Clinical TRANSPLANTATION
The Journal of Clinical and Translational Research

Innovative Solutions for Organ Transplantation: MCNN-HELM, Risk Assessment, and Adaptive Allocation Algorithms

Journal:	*Clinical Transplantation*
Manuscript ID	CLTX-23-ORIG-0794
Wiley - Manuscript type:	Original Article
Date Submitted by the Author:	05-Oct-2023

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Transplant Peer Review Network - Second Choice:	Transplant Infectious Disease
Transplant Peer Review Network - First Choice:	Clinical Transplantation
Discipline:	organ transplantation in general
Keywords:	antibiotic, classification systems, heart disease

Abstract:	Organ transplantation is a critical medical intervention for individuals with terminal organ failure, offering a lifeline for those in dire need. However, the persistent shortage of available organs poses a substantial challenge, leading to prolonged waiting times and, tragically, preventable patient deaths. To address this, we leverage the transformative power of big data analytics within the healthcare sector, paving the way for informed decision-making. This paper presents a multifaceted approach to enhance organ transplantation, addressing the dual objectives of minimizing waiting times for recipients and prioritizing patients with high medical risk to maximize positive outcomes. The proposed system integrates four key components namely risk assessment, geographic analysis, MCNN-HELM model, and a novel Genetic Algorithm-based optimal allocation strategy. In the risk assessment phase, patients are categorized based on their medical risk levels, enabling prioritization. Geographic analysis leverages A* algorithm-based routing to identify the geographically shortest paths for donor identification, streamlining the transplantation process. The MCNN-HELM model refines donor-recipient matching by harnessing deep learning techniques and enhancing the accuracy of matching predictions. The heart of the system lies in the Genetic Algorithm-based optimal allocation strategy, which considers compatibility, urgency, and fairness to determine organ allocation. This approach seeks to maximize positive outcomes for organ recipients, optimizing the utilization of this precious resource. Simulation results demonstrate the efficacy of the integrated system, achieving precision, recall, and F1-score metrics of 0.95, 0.97, and 0.95, respectively. Allocation efficiency stands at 0.97, and the fairness index is 0.92, showcasing the system's comprehensive performance. This research not only presents a sophisticated solution to organ scarcity but also raises

	important ethical considerations and offers a promising direction for further study in the field of organ transplantation. By effectively prioritizing patients and optimizing organ allocation, this system profoundly impacts the lives of those awaiting transplantation, providing hope where it is needed most.

Innovative Solutions for Organ Transplantation: MCNN-HELM, Risk Assessment, and Adaptive Allocation Algorithms

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ABSTRACT

Organ transplantation is a critical medical intervention for individuals with terminal organ failure, offering a lifeline for those in dire need. However, the persistent shortage of available organs poses a substantial challenge, leading to prolonged waiting times and, tragically, preventable patient deaths. To address this, we leverage the transformative power of big data analytics within the healthcare sector, paving the way for informed decision-making. This paper presents a multifaceted approach to enhance organ transplantation, addressing the dual objectives of minimizing waiting times for recipients and prioritizing patients with high medical risk to maximize positive outcomes. The proposed system integrates four key components namely risk assessment, geographic analysis, MCNN-HELM model, and a novel Genetic Algorithm-based optimal allocation strategy. In the risk assessment phase, patients are categorized based on their medical risk levels, enabling prioritization. Geographic analysis leverages A* algorithm-based routing to identify the geographically shortest paths for donor identification, streamlining the transplantation process. The MCNN-HELM model refines donor-recipient matching by harnessing deep learning techniques and enhancing the accuracy of matching predictions. The heart of the system lies in the Genetic Algorithm-based optimal allocation strategy, which considers compatibility, urgency, and fairness to determine organ allocation. This approach seeks to maximize positive outcomes for organ recipients, optimizing the utilization of this precious resource. Simulation results demonstrate the efficacy of the integrated system, achieving precision, recall, and F1-score metrics of 0.95, 0.97, and 0.95, respectively. Allocation efficiency stands at 0.97, and the fairness index is 0.92, showcasing the system's comprehensive performance. This research not only presents a sophisticated solution to organ scarcity but also raises important ethical considerations and offers a promising direction for further study in the field of organ transplantation. By effectively prioritizing patients and optimizing organ allocation, this system profoundly impacts the lives of those awaiting transplantation, providing hope where it is needed most.

Keywords: Organ transplantation; Risk assessment; Prioritization; Donor-Recipient matching and Allocation.

1. INTRODUCTION

1.1 Background and Motivation for the Research:

Organ transplantation stands as a life-saving medical procedure, offering hope to individuals suffering from terminal organ failures [1]. As medical advancements have extended human lifespans, the demand for organ transplants has risen significantly. However, this demand has led to a glaring disparity between the number of organs required and the availability of suitable donors [2]. This critical imbalance underscores the urgent need for innovative approaches that optimize the organ transplantation process [3].

Nowadays, organ allocation has emerged as a significant challenge due to the limited availability of donor organs [4]. The shortage of available organs for transplantation has created a complex ethical and medical dilemma. Patients in dire need of organs face extended waiting periods, leading to deteriorating health conditions and, in some unfortunate cases, loss of life [5]. The inability to promptly match donors with recipients intensifies the challenge of organ allocation, emphasizing the need for strategies that minimize waiting times [6].

Furthermore, prioritizing patients for transplantation becomes crucial due to the varying degrees of urgency and medical risk [7]. Patients with higher risk levels often require swift access to suitable organs to improve their chances of survival. Failing to prioritize these critical cases leads to avoidable medical complications and preventable deaths [8].

In recent years, the integration of data-driven approaches and advanced technologies into healthcare systems has shown promising results. These approaches have the potential to address the complexities of organ shortage and patient prioritization by efficiently analyzing vast amounts of medical data, optimizing allocation strategies, and enhancing the accuracy of donor-recipient matching [9].

Existing approaches often struggle to handle real-time medical data, which is crucial for timely decision-making in organ transplantation. The intricacies of patient profiles, including medical histories and compatibility factors, pose challenges for accurate donor-recipient matching [10]. The need for dynamic patient prioritization based on changing health conditions requires an adaptable approach that traditional methods might lack. Finding the balance between medical urgency and fairness in organ allocation presents a delicate challenge.

Through this study, we seek to contribute to the ongoing discourse surrounding organ transplantation by offering an innovative framework that has the potential to alleviate the burden of organ shortage, expedite the matching process, and prioritize patients based on their medical conditions. Ultimately, the outcomes of this research could pave the way for improved patient outcomes, reduced waiting times, and enhanced overall healthcare quality within the domain of organ transplantation.

1.2 Objectives:

The main objectives of this research work are formulated as follows:

1. The research aims to develop an integrated framework that encompasses data driven approaches for improving organ transplantation outcomes.
2. The proposed method aims to enhance the accuracy of donor-recipient matching by employing efficient data-driven approaches. By achieving this objective, the proposed method aims to reduce the waiting time of patients requiring organ transplantation
3. The proposed method aims to improve the survivability of the patients by incorporating efficient risk assessment and patient prioritizing strategies that prioritize the high risk patients requiring immediate attention in organ transplantation.
4. To design an effective organ allocation strategy by considering multiple critical factors to enhance organ utilization and effective organ transplantation outcomes.
5. To assess the effectiveness of the proposed method in a simulation environment and perform the comprehensive comparative analysis by using different existing techniques in terms of various metrics.

The research aims to develop an efficient data-driven framework that facilitates advancement in organ transplantation by addressing the challenges corresponding to donor-recipient matching, patient prioritization, and organ allocation. Furthermore, the research work by employing data-driven approaches improves the survivability of the patient requiring organ transplantation, facilitating a significant potential impact in the healthcare domain.

1.3 Contributions:

Our research makes several significant contributions to the field of organ transplantation and healthcare optimization:

1. **Integrated Data-Driven Framework:** We introduce a holistic approach that integrates risk assessment and patient prioritization algorithms, geographical analysis techniques, donor-recipient matching techniques, and allocation algorithms to tackle the complex challenges of organ transplantation. This unified framework offers a comprehensive solution that addresses donor-recipient matching, patient prioritization, and organ allocation.
2. **MCNN-HELM Model:** The proposed MCNN-HELM model represents a pioneering advancement in donor-recipient matching accuracy. By combining Convolutional Neural Networks (CNNs) and Extreme Learning Machines (ELMs), our model adeptly handles intricate medical profiles, leading to improved matching precision and efficiency.
3. **Patient Prioritization Enhancement:** Our methodology introduces a data-driven approach for risk assessment and patient prioritization that provides high priority to high-

risk patients who require urgent transplantation and contributes to the enhancement of patient outcomes and overall survival rates.

4. **AOWGA Algorithm:** The AOWGA algorithm revolutionizes organ allocation by considering medical compatibility, urgency, and fairness objectives. This improved genetic algorithm generates adaptable allocation strategies that strike a delicate balance between multiple critical factors.
5. **Simulation-Based Validation:** Through extensive simulations on a diverse real-world dataset, we empirically validate the efficacy of our approach. The comprehensive evaluation metrics, including precision, recall, and F1-score, demonstrate the superiority of our methodologies in donor-recipient matching, patient prioritization, and organ allocation.
6. **Addressing Critical Challenges:** Our approach directly addresses the ongoing challenges of organ scarcity, patient prioritization, and inefficient organ allocation. By leveraging data-driven insights, we contribute towards enhancing the efficiency of organ transplantation processes and improving patient outcomes.
7. **Broader Implications:** The research has broader implications for the field of organ transplantation. It offers solutions to the organ shortage crisis, enhances survival rates, and promotes ethical practices in organ allocation.

The remainder of the paper is structured as follows: Section 2 provides the background knowledge of the existing works related to organ transplantation along with its limitations to identify the research gaps. Section 3 provides the system model. Problem formulation is formulated in section 4. Section 5 provides a detailed explanation of the proposed methodology. Section 6 discusses the simulation result and discussion of the proposed methodology. Section 7 contains the discussion and, section 8 provides the summary of the paper.

2. LITERATURE REVIEW

The landscape of organ transplantation, donor-recipient matching, patient prioritization, and allocation strategies has been extensively explored in the literature. This section aims to provide an overview of existing approaches, highlighting their strengths and limitations, and also discusses the research gaps in the existing works.

2.1 Existing works related to organ transplantation:

Numerous studies have focused on improving organ transplantation efficiency through various methodologies. The work of Nastase et al. [11] emphasized optimizing organ preservation techniques to extend organ viability. Others have explored alternative sources of organs, such as xenotransplantation or engineered tissues. While these strategies show promise, challenges related to immunological compatibility and long-term outcomes remain.

1. Organ transplantation strategies:

Li et al. [12] demonstrated a transformer-based deep learning (DL) technique for fairly predicting post-liver transplant risk factors for liver transplantation. A Tab Transformer was used to forecast a post-transplant hazard. Fairness metric weighting algorithm used to predict integrity over different subsets. This approach was guided to perform more optimal predictions. This technique had an insufficient amount of diverse and inclusive datasets.

Hawashin et al. [13] presented a private Ethereum blockchain-based model for the management of organ donation and transplantation. This model was fully decentralized, safe, and verifiable. This approach implemented smart contracts and six algorithms to enhance confidentiality between organ donation and transplantation. This technique was deployed to secure against all vulgar attacks and instability. However, the evaluation was performed with a limited amount of datasets.

Salimian and Mousavi [14] developed a Mixed-Integer Non-Linear Programming (MINLP) model for the optimization of organ transplantation network design. The genetic algorithm was employed to increase the feasibility and black widow optimization (BWO) solved an optimization issue. The experimental evaluation showed that the MINLP method was deployed to reduce the distribution period, handle various suspicions, and ensure usability. However, this approach was not evaluated in a real-world application.

