KIDNEY TRANSPLANTATION AND SURVIVAL PREDICTION

A Project Report

Submitted to the APJ Abdul Kalam Technological University

in partial fulfillment of requirements for the award of degree

Bachelor of Technology

in

Computer Science and Engineering

by

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CERTIFICATE

This is to certify that the report entitled **KIDNEY TRANSPLANTATION AND SURVIVAL PREDICTION** submitted by **ALEN P SAJI** (CEK20CS005), **AZULAJ A** (CEK20CS011), **DEEPAK D** (CEK20CS015), **MUHAMMED HASSIL H** (CEK20CS029) to the APJ Abdul Kalam Technological University in partial fulfillment of the B.Tech. degree in Computer Science and Engineering is a bonafide record of the project work carried out by them under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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We hereby declare that the project report **KIDNEY TRANSPLANTATION AND SURVIVAL PREDICTION** , submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by us under supervision of **Prof.AJEESH S**

This submission represents our ideas in our own words and where ideas or words of others have been included, we have adequately and accurately cited and referenced the original sources.

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Abstract

Kidney transplantation has become a pivotal aspect of modern healthcare, offering individuals hope for extended life and improved quality of life. However, the success and efficiency of kidney donation and transplantation processes have historically been challenging to predict and manage. The emergence of advanced artificial intelligence (AI) technologies has revolutionized this field, providing unprecedented opportunities for optimization and decision-making support.

This paper proposes an innovative AI-enabled system designed to streamline and enhance all aspects of kidney donation and transplantation management. The system operates through a centralized platform where data inputted by healthcare professionals, specifically doctors, is meticulously analyzed by trained analysts. The data is structured and processed using CSV files, facilitating efficient storage, retrieval, and manipulation.

The proposed system leverages AI algorithms to predict the success rates of kidney transplantation procedures, assess compatibility between donors and recipients, and optimize organ allocation strategies. By harnessing the power of data analytics and AI-driven insights, healthcare professionals can make more informed decisions, enhance patient outcomes, and maximize the utilization of precious organ resources.

In conclusion, the integration of AI technology into kidney donation and transplantation management holds immense promise for revolutionizing the field, ultimately improving patient care and advancing medical science.

Acknowledgement

We take this opportunity to express our deepest sense of gratitude and sincere thanks to everyone who helped us to complete this work successfully. We express our sincere thanks to **Dr. BHADRAN V**, Principal, College of Engineering Kottarakkara for providing us with all the necessary facilities and support.

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Chapter 1

Introduction

1.1 General Background

Kidney transplantation stands as a transformative frontier in modern medicine, offering a second chance at life for individuals grappling with terminal organ failure. This intricate medical procedure involves the surgical replacement of a failing organ with a healthy one obtained from either a living or deceased donor. The triumphs of organ transplantation, encompassing kidneys have revolutionized the landscape of healthcare, yet the journey from transplant to sustained survival is a complex odyssey marked by scientific advancements, ethical considerations, and the pressing challenge of kidney scarcity. Survival prediction in the realm of organ transplantation has become a crucial facet of patient care, influencing medical decisions and shaping post-transplant strategies. As medical science intertwines with technological innovations, healthcare professionals increas- ingly rely on sophisticated predictive models. These models consider an intricate web of variables, including recipient age, overall health, and the compatibility of the donor-recipient pair. The advent of precision medicine has allowed for tailoring these predictions to individualized patient profiles, ushering in an era where treatment plans are finely tuned to maximize the chances of long-term survival. The cornerstone of successful transplantation lies in the delicate balance between the immune system and the transplanted organ. Immunological compatibility, advance ments in immunosuppressive medications, and the meticulous matching of donor and recipient characteristics contribute to mitigating the risk of rejection and improving post-transplant outcomes. However, the landscape is not without challenges. The perennial shortage of donor organs presents a formidable obstacle, leading to lengthy waiting lists and, tragically, the loss of lives before suitable organs become available. This dilemma underscores the urgent need for continued research into innovative solutions, such as xenotransplantation and bioengineering, to expand the pool of viable donor organs and alleviate the burden on transplant candidates. In this intricate dance between medical science and the human condition, organ transplantation and survival prediction unfold as a tapestry of hope, ethical quandaries, and scientific progress. As researchers strive to unravel the complexities inherent in transplantation, the field holds promise for not only extending lives but also reshaping our understanding of resilience and the boundaries of medical possibility.

1.2 Scope of the System

The scope of kidney transplantation and survival prediction encompasses a broad and dynamic terrain, reflecting the interdisciplinary nature of this field. At its core, the scope involves refining and expanding the methodologies employed in predicting post-transplant survival. This includes harnessing the power of data analytics, machine learning, and artificial intelligence to create increasingly sophisticated predictive models that consider an array of patient-specific factors. Moreover, the scope extends to the continual enhancement of immunosuppressive therapies, aiming to strike a delicate balance between preventing organ rejection and minimizing adverse effects. The exploration of alternative sources of organs, such as xenotransplantation and advancements in bioengineering, widens the horizon by offering potential solutions to the perennial organ shortage crisis. Addressing ethical considerations in organ allocation is an integral facet of the scope, as efforts are directed towards creating fair and just systems that maximize the benefits to recipients while ensuring transparency and equity. Additionally, the scope embraces the challenge of streamlining the transplantation process, from donor identification and organ procurement to surgical procedures and post-operative care. As technology evolves, the integration of telemedicine and remote monitoring into post-transplant management represents an exciting frontier within the scope, promising improved patient care and outcomes.

Ultimately, the scope of organ transplantation and survival prediction extends beyond the confines of medical science alone. It encompasses ethical, social, and technological dimensions, aiming to create a comprehensive framework that not only saves lives through successful transplants but also addresses the systemic challenges inherent in organ procurement, allocation, and long-term patient care.

1.3 Problem Statement

It is hard for doctors to memorize the data of each patients which is one of the main problems. Calculating the survival outcome of each person is hard and sometime it can turn out to be wrong and we aim to solve this problem.At present advanced ML based techniques are not seriously employed.

1.4 Need and Significance

The need and significance of a project on kidney transplantation and survival prediction using machine learning are profound due to several reasons:

1. Enhanced Patient Care: By leveraging machine learning algorithms, healthcare professionals can better predict outcomes for kidney transplant recipients, allowing for personalized care plans tailored to individual patient needs. This can lead to improved patient satisfaction and quality of life.

2. Optimized Resource Allocation: Accurate survival prediction models enable healthcare providers to allocate resources more efficiently, including organ allocation, staffing, and post-transplant care, thus maximizing the impact of limited healthcare resources.

3. Reduced Healthcare Costs: By identifying high-risk patients early and intervening proactively, machine learning-based prediction models can help prevent costly complications and hospital readmissions, ultimately reducing healthcare expenditure associated with kidney transplantation.

4. Improved Transplant Success Rates: Machine learning algorithms can analyze large datasets to identify patterns and factors that contribute to transplant success or failure. By understanding these factors, transplant programs can optimize donor-

recipient matching and post-transplant management protocols, leading to higher success rates and improved long-term graft survival.

5. Advancement in Research: Projects focusing on kidney transplantation and survival prediction using machine learning contribute to the advancement of medical research in the field. Insights gained from analyzing large datasets can lead to the discovery of novel biomarkers, therapeutic targets, and treatment strategies for improving transplant outcomes.

6. Empowering Clinical Decision Making: Machine learning models provide clinicians with valuable decision support tools, enabling them to make more informed decisions regarding patient care, medication management, and follow-up protocols. This empowers healthcare providers to deliver more personalized and effective care to kidney transplant recipients.

1.5 Scheme of The System

1. **Data Collection and Preprocessing**: Describe the sources of data utilized, such as electronic health records, demographic information, and laboratory results. Explain the preprocessing steps undertaken to clean and prepare the data, including handling missing values, outlier detection, and normalization.

2. **Feature Selection and Extraction**:Discuss the process of selecting relevant features or variables from the dataset, considering factors such as clinical relevance and predictive power. Detail any feature extraction techniques employed to derive additional information from the raw data, such as principal component analysis or signal processing methods.

3. **Machine Learning Models**: Present the machine learning algorithms and models utilized for predicting kidney transplant survival rates. Explain the rationale behind the selection of these models, considering factors such as model interpretability, computational efficiency, and performance metrics. Provide details on model training, validation, and evaluation procedures, including cross-validation techniques and hyperparameter tuning.

4. **Performance Evaluation**: Evaluate the performance of the developed models in predicting kidney transplant survival rates, utilizing appropriate evaluation metrics such as accuracy, precision.Compare the performance of different models and algorithms, identifying strengths, weaknesses, and areas for improvement.

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Chapter 2

Literature Review

[1]Kidney transplant in the next decade: Strategies, challenges and vision of the future.
Auth: Domingo Hernández , Abelardo Caballero

In the pursuit of enhancing kidney transplantation (KT) outcomes over the next decade, multifaceted strategies are imperative. Mitigating chronic dysfunction and graft loss necessitates a comprehensive approach. This involves refining immunosuppressive protocols, implementing precision medicine techniques to tailor treatments, and exploring innovative therapies to address underlying causes of graft deterioration.

To prolong patient survival post-KT, efforts must extend beyond graft management. Strategies encompass optimizing pre-transplant patient selection, managing comorbidities effectively, and enhancing post-transplant care coordination to mitigate complications.

Increasing organ procurement and distribution demands systemic improvements. This entails expanding deceased and living donor pools through public awareness campaigns, incentivizing donation, and streamlining allocation policies to ensure equitable access. Fostering research and training initiatives is pivotal. Investing in translational research to innovate transplantation techniques, advancing donor-derived organ preservation methods, and providing comprehensive training for healthcare professionals are paramount.

Lastly, optimizing clinical practice via scientific registries is crucial. By consolidating and analyzing comprehensive datasets, insights into outcomes, trends, and best practices can inform evidence-based decision-making, driving continuous quality improvement in KT.

In sum, by addressing these interconnected objectives, the transplantation community can aspire to significantly enhance KT outcomes, patient survival rates, organ procurement and allocation, research advancements, and clinical practice optimization over the forthcoming decade.

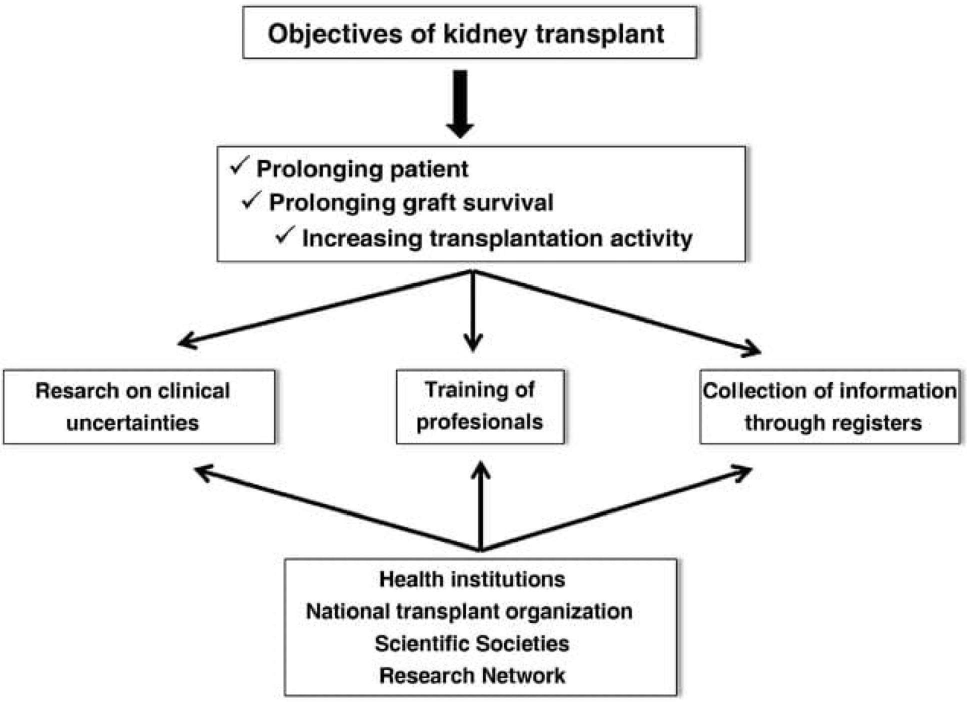

Figure 2.1: Objectives to be achieved in the next decade in kidney transplantation

Prolonging patient survival in kidney transplantation (KT) necessitates a multifaceted approach addressing clinical, socio-economic, and technological challenges. Prophylactic measures, guided by multidisciplinary consensus, are vital to mitigate risks associated with emerging pandemics. Incorporating comorbid factors into predictive models aids in therapeutic decision-making, particularly for high- and intermediate-risk patients. Predictive models, bolstered by artificial intelligence, optimize survival predictions, facilitating tailored therapeutic interventions post-transplantation.

