Predictive Modeling for Organ Transplantation Outcomes

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Abstract **—** The prevalence of end-stage renal disease in the U.S. has grown significantly, and continues to do so. Organ transplantation generally has better overall patient outcomes than dialysis. But there is a significant shortage of kidneys. This shortage is exacerbated by the need for kidneys for patients with dual organ transplantations. So the kidney allocation problem is a significant challenge. Predictive analytics based clinical decision support systems need to be developed to help physicians make difficult organ allocation decisions. In this paper, we investigate two different classifiers to predict the outcomes of kidney-liver dual transplant patients. The models were evaluated on the basis of overall accuracy, root mean squared error and Area under ROC. UNOS data was used to develop the models.

Keywords— Transplant, Kindey, Liver, Dual Organ,, Bayes Network, Multilayer Perceptron

I. Introduction

The prevalence of end-stage renal disease (ESRD) in the U.S. has grown from approximately 10,000 patients in 1973, to 86,354 in 1983, to 615,899 by the end of 2011 [1, 2, 3]. Treatment of ESRD includes dialysis and kidney transplantation. Despite the higher cost of dialysis and improvement in the quality of treatment, patients undergoing dialysis experience an increased morbidity and mortality, and a decreased quality of life. Transplants can be either from a deceased-donor transplant or a living-donor transplant. Transplant patients enjoy a better quality of life, along with decreased mortality and morbidity, when compared to patients on dialysis. So transplant has a lower cost, both in human and financial terms.

But, the demand for kidneys for transplantation far outstrips the supply. As such, the active wait list for kidneys is far greater than the number of transplants performed (Figure 1). The waiting time for kidney transplant continues to increase. The wait list continues to grow while the number of kidney transplants performed remains almost constant. This acute shortage of organs remains a challenge.

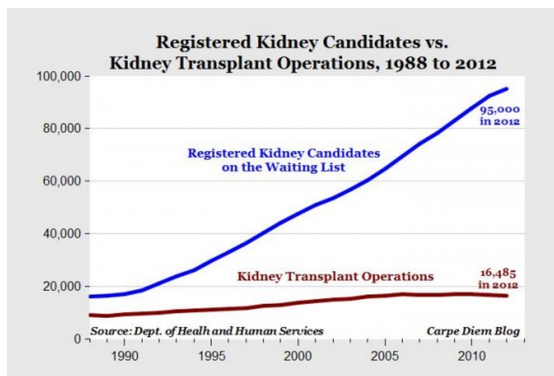

Figure 1: Supply and Demand for Kidneys
(source: www.aei-ideas.org)

An additional challenge is that deceased-donor kidneys have to supply organs to patients with dual organ failure in addition to those with kidney failure alone. Such patients have a combined kidney /liver, kidney /heart, kidney/pancreas or kidney/small bowel failures which compounds the problem of allocation. So it would be useful to predict the outcomes of dual organ transplantation, as a basis to develop clinical decision support systems to facilitate the organ allocation decision to help achieve greater graft success.

An approach to effectively manage organ graft success, and thereby successful transplantation, requires us to better understand the drivers and develop methods that can help guide related healthcare decisions. To achieve this, we develop different models in this study that may be used to develop clinical decision support solutions. We focus on two machine learning approaches of Multilayer Perceptron and Bayes Network. We apply them to predict transplant outcomes in individuals undergoing liver-kidney dual-organ transplantation. The models are developed using WEKA.

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II. Literature Review

The core of the kidney allocation problem for transplantation is the trade-off between clinical efficiency and equity [4]. The equity issues have been addressed through sequential stochastic assignment models that demonstrate the inefficiency created when patients are given the right to accept or deny a kidney, a queuing model that can increase the effective availability of organs by controlling patient choices, and a dynamic resource allocation simulation model that focuses on reduced waiting for transplantation [5] .

Other modeling approaches have been made to address clinical efficiency. A neural network approach was found to be more accurate and sensitive than Cox regression in predicting a live-donor kidney transplant survival [6]. Further, neural network models were found to be more sensitive to predicting a post-transplant complication than traditional statistical models [7].

To further our understanding of clinical efficiency, we develop a Bayesian Network model to predict transplantation outcomes, and compare model performance to a Multilayer Perceptron neural network model. We specifically focus on dual liver-kidney transplantation.

III. Methodology and Modeling

In order to predict the organ transplantation outcome, we have implemented two classifiers: Multilayer Perceptron (MLP) and Bayesian Networks (BN). Bayesian Networks are the directed acyclic graphs which facilitate the representation of joint probability distributions over a set of random variables [8]. Multilayer Perceptron is a feed forward neural network with one or more hidden layers between input and output. Feed Forward means data flows from one direction to another i.e. from input nodes towards the output node. This network is trained with a back propagation learning algorithm. MLP helps in distinguish between the data that is not linearly separable. Except input nodes all nodes consist of a non-linear activation function [9]. Input layer consist of a set of input parameters based on which prediction has to be made, hidden layer consist of a set of hidden nodes which helps in solving the non-linear data problem, these nodes helps in converting input data into the form which can be used by the output node and lastly output layer consist of a output node with a non-linear activation function to make the prediction. The tool which we have used to classify and analyze the results is WEKA.

IV. Data Analysis and Results

The national The United Network for Organ Sharing (UNOS) database was used to extract data which involved two categories of dual liver-kidney organ transplant patients. The simultaneous kidney liver transplant (SKLT) patients get both organs at the same time (effectively), while other patients receive the kidney after liver (KALT). The KALT patients chosen were those that underwent kidney transplantation within a year of the liver transplant, so that their general risk profile would be similar to the SKLT patients, and were combined to form a single study dataset. This data set is a convenience sample of equal number (179 each) of SKLT and KALT patients. The dependent outcome variable is PX_STAT (Recipient Status). In addition, specific donor and recipient independent variables were selected based on clinical theory and experience. These are shown in Table 1.

