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Ensemble machine learning to predict family consent for organ donation

MD Ehsan Khan
Binghamton University--SUNY, mkhan95@binghamton.edu

Ensemble Machine Learning to Predict Family Consent for Organ Donation

BY

MD Ehsan Khan

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THESIS

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Dr. Sang Won Yoon, Committee Chair and Faculty Advisor
Department of Systems Science and Industrial Engineering

Dr. Mohammad T. Khasawneh, Committee Member
Department of Systems Science and Industrial Engineering

Dr. Amy Friedman, Committee Member
Executive Vice President and Chief Medical Officer at **LiveOn**NY

Kristin Delli Carpini, Committee Member
Director of Performance Improvement and Regulatory Compliance at **LiveOn**NY

Abstract

There is ever increasing disparity between number of organs needed for transplantation and numbers available for donation to save lives. As a result, thousands of people die every year waiting for organs. Therefore, it is now more important than ever before to take serious actions to decrease this disparity. One way to bridge gap between organ demand and supply is to increase family consent for organ donation. This research studied the factors associated with family consent. Machine Learning approach had been used in very few literature to understand factors related to family consent. This study uses six Ensemble Machine Learning models to accurately predict family consent outcome (yes/no). All family approaches data between January 2016 and March 2018 from an Organ Procurement Organization (OPO) based in New York city is used to build the family consent prediction model. The experimental results reveals that eXtreme Gradient Boosting (XGB) Machine Learning model performs better than other ensemble models with AUC of 0.8946 and accuracy of 81.7% after normalizing features and using LDA for dimension reduction and then tuning parameters using grid search method. 24 out of 29 features are identified as important features by XGB model. The model is used to calculate probability of consent before approaching family as the values for different features are available real-time after patient is referred to OPO for medical evaluation and suitability. The experimental result shows that the accuracy of the model increases from 77.6% to 91.5% as value for factors are added real-time. This model is also used for selecting the best staff for a particular case to approach family based on their past experience. Staff work schedule is incorporated with the model to select the top three staff based on likelihood of getting consent from family for organ donation. This recommendation system can be used as a potential staff dispatch model for OPO to further improve the consent from family for organ donation and save more lives by customizing the staff deployment procedure based on the characteristics of donor referral.

Dedication

To my Advisor, Mentor, Parents, Friends, Love of Life

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Contents

List of Tables

List of Figures

Nomenclatures

n	A node in Decision Tree
p	Number of input features in Extra Tree classifier
$p(y/x)$	Probability of output class given a predictor
x_i	A vector that includes discrete or continuous in Logistic Regression
y_i	Target variable
$\hat{y}$	Predicted outcome
CI	Confidence Interval
CR	Consent Rate
D	Training set
EI_1	Early Interaction phase I
EI_2	Early Interaction phase II
EI_3	Early Interaction phase III
Input i	Number of predictor variables (1, 2, ..., S)
Input j	Set of all data level preprocessing methods (1, 2, ..., 4)
K	Subset of features
N	Sample size
OR	Odds ratio
α	Cronbach's alpha to measure internal consistency
β	Correlation coefficient range from 0 to 1
β_0	Y-intercept in Logistic Regression

Abbreviations

AB	AdaBoost
AUC	Area Under the Curve
CMS	Center for Medicare Medicaid
CNR	Consent Not Recovered
DCD	Donation after Circulatory Death
DSA	Donor Service Area
EI	Early Interaction
ET	Extra Tree
FAMC	Factorial Analysis Multiple Correspondance
FPA	First Person Authorization
FSC	Family Service Coordinator
GB	Gradient Boosting
GEE	Generalized Estimating Equation
HRSA	Health Resources and Services Administration
IHI	Institute of Healthcare Improvement
LDA	Linear Discriminant Analysis
ML	Machine Learning
NOK	Next Of Kin
NOTA	National Organ Transplant Act
OD	Organ Donation

OPO	Organ Procurement Organization
OPTN	Organ Procurement and Transplantation Network
PCA	Principal Component Analysis
PDSA	Plan Do Study Act
RF	Random Forest
SMOTE	Synthetic Minority Oversampling Technique
SRTR	Scientific Registry for Transplant Recipients
UNOS	United Network for Organ Sharing
XGB	eXtreme Gradient Boosting

Chapter 1

Introduction

The importance of deceased organ donation is extensively discussed among healthcare professionals. Transplantable organ deficiency is a single greatest public health issues in the United States. Despite increasing awareness among public about deceased organ donation and using innovative minds and technologies in the field of engineering and medicines, there is still a huge gap between deceased organ demand and supply. The number of deceased organ donors had increased from 4,080 in 1988 to 7,731 in 2017 (OPTN 2017). This steady increase is still not abundant to satisfy organ demand of all those people who are waiting for organ transplantation. Therefore, this shortage of transplantable organs poses critical threat to lives of many people who need organs to survive. According to data reported in 2012, 6,259 patients died while waiting for organ transplant (OPTN 2017). Out of 79 people receiving organ transplants in the United States, 18 individuals die each day while waiting (US Department of Health and Human Services). There is 3-5% increase in the organ demand every year (SRTR). With the ever increasing gap between the number of deceased donated organs and wait-listed patients, increasing efforts must be made to increase deceased organ donation rates (Chon et al., 2014). As of March 2016, 117,990 candidates needed lifesaving organs (OPTN).

To satisfy the demand of organ transplants, concerns regarding allocation of donated organ were addressed for the first time in 1970s by Organ Procurement and Transplantation Network (OPTN) (Liverman et al., 2006) This led to the formation of Organ Procurement Organization (OPO) (Liverman et al., 2006). The National Organ Transplant Act (NOTA) of 1984 was introduced to help ensure that the organ donation processes are carried out in a fair and efficient way. This will help to lead to equitable distribution of donated organs. The act established the national OPTN for matching donor organs to waiting recipients. The OPTN is managed through the United Network for Organ Sharing (UNOS) located in Richmond, Virginia. UNOS works with 58 federally designated OPOs across the country to place organs locally, regionally and nationally. As of April 30, 2018, there are 58 OPOs in the United States (US Department of Health and Human Services). Each of these OPO serve different geographical areas, which is referred as Donation Service Area (DSA). OPOs act as an ambassador for offering opportunities for volunteering and helping to raise awareness among public regarding the importance of organ donation and for registering interest candidate as a deceased organ donor. These OPOs have two major roles in their DSA. The first role is to increase the number of registered organ donors by encouraging donor sign-ups through First Person Authorization (FPA). They reach to communities by sponsoring campaigns, organizing programs in schools, worksites, faith institution, sharing print and electronic materials, etc.

The second role of every OPO is to coordinate the deceased organ donation process. When donors are willing to donate, representatives from the OPO evaluate the potential donors, checks if the donors are in the registry, discuss donation with family members, contact OPTN computer system that match donors and recipients, obtain a match list for the specific donor, and finally arrange the recovery and transport of the deceased donated organs. Furthermore, OPO also provides support for donor families and volunteer opportunities for interested individuals. OPO deploys several types of staff such as organ procurement coordinators, requestors, donor family specialists, hospital service specialists, and professionals in public relations communications, and health education including administrative personnel. There are many complex series of processes involved in the deceased organ donation. All these processes can be be illustrated in a simplified manner by Figure 1.1. These processes are coordinated by medical professionals at OPO and hospitals.

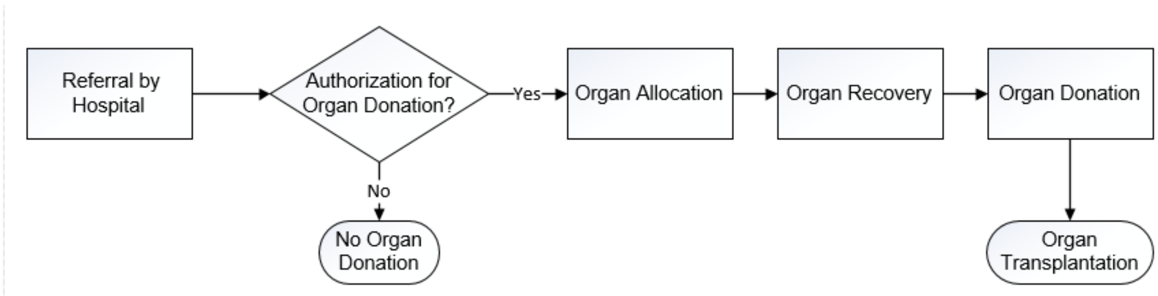

Figure 1.1: High Level Deceased Organ Donation Processes

There are 12 important steps in deceased organ donation processes. These steps are carried both at hospital and OPO. These processes involve both OPO and hospital staff. The detailed description of all these processes are elaborated below:

1. *Identification of the Potential Donor by the Hospital*: Healthcare professionals at hospital identify a potential candidate for donation after the clinical trigger is met. Clinical trigger consists of Glasgow Coma Score of less than or equal to 5, or a plan for family to discontinue mechanical or pharmacological support for end of life. The nature of injury leads a physician to determine the patient is brain dead or a potential donation after circulatory death (DCD) candidate.

2. *Evaluation of Donor Eligibility*: Regulatory agencies and individual hospital policies require all patient deaths and imminent deaths to be referred to OPO

in a timely manner for assessment of donation potential. This requirement ensures that all patients and their families are afforded the opportunity to donate organs, eyes and tissues if they choose and are medically suitable. OPO is called on all patients' deaths by hospitals. Information is provided on the patient's medical status and the OPO recovery coordinator evaluates the patient. The evaluation includes a medical and social history and physical examination of the patient. This determines whether or not the patient is a suitable candidate for deceased organ donation.

3. *Authorization for Organ Recovery*: If the patient is a candidate for deceased organ and/or tissue donation, at an appropriate time the legal next-of-kin is approached with the opportunity of donation. If a donor designation or individual authorization by the decedent cannot be identified, the family must give their consent in order for the donation process to proceed. If the family consent, the legal NOK signs a donor consent form.

4. *Medical Maintenance of Patient*: After family consent or donor designation has been provided, the OPO clinical coordinator, in concert with the hospital staff, maintains the patient medically. In few cases, physician support is requested on a consultation basis.

5. *Matching Organs to Potential Recipients*: Information on the organs available for donation, the donor's blood type and body size is provided to UNOS by the OPO clinical coordinator. The UNOS computer then matches the donated organs to potential recipients. Recipient selection is based on blood type, body size, medical urgency and length of time on the waiting list. The heart, liver and lungs are matched by blood type and body size. In matching the pancreas and kidneys, genetic tissue type is also considered.

6. *Offering Organs Regionally, Then Nationally*: A computerized list of waiting

patients in the matching blood group is provided to the OPO coordinator who seeks to match organs with recipients in the OPO DSA. If a match cannot be made for a specific organ within this area, the organ is offered on a regional basis, then nationally, if necessary.

7. *Placing Organs and Coordinating Recovery*: After a recipient match has been found, the OPO coordinator calls the transplant center for the patient who matches the donated organ(s). The patient's transplant surgeon is responsible for making the decision whether to accept the organ. If the surgeon declines the organ for that patient, the OPO coordinator contacts the transplant surgeon of the next patient on the list. This process continues for each organ until all of the organs have been appropriately matched with recipients. Then, the OPO coordinator arranges for the operating room (for the recovery of the organs) and the arrival and departure times of the transplant surgery teams.

8. *Surgical Recovery of Organs*: When the surgical team arrives, the donor is taken to the operating room where the organs and tissues are recovered through a surgical procedure. In accordance with federal law, physicians recovering the organs do not participate in the donor's care prior to the determination of brain death.

9. *Preparing Recipients for Surgery*: After the recipients have been identified, they are called by their transplant surgeons for the final pre-operative preparations while the organ recovery process is occurring at the donor hospital. Upon the organs' arrival at the transplant hospital, the recipients are taken to surgery and the transplants are performed.

10. *Distribution of Organs*: The OPO coordinator takes a sample of the lymph node tissue to a laboratory for tissue typing and subsequent matching with

recipients. Other organs are taken directly to the recipients by the surgical recovery teams.

11. *Funeral and Burial Plans*: After the recovery process has occurred, the donor family can proceed with funeral or burial plans, which are not affected by deceased organ donation. Organ and tissue donation is a dignified and respectful process.

12. *Follow-up with Family and Hospital*: OPO follows up each donation by sending letters to the donor family, hospital staff, physicians and nurses regarding organs and tissues that have been recovered.

1.1 Research Problems and Questions

Despite arduous work by OPO to meet the increasing demand for organs transplantation, the number of patients on the waiting list has been increasing every year. Therefore, some crucial steps have to be taken to increase the number of organs for transplantation and save lives. One of the important steps to increase organ supply is to increase the consent rate. Consent rate is defined as getting consent from the family or donor for deceased organ donation. There are many factors associated with family consent. It is important to understand and analyze these factors. Identification of important factors involve in getting consent for deceased organ donation lead to the following research questions:

1. What are the factors which significantly affect the consent rate for deceased organ donation?

   The study of factors influencing consent rate is an important topic for improving organ donation decision for the family. Assessing the relationship between donor variables and family consent and decline for organ donation can lead to formulating strategies to increased deceased organs supply.

2. Is there any trend in factors and consent from family for organ donation?

   There are few factors which are more important than others and have direct correlations with family consent. These factors can be significant predictors of getting consent from family for organ donation. Such factors need to be identified and given more importances while dealing with family to discuss about deceased organ donation.

3. In what ways Machine Learning (ML) and data mining techniques can be used to solve deceased organ supply crisis?

   There are very few publications that have used ML methodologies and models to answer important questions related to organ donation. Many publications have used basic statistical tests and techniques to find relationship between different factors. Complex ML models can also be used to find reasons for organ demand and supply crisis.

4. How likely is it to get consent from family for organ donation if all the important factors are treated equally?

   The probability of getting consent from family can be calculated for all the donors given all the factors associated. This will help in analyzing factors that is very closely related to outcome variable (family consent yes or no).

1.2 Research Objectives

The primary goal of this project is to build prediction models to predict family consent outcome (yes/no) given all the factors associated. One and half years data is obtained from New York city based OPO and used for building prediction model. There are 29 variables associated with characteristics of donor, next-of-kin (NOK), and requestor. These variables are chosen based on literature review and domain expert recommendations. The output class is family consent (yes/no) for organ donation. The research aims at finding the best prediction model which can accurately predict the organ donation decision outcome. This research also aims at understanding how several factors involved with organ donors affect the consent rate. Machine learning models will be used to build the prediction models, which can be used as a decision support system to better understand and analyze factors and improve consent rate. In order to address questions and accomplish research objectives, the following topics have been covered in this report:

- Review of literatures to find out the factors involved in organ donation
- Review of literatures to explore statistical techniques used to answer organ donation related statistical questions
- Application of different data mining preprocessing techniques to perform feature engineering on the dataset
- Calculation of the probability of getting consent given all the factors related to organ donation before approaching family
- Experimentation of different models with machine learning methods, model configuration and feature subsets to improve predictability

- Application of parameter tuning methods to tune the parameters associated with different ensemble machine learning methods

1.3 Significance of the Research

Many studies analyzed factors associated with consent from family for organ donation. Most of the studies had used basic statistical tests such as chi-square test, t-test, two proportion z-test etc. Few studies had used logistic regression model to find out significant factors based on p-values. However, very limited studies had used any ML algorithms to find association between different factors related to consent and build prediction model to determine the outcome of family consent outcome before approaching them. This study uses six machine learning algorithms and accurately predicts the outcome of family consent (yes/no). Furthermore, this study calculates probability of getting family consent given all the factors related to deceased, NOK, and requestor's characteristics.