While kidney transplant waitlist (WL) mortality remains notable, identifying at-risk patients through robust risk models enhances prioritization for transplantation. Frailty detection in WL patients, coupled with multidisciplinary prehabilitation programs, mitigates mortality risks and improves post-transplant outcomes. Moreover,

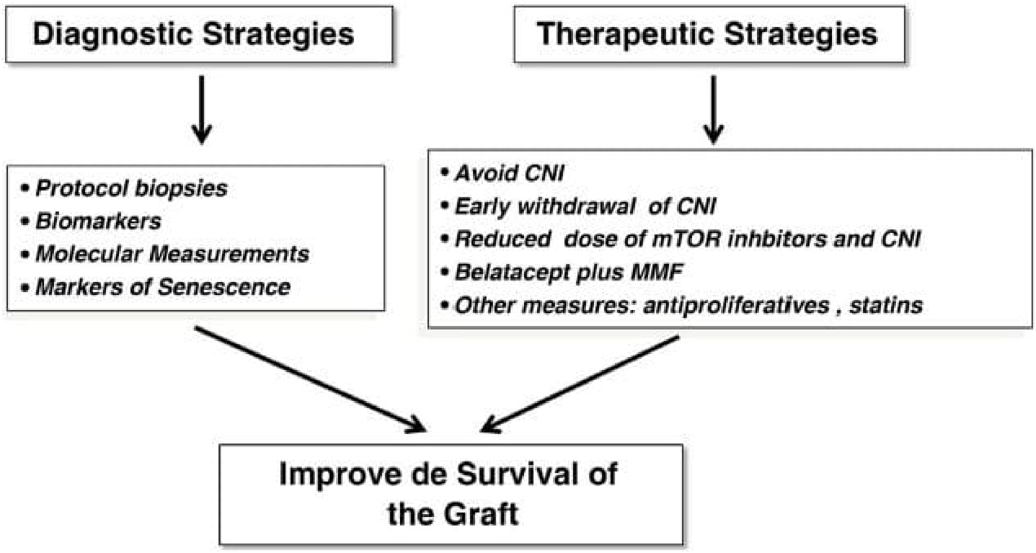

Figure 2.2: Diagnostic strategies and therapeutic measures aimed at improving renal transplant survival outcomes.

preemptive identification of WL patients prone to post-transplant dialysis dependence (PTDD) aids in proactive management strategies.

Embracing new technologies such as virtual consulting, adherence-promoting applications, and electronic monitoring devices enhances patient care and transplant management. Systematic incorporation of advanced chronic kidney disease consultation optimizes pre-transplant management, ensuring better outcomes for patients with deteriorating renal function awaiting transplantation.

In conclusion, a comprehensive approach integrating predictive modeling, multidisciplinary interventions, and technological innovations is imperative to prolong patient survival and optimize kidney transplantation outcomes amidst evolving clinical and socio-economic landscapes.

[2]Application of Machine Learning in Chronic Kidney Disease: Current Status and Future Prospects.

Auth : Charlotte Delrue , Sander De Bruyne and Marijn M. Speeckaert.

The emergence of artificial intelligence (AI) and machine learning (ML) has catalyzed a transformative shift in the landscape of clinical medicine, offering unprecedented opportunities to enhance medical practice and research. This narrative review delves into the current status and future prospects of applying ML specifically to chronic kidney disease (CKD), a condition presenting complex challenges in diagnosis, management, and treatment.

At its core, ML operates at the intersection of statistics and computer science, empowering computers to extract actionable insights from vast and intricate datasets. In the context of CKD, where data volume and complexity abound, ML presents an intriguing landscape for constructing sophisticated statistical models and refining data interpretation methodologies. By leveraging ML techniques, clinicians can potentially uncover hidden patterns within patient data, leading to more accurate diagnoses, prognoses, and treatment recommendations.

The integration of ML into clinical algorithms holds the promise of enhancing efficiency and standardizing data interpretation practices in nephrology. By automating tasks such as risk prediction, treatment response evaluation, and outcome forecasting, ML algorithms can augment clinical decision-making processes, ultimately leading to improved patient care and outcomes.

However, the realization of these promises hinges on effective collaboration between clinicians and data scientists. Together, they must define robust data-sharing frameworks, establish guidelines for responsible data usage, and navigate ethical considerations surrounding patient privacy and consent. Through interdisciplinary collaboration, the healthcare community can harness the full potential of ML to advance precision diagnostics and personalized medicine in the context of CKD.

As the field of ML continues to evolve, ongoing research and innovation will be essential to further refine algorithms, validate findings, and integrate ML-driven approaches into routine clinical practice. By fostering a culture of collaboration and innovation, the healthcare community can unlock new insights, optimize patient care pathways, and ultimately improve outcomes for individuals living with CKD.

[3] A comparative analysis of survival of patients on dialysis and after kidney transplantation.

Auth : Mohammed A. Kaballo, Mark Canney, Patrick O'Kelly, Yvonne Williams, Conall M. O'Seaghdha1 and Peter J. Conlon

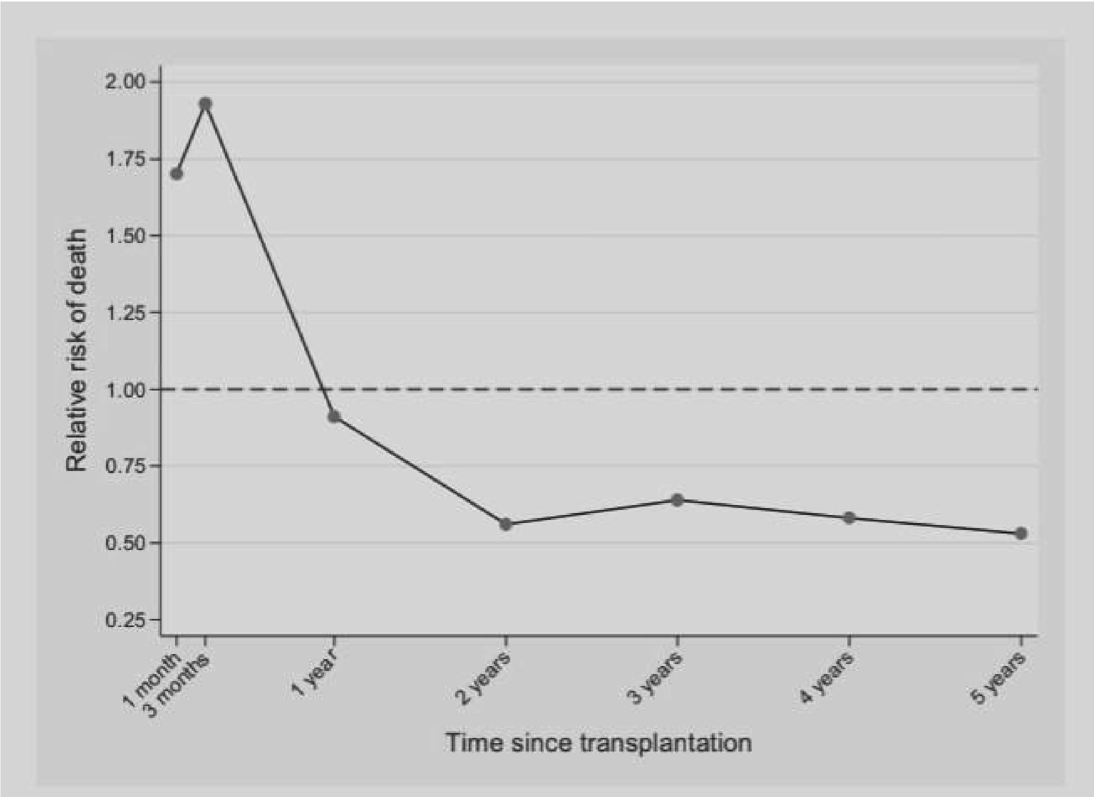

Figure 2.3: Adjusted relative risk of death for transplant recipients compared with on-pool dialysis patients during the first 5 years post-transplant.

In this retrospective analysis conducted in Ireland, the survival rates of kidney transplant recipients, patients awaiting transplantation, and non-listed dialysis patients were compared to understand the dynamics of mortality risk across these groups. The study unveiled a nuanced pattern wherein kidney transplant recipients initially faced a higher risk of mortality in the immediate post-transplant period, contrasting with patients on dialysis and those awaiting transplantation. However, over the long term, transplant recipients exhibited significantly superior survival outcomes compared to their counterparts.

Analyzing data from 3597 patients, the study found varying annual death rates per 100 patient-years at risk: 16.5 for dialysis patients, 2.4 for those on the waiting list, and 1.2 for transplant recipients. Notably, patients with diabetes exhibited the highest mortality rates across all groups, indicative of the complex interplay between comorbidities and survival outcomes.

Through meticulous adjustment for key factors such as age, cause of end-stage kidney disease (ESKD), duration from first treatment for ESKD to waitlist placement, and the year of initial listing, the study elucidated important trends. Patients on dialysis faced a relative risk of death approximately five times higher than those on the waiting list. However, this risk differential gradually diminished within one year post-transplantation. Subsequently, transplant recipients displayed a remarkable 47percent lower risk of mortality compared to their counterparts on the waiting list over a five-year span.

These findings underscore the profound and enduring survival benefits associated with kidney transplantation, despite the transient heightened risk observed immediately after transplantation. Timely transplantation emerges as a crucial determinant in enhancing patient outcomes, emphasizing the imperative for streamlined organ allocation processes and efficient transplant protocols within kidney transplant programs.

The study not only enhances our understanding of mortality dynamics in kidney transplant candidates and recipients but also underscores the pivotal role of transplantation in mitigating mortality risks and improving long-term survival prospects for individuals with end-stage kidney disease. These insights underscore the critical importance of prioritizing timely access to transplantation in clinical practice and healthcare policy.

[4] A Detailed Study On The Quality Of Life of Kidney Transplant Patients.

Auth : Yin Jiali , Amanda .J and Shao Qilu.

As the population of kidney transplant recipients continues to grow, understanding and improving the quality of life (QoL) after transplantation becomes increasingly important. This case study aimed to summarize the instruments used to measure the QoL of kidney transplant patients, describe their QoL, and outline the characteristics of participants in the selected articles.

The findings revealed that, compared to norms established by the SF-36, kidney transplant recipients reported lower QoL scores in dimensions such as Role Physical (RP), General Health (GH), Social Functioning (SF), and Role Emotional (RE). This suggests that kidney transplant patients may experience challenges in physical and emotional functioning, as well as in their general perception of health and social interactions.

The conclusion drawn from these findings is that the QoL of kidney transplant recipients, particularly in certain dimensions, is lower than that of the normal population. To address these disparities, targeted health education interventions using models such as the Knowledge-Attitude-Practice (KAP) Model can be implemented by nurses. By focusing on improving patients' knowledge, attitudes, and behaviors related to their post-transplant care, nurses can help enhance QoL outcomes over time.

In summary, it states that the importance of assessing and addressing QoL issues in kidney transplant recipients. Through targeted interventions and ongoing support, healthcare professionals can work towards improving the overall well-being and satisfaction of individuals following kidney transplantation.

Chapter 3

System Study

System analysis is a comprehensive process involving the gathering and interpretation of facts, aimed at diagnosing existing problems within a system and recommending improvements. It is fundamentally a problem-solving activity that necessitates close collaboration between system users and developers. In this intricate process, the system analyst assumes the role of an interrogator, delving deep into the intricacies of the present system. The analysis entails a holistic view of the system, identifying its inputs and tracing the outputs through various phases of processing. To achieve this, a meticulous study of processes is conducted using a variety of techniques such as interviews, questionnaires, and observations. The data collected from these sources undergoes thorough scrutiny to derive meaningful conclusions, providing an understanding of how the system operates in its current state, referred to as the existing system.

