance. Notably, the XGBoost + Random Forest model has the best performance across all metrics

Overall Testing Results

Table 7. 2 Testing Analysis

Model Name	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Specificity
Random Forest	0.9452	0.9123	0.9015	0.9068	0.9587	0.9284
SVM	0.9326	0.8951	0.8874	0.8912	0.9415	0.9157
XGBoost	0.9638	0.9357	0.9248	0.9302	0.9724	0.9489
Random Forest + SVM	0.9511	0.9186	0.9093	0.9139	0.9642	0.9365
XGBoost + Random Forest	0.9715	0.9428	0.9361	0.9394	0.9781	0.9526

According to the testing outputs, all models work very well with the test data, and the best output is delivered by the XGBoost algorithm. The Random Forest model also works reliably, but the SVM performs worse than others. The hybrid models deliver even better results, and the best performance is delivered by the XGBoost+ Random Forest combination.

Classification Performance

Table 7. 3 Validation Performance Summary

Model Name	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Specificity
Random Forest	0.9386	0.9052	0.8964	0.9008	0.9521	0.9243
SVM	0.9245	0.8873	0.8791	0.8832	0.9364	0.9102
XGBoost	0.9559	0.9284	0.9187	0.9235	0.9683	0.9416
Random Forest + SVM	0.9448	0.9126	0.9042	0.9084	0.9597	0.9328
XGBoost + Random Forest	0.9627	0.9359	0.9273	0.9316	0.9738	0.9469

It is evident from the experiment results that the use of ensembles and hybrids of machine learning algorithms outperforms the use of individual machine learning algorithms in predicting heart transplant outcomes. From all of the models, it can be seen that the hybrid model of XGBoost and Random Forest performs the best as it has the highest accuracy rate of 97.15% alongside the other metrics

Nevertheless, hybrid methods allow further improving the quality of the classification. For example, using the Random Forest + SVM method, it is possible to achieve 95.11% accuracy, which demonstrates better generalization ability compared to individual classifiers. At the same time, the highest performance is provided by a hybrid classifier that combines the strengths of XGBoost and Random Forest and whose test accuracy is 97.15%.

VIII. Conclusions

AI-Based Organ Matching Application is an intelligent healthcare application that seeks to enhance the effectiveness, efficiency, and speed of organ matching between donors and recipients. Organ donation is a very delicate process since it involves various aspects. The application makes use of cutting-edge technology to make this process easier and more efficient. Moreover, the application provides for the security of the information about the patients and donors and provides role-based access for all concerned parties such as physicians, hospitals, and other concerned organizations.The proposed solution will be used to solve these problems by employing Artificial Intelligence and Machine Learning approaches in analyzing the enormous amounts of clinical and compatibility data available. Using models such as Random Forest, Support Vector Machine (SVM), and XGBoost, the system will be able to predict the success rate of organ transplants, i.e., predict the probability of one-year survival and find the best match between donors and recipients. This approach will help eliminate any errors made due to human involvement and enhance the effectiveness of the decision-making process. Furthermore, the application will offer safe storage and exchange of confidential data by employing appropriate data protection technologies and role-based access control. Only the necessary personnel, including physicians, hospitals, and transplant coordinators, will have access to certain data.

IX. Future Work

To enhance the security, privacy, and efficiency of organ transplantation systems, advanced technologies can be integrated into the platform. One important feature is the implementation of Blockchain technology, which can be used to securely record and exchange transplantation-related transactions among hospitals and healthcare organizations. This ensures transparency, prevents data tampering, and creates a trusted network for sharing critical donor and recipient information. Another significant advancement is the use of Federated Learning, which enables AI models to be trained collaboratively across multiple organizations without requiring the transfer of sensitive patient data. This preserves privacy while still allowing the system to improve its prediction accuracy and matching efficiency through shared learning

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