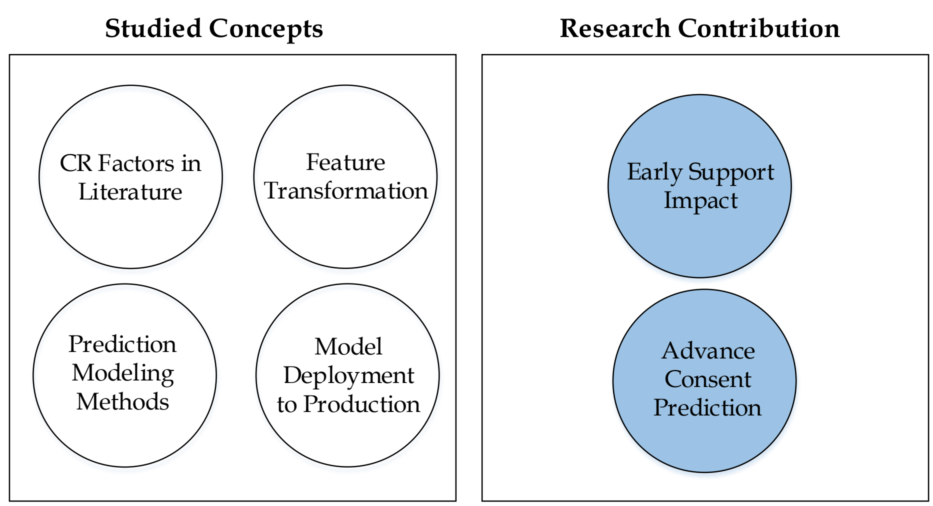

Figure 1.2: Research Contribution

The model proposed in this study have significantly better predictability compared to other models. The final optimized model can be used as a decision support system to better understand factors associated with deceased organ donation. After understanding all the factors, it will be helpful in devising strategies to increase consent rate. Also, the model will help hospital family services directors at any OPO to deploy plans and strategies to select best staff to do effective organ donation request. Figure 1.2 illustrates unique contribution of this research. From this research, after studying four concepts, two unique topics are added to the organ donation world. Early Support to family analysis is a unique analysis being done in this study, which is rarely discussed in any literature. Also, advance consent prediction model is being developed to predict consent before approaching family to discuss about organ donation. Some of the additional contributions of this research are listed below:

- Build decision support system in the form of final optimized prediction model to predict family consent for deceased organ donation
- Perform statistical analysis for significant factors associated with organ donation
- Highlight data integrity issues hidden in the dataset
- Calculate probability of getting family consent given all the factors
- Recommend best practices related to significant predictors of organ donation
- Apply feature engineering methodologies to improve the predictability of final prediction model
- Select best staff for a particular case to approach family to maximize family consent

1.4 Assumptions

There are four important assumptions made in the preprocessing and model building phases of this research. All these assumptions are made based on organ donation domain knowledge and expert recommendation. These assumptions are made to simplify the understanding of the prediction model and avoid data handling errors while building ML algorithms thereby avoiding any discrepancies in the predictability of organ donation outcome. All these assumptions are listed below:

- Data used in this research is extracted from a database using Microsoft SQL server of the OPO. All the dataset extracted from the OPO website is assumed to be correctly entered by OPO staff
- Variables with more than fifty percent of missing values are excluded from the analysis and the prediction model building
- Categorical variables with less than 30 counts of levels are merged with other category
- All the missing values for both continuous and categorical variables are excluded from prediction model

1.5 Thesis Overview

The first chapter presents importance and overview of organ donation and touched base on the need and significance of this research. Chapter 2 has been organized to provide a general literature review surrounding factors related to family consent for organ donation. Different statistical methods used to detect significant factors in different literatures have been reviewed. Chapter 3 begins with the data description and exploratory data analysis of donor, next-of-kin, and requestor characteristics followed by qualitative analysis and data description. This chapter also includes review on data preprocessing techniques. Chapter 4 explains the experimental results of prediction models. Comparison of multiple models and validation of results are also included in this chapter. Finally, Chapter 5 concludes with the unique contribution of this research and possible future research areas.

Chapter 2

Literature Review

This chapter covers literature review related to factors affecting consent from family for deceased organ donation. The reviewed literature incorporates practices involved in organ donation. The prime objective is to acquire knowledge and understanding of factors involved in organ donation to improve the consent rate.

The literature review is divided into two sections. Section 2.1 shelters factors involved with family consent for organ donation. Section 2.2 describes statistical methodologies used for shortlisting significant factors involved with family consent.

2.1 Factors Affecting Family Consent

Due to insufficient deceased organs, it is very difficult to meet the demand for organ transplantation (Klein et al., 2010). Due to the shortage of organ, even organs from not brain-dead donors [donors after circulatory determination of death(DCDD)] whose organs are at higher risk of organs failure after the transplantation are being used (Goldberg et al., 2013). Therefore, efforts have been made to address this organ deficiency. One of the important ways to improve the organ pool is to improve donation consent rates (Sheehy et al., 2003, Delmonico et al., 2005, Ojo et al., 2005, Klein et al., 2010). One study stated that family members played pivotal roles in making donation decision at the time of death (Rodrigue et al., 2006). This study examined several factors related to organ donation decision. These factors were divided into five categories.

Deceased Characteristics

Deceased sociodemographic variables, donation intentions, and cause of death are significantly related to donation decision. Sociodemographic variables include age, gender, race, marital status, education, and employment status.

One study showed that patients who were younger, white, and not married were more likely for NOK to give consent for organ donation (Rodrigue et al., 2006). Another study revealed that white, absence of religion, Anglican Christianity, Buddhism, and Hinduism were directly associated with definite desire to donate all organs (Webb et al., 2015). However, Islam religion did not correlate with definite wish to donate. Another study found that consent was significantly more likely to obtain from white patients compared to Hispanics, other races, blacks, and Asians (Goldberg et al., 2013). For many people, religious faith with altruistic belief system was provided by religion, while for others, donation was not encouraging within their religion (Irving et al., 2011). Many people from the same religion held different beliefs regarding organ donation. Therefore, it is extremely important to hold open discussion among religious leaders to take definitive stance on the topic and encourage people to donate organs to save lives thereby removing misunderstanding about their belief systems (Irving et al., 2011). Another study held similar stance on religious beliefs regarding organ donation (Ghorbani et al., 2011). According to a recent research, gender and race were not significant factors related to consent from family for organ donation (Shah et al., 2018).

Age groups 18 to 24 years and 25 to 34 years were not significantly correlated with decision to donate (Webb et al., 2015). The lowest consent rates were seen among patient's aged 55-64 years and greater than or equal to 65 years (Goldberg et al., 2013). Another study stated that younger donors, 18-39 years had higher consent rate(Shah et al., 2018). Deceased donation intentions were significantly related to donation as agreed by previous research (Burroughs et al., 1998, Martınez et al., 2001, Siminoff et al., 2001, Sque et al., 2005). It was more likely to get consent for donation if patients are registered to be organ donor on their drivers license, or some other types of documentation and had spoken to family members or others about organ donation. This study also concluded that patients gender, education level, cause of death and hospital length of stay are not significantly associated with NOK donation decision. However, another study contended that consent was closely associated with deaths due to trauma (Siminoff et al., 2001), which was supported by another study (Shah et al., 2018). Along with trauma, head injury as a cause of death was also closely related to consent. Moreover, socioeconomic factors like marital status as single, college or higher levels of education, family median household incomes greater than forty-five thousand and residents of counties with poverty rates lower than the state and national poverty rates were highly correlated with higher consent from family. Another study found that deceased education and income did not affect consent (Siminoff et al., 2001). However, one study found candidates with higher levels of education had higher consent rate (Shah et al., 2018). Table 2.1 summarizes factors related to deceased donor characteristics and related publications.

Table 2.1: Factors Related to Deceased Donor Characteristics

Factor	**Publication**
Age	Rodrigue et al. (2006), Padela et al. (2011) Goldberg et al. (2013), Webb et al. (2015)
Cause of Death	Rodrigue et al. (2006), Padela et al. (2011)
Donation Intention Known	Rodrigue et al. (2006)
Education	Rodrigue et al. (2006)
Employement Status	Rodrigue et al. (2006)
Ethnicity	Rodrigue et al. (2006), Padela et al. (2011) Goldberg et al. (2013), Webb et al. (2015) Chandler et al. (2017)
Gender	Rodrigue et al. (2006), Webb et al. (2015)
Have Children	Webb et al. (2015)
Income	Walker et al. (2013)
Insurance	Padela et al. (2011)
Marital Status	Rodrigue et al. (2006), Webb et al. (2015)
Religion	Ghorbani et al. (2011), Irving et al. (2011) Webb et al. (2015), Chandler et al. (2017)

NOK Characteristics

NOK characteristics are closely related to family consent for organ donation. If NOKs were white and employed, then it was more likely to get consent (Rodrigue et al., 2006). Similarly, if NOK relationship to the deceased was either parents and adult then there was higher chance of getting consent (Rodrigue et al., 2006, Shah et al., 2018). Furthermore, if NOK knew the intention of deceased, then it was easier for them to make decision and give consent for organ donation (Siminoff et al., 2001, Rodrigue et al., 2006). The intention of deceased could be in the form of a driver's license designation, a signed donor card or a discussion with other family members. Also, if NOK with more favorable attitudes toward organ transplantation and donation were more likely to give consent (Siminoff et al., 2001, Rodrigue et al., 2006).

Family's understanding of brain stem death is significant factors of determining consent from family. Relationship between understanding the concept of brain stem death by family and consent is mentioned in a research paper (Simpkin et al., 2009). However, another paper showed that there was no significant increase in the consent from families who clearly understood brain stem death (Frutos et al., 2005). One study surveyed 71 families and found that 68% of families who consented had a significantly better understanding of the concept of brain stem death than 32%, who did not consent (Simpkin et al., 2009). Similarly, in another study of review of 285 families, 71% of families who had clear understanding of brain stem death consented while 29% of those with inaccurate and incomplete knowledge of brain stem death did not consent (Rodrigue et al., 2006). This is supported by another study where 6.2% of 146 potentials organ donor families refused donation due to lack of proper understanding of brain stem death. One study mentioned that 70.5% of NOK who had complete knowledge of brain stem death agreed to donation, while 29.2% of those families with incomplete or inaccurate knowledge of brain stem death denied organ donation (Rodrigue et al., 2006). In another study, a protocol that was used to do brain flow scan to confirm brain stem death increased consent from 44% to 71% (Simpkin et al., 2009). Lack of understanding or rejection of brain death was directly related to refusal of donation although still there were many families despite poor understanding of the brain stem death still consent (Rodrigue et al., 2008, Chandler et al., 2017). Sometimes family confusion might be due to language and behavior of healthcare professionals (Siminoff et al., 2001). According to one study, NOK gender, age, marital status and educational level were not significantly with family decision for organ donation (Rodrigue et al., 2006). Table 2.2 summarizes factors related to NOK characteristics and related publications.

Table 2.2: Factors Related to Next-of-kin Characteristics

Factor	Publication
Age Gender Race Marital Status Relationship to Donor Education Employment Status Attitudes Towards OD Beliefs About OD Donation Intention Known	Rodrigue et al. (2006)
Knowledge of BD	Rodrigue et al. (2006), Simpkin et al. (2009) Ghorbani et al. (2011), Padela et al. (2011) Chandler et al. (2017)

Requestor Characteristics

There are many studies that revealed that one of the most influencing consent is the approach and expertise of the person making approach to family for organ donation. Fourteen studies outlined differences in consent rates to be closely connected with which professionals are involved with the request process (Simpkin et al., 2009). In one study of 707 requests for organ donation, the consent rate was 72% when both hospital staff and coordinators from an organ procurement organization (OPO) approached families (Simpkin et al., 2009). In the same study, it was found that consent rate was only 53% when hospital staff alone approached family for organ donation, compared to consent rate of 62% when coordinators from OPO alone approached family. Similarly, in the same paper, in a retrospective study in Texas of 185 medically suitable organ donors over one year, revealed that when OPO alone approached family, consent rate was 67%, 9% when hospital staff alone approached the family, and 75% when approached made collaboratively. It was also reported in the same paper that families stated that the conversations with OPO staff were very crucial to their donation decision. Talking to OPO staff and spending more time with them before making donation decision were closely associated with donation. These findings were supported by other study, which suggested that consent rates were considerably higher when OPO staff asked for consent from family (Chandler et al., 2017).

However, few other studies suggested that consent rates were higher when a member of the healthcare team raised the subject of organ donation, and such studies also showed strong evidence that families preferred when requests came from physicians (Rodrigue et al., 2006). The recent study in U.K. compared the consent rates for collaborative requests (by transplant coordinator and clinical team) and requests by clinical team alone, failed to find association (Ebadat et al., 2014). This study also found that consent rates were higher with matched race of donor and OPO staff (66% vs. 52%), family approached by female OPO staff (67% vs. 56%), if approach initiated by OPO staff (69% vs. 49%), and if consent rate was dependent on time of day the approach occurred: 6:00 am to noon (56%), noon to 6:00 pm (67%), 6:00 pm to midnight (68%), and midnight to 6:00 am (45%). The approach with family that led to consent lasted longer than those declining (67 vs. 43 minutes). The ultimate conclusion was that variables such as race and sex of OPO staff and time of day of approach should be considered before approaching a family for organ donation. Donation rates might improve if translators were avoided during the approach.

Another study found that initial request followed by discussion with an OPO coordinator ensured that family was almost three times as likely to give consent compared with other patterns (Siminoff et al., 2001). Families who had more contacts with OPO staff were 3 times as likely to donate irrespective of other factors. Consent rates differed significantly based on who first mentioned organ donation and who actually made formal approach to family. One study found that donation was more likely when an OPO staff (72.2%) or a family member (74.0%) first mentioned it,

Table 2.3: Factors Related to Requestor Characteristics

Factor	**Publication**
Amount of Time Spent	Padela et al.(2011)
Donation Requester	Rodrigue et al. (2006), Simpkin et al. (2009) Padela et al. (2011), Chandler et al. (2017)
First Mention of Donation	Rodrigue et al. (2006)
Number of Discussions	Padela et al. (2011)
Perceived Compassion	Rodrigue et al. (2006)
Perceived Sensitivity	Rodrigue et al. (2006)

rather when it was first raised by a physician, unit nurse, social worker or hospital clergy/chaplin (34.2%) (Rodrigue et al., 2006). Also, NOK was likely to donate when the person who asked for consent was an OPO staff (75.9% vs. 36.7%) for non-OPO professionals). Furthermore, interpersonal skills of the requestor also appeared to be significant factors for getting consent from family. Family who perceive OPO staff more compassionate and sensitive, gave consent to organ donation. The consent rate was as high as 67.4% than the requestor who perceived to be only slightly compassionate (29.9%) or not compassionate at all (17.5%). Table 2.3 summarizes factors related to requestor characteristics and related publications.

Communication Processes

Early research indicated that timing of the request to donate did not impact consent rates (MORRIS JR et al., 1989). The Institute of Medicine (2006) reported that early and consistent involvement with the family with an emphasis on effective communication increased donor rates, especially if there was an in-house coordinator. Other research on in-house coordinators found similar results (Shafer et al., 2004). One study concluded that NOK who thought that the timing of the donation discussion was appropriate, 68.4% donated (vs. 31.6% who did not donate), whereas only

17.9% consented to donation if they considered the timing to be poor (Rodrigue et al., 2006). This study also mentioned that the family with an adequate explanation and definition of brain death appears to be more important than the timing of approach and explanation of brain death.

However, the timing of the brain death explanation was not significantly associated with the donation decision. Donation occurred at the same rates regardless of whether the brain death explanation occurred before (56.0%) or after (53.7%) or at the same time (50.0%) donation was discussed with family. Consent rate did not differ significantly based on whether others were involved in the decision making (53.4%) or not (47.8%). However, the nature of these discussions appeared to be important. Whenever there was disagreement between family members regarding organ donation decision, consent rate was significantly lesser (34.4%) than where there was full agreement about the decision (62.1%).

