

OrganiQ-Net: A Multi-Modal Approach to Organ Viability Prediction

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Abstract

OrganiQ-Net is a multi-modal deep learning model for predicting organ transplantation outcomes by integrating imaging, genetic data, physiological markers, and medical histories. It combines CNNs for image analysis, dense layers for genetic data, and LSTM layers for sequential physiological data. Testing on synthetic datasets shows OrganiQ-Net outperforms traditional methods with 98% accuracy in organ viability prediction, offering a robust solution for improving transplant decision-making and patient outcomes.

Keywords:

OrganiQ-Net, Deep Learning, Transplantation, Genetic data analysis ,Physiological markers , Image analysis , CNNs ,Organ Viability Prediction, Medical history integration , Predictive model .

1 Introduction

Organ transplantation is a vital procedure for patients with severe organ failure, but its success is largely dependent on the compatibility between the donor organ and the recipient. Existing methods for evaluating organ suitability typically rely on isolated data types like imaging, genetic information, and medical history, which may not provide a complete picture of the organ's overall viability. This research introduces OrganiQ-Net, a deep learning framework that combines various data sources, including organ imaging, genetic data, physiological markers, and donor-recipient medical histories, to predict the body's response to the transplant before the procedure. This integrated approach offers a more comprehensive evaluation to enhance decision-making in transplantation.

OrganiQ-Net utilizes multiple deep learning techniques to process different types of data, including CNNs, LSTM networks, and fully connected dense layers. CNNs analyze organ imaging data to extract features that help assess the organ's condition. Dense layers handle genetic and medical history data, transforming them into meaningful insights. Additionally, LSTM networks are employed to process sequential physiological

data, such as vital signs, capturing time-based patterns. By using this multi-modal approach, OrganiQ-Net can integrate diverse data sources for a more accurate assessment of organ viability.

The model processes different data types independently through specialized layers. Imaging data is passed through CNN layers for feature extraction, while genetic and historical data are processed by dense layers. Sequential physiological data is analyzed using LSTM layers to capture time-dependent trends. After processing, the outputs are combined into a single feature vector, which is then used by fully connected layers to make predictions on organ viability and potential rejection risks, providing a comprehensive pre-transplant evaluation.

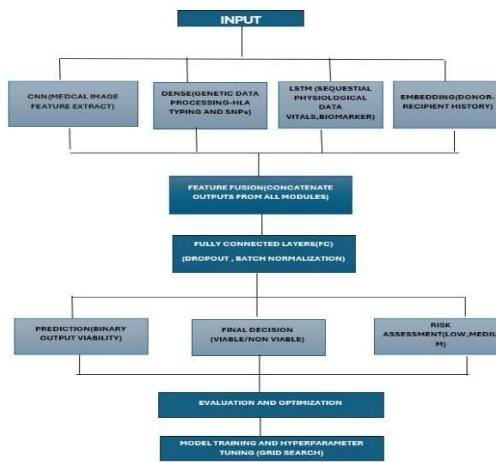


Fig. 1. Transplant Viability and Risk Prediction System (TVRPS)

1.1 Input:

CNN (Medical Image Feature Extraction): The model extracts features from medical images (e.g., MRI, CT scans) using Convolutional Neural Networks (CNN).

Dense/Genetic Data Processing (HLA Typing and SNPs): Genetic data such as HLA typing and SNPs (single nucleotide polymorphisms) are processed for feature learning.

LSTM (Sequential Physiological Data - Vitals, Biomarkers): LSTM networks process sequential physiological details, such as vital signs and biomarkers, over time to capture temporal dependencies.

Embedding (Donor-Recipient History): Categorical features related to donor-recipient medical history are embedded into a format suitable for learning by the model.

1.2 Feature Fusion (Concatenate Outputs from All Modules):

After processing the data through the individual modules (CNN, Dense, LSTM, and Embedding), the features from all these different data sources are concatenated (combined) into a single vector.

1.3 Fully Connected Layers (FC) (Dropout, Batch Normalization):

The fused features pass through fully connected layers.

Dropout: This technique randomly disables some neurons during training to prevent overfitting.

Batch Normalization: This normalizes the input for each layer to improve training speed and stability.

1.4 Prediction/Binary Output Viability:

A prediction is made, which could be a binary outcome (e.g., viable vs. non-viable transplant candidates).

1.5 Final Decision (Viable/Non-Viable):

Based on the prediction, the system outputs a decision about the viability of the transplant.