During the examination of the existing system, areas of concern or inefficiencies are pinpointed, marking the transition for the system designer into the role of a problem solver. The designer endeavors to address these identified issues, proposing solutions that collectively form the blueprint of the proposed system. This proposal is meticulously crafted to align with the organization's objectives and address the shortcomings of the existing system effectively. Following the formulation of the proposal, it undergoes a critical comparison with the existing system, ensuring that the proposed changes are both feasible and advantageous.

Subsequently, the proposal is presented to the system users for their evaluation and endorsement. User feedback plays a pivotal role in refining the proposal, as adjustments and modifications are made based on user preferences and requirements. This iterative process continues until the user is satisfied with the proposed system, ensuring that the final solution meets their expectations and aligns with organizational objectives. Ultimately, the success of the system analysis process hinges on effective communication, thorough analysis, and a collaborative approach towards problem-solving, culminating in the development of a robust and efficient system tailored to meet the needs of its users.

3.1 Existing System

Currently ML based systems are not widely used in the medical industry. ML-based prediction models raise important ethical and regulatory concerns related to patient privacy, fairness, transparency, and accountability. Many ML algorithms, especially complex ones like deep learning models, lack interpretability, making it challenging to understand the underlying factors driving predictions. This limits the clinical utility of the models, as healthcare providers may be reluctant to trust predictions without clear explanations.

3.2 Proposed System

Using an AI model, we predict whether a patient will survive after kidney transplantation before the procedure occurs. With our innovative web part we try to make our users more comfortable and more understantable.And with the use of ML algorithms such as Random Forest ,Linear Regression etc we try to obtain high accuracy results compared to the existing systems.

3.3 Key Features of Proposed System

1. **Portability**: The system will be designed to be portable, allowing users to access our system on standalone devices, enhancing accessibility and convenience.
2. **User Interface (UI)**: A user-friendly dashboard providing an overview of the patient's profile, prediction results, and relevant clinical information.
3. **Prediction Model Integration** : Our system consist of ML prediction model which predicts the survival outcome.
4. **Access Controls**: Role-based access controls and audit trails to manage user permissions, track data access, and enforce data governance policies to protect against unauthorized access or misuse.

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Chapter 4

DATASETS

The dataset utilized in the kidney transplantation system is sourced from Kaggle, a prominent platform for data science enthusiasts, researchers, and practitioners. Kaggle hosts a diverse array of datasets spanning various domains, including healthcare and medical research. By leveraging datasets from Kaggle, researchers and data scientists can access valuable resources to explore, analyze, and derive insights into topics related to kidney transplantation, such as patient demographics, clinical outcomes, organ donor information, and post-transplant complications. Kaggle's datasets often come with detailed documentation and metadata, facilitating robust analysis and interpretation. This integration of Kaggle datasets into the kidney transplantation system enables researchers to tap into a wealth of data-driven knowledge and contribute to advancements in healthcare and medical research.

4.1 Dataset Characteristics

4.1.1 Parameters used in the system.

These are the parameters used in the system.

age - age

bp - blood pressure

al - albumin

su - sugar

pc - pus cell

pcc - pus cell clumps

ba - bacteria

bgr - blood glucose random

bu - blood urea

sc - serum creatinine

hemo - hemoglobin

wc - white blood cell count

rc - red blood cell count

htn - hypertension

bg - blood group

1.Age(numerical)age in years

2.Blood Pressure(80-120)bp in mm/Hg

3.Albumin(0,1,2)al - (0,1,2,3,4,5)

4.Sugar(0,1,2,2.5)su - (0,1,2,3,4,5)

5.Pus Cell (0) pc - (0-normal,1-abnormal)

6.Pus Cell clumps(1)pcc - (1-present,0-not present)

7.Bacteria(0)ba - (1-present,0-notpresent)

8.Blood Glucose Random(numerical)bgr in mgs/dl

9.Blood Urea(numerical) bu in mgs/dl

10.Serum Creatinine(numerical)

11.Hemoglobin(numerical)hemo in gms

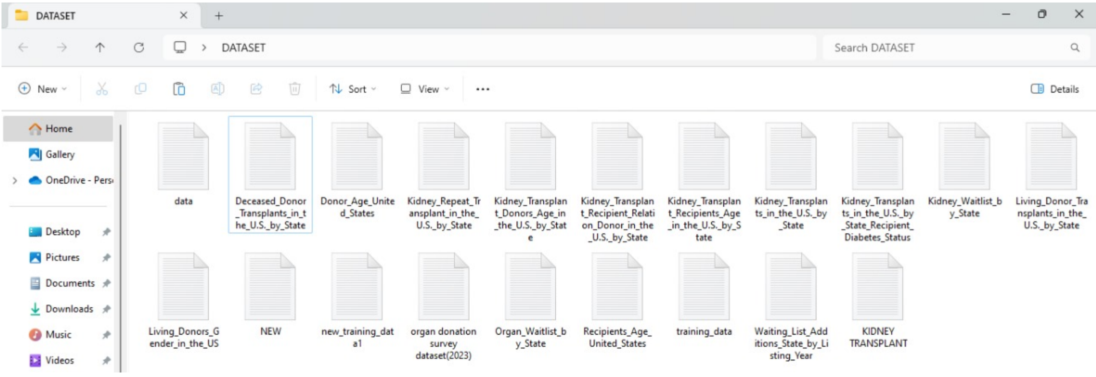
12.White Blood Cell Count(numerical)wc in cells/cumm

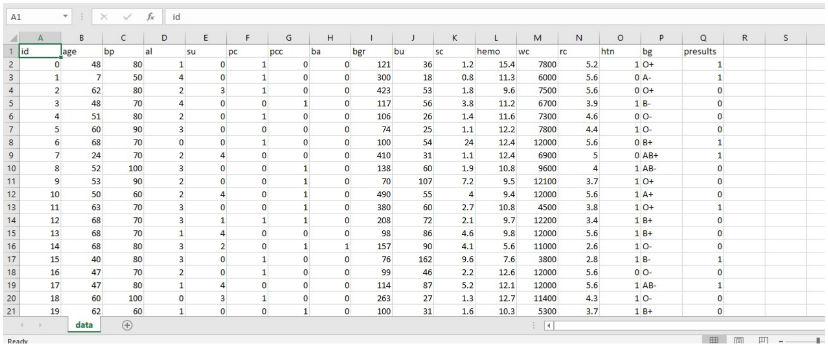
13.Red Blood Cell Count(numerical) rc in millions/cmm

14.Hypertension(nominal)htn -(1-yes,0-no)

15.Blood Group(Text) bg-(A+,A-,B+,B-,O+,O-,AB+,AB-)

4.2 samples of Dataset





	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	id	age	bp	al	su	pc	pcc	ba	bgr	bu	sc	hemo	wc	rc	htn	bg	presults
2	0	48	80	1	0	1	0	0	121	36	1.2	15.4	7800	5.2	1	O+	1
3	1	7	50	4	0	1	0	0	300	18	0.8	11.3	6000	5.6	0	A-	1
4	2	62	80	2	3	1	0	0	423	53	1.8	9.6	7500	5.6	0	O+	0
5	3	48	70	4	0	0	1	0	117	56	3.8	11.2	6700	3.9	1	B-	0
6	4	51	80	2	0	1	0	0	106	26	1.4	11.6	7300	4.6	0	O-	0
7	5	60	90	3	0	0	0	0	74	25	1.1	12.2	7800	4.4	1	O-	0
8	6	68	70	0	0	1	0	0	100	54	24	12.4	12000	5.6	0	B+	1
9	7	24	70	2	4	0	0	0	410	31	1.1	12.4	6900	5	0	AB+	1
10	8	52	100	3	0	0	1	0	138	60	1.9	10.8	9600	4	1	AB-	0
11	9	53	90	2	0	0	1	0	70	107	7.2	9.5	12100	3.7	1	O+	0
12	10	50	60	2	4	0	1	0	490	55	4	9.4	12000	5.6	1	A+	0
13	11	63	70	3	0	0	1	0	380	60	2.7	10.8	4500	3.8	1	O+	1
14	12	68	70	3	1	1	1	0	208	72	2.1	9.7	12200	3.4	1	B+	0
15	13	68	70	1	4	0	0	0	98	86	4.6	9.8	12000	5.6	1	B+	0
16	14	68	80	3	2	0	1	1	157	90	4.1	5.6	11000	2.6	1	O-	0
17	15	40	80	3	0	1	0	0	76	162	9.6	7.6	3800	2.8	1	B-	1
18	16	47	70	2	0	1	0	0	99	46	2.2	12.6	12000	5.6	0	O-	0
19	17	47	80	1	4	0	0	0	114	87	5.2	12.1	12000	5.6	1	AB-	1
20	18	60	100	0	3	1	0	0	263	27	1.3	12.7	11400	4.3	1	O-	0
21	19	62	60	1	0	0	1	0	100	31	1.6	10.3	5300	3.7	1	B+	0

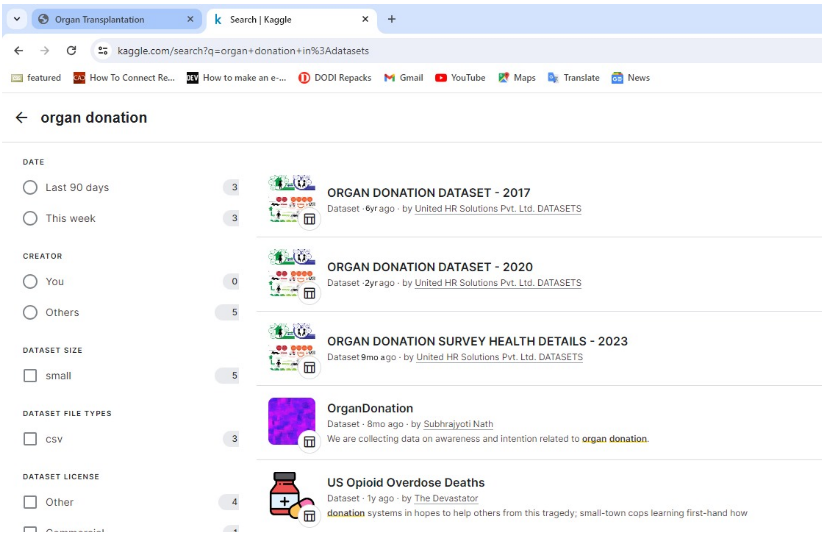


Figure 4.1: Dataset

Chapter 5

System Design and Technologies

The development of a robust kidney transplantation survival prediction system utilizing machine learning (ML) algorithms is a critical initiative aimed at enhancing patient outcomes and optimizing healthcare resources. This section offers an overview of the structured approach undertaken in crafting the proposed system, emphasizing the key methodologies, components, and technologies harnessed to achieve its overarching objectives.

he envisioned system endeavors to streamline decision-making processes by furnishing clinicians with accurate prognostic insights regarding kidney transplant outcomes. By harnessing diverse ML algorithms, including but not limited to Random Forest, Support Vector Machines (SVM), and Gradient Boosting, the system endeavors to furnish a comprehensive predictive model capable of assessing patient-specific risk factors and forecasting survival probabilities post-transplantation.

This section delineates the significance of the proposed predictive system, elucidates the methodological framework employed in its development, and provides a comprehensive overview of the constituent components and functionalities integrated into the system. Furthermore, it underscores the potential impact of such a system in augmenting clinical decision-making, improving patient care, and fostering advancements in the field of transplant medicine.

5.1 Modules

Mainly there are Six modules in our system, they are Admin,User(patient),Donor,Doctor,Analyst, ML algorithms.