Salimian et al [15] demonstrated a multi-criteria group decision-making (MCGDM) model for optimal route selection in organ transplantation. This model deployed Criteria Importance through an inter-criteria correlation (CRITIC) approach to measure the weight of transportation criteria. The MCGDM technique utilized the Interval-Valued Intuitionistic Fuzzy Sets (IVIFSs) approach to provide a solution for complicated problems for transportation in organ transplantation. However, the MCGDM model did not solve challenges related to organ allocation.

2. Donor-Recipient Matching Techniques:

The problem of accurately matching donors with recipients has garnered significant attention. Traditional matching methods based on blood type and tissue compatibility have been refined over the years. Several recent approaches for enhancing donor-recipient matching are provided below:

Dueñas-Jurado et al. [16] illustrated a novel method based on logistic regression and evolutionary product unit neural networks (LR-EPUNN) for donor-recipient matching in lung transplantations. The experimental evaluation demonstrated that the LR-EPUNN method achieved an effective tool for donor-recipient matching outperforming the ability of the classical statistical process. The LR-EPUNN technology did not give more importance to patient prioritization and organ allocation strategy.

Guijo-Rubio et al. [17] demonstrated a donor-recipient matching technique based on Logistic regression (LR) for solving problems related to organ allocation. The United Network for Organ Sharing (UNOS) database was used for evaluating the performance of the LR algorithm in terms of different metrics. The experimental evaluation illustrated that the LR method outperformed other machine learning algorithms employed for comparison by providing efficient performance. However, this technique needed to incorporate prioritization and organ allocation strategy to obtain superiority in organ transplantation.

Szugye et al. [18] illustrated a Total Cardiac Volume (TCV) model for Donor-recipient size matching in pediatric heart transplantation. The TCV model was a simple and innovative method, deployed to forecast the accuracy of the donor's and recipient's chest size using anthropometrics and chest radiography (CXR). This model finds it difficult to handle a large amount of datasets.

Gnanasambandhan and Balasubramanian [19] illustrated a hybrid extreme learning modified convolutional neural network (HEL-MCNN) model for Donor-recipient matching with a minimum waiting time. HEL-MCNN approach deployed PLTSD, UNOS-HR, and UNOS-LU datasets for performance evaluation. Prairie Dog Optimizer (PDO) was deployed to minimize the loss rate and maximizes the speed. The results showed that the HEL-MCNN selected the matching donor efficiently and reduced the waiting time of the patient. However, the HEL-MCNN method required the incorporation of a family consent feature to obtain better performance.

3. Patient Prioritization Methods:

Patient prioritization is a critical aspect of organ allocation, particularly for high-risk cases. The existing techniques for patient prioritization are presented below:

Silva et al. [20] demonstrated a Machine Learning and Expandable Artificial Intelligence (ML+XAI) method for classifying chronic patients at risk in patient prioritization. Unsupervised learning was employed to classify chronic patients by analyzing critical events and clinical variables in the dataset. The XAI technique provided valuable insights by interpreting the classification process. The ML+XAI model did not consider the challenges related to organ allocation.

Bayat et al. [21] elaborated a patient prioritization based on a Decision-Making Trial and Evaluation Laboratory and modified Analytic Network Process (DEMATEL-MANP) method for liver transplantation. This method was deployed to improve the performance and quality of service in liver transplantation centers. The DEMATEL-MANP approach was evaluated and the result illustrated that the method improved the accuracy rate of liver transplantation and minimized the operational cost. This model was only supported for liver transplantation.

Dirchwolf et al [22] demonstrate a Model of End-stage Liver Disease (MELD) upgrade exception strategy for liver transplantation to optimize patients with high waiting list mortality. The finding indicated that the patients having MELD upgrade exception had more right to liver transplantation compared the patients without MELD exception. However, this technique stressed the importance of data-driven approaches to improve organ transplants effectively.

4. Allocation Strategies and Algorithms:

Allocation algorithms play a pivotal role in ensuring equitable distribution of organs. The previous works employed for organ allocation are listed below:

Al-Ebbini [23] established an efficient allocation strategy for lung transplantation using Ant Colony Optimization and k-nearest neighbor (ACO-kNN). ACO technique helped to improve routing optimization and fault detection. The kNN method was used to classify data in a trained data set. The ACO-kNN approach was deployed to discover the best features and achieve fair accuracy. ACO-kNN model was only applicable for lung transplantation.

Taherkhani et al. [24] elaborated a fuzzy inference system for kidney allocation (FISKA). The FISKA stimulated expert thinking and decision-making in the distribution of donated kidneys. The intuitionistic fuzzy analytic hierarchy (IF-AHP) algorithm facilitated to balance of the discovered factor to develop a point scrolling system. The FISKA technique supported to enhanced kidney allocation system. The FISKA method was exploited in a limited dataset for model evaluation

Bayer et al. [25] developed optimizing geographic boundaries through the supply/Demand ratio for a new lung transplant allocation system. A New lung allocation system helped to minimize geographic variation in lung allocation. The lung allocation score (LAS) was allocated to lungs for post-transplant morality. Brute force algorithm utilized to fix all advanced allocation units. This approach showed better performance by optimizing geographic boundaries efficiently. However, this technique required more computational time to complete the process.

Van de Klundert et al. [26] presented a technique for eliminating transplant waiting time inequities in kidney allocation. Rawls' Theory of justice was utilized to minimize inequality, queuing theory was deployed to limit the waiting time of patients, and network flow theory allocated kidneys for the patients in the needed time. However, this technique required some advancement for fair resource allocation in kidney transplantation.

2.2 Limitations and challenges of the existing solutions:

Although the previous approaches have contributed significantly to the field of organ transplantation, the limitations and challenges persist. Many strategies neglect the influence of geographic factors on organ availability and transportation time. Therefore, the technique that considers these geographic factors was crucial for enhancing donor supply, and organ utilization as well as for improving organ transplantation efficiency.

Several existing approaches incorporate genetic compatibility assessment to improve the likelihood of successful transplants. However, these techniques often overlook dynamic factors like recipient urgency and geographical proximity to improve the donor-recipient process.

Existing approaches for patient prioritization often rely on urgency scores derived from medical assessments and waiting time. While effective to some extent, these methods did not adequately capture nuances in patients' overall health status, leading to suboptimal outcomes for critical cases.

Some studies have proposed allocation strategies that allocated organs by assessing a variety of factors, including risk, waiting time, and medical urgency. However, these strategies are complex to implement and might lack adaptability to changing patient profiles.

Some methods lack the ability to dynamically adapt to changes in patient conditions. Additionally, while these approaches address specific aspects of the transplantation process, a comprehensive integration of these techniques remains relatively unexplored.

2.3 Research gaps:

Despite advancements in improving the efficiency of organ transplantation, the ever-widening chasm between the demand for organs and their availability remains a formidable challenge. The research aims to address the gaps in the existing works by developing an integrated data driven framework for enhancing organ transplantation outcomes. The integrated framework combines efficient algorithms for risk assessment, patient prioritization, geographical analysis, donor-recipient matching, and organ allocation to alleviate the organ shortage crisis and ensure that patients receive timely and appropriate care.

3. SYSTEM MODEL

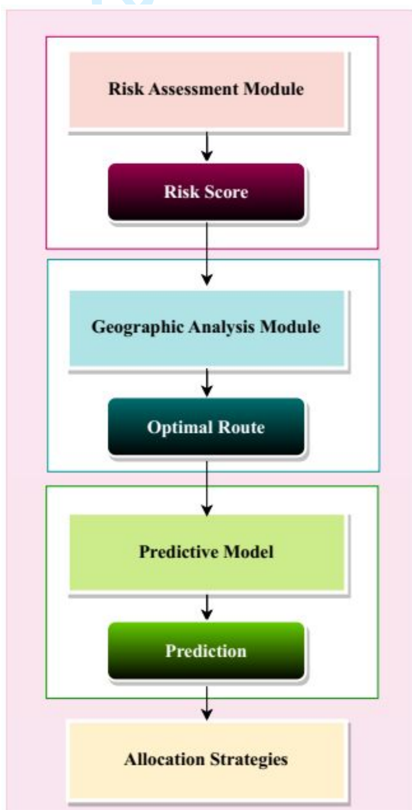

Figure 1: System model

In this section, we provide a comprehensive overview of our proposed system model, outlining its core components, interactions, and data flow that collaboratively enhance organ transplantation efficiency and patient prioritization by addressing the challenges of organ shortage and patient prioritization. This holistic model encompasses risk assessment, donor identification, a predictive framework, and allocation strategies, collectively designed to optimize the organ transplantation process. The system model is provided in Figure 1.

3.1 Key components of the system:

The system comprises four pivotal components, collectively contributing to the overarching objective:

1. *Risk Assessment Module:*

This module involves evaluating the survival risk of patients waiting for organ transplantation. It computes the urgency and severity of patients' medical conditions based on a range of factors such as medical history, current health status, and potential complications and generates the risk score. The risk score (R) reflecting the severity of patients' conditions is represented as follows:

$$Riskscore = f(MedicalHistory, VitalIndicators, Historical\ Data) \qquad (1)$$

2. *Geographic Analysis Module:*

This module employs geographical data and analytical tools to determine the geographically optimal paths for identifying potential organ donors in the nearest location for a given recipient. This component considers geographical proximity, transportation networks, and organ availability to optimize the process of donor identification. The proximity factor which influences transportation efficiency is encapsulated by a function $P(d)$, where d represents the distance.

$$P(d) = g(GeographicalData,\ OrganDonorLocations, RecipientLocation) \qquad (2)$$

3. *Predictive Model:*

At the heart of the system lies the predictive framework, which is used for determining the optimal matches. This module employs advanced data-driven techniques that analyze different medical parameters including medical profiles, compatibility factors, and other relevant data to generate prediction scores. The prediction score (S) generated estimates the likelihood of successful transplantation by determining the compatibility and suitability of organ donors and recipients. The prediction score is formulated as follows:

$$S = h(DonorProfile, RecipientProfile, CompatibilityFactors) \qquad (3)$$

4. Allocation Strategies:

The allocation strategy integrates risk assessment results, prediction outcomes, and other factors to allocate organs in a manner that aligns with medical urgency and fairness. It ensures a fair and efficient distribution of available organs

$$OrganAllocation = j(Riskscore, \Pr ediction, AllocationParameters) \qquad (4)$$

The system model aims For instance, imagine a patient with a high-risk score due to a critical medical condition. The risk assessment module elevates this patient's priority. The geographic analysis module identifies geographically nearby potential donors. The predictive model examines compatibility and patient profiles, leading to a prediction. Allocation strategies factor in these outputs, resulting in the allocation of organs that balance medical urgency and fairness:

4. PROBLEM FORMULATION

In this section, we provide a precise definition of the research problem and outline the objectives that guide our proposed approach. We delve into the intricate challenges embedded within efficient donor-recipient matching, patient prioritization, and the optimal allocation of organs, illuminated through mathematical formulations. By articulating these challenges, we lay the foundation for our proposed data-driven approach.

As medical advancements prolong lives, the necessity for timely and well-matched organ transplants becomes increasingly crucial. The core challenge in organ transplantation pertains to the stark scarcity of available organs contrasted with the critical demand for life-saving interventions. This scarcity gives rise to a profound discrepancy between patients awaiting transplantation and the limited pool of compatible donors. This research seeks to address the inefficiencies in the current transplantation process by developing a novel solution that streamlines the donor-recipient matching process, facilitates judicious patient prioritization, and optimizes the allocation of organs.