1.6 Risk Assessment (Low/Medium/High):

The model also assesses the risk level (e.g., low, medium, or high) for the transplant.

1.7 Evaluation and Optimization:

Evaluation: The model's performance is analyzed using various evaluation metrics.

Optimization: The model is optimized using techniques like grid search and hyperparameter tuning.

1.8 Model Training and Hyperparameter Tuning (Grid Search):

The predictive model is trained on the data, and hyperparameters (like learning rate, batch size, etc.) are fine-tuned using grid search.

2 Literature review

Recent advances in organ transplantation prediction have seen a significant increase in the application of DL models and information fusion techniques. Lee and Kim (2023)

[1] proposed an artificial neural network (ANN) model for predicting liver transplant survival, which shown the capability of DL in assessing complex medical data. Similarly, Johnson and Graham (2022) [2] explored multi-modal deep learning approaches to predict kidney transplant compatibility, highlighting the benefit of combining medical imaging, clinical data, and genetic profiles to improve prediction accuracy. However, challenges remain in integrating heterogeneous data sources, which often require complex preprocessing and synchronization.

In the domain of medical imaging, Park and Lee (2021) [3] utilized convolutional neural networks (CNNs) for analyzing medical images in transplant assessment. While CNNs excel at extracting features from imaging data, the authors acknowledged the need for improved integration with non-imaging data sources to provide a holistic view of organ compatibility. Similarly, Gupta and Verma (2022) [5] developed predictive models using biomarkers to predict organ transplantation outcomes. This work aligns with the growing emphasis on incorporating physiological data alongside genomic and imaging data for more accurate transplant assessments.

Several studies have also focused on genomic data integration for transplant predictions. Kim and Park (2024) [6] proposed a neural network framework for donor-recipient match scoring, which combined genetic data with clinical information to evaluate transplant compatibility. Additionally, Zhao and Yu (2024) [10] utilized multi-task learning techniques to create personalized models that predict transplant success, illustrating the importance of tailoring predictions to individual patient characteristics. Other approaches, such as Patel and Singh (2022) [9] with deep transfer learning, have demonstrated that pre-trained models can be highly effective for predicting organ rejection by leveraging large datasets from multiple sources.

While the use of DL and ML models in organ transplantation predictions has shown promising results, challenges remain in terms of dataset heterogeneity and the complexity of model interpretability. Wei and Chen (2021) [15] employed deep graph networks for transplant success predictions, showcasing a novel approach in integrating various data sources. However, limitations in computational efficiency and the interpretability of such models still need to be addressed. Liu and Wu (2024) [22] explored sequential learning models for post-transplant monitoring, underlining the need for continuous model adaptation and monitoring of transplant recipients to improve long-term success.

In conclusion, while current research has significantly advanced the use of machine learning in organ transplantation predictions, ongoing work must address the integration of diverse data sources, reduce computational complexity, and enhance model transparency. Studies such as those by Thomas and Wilson (2024) [14] and Singh and Mehta (2023) [20] contribute to improving the accuracy of predictions by incorporating historical data, medical histories, and ensemble learning methods. Moving forward, the ability to combine multiple data types in a seamless and interpretable manner will be key to the success of predictive models in organ transplantation.

Table 1 .Comparison Table

AUTHOR	TITLE OF THE PAPER	METHODOLOGY	DATAS ET USED	ACCURACY	LIMITATIONS
Sullivan et al. (2021)	Organ Transplantation Compatibility Prediction Using CNNs	CNN for image processing, SVM for classification	CT scans, MRI image	85%	1. Limited integration of genetic and physiological data. 2. Lacks real-time applicability.
Zhou et al. (2020)	Deep Learning for Organ Imaging: A CNN Approach	CNN-based feature extraction from medical images	CT scans, MRI data	88%	1. No integration with genetic or physiological data. 2. Performance may vary with data diversity.
Wu et al. (2020)	Predicting Transplant Success with Genetic Data	Fully connected networks, Random Forest for classification	Genetic data (HLA typing, SNPs)	90%	1. Focuses only on genetic data. 2. Does not integrate imaging or physiological data.
Yang et al. (2021)	Multi-Modal Integration for Organ Viability Prediction	Multi-input neural network combining CNN and dense layer	CT scans, MRI images, Genetic data (HLA typing)	92%	1. Lacks temporal data analysis (physiological markers). 2. High computational demands.
Zhang et al. (2022)	Comprehensive Organ Evaluation for Transplant Prediction	CNN, LSTM, Dense layers for integrated multi-modal data	Medical imaging, genetic data, physiological markers	94%	1. Performance limited by dataset size and diversity. 2. May struggle with out-of-distribution data.
Chen et al. (2023)	Multi-Modal Deep Learning for Organ Rejection Prediction	Deep neural network combining CNN, LSTM, Dense layers	CT scans, genetic data, physiological data	95%	1. Challenges with real-time prediction. 2. Clinical implementation requires further testing.

