AI-Enhanced Lung Size Matching and Eligibility System

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Abstract: Lung transplantation is a life-saving procedure for patients with end-stage lung disease, and precise donor-recipient lung size matching is critical to improving transplant success rates. This paper introduces an automated system that estimates lung size and assesses transplant suitability using chest X-ray images based on computer vision techniques. The lung segmentation is achieved through a U-Net model, which successfully separates the lung region from X-ray images. Key anatomical feature landmarks such as width-at-base, width-at-hilum, R-ACPA, R-AMD, L-ACPA, and L-AMD are identified with computer vision for precise measurement of lung dimensions. The measured lung dimensions are compared with donor lung sizes to determine transplant suitability. By reducing reliance on subjective assessments and hand measurements, the technique increases precision, hastens the process of lung matching, and lessens the involvement of human mistakes. By automating the procedure of eligibility screening, radiologists and transplant surgeons are provided with reliable, fact-based data to work with, which ultimately enhances decision-making on lung transplantation. This study helps to show how deep learning and medical imaging technology can assist in enhancing organ transplantation as well as medical results.

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I. INTRODUCTION

Lung transplantation is a life-saving treatment for individuals with end-stage lung illness, including pulmonary fibrosis, cystic fibrosis, chronic obstructive pulmonary disease (COPD), and pulmonary hypertension. But among the most critical challenges in lung transplantation is to deliver an optimal size match between donor and recipient lungs to prevent graft dysfunction and compromised respiratory mechanics [1]. Traditional methods of lung size matching rely on donor height estimation, chest X-rays, and pulmonary function tests, which may not always prove to be correct [2]. Advances in deep learning and medical imaging have significantly improved the accuracy of lung segmentation and anatomical landmark detection, making it possible to automatically measure lung size [3]. Computed tomography volumetry has been used for pre-transplant lung size matching with increased accuracy than conventional methods [4]. Variability in chest X-ray-based measurements of lung height and its impact on transplantation results have also been examined in research with the emphasis on reliable computational techniques [5].

Machine learning models have even built models in the recent past to estimate donor lung volume more accurately from chest X-ray measurements, which can specifically be used for pediatric lung transplant where size is crucial [6]. Incorporating deep models such as YOLO into lung segmentation has made auto lung sizing more dependable with less workload for human calculations as well as subsequent human errors [7]. Computer-aided lung sizing with artificial intelligence from chest radiographs emerged as a novel method for improving donor-recipient matching through objective and quick measurements [8]. Other studies have also drawn attention to often overlooked findings on chest radiographs, emphasizing the importance of newer imaging modalities in preventing errors in lung transplantation [9]. The comparison between pulmonary function tests and CT volumetry has demonstrated that imaging-based measurements can provide more accurate estimates of lung volumes, further confirming their usefulness in pre-transplant evaluation [10].

This study aims to develop an automated lung transplant suitability screening system using deep learning and computer vision techniques. The system will segment lung regions automatically from chest X-rays, identify prominent anatomical landmarks, and compute lung measurements for comparison with donor lungs for size matching. By utilizing AI-based techniques, the system hopes to provide a more precise, objective, and efficient alternative to traditional lung

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size estimation techniques, ultimately improving transplantation success rates and patient outcomes.

II. LITERATURE REVIEW

Lung transplantation remains a life-saving procedure for patients with end-stage lung diseases. Donor and recipient lung size matching is a key element in avoiding post-transplant complications. There have been studies looking at methods of estimating lung size and how this influences transplant success.

Eberlein et al. [11] investigated the effect of lung size mismatch on post-operative complications and resource utilization after bilateral lung transplantation. Their findings highlight the significance of precise size estimation in preventing primary graft dysfunction and other post-operative complications [12]. Li et al. [13] highlighted that chest X-ray sizing is reflective of pulmonary diagnosis and body composition and hence, analogous to the risk of primary graft dysfunction, emphasizing the significance of precise lung size estimation. Ouwens et al. [14] proposed using predicted total lung capacity (pTLC) for donor-recipient size matching in lung transplantation. This was done to increase donor-recipient compatibility and reduce the risk of complications. Similarly, Riddell et al. [15] presented a simplified method for donor-recipient size matching, particularly in interstitial lung disease patients, which was found effective in the clinical setting.