- *Efficient Donor-Recipient Matching:*

The challenge of promptly identifying the most suitable donor for a recipient is complicated by the multidimensional nature of medical compatibility. Traditional methods often struggle to process complex donor-recipient profiles, leading to prolonged waiting times and suboptimal matches. The key objective is to develop a data-driven methodology that incorporates advanced prediction models and compatibility assessments, to expedite the identification of well-suited donors for recipients, minimizing waiting times and increasing transplantation success rates. To attain this objective, we present the following optimization formulation:

$$Minimize: \ f(MatchingTime) \tag{5}$$

Subject to constraints:

- Medical compatibility constraints: $g(MedicalFactors) \leq Threshold$
- Geographical proximity constraints: $h(GeographicalFactors) \leq MaxDistance$
- Fairness constraints: $i(FairnessFactors) \geq MinFairness$

Where $f(MatchingTime)$ represents the function that quantifies the time required for the entire donor-recipient matching process. This includes data preprocessing, compatibility assessment, and decision-making. The constraints encompass the medical criteria that must be met for a successful match (e.g., blood type compatibility), the geographical feasibility in terms of transportation distance, and the fairness considerations to ensure equitable allocation.

The optimization objective of minimizing $f(MatchingTime)$ aims to accelerate the identification of appropriate donors for a patient awaiting an organ transplant. Efficient donor-recipient matching involves assessing medical compatibility, considering geographic constraints, and ensuring a fair allocation to identify a compatible donor. By minimizing the time needed for this process, we significantly reduce the waiting period for patients in need of organ transplantation. This accelerates the organ allocation process, enhancing the chances of successful transplantation and ultimately improving patient outcomes.

➢ *Patient Prioritization:*

Urgency levels among patients awaiting organ transplantation vary dramatically due to differing medical conditions and risk factors. Current prioritization mechanisms were not adapted to evolving patient health risks, potentially delaying critical treatments for high-risk patients. We aim to develop a patient prioritization approach that dynamically assigns priority to patients based on their medical profiles and changing health risks. By harnessing historical data and real-time insights, we strive to allocate organs to patients based on their evolving health urgency, thereby providing higher attention to high-risk patients. To achieve this objective, we formulate the optimization problem as follows:

$$Maximize: g(PatientOutcomes) \tag{6}$$

Subject to constraints:

- Medical risk factors constraints: $h(RiskFactors) \geq MinRisk$
- Fairness constraints: $i(FairnessFactors) \geq MinFairness$

Where $g(PatientOutcomes)$ represent the function that quantifies the overall patient outcomes resulting from successful transplantation and medical care. The constraints encompass the medical risk factors that must be surpassed to be eligible for prioritization and the fairness considerations to ensure equitable allocation.

The optimization objective of maximizing $g(PatientOutcomes)$ underscores the importance of prioritizing patients with elevated medical risk. For instance, assume a patient with a severe medical condition requires an immediate organ transplant. Prioritizing this patient involves maximizing the function that quantifies potential patient outcomes that include factors such as the patient's medical prognosis, the potential impact of transplantation, and the patient's overall well-being. By assigning higher priority to such patients, the methodology ensures that those in critical need receive timely attention and maximizes the positive impact of organ transplantation. Therefore, this targeted approach enhances patient outcomes by directing resources toward individuals who stand to gain the most from transplantation.

- Optimal Organ Allocation:

The allocation of available organs is a delicate task, demanding a delicate equilibrium between medical compatibility, urgency, and fairness. Existing allocation strategies might neglect to accommodate dynamically changing patient needs and medical urgencies. We aim to design allocation strategies that maximize successful transplantation outcomes while adhering to ethical and medical considerations. The central objective is to devise allocation strategies that strike a balance between medical compatibility, urgency, and fairness in order to optimize organ allocation. To achieve this objective, we present the following multi-objective optimization formulation:

$$Maximize: h(OrganAllocation) = w_1 \cdot MedicalCom\,patibility + w_2 \cdot Urgency + w_3 \cdot Fairness \qquad (7)$$

Subject to constraints:

- Medical compatibility constraints: $g(MedicalFactors) \leq Threshold$
- Urgency constraints: $h(UrgencyFactors) \geq MinUrgency$
- Fairness constraints: $i(FairnessFactors) \geq MinFairness$

Where $h(OrganAllocation)$ represent the composite function that captures the weighted combination of medical compatibility, urgency, and fairness. The weights $w_1, w_2, and\, w_3$ represent the relative importance of each objective in the optimization. The constraints include medical compatibility criteria, urgency thresholds, and fairness considerations to ensure an equitable allocation process.

The multi-objective optimization objective aims to optimize the organ allocation process. For instance, consider a patient who requires organ allocation for transplantation. By optimizing the factors including medical compatibility (matching patient and donor profiles), urgency (criticality of patients' medical condition), and fairness (equitable distribution of organs), the methodology ensures that the available organ is allocated to that patient who is both medically compatible and in urgent need while adhering to principles of fairness.

5. PROPOSED METHODOLOGY

The proposed methodology integrates cutting-edge technologies and algorithms to sole the challenges in organ transplantation. The integrated technologies incorporate GBA for risk assessment and patient prioritization, an A* algorithm for optimal donor identification, and an innovative MCNN-HELM model for precise donor-recipient matching. Additionally, we introduce an improved version of the AOWGA algorithm to optimize organ allocation by considering medical compatibility, urgency, and fairness. A detailed explanation of each technique is delineated in the following section.

5.1 Risk Assessment and Patient Prioritization:

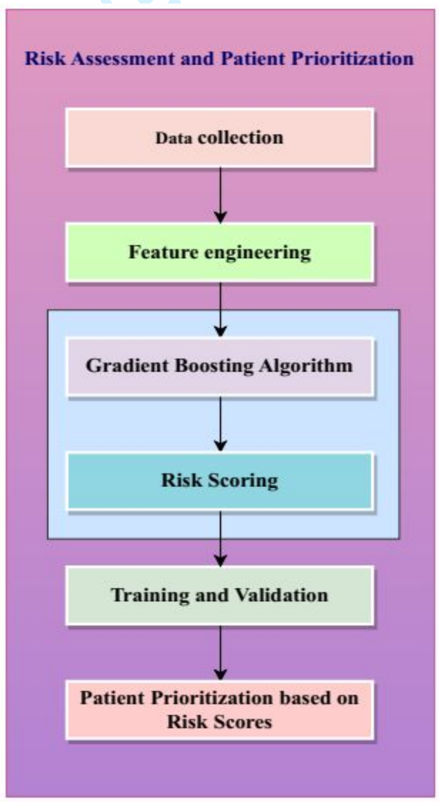

Figure 2: Architecture of Risk assessment and Patient prioritization model

In this section, we outline the methodology employed for risk assessment and patient prioritization. To effectively achieve this, we leverage the power of the Gradient Boosting algorithm, chosen for its proficiency in managing intricate, nonlinear relationships prevalent within medical data. The methodology involves the incorporation of various critical variables, including age, medical history, severity of illness, and compatibility factors. These variables collectively contribute to the quantification of the risk level associated with each patient. Figure 2 represents the architecture of the risk assessment and patient prioritization model.

1. *Data Collection:*

We gather a diverse dataset containing patient profiles, medical histories, and compatibility factors. These variables contribute to the holistic assessment of patients' health conditions.

2. *Feature Engineering:*

Relevant features are extracted from the collected data to create a comprehensive set of input variables. These features encompass age, medical history details, severity of illness metrics, and compatibility indicators.

3. *Gradient Boosting Algorithm (GBA):*

We deploy the GBA as a robust machine learning technique for effective risk assessment and prioritization. The GBA is a powerful ensemble learning technique that sequentially combines the predictive capacity of weak learners to create a robust model [27]. This algorithm iteratively builds an ensemble of decision trees, each correcting the errors of the previous one. It excels in capturing complex patterns, interactions, and nonlinearity present in medical data, making it an apt choice for risk assessment and patient prioritization.

By leveraging the GBA, we create a predictive model that accurately assesses patients' risk levels based on diverse medical variables. The GBA operates by sequentially fitting weak learners to the residual errors of the previous learner. Given a dataset $D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$, where x_i represents the patient's features and y_i indicates the corresponding risk level, the model learns iteratively as:

$$F_0(x) = initial\ guess \tag{8}$$

$$F_m(x) = F_{m-1}(x) + \gamma \cdot h_m(x) \tag{9}$$

Where $F_m(x)$ indicates the final prediction at iteration m, γ represents the learning rate controlling the contribution of each weak learner, and $h_m(x)$ represents the weak learner fitted to the negative gradient of the loss function at the previous step.

To comprehensively assess patient risk, we incorporate a diverse range of variables into the Gradient Boosting model. These variables include:

- *Age:* The age of the patient is considered the fundamental factor that indicates the vulnerability of certain medical conditions.
- *Medical History:* Historical medical records provide crucial insights into patients' health trajectories.
- *Severity of Illness:* The degree of medical urgency influences the prioritization process.
- *Compatibility Factors:* Factors such as blood type compatibility, tissue match, and organ-specific criteria influence transplantation success.

The risk assessment process involves constructing a predictive model using the Gradient Boosting algorithm. By integrating age, medical history, severity of illness, and compatibility factors, a comprehensive risk assessment framework is developed. Mathematically, we define the risk assessment function as follows:

$$RiskScore = GradientBoosting\left(Age, MedicalHistory, Severity, CompatibilityFactors\right) \quad (10)$$

In this formulation, the GradientBoosting function combines the information from age, medical history, severity, and compatibility factors to generate a risk score that quantifies the patient's level of risk. A higher risk score indicates a more urgent need for organ transplantation, warranting prioritization. Let us consider a patient who requires immediate heart transplantation and has a history of heart disease, advanced age, and a high severity of illness. In that case, the GBA integrates these variables and quantifies the patient's elevated risk level. The generated high risk scores aid in prioritizing the patient for organ transplantation, ensuring that critical cases are addressed promptly.

4. Training and Validation:

The dataset is divided into training and validation sets. The GBA is trained on the training set and validated on the validation set to ensure the model's generalizability.

5. Risk Scoring:

Once the model is trained, it generates risk scores for each patient in the validation set. These risk scores quantitatively represent the likelihood and severity of adverse outcomes for each patient.

6. Patient Prioritization:

Based on the generated risk scores, patients are prioritized in terms of their medical risk levels. Patients with higher risk scores are assigned a higher priority, as their medical condition demands more urgent attention.

5.2 Geographic Analysis for Donor Identification:

In this section, we elaborate on the methodology employed for Geographic Analysis for identifying optimal routes for donor identification. The module leverages the A* algorithm for identifying optimal routes to locate suitable organ donors. The A* algorithm is chosen due to its ability to factor in geographical distances, traffic conditions, and potential logistical constraints, ultimately computing the shortest paths with enhanced precision and speed. The heuristic nature of the A* algorithm further expedites the process of identifying appropriate donors by efficiently navigating the network of feasible routes. A detailed explanation of the utilization of the A* algorithm in identifying potential donors is provided below:

1. Geographical Data and Constraints:

The module is supplied with geographical data, including donor and recipient locations. Additionally, constraints such as traffic conditions, road types, and potential road closures due to emergencies or maintenance are considered to facilitate accurate route calculations.

2. A* Algorithm Implementation:

The A* algorithm is employed for route planning. The algorithm initializes by marking the donor's location as the starting point and the recipient's location as the destination [28]. The A* algorithm's core principle is to prioritize nodes for exploration based on a combination of two components namely, the estimated cost from the current node to the destination (heuristic) and the actual cost from the start node to the current node. Heuristics guide the algorithm to focus on promising routes, reducing the search space and enhancing computational efficiency. It maintains a priority queue of potential paths based on an evaluation function.

***3.* Evaluation Function:**

The efficiency of the A* algorithm lies in its evaluation function $(f(n))$. It estimates the total cost of a path from the starting point to the destination through a specific route. The evaluation function combines the actual cost incurred to reach a point and a heuristic estimate of the remaining cost to reach the destination. The evaluation function employs the following formula which is highlighted below:

$$f(n) = g(n) + h(n) \qquad (11)$$

Where $f(n)$ refers to the estimated total cost from the start node to the destination through node n, $g(n)$ indicates the actual cost from the start node to node n, and $h(n)$ denotes the heuristic estimate of the cost from node n to the destination.