There were various communication strategies which might be more effective during donation discussions with family (Chandler et al., 2017). Requestors who had the habit of quickly reassuring responses might be misunderstood by family concerns and be perceived as salesmanship (Eckenrod, 2008). Also, it was important to have considerate listening and acceptance of family feelings and concerns (Elizabeth Weathersbee and Maynard, 2009). Appropriate body language, gestures, tone of voice and dress built feelings of trust and safety in families (Zink and Wertlieb, 2006). The similar study also mentioned that some communication strategies intended to secure consent might also offend families or backfire for other reasons. A range of organ donation-specific persuasive techniques and approaches were addressed in the literature, including a "presumptive approach" (that assumes families will wish to donate) (Zink and Wertlieb, 2006). This type of approach might cause requestors to fail to response effectively to family objections. Also, some communication strategies such

Table 2.4: Factors Related to Communication Process

Factor	**Publication**
Given enough time to make decision	Rodrigue et al. (2006) Simpkin et al. (2009)
Invovlemnet of others in donation	Rodrigue et al. (2006)
Place of Request	Rodrigueet al. (2006) Simpkin et al. (2009) Chandler et al. (2017)
Timing of Brain Death explanation given	Rodrigue et al. (2006)
Timing of Initial Donation Discussion	Rodrigue et al. (2006) Simpkin et al. (2009) Padela et al. (2011) Walker et al.(2013) Chandler et al. (2017)

as feeling of guilt might backfire by offending families (Aldridge and Guy, 2008).

In many literatures, evidence that a private location for discussion about organ donation improved consent from family was clearly documented. In two studies, consent rates for requests made in settings that provided little privacy (requests made by telephone, in the patient's room, at the nursing station, or in the hallway) were 45% and 30% compared with consent rates of 56% and 52% in more private settings (Simpkin et al., 2009). However, another study showed no significant benefit of a private setting for organ donation requests (Siminoff et al., 2002). Another literature emphasized the importance of location of the request setting in which approacher approach family for organ donation (Chandler et al., 2017). Private, calm, and comfortable location should be used for discussions of organ donation with family. It was not advisable to use hallways, bedside, nursing station and public waiting rooms to discuss with family about organ donation. Table 2.4 summarizes factors related to communication process during organ donation process and related publications.

Overall Satisfaction with Healthcare Team

One study assessed the degree to which NOK was satisfied with the care received by their loved one before and after death, the medical staff communication with the family about the loved one's medical status, prognosis, and the degree of respect shown by the medical team towards their loved one's and family members (Rodrigue et al., 2006). The overall finding was that satisfaction ratings were significantly higher for family who consented to donation (44.5% vs. 39.3%). However, another study found that there was no association between the decision to donate and the hospital environmental variables or Hospital health care providers (HCP) sociodemographic characteristics (including age, sex, ethnicity, religious affiliation, and professional role) (Siminoff et al., 2001).

However, this study contended that HCP's attitudes toward organ donation correlated with consent rates, their comfort with answering families questions about donation was significantly associated with organ donation. Although, overall satisfaction with hospital care was not correlated with the donation decision, socio emotional and communication issues were important. Families who believed that one or more HCPs involved in their relatives' care were not caring or concerned were less likely to donate (56.6% vs. 43.4%). Families who felt harassed or pressured to make a decision were also less likely to donate (65.9% vs. 34.1%). Health care practitioner assessment of a family's initial reaction to the issue of donation was strongly associated with the donation decision. Less than half the HCPs (46.9%) correctly ascertained family's initial response to the request to donate organs. Table 2.5 summarizes publications related to overall satisfaction with healthcare team.

Table 2.5: Factors Related to Satisfaction of Healthcare Team

Factor	**Publication**
Overall Satisfaction of Healthcare Team	Rodrigue et al. (2006) Simpkin et al. (2009) Irving et al. (2011) Walker et al. (2013) Chandler et al. (2017)

2.2 Statistical Methodologies in Literature

There are many statistical methods used in many studies to determine important factors contributing to the consent from the family for organ donation. Some of the important statistical analysis methods used in different literatures are described below.

Wilcoxon rank-sum and Kruskal-Wallis tests were used to analyze continuous variables, and chi-square test for categorical variables (Goldberg et al., 2013). This paper also used generalized estimating equation (GEE) models using a logit link with an exchangeable correlation structure and robust variance estimates to identify factors associated with consent for organ donation. In the same study, for secondary analysis, GEE models were fit to identify attributes associated having organ consent process meet OPO specifications of effective request, among those for whom consent was requested. Furthermore, this study also performed a non-parametric test of trends to determine if the number of eligible deaths, consented deaths, and actual donors changed over time. One study used descriptive statistics along with bivariate analysis of the relation between family decision (donation or refusal) and different variables included in the instrument using chi-square test and t-test (Martınez et al., 2001). This study also used logistic regression analysis to assess the predictive power of the family decision variables. Also, this study examined the potential relations between variables from a multivariate approach, using factorial analysis of multiple correspondence (FAMC).

A new instrument was developed by the research team to compare attitudes of donor and non-donor families to the families decision to donate or not donate the organs of a deceased family member. 40 Likert-scaled items and 3 open-ended questions were developed based on content gathered from initial interviews with non-donor families, the variable literature, and the experiences of staff from the OPO (Exley et al., 2002). This study tested usability, timing and readability by a pilot test of the survey instrument with donor and non-donor families and with OPO staff. Data gathered were used to apply factor analysis to the items of the tool to establish the construct validity of the instrument. Factor analysis is a method for identifying clusters of related variables within an instrument. Each cluster or factor consists of items from the instrument that share similar qualities or attributes. When the clusters confirm proposed shared attributes (determined during development of the instrument), an evidence of construct validity is provided. The reliability of the instrument was assessed by using the Cronbach α for internal consistency. Internal consistency is a form of reliability that indicates the degree of homogeneity or likeness among the items in the same cluster or factor. Values range from 0 to 1, and higher Cronbach α values indicate that items within a cluster are similar (internally consistent). In general, α greater than or equal to 0.7 is acceptable for a new instrument. This paper also used chi-square test to determine the most significant factors affecting the family decision for organ donation along with discriminant analysis to compare actual versus expected number of donors and non-donors and the related accuracy.

Ordered logistic regression models were used to test the association between justification of organ donation after death and all independent variables (Padela et al., 2011). Bivariate analysis was also conducted for all independent variables to assess their effect on whether respondents felt organ donation were justified, and unadjusted odds rations (OD) were calculated. Also, three separate multivariate ordered logistic regression analysis were done (Padela et al., 2011). One study analyzed data using a comparative, thematic approach and multivariate statistics, focusing on detection of important similarities and differences between cases (Walker et al., 2013a). This paper also used Friedman test to find a significant difference in scores over time for the bereavement scale of depersonalization, which measured deep and intense bereavement.

Similarly, another study used chi-square statistic for measuring association for ordination categorical data while t-test was used to assess continuous variables. Bivariate relationships were compared between the primary predictors of interest-ethnicity (White vs. African America) and three dependent variables (Siminoff et al., 2006). In the same paper, for the bivariate analysis, the independent variables were collapsed into two categories (agree vs. disagree) from 4-point Likert scales, but were used as 4-point Likert scales for the logistic regression analysis. Similarly, univariate relationships between the questionnaire items and the NOK donation decision (donation or refusal) were examined using t-tests for continuous variables, the Fishers exact test for variables with two categories or a 2-tailed chi-square test for variables with three or more categories (Rodrigue et al., 2006). In addition to this, the paper also used logistic regression to examine the predictive relationship between modifiable variables that were statistically significant in the univariate analyses and the NOK donation decision. Table 2.6 summarizes all the publications and the methodologies used for factors analysis related to organ donation.

Table 2.6: Statistical Methodologies in Literature

Methods	Publications
Statistical Tests	Simpkin et al. (2009), Hong et al. (2011) Goldberg et al. (2013), Webb et al. (2015) Chandler et al. (2017)
Logistic Regression (LR)	Siminoff et al. (2001), Rodrigue et al. (2006) Ghorbani et al. (2011), Irving et al. (2011) Godin et al. (2008), Walker et al. (2013b) Rabinstein et al. (2012) Webb et al. (2015), Shah et al. (2018)
Principal Component Analysis (PCA)	Robbins et al. (2001)
Linear Discriminant Analysis (LDA)	Mostafa (2008)
Artificial Neural Network (ANN)	Mostafa (2008), Schleich et al. (2013)

2.3 Summary

In many literatures basic statistical methods are used for analyzing the factors related to family consent for organ donation. Machine learning algorithms proposed in this study have been used in very few literature. Logistic Regression has been used in few literatures to compute p-values to determine significant factors. This research used ensemble machine learning approach to predict consent from family for organ donation. This will help professionals in the organ donation world to make more informed and data driven decisions.

Chapter 3

Methodology

In this chapter, the research methodologies are explained from the data mining techniques used, description of data, attributes, functions, to computed calculations and analysis. In Section 3.1, the steps in the research methodologies are presented in the order of application giving a general description of each step. Section 3.2 provides detailed description of the data used, data source, shape, volume, variables, and number of records or sample size used. In section 3.3, Early Interaction Analysis is explained. Section 3.4 explains how data preprocessing was performed and how different categorical variable levels were combined. Section 3.5 describes the development of the many prediction models used to classify family consent outcome into two categories (family consent: yes/no).

3.1 Research Framework

The objective of this research is to develop the prediction model for classifying and predicting family consent for organ donation. The research methodologies follow consecutive steps, starting with data collection, building prediction models and comparing and validating results. Figure 3.1 shows all the steps of the data mining and model building process flow. First, dataset is extracted from the OPO database. Then, dataset is divided into training, testing, and validation set. Features transformation and dimension reduction are performed followed by data sampling and tuning parameters of models. Then, prediction models were developed and their performance measures are compared. Finally, the proposed model is applied to the real-time data extracted from the database.

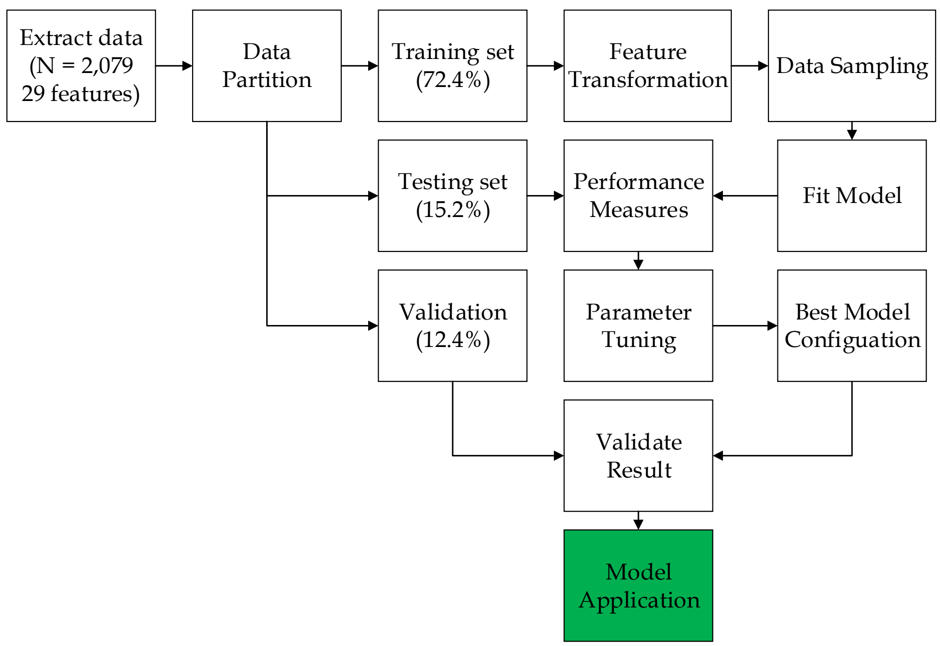

Figure 3.1: Machine Learning Model Building Processes

3.2 Data Description

This research uses database of an Organ Procurement Organization based on New York City, **LiveOn**NY. The database consists of all the information regarding all the referrals for organ donation from 92 hospitals in the state of New York. All the variables used in this study are extracted using Microsoft SQL Server Management Studio 2012. Data is cross checked in iTransplant website before using it for analysis purpose in Python 3.6. Levels of categorical variables such as Hospital Unit, Cause of Death, etc. are combined based on the frequency or occurrence in the dataset. The levels with less than 30 counts are combined with other category. Categorical variables are described with frequency distributions whereas measures of central tendency such as mean and/or median and standard deviation (SD) are used for continuous variables.

This study includes all the referrals from the hospital with organ outcome of donor, Consent Not Recovered (CNR), and no authorization. These organ outcomes are collectively known as 'approaches' in the world of organ donation. There are 2,079 (N = 2,079) approaches from January 2016 through March 2018, out of which 31.4% are donors, 10.3% CNR, and 58.3% no authorization. There are 29 variables associated with family, out of which 24 are categorical variables and 5 are continuous variables. Table 3.1 summarizes descriptive statistics for the entire dataset used in this study. Figure 3.2 illustrates number of approaches and consent rate over over three years. Number of donors is increased from 2016 to 2017, however, consent rate

Table 3.1: Data Descriptive Statistics

	Total	**2016**	**2017**	**Jan. - Mar. 2018**	**2018 Annualized***
Referral	**9,694**	**4,011**	**4,354**	**1,329**	**5,390**
Approaches	2,081	847	974	260	1,055
Donor	653	271	296	86	349
Consent Not Recovered (CNR)	214	96	99	19	77
No Authorization	1,214	480	579	155	629

*As of 04/19/2018

is decreased from 43.3% to 40.6%.

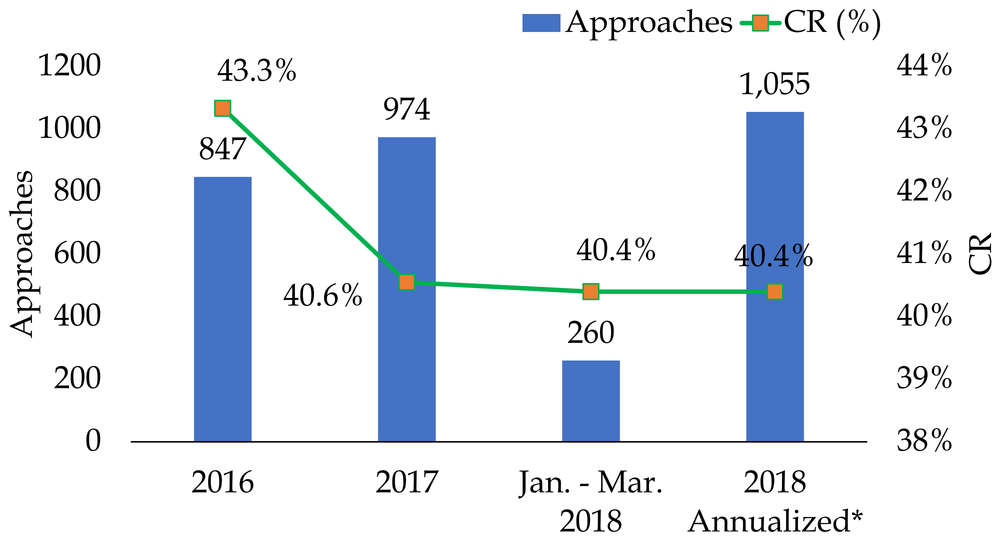

Figure 3.2: Overall Approaches and Consent Rate Trend

There are many factors related to deceased organ donor. Table 3.2 summarizes all the factors related to deceased characteristics. They are age, gender, race, religion, First Person Authorization (FPA), and Cause of Death (COD). Age is categorized into six different groups based on UNOS report of the OPO. The descriptive statistics shows that age between 50 and 59 years has highest frequency of 152, which has 71.1% consent rate. The second highest approach is among the age group of 18 and 39 years, which has 82.5% consent rate. It shows that the lowest consent rate is among the age group 50 and 59 years old. Similarly, male has highest consent rate of 76.7% compared to female of 74.9% .