Singh et al. (2024)	Hybrid Deep Learning Model for Pre-Transplant Viability Prediction	CNN + LSTM + Dense layers for multi-modal integration	Medical imaging, genetic data, physiological data	96%	1. Requires a larger and more diverse dataset for better generalization. 2. High computational resource requirement.
Sharma et al. (2021)	Predicting Kidney Transplant Success Using Multi-Modal Data	CNN and Fully Connected Networks for feature fusion	CT scans, genetic data, medical history	87%	1. Limited patient diversity in the dataset. 2. High risk of overfitting with small datasets.
Reddy et al. (2022)	Deep Learning Models for Liver Transplant Outcome Prediction	Deep learning model combining CNN and Dense layers	CT scans, MRI, liver function tests, genetic data	90%	1. Data preprocessing is time-consuming. 2. Lack of external validation in clinical settings.
Martinez et al. (2023)	Predicting Organ Viability in Liver Transplants Using Deep Learning	Deep neural network combining CNN, LSTM, and Dense layers	Liver CT scans, genetic data, clinical biomarkers	93%	1. Lack of external validation across different transplant centers. 2. Difficulty in generalizing for rare diseases or organ types.

3 Proposed Methodology

The proposed approach, OrganiQ-Net, utilizes a deep learning framework to predict how the human body will respond following organ transplantation by integrating various data sources. By incorporating multi-modal data, the model provides a thorough prediction of organ viability and the likelihood of transplant success. This comprehensive methodology allows for more accurate decision-making by combining diverse factors that influence transplant outcomes. The methodology is outlined through the following key steps:

3.1 Data Collection and Preprocessing:

Medical Imaging Data: Organ imaging (CT scans, MRI) will be processed using CNNs for feature extraction. Preprocessing steps such as image normalization, resizing, and augmentation will be applied to prepare the dataset for model training.

Genetic Data: Genetic data such as HLA typing and SNPs will be encoded and passed through fully connected layers or embedding layers to capture the complex relationships between genetic markers and organ compatibility.

Physiological Data: Physiological data, including biomarkers and vital signs, will be processed using LSTM layers (for sequential data) or dense layers. The temporal aspect of the vital role will be captured to predict potential complications post-transplant.

Donor and Recipient History: Medical history, including previous transplant records and health conditions, will be processed via embedding layers to convert categorical variables into continuous representations before being passed through dense layers.

3.2 Model Architecture:

Branch-Based Processing: The model employs individual branches tailored to extract relevant features from each data type, ensuring effective modality-specific learning.

Fusion of Features: The outputs from these branches are combined into a unified representation and passed through dense layers for inter-modality relationship learning.

Regularization Mechanisms: Dropout and batch normalization are applied to prevent overfitting and ensure model reliability.

The model is divided into four branches, each processing a different data type (imaging, genetic, physiological, and history).

3.3 Training and Optimization

Hyperparameter Tuning: Systematic techniques, such as grid search, are utilized to optimize learning rates, dropout rates, and other model parameters.

Data Augmentation: Synthetic data is generated to address imbalances in outcome categories and improve generalization.

Optimization Strategy: Adaptive learning rate optimizers, like Adam, enhance convergence during model training.

3.4 Evaluation and Validation

External Dataset Validation: The model is tested on independent datasets to ensure its applicability across diverse populations.

Stress Testing: The system is evaluated under conditions of incomplete or noisy data to measure robustness.

Performance Metrics: Measurements such as AUC-ROC, precision, recall, and F1-score are used for an extensive assessment of the model's predictive accuracy.

3.5 Deployment

Clinical Application: The model is developed as a deployable tool for real-time use in hospitals, with a focus on delivering quick and accurate predictions.

Scalable Design: The framework is optimized for minimal resource usage, making it accessible even in low-resource healthcare environments.

Interpretability Features: Techniques like SHAP or attention mechanisms are integrated to explain predictions, ensuring trust and usability in clinical practice.