VARIABLE	DEFINITION
KALTYN	Years between Liver and Kidney Transplant (0=SKLT, 1=KALT)
AGE_DON	DONOR AGE (YRS)
BMI_DON_CALC	Donor BMI - Pre/At Donation Calculated
AGE	RECIPIENT AGE (YRS)
BMI_CALC	Calculated Recipient BMI
DIAB	RECIPIENT DIABETES @ REGISTRATION
DRUGTRT_HYP	RECIPIENT DRUG TREATED SYSTEMIC HTN @ REGISTRATION
HCV_SEROSTATUS	RECIPIENT HEP C STATUS
CREAT_TX	RECIPIENT SERUM CREATININE AT TIME OF TX
ALBUMIN_TX	SERUM ALBUMIN AT TIME OF TX
MELD_PELD_LAB_ SCORE	MELD SCORE
PX_STAT (outcome)	RECIPIENT STATUS D R L A (Died, ReTX, Lost, Alive)

Table I: Variables from the UNOS database

For the development of the MLP prediction model for transplantation outcome, a study dataset of 358 patients who are both SKLT and KALT was used. The outcome classes correspond to the status of the recipient (Died, ReTX, Lost, Alive). ReTX is the need for re-transplantation, while Lost is that the patient was "lost" due to non-follow-up.

Two-thirds or 236 records were used to train the model and 122 records were used to test the 11 node 1 hidden layer network model. A total of 11 clinically relevant attributes (both organ donor and recipient variables) were used as inputs to generate one of the four outcome classes. These attributes are shown in Table I. A total of 69 instances out of 122 instances are correctly classified with MLP with 10 hidden layers and a total of 78 instances out of 122 instances are correctly classified with BN.

Table II shows the results of both the classifiers and it is found that the accuracy of BN is clearly better than MLP, and the weighted average of ROC curve plotted for False

Positive Rate on x-axis and True Positive Rate on y-axis is better for BN than the MLP. Also, the Root Mean Squared Error is better for BN than MLP. This clearly shows that, for this study dataset, the BN model outperforms the MLP model in predicting outcomes.

Tables III and IV shows the confusion matrix for the two models considered. In the confusion matrix, each column represents the instances in a predicted class and each row represents the instances in an actual class. Clearly the prediction accuracy for re-transplant is best in both models, and being better in the BN model.

Table II: Accuracy, RMSE and ROC Area from BN and MLP Models

Classifier	Accuracy	RMSE	ROC Area
MLP	56.5574%	0.4262	0.753
BN	63.9344%	0.3467	0.814

Table III: Confusion Matrix for MLP Model

Actual Class	Predicted Class			
	R	A	D	L
Re-transplant (R)	41	7	3	0
Alive (A)	10	12	12	0
Dead (D)	2	14	16	1
Lost (L)	0	2	2	0

Table IV: Confusion Matrix for BN Model

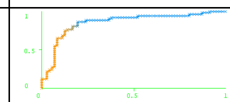
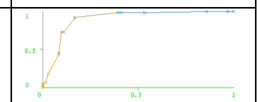
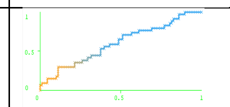
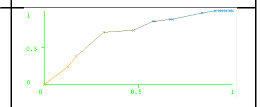
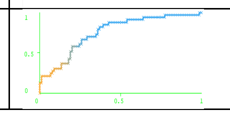
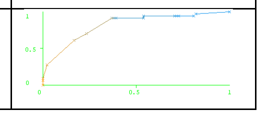
Actual Class	Predicted Class			
	R	A	D	L
Re-transplant (R)	47	3	1	0
Alive (A)	9	8	17	0
Dead (D)	3	7	23	0
Lost (L)	0	1	3	0

Table V shows the Area under ROC for each of the four classes for both the MLP and BN models. To plot an ROC curve for multiclass classifier, one class for which the ROC curve needs to be plotted is considered as one class and all the remaining classes are considered as another class. In this way ROC curve for multiclass classification is plotted in a way similar to that of ROC curve for binary class classification to illustrate the performance of the model in terms of true positive rate against false positive rate. Table VI shows samples of the ROCs.

Table V: Area under ROC for Different Classes of Wellness

Actual Class	Area under ROC	
	MLP	BN
Re-transplant (R)	0.853	0.898
Alive (A)	0.599	0.699
Dead (D)	0.753	0.815
Lost (L)	0.790	0.727

Table VI: Sample Area under ROC Graphs for Wellness

Health Condition Assessment	Area under ROC	
	MLP	BN
Re-transplant (R)		
Alive (A)		
Dead (D)		

V. CONCLUSION AND FUTURE ENHANCEMENTS

This paper describes two models, MLP and BN, to predict the outcomes in dual organ (Kidney-Liver) transplant patients. It is been found that the predictions with the accuracy of 55.56% for the MLP model and an accuracy of 63.93% for the BN model, indicating the latter being a better approach. But at the class level, both model predicted much better for the re-transplantation class as seen in the confusion matrix. Also, Area under ROC was higher in both models, with the BN model again being slightly better.

This indicates that the BN model on the whole appears to outperform the MLP model, with predictive power being better along the re-transplantation dimension. Appropriate predictive models like those developed in this study may be used to develop individual/clinical decision support solutions, to help physicians addressing the organ allocation problem. We expect to continue this research to improve the accuracy of the models by expanding the dataset and the variables used and explore other models.

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