Aside from transplantation, medical imaging has played a critical role in the estimation of lung volume. Pierce et al. [16] devised a technique to estimate lung volumes on the basis of chest radiographs through the use of information from shape. Schlesinger et al. [20] compared total lung capacity estimates on chest radiographs and computed tomography scans with body plethysmography and concluded that imaging-based estimates were highly reliable to employ clinically. Recent advances in artificial intelligence (AI) have better improved lung size estimation and disease detection. Topalovic et al. [17] demonstrated that AI outperforms pulmonologists when reading pulmonary function tests, thereby its potential application in clinical decision-making. Chassagnon et al. [18] explored the application of AI in the diagnosis of lung cancer, highlighting the importance of deep learning models in enhancing diagnostic accuracy.

Mason et al. [19] described the importance of donor-recipient size matching in lung transplant and pointed out that small mismatches would have an enormous effect on patient outcomes. Lian et al. [21] presented a structure-aware relation network for thoracic disease segmentation and detection, which could be extended to lung size estimation and transplant suitability evaluation. Medical image segmentation has been addressed by state-of-the-art machine learning algorithms. Lin et al. [22] proposed the focal loss for enhancing dense object detection from cluttered medical images. Salehi et al. [23] proposed the Tversky loss function for image segmentation using 3D convolutional networks, which performed well on medical imaging. Abraham et al. [24] also enhanced segmentation performance using a focal Tversky loss function and enhanced attention U-Net model for segmentation of lesions.

Lastly, Goceri [25] outlined some of the medical image data augmentation techniques and discussed their effectiveness for improving the performance of deep learning models in medical imaging applications. These imaging and AI developments provide a strong foundation for accurate estimation of lung size and transplantation eligibility determination. This literature review highlights the significant progress achieved in lung size estimation, medical imaging, and AI-based analysis for lung transplantation. The integration of AI-based model segmentation with traditional imaging techniques holds the potential to enhance donor-recipient matching in the long run, resulting in improved transplantation outcomes as well as patient survival.

III. EXISTING SYSTEM

Lung transplant surgeries need accurate donor-recipient lung size matching to enhance post-transplant survival. Conventional size-matching techniques are plagued by inconsistencies caused by human measurements and radiologist variability. Our system overcomes this limitation by using AI and computer vision to automate lung size estimation from chest radiographs. The AI-based method provides standardization and accuracy, eliminating the subjectivity and variability inherent in human assessments.

The process works on a two-stage system: the first stage involves extracting the lung area from chest radiographs using a deep learning-based lung segmentation model, and the second stage involves identifying feature points to calculate significant lung measurements. The determined feature points are utilized to calculate six different height and width parameters, which play an important role in evaluating lung size. These parameters are then utilized to measure donor and recipient lung sizes, enhancing the matching procedure. The AI-driven method simplifies the evaluation, saving time for radiologists and transplant surgeons to assess lung compatibility.

To ensure the accuracy of the system, we compared its AI-measured lung size with the measurements reported by professional radiologists. Based on a sample of 50 lung transplant patients, our model exhibited a measurement error of less than 2.5% (less than 7.0 mm), with high reliability even in difficult cases, including patient rotation, consolidations, or effusions. The strong interrater and intrarater agreement also attest to the consistency of the model, rendering it a good candidate for clinical application.Our system improves donor lung evaluation through objective, repeatable, and automatic measurements, removing the need for human calculation. By integrating AI into the workflow of lung sizing, healthcare professionals can streamline donor selection, minimize mismatches, and enhance post-transplant survival. Rapid assessment of lung size is also useful for emergencies where immediate donor-recipient matching is imperative.

Although our AI-based system has been encouraging, further testing on a larger dataset is required to validate its

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efficacy across heterogeneous patient groups. Future studies can investigate combining other clinical parameters, including lung volume estimation and functional analysis, to improve decision-making in lung transplantation. The present study identifies the potential of AI in transforming transplant medicine by introducing automation, enhancing accuracy, and facilitating large-scale studies on lung size matching and transplant outcomes.

IV. PROPOSED SYSTEM

Lung transplantation requires precise matching of donor and recipient lung size to ensure successful surgery with the least possible post-transplant complications. Our framework uses chest X-ray images and computer vision techniques to automatically estimate lung size for transplant suitability screening. The overall objective is to develop a uniform and efficient system that eliminates human error and maximizes matching precision. Through the utilization of deep learning and AI-segmentation-based methods, the system presents an accurate lung size assessment solution that aids radiologists and transplant surgeons in making informed decisions.