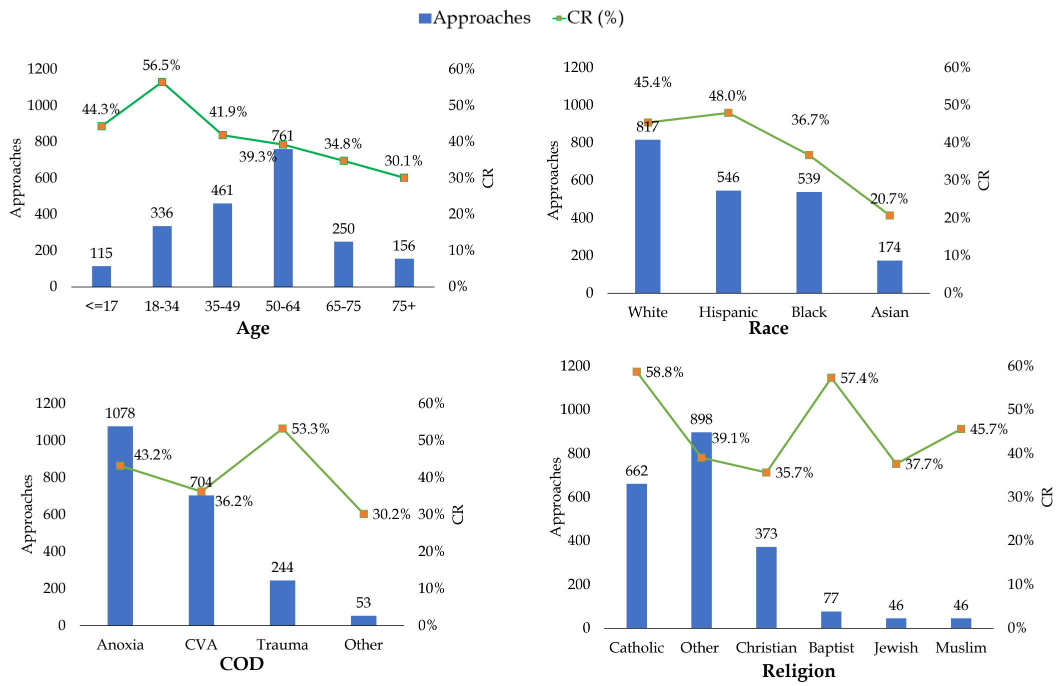

Figure 3.3: Approaches and Consent Rate Trend of Donor Characteristics

Highest consent rate of 78.9% is found among Hispanic, while among white deceased donors, the consent rate is 77.6%. The lowest consent rate of 57.9% is found among Asian. The number of approaches for Asian is also smaller than other people of other ethnicity. Christian religion has the highest consent rate of 83.6%, while religion with other category has lowest consent rate of 68.9%. FPA donors are those donors who are already registered voluntarily to donate after they die. There are 92.8% consent among FPA donors. There are only 69 FPA registered donors out of 552 approaches. Obviously, consent rate for FPA donor has higher consent rate as expected.

Figure 3.3 illustrates frequency and consent distribution for donor characteristics such as age, race, cause of death and religion. Catholic and Baptist have higher consent rate compared to others. Similarly, one who is dying due to trauma has higher consent rate. While doing analysis for religion, there were more than 20 different religions. So, based on frequency distribution, religion with less than 30 approaches were categorized as other category. This is the reason for higher number of approaches for other category. Similarly, Muslim religion has the lowest consent rate. The trend in donor characteristics is quiet obvious to spot out and strategies can be devised to target those donors who have lower consent rate. For example, Asian community has to be educated about benefit of organ donation more than any other ethnicity. Similarly, still there is misconception among Muslim community that organ donation is not allowed in Islam. However, Islam religion as stated in Quran, to save one life is like saving the entire humanity. Therefore, no religion prohibits organ donation, however, it's the people who misinterpret the religion and make preconceived notion in their mind about reservation of organ donation. Therefore, it is more important to create awareness about organ donation among people of all religions.

Table 3.2: Deceased Donor Characteristics Descriptive Statistics

Factor		**N**	**Consent n (%)**	**No Consent n (%)**
Age (years)	0-17	39	29 (74.4)	10 (25.6)
	18-39	143	118 (82.5)	25 (17.5)
	40-49	79	60 (75.9)	19 (24.1)
	50-59	152	108 (71.1)	44 (28.9)
	60-69	94	67 (71.3)	27 (28.7)
	70+	45	37 (82.2)	8 (17.8)
Gender	Female	231	173 (74.9)	58 (25.1)
	Male	321	246 (76.7)	75 (23.3)
Race	Asian	33	19 (57.6)	14 (42.4)
	Black	143	106 (74.1)	37 (25.9)
	Hispanic	171	135 (78.9)	36 (21.1)
	White	205	159 (77.6)	46 (22.4)
Religion	Catholic	248	189 (76.2)	59 (23.8)
	Christian	140	117 (83.6)	23 (16.4)
	Other	164	113 (68.9)	51 (31.1)
FPA	No	483	355 (73.5)	128 (26.5)
	Yes	69	64 (92.8)	5 (7.2)
COD	Anoxia	293	226 (77.1)	67 (22.9)
	CVA/Stroke	169	122 (72.2)	47 (27.8)
	Head Trauma	82	66 (80.5)	16 (19.5)
	Other	8	5 (62.5)	3 (37.5)

Table 3.3 summarizes all the factors related to NOK. The only variables associated to family are relationship of family to deceased donor and their gender. Out of 552 approaches, the highest sample size is among sister of deceased donor. For majority of the approaches, sister is encountered many times as the NOK for organ

donation discussion. The highest consent rate is when the NOK is daughter and the lowest is among husband and mother. Similarly, if the NOK gender is male then it is less likely to get family consent compared to female. The highest consent rate is found among female NOK.

Table 3.3: NOK Characteristics Descriptive Statistics

Factor		**N**	**Consent n (%)**	**No Consent n (%)**
Relationship	Brother	39	29 (74.4)	10 (25.6)
	Daughter	143	118 (82.5)	25 (17.5)
	Father	79	60 (75.9)	19 (24.1)
	Husband	152	108 (71.1)	44 (28.9)
	Mother	94	67 (71.3)	27 (28.7)
	Other	45	37 (82.2)	8 (17.8)
	Partner	231	173 (74.9)	58 (25.1)
	Sister	321	246 (76.7)	75 (23.3)
	Son	33	19 (57.6)	14 (42.4)
	Spouse	143	106 (74.1)	37 (25.9)
	Wife	171	135 (78.9)	36 (21.1)
Gender	Female	205	159 (77.6)	46 (22.4)
	Male	248	189 (76.2)	59 (23.8)
	Unknown	140	117 (83.6)	23 (16.4)

Table 3.4 summarizes all the factors related to hospitals. Caller title is the hospital staff who give call to OPO for organ and tissue referral of deceased donor. It is observed that for most of the time Medical Doctor (MD) and Registered Nurse (RN) give call to OPO. The highest consent rate of 87.5% is when Physician Assistant (PA) refers case by calling an OPO. Similarly, the lowest consent rate is when MD refers the case to OPO. There are many hospital units where patients are hospitalized. The highest number of referral comes from Intensive Care Unit (ICU). However, the highest consent rate of 83.1% is when the patient is hospitalized in Surgical Intensive

Care Unit (SICU). Similarly, hospital county also plays an important role in the organ donation. There are many hospitals located in different county. From the dataset, the OPO gets highest referral calls from New York county. Out of 552 approaches over the period of one and half years, there are 130 approaches from New York county. However, the highest consent rate is when the hospital is located at Suffolk county and the lowest when hospital is located in New York county. It is found that hospitals which are not associated to any health systems have highest consent rate of 80.6% compared to the lowest consent rate when the hospitals are affiliated to NYP HS Affiliates.

Table 3.4: Hospital Related Factor Descriptive Statistics

Factor		**N**	**Consent** n (%)	**No Consent** n (%)
Caller Title	MD	245	184 (75.1)	61 (24.9)
	PA	32	28 (87.5)	18 (25.0)
	RN	203	153 (75.4)	4 (12.5)
	Other	72	54 (75.0)	50 (24.6)
Hospital Unit	CCU	58	42 (72.4)	16 (27.6)
	ICU	114	92 (80.7)	22 (19.3)
	MICU	94	69 (73.4)	25 (26.6)
	PICU	26	20 (76.9)	6 (23.1)
	SICU	59	49 (83.1)	10 (16.9)
	Other	201	147 (73.1)	54 (26.9)
Hospital County	Bronx	110	87 (79.1)	23 (20.9)
	Kings	68	50 (73.5)	18 (26.5)
	Nassau	55	37 (67.3)	18 (32.7)
	New York	130	91 (70.0)	39 (30.0)
	Suffolk	74	64 (86.5)	10 (13.5)
	Westchester	53	38 (71.7)	15 (28.3)
	Other	62	52 (83.9)	10 (16.1)
Health System	HHC	109	84 (77.1)	25 (22.9)
	Montefiore HS	26	18 (69.2)	8 (30.8)
	Mount Sinai HS	46	33 (71.7)	13 (28.3)
	Mount Sinai HS Affiliates	35	25 (71.4)	10 (28.6)
	NSLIJ	53	40 (75.5)	13 (24.5)
	NYP HS	53	37 (69.8)	16 (30.2)
	NYP HS Affiliates	17	11 (64.7)	6 (35.3)
	Westchester Hospitals	43	34 (79.1)	9 (20.9)
	Other HS	170	137 (80.6)	33 (19.4)

There are many factors related to OPO, which affect consent from family for organ donation. Table 3.5 and 3.6 summarizes all the factors related to OPO. Out of 552 approaches, there are 48 approaches where OPO staff have no conversation with family before formal approach date. Therefore, the consent rate is the lowest, 39.6%. Similarly, for all the approaches where there are three or more than three approaches, the consent rate is highest, 93.2%. This means number of conversations with family before formal approach date is directly proportional to the consent rate. So, in order to increase the consent rate, it is recommended to have more number of conversations with family before discussing directly with family about organ donation. Similarly, number of staff involved per case with family before formal approach date is also directly proportional to consent rate. The highest consent rate of 78.8% when at least 4 OPO staff are involved in the approach. Similarly, the lowest consent rate, as expected, is among the cases where there is only 1 staff involved with the cases. When family and hospital staff are not involved in the initial mention of organ donation, there is higher consent rate.

Similarly, there are 498 approaches made by Family Service Coordinator (FSC), which has the consent rate of 75.7%. This shows that most of the approaches are made by FSC. However, the approach made by Donor Evaluation Coordinator (DEC) have the highest consent rate of 84.0%. Team Long Island (L) has the highest consent rate of 78.4% and team city has the lowest consent rate of 72.9%. Whenever there is Care Team Brief (CTB) for approaches, there is higher consent rate. Out of 552 approaches, there are 516 cases where CTW are done. Private setting yields higher consent rate of 77.2% compared to talking to family in the public place without concerning too much about privacy of the deceased donor.

Similarly, if the donation is mentioned prior to deceased death, referral, and family arrival, then there is less likely to get consent from family. If the OPO involves hospital, there is higher chance of getting no consent from family as the hospital staff are not well trained to approach family for organ donation.

Table 3.7 summarizes all the additional continuous factors used in this research related to OPO. Referral to first staff onsite are calculated by subtracting the first staff onsite date from date of referral. The recorded measurement is in hours. The highest number of approaches are between 2.1 and 3.0. For for many approaches, staff reach onsite (donor hospital) with 3 hours of the referral by hospital staff to OPO. The highest consent rate of 83.1% when staff reach onsite within one hour of case referral. The lowest consent rate is among hour group of more than 7 hours of referral. Similarly, the highest consent rate is when family is formally approached for organ donation within 6 days of referral by hospital staff. The consent rate is lowest when number of days between referral and formal approach time reach more than 7 days.

Table 3.5: OPO Related Factors Descriptive Statistics 1

Factor		**N**	**Consent** n (%)	**No Consent** n (%)
# Conversation	0	48	19 (39.6)	29 (60.4)
	1	283	200 (70.7)	83 (29.3)
	2	162	145 (89.5)	17 (10.5)
	3+	59	55 (93.2)	4 (6.8)
# Staff Involved	1	32	21 (65.6)	11 (34.4)
	2	87	67 (77.0)	20 (23.0)
	3	103	77 (74.8)	26 (25.2)
	4	85	67 (78.8)	18 (21.2)
	5	60	44 (73.3)	16 (26.7)
	6	61	48 (78.7)	13 (21.3)
	7+	124	95 (76.6)	29 (23.4)
DSA	No	9	5 (55.6)	4 (44.4)
	Yes	543	415 (76.4)	129 (23.8)
Initial Mention By	Family	79	69 (87.3)	10 (12.7)
	HospitalStaff	47	27 (57.4)	20 (42.6)
	NoPreviousMention	419	316 (75.4)	103 (24.6)
	Other	7	7 (100.0)	0 (0.0)
Formal Request By	DEC	25	21 (84.0)	4 (16.0)
	FSC	498	377 (75.7)	121 (24.3)
	Other	29	21 (72.4)	8 (27.6)
Team	C	192	140 (72.9)	52 (27.1)
	L	139	109 (78.4)	30 (21.6)
	N	221	170 (76.9)	51 (23.1)
CTB	No	36	20 (55.6)	16 (44.4)
	Yes	516	399 (77.3)	117 (22.7)
Private Setting	No	9	0 (0.0)	9 (100.0)
	Yes	543	419 (77.2)	124 (22.8)

Table 3.6: OPO Related Factors Descriptive Statistics 2

Factor		**N**	**Consent n (%)**	**No Consent n (%)**
Donation Mention Prior To Deceased Death	No	506	387 (76.5)	119 (23.5)
	Yes	46	32 (69.6)	14 (30.4)
Donation Discuss Prior to Referral	No	524	401 (76.5)	123 (23.5)
	Yes	28	18 (64.3)	10 (35.7)
Donation Mention Prior to Family Arrival	No	508	388 (76.4)	120 (23.6)
	Yes	44	31 (70.5)	13 (29.5)
Donation Discuss Prior to OPO Speaking With Family	No	484	372 (76.9)	112 (23.1)
	Yes	68	47 (69.1)	21 (30.9)
OPO Involve Hospital	No	9	8 (88.9)	1 (11.1)
	Yes	543	411 (75.7)	132 (24.3)
NOK Identified	No	1	0 (0.0)	1 (100.0)
	Yes	551	419 (76.0)	132 (24.0)
NOK Available	No	6	3 (50.0)	3 (50.0)
	Yes	546	416 (76.2)	130 (23.8)
Discuss Benefits	No	15	2 (13.3)	13 (86.7)
	Yes	537	417 (77.7)	120 (22.3)

Table 3.7: OPO Related Factors Descriptive Statistics 3

Factor		**N**	**Consent** n (%)	**No Consent** n (%)
Referral to Staff Onsite (hrs.)	<0	12	9 (75.0)	3 (25.0)
	0-1.0	59	49 (83.1)	10 (16.9)
	1.1-2.0	131	95 (72.5)	36 (27.5)
	2.1-3.0	141	116 (82.3)	25 (17.7)
	3.1-4.0	89	63 (70.8)	26 (29.2)
	4.1-5.0	46	32 (69.6)	14 (30.4)
	5.1-6.0	19	14 (73.7)	5 (26.3)
	6.1-7.0	17	13 (76.5)	4 (23.5)
	7+	38	28 (73.7)	10 (26.3)
Referral to Formal	0-8.0 hrs.	55	38 (69.1)	17 (30.9)
	8.1-12.0 hrs.	24	17 (70.8)	7 (29.2)
	12.1-24.0 hrs.	73	54 (74.0)	19 (26.0)
	2 days	137	113 (82.5)	24 (17.5)
	3 days	92	69 (75.0)	23 (25.0)
	4 days	67	53 (79.1)	14 (20.9)
	5 days	34	24 (70.6)	10 (29.4)
	6 days	20	18 (90.0)	2 (10.0)
	7 days	9	5 (55.6)	4 (44.4)
	7+ days	41	28 (68.3)	13 (31.7)

There are many OPO related timing factors which affect family consent. For example, time difference between patient is admitted in the hospital and when the clinical trigger is met is one example of timing factor which affects family consent. Table 3.8 summarizes average hours between two different timings for both consented and declined approaches. The average hours between admission and clinical trigger met is 15.5 hours for consented approaches and 18.4 hours for approaches family declined consent for organ donation. Similarly, hospital refers the case to OPO in 8 hours after clinical trigger is met for consented cases. However, for declined approaches, the average hours is 9.8. Early interaction to formal approach average hour is same for both consented and declined approaches. This may be due to the fact that many approaches time difference between early interaction and formal approach is less than or equal to 5 hours. Due to this, average hours is skewed and hence, there is no difference between consented and declined approaches.