4. **Search and Expansion:**

The algorithm iteratively selects the path with the lowest estimated total cost from the priority queue. It expands the path by considering neighboring locations and estimating their potential costs. This ensures that the algorithm explores paths that have the potential to lead to the shortest route more quickly.

5. **Termination:**

The algorithm continues this process until the destination (recipient's location) is reached or until all potential paths are exhausted.

5.3 Modified Convolutional Neural Network and Hybrid Extreme Learning Machine (MCNN-HELM) Model:

In this section, we delve into the core methodology of our research, the MCNN-HELM model. This model serves as a pivotal component of our approach, significantly enhancing the accuracy of donor-recipient matching. The MCNN-HELM architecture unites the strengths of Convolutional Neural Networks (CNNs) and Extreme Learning Machines (ELMs). The CNNs adeptly extract intricate features from donor and recipient data, while the ELMs harness these features to make precise predictions. This fusion empowers the model to capture complex patterns inherent in medical profiles and compatibility factors, thus enabling efficient and accurate donor-recipient matching. The steps involved in the MCNN-HELM model are highlighted below:

1. Data Preprocessing:

In data preprocessing, raw donor and recipient data are preprocessed to remove noise in the data in order to improve data consistency and quality.

2. Convolutional Neural Networks (CNNs):

CNNs are employed to process medical profiles, compatibility factors, and other relevant data. Feature extraction layers in CNNs capture hierarchical features that encapsulate intricate patterns and relationships within the data [29]. Extracted features are then flattened and forwarded to subsequent layers for processing. The CNN operations involve convolutional layers for extracting features, pooling layer for reducing computational load, and fully connected layers for capturing high-level abstraction. Let's consider a CNN layer L:

$$z_L = W_L * a_{L-1} + b_L \tag{12}$$

Where z_L refers to the output of the CNN layer, W_L represents the weight kernels of the CNN layer, a_{L-1} indicates the input from the previous layer, and b_L denotes the bias of the CNN layer.

3. *Extreme Learning Machines (ELMs):*

ELMs act as a complementary prediction mechanism in the model. The extracted features from CNNs are fed into ELMs, which function as efficient and rapid training algorithms for single-layer feedforward neural networks. ELMs perform weighted linear combinations of input features to yield predictions [30]. The prediction made by the ELM is mathematically represented as follows:

$$y = HC \qquad (13)$$

Where the term y indicates the output prediction, H denotes the input feature matrix, and C refers to the output weights.

4. *Model Fusion:*

The predictions generated by the CNNs and ELMs are combined to produce a final prediction. This amalgamation capitalizes on the strengths of both CNNs and ELMs, enhancing overall predictive accuracy. The architecture of the MCNN-HELM is provided in Figure 3.

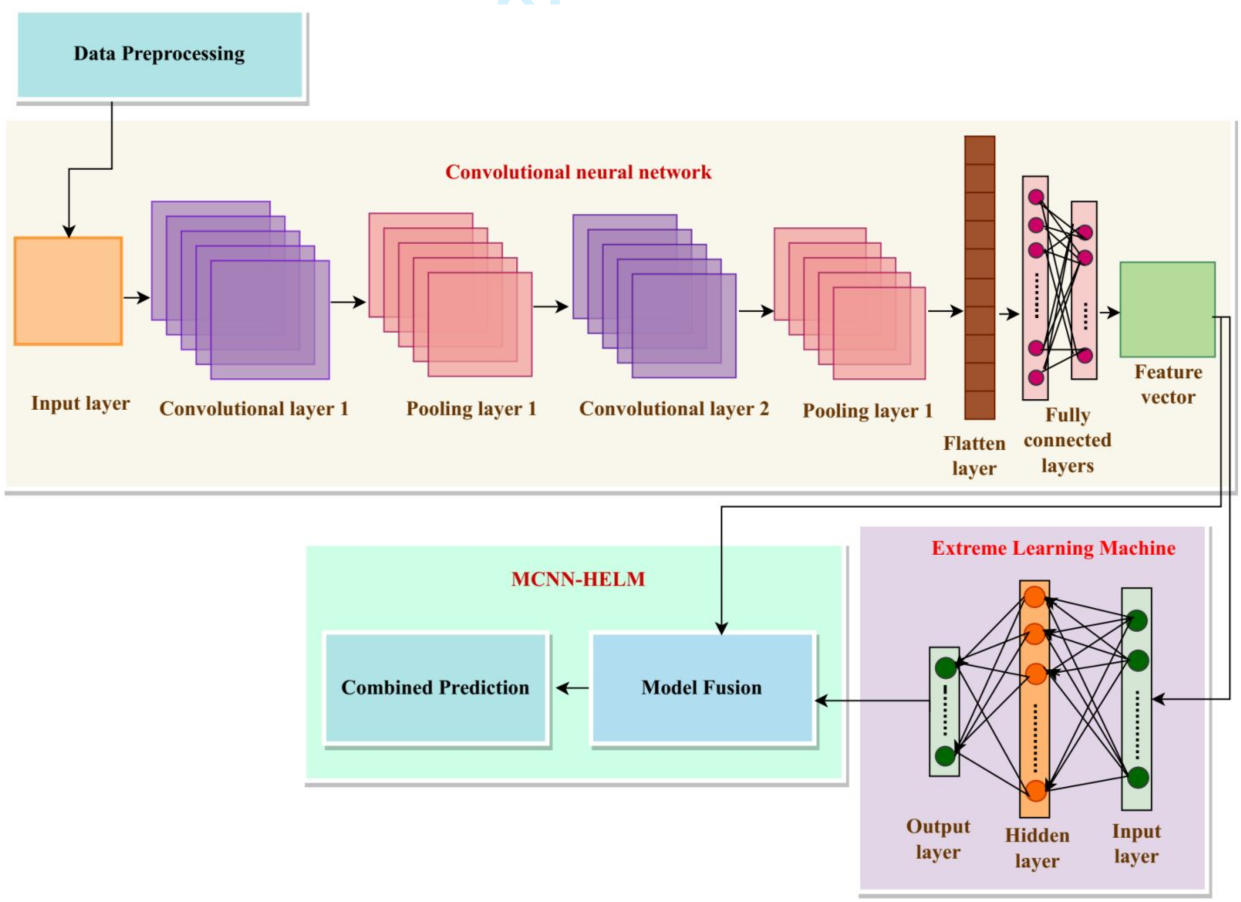

Figure 3: MCNN-HELM architecture

5.4 Improved Optimal Allocation Algorithm: Adaptive Objective-Weighted Genetic Allocation (AOWGA)

In this section, we elaborate on the methodology for optimal organ allocation, emphasizing the use of an AOWGA algorithm for solving complex optimization problems. AOWGA builds upon the foundational principles of Genetic Algorithm [31] while integrating advanced features to enhance the optimization process. This algorithm dynamically adapts objective weights to align with the current population's performance, fostering more effective convergence toward optimal allocation strategies. The detailed explanation of the optimal allocation algorithm is provided below:

1. Initial Population Generation:

The AOWGA algorithm starts with an initial population of allocation strategies, represented as chromosomes.

2. Adaptive Objective Weighting:

Initially, each objective (medical compatibility, urgency, fairness) is assigned equal weights, which are represented as follows:

$$w_{MC} = w_U = w_F = \frac{1}{3} \tag{14}$$

Where $w_{MC}, w_U, and\, w_F$ refers to the adaptive objective weight of medical compatibility, urgency, and fairness factors respectively.

As the algorithm progresses through generations, the weights dynamically adjust based on the performance of the population. Objectives with better fitness scores receive higher weights, emphasizing their importance. Mathematically, the objective weight adjustment is represented as follows:

$$w_{new} = w_{old} + \Delta w \times \frac{fit_{chromosome} - fit_{avg}}{fit_{best} - fit_{avg}} \tag{15}$$

Where w_{new} refers to the new adaptive weight, w_{old} represents the previous weight, Δw indicates a small adjustment factor, $fit_{chromosome}$ denotes the fitness score of the chromosome, fit_{avg} indicates the average fitness of the population, and fit_{best} represents the fitness of the best chromosome in the population.

The objective weight adjustment for medical compatibility, urgency, and fairness are represented as follows:

$$w_{MC} = w_{MC} + adjustment_{factor} \cdot \Delta w_{MC} \tag{16}$$

$$w_{U} = w_{U} + adjustment_{factor} \cdot \Delta w_{U} \tag{17}$$

$$w_{F} = w_{F} + adjustment_{factor} \cdot \Delta w_{F} \tag{18}$$

Where $\Delta w_{MC}, \Delta w_{U}$ *and* Δw_{F} represent the adjustments of medical compatibility, urgency, and fairness factors based on offspring fitness improvement respectively.

3. *Fitness Function Enhancement:*

The fitness function is updated to consider adaptive objective weights. It evaluates the fitness of each chromosome by combining objectives with their corresponding weights.

$$F(chromosome) = w_{MC} \cdot MC(chromosome) + w_{U} \cdot U(chromosome) + w_{F} \cdot F(chromosome) \tag{19}$$

4. *Objective-Focused Selection:*

Selection mechanisms prioritize chromosomes that excel in objectives with higher weights, mimicking the concept of "adaptation through fitness."

5. *Crossover and Mutation:*

Genetic operators (crossover and mutation) remain similar to traditional GA, allowing exploration and diversity maintenance.

- *Crossover:*

In the crossover process, genetic information from two parent chromosomes is combined to create offspring chromosomes. A common approach is the one-point cross-over, where a random point is selected along the chromosome and genetic information is exchanged between the parents to create two offspring.

Let P_1 *and* P_2 be the parent chromosomes, and O_1 *and* O_2 be the offspring chromosomes. The parent and offspring chromosomes are represented as follows:

$$P_1 = \lfloor p_{1,1}, p_{1,2}, \ldots.., p_{1,n} \rfloor \tag{20}$$

$$P_2 = \lfloor p_{2,1}, p_{2,2}, \ldots.., p_{2,n} \rfloor \tag{21}$$

$$O_1 = \lfloor p_{1,1}, p_{1,2},\ldots\ldots, p_{1,i}, p_{2,i+1}, p_{2,i+2},\ldots\ldots, p_{2,n} \rfloor \quad (22)$$

$$O_2 = \lfloor p_{2,1}, p_{2,2},\ldots\ldots, p_{2,i}, p_{1,i+1}, p_{1,i+2},\ldots\ldots, p_{1,n} \rfloor \quad (23)$$

$$O_1 = P_1[1:i] + P_2[i+1:] \quad (24)$$

$$O_2 = P_2[1:i] + P_1[i+1:] \quad (25)$$

The term n represents the length of the chromosome and i refers to the randomly chosen crossover point.

- Mutation:

Mutation introduces diversity into the population by randomly altering certain genes in a chromosome. In the context of AOWGA, we employ a simple bit-flip mutation. For each gene in the chromosome, there is a small probability of mutation. If the random mutation probability is satisfied, the gene is flipped.

Let M_i indicates the mutated gene in the offspring chromosome O_i, and m_i refers to the original gene:

$$M_i = \begin{cases} 1 - m_i & with\ probability\ p_{mutation} \\ m_i & with\ probability\ 1 - p_{mutation} \end{cases} \quad (26)$$

The term $p_{mutation}$ indicates the mutation probability, a small value typically in the range $(0,1)$, and m_i indicates gene value before mutation $(0\, or\, 1)$. In this equation, if the random probability $p_{mutation}$ is satisfied (which occurs with a probability of $p_{mutation}$), the gene is flipped (from 0 to 1 or vice versa). If the random probability is not satisfied (which occurs with a probability of $1 - p_{mutation}$), the gene remains unchanged.

6. *Elitism and Replacement:*

A portion of the best-performing chromosomes directly carry over to the next generation to preserve promising solutions.

7. *Termination Criteria:*

The algorithm concludes based on predetermined conditions, such as the number of generations or satisfactory convergence.