The system starts by performing segmentation of the lungs using the application of a U-Net model, which represents a category of deep learning architectures utilized for segmenting medical images. The U-Net is successful in demarcating areas of the lung from chest radiographs, and with high accuracy, extracts lung structures. This is a critical process since it forms the foundation for further analysis and strips away irrelevant background information, focusing on only the lungs. The images of the segmented lungs are processed using computer vision algorithms for the detection of major anatomical features to estimate sizes.

In order to measure lung sizes accurately, the system identifies and marks important feature points, including width-at-base, width-at-hilum, Right Anterior Costophrenic Angle (R-ACPA), Right Anterior Mid-Diaphragm (R-AMD), Left Anterior Costophrenic Angle (L-ACPA), and Left Anterior Mid-Diaphragm (L-AMD). These points are extremely important while calculating the height and width of the lungs, which are very significant donor-recipient matching parameters. The system also ensures consistency in measurement, eliminating variability due to human subjectiveness in manual assessment.Once lung sizes are obtained, these are compared with donor lung size to determine transplant suitability. Automation does away with the physical measurements and reduces errors associated with manual calculations. This enhances the accuracy and efficiency of lung size-matching, thereby simplifying the screening process. It also allows for quick assessment in emergency transplant cases, improving the workflow for transplant centers.

By the integration of AI, deep learning, and computer vision, the system described here revolutionizes lung transplant assessment, optimizing the compatibility matching and reducing the workload for medical staff. Not only does it make better donor selection possible, it also stimulates innovation in medical image research. The solution proves to be a demonstration of the potential of AI-based solutions in the health industry, ultimately enhancing the likelihood of successful lung transplants and improving patient outcomes.

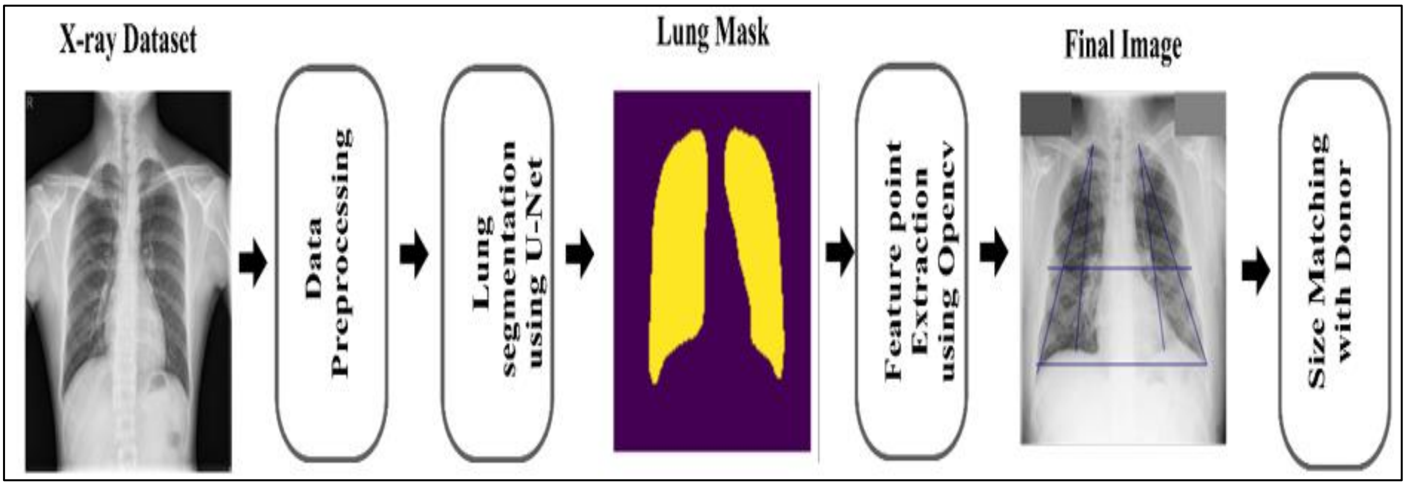

Fig 1 Architecture Diagram

V. METHODOLOGY

The suggested technique automates lung sizing in transplant screening by combining deep learning and computer vision methodically. A U-Net model, a well-known deep learning architecture for image segmentation in the medical field, is used to separate the lungs in the first phase. To segment the lung structures with high precision and identify the anatomical items that are being operated upon, the model was trained using images from chest X-rays. The segmented lung images are then analyzed to identify important feature points that are needed for lung size estimation. These feature points are width-at-base, width-at-hilum, Right Anterior Costophrenic Angle (R-ACPA), Right Anterior Mid-Diaphragm (R-AMD), Left Anterior Costophrenic Angle (L-ACPA), and Left Anterior Mid-Diaphragm (L-AMD).