Table 3.8: Time Difference Between Consented and Declined Approaches

Timing	**Avg. Hours**	
	Consented	**Declined**
Admission to Clinical Trigger	15.5	18.4
Clinical Trigger to Referral	8.0	9.8
Referral to First Staff Onsite	2.6	2.7
First Staff Onsite to Early Interaction	41.6	39.8
Early Interaction to Formal Approach	0.1	0.1

After analyzing average hours between different timings for consented and declined approaches, it is also important to get more insights by analyzing the time differences where there are statistical significant differences. Based on statistical significance and frequency distribution, hours are grouped into different categories for all the timing related factors. Table 3.9 summarizes timing factors which have statistical significance in time differences. First, if the referral is made within 24 hours after patient is admitted to the hospital then there is higher chance of getting consent for organ donation. There are 886 approaches where referral is made within 24 hours of patient admission in the hospital. Similarly, referral made after 24 hours of patient admission has lower consent rate of 36.8%. Unfortunately, there is higher approaches for this scenario. Second, referral made before clinical trigger is met has consent rate of 51.3%, which is the second highest. The standard time between clinical trigger met and referral is one hour. As shown in Table 3.9, there are only 170 approaches which meet the standard. Referral made within 7 hours of clinical trigger is associated with highest consent rate of 53.7%. After conducting statistical testing using two proportion $z-test$ it is found there is statistical significant difference between referral made within 7 hours and after 7 hours of clinical trigger is met. Thus, it is recommended to refer case within 7 hours of clinical trigger. For formal approach and Brain Dead (BD) declaration analysis, only BD approaches are taken into consideration. There are 1,506 brain dead approaches out of 2,079. Formal approach before BD declaration consent rate is calculated by using total number of consents as numerator and total BD approaches as denominator. For formal approach after BD approaches, consent rate denominator is considered as the total number of BD approaches where formal approaches were not before BD declaration.

Table 3.9: Statistical Difference in OD Timings

		Approaches	**CR (%)**	**P-Value**
Admission to Referral	0-24 hrs.	886	47.7	<0.05
	>24 hrs.	1,149	36.8	
Clinical Trigger to Referral	<0 hrs.	351	51.3	<0.05
	0-1 hrs.	170	45.3	
	1.1-7 hrs.	419	53.7	
	>7 hrs.	759	44.8	
Formal Approach	Before BD (17.5 hrs.)	219	29.3	<0.05
	After BD (7.4 hrs.)	391	51.6	
Referral to First Staff Onsite	0-4 hrs.	1,457	44.3	<0.05
	>4 hrs.	289	35.9	
First Staff Onsite to Formal Approach	0-24 hrs.	621	41.6	<0.05
	>24 hrs.	1,041	46.8	
# Conversation before Formal Approach	No Conversation	456	37.5	<0.05
	1	590	44.9	
	>1	355	59.3	

3.3 Early Interaction Analysis

Early interaction with family is considered one of the best practices in the world of organ donation to support family in every possible ways. There are many OPOs in the United States, who are practicing Early Interaction with family to maximize the consent from family for organ donation. Early Interaction is also known as Early support in some OPOs. Supporting family before approaching them to discuss about organ donation is directly related to higher consent rate. Therefore, **LiveOn**NY has also started Early Interaction program since August, 2016. Early Interaction analysis has been conducted in this research to examine it's effect on the overall consent rate. Section 3.3.1 describes history of early interaction based on literature review.

3.3.1 History of Early Interaction

Early in 2010, Virginia based OPO, LifeNet Health, began a program to utilize donor family volunteers in the preapproach consent huddle which occurs prior to discussing organ donation with potential donor families. The role of the donor family volunteer was to listen to the coordinator describe the situation that the potential donor family was faced with and for the donor family volunteer to share their perspective as someone who had been in a similar situationhearing the news that their loved one was brain dead and receiving information about the opportunity to save lives through organ donation. After one particularly busy 24 hour period where one donor family volunteer participated in three consent huddles with three different coordinators at three different hospitals, LifeNet Health received this critically important feedback:

"I don't understand why you wait so long to begin supporting these families. If you

know they are going to hear the worst news imaginable, why dont you start supporting them before that happens? Waiting for my daughter to be declared brain dead was the worst three days of my life. Then the coordinator walked in and started supporting me and I felt better."

Other donor family volunteers had voiced similar concerns about OPO waiting so long to start support of the families of potential organ donors. Organizationally, LifeNet Health really did not have an answer to this question. They knew that early support of organ donor families increased the likelihood of the family consenting to donation. They also knew that that early support of donor families is a nationally recognized best practice common among organ procurement organizations achieving and exceeding the CMS required 75% conversion rate. Furthermore, they were also aware of the fact that there is published literature supporting this practice, but have yet to integrate this early support model into the care they provide. LifeNet Health had implemented all of the best practices surrounding consent except for early support of potential donor families. They had worked collaboratively with donor hospitals to incorporate these other best practices and yet had made only incremental progress toward achieving the 75% conversion rate.

The primary impediment to implementing this practice was resistance from donor hospitals. Donor hospitals felt that caring for potential donor families is the responsibility of the hospital and that they do it well. While many hospitals did this well, the available evidence indicated that early support of donor families by specially trained OPO staff was the right thing to do for potential donor families, it was the right thing for the patients on the waiting list and it was the right thing to do for hospitals and the communities they serve.

In 2003, the organ donation and transplant community partnered with the Health Resources and Services Administration (HRSA) and the Institute for Healthcare Improvement (IHI) to increase the number of organ donors recovered and the number of organs available for transplantation. The three estates, donor hospitals, OPO, and transplant centers began implementing best practices involving early referral and support of potential deceased organ donors to maintain organ function, support of potential deceased organ donor families to maximize consent, and engagement of transplant centers to increase organ acceptance and transplantation (Shafer et al., 2006).

In 2006, as part of this initiative to increase the number of donors and lives saved, LifeNet Health implemented role specialization, carving out the process of potential donor family support as a standalone position within the Clinical Services division. Prior to the implementation of the Family Support Coordinator (FSC) position, the responsibility for supporting donor families and obtaining consent fell within the roles and responsibilities of the clinical transplant coordinator staff. They felt that assigning the primary responsibility for obtaining consent to a specialized group focusing on family support would allow them to recruit individuals with a skill set unique to the role. These individuals would then interact with potential donor families more frequently than transplant coordinators in the older generalist model, and would allow the organization to better measure and improve consent performance. The clinical transplant coordinator staff felt that they were pulled in many directions trying to simultaneously manage hospital processes, potential donor care and the needs of grieving families, never feeling as they they were able to master any one of these distinct roles. Their result shows that they have at times exceeded the 75% conversion rate benchmark established by CMS, but that they have not yet achieved the goal of sustaining the conversion rate. The linear regression indicates that they were making incremental progress; however, the variations from month to month indicated that there were other factors beyond the need for role specialization that influence or impeded the ability of their Family Support Coordinator staff to obtain consent for donation.

LifeNet Health had undertaken training to equip our staff with the necessary tools to discuss the first three barriers identified by the authors. They have partnered with Eastern Virginia Medical School Theresa A. Thomas Professional Skills Training Center to develop scenariobased role play training using standardized patients who serve as NOK. All clinical staff, including family support coordinators and clinical transplant coordinators, attended the training on a biannual basis. The attendees were provided with individualized checklist scores completed by the standardized NOKs and teaching associates.

On October 6, 2010, LifeNet Health convened a consent performance improvement team composed of Family Support Coordinators, Transplant Coordinators, Team Leaders, Clinical Services Managers, the Manager of Hospital Services, and the Director of Clinical Services. They reviewed the data provided earlier in this paper with regard to the persistent frequency of donation prementions and the impact of this on the nonregistered consent rate numbers year to date. They felt a tremendous sense of urgency to immediately address the low consent and conversion rate numbers and the lack of available organs for transplantationthis was their obligation to the patients on the waiting list. They could not continue to work the same way they had in the past. Working together, the team developed a referral and family support strategy to improve communication with physicians and optimize family support opportunities. As they had done for the last six years, they employed the Plan, Do, Study, Act methodology for improvement (PDSA, also known as the Deming Cycle (Deming, 1986)), which allowed for rapid change with short test cycles. They had five years worth of data that showed only incremental improvement and the team agreed that adopting the practice of early support of donor families was an urgent imperative.

3.3.2 Early Interaction at LiveOnNY

LiveOnNY is a New York city based OPO involved actively in the organ donation and procurement process. In August 2016, they started Early Interaction program with the goal of increasing consent from family for organ donation. According to them Early Interaction is also referred as early support. Early support or Early Interaction is defined as psycho, social support of potential organ donor families to facilitate a relationship, assist the family with coping and assist with hospital logistics. It is basically a tool to facilitate a team approach with the hospital care team when support families. It is a proven way to improve consent rate. Early support can be started at anytime after the referral of a potential organ donor, if a family need is identified. Early support can be provided to family in many forms. Some of them are listed below:

- Simply listen to the family and encourage them to share stories about their loved ones
- Help them identify ways to cope with their feelings
- Encourage self care
- Encourage support each other
- Make sure the family members are eating and drinking, and getting rest
- Help facilitate extended visiting hours
- Help facilitate access to resources within the hospital
- Help facilitate spiritual support

- If there are small children, offer to watch the children so parents can visit their family member
- Be an advocate for the family and a liaison to the hospital staff

The official onsite staff training started in August 2016. Since then, every onsite at the hospital from **LiveOn**NY encouraged to do early interaction for all the cases. All the fields such as initial contact with family date, grave prognosis date, etc. are recored in the database. These fields are created after introducing the early interaction program in August 2016. There was another intense follow-up staff training for early interaction occurred in August 2017 followed by another training in January 2018.

Phase I considers all the approaches between August 2016 and July 2017. There are 925 approaches, out of which 146 approaches have Early Interaction and 199 approaches do not have early interaction with family before formal approach. Phase II includes all the approaches made with family between August and December 2017. There are 396 approaches, out of which 149 have early interaction and 67 do not have any interaction with family before formal approach. For phase III, all the approaches between January and April 2018 are included. There are 275 approaches in which 121 have Early Interaction while there are only 19 cases where Early Interaction do not happen. Table 3.10 summarizes consent rate for all three phases for both Early and Not Early Interaction approaches. Consent rate is significantly higher for EI approaches.

Table 3.10: Consent rate Comparison for EI and Not EI

Phase	**EI (CR)**	**Not EI (CR)**
I	59.6%	10.6%
II	61.7%	4.5%
III	50.4%	10.5%

After analyzing at consent rate, it is important track progress of early interaction. Figure 3.4 illustrates progress for different measures for EI analysis. The percentage of approaches where EI happen increased from phase EI_1 to EI_2. However, in EI_2 the percentage of EI approaches decreases to 50.4%. Even though there is increase in the number of Early Interaction, there is significant reduction in data entry errors. Data entry errors included all those approaches, where Initial Contact with AP date is recorded after Formal Approach date. 45.4% of all the approaches in phase I have data entry errors, while in EI_3 there is only 25.8%. This is the result of staff training. Similarly, there are many approaches where the organ outcome is No Authorization, staff do not record Initial Contact with AP date. One of the components of the staff training is to record AP dates for every approaches. Therefore, there is significant reduction in percentage of AP missing dates.

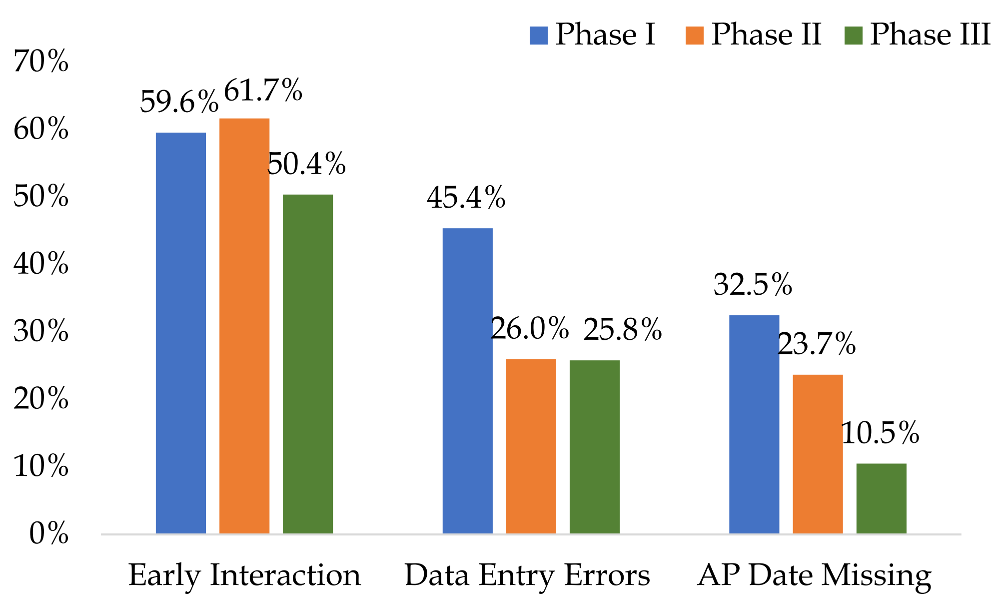

Figure 3.4: Early Interaction Phase Comparison

3.4 Data Preprocessing

Some attributes and records are removed due to higher number of missing values and incorrect values. For this research, all the survey administration variables are removed except the region attribute since one objective of this research is to investigate the predictive ability of the family consent attributes. Before starting with feature selection, removing missing values and incorrect records is a major step of data preprocessing since if missing values remain in dataset, the development of the model will be affected. For example, when missing values are present in the input file to the neural network, they can be interpreted as valid input values rather than missing values since the prediction model cannot recognize that these are missing values. Similar trend follows for outliers or incorrect values. The attribute of family consent for organ donation is categorized as consent yes and consent no.

3.5 Prediction Models

The focus of this research is is predicting family consent for organ donation to increase number of donors to save lives of more than 100,000 people who are on waiting lists for organ transplantation. There are some controllable and uncontrollable variables. In this research, several data mining methods were used to build prediction models and compare the performance of of many models and chose the one that provides better accuracy and results. For this type of dataset there are few researchers who had used data mining methods to see the predictability and important feature selection. This study uses several machine learning models and come up with the best model to predict the family approach outcome for organ donation.

3.5.1 Logistic Regression

Logistic regression is one of the most widely spread statistical models for making prediction and multivariate analysis. It is a type of multiple regression, and its main purpose is to analyze the interaction between multiple independent variables (also called predictors) and the dependent variables. The probability of the event occurring for a particular subject can be evaluated with the help of binary logistic regression..Consider the data set, where the response default falls into one of two categories, Yes or No. Logistic regression models the probability that Y belongs to a particular category (Hastie et al., 2009). The regression problem can be formulated in another way: continuous variable can be predicted with the values within the interval of instead of predicting a binary variable, for all values of the independent variables. This can be achieved by using a equation (logit transform).