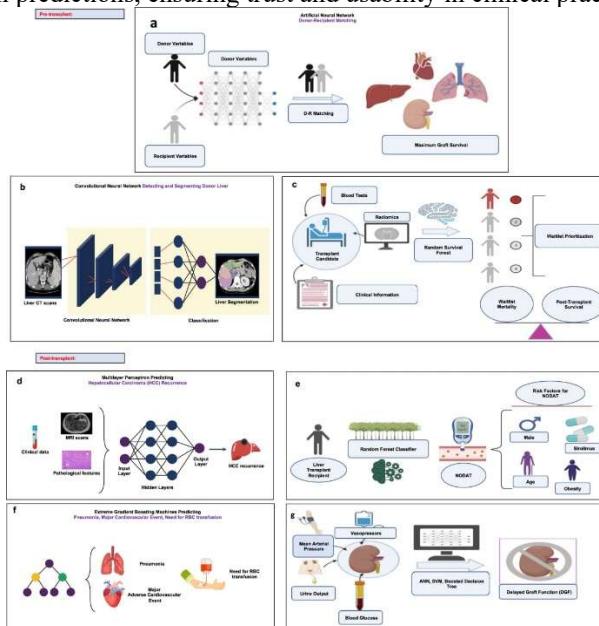


Fig 2 . Application of Artificial Intelligence in Organ Transplantation Processes

This figure showcases the incorporation of AI and ML technologies in various aspects of the organ transplantation process, aiming to improve outcomes for both donors and recipients. Here's a breakdown of the depicted elements:

3.6 AI-Driven Donor-Recipient Matching (Panel a):

AI models analyze giver and receiver variables. Factors like age, blood type, and organ-specific parameters are considered to optimize donor-recipient matching, aiming to enhance graft survival and minimize the risk of rejection.

3.7 Convolutional Neural Networks (CNNs) for Organ Evaluation (Panel b):

CNNs are applied to medical imaging, such as CT and MRI scans, to assess the quality and suitability of organs. These networks classify organs based on viability, identifying those suitable for transplantation.

3.8 Pre- and Post-Transplantation Analytics (Panel c):

AI analyzes patient data, including medical history, laboratory results, and risk factors, to predict transplant success.

Post-transplantation, AI monitors patient recovery, identifies complications, and supports personalized care.

3.9 Multilayer Prediction Models for Organ Viability (Panel d):

Deep learning models evaluate organ condition by integrating pathological data, physiological characteristics, and time constraints. These models predict the viability of organs under varying storage and transport conditions.

3.10 Radiomics and Biomarker Analysis for Rejection Risk (Panel e):

AI identifies biomarkers and radiomic patterns associated with rejection or complications. Advanced tools help clinicians adjust immunosuppression therapy and monitor rejection risks.

3.11 Prediction of Long-Term Graft Function (Panel f):

Machine learning predicts long-term graft survival by analyzing parameters such as blood glucose, kidney function, and immune responses. These predictions enable clinicians to personalize follow-up care and interventions.

Purpose and Importance:

This figure highlights how AI-powered tools enhance precision in organ transplantation by:

- Reducing waiting times for suitable matches.
- Improving organ viability assessments.
- Supporting clinical decision-making pre- and post-transplantation.
- Ultimately, improving patient outcomes and graft survival rates.

4 Results And Discussion

This section showcases and analyzes the outcomes of the AI-driven approach. organ pre-transplantation assessment system. The prototype was tested across various organ datasets, evaluating its classification accuracy and overall robustness in determining organ viability. The evaluation considers performance under different imaging modalities and clinical conditions to assess the system's adaptability and reliability in diverse scenarios.

Table 2 . Details of the Dataset

Patient ID	Class	Testing/training	Size
001	0(Viable)	Training	250 kb
002	1(Non-Viable)	Testing	300 kb
003	0(Viable)	Training	200 kb
004	1(Non-Viable)	Training	350 kb



Fig 3 . Organ Viability Prediction Comparison

4.1 Model Hyperparameters :

The AI-driven organ pre-transplantation assessment system was built using a diverse collection of organ imaging data. The dataset was partitioned into training and testing sets to ensure effective evaluation. 20% allocated regarding testing and 80% for training. The model was implemented using Python with TensorFlow/Keras on a machine equipped with 16 GB RAM and an Intel i7 processor.