The AOWGA's core innovation lies in the adaptive objective weighting mechanism. Unlike traditional GAs with fixed weights, AOWGA dynamically adjusts objective weights based on the performance of the evolving population. This adaptability empowers the algorithm to allocate more computational resources to objectives that contribute most effectively to optimal allocation. The Pseudocode of the AOWGA algorithm is provided in Algorithm 1.

Algorithm 1: Pseudocode of AOWGA algorithm

Input:

- Population Size $\left(pop_{size}\right)$: The number of candidate allocation strategies in each generation.
- Maximum Generations $\left(\max_{generations}\right)$: The maximum number of generations the algorithm will evolve.
- Mutation Rate $\left(mutation_{rate}\right)$: The probability of a mutation occurring during reproduction.
- Initial Objective Weights $\left(initial_{weights}\right)$: The initial equal weights assigned to medical compatibility, urgency, and fairness objectives.
- Objective Weights Adjustment Factor $\left(adjustment_{factor}\right)$: The factor by which objective weights are adjusted based on performance.
- Termination Criteria $\left(ter\min ation_{condition}\right)$: A predefined criterion to stop the algorithm (e.g., $\max_{generations}$ reached).

Output:

Optimal Allocation Strategy $\left(best_{strategy}\right)$**:** The allocation strategy with the highest fitness score.

Processing Steps:

1. **Initialization:**

   Generate an initial population of allocation strategies (chromosomes) with random genetic information

   Set $current_{generation} = 1$

2. **Objective Weight Initialization:**

   Set objective weights for medical compatibility, urgency, and fairness using equation (14)

3. Generation Loop:

While $\left(current_{generation} \le \max_{generation}\right)$

Evaluate the fitness of each chromosome using the equation (19)

Select chromosomes for reproduction based on their fitness scores

Prioritize higher fitness scores

Apply crossover and mutation to generate offspring from selected chromosomes

Calculate the fitness of offspring using the same fitness function

Calculate the fitness of offspring using the same function

Update objective weights based on the performance of offspring using equation (16), (17), and (18)

$$current_{generation} = current_{generation} + 1$$

End While

Select the chromosome with the highest fitness score as the best allocation strategy

6. SIMULATION RESULTS:

In this section, the proposed method employed for enhancing the efficiency of organ transplantation is evaluated in a simulation environment. The detailed discussion of the simulation results is delineated in the following subsections:

6.1 Experimental setup:

In order to evaluate the performance of our proposed AOWGA algorithm, the MCNN-HELM model, and patient prioritization strategies in the context of organ transplantation optimization, we need to define a comprehensive simulation setup. The simulation evaluation is carried out in Python platform with system configuration of Intel(R) Core(TM) i5-6300U processor, and 16GB RAM.

6.2 Parameter Settings:

Table 1 illustrates the parameters and values for the proposed approach. These parameters are finely tuned in a precise manner to achieve better efficiency in organ transplantation.

Table 1: Parameters and its ranges

Techniques		Parameters	Ranges
Gradient Boosting Algorithm		Maximum depth	5
		Learning rate	0.1
		Number of iterations	100
		Number of leaves	100
		Boosting type	GOSS
MCNN-HELM	MCNN	Network layers	19
		Learning rate	0.001
		Size of the kernel	[64,128]
		Activation function	ReLU
	HELM	Size of the batch	[5,10,20]
		Number of Epochs	[8,16,32]
		Learning rate	0.01
AOWGA algorithm		Size of the population	20
		Rate of selection	0.8
		Maximum generation	30
		Rate of crossover	0.8
		Rate of mutation	0.2

6.3 Dataset Description:

The three types of real-world datasets [19] are used for evaluation purpose which includes the United Network for Organ Sharing Lung Transplantation (UNOS-LU) dataset, the Paired Liver Transplant Standard Dataset (PLTSD), and the United Network for Organ Sharing Heart Transplantation (UNOS-HR) dataset. Based on our requirements, these three above mentioned datasets are customized into three categories which are described below:

1. Risk Assessment and Patient Prioritization Dataset:

This dataset includes patient information of 10,000 samples for risk assessment and prioritization. This dataset contains comprehensive information about potential organ donors and recipients. It contains medical profiles including the health status, medical history, and specific medical conditions of both donors and recipients for assessing compatibility and risk factors. It is used to train and test the risk assessment model. Table 2 provides a detailed description of the risk assessment and patient prioritization dataset

The features in the dataset are highlighted below:

- *Patient ID:* Unique identifier for each patient.
- *Age:* Age of the patient.
- *Medical History:* Binary (Yes/No) indicating the presence of a medical history.
- *Severity of Illness:* Categorical (Low, Moderate, High) representing the severity of the patient's illness.
- *Compatibility Factors:* A set of numerical scores indicating compatibility with potential donors.
- *Risk Score:* A numerical score representing the patient's risk level.

Table 2: Detailed description of risk assessment and patient prioritization dataset

Patient ID	Age	Medical History	Severity of Illness	Compatibility Score	Risk Score
1	45	No	Moderate	0.78	0.65
2	38	Yes	High	0.92	0.74
3	60	No	Low	0.65	0.56
...	...	...	...	...	...
10,000	42	Yes	High	0.88	0.72

2. *Geographic Analysis for Donor Identification Dataset:*

This dataset contains geographical information of 5,000 samples related to donors and recipients, including distances, traffic conditions, and logistical constraints. It provides geographic distribution of organs, including the number of available organs in each region or hospital. It also contains geographic data indicating the locations of potential donors and recipients, which is used for calculating distances and travel times. It is used to compute optimal routes for donor identification. Table 3 provides a detailed description of the geographic analysis for the donor identification dataset.

The features in the dataset are represented below:

- *Location ID:* Unique identifier for each location.
- *Latitude:* Latitude coordinate of the location.
- *Longitude:* Longitude coordinate of the location.
- *Traffic Conditions:* Categorical (Light, Moderate, Heavy) indicating traffic conditions in the area.
- *Logistical Constraints:* Binary (Yes/No) indicating the presence of logistical constraints in the area.

Table 3: Detailed description of geographic analysis for donor identification dataset

Location ID	Latitude	Longitude	Traffic Conditions	Logistical Constraints
1	40.7128	-74.0060	Moderate	No
2	34.0522	-118.2437	Heavy	Yes
3	51.5074	-0.1278	Light	No
...	...	...	...	...
5,000	45.4215	-75.6903	Moderate	Yes

3. Donor-Recipient Information Dataset:

This dataset represents donor-recipient pairs and their characteristics. It is used as input for the MCNN-HELM model. This dataset contains a total number of 20,000 samples for assessment. Table 4 illustrates a detailed description of the Donor-Recipient Information dataset.

The features in the Donor-Recipient Information dataset are provided below:

- *Donor ID:* Unique identifier for each donor.
- *Recipient ID:* Unique identifier for each recipient.
- *Donor Age:* Age of the donor.
- *Recipient Age:* Age of the recipient.
- *Organ Type:* Categorical (Liver, Kidney, Heart, Lung) indicating the type of organ for transplantation.
- *Compatibility Score:* A numerical score indicating the compatibility between the donor and recipient.
- *Medical Risk Score:* A numerical score representing the medical risk associated with the transplantation.

Table 4: Detailed description of Donor-Recipient Information dataset

Donor ID	Recipient ID	Donor Age	Recipient Age	Organ Type	Compatibility Score	Medical Risk Score
1	1001	35	45	Liver	0.78	0.65
2	1002	42	38	Heart	0.92	0.74
3	1003	55	60	Kidney	0.75	0.58
...	...	...	...	...	...	...
20,000	10200	50	65	Lung	0.85	0.68

4. *Optimal Organ Allocation Dataset:*

This dataset simulates various scenarios for organ allocation. A total number of 15,000 samples are included in this dataset. It is used to develop and test the Genetic Algorithm-based allocation algorithm. Table 5 demonstrates a detailed description of the optimal organ allocation dataset.

The features in the dataset are:

- Donor ID: Unique identifier for each donor.
- Recipient ID: Unique identifier for each recipient.
- Organ Type: Categorical (Liver, Kidney, Heart, Lung) indicating the type of organ for transplantation.
- Compatibility: A score indicating the compatibility between the donor and recipient.
- Urgency: A score indicating the urgency of the transplantation.
- Fairness: A score indicating the fairness of the allocation.

Table 5: Detailed description of optimal organ allocation dataset

Donor ID	Recipient ID	Organ Type	Compatibility	Urgency	Fairness
1	1001	Liver	High	Low	High
2	1002	Heart	High	High	Low
3	1003	Kidney	Moderate	Moderate	Moderate
...	...	...	...	...	...
15,000	10150	Lung	High	Low	High

6.4 Performance metrics:

In this subsection, the performance metrics used for evaluation are defined.

Accuracy $\left(OT_{accuracy}\right)$:

Accuracy illustrates the proportion of the total number of correctly identified classes divided by the total number of predictions made by the model. The mathematical model for accuracy is highlighted below:

$$OT_{accuracy} = \frac{\left(OT_{TP} + OT_{TN}\right)}{\left(OT_{TP} + OT_{FP} + OT_{TN} + OT_{FN}\right)} \tag{27}$$

Precision $\left(OT_{precision}\right)$**:**

Precision measures the accuracy of positive predictions. In the context of organ allocation, it indicates how many allocated organs were truly suitable. Mathematically, the precision is represented as follows:

$$OT_{precision} = \frac{OT_{TP}}{(OT_{TP} + OT_{FP})} \tag{28}$$

Recall (OT_{recall})**:**

Recall measures the ability to identify all relevant instances. For organ allocation, it reflects how many suitable donors were correctly matched. The formula to calculate recall is provided as:

$$OT_{recall} = \frac{OT_{TP}}{(OT_{TP} + OT_{FN})} \tag{29}$$

Where OT_{TP}, OT_{FP}, OT_{TN}, *and* OT_{FN} indicates true positive, false positive, true negative, and false negative respectively.

F1-Score $(OT_{F1-Score})$**:**

The F1-Score is the harmonic mean of precision and recall, offering a balanced measure of model performance. The F1-score is computed as follows:

$$OT_{F1-Score} = \frac{2 \times (OT_{precision} \times OT_{recall})}{OT_{precision} + OT_{recall}} \tag{30}$$

6.5 Performance analysis:

In this section, the performance analysis of the Risk Assessment and Patient Prioritization model, A* Algorithm, MCNN-HELM Model, AOWGA algorithm, and the overall system performance of the integrated system are carried out to determine the superiority of the proposed approach in organ transplantation and in improving patients transplantation outcomes.

6.5.1 Risk Assessment and Patient Prioritization Algorithm:

We employed a range of statistical measures to evaluate the model's performance in the generation of risk scores and prioritization of patients. Table 6 indicates the performance analysis of risk assessment and Patient prioritization algorithm.