Logistic regression is approached by learning from function as $p(y/x)$. Y is discrete value, and x is a vector that includes discrete or continuous values. The algorithm is directly estimating parameters from training data.

$$log \frac{p(x)}{1 - p(x)} = \beta_o + x\beta \tag{3.7}$$

$$P(x; b, w) = \frac{e^{\beta_o + x\beta}}{1 + e^{\beta_o + x\beta}} \tag{3.8}$$

$$P(Y = 1|X) = \frac{1}{1 + e^{w_o + \sum_{i=1}^{n} w_i x_i}} \tag{3.9}$$

$$P(Y = 1|X) = \frac{e^{w_o + \sum_{i=1}^{n} w_i x_i}}{1 + e^{w_o + \sum_{i=1}^{n} w_i x_i}} \tag{3.10}$$

As shown in Equation (3.10), logistic regression is similar to linear regression model except few difference in output. For example, in classification, it is required to classify output. Logistic regression classify output by using Equation (3.10). In this method, there is binary classification as $y = 1$ and $y = 0$. By using logistic regression equation, the algorithm determines probability. Afterwards, the algorithm classifies the testing value by using threshold. After optimizing the parameters of equations, it is time to predict output of testing data (Gray et al., 2016). The Logistic Regression is a linear classifier on x value. At the same time, the LR is a function approximation algorithm to use training data to directly estimate $p(y = x)$(Gray et al., 2016).

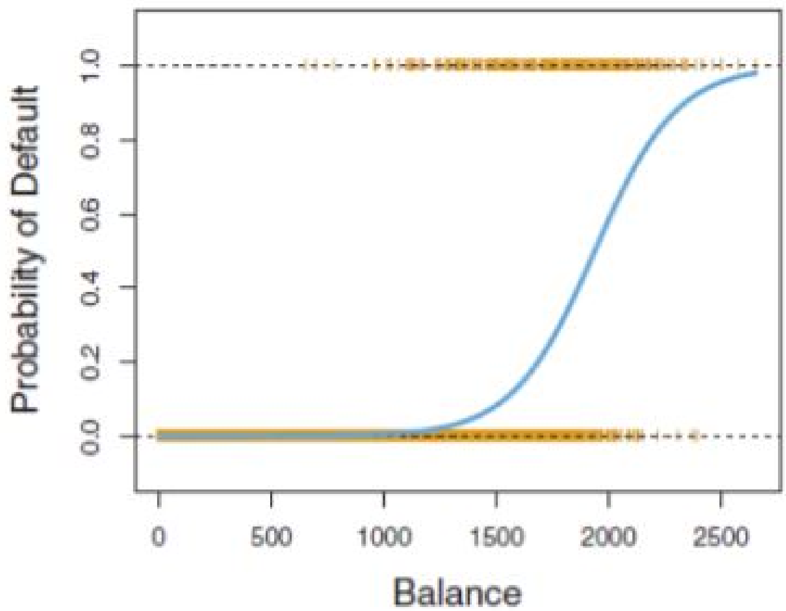

Figure 3.5: Predicted Probabilities of Default by Logistic Regression

Image Source: Adapted from (James et al., 2013)

3.5.2 Naive Bayes

Naive Bayes algorithm is supervised machine learning technique used for classification. It is a simple method based on Bayes theorem. It is a probabilistic statistical classifier used to determine the probability of the outcomes (Dey et al., 2016). The word Nave specifies the assumption of conditional independence among different features or attributes. This assumption greatly helps in reducing the computational complexity to simple probability multiplication (Yoo et al., 2012). To select a label for an input value, first prior probability of every label is calculated by obtaining the frequency of each label in the training dataset. The influence of each attribute is joined with this prior probability to get a likelihood estimate for every label. The label with highest likelihood is then given to the input value (Han et al., 2011). Since the classifier considers calculation of frequencies of attributes in training dataset, it requires small set of training data to arrive at accurate parameter estimator. The main disadvantage of this method is the fundamental assumption which considers that all the attributes are independent. This assumption is unrealistic as in most of the real-world problems the features are often dependent on each other. For instance, in the healthcare sector, health conditions of patients and various patient symptoms are highly related with each other, which may cause deviations in the classification results. Despite this assumption, Nave Bayes classifier produces good performance in terms of classification accuracy.

This algorithm is a generative-based model because features are produced independently. It is the simplest model for a machine-learning algorithm. But it also works well for real-world applications. The algorithm considers an unknown target function as $p(y = x)$. In order to learn, $P(y = x)$ is used in training data to calculate $p(x = y)$ and $p(y)$. Probability is calculated using $p(y = x)$ as seen in Equation (3.11) (Dai et al., 2015).

$$P(Y = y_i|X = x_k) = \frac{P(X = x_k|Y = y_i)p(Y = y_i)}{\sum_j P(X = x_k|Y = y_i)p(Y = y_{i)}} \tag{3.11}$$

For instance, in order to classify output y, the algorithm is using prior distribution $p(y)$. Afterwards, a sequence of events is made by selecting each event independently from conditional distribution $p(x = y)$. (An event could be repeated many times). Prior distribution $p(y)$ and conditional distribution $p(x = y)$ can be calculated from the training data set. The algorithm can make predictions for the test set by pondering at likelihoods from distributions. At the same time, parameters can be estimated using maximum likelihood or Bayesian estimates. Alternatively, a smoothed estimate can be used (Dai et al., 2015).

3.5.3 Decision Tree

A Decision Tree is a classification technique that focuses on an easily understandable representation form and is one of the most common learning methods. Decision Trees use data sets that consist of attribute vectors, which in turn contain a set of classification attributes describing the vector and a class attribute assigning the data entry to a certain class. A Decision Tree is built by iteratively splitting the data set on the attribute that separates the data as well as possible into the different existing classes until a certain stop criterion is reached. The representation form enables users to get a quick overview of the data, since Decision Trees can easily be visualized in a tree structured format, which is easy to understand for humans.

Decision tree classifier is a simple flowchart-like tree. It is one of the most practical and widely used algorithm. Decision tree construction follows top down approach by recursively employing divide and conquer method (Yoo et al., 2012). It classifies the instances by sorting them from the root node to a particular leaf node which corresponds to the classification result of a given instance. Every node in the tree is test of certain attribute, and each branch from a node will correspond to one of the probable values for that attribute. Classification of an instance is performed by starting from the root node, attribute defined by this node is tested, and then corresponding to the value of the attribute further nodes are tested. This process of testing the node and moving down the decision tree branch is repeated for subtree of the new nodes. To select the best attribute that is useful for classifying, statistical property called information gain is used, this measure helps in selecting candidate attribute at each node while growing the tree (Mitchell, 1997). Decision tree construction is training step of classification. Learned tree can be converted to if -then rules to enhance the human readability (Mitchell, 1997). Advantage of this algorithm is that it provides good visualization of the data enabling better understanding of overall data structure and major disadvantage is decision tree becomes complex when the number of attributes to be considered is very large. Tree pruning is one of the method to overcome this problem. It also resolves problem of overfitting (Yoo et al., 2012).

One of the first algorithms concerning Decision Tree training were the Iterative Dichotomiser 3 (ID3) and its successor the C4.5 algorithm, both developed by Ross Quinlan in 1986 and 1993 (Quinlan, 1986, Salzberg, 1994). These algorithms formed the basis for many further developments. Decision trees are directed trees, which are used as a decision support tool. They represent decision rules and illustrate successive decisions. In Decision Trees, nodes can be separated into the root node, inner nodes, and end nodes, also called leafs. The root node represents the start of the decision support process and has no incoming edges. The inner nodes have exactly one incoming edge and have at least two outgoing edges. They contain a test based on an attribute of the data set (Liu and Özsu, 2009). For instance, such a test might ask: Is the customer older than 35 for the attribute age?. Leaf nodes consist of an answer to the decision problem, which is mostly represented by a class prediction. As an example, a decision problem might be the question whether a customer in an online shop will make a purchase or not, with the class predictions being yes and no. Leaf nodes have no outgoing and exactly one incoming edge. Edges represent the decision taken from the previous node.

Given a node n, all following nodes that are separated by exactly one edge to n are called children of n, while n is called parent of all its child nodes.Training a Decision Tree is a common data mining method that is mainly used for classification purposes. Its goal is to predict the value of a target attribute, based on a number of input attributes. Training a Decision Tree in a supervised scenario is done by using a training set to find patterns within the data and build the Decision Tree. Afterwards, a set of previously unseen examples can be used to predict their target attributes value.

Training a Decision Tree is a common data mining method that is mainly used for classification purposes. Its goal is to predict the value of a target attribute, based on a number of input attributes. Training a Decision Tree in a supervised scenario is done by using a training set to find patterns within the data and build the Decision Tree. Afterwards, a set of previously unseen examples can be used to predict their target attributes value.

In order to train a Decision Tree and thereby create a classifier, a training set is needed containing a target attribute, input attributes, a split criterion and a stop criterion. At a given node, the split criterion calculates a value for all attributes. This value represents a measure of the amount of information that is gained by splitting the node using this attribute. Afterwards, the best value from all attributes is taken and the node is split into the different outcomes of the respective attribute. At this point, the process of finding the best split among the attributes is applied recursively to all generated sub trees until a stop criterion is reached.Common stop criteria are:

- The maximum height of the tree has been reached.
- The number of records in the node is less than the allowed minimum.

- The best split criterion does not overcome a certain threshold in terms of gained information.

If the splitting attribute is of numeric type there is no possibility to split the records into all outcomes of the attribute. This is one of the main upgrades of the C4.5 Decision Tree compared to the ID3. The C4.5 is additionally able to calculate the best splitting points for numeric attributes as well and split them by using greater than or equal and smaller than operators. Training a Decision Tree with this automated process can result in large Decision Trees with sections of very little power in terms of classification. Additionally, trees tend to be overfitted, which means that they fit the training instances too closely. This results in bad performances when these trees are applied to unseen data. Therefore, a technique called pruning has been developed. Its objective is to remove the less or non-productive parts from the Decision Tree, such as parts based on noisy or erroneous data or parts that are overfitted. This often results in further improvements in terms of accuracy and shrinks down the tree size. This process is especially important, due to the fact that every realworld data set contains erroneous or noisy data.

After training a Decision Tree, the tree is used in order to predict the class labels for unseen data records. To do so, the record is passed down from the root node to a leaf testing the corresponding attribute at each node and following the edges to the appropriate leaf. The algorithm starts by testing whether the stop criterion has been reached or not. If so, the current Node is labeled with the most common value of all existing class labels for the training set. If the stop criterion is not true, the algorithm calculates the split value for all attributes and labels the node with the attribute corresponding to the best split value. Afterwards, it splits the node into multiple nodes, one for each value of the chosen attribute. The algorithm calls the same process recursively for all training subsets, containing all data records with the corresponding value of the chosen attribute.

3.5.4 Random Forest

Random forest is an algorithm for classification developed by Leo Breiman that uses an ensemble of classification trees (Breiman et al., 1984, Breiman, 2001, Friedman et al., 2001, Ripley, 2007). Each of the classification trees is built using a bootstrap sample of the data, and at each split candidate set of variables is a random subset of the variables. Thus, random forest uses both bagging (bootstrap aggregation), a successful approach for combining unstable learners,and random variable selection for tree building (Breiman, 1996, Friedman et al., 2001). Each tree is unpruned (grown fully), so as to obtain low-bias trees; at the same time, bagging and random variable selection result in low correlation of the individual trees. The algorithm yields an ensemble that can achieve both low bias and low variance (from averaging over a large ensemble of low-bias, high-variance but low correlation trees).

Random forest has excellent performance in classification tasks, comparable to other models. It has several characteristics that make it ideal for different types of dataset. It can be used when there are many more variables than observations. It can also be used both for two-class and multi-class problems of more than two classes. It has good predictive performance even when most predictive variables are noise, and therefore it does not require a pre-selection it shows strong robustness with respect to large feature sets (Hua et al., 2004). This classifier does not usually over-fit. It can handle a mixture of categorical and continuous variables and incorporates interactions among predictors or variables. The output class is invariant to monotone transformations of the predictors.

3.5.5 Extra Tree

The Extra-Tree method (stands for extremely randomized trees) is proposed by Geurts, Ernst, and Wehenskel, with the main objective of further randomizing tree building in the context of numerical input features, where the choice of the optimal cut-point is responsible for a large proportion of the variance of the induced tree (Geurts et al., 2006). With respect to random forests, the method drops the idea of using bootstrap copies of the learning sample, and instead of trying to find an optimal cut-point for each one of the K randomly chosen features at each node, it selects a cut-point at random. This idea is rather productive in the context of many problems characterized by a large number of numerical features varying more or less continuously: it leads often to increased accuracy thanks to its smoothing and at the same time significantly reduces computational burdens linked to the determination of optimal cut-points in standard trees and in random forests. From a statistical point of view, dropping the bootstrapping idea leads to an advantage in terms of bias, whereas the cut-point randomization has often an excellent variance reduction effect. This method has yielded state-of-the-art results in several high-dimensional complex problems. From a functional point of view, the Extra-Tree method produces piece-wise multilinear approximations, rather than the piece-wise constant ones of random forests (Geurts et al., 2006).

This method is similar to the Random Forests algorithm in the sense that it is based on selecting at each node a random subset of K features to decide on the split. Unlike in the Random Forests method, each tree is built from the complete learning sample (no bootstrap copying) and, most importantly, for each of the features (randomly selected at each interior node) a discretization threshold (cut-point) is selected at random to define a split, instead of choosing the best cut-point based on the local sample (as in Tree Bagging or in the Random Forests method). As a consequence, when K is fixed to one, the resulting tree structure is actually selected independently of the output labels of the training set. In practice, the algorithm only depends on a single main parameter, K. Good default values of K have been found empirically to be $K = \sqrt{2}$ for classification problems and $K = p$ for regression problems, where p is the number of input features (Geurts et al., 2006). Experiments show that this method is most of the time competitive with Random Forests in terms of accuracy, and sometimes superior (Geurts et al., 2006). Because it removes the need for the optimization of the discretization thresholds, it has also a clear advantage in terms of computing times and ease of implementation. The reader is referred to (Geurts et al., 2006) for a more formal description of the algorithm and a detailed discussion of its main features.

3.5.6 Bagging

Bagging is a machine learning ensemble meta-algorithm designed to improve the stability and accuracy of machine learning algorithms used in statistical classification and regression. It also reduces variance and helps to avoid over-fitting. Although it is usually applied to decision tree methods, it can be used with any type of method. Bagging is a special case of the model averaging approach. Bagging is also called bootstrap aggregating, which is proposed by Leo Breiman in 1994 to improve classification by combining classifications of randomly generated training sets (Breiman, 1996).

Given a standard training set D of size n, bagging generates m new training sets D_i , each of size n', by sampling from D uniformly and with replacement. By sampling with replacement, some observations may be repeated in each D_i. If $n' = n$, then for large n the set D_i is expected to have the fraction $(1 - 1/e)(\approx 63.2\%)$ of the unique examples of D_i the rest being duplicates (Aslam et al., 2007). This kind of sample is known as bootstrap sample. The m models are fitted using the above m bootstrap samples and combined by averaging the output (for regression) or voting (for classification). Bagging leads to "improvments for unstable procedures" (Breiman, 1996). This include, for example, artificial neural networks, classification and regression trees, and subset selection in linear regression. An interesting application of bagging showing improvement in preimage learning is provided in two papers (Sahu et al., 2011, Shinde et al., 2014). Bagging leads to "improvements for unstable procedures", which include, for example, artificial neural networks, classification and regression trees, and subset selection in linear regression(Breiman, 1996).

3.5.7 Gradient Boosting

Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.The idea of gradient boosting originated in the observation by Leo Breiman that boosting can be interpreted as an optimization algorithm on a suitable cost function (**?**). Explicit regression gradient boosting algorithms were subsequently developed by Jerome H. Friedman simultaneously with the more general functional gradient boosting perspective of Llew Mason, Jonathan Baxter, Peter Bartlett and Marcus Frean (Elder, 1999, Ridgeway, 1999, Mason et al., 2000). The latter two papers introduced the abstract view of boosting algorithms as iterative functional gradient descent algorithms. The algorithms optimize a cost function over function space by iteratively choosing a function (weak hypothesis) that points in the negative gradient direction. This functional gradient view of boosting has led to the development of boosting algorithms in many areas of machine learning and statistics beyond regression and classification.