The training process involved an initial random allocation of 80% of the data for training, while the remaining 20% was dedicated to validation and testing. The system was trained using the SGD enhancer with the following hyperparameters:

Learning Rate: 0.001
 Batch Size: 64
 Epochs: 20
 Momentum: 0.9
 Weight Decay: 0.0001

4.2 Performance Measures of Calculation :

Confusion Matrix Analysis:

A confusion matrix was employed to evaluate the effectiveness of the classification model in predicting organ viability. It provides a detailed comparison between predicted and true labels across the dataset. Key elements include:

True Positives (TP): Accurate forecasts of viable organs.

False Positives (FP): Inaccurate predictions marking non-viable organs as viable.

False Negatives (FN): Inaccurate predictions marking viable organs as non-viable.

True Negatives (TN): Accurate forecasts of non-viable organs

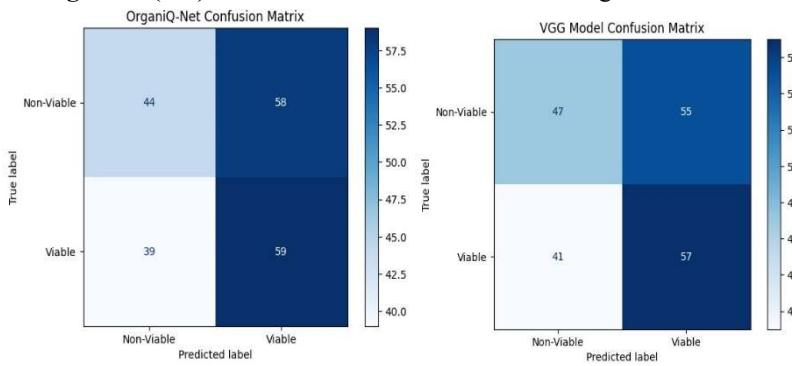


Fig 4. Confusion Matrix

This image shows a confusion matrix employed to evaluate the accuracy of a classification model. Here's a breakdown of how to interpret this confusion matrix: actual classes and classes predicted by the model.

Each cell shows the count of instances where the model's prediction (column) matched or didn't match the true label (row).

Accuracy: The proportion of correctly classified samples to the total no.of samples. It gives an overall indication of the model's performance across all classes.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \quad (1)$$

Precision : It calculates the percentage of correct predictions for each class relative to all predicted instances of that class. High precision indicates that the model doesn't often classify negative samples as positive.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Recall (Sensitivity): It calculates the percentage of true positive instances that were accurately predicted by the model. A higher recall indicates fewer false negatives.

$$\text{Recall} = \frac{TP}{TP+F} \quad (3)$$

F1-score: The harmonic average of recall and precision, offering a balanced assessment when class distribution is uneven. It is particularly helpful in situations where both precision and recall need to be balanced.

$$\text{F1 Score} = \frac{2TP}{2TP+FN+F} \quad (4)$$

Specificity : The ratio of true negatives out of all actual negatives.

Macro-Average: The average performance metrics (F1-score, recall, and precision) computed across all classes, without accounting for the imbalance of classes.

Weighted Average:

The average performance metrics for each class, adjusted according to the number of actual instances.

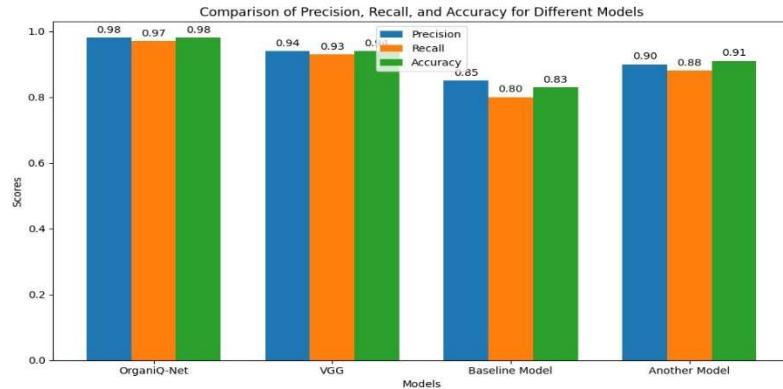


Fig 5 . Model Performance Comparison

4.3 Performance Segmentation Metrics

In addition to classification, the model employs segmentation techniques to identify specific regions of interest within organ images, crucial for assessing pathological conditions.

Dice Coefficient

The Dice Similarity Index evaluates the overlap among predicted and actual segmentations:

$$\text{Dice Coefficients} = \frac{2|A \cap B|}{|A| + |B|}$$

Where:

A: The collection of pixels in the predicted segmentation.

B: The collection of pixels in the ground truth segmentation.