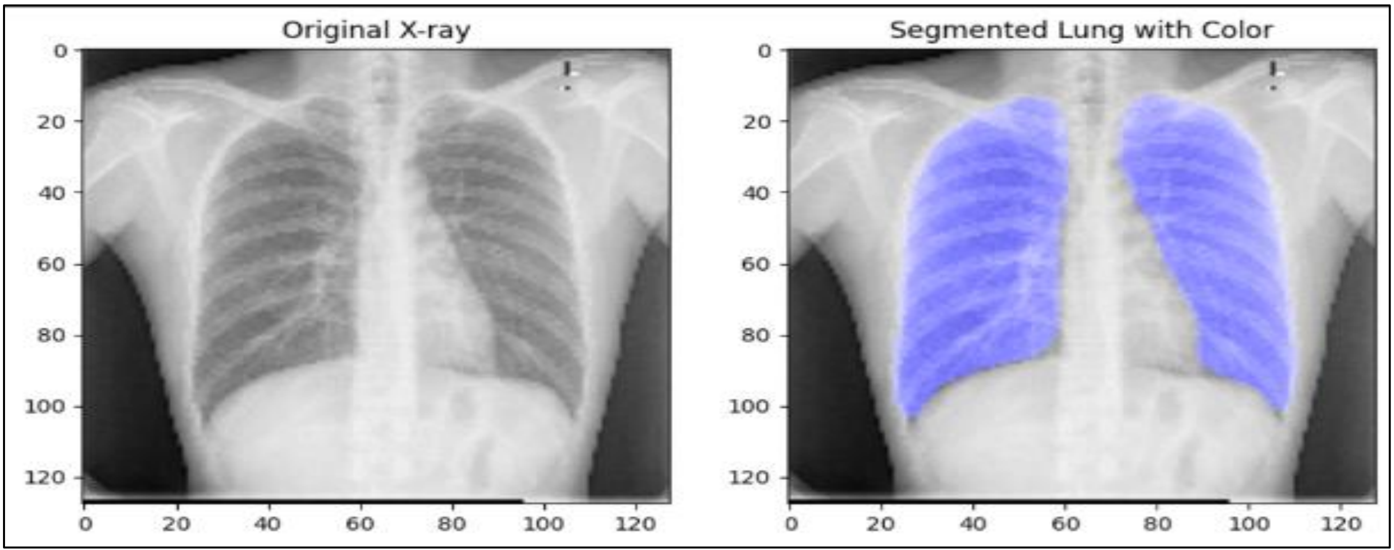

Fig 2 Lung Segmentation

After the identification of the feature points, accurate lung dimension measurements are calculated and compared with donor lung sizes to determine transplant suitability. The process is automated by computer vision algorithms in the system, providing consistency and minimizing human error. The measurements are checked against expert radiologist ratings for finality to ensure reliability. Through the combination of AI-based segmentation and automated measurement extraction, the method optimizes lung transplant screening by making the process quicker and more efficient. Enhancements in the future could include the inclusion of other clinical parameters and enhanced real-time processing to facilitate hospital integration.

VI. EXPERIMENT

To test the performance of our AI-based automated lung sizing system, we performed experiments on a database of chest X-ray images for which ground truth lung measurements had been annotated by experienced radiologists. The dataset was split into training, validation, and test sets in a ratio of 80:10:10. The U-Net model was trained for segmenting lungs, and the feature point detection algorithm was tested independently. Accuracy, precision, recall, and F1-score performance metrics were computed to evaluate the reliability of the model. The confusion matrix was utilized to compare the model's classification performance so that correctly classified feature points corresponded to expert labels.