Similar to other boosting methods, gradient boosting combines weak "learners" into a single strong learner in an iterative fashion. It is easiest to explain in the least-squares regression setting, where the goal is to "teach" a model F to predict values of the form $\hat{y} = F(x)$ by minimizing the mean squared error $(\hat{y} - y)^2$, averaged over some training set of actual values of the output variable y (**?**). At each stage m, $1 \leq m \leq M$, of gradient boosting, it may be assumed that there is some imperfect model F_m (at the outset, a very weak model that just predicts the mean y in the training set could be used. The gradient boosting algorithm improves on F_m by constructing a new model that adds an estimator h to provide a better model: $F_{m+1}(x) = F_x(x) + h(x)$. To find h, the gradient boosting solution starts with the observation that a perfect h would imply Equation (3.12) or Equation (3.13).

$$F_{m+1}(x) = F_m(x) + h(x) = y \tag{3.12}$$

or, equivalently,

$$h(x) = y - F_m(x) \tag{3.13}$$

3.5.8 Extreme Gradient Boosting (XGB)

XGB is a model designed and optimized for boosting trees algorithms (Song et al., 2016). Gradient boosting trees model is originally proposed by Friedman (Friedman et al., 2001). The underlying algorithm of XGB is similar to gradient boosting. Specifically, it is an extension of the classic gbm algorithm. It is used for supervised learning problems, where the training data (with multiple features) x_{i} is used to predict a target variable y_i. It is similar to gradient boosting framework but more efficient. It has both linear model solver and tree learning algorithms. This makes XGB at least 10 times faster than existing gradient boosting implementations. It supports various objective functions, including regression, classification and ranking. Since it is very high in predictive power but relatively slow with implementation, XGB becomes an ideal fit for many competitions. It also has additional features for doing cross validation and finding important variables. There are many parameters which need to be controlled to optimize the model.

While researching for better techniques for data analysis and prediction on-line, it is found that XGB gives much better performance results than Linear Regression or Random Forest Regression. XGB or Extreme Gradient Boosting is a library that is designed, and optimized for boosted (tree) algorithms, which aims to provide a scalable, portable and accurate framework for large scale tree boosting. It is an improvement on the existing Gradient Boosting technique. More importantly, it is developed with both deep consideration in terms of systems optimization and principles in machine learning. The goal of this library is to push the extreme of the computation limits of machines to provide a scalable, portable and accurate library.

XGB has become a widely used and really popular tool among Kaggle competitors and Data Scientists in industry, as it has been battle tested for production on large-scale problems. It is a highly flexible and versatile tool that can work through most regression, classification and ranking problems as well as user-built objective functions. As an open-source software, it is easily accessible and it may be used through different platforms and interfaces. The amazing portability and compatibility of the system permits its usage on all three Windows, Linux and OS X. It also supports training on distributed cloud platforms like AWS, Azure, GCE among others and it is easily connected to large-scale cloud data flow systems such as Flink and

Spark. Although it is built and initially used in the Command Line Interface (CLI) by its creator (Tianqi Chen), it can also be loaded and used in various languages and interfaces such as Python, C++, R, Julia, Scala and Java.

XGB is developed by Tianqi Chen and now is part of a wider collection of open-source libraries developed by the Distributed Machine Learning Community (DMLC). XGB is a scalable and accurate implementation of gradient boosting machines and it has proven to push the limits of computing power for boosted trees algorithms as it is built and developed for the sole purpose of model performance and computational speed. Specifically, it is engineered to exploit every bit of memory and hardware resources for tree boosting algorithms. The implementation of XGB offers several advanced features for model tuning, computing environments and algorithm enhancement. It is capable of performing the three main forms of gradient boosting (Gradient Boosting (GB), Stochastic GB and Regularized GB) and it is robust enough to support fine tuning and addition of regularization parameters. According to Tianqi Chen, the latter is what makes it superior and different to other libraries.

Chapter 4

Experimental Results and Analysis

The primary goal of this study is to identify the set of features significantly associated with family consent for organ donation and later evaluate the performance of the selected predictors variables on different types of machine learning models. The data is partitioned into training and test set. Training set consists of 80% of the data while testing consists of 20%.

4.1 Family Consent Prediction Models

Family Consent Prediction Models were built using six different types of ensemble machine learning algorithms. Since, the output class for this study is binary, all the models use in the model building process are classifiers. They are eXtreme Gradient Boosting, Gradient Boosting, Bagging, AdaBoost, Extra Tree, and Random Forest.

4.2 Models Comparison

In order to compare results of all the models, various performance measures are used. Accuracy and Area Under Curve (AUC) measures are used in this study to compare the performance of different models. As discussed in chapter 3, values for continuous variables are transformed using different methods. Data transformation is an important part of data pre-processing. Therefore, this study uses data transformation using different methods to find out if there is any effect on the performance measures. Performance measures are compared before and after data transformation. Table 4.1 shows the comparison of all the models for all the performance measures before doing any data transformation for training dataset. The result shows that Extra Tree accurately predict the training accuracy after training the model with 100% accuracy. Similarly, Table 4.2 shows testing score, in which eXtreme Grading Boosting (XGB) has highest AUC score. The training and testing performance measures are not close to each other. Therefore, there can be problem of over-fitting of the model. In order to avoid over-fitting, training and testing performance measures should be close to each other.

Table 4.1: Training Accuracy and AUC Score before Data Transformation

Classifier	**Accuracy**	**AUC**
eXtreme Gradient Boosting	0.9145	0.9824
Gradient Boosting	0.9456	0.9935
Bagging	0.9845	0.9973
AdaBoost	0.8705	0.9329
Extra Tree	1.0000	1.0000
Random Forest	0.9896	0.9996

Table 4.2: Testing Accuracy and AUC Score before Data Transformation

Classifier	**Accuracy**	**AUC**
eXtreme Gradient Boosting	0.8171	0.7620
Gradient Boosting	0.8049	0.7611
Bagging	0.7683	0.7059
AdaBoost	0.7561	0.5738
Extra Tree	0.7561	0.6814
Random Forest	0.8537	0.7090

Similarly, after transforming features using different transformation methods, the results as shown in Table 4.3 gives a slightly different result. Normalization of features values gave better result in terms of AUC. Overall results comparison show that data transformation gave better result using Normalization and function transformer using $Log1p$ methods. Therefore, this study decides to do transformation using normalization method for data pre-processing. Built in python library called *StandardScalar* is being used for normalization and library called Function Transformer is being used for $Log1p$. Tables 4.3 and 4.4 show that after transforming features using normalization methods performs better than using function transformer. Even though XGB performs better than other models after transforming data using $Log1p$ in terms of AUC score, overall performance of all other models performs better with Normalization methods of feature transformation.

Table 4.3: Testing Accuracy and AUC Score after Normalizing Data

Classifier	**Accuracy**	**AUC**
eXtreme Gradient Boosting	0.8049	0.7302
Gradient Boosting	0.7683	0.7118
Bagging	0.6707	0.5806
AdaBoost	0.8049	0.8087
Extra Tree	0.7683	0.6003
Random Forest	0.8171	0.6871

Table 4.4: Testing Accuracy and AUC Score after Using *Log*1*p* of Features

Classifier	Accuracy	AUC
eXtreme Gradient Boosting	0.8049	0.7987
Gradient Boosting	0.8049	0.7135
Bagging	0.7439	0.7456
AdaBoost	0.7927	0.7460
Extra Tree	0.7317	0.6153
Random Forest	0.7805	0.6934

In this Study, dimension reduction techniques such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are used to the see the effects on performance measures. Table 4.5 shows training accuracy and AUC scores for all the models after using LDA to reduce dimension of data. Similarly, Table 4.6 shows testing performance measures for after using LDA to reduce dimension of data. The result shows that except XGB all other classifiers are over-fitting the models because there is greater difference between training and testing accuracy.

Table 4.5: Training Accuracy and AUC Score after Using LDA

Classifier	Accuracy	AUC
eXtreme Gradient Boosting	0.8394	0.8950
Gradient Boosting	0.9145	0.9728
Bagging	0.9663	0.9954
AdaBoost	0.8187	0.8778
Extra Tree	1.0000	1.0000
Random Forest	0.9689	0.9954

Table 4.6: Testing Accuracy and AUC Score after Using LDA

Classifier	Accuracy	AUC
eXtreme Gradient Boosting	0.8171	0.8536
Gradient Boosting	0.8171	0.8325
Bagging	0.8049	0.8369
AdaBoost	0.8049	0.8125
Extra Tree	0.8171	0.7888
Random Forest	0.8049	0.8039

Similarly, PCA is used to reduce the dimension of data. In order to apply PCA, it is important to determine the optimal number of components to use in order to get better performance measures. Figure 4.1 illustrates component 1 vs. component 2 for output class of data. It shows that most of the output classes are clustered around one place. Figure 4.1 can be used to visualize the entire dataset into two components.

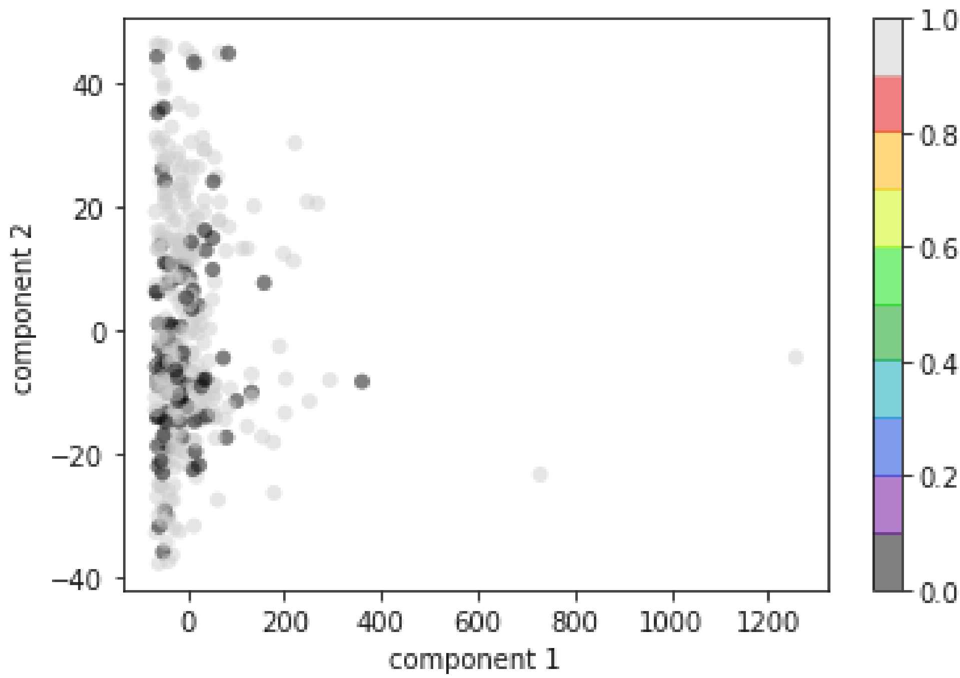

Figure 4.1: PCA Components for Data Output Class

Before using PCA, it is important to determine optimal number of components to reduce the data to thereby optimizing the performance measures. Figure 4.2 illustrates cumulative explained variance vs. number of components. It can be concluded that after 2 components explained variance gains stability. Therefore, two components can be used to capture all the explained variances of the data.

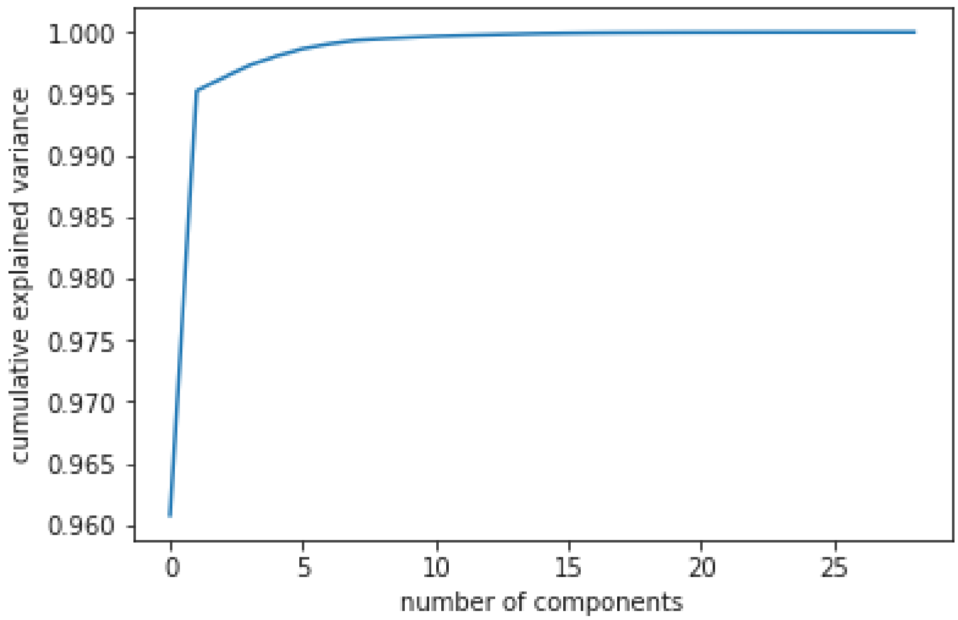

Figure 4.2: Number of PCA Components

Table 4.7 illustrates the performance measures after reducing dimension of features using PCA method using two components. The testing accuracy does not perform well compared to LDA. The highest accuracy obtained by using XGB is 70.73%. Therefore, this study decides to use LDA to reduce the dimension of data as it performed better than PCA.

Table 4.7: Testing Accuracy and AUC Score after Using PCA

Classifier	Accuracy	AUC
eXtreme Gradient Boosting	0.7073	0.6049
Gradient Boosting	0.7439	0.6739
Bagging	0.6585	0.6002
AdaBoost	0.7439	0.6843
Extra Tree	0.6585	0.6570
Random Forest	0.6585	0.5970

4.3 Best Model Selection

After comparing the performance measures of all the ten models, best performing algorithms are selected to do further tuning of parameters to improved accuracy and AUC score. Parameters for different models are optimized to get the best performance measures. Oversampling and under-sampling methods are using to calculate their effect on the performance measures.

4.3.1 Effect of Under and Over Sampling

Sampling data is an important part of preprocessing in machine learning method. There are two types of sampling in machine learning domain. They are under sampling and over sampling. These two techniques are data analysis techniques used to adjust the output class distribution of a data set. In other words, these methods are used to adjust the ratio between the different classes or categories represented. In this study, for over sampling of data, Synthetic Minority Over Sampling (SMOTE) technique is used to sample the training data to balance the output binary class distribution. Similarly, for under sampling, NearMiss method is used. Table 4.8 summarizes the accuracy and AUC score for each classifier after doing over sampling of training dataset using SMOTE method and Table 4.9 using NearMiss method. The result shows that over sampling method produces better result compared to under sampling. The highest accuracy is obtained using XGB classifier of 79.49%.