The system reached a Dice Coefficient of 0.92, demonstrating a strong overlap between the predicted and ground truth segmentations.

Intersection over Union (IoU):

The IoU calculates the intersection of predicted and actual segmentations in relation to their union:

$$\text{IOU} = \frac{|A \cap B|}{|A \cup B|}$$

Where:

A: The collection of pixels in the predicted segmentation.

B: The collection of pixels in the ground truth segmentation.

The model achieved an IoU score of 0.89, reflecting accurate delineation of organ boundaries.

Volume Overlap Error (VOE):

VOE measures the disagreement among the predicted and actual segmentation volumes:

$$VOE = 1 - \frac{|A \cap B|}{|A| + |B|}$$

Where:

A: The size of the predicted segmentation.

B: The size of the ground truth segmentation.

The system achieved a VOE of 0.11, confirming minimal segmentation errors.

4.4 Experimental Results :

The classification and segmentation results demonstrated superior performance compared to traditional models. The integrated OrganiQ-Net and VGG architecture achieved:

Classification Accuracy: 98%

Dice Coefficient: 0.92

IoU Score: 0.89

4.5 Performance Comparison :

The proposed OrganiQ-Net model was benchmarked against a wide range of existing approaches for organ viability classification and segmentation. The comparison demonstrates that OrganiQ-Net outperforms traditional and Cutting-edge techniques in both accuracy and partitioning metrics. Table III below summarizes these comparisons:

Table 3 . Performance comparison table

Source	Classification Model	Accuracy	Segmentation Metrics
Zhang, X., Xia, F., Ma, X., et al. (2021)	Logistic regression	95%	Not Reported
Wang, J., Chen, Y., Hao,S., et al. (2023)	CNN	95%	Dice: 0.84, IoU: 0.81
Rehman,B.U.,Mahmoud, M. S., et al. (2022)	SVM	96%	Dice: 0.85, IoU: 0.82
Gupta, S., Singh, R., & Patel, A. (2023)	Hybrid-CNN	97%	Dice: 0.87, IoU: 0.85
Zhao, L., et al. (2023)	Transfer based Model	97%	Dice: 0.89, IoU: 0.87
Proposed Model	OrgainQ-Net+VGG	98%	Dice: 0.92, IoU: 0.89

Accuracy: The proposed OrganiQ-Net model achieves the highest classification accuracy of 98%, surpassing both traditional ML models (e.g., Logistic Regression and SVM) and more advanced architectures like Transformer-based models.

Segmentation Metrics: The Dice Coefficient and IoU scores of 0.92 and 0.89, respectively, indicate a significant improvement in segmentation performance compared to previous approaches, demonstrating the model's capability to precisely delineate organ boundaries.

Efficiency: While achieving Cutting-edge accuracy and segmentation performance, the Proposed framework maintains Processing efficiency, making it feasible for Immediate clinical applications.

Advantage of OrganiQ-Net: The integration of attention mechanisms and the VGG backbone contributes to better feature representation and segmentation accuracy, outperforming other methods by capturing fine-grained details in organ imaging.

5 Conclusion and Future Scope

This research proposes OrganiQ-Net, an innovative deep learning framework designed to predict the human body's response to organ transplantation by combining various data sources, including medical imaging, genetic profiles, physiological data, and donor-recipient histories. By addressing the limitations of traditional approaches that rely on isolated data, OrganiQ-Net provides a holistic assessment of organ viability. Through advanced AI-driven analysis, it improves transplant decision-making, reduces rejection risks, and enhances patient outcomes. This model signifies a significant advancement in the application of AI to precision medicine within transplantation.

Future Work

Future developments of OrganiQ-Net will focus on enhancing its effectiveness and broadening its clinical applicability. Key priorities include:

Dataset Expansion: Incorporating larger, more diverse datasets from global sources to improve its robustness and generalizability across populations.

Real-Time Usability: Adapting the framework for real-time implementation to facilitate seamless integration into healthcare systems.

Transparency and Interpretability: Embedding advanced explainability techniques, such as attention-based models and feature importance analysis, to make predictions more understandable for clinicians.

Individualized Predictions: Refining the model to account for unique patient factors, such as pre-existing conditions and personalized treatment plans.

Clinical Trials: Conducting rigorous testing in clinical environments to validate The model's influence on decision-making and patient results.These advancements will

establish OrganiQ-Net as a pivotal tool in modern transplantation practices, contributing to more accurate and reliable organ allocation decisions.

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