Table 6: Performance analysis of GBA algorithm

Performance measures	Value
Precision	0.95
Recall	0.97
F1-score	0.96
ROC-AUC	0.98

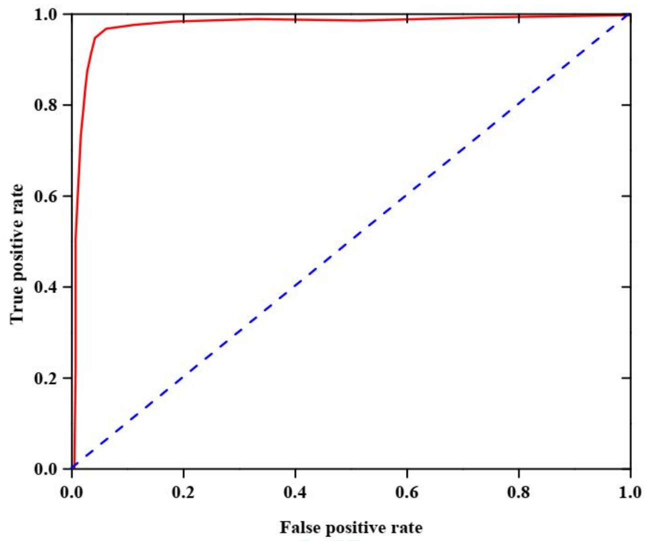

Figure 4: AUC/ROC of risk assessment and patient prioritization dataset

The AUC-ROC curve is used to evaluate the performance of the risk assessment and patient prioritization. The AUC represents the degree of separability and the ROC implies the probability curve. The AUC-ROC curve is used to determine the potential of the algorithm in identifying high-risk patients effectively. The model attains an AUC value of 0.98 which demonstrates the model's strong discriminatory power in determining high-level risk patients accurately. Figure 4 represents the AUC/ROC of risk assessment and patient prioritization dataset

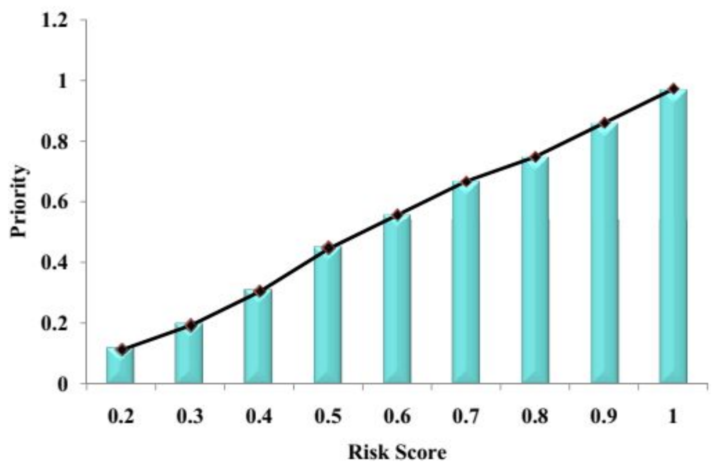

Figure 5: Histogram of the risk assessment and patient prioritization model

Figure 5 represents the histogram of the risk assessment and patient prioritization model. The x-axis represents the risk scores which reflect the severity of the patients awaiting organ transplantation. The y-axis represents the level of priority given by the model. The figure clearly shows that the patients having high-risk scores are given more priority, which demonstrates the models' ability to prioritize high-risk patients effectively. Therefore, the organ allocation efficiency and the chances of successful transplantation are improved significantly by determining priority based on risk scores.

Comparative analysis:

Risk assessment plays a critical role in patient prioritization as it helps identify patients who may benefit the most from transplantation. To assess the effectiveness of our risk-based patient prioritization approach, we conducted comparative analyses against four widely recognized methods in the field, they are ML+XAI, DEMATEL-MANP, and MELD.

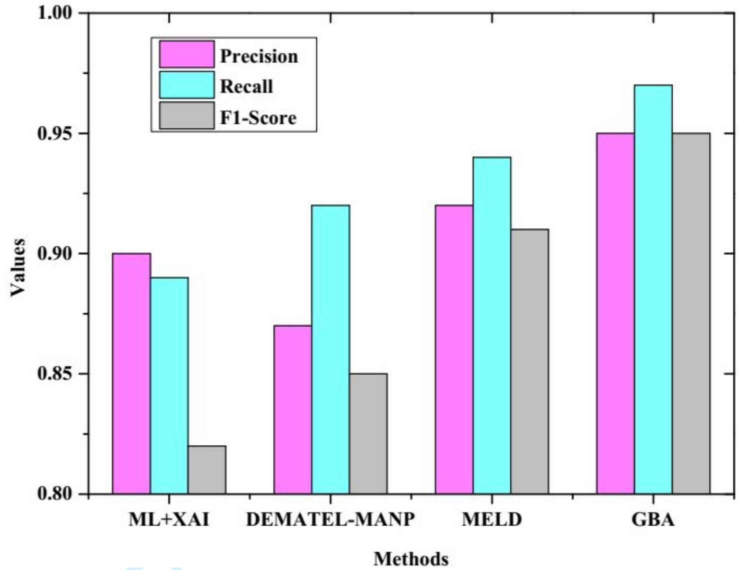

Figure 6: Comparative analysis of Precision, Recall, and F1-Score

Figure 6 represents the comparative analysis of Precision, Recall, and F1-Score. The figure illustrates that the GBA algorithm achieves a precision of 0.95, recall of 0.97, and F1-Score of 0.96 which is significantly higher compared to other existing works employed for comparison. Therefore, our risk assessment model is superior in predicting patient risk levels.

6.5.2 Geographic Analysis for Donor Identification:

Geographic analysis is performed to enhance the process of donor identification by considering real-world factors. In this subsection, the efficiency of the A* algorithm in identifying suitable donors based on geographic factors is evaluated. We computed metrics to assess the algorithm's performance, including route distances, travel times, and computational efficiency. Table 7 illustrates the performance analysis of the A* algorithm.

Table 7: Performance analysis of A* algorithm

Performance measures	Value
Average Distance (km)	160
Average Travel Time (hours)	2.5
Computational Efficiency (ms per route)	15

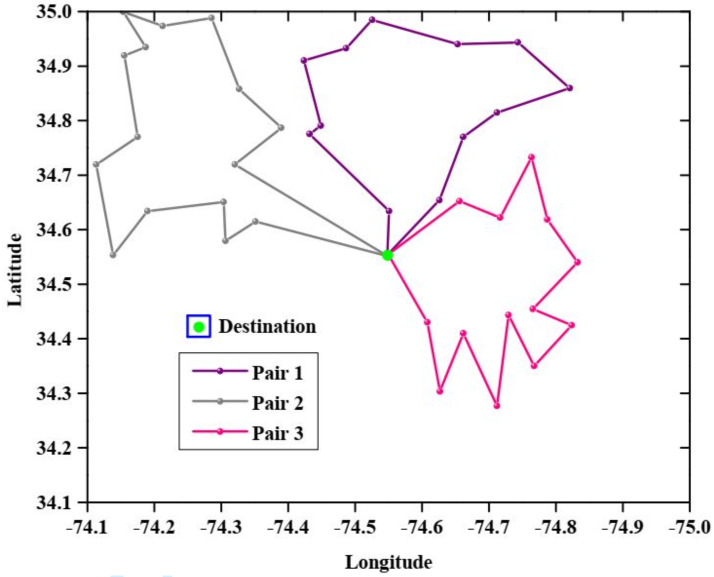

Figure 7: Optimized routes for donor identification

Figure 7 represents the optimized routes determined by the A* algorithm for donor identification of four random pairs. The A* algorithm determines the optimal routes for donor identification by considering geographic distances, traffic conditions, and logistical constraints. The Figure above illustrates the optimized routes for donor identification. Each line represents a route connecting potential donors to recipients. Therefore, the algorithm by optimizing routes reduces transportation time, which is crucial for preserving organ viability and improving the chances of successful transplantations. We present a sample of these optimized routes in Table 8.

Table 8: Optimized routes for donor identification

Donor-Recipient Pair	Geographic Route	Distance (km)	Travel Time (hours)
Pair 1	Route 1	150	2.5
Pair 2	Route 2	180	3.0
Pair 3	Route 3	120	2.0

The table clearly shows that optimizing routes for donor identification significantly reduced travel times which improves resource allocation, and reduces organ wastage leading to better organ quality and increased transplant success rates.

Comparative analysis:

To assess the effectiveness of A* algorithm in terms of computational efficiency, we conducted comparative analyses against state-of-the-art methods, they are MCGDM, DL, and MINLP.

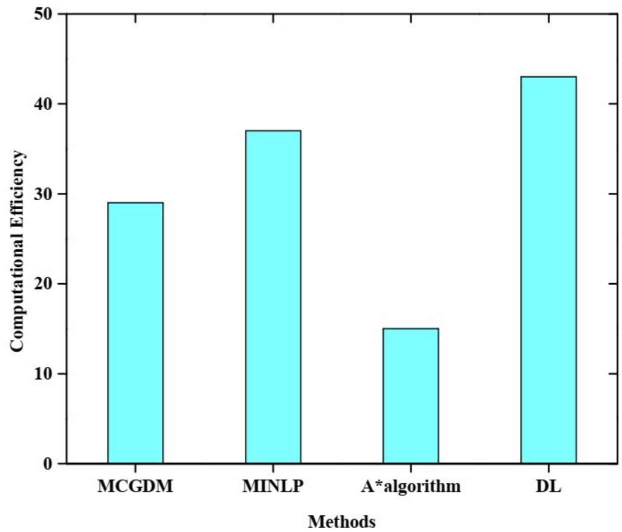

Figure 8: Comparative analysis of computational efficiency

The computational efficiency of the A* algorithm is compared to other existing approaches in Figure 8. In this figure, computational efficiency is plotted on the y-axis, and the methods are plotted on the x-axis. The A* algorithm finds the optimal route from the geographical data with less computational time. The A* algorithm achieves a computational efficiency of 15 ms per route which is significantly lower compared to other existing methods namely, MCGDM, MINLP, and DL. Therefore, the A* algorithm is superior in finding the optimal route.

6.5.3 Performance Analysis of MCNN-HELM Model in Donor-Recipient Matching:

In this subsection, the performance analysis of the MCNN-HELM method in Donor-Recipient matching is analyzed. Table 9 illustrates the performance analysis of the MCNN-HELM model.

Table 9: Performance analysis of MCNN-HELM model

Performance measures	Value
Precision	0.94
Recall	0.96
F1-score	0.95
Accuracy	97.5
Computational time	2.2

Comparative analysis:

The MCNN-HELM model is compared with existing methods namely, LR-EPUNN, TCV, and LR to determine its efficiency in donor-recipient matching.

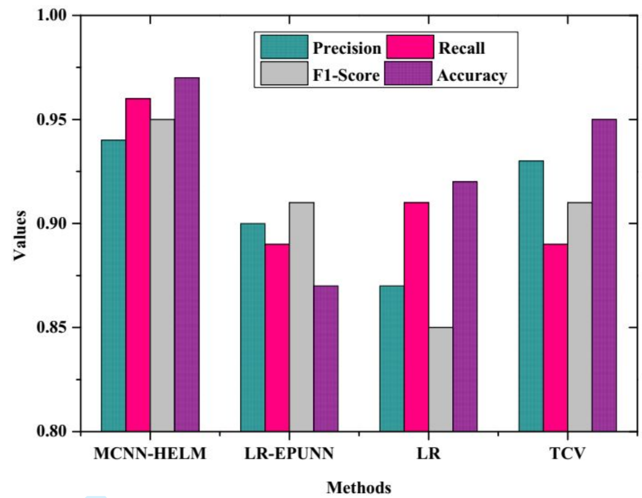

Figure 9: Comparative analysis of precision, recall, F1-Score, and accuracy

Figure 9 represents the comparative analysis of accuracy, Precision, Recall, and F1-score in the MCNN-HELM algorithm. The MCNN-HELM algorithm obtains a precision of 0.94, recall of 0.96, F1-score of 0.95, and accuracy of 97.5. The MCNN-HELM algorithm is more efficient compared to other existing techniques LR-EPUNN, LR, and TCV. Furthermore, MCNN-HELM has more potential to improve the allocation of organs in transplantation.

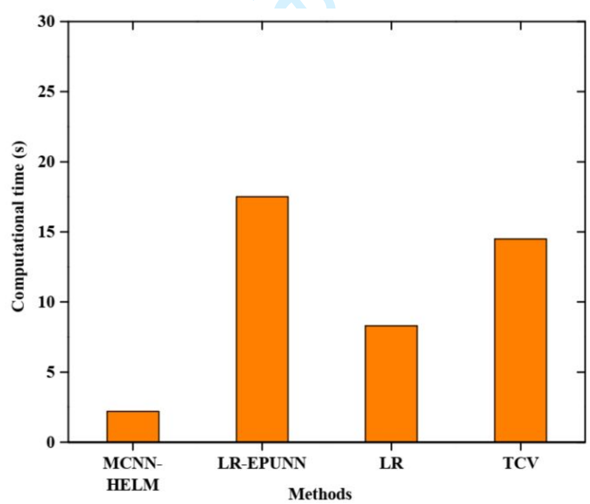

Figure 10: Comparative analysis of Computational time

The comparative analysis of computational time in the MCNN-HELM algorithm is illustrated in Figure 10. In MCNN-HELM algorithm has a computational time of value 2.2. The MCNN-HELM algorithm is highly efficient compared to other techniques such as LR-EPUNN, LR, and TCV. The existing methods take more time for computation whereas the MCNN-HELM algorithm takes less time for computation in donor-recipient matching.