5.1.1 Admin

The Admin module serves as a pivotal component in the efficient management of hospital resources and organ donation processes. Here's a brief overview of its functionalities:

1. **Add Doctor**: Allows admin to seamlessly incorporate doctors into hospital staff, providing them with essential login credentials for access to their designated dashboards
2. **View Doctor**: Provides admin with a comprehensive view of doctor details, enabling them to make modifications as necessary to ensure accurate and up-to-date records.
3. **Manage Organ Need Request** : Facilitates the meticulous management of organ requests, from their initiation to approval by hospitals, ensuring timely and effective responses to organ needs.
4. **Assign Doctor For Organ Need Request**: Empowers admin to efficiently assign doctors to donors based on specific requests, streamlining the process for users seeking organ donations.
5. **Manage Organ Donation**: Enables systematic management of organ donations within hospitals, ensuring proper storage and allocation in response to user requests for needed organs.
6. **View User Details**: Provides admin with access to comprehensive user and doctor details, facilitating effective oversight and maintenance of vital information

Overall, the Admin module plays a crucial role in enhancing the coordination and effectiveness of hospital operations and organ donation processes, ultimately contributing to improved healthcare delivery and patient outcomes.

5.1.2 User

User module provides users with a seamless platform to contribute to the noble cause of organ donation while also facilitating those in need of organs to find suitable matches. Here's a brief overview of its key functionalities:

1. **Add Details**: Users can register their profiles and enter details including their name, contact information, address.

2. **Add Organ Request**: Users can submit requests for needed organ through the platform, streamlining the process of connecting donors with recipients.

3. **View My Organ Request Status**: Users can track the status of their organ requests, including whether they have been approved or not, providing transparency and peace of mind throughout the donation process.

5.1.3 Doctor

The Doctor Module serves as a vital component in facilitating the coordination of organ donation and transplantation processes, ensuring efficient communication and decision-making among medical professionals. Here's an outline of its key functionalities:

1. **View Organ Donation Requests**: Doctors can access a centralized platform to view incoming organ donation requests submitted by users. This feature allows doctors to review donation details, including donor information and the organs being offered for donation.

2. **Approve Organ Donation Requests**: Upon evaluating the donated organs, doctors can approve or decline organ donation requests. Approved requests proceed to the transplantation process, while declined requests may be accompanied by explanations or recommendations for further actions.

3. **Sends public notes and personalized messages** :Doctor can send public notes which will be recieved by all the users . Doctor can also send personalized messages to patients who are waiting for organ recieval.

4. **Monitors the survival outcome**:Doctor can obtain the prediction outcome and its basis the doctor sends the organ approval requests to the patients.

5.1.4 Donor

This module empowers donors to register their intent, provide essential information about their donated organs, and engage in transparent communication with medical professionals throughout the donation process. With features for tracking donation status, updating preferences, and accessing educational resources, the Donor Module ensures a seamless and informed experience for donors, ultimately playing a vital role in enhancing organ donation rates and improving patient outcomes.

1. **Register as a Donor**: Donors can register on the platform by providing essential personal information such as name, details.

2. **Provide health paramaters**:Donor can provide the health parameters which will be used for the prediction.

5.1.5 Analyst

The Analyst role in organ donation and transplantation involves critical tasks in data management and analysisAanalysts play a pivotal role in gathering the necessary information for informed decision-making. Subsequently, analysts meticulously clean and preprocess the collected data, addressing issues like missing values and outliers to ensure its accuracy and consistency. Through these essential steps, analysts lay the foundation for meaningful analysis and insights that drive advancements in organ donation practices and healthcare delivery.

1. **Data Collection and Integration**: Responsible for gathering data related to organ donation, transplantation, and healthcare facilities. This involves sourcing data from hospitals, organ procurement organizations, and other relevant sources.

2. **Data Cleaning and Preprocessing**:Performs data cleaning tasks such as handling missing values, dealing with outliers, and ensuring data consistency to prepare it for analysis.

3. **uploads the test data**: uploads the test data into the ML models to produce output.

4. **uploads the output file into the web**: uploads the output file from ML algorithm into the web part.

5.1.6 ML algorithms

Machine learning algorithms play a pivotal role in the development of the organ donation and transplantation system, facilitating data-driven decision-making and enhancing overall efficiency and accuracy. Here's a brief introduction to some of the key machine learning algorithms utilized in the system:

Random Forest, Support Vector Machine (SVM), Logistic Regression (LR), and AdaBoost are among the diverse set of machine learning algorithms employed in the system. Random Forest, known for its robustness and ability to handle complex datasets, is utilized for tasks such as organ donation prediction and classification. SVM, on the other hand, excels in separating data points into distinct classes, making it invaluable for donor-recipient matching and outcome prediction. Logistic Regression, a foundational algorithm for binary classification tasks, finds application in various aspects of the system, including risk assessment and patient profiling. Meanwhile, AdaBoost's ensemble approach enhances the performance of weak classifiers, contributing to improved decision support and outcome prediction in the organ donation and transplantation process.

By leveraging these machine learning algorithms, the system can effectively analyze vast amounts of data related to organ donation, transplantation, and healthcare facilities. From data collection and integration to cleaning and preprocessing, these algorithms enable the extraction of meaningful insights that drive informed decision-making, optimize resource allocation, and ultimately enhance patient outcomes in the organ donation and transplantation domain.

Certainly! Here's a brief explanation of each machine learning algorithm mentioned:

1. **Random Forest**: Random Forest is an ensemble learning method used for both classification and regression tasks. It operates by constructing multiple decision

trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of individual trees. It's known for its robustness against overfitting and ability to handle large datasets with high dimensionality.

2. **Support Vector Machine (SVM)**: - SVM is a powerful supervised learning algorithm used for classification and regression tasks. It works by finding the optimal hyperplane that best separates data points into different classes. SVM aims to maximize the margin between classes, making it effective in handling both linearly separable and non-linearly separable datasets. It's widely used in various applications due to its versatility and effectiveness, particularly in cases where the data is not linearly separable.

3. **Logistic Regression (LR)**: - Logistic Regression is a fundamental binary classification algorithm used to model the probability of a binary outcome based on one or more predictor variables. Despite its name, logistic regression is a linear model and is commonly used for tasks like spam detection, disease prediction, and customer churn analysis. It's simple yet effective and provides interpretable results, making it a popular choice for many classification problems.

4. **AdaBoost (Adaptive Boosting)**: - AdaBoost is an ensemble learning method that combines multiple weak classifiers to create a strong classifier. It works by sequentially training a series of classifiers, with each subsequent classifier giving more weight to misclassified data points from the previous classifier. By iteratively focusing on the most challenging examples, AdaBoost improves classification performance and is particularly effective in boosting the performance of weak learners. It's commonly used in applications like face detection and text classification.

5. **Decision Tree**: Decision Tree is a non-parametric supervised learning method used for classification and regression tasks. It partitions the feature space into a set of simple decision rules based on the training data. Each internal node of the tree represents a decision based on a feature, and each leaf node represents the outcome or prediction. Decision Trees are easy to interpret and visualize, making them useful for understanding the decision-making process. However,

they are prone to overfitting, especially with complex datasets. Random Forest, as an ensemble of Decision Trees, addresses this limitation by combining multiple trees to improve generalization and robustness.

Each of these machine learning algorithms has its strengths and weaknesses, and the choice of algorithm depends on factors such as the nature of the data, the problem domain, computational resources, and performance requirements. In the context of the organ donation and transplantation system, these algorithms could be utilized for tasks such as donor-recipient matching, outcome prediction, and decision support.

5.2 Implementation

The development process for implementing a kidney transplantation survival prediction system, including a web component, involves several crucial steps:

1. **Project Setup**:Set up the development environment for the web platform. Choose appropriate frameworks and libraries for web development.

2. **UI Design**: Design user interfaces for the web application, ensuring intuitive navigation and user-friendly layouts. Utilize chosen frameworks to streamline the design process.

3. **Integration with Web Platform**: Gather relevant data related to kidney transplantation, including patient demographics, medical history, donor information, and post-transplant outcomes. Preprocess the data, handling missing values and transforming it into a suitable format for machine learning algorithms.

4. **User Interaction**: Implementing real-time gesture detection functionality using machine learning or custom algorithms.

5. **Authentication and Security**: Integrating word recommendation features based on gesture input and context.

6. **Testing and Optimization**: Conduct thorough testing of both the web application and the machine learning algorithms. Test the accuracy, robustness, and

performance of the predictive models. Optimize the system to improve speed, reliability, and user experience based on testing results.

7. **Deployment and Maintenance**: Preparing the app for deployment to app stores, generating release builds, and submitting for review and approval.

5.2.1 Architecture

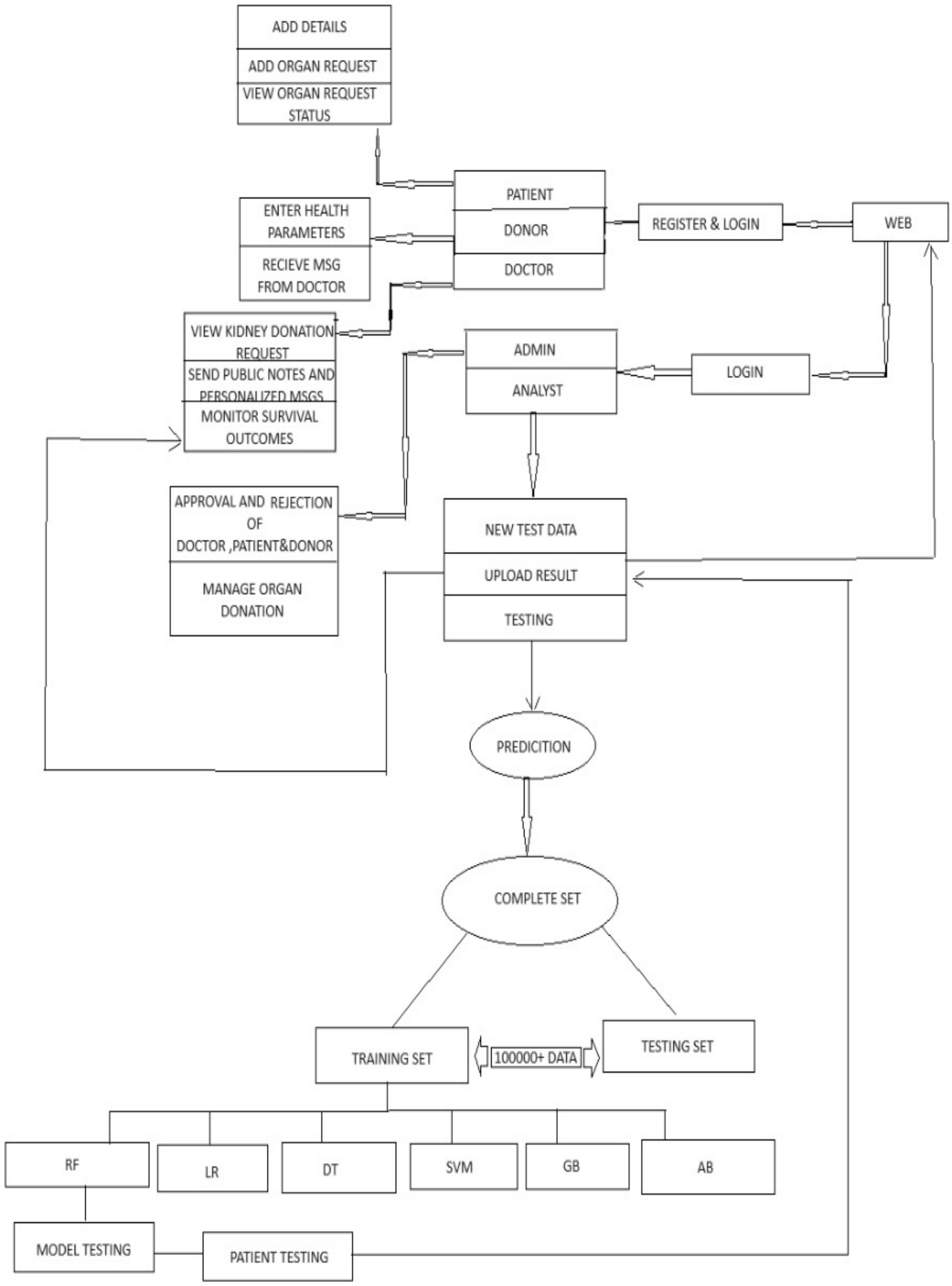


Figure 5.1: Architecture

Here's how it generally works: 1.Data Collection: The system collects relevant data from patients who have undergone kidney transplantation surgeries. This data includes patient demographics, medical history, pre-transplant conditions, post-transplant medications, and other relevant factors. 2.Data Preprocessing: Before feeding the data into the machine learning models, preprocessing steps are performed. This involves handling missing values, encoding categorical variables, and scaling numerical features to ensure uniformity and compat- ibility with the algorithms. 3.Feature Selection/Engineering: Relevant features that contribute significantly to predicting survival outcomes are selected or engineered. This step helps in improving the accuracy of the models by focusing on the most informative attributes. 4.Model Training: The pre processed data is then divided into training and testing sets. The selected machine learning algorithms are trained on the training data to learn the patterns and relationships between input features and the survival outcome. 5.Model Evaluation: After training, the models are evaluated using the testing data to assess their performance. 6.Result Presentation: The prediction results, along with any associated probabili- ties or confidence scores, are displayed to the user via the web application interface.