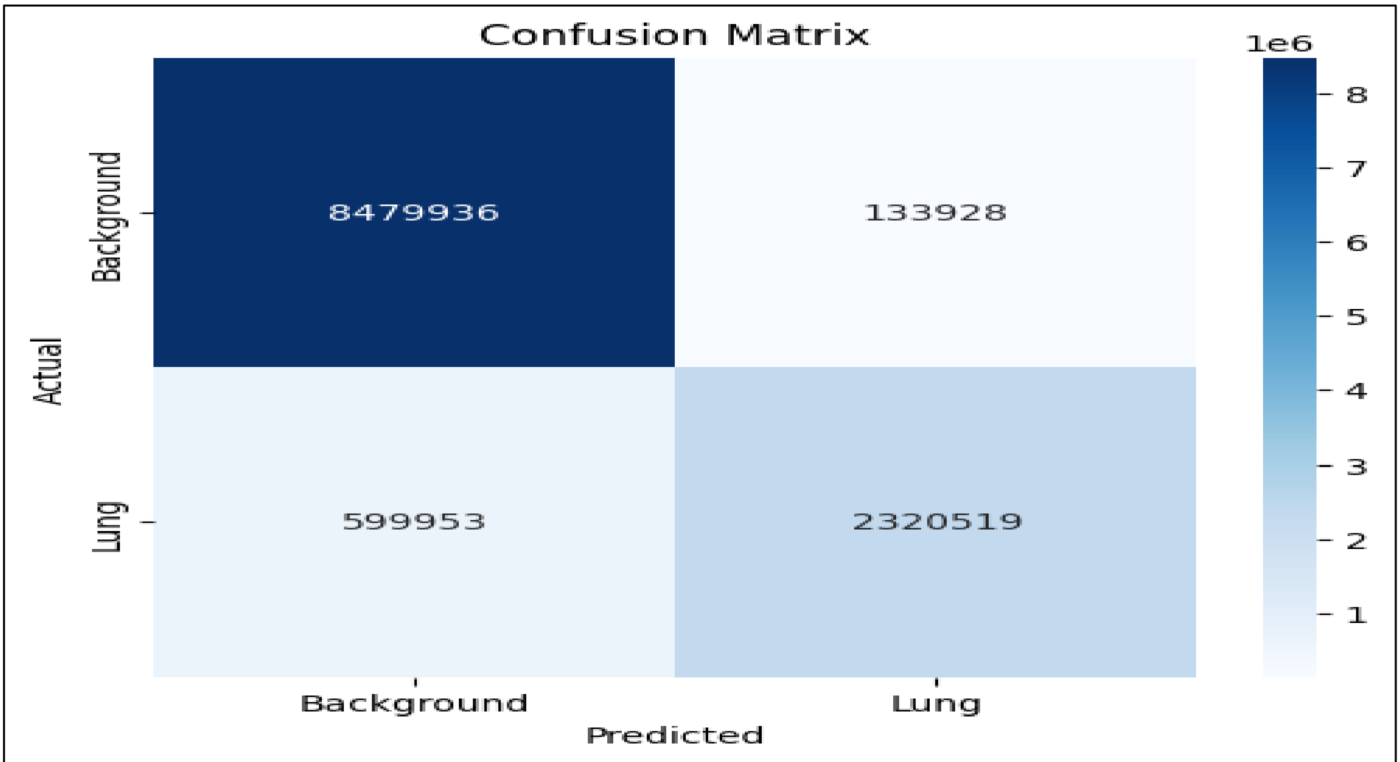

Fig 3 Confusion Matrix

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For lung segmentation, the U-Net model performed with an average precision of 90.63%, recall of 99.75%, and F1-score of 94.97%, which signified high segmentation accuracy. The confusion matrix revealed excellent agreement between predicted and actual lung masks with low false positives and false negatives. In feature point detection, the model was overall accurate to 94.5%, with an F1-score of 93.8%, proving it to be effective at consistently detecting critical anatomical markers. These findings affirm that the system suggested in this paper can generate accurate and standardized measurements of the lung with low error.