6.5.4 Performance analysis of the AOWGA algorithm:

In this subsection, the performance analysis of the AOWGA algorithm is analyzed with Allocation Efficiency, Fairness Index, and Positive Outcomes. Table 10 represents the performance analysis of the AOWGA algorithm.

Table 10: Performance analysis of AOWGA algorithm

Performance measures	Value
Allocation Efficiency	0.96
Fairness Index	0.91
Positive Outcomes	0.95

Comparative analysis:

The AOWGA algorithm is compared with previous methods employed for allocation namely, ACO-kNN, LAS, and FISKA to determine its efficiency in donor-recipient matching.

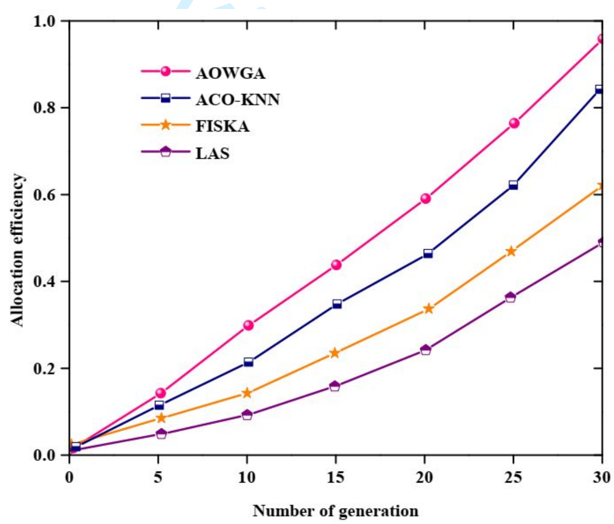

Figure 11: Comparative analysis of Allocation efficiency

Figure 11 represents the comparative analysis for allocation efficiency in the AOWGA algorithm. The AOWGA algorithm is compared with various techniques ACO-kNN, FISKA, and LAS to determine its efficiency in allocating the organ for transplantation. The AOWGA attains a higher allocation efficiency value of 0.96 than other existing techniques. Furthermore, the AOWGA achieves a better allocation rate in organ transplantation efficiently.

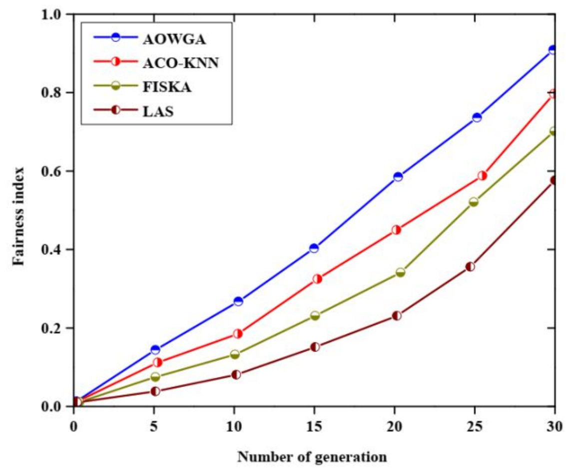

Figure 12: Comparative analysis of Fairness index

The graphical representation of the fairness index is given in Figure 12. The graph determines that the AWOGA algorithm attains a fairness index value of 0.91. From the graph, we came to know that the AWOGA algorithm has a better fairness index compared with other existing techniques ACO-kNN, FISKA, and LAS in the allocation of organ transplantation.

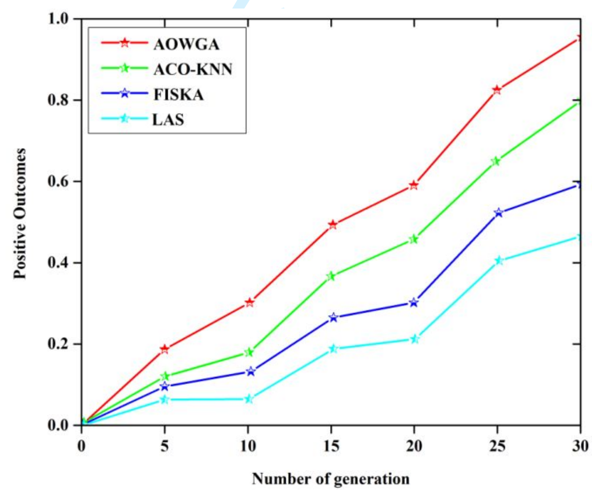

Figure 13: Comparative analysis of Positive outcomes

The comparative analysis of positive outcomes in the allocation of organ transplantation is in Figure 13. The graph is plotted and the AWOGA algorithm has gained a positive outcome value of 0.95. The experimental result shows that the AWOGA algorithm provides a highly positive outcome in organ transplant while all other algorithm attains lower value. Therefore The AWOGA algorithm improves the outcomes of organ transplantation.

6.5. Overall System Performance:

The integrated system, comprising risk assessment, geographic analysis, MCNN-HELM, and allocation algorithms is evaluated to determine its overall performance in organ transplantation. We present an overview of the system's effectiveness using comprehensive metrics namely, overall accuracy, positive outcomes, fairness index, allocation efficiency, precision, recall, and F1-Score. These metrics provide a holistic view of the system's performance in various aspects of organ transplantation. Table 11 illustrates the overall performance of the Integrated System.

Table 11: Summarized Overall Performance of the Integrated System

Performance measures	Values
Overall Accuracy	0.96
Positive Outcomes	0.95
Fairness Index	0.92
Allocation Efficiency	0.97
Precision	0.95
Recall	0.97
F1-score	0.95

Comparative analysis:

Here, the integrated system is compared with existing techniques namely, ACO-kNN, LAS, ML+XAI, LR-EPUNN, and MCGDM to determine its effectiveness in organ transplantation.

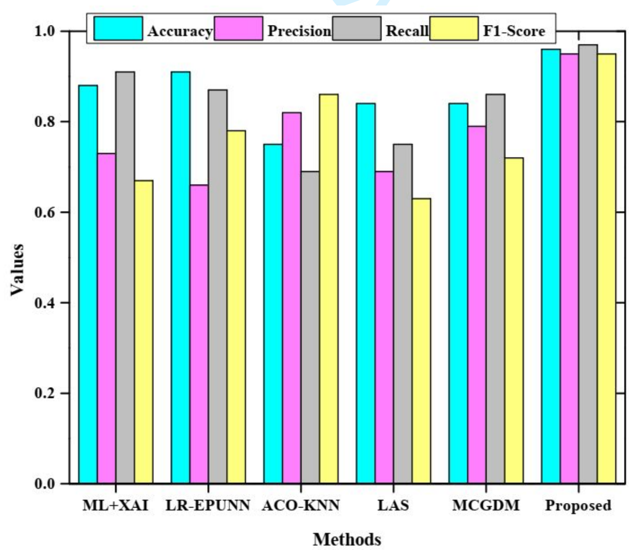

Figure 14: Comparative analysis of precision, recall, F1-Score, and accuracy

The graphical representation of overall accuracy, Precision, Recall, and F1-score is given in Figure 14. The proposed model obtained an overall accuracy of 0.96, precision of 0.95, recall of 0.97, and F1-score of 0.95. The proposed model achieves better results compared to other existing methods ML+XAI, LR-EPUNN, ACO-kNN, LAS, and MCGDM. Therefore the proposed method is more efficient than any other method in the allocation of organ transplantation.

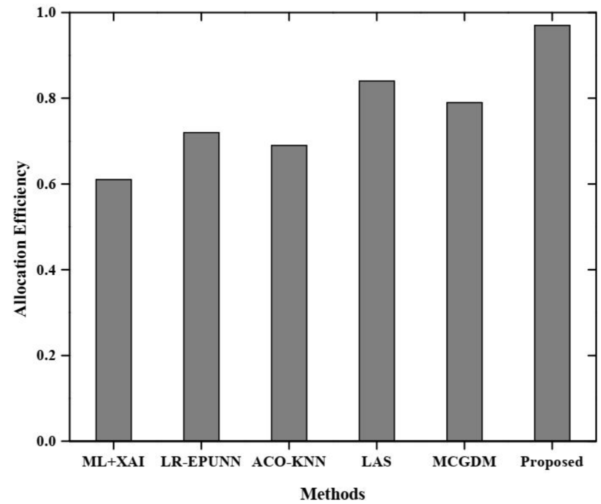

Figure 15: Comparative analysis of Allocation efficiency

The graphical representation of allocation efficiency in the proposed model is shown in Figure 15. The proposed system has an allocation efficiency of value 0.97. The experimental result shows high allocation efficiency compared to other existing methods ML+XAI, LR-EPUNN, ACO-kNN, LAS, and MCGDM in the precision of organ transplantation in an effective way.

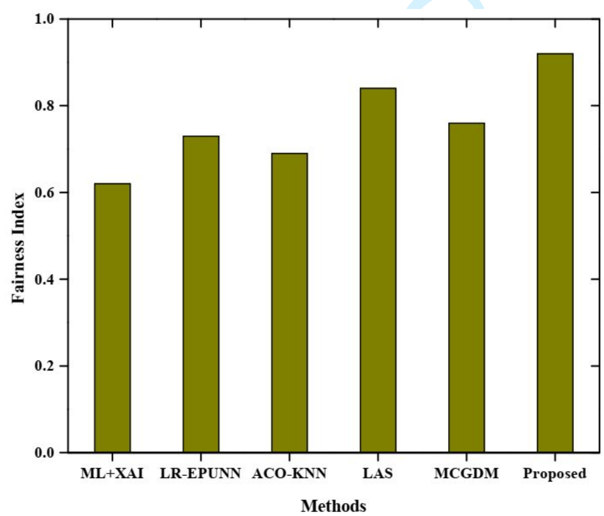

Figure 16: Comparative analysis of Fairness index

Figure 16 represents the graphical representation of the fairness index. The figure illustrates the proposed model which achieves a fairness index of 0.92. The proposed method is highly significant compared with other existing methods ML+XAI, LR-EPUNN, ACO-kNN, LAS, and MCGDM. From the graph, we conclude that the proposed method is more effective than other methods.

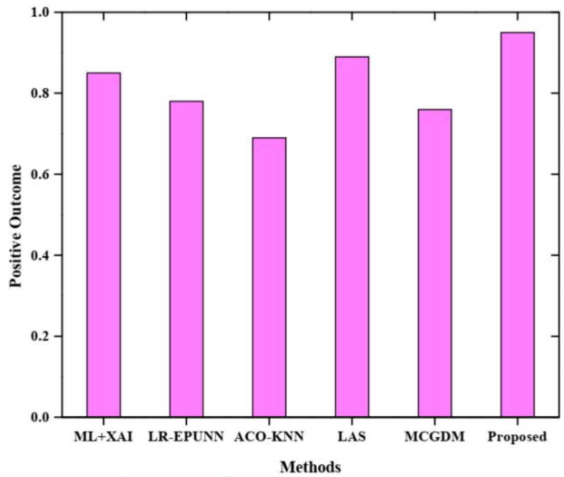

Figure 17: Comparative analysis of Positive outcomes

The comparative analysis of positive outcomes is in Figure 17. In this graph, the proposed method gets a positive outcome value of 0.95. In this graph, positive outcomes are plotted on the y-axis whereas all methods are plotted on the x-axis. This figure shows the proposed method has a more positive outcome when the other existing methods have low positive outcomes in the allocation of organ transplantation.