5.2.2 Webpage designing

Webpage designing using PHP, JavaScript, and Bootstrap involves combining server-side scripting, client-side scripting, and front-end framework techniques to create dynamic, responsive, and visually appealing webpages. Here's an overview of how each technology contributes to the webpage design process:

1. PHP (Hypertext Preprocessor): - PHP is a server-side scripting language commonly used for dynamic web development. - It allows you to generate dynamic content, interact with databases, handle form submissions, and perform other server-side tasks. - In webpage designing, PHP is often used to generate HTML content dynamically based on user input or other parameters.

2. JavaScript: - JavaScript is a client-side scripting language that adds interactivity and dynamic behavior to webpages. - It enables features such as form validation, DOM manipulation, animations, and asynchronous communication with servers (AJAX). - JavaScript frameworks/libraries like jQuery, React, or Vue.js are often used to streamline development and enhance functionality.

3. Bootstrap: - Bootstrap is a popular front-end framework for building responsive and mobile-first websites. - It provides a collection of CSS and JavaScript components (e.g., grids, forms, buttons, navigation) that can be easily customized and integrated into webpages. - Bootstrap's grid system facilitates responsive design, allowing webpages to adapt to different screen sizes and devices. - It also offers pre-styled components and utilities for creating consistent and visually appealing user interfaces.

Here's how these technologies can be combined in the webpage designing process:

1. Server-Side Development with PHP: - Use PHP to handle server-side tasks such as processing form submissions, querying databases, and generating dynamic content.

PHP can dynamically generate HTML content based on data retrieved from databases or user input.

2. Client-Side Interaction with JavaScript: - Enhance user experience by adding interactive features using JavaScript.

Implement client-side form validation to provide immediate feedback to users.

Use JavaScript to create dynamic content updates without requiring full page reloads (e.g., updating content via AJAX requests).

3. Responsive Design with Bootstrap: - Utilize Bootstrap's grid system to create responsive layouts that adapt to different screen sizes.

Leverage Bootstrap's pre-styled components and utilities to design consistent and visually appealing interfaces.

Customize Bootstrap styles and components to match the design requirements of your webpage.

4. Integration and Testing: Integrate PHP, JavaScript, and Bootstrap components seamlessly within your webpage.

Test the webpage across various devices and screen sizes to ensure responsiveness and functionality.

Debug any issues and optimize performance for an optimal user experience.

By leveraging PHP, JavaScript, and Bootstrap together, you can create dynamic, interactive, and visually appealing webpages that meet the needs of modern web users.

5.3 System flow

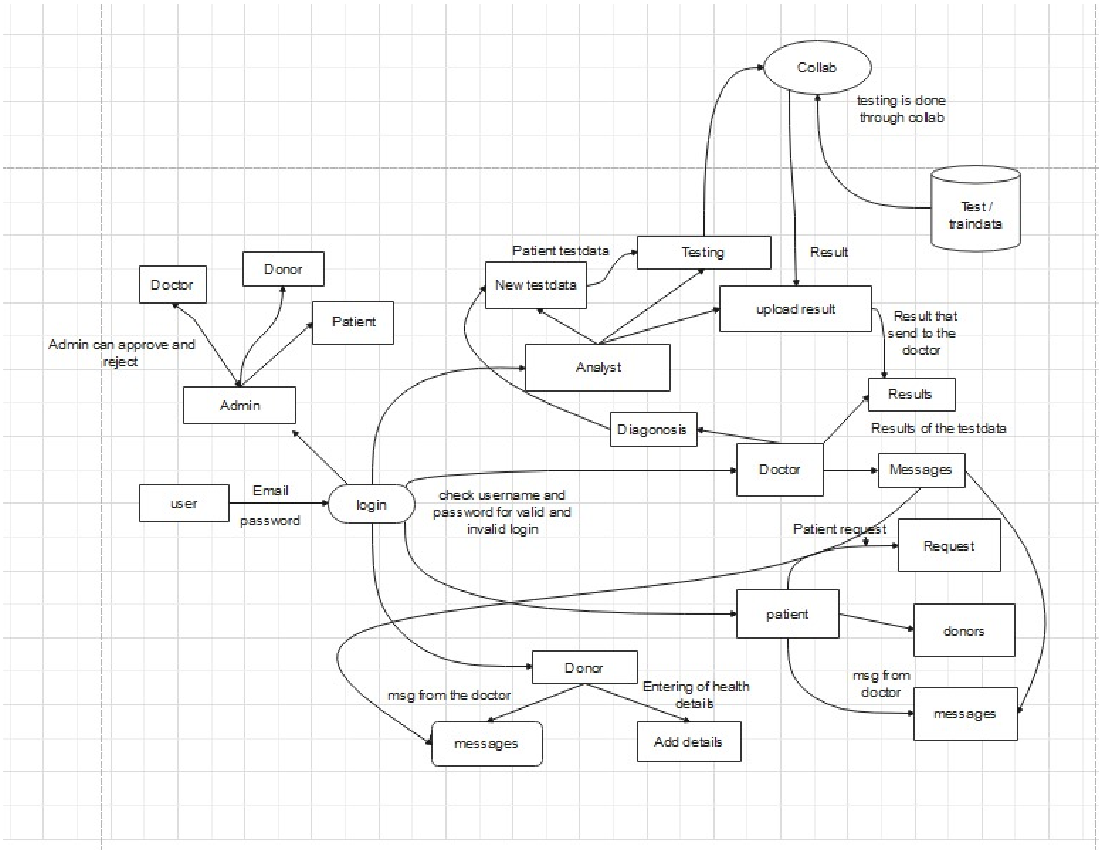


Figure 5.2: System flow Diagram

5.3.1 ML Algorithm testing

Comparing the accuracies of the tested machine learning algorithms, we observe the following:

1. Support Vector Machine (SVM), Random Forest (RF), and Decision Tree models all achieved the highest accuracy of 92.04 percentage. This indicates that these algorithms performed equally well on your dataset.

2.Logistic Regression (LR) achieved a slightly lower accuracy of 91.04 percentage, which is still quite high but marginally less accurate compared to SVM, RF, and Decision Tree.

3.Gradient Boosting achieved an accuracy of 72.14 percentage, which is significantly lower than the other algorithms. This might suggest that Gradient Boosting did not perform well on this particular dataset compared to the other algorithms.

4. AdaBoost achieved an accuracy of 76.12 percentage, which is also lower compared to SVM, RF, and Decision Tree but higher than Gradient Boosting. AdaBoost seems to perform better than Gradient Boosting but not as well as the top three algorithms.

In summary, based on the provided accuracies SVM, Random Forest, and Decision Tree performed equally well and are the top-performing algorithms. Logistic Regression performed slightly worse than the top three algorithms but still achieved a high accuracy. Gradient Boosting and AdaBoost performed relatively poorer compared to the other algorithms.

SL.NO	ALGORITHMS	ACCURACY
1	RANDOM FOREST CLASSIFIER	92.04%
2	DECISION TREE	92.04%
3	LINEAR REGRESSION	91.04%
4	SVM	92.04%
5	GRADIENT BOOSTING	72.14%
6	ADABOOST	76.12%

Figure 5.3: accuracy table

5.3.2 Selection of ML model

Selecting the Random Forest (RF) algorithm for model development, despite having similar accuracies with SVM and Decision Tree, could be attributed to several factors. Let's delve into why RF might be chosen over other algorithms:

1. Ensemble Learning: RF is an ensemble learning method that combines multiple decision trees to improve predictive performance and reduce overfitting. It aggregates the predictions of multiple trees, which can lead to more robust and stable models compared to individual trees (like Decision Tree). This inherent property of RF makes it appealing as it tends to generalize well and can handle complex relationships within the data.

2. Handling Non-Linearity: RF is capable of capturing complex nonlinear relationships in the data due to its ability to create decision boundaries using multiple trees. This can be particularly advantageous if the relationship between features and the target variable is nonlinear. In contrast, SVM, while powerful, might struggle with highly nonlinear data unless appropriate kernel functions are selected and tuned.

3. Feature Importance: RF provides a feature importance measure, which can be valuable for understanding which features are most influential in predicting the target variable. This can aid in feature selection and interpretation of the model. Understanding feature importance can provide insights into the underlying patterns in the data and guide further analysis or decision-making.

4. Robustness to Overfitting: RF tends to be less prone to overfitting compared to individual decision trees, especially when a large number of trees are used in the ensemble. It achieves this by averaging the predictions of multiple trees, thereby reducing the variance of the model. While SVM can also be regularized to prevent overfitting, RF's inherent ensemble nature often provides a more straightforward approach to achieving robustness.

5. Ease of Implementation and Interpretation: RF is relatively easy to implement and less sensitive to hyperparameter tuning compared to some other algorithms like SVM. This can be advantageous in practical applications, especially when computational resources or expertise are limited.

5.4 Model Training

1. **Training Phase**:

   During the training phase, the Random Forest model learns from the features and labels in the training data to create a predictive model. The model is trained to capture patterns and relationships between the input features and the target variable (labels). With a large dataset of over 100,000 records, training the Random Forest model on 80 percentage of the data provides ample information for the model to learn from. Random Forest is particularly effective with large datasets due to its ability to handle high dimensionality and complex relationships.

2. **Testing Phase**:

   After training the model, it's evaluated using the remaining 20 percentage of the data (test data) that the model hasn't seen during training. This step is crucial for assessing how well the model generalizes to unseen data. The reported accuracy of 98 percentage on the test data indicates that the model performs exceptionally well in making predictions on this subset of data. This high accuracy suggests that the model has learned the underlying patterns in the training data and can accurately predict the outcomes for unseen instances.

3. **Generalization and Validation**:

   The test accuracy of 98 percentage demonstrates that the Random Forest model generalizes well to new, unseen data, which is a desirable characteristic. It suggests that the model is robust and not overfitting to the training data. However, it's important to note that achieving 98 percentage accuracy on the test data doesn't necessarily mean the model will perform equally well on entirely new, real-world data. Additional validation and testing on external datasets are typically conducted to confirm the model's generalization ability.