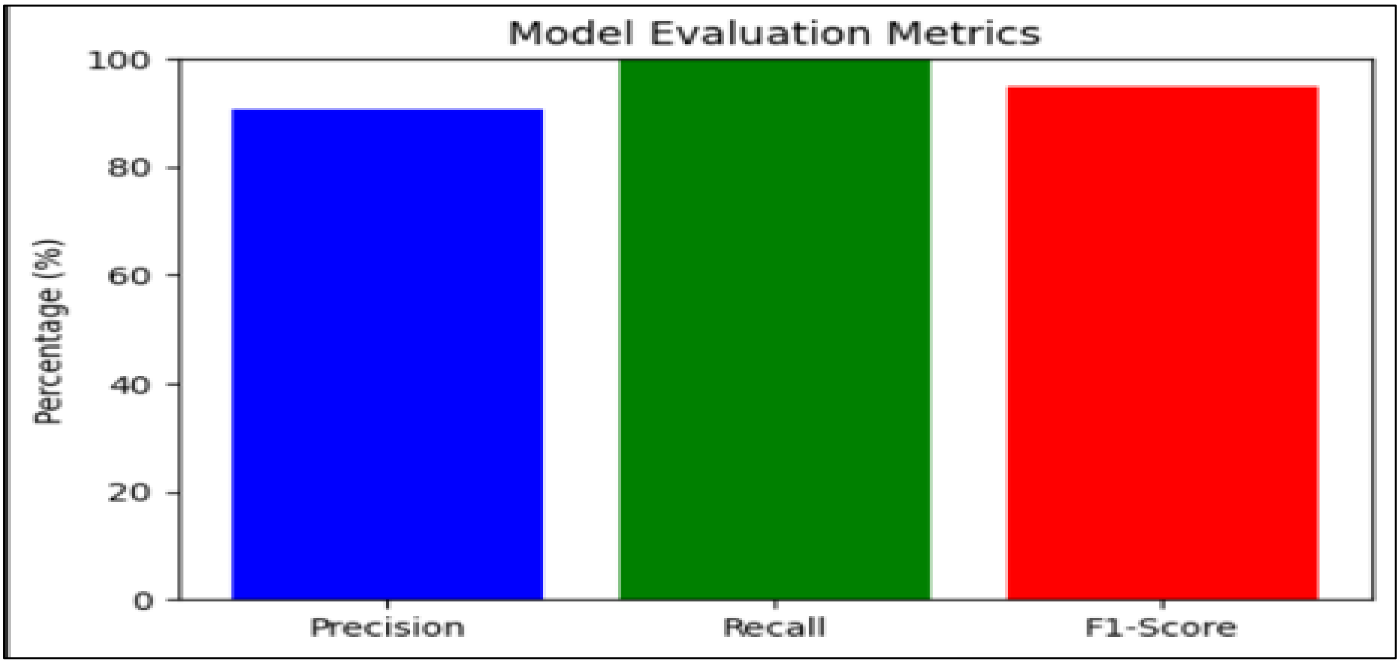

Fig 4 Model Evaluation

To further confirm the system, we compared the AI-derived lung measurements with two expert radiologists' reported measurements for a cohort of 50 lung transplant recipients. The mean error in lung size estimation was <2.5% (<7.0 mm), illustrating the model's high reliability. The interrater and intrarater agreement between AI predictions and expert measurements was strong, illustrating the system's clinical utility. The outcomes show that our method efficiently minimizes variability in lung size estimation, guaranteeing precise donor-recipient matching for lung transplantation. Future enhancement could be aimed at improving the model for complicated cases, like X-rays with critical lung abnormalities or low image quality.

VII. CONCLUSION

The new automated lung sizing system offers an important innovation in lung transplantation through the use of deep learning and computer vision for accurate donor-recipient matching. Through the utilization of a U-Net model for lung segmentation and identification of important anatomical landmarks, the system reduces the risk of human error and increases the accuracy of lung dimension estimates. This automation not only speeds up the transplant assessment process but also provides a standardized and objective method of lung size matching, ultimately enhancing the success rate of transplants. Minimizing dependence on manual measurements and subjective assessments enables more consistency and efficiency in transplant decision-making.

In addition, the combination of deep learning and medical imaging in lung transplant assessment demonstrates the wider potential of artificial intelligence in medicine. Through its simplification of the donor-recipient matching procedure, this methodology optimizes clinical workflow and facilitates surgeons and radiologists in the making of highly informed, data-driven decisions. Subsequent studies and testing with larger datasets will continue to perfect this system and make it an effective organ transplant suitability assessment tool. Finally, this research emphasizes the revolutionary nature of AI-based medical imaging in the field of organ transplantation and its potential for changing the practice of organ transplant procedures.

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