Table 4.8: Over Sampling Using SMOTE Method

Classifier	**Accuracy**	**AUC**
eXtreme Gradient Boosting	0.7949	0.6499
Gradient Boosting	0.7821	0.5916
Bagging	0.6538	0.6045
AdaBoost	0.7564	0.6961
Extra Tree	0.6795	0.7001
Random Forest	0.7179	0.5285

Table 4.9: Under Sampling Using NearMiss Method

Classifier	**Accuracy**	**AUC**
eXtreme Gradient Boosting	0.5128	0.6253
Gradient Boosting	0.5385	0.6395
Bagging	0.4872	0.5964
AdaBoost	0.4744	0.5858
Extra Tree	0.4872	0.6486
Random Forest	0.5128	0.6028

4.3.2 Parameter Tuning

Usually ML algorithms have parameters which need to be learned by analyzing at the data. There are however things which are not learned from the data and must be defined by the person using these algorithms. Since parameters are not learned, they are supplied by the programmer or scientist. These hyper parameters affect the performance of the model significantly and so finding the right values for these is important. This procedure of finding the right hyper parameters is called Parameter Tuning. In this study, all the ensemble machine learning models are chosen to do parameter tuning using grid search method inside sci-kit learn library in python. After parameters tuning performance measures are again compared to see the improved in the overall performance measures. Table 4.10 summarizes all the optimized parameters based on AUC score for all the models. With these parameters all the models are evaluated and the performance measures are listed in Table 4.11. The result shows that after using the optimized parameters, eXtreme Gradient Boosting model performs better than other models in terms of AUC score. All other models are also significantly improved after tuning the parameters.

Table 4.10: Tuned Parameters for all the Models

Parameter	**XGB**	**GB**	**Bagging**	**AB**	**ET**	**RF**
min_samples_leaf	N/A	17	N/A	N/A	6	18
min_samples_split	N/A	4	N/A	N/A	4	3
n_estimators	11	120	600	100	32	9
max_depth	5	3	N/A	N/A	7	2
max_features	N/A	auto	4	N/A	6	5
max_samples	N/A	N/A	3	N/A	N/A	N/A

Table 4.11: Performance Measures after Parameter Tuning

Classifier	**Accuracy**	**AUC**
eXtreme Gradient Boosting	0.8171	0.8946
Gradient Boosting	0.8005	0.8705
Bagging	0.7749	0.8049
AdaBoost	0.7638	0.8038
Extra Tree	0.7765	0.8465
Random Forest	0.7825	0.8325

4.3.3 Effect of Feature Selection

Feature selections are performed using XGB classifier. Before tuning the parameters the best performing model in terms of AUC score is XGB classifier. Therefore, feature importance rate are calculated using XGB classifier as shown in Figure 4.3. Out of 29 features 21 have importance rate greater than 0, which means the remaining 8 features are not important. Models are evaluated after selecting all important 21 features as shown in Figure 4.3.

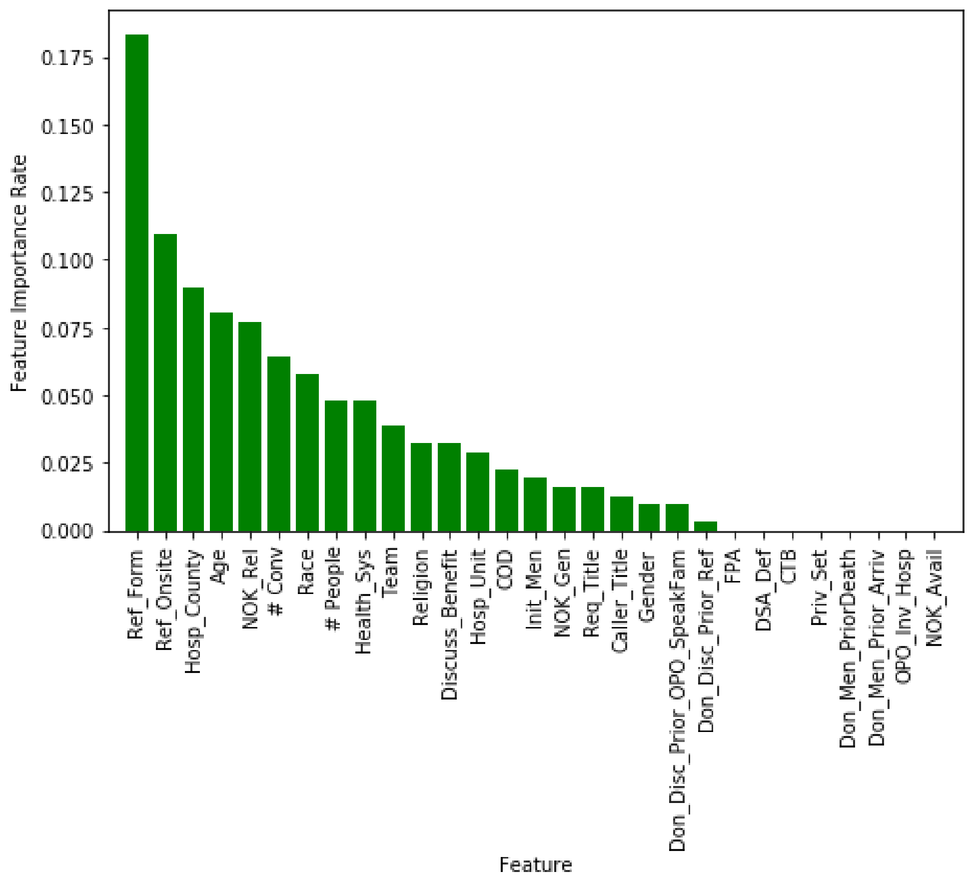

Figure 4.3: Feature Importance Rate by XGB Classifier

Table 4.12 shows the performance measures for all the 21 features. The Result shows that the models do not perform well after selecting the important features. The highest AUC score of 0.8494 is achieved using XGB classifier. Also, the models are evaluated selecting only top 10 important features using XGB classifier as shown in Table 4.13. The result shows that performance measures degrade after compared to results with 21 features. This is because some of the important informations captured by the model is lost when removing all the 11 features.

Table 4.12: Performance Measures with 21 Important Features

Classifier	Accuracy	AUC
eXtreme Gradient Boosting	0.8171	0.8494
Gradient Boosting	0.8080	0.8205
Bagging	0.7849	0.8228
AdaBoost	0.8059	0.8006
Extra Tree	0.7771	0.8157
Random Forest	0.8024	0.8257

Table 4.13: Performance Measures with top 10 Important Features

Classifier	Accuracy	AUC
eXtreme Gradient Boosting	0.7561	0.7585
Gradient Boosting	0.7927	0.7438
Bagging	0.8049	0.7467
AdaBoost	0.8049	0.7273
Extra Tree	0.8049	0.7689
Random Forest	0.8049	0.7197

4.3.4 Model Validation

In order to validate the models proposed, it is important to use cross-validation technique to validate the result. 10 folds cross validation is using to obtain the accuracy from validation datasets. Figure 4.3 illustrates box-plot for accuracy scores for different sets of 10 folds cross validation for all the models.

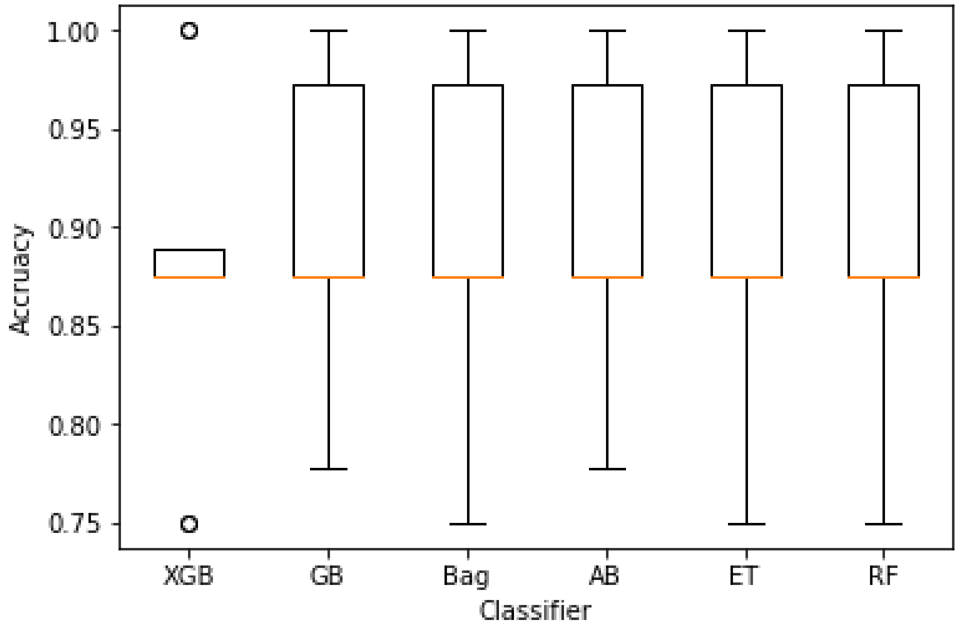

Figure 4.4: $10 - Fold$ Validation Accuracy

Table 4.14 summarizes all the average accuracy scores for all the classifiers. The highest achieved average accuracy of 83.78% is achieved by XGB model. These average scores are very close to accuracy obtained after reducing the dimension of data using LDA method. This shows that the model performs as expected.

Table 4.14: $10 - Fold$ Cross Validation Average Accuracy Scores

Classifier	**Accuracy (%)**
eXtreme Gradient Boosting	83.78
Gradient Boosting	80.42
Bagging	79.17
AdaBoost	77.41
Extra Tree	78.92
Random Forest	79.18

4.3.5 Model Application

After prediction model is built and validated, it is now important to see how can the model be used to solve real life problems. The proposed model in this study is applied in two different ways. Fist, this model can be used to dynamically calculate probability of getting family consent before formally approaching family as information are entered in the database by OPO staff. Figure 4.5 illustrates model accuracy as factors added. AFDR stands for available factors during referral. There are donor characteristics as well few other timing factors available when hospital refer case to OPO. When OPO staff arrive hospital more information about family and donor is acquired. Accuracy increases significantly after getting family information.

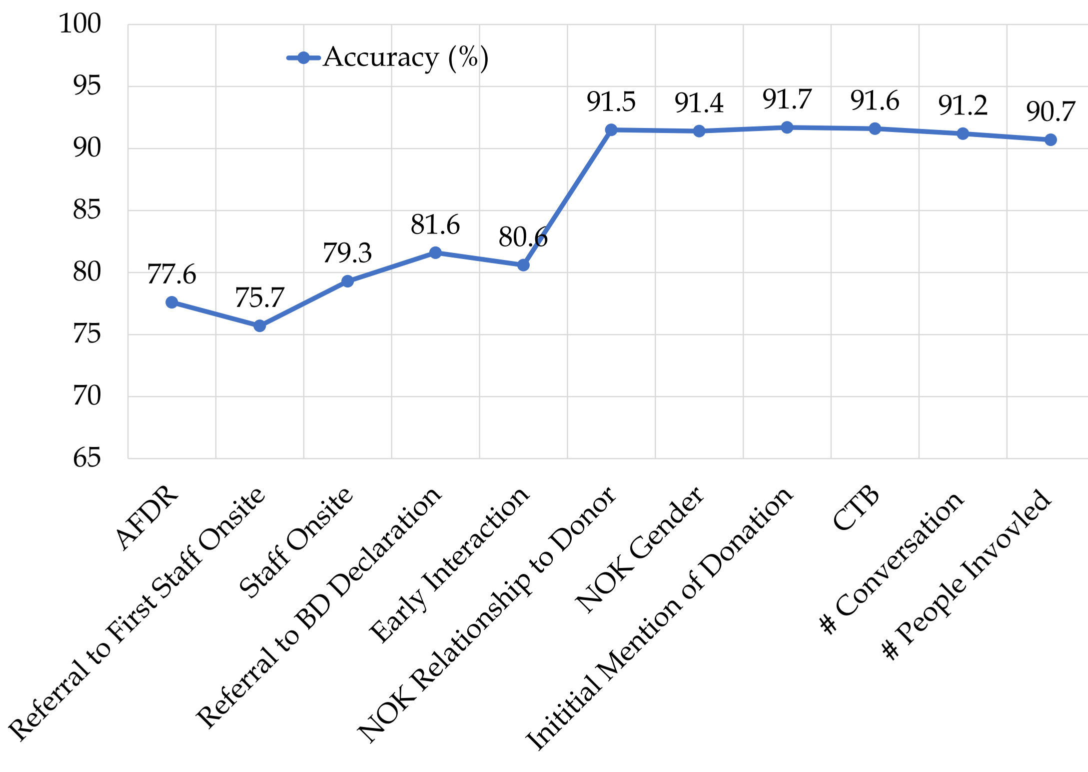

Figure 4.5: Model Accuracy after adding Factors

The proposed model can also be used as a staff recommendation system for pending cases. Table 4.15 shows approachers (A1, A2, A3, A4, A5) probability of family consent for each pending case. Based on probability of consent calculated by the proposed model, the approacher with the highest probability can be recommended to approach family for organ donation. Work schedule for approachers are also incorporated into the model. All these five approachers were on schedule for next three days whenever these pending cases are extracted from the OPO database. For case 1 the proposed model is recommending staff, A3 to approach family while for case 2, the model recommends staff, A2 and A3.

Table 4.15: Staff Recommendation by Proposed Model

Case	A1	A2	A3	A4	A5	Who should Approach Family?
1	0.2086	0.2768	**0.2906**	0.2551	0.2551	A3
2	0.3682	**0.5394**	**0.5394**	0.4262	0.4262	A2, A3
3	0.2263	**0.3703**	**0.3703**	0.3188	0.3188	A2, A3
4	0.1273	**0.3577**	**0.3577**	0.2951	0.2951	A2, A3
5	**0.6250**	0.6230	0.6230	0.5680	0.5680	A1
6	0.3845	**0.6807**	**0.6807**	0.6158	0.6158	A2, A3
7	0.2292	0.3269	**0.3428**	0.2816	0.2816	A3
8	0.5254	0.6429	0.6429	**0.6479**	**0.6479**	A4,A5
9	0.3403	**0.5124**	**0.5124**	0.4413	0.4413	A2,A3
10	0.2027	**0.3712**	**0.3712**	0.3196	0.3196	A2,A3

A1, A2, A3, A4, and A5 are FSCs who are on schedule for next three days

4.4 Summary

The experimental results shows that the best performing model is eXtreme Gradient Boosting with AUC score of 0.8946. So, the best model for this study data set is eXtreme Gradient Boosting classifier, which can accurately predict family consent for organ donation with error percentage of 10.50%. This means out of 100 family approached for organ donation, 90 of them can be accurately predicted given all the features.

Chapter 5

Conclusion and Future Research

This study applies machine learning algorithms to understand important factors and predict family consent outcome based on different factors related to donor, family, requestor, and hospitals. The model proposes in this study, eXtreme Gradient Boosting classifier, can be used to predict if the family will give consent or not based on different factors. Also, this study outlines all the important factors related to family consent. These factors can be shared with OPO staff, management, and executive board members to make more informed and data driven decisions to improve consent rate and solve transplantable organ shortage crisis. eXtreme Gradient Boosting classifier can accurately predict family consent outcome with AUC score of 0.8946 and with error rate of only 10.50%. This model can be applied for every case on board to calculate probability of getting family consent before formal approach. Also, this model will be helpful in selecting best staff to approach family based on the likelihood of family consent. Furthermore, accuracy of the proposed model can be tracked as more informations are added dynamically into th database. This will help in robustness and reliability of the model performance.

In the future, this study can be extended to include more features related to family consent. Also, sample size can be increased to increase accuracy of the prediction model. The performance of base model can be significantly improved if more balanced dataset can be collected in terms of family consent outcome. In this study, there were 65% consent yes from family, while there were only 35% consent no from family. The base model result could be better if output class is more balanced. Therefore, more balanced dataset can be collected to make prediction model robust. In addition to these, anomaly detection algorithms can be used to find out outliers hidden in continuous variables. Also, model stacking data mining techniques can be used to improve the robustness and reliability of the prediction model. The most important future step will be to deploy the proposed model into the production environment in the real-time activity dashboard. The real application of this prediction model is only when the model can be actually used to predict the consent as soon as hospital refer the case to OPO from the family dynamically inbuilt with the existing dashboard. There are many technologies existing in the market which can be embedded with the existing report and dashboard. This process can be fully optimized and staff recommendation system can be instituted into the real-time dashboard to select best staff to approach family as soon as referral comes from hospital. This application can play pivotal role in approaching family thereby maximizing the consent for organ donation to save more lives.

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