4. **Comparison with Random Guess**:

   The reported testing accuracy of random data at 92.04 percentage indicates how well the model performs compared to random guessing. Random guessing

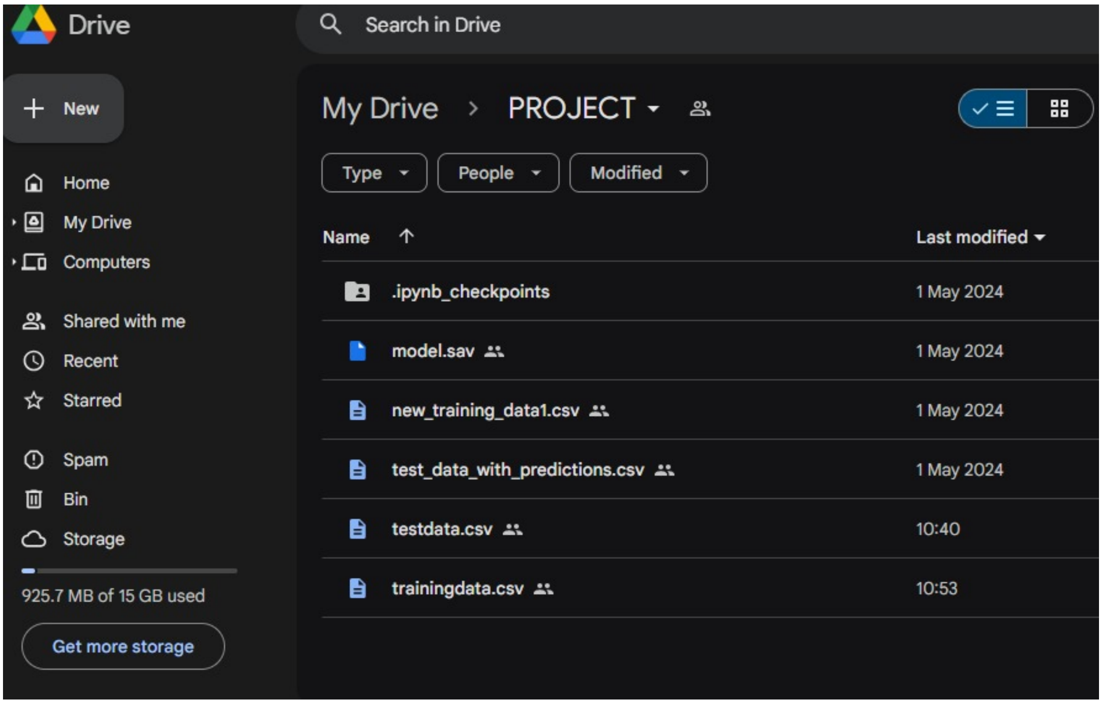


Figure 5.4: Model

would yield an accuracy close to the class distribution in the dataset. Achieving an accuracy of 92.04 percentage on random data demonstrates that the model significantly outperforms random guessing, reinforcing its effectiveness in making accurate predictions.

5.5 Testing and validation

1. **Mounting Google Drive**: This mounts your Google Drive to access files stored in it within the Colab environment.

2. **Loading Training Data and Model Generation**: It loads the training data fromthe CSV file named ’training data. csv’. Performs one-hot encoding on the ’trainingdata’ column. Assigns the ’survived’ column to the labels. Trains a RandomForestclassifier (clf) using the training data and labels.

3. **Loading Pre-trained Model**: It loads a pre-trained Random Forest classifier from a saved file named ’hupclf.sav’ using pickle.

4. **Verification**: It reloads the training data and prepares it for verification.

5. **Loading Test Data**: It loads the test data from the CSV file named ’test data. csv’. Performs one-hot encoding on the test data.

6. **Aligning Test Data with Training Data Columns**: It ensures that the columns of the test data match those of the training data by adding missing columns and reordering them accordingly.

7. **Making Predictions**: It uses the pre-trained model (hupmodel) to make predictions on the test data.

8. **Post-processing**: It adds the predicted ’survived’ values to the test data.

9. **Optional Saving of Prediction**: It optionally saves the test data with predicted’survived’ values to a new CSV file named ’test data with predictions. csv’.

10. **Displaying Results**: It prints the test data with predicted ’survived’ values.

```
from google.colab import drive
drive.mount('/content/drive')
cd /content/drive/MyDrive/PROJECT
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
Load training data
train df = pd.read csv('training data. csv')
train data = pd.get dummies(train df['trainingdata'])
train labels = train df['survived']
Train a Random Forest classifier
clf = RandomForestClassifier()
clf.fit(train data, train labels)
import pickle
filename = 'hupclf.sav'
pickle.dump(clf, open(filename, 'wb'))
import pickle
filename = 'hupclf.sav'
hupmodel = pickle.load(open(filename, 'rb'))
import pandas as pd
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
Load training data
train df = pd.read csv('training data.csv')
train data = pd.get dummies(train df['trainingdata'])
train labels = train df['survived']
Load test data
test df = pd.read csv('test data.csv')
test data = pd.get dummies(test df['trainingdata'])
missing cols = set(train data.columns) - set(test data.columns)
for col in missing cols:
test data[col] = 0
test data = test data[train data.columns]
```

predictions = hupmodel.predict(test data)

test df['survived'] = predictions

test df.to csv('test data with predictions.csv', index=False)

Display test data with predicted 'survived' values

print(test df)

5.5.1 Accuracy graph obtained after Testing

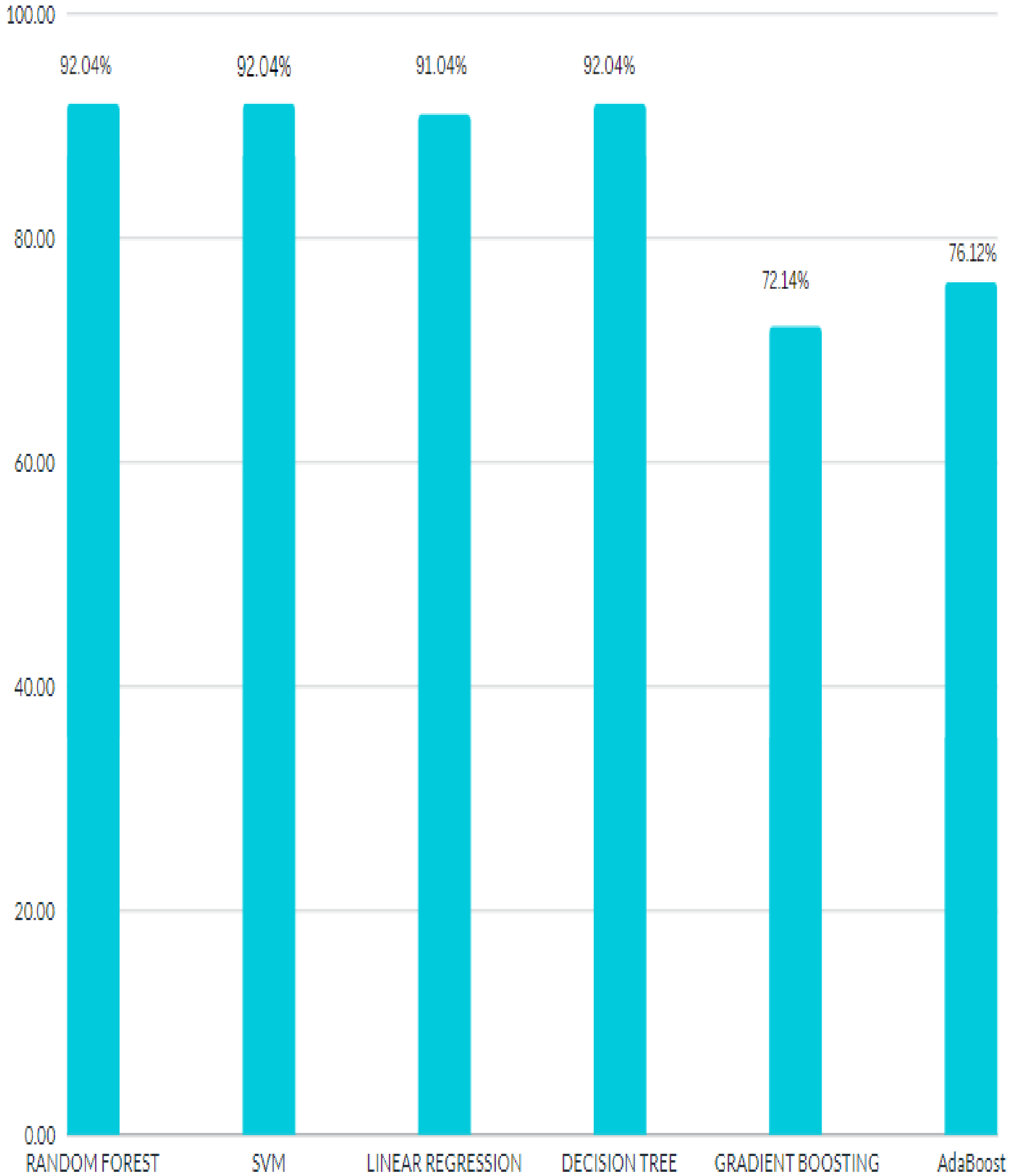


Figure 5.5: accuracy graph

5.6 Verification and Output

The Random Forest model was trained on a dataset comprising over 100,000 records, with 80 percentage of the data allocated for training and the remaining 20 percentage for testing. Following the training phase, the model was saved as ”model.sav” for future use. During testing, the model demonstrated excellent performance on the test dataset. This high level of accuracy underscores the model’s ability to effectively generalize to unseen data and accurately predict outcomes. Furthermore, the model’s performance was assessed against random data, yielding a strong accuracy. This comparison highlights the model’s superiority over random guessing, reaffirming its efficacy in making precise predictions. The observed accuracies validate the robustness and predictive power of the Random Forest model, providing confidence in its deployment for real-world applications.

The trained Random Forest model, saved as ”model.sav,” exhibits excellent performance on the test dataset, indicating its proficiency in making accurate predictions. This high level of accuracy underscores the model’s capability to generalize well to new, unseen data and effectively capture underlying patterns. Additionally, when evaluated against random data, the model demonstrates its superiority with a strong accuracy, significantly outperforming random guessing. These results validate the reliability and effectiveness of the Random Forest model, affirming its suitability for deployment in practical scenarios, such as predictive analytics in healthcare, finance, and other domains where precision and robustness are paramount.

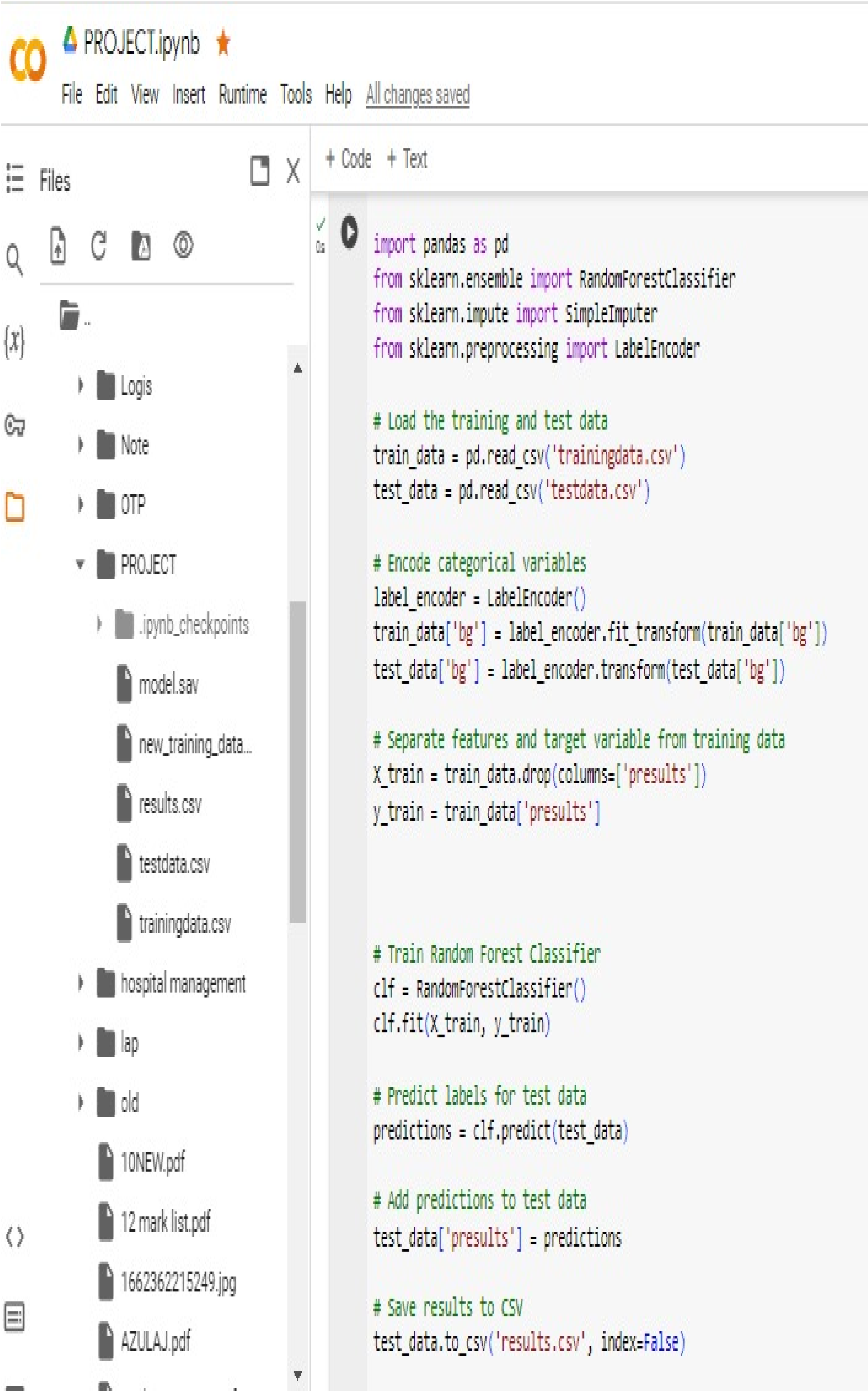


Figure 5.6: output

Chapter 6

Results and Discussion

The kidney transplantation survival prediction project utilized various machine learning algorithms, including SVM, LR, Adaboost, Decision Tree, and Random Forest. After rigorous evaluation and comparison, the Random Forest model emerged as the most accurate, achieving an impressive accuracy of 92.04 percent. This indicates the model's ability to predict patient survival outcomes post-transplantation with a high degree of precision.