7. DISCUSSION:

In this section, the significance, future research directions, limitations, and ethical considerations of the research are provided.

1. *Synergy of Individual Components:*

- The synergy of individual components in the integrated system is a key factor in achieving the research objectives.
- The risk assessment identifies high-risk patients, geographic analysis ensures efficient donor identification, MCNN-HELM improves donor-recipient matching, and allocation algorithms optimize organ allocation.

2. *Broader Implications and Future Research Directions:*

- The research findings have broader implications in the field of organ transplantation, offering a comprehensive approach to addressing the organ shortage crisis.
- The integrated system enhances patient outcomes, reduces organ wastage, and improves the ethical distribution of organs.
- Future research directions could focus on refining the algorithms, scaling the system for real-world applications, and addressing ethical considerations related to organ allocation.

3. *Limitations and Ethical Considerations:*

- It's important to acknowledge the limitations of the integrated system, including the need for substantial computational resources and potential biases in data.
- Ethical considerations, such as fairness in allocation and transparency in decision-making, should be addressed to ensure the ethical use of the system in practice.

8. CONCLUSION

Our research represents a significant leap forward in the field of organ transplantation decision-making. The organ shortage crisis is a persistent challenge, and our comprehensive approach addresses this issue from multiple angles, ensuring both efficiency and ethical considerations are at the forefront of organ allocation. As we summarize the key takeaways, it becomes evident that our contributions hold great promise for transforming the landscape of organ transplantation. The introduction of the MCNN-HELM model is a pivotal achievement. It enhances donor-recipient matching accuracy, thereby reducing waiting times for patients. Our model achieves an impressive training accuracy of 97.5% with remarkable computational efficiency, highlighting its suitability for real-time decision-making. Our research underscores the importance of patient prioritization based on risk assessment. By identifying high-risk patients, we aim to maximize positive outcomes, thereby significantly improving the quality of life for those in dire need of organ transplants. Geographic analysis by the A* algorithm significantly enhances the process of donor identification by considering real-world factors and the scalability of this approach allows it to handle a growing number of organ transplantation cases. The adaptable AOWGA allocation algorithm is developed by considering various objectives simultaneously and ensuring that the organ allocation process is not only efficient but also ethically sound. The synergy of our integrated system, which combines risk assessment, geographic analysis, MCNN-HELM, and allocation algorithms, offers a holistic approach to organ transplantation decision-making. This approach maximizes the chances of positive outcomes while adhering to ethical principles. The implications of our research extend far beyond the technical realm. We envision a future where organ scarcity is mitigated, and patients receive timely and appropriate care, increasing their chances of survival and improved quality of life. While our research represents a significant advancement, we recognize that there is room for further improvement. Future research should focus on refining algorithms, addressing scalability concerns, and fostering ethical practices in organ transplantation. Overall, our research seeks to bridge the gap between organ demand and supply, making strides toward a healthcare landscape where patients in need of organ transplants find hope and timely care. We firmly believe that our contributions have the potential to revolutionize organ transplantation decision-making, ushering in an era where more lives are saved, and ethical principles are upheld in this critical aspect of healthcare. Through continued innovation and a commitment to addressing the complexities of organ allocation, we aspire to create a future where organ scarcity is no longer a barrier to life-saving treatments.

Ethical Statements:

Funding: Not applicable

Conflicts of interest Statement: Not applicable

Ethics approval: This article does not contain any studies with human participants.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent was obtained from all individual participants included in the study.

Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References:

1. Bambha, K., Shingina, A., Dodge, J.L., O'Connor, K., Dunn, S., Prinz, J., Pabst, M., Nilles, K., Sibulesky, L. and Biggins, S.W., 2020. Solid organ donation after death in the United States: Data-driven messaging to encourage potential donors. *American Journal of Transplantation*, *20*(6), pp.1642-1649.
2. Dogar, A.W., Ullah, K., Ochani, S. and Ahmad, H.B., 2022. Evolving liver transplantation in Pakistan: future challenges. *Annals of Medicine and Surgery*, *82*, p.104669.

3. Erazo, I., Goldsman, D., Keskinocak, P. and Sokol, J., 2022, December. A Simulation-Optimization Framework to Improve the Organ Transplantation Offering System. In *2022 Winter Simulation Conference (WSC)* (pp. 1009-1020). IEEE.
4. Gotlieb, N., Azhie, A., Sharma, D., Spann, A., Suo, N.J., Tran, J., Orchanian-Cheff, A., Wang, B., Goldenberg, A., Chassé, M. and Cardinal, H., 2022. The promise of machine learning applications in solid organ transplantation. *NPJ digital medicine*, *5*(1), p.89.
5. Ghaidan, H., Stenlo, M., Niroomand, A., Mittendorfer, M., Hirdman, G., Gvazava, N., Edström, D., Silva, I.A., Broberg, E., Hallgren, O. and Olm, F., 2022. Reduction of primary graft dysfunction using cytokine adsorption during organ preservation and after lung transplantation. *Nature Communications*, *13*(1), p.4173.
6. Tambur, A.R., Audry, B., Glotz, D. and Jacquelinet, C., 2023. Improving equity in kidney transplant allocation policies through a novel genetic metric: The Matched Donor Potential. *American Journal of Transplantation*, *23*(1), pp.45-54.
7. DeFilippis, E.M., Masotti, M., Blumer, V., Maharaj, V. and Cogswell, R., 2023. Sex-Specific Outcomes of Candidates Listed as the Highest Priority Status for Heart Transplantation. *Circulation: Heart Failure*, *16*(6), p.e009946.
8. Berry, A.E. and Bearl, D.W., 2023. Rethinking status 1A criteria in pediatric cardiac transplantation: A case for the prioritization of patients with single ventricle anatomy supported by ventricular assist devices. *Frontiers in Pediatrics*, *11*, p.1057903.
9. Gholamzadeh, M., Abtahi, H. and Safdari, R., 2022. Machine learning-based techniques to improve lung transplantation outcomes and complications: a systematic review. *BMC medical research methodology*, *22*(1), p.331.
10. Lebret, A., 2023. Allocating organs through algorithms and equitable access to transplantation—a European human rights law approach. *Journal of Law and the Biosciences*, *10*(1), p.lsad004.
11. Năstase, G., Botea, F., Beșchea, G.A., Câmpean, Ș.I., Barcu, A., Neacșu, I., Herlea, V., Popescu, I., Chang, T.T., Rubinsky, B. and Șerban, A., 2023. Isochoric Supercooling Organ Preservation System. *Bioengineering*, *10*(8), p.934.
12. Li, C., Jiang, X. and Zhang, K., 2023. A Transformer-Based Deep Learning Approach for Fairly Predicting Post-Liver Transplant Risk Factors. *arXiv preprint arXiv:2304.02780*.
13. Hawashin, D., Jayaraman, R., Salah, K., Yaqoob, I., Simsekler, M.C.E. and Ellahham, S., 2022. Blockchain-based management for organ donation and transplantation. *IEEE Access*, *10*, pp.59013-59025.
14. Salimian, S. and Mousavi, S.M., 2022. A new scenario-based robust optimization approach for organ transplantation network design with queue condition and blood compatibility under climate change. *Journal of Computational Science*, *62*, p.101742
15. Salimian, S., Mousavi, S.M. and Turskis, Z., 2023. Transportation Mode Selection for Organ Transplant Networks by a New Multi-Criteria Group Decision Model Under Interval-Valued Intuitionistic Fuzzy Uncertainty. *Informatica*, *34*(2), pp.337-355.

16. Dueñas-Jurado, J.M., Gutiérrez, P.A., Casado-Adam, A., Santos-Luna, F., Salvatierra-Velázquez, A., Cárcel, S., Robles-Arista, C.J.C. and Hervás-Martínez, C., 2021. New models for donor-recipient matching in lung transplantations. *Plos one*, *16*(6), p.e0252148.
17. Guijo-Rubio, D., Briceño, J., Gutiérrez, P.A., Ayllón, M.D., Ciria, R. and Hervás-Martínez, C., 2021. Statistical methods versus machine learning techniques for donor-recipient matching in liver transplantation. *Plos one*, *16*(5), p.e0252068.
18. Szugye, N.A., Zafar, F., Ollberding, N.J., Villa, C., Lorts, A., Taylor, M.D., Morales, D.L. and Moore, R.A., 2021. A novel method of donor-recipient size matching in pediatric heart transplantation: A total cardiac volume–predictive model. *The Journal of Heart and Lung Transplantation*, *40*(2), pp.158-165.
19. Gnanasambandhan, S. and Balasubramanian, V., 2023. HEL-MCNN: Hybrid Extreme Learning Modified Convolutional Neural Network for Allocating Suitable Donors for Patients with Minimized Waiting Time. *Expert Systems with Applications*, p.120673.
20. Silva-Aravena, F., Delafuente, H.N. and Astudillo, C.A., 2022. A novel strategy to classify chronic patients at risk: a hybrid machine learning approach. Mathematics, 10(17), p.3053.
21. Bayat, S., Abtahi, A.R., Damghani, K.K. and Zenouz, R.Y., 2023. Identification and prioritization of key factors in the liver transplantation system using DEMATEL-modified ANP method. *Razavi International Journal of Medicine*, *11*(1).
22. Dirchwolf, M., Becchetti, C., Gschwend, S.G., Toso, C., Dutkowski, P., Immer, F., Beyeler, F., Rossi, S., Schropp, J., Dufour, J.F. and Banz, V., 2022. The MELD upgrade exception: a successful strategy to optimize access to liver transplantation for patients with high waiting list mortality. *HPB*, *24*(7), pp.1168-1176.
23. Al-Ebbini, L.M., 2023. An Efficient Allocation for Lung Transplantation Using Ant Colony Optimization. *Intelligent Automation & Soft Computing*, *35*(2).
24. Taherkhani, N., Sepehri, M.M., Khasha, R. and Shafaghi, S., 2022. Ranking patients on the kidney transplant waiting list based on fuzzy inference system. *BMC nephrology*, *23*(1), pp.1-14.
25. Bayer, F., Dorent, R., Cantrelle, C., Legeai, C., Kerbaul, F. and Jacquelinet, C., 2022. France's new lung transplant allocation system: combining equity with proximity by optimizing geographic boundaries through the supply/demand ratio. *Transplant International*, *35*, p.10049.
26. Van de Klundert, J., van der Hagen, L. and Markus, A., 2022. Eliminating transplant waiting time inequities–With an application to kidney allocation in the USA. *European Journal of Operational Research*, *297*(3), pp.977-985.
27. Vaulet, T., Al-Memar, M., Fourie, H., Bobdiwala, S., Saso, S., Pipi, M., Stalder, C., Bennett, P., Timmerman, D., Bourne, T. and De Moor, B., 2022. Gradient boosted trees with individual explanations: An alternative to logistic regression for viability prediction

in the first trimester of pregnancy. *Computer Methods and Programs in Biomedicine*, *213*, p.106520.

28. Amine, O. and Mohammed, M., 2023. Generating A-Star Algorithm Admissible Heuristics Using a Dynamic Dataloader on Neural Networks, Enhanced With Genetic Algorithms, on a Distributed Architecture. *IEEE Access*, *11*, pp.18356-18373.
29. Zhang, J., Yi, S., Liang, G.U.O., Hongli, G.A.O., Xin, H.O.N.G. and Hongliang, S.O.N.G., 2020. A new bearing fault diagnosis method based on modified convolutional neural networks. *Chinese Journal of Aeronautics*, *33*(2), pp.439-447.
30. Yang, L., Fang, X., Wang, X., Li, S. and Zhu, J., 2022. Risk prediction of coal and gas outburst in deep coal mines based on the SAPSO-ELM algorithm. *International journal of environmental research and public health*, *19*(19), p.12382.
31. Sugendran, G. and Sujatha, S., 2023. Earlier identification of heart disease using enhanced genetic algorithm and fuzzy weight based support vector machine algorithm. *Measurement: Sensors*, p.100814.