The high accuracy achieved by the Random Forest model underscores the effectiveness of ensemble learning techniques in handling complex datasets such as those related to kidney transplantation. By aggregating the predictions of multiple decision trees, Random Forest can capture intricate relationships between various factors influencing transplant survival, including donor-recipient compatibility, patient demographics, and medical history.

The success of the Random Forest model can also be attributed to the comprehensive preprocessing and feature extraction techniques employed. These steps ensured that relevant information was extracted from the dataset, enabling the model to make accurate predictions. Moreover, feature importance analysis provided insights into the factors driving transplant survival, guiding future research and clinical decision-making.

From a clinical perspective, the predictive models developed in this project hold immense promise for improving patient care and outcomes in kidney transplantation. By identifying patients at higher risk of complications or rejection early on, healthcare professionals can intervene proactively, potentially preventing adverse outcomes and improving overall transplant success rates.

However, it's essential to acknowledge the limitations and challenges associated with predictive modeling in healthcare. These include the need for large and diverse datasets, potential biases in the data, and the dynamic nature of medical conditions. Additionally, the ethical implications of using predictive models in clinical decision-making must be carefully considered, with a focus on patient privacy, transparency, and equity.

Overall, the kidney transplantation survival prediction project demonstrates the potential of machine learning to enhance healthcare delivery and improve patient outcomes. Continued research, validation, and integration of predictive models into clinical practice are essential steps towards realizing these benefits and ensuring the ethical and responsible use of technology in healthcare.

id	age	bp	al	su	pc	pcc	ba	bgr	bu	sc	hemo	wc	rc	htn	bg
0	48	80	1	0	1	0	0	121	36	1.2	15.4	7800	5.2	1	O+
1	7	50	4	0	1	0	0	300	18	0.8	11.3	6000	5.6	0	A-
2	62	80	2	3	1	0	0	423	53	1.8	9.6	7500	5.6	0	O+
3	48	70	4	0	0	1	0	117	56	3.8	11.2	6700	3.9	1	B-
4	51	80	2	0	1	0	0	106	26	1.4	11.6	7300	4.6	0	O-
5	60	90	3	0	0	0	0	74	25	1.1	12.2	7800	4.4	1	O-
6	68	70	0	0	1	0	0	100	54	24	12.4	12000	5.6	0	B+
7	24	70	2	4	0	0	0	410	31	1.1	12.4	6900	5	0	AB+
8	52	100	3	0	0	1	0	138	60	1.9	10.8	9600	4	1	AB-
9	53	90	2	0	0	1	0	70	107	7.2	9.5	12100	3.7	1	O+
10	50	60	2	4	0	1	0	490	55	4	9.4	12000	5.6	1	A+

Figure 6.1: test data

id	age	bp	al	su	pc	pcc	ba	bgr	bu	sc	hemo	wc	rc	htn	bg	presults
0	48	80	1	0	1	0	0	121	36	1.2	15.4	7800	5.2	1	6	1
1	7	50	4	0	1	0	0	300	18	0.8	11.3	6000	5.6	0	1	1
2	62	80	2	3	1	0	0	423	53	1.8	9.6	7500	5.6	0	6	0
3	48	70	4	0	0	1	0	117	56	3.8	11.2	6700	3.9	1	5	0
4	51	80	2	0	1	0	0	106	26	1.4	11.6	7300	4.6	0	7	0
5	60	90	3	0	0	0	0	74	25	1.1	12.2	7800	4.4	1	7	0
6	68	70	0	0	1	0	0	100	54	24	12.4	12000	5.6	0	4	1
7	24	70	2	4	0	0	0	410	31	1.1	12.4	6900	5	0	2	1
8	52	100	3	0	0	1	0	138	60	1.9	10.8	9600	4	1	3	0
9	53	90	2	0	0	1	0	70	107	7.2	9.5	12100	3.7	1	6	0
10	50	60	2	4	0	1	0	490	55	4	9.4	12000	5.6	1	0	0

Figure 6.2: result data

Chapter 7

Future Scope

1. **Enhanced Model Accuracy**: Continuous refinement and optimization of the machine learning models can lead to even higher prediction accuracies. This could involve the incorporation of additional data sources, more advanced feature engineering techniques, and fine-tuning of model parameters.

2. **Real-Time Monitoring**: Integration of the predictive models into healthcare systems could enable real-time monitoring of transplant patients. This would allow healthcare professionals to identify patients at higher risk of complications or rejection early on, facilitating timely interventions and improving overall patient outcomes.

3. **Personalized Medicine**: Further research into personalized medicine approaches could enable the tailoring of treatment plans based on individual patient characteristics and predicted outcomes. This could lead to more effective and targeted interventions, ultimately improving patient care and reducing healthcare costs.

4. **Long-Term Follow-Up**: Extending the scope of the project to include long-term follow-up data could provide insights into the factors influencing patient survival beyond the immediate post-transplant period. This could help identify trends and patterns that contribute to long-term transplant success and inform future treatment strategies.

5. **Clinical Decision Support Systemst**: Integration of the predictive models into clinical decision support systems could assist healthcare providers in

making informed decisions regarding patient care. By providing evidence-based recommendations, these systems could help optimize treatment plans and improve patient outcomes.

6. **Global Application**: Scaling the project to a larger population and across different healthcare settings could enable the development of more robust and generalisable predictive models. This would facilitate the application of the models in diverse healthcare contexts, ultimately benefiting a broader range of patients worldwide.

Overall, the future scope of the kidney transplantation survival prediction project using machine learning is vast and holds the potential to significantly impact patient care and outcomes in the field of organ transplantation. Continued research, collaboration, and innovation are key to realizing these opportunities and maximizing the benefits of predictive modeling in healthcare.

Chapter 8

Conclusion

Based on the analysis involving data preprocessing, feature extraction, and the utilization of various machine learning algorithms including SVM, LR, Adaboost, Decision Tree, and Random Forest for kidney transplantation survival prediction, the Random Forest model emerges as the most accurate with an impressive 92.04 percent accuracy. The success of the Random Forest model can be attributed not only to the ensemble learning approach but also to the comprehensive preprocessing and feature extraction techniques employed. These steps ensure that relevant information is extracted from the dataset, enabling the model to make accurate predictions based on factors such as donor-recipient compatibility, patient demographics, and medical history.

From a moral perspective, the application of machine learning in healthcare, particularly in predicting survival outcomes for kidney transplantation, holds immense promise. By leveraging data-driven insights, healthcare professionals can make more informed decisions, ultimately leading to better patient care and outcomes. However, it's crucial to ensure that these technologies are implemented ethically, with a focus on patient privacy, transparency, and equity. Additionally, continued research and validation are essential to maximize the benefits of these predictive models while minimizing potential biases or unintended consequences. Ultimately, the ethical use of machine learning in healthcare can empower both patients and healthcare providers, fostering trust and improving overall healthcare delivery.

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Appendix

SCREENSHOT OF OUTPUT

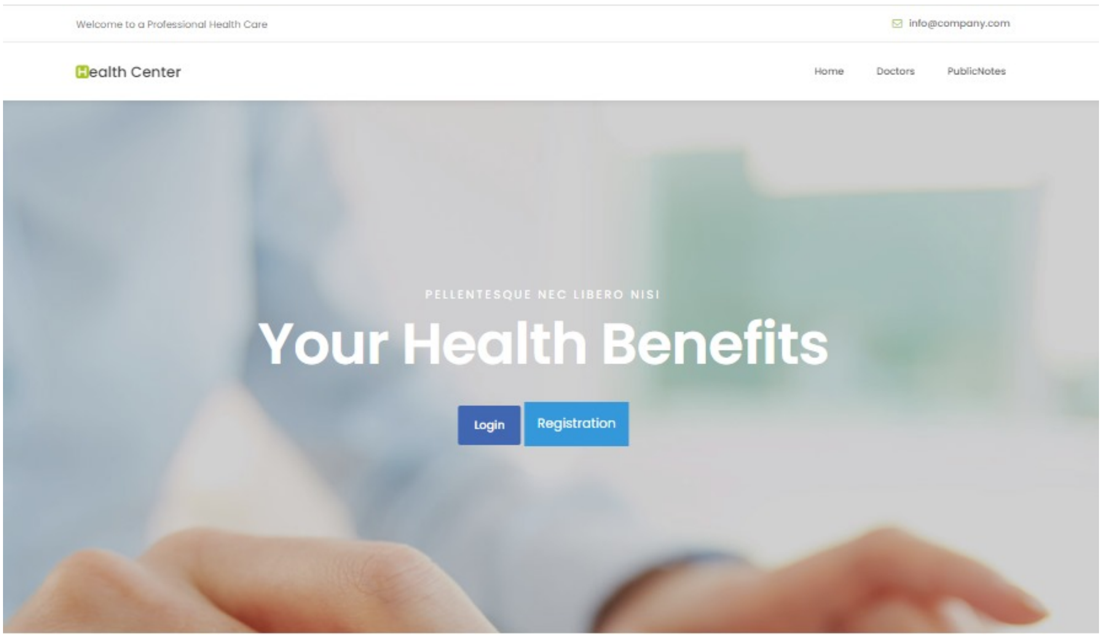

Figure 8.1: Login and registration page

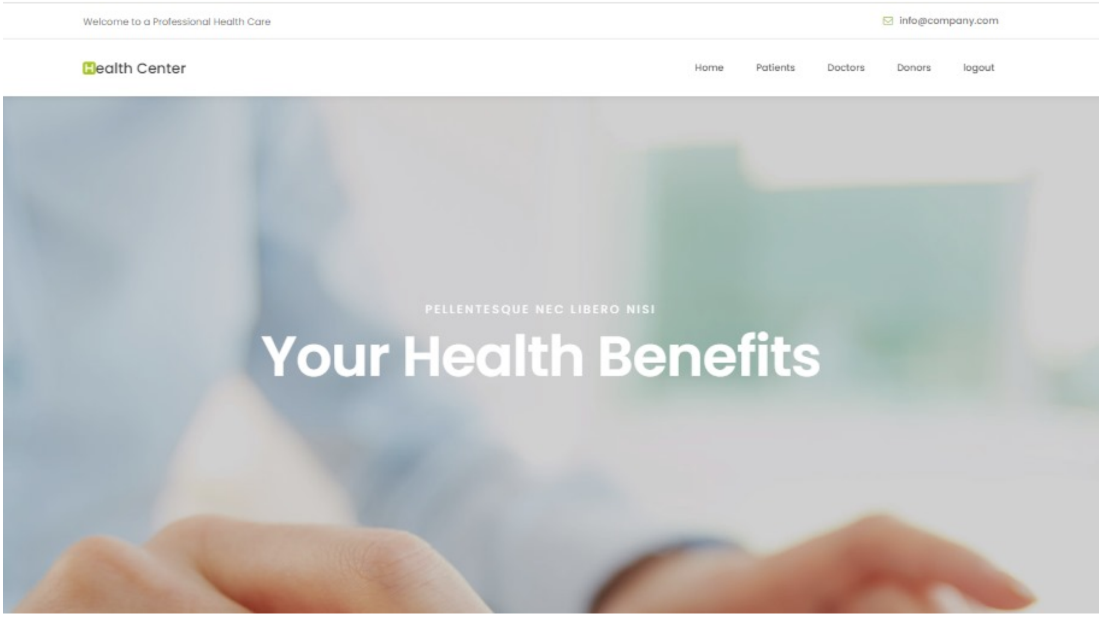

Figure 8.2: admin page

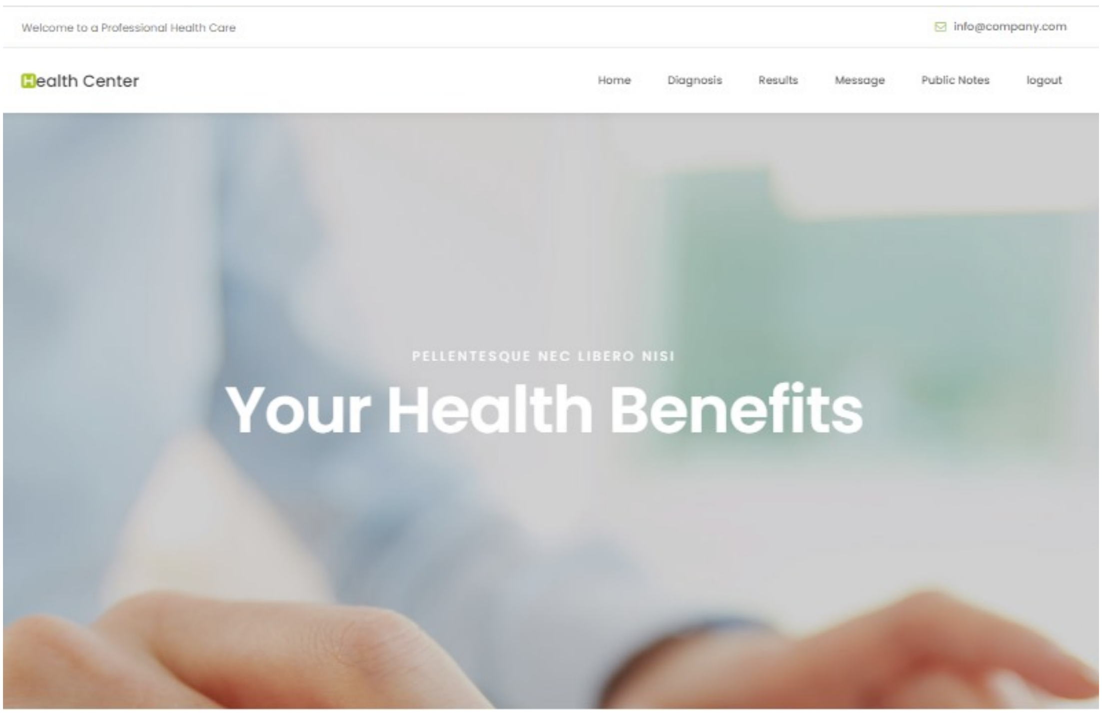

Figure 8.3: doctor page

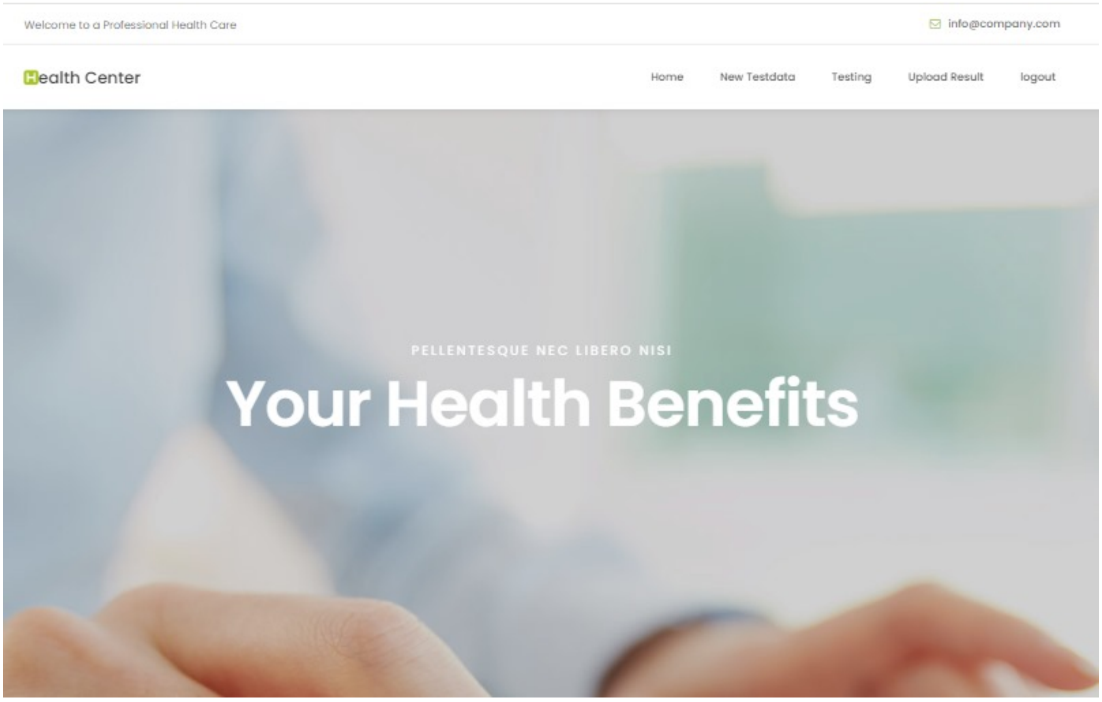

Figure 8.4: analyst page

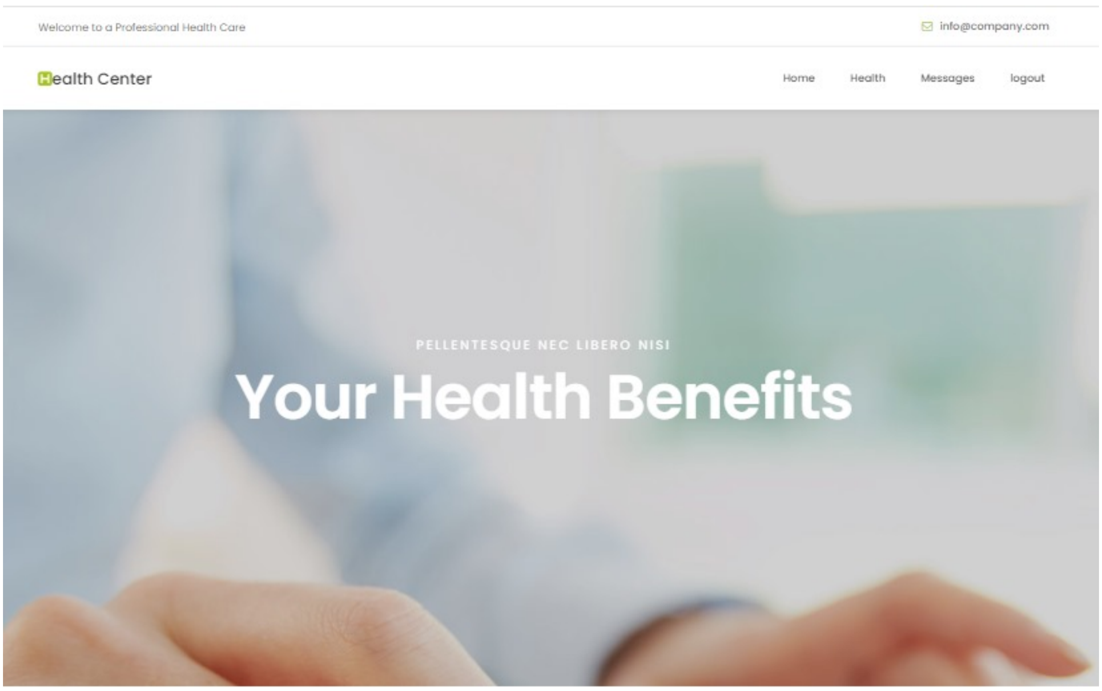

Figure 8.5: donor page

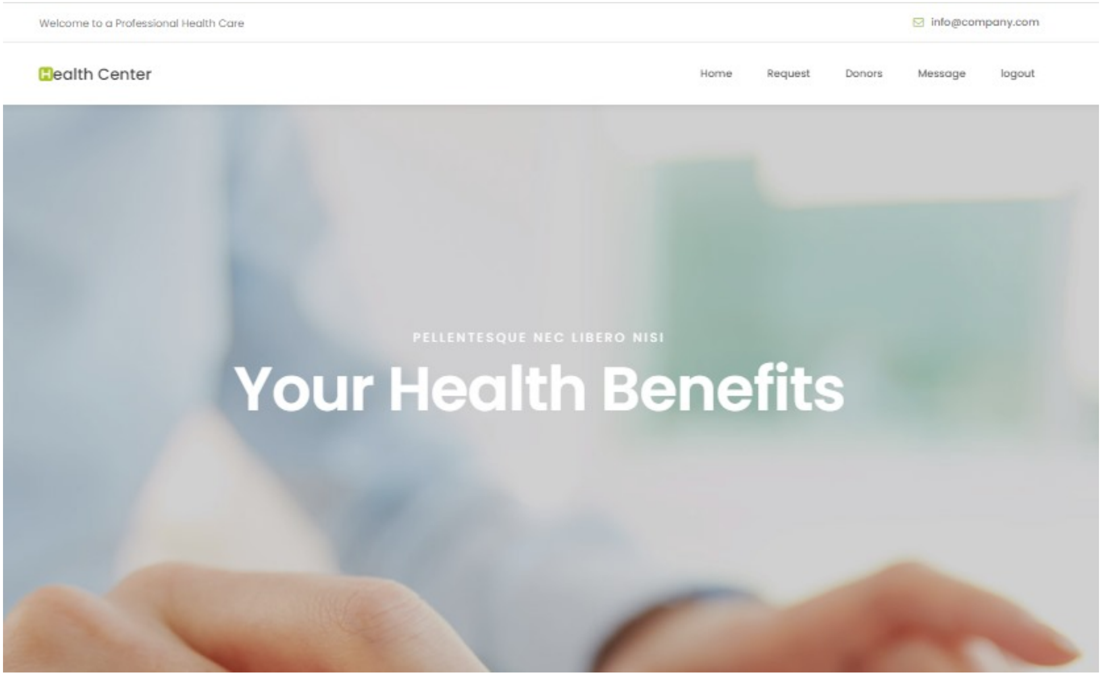

Figure 8.6: patient page

Table	Action						Rows	Type	Collation	Size	Overhead
dhealth	Browse	Structure	Search	Insert	Empty	Drop	1	MyISAM	latin1_swedish_ci	1.1 KiB	-
dig	Browse	Structure	Search	Insert	Empty	Drop	6	MyISAM	latin1_swedish_ci	2.5 KiB	-
doctor	Browse	Structure	Search	Insert	Empty	Drop	2	MyISAM	latin1_swedish_ci	2.2 KiB	-
dreg	Browse	Structure	Search	Insert	Empty	Drop	4	MyISAM	latin1_swedish_ci	2.3 KiB	-
login	Browse	Structure	Search	Insert	Empty	Drop	15	MyISAM	latin1_swedish_ci	1.8 KiB	-
msg	Browse	Structure	Search	Insert	Empty	Drop	3	MyISAM	latin1_swedish_ci	1.3 KiB	-
note	Browse	Structure	Search	Insert	Empty	Drop	0	MyISAM	latin1_swedish_ci	1.0 KiB	-
preg	Browse	Structure	Search	Insert	Empty	Drop	7	MyISAM	latin1_swedish_ci	2.6 KiB	-
request	Browse	Structure	Search	Insert	Empty	Drop	3	MyISAM	latin1_swedish_ci	2.2 KiB	-
test	Browse	Structure	Search	Insert	Empty	Drop	1	MyISAM	latin1_swedish_ci	2.2 KiB	-
10 tables	Sum						42	InnoDB	utf8mb4_unicode_ci	19.3 KiB	0 B

Figure 8.7: db tables