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REAL-TIME DELAY PREDICTION FOR KIDNEY TRANSPLANTATION SYSTEM

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ABSTRACT

We present a combined simulation and machine learning framework for predicting, at the time of end-stage renal disease patient's registration on the kidney transplantation waitlist, whether the patient will receive a transplant before their health deteriorates. If the patient is predicted to receive a transplant, we predict their time on the waitlist before receiving the transplant. We accomplish this by developing a discrete-event simulation model of the kidney transplantation system using patient-related and organ donor-related information. We use the validated model to record clinical and operational features for each patient at the time of their registration, which is then used to train machine learning algorithms to predict the transplantation waitlist outcome, and, in turn, the organ allocation time. Our approach is suitable for generating real-time delay predictions for complex queuing systems where data regarding state of the queueing system that can be used to train ML methods is not maintained.

1 INTRODUCTION

The substantial shortage of donated kidneys in India results in an increasingly long waitlist of end-stage renal disease (ESRD) patients awaiting a transplant, creating uncertainties among ESRD patients about whether they will receive a transplant or not before their health deteriorates. A first step towards alleviating the uncertainty is to provide providers and/or patients with information regarding whether they will receive a transplant or not – at the time of their registration on the kidney transplantation waitlist – and if the patient is predicted to receive a transplant, the wait time of the candidate before receiving the transplant. This can help providers and/or patients make an informed decision about whether they should continue on the waitlist or explore alternative transplant options (such as living donors).

In an effort to provide real-time delay prediction estimates to patients visiting an Indian public healthcare facility, we present a combined simulation and machine learning (ML) approach that involves the following steps: (a) development of a discrete-event simulation (DES) model of the kidney transplantation system, (b) generation of system state (waitlist) and patient data (e.g., clinical and logistical characteristics) for each ESRD patient at the time of their registration on the transplant waitlist, (c) training ML methods on the data generated in step (b) to predict whether or not a patient will receive a transplant prior to their health state deterioration (classification), and (c) estimation of the time to organ allocation for patients predicted to receive an organ by training ML methods on data from step (b) (regression). We measure ML method performance for the classification problem via the area under curve (AUC) score and the regression problem via the root mean squared error (RMSE) and the mean absolute percentage error (MAPE) metrics. A significant proportion of the existing literature used historically available queue log data to train ML predictors for real-time delay predictions. However, in situations where such queue log data is not maintained, our approach can be useful.

2 TRAINING DATASET GENERATION FOR CLASSIFICATION AND REGRESSION

We developed a DES model of the kidney transplantation system on the Python computing platform using ESRD patient-related and organ-related information such as interarrival time, ESRD patient removal time due to death, etc., that were estimated from multiple sources including waitlist data available on the state organ transplantation authority website, annual aggregate organ donation data, and other clinical literature. The simulated kidney transplantation system was that present in the Indian state of Kerela. The simulation outcomes showed that the average 2-year and 5-year probabilities of receiving a transplant while on the waitlist were approximately 9% and 18% respectively, while the average wait time to allocation was 798 days with a standard deviation of 8.97 days. This motivated us to develop a classification model that will predict whether a patient will receive a transplant at the time of registration on the waitlist.

We used the DES model to record the clinical (e.g., time on dialysis at the point of registration), logistical (e.g., district of origin of the patient and transplant hospital of registration), and waitlist related features (e.g., number of patients of each blood group above the current patient on the waitlist). The label for the classification exercise was whether or not the patient on the waitlist will receive a transplant prior to their time of removal from the waitlist due to death. For those who did receive an organ, we recorded the time to allocation from their time of registration. This formed the label for the regression exercise.

3 CLASSIFICATION AND REGRESSION RESULTS

The training dataset thus consisted of a total of 23 features representing the patient characteristics and the state of the queueing system at the time of registration and the classification/regression labels. We split the input data into training and test sets with a 75/25 split ratio and scaled using the MinMaxScaler function of the *scikit-learn* package. The input dataset consisted of 929 successful allocations out of a total of 3945 patients. The training dataset was balanced using the Synthetic Minority Oversampling Technique. We used a subset of the simulation-generated dataset developed for classification, obtained by restricting the dataset to only those cases where a transplant was successful, for training the regression models. We applied several methods, including support vector machines (SVM), decision tree methods such as bagging and random forests, and artificial neural networks (ANN) - as classifiers and regressors on the dataset. Before training the model, we optimized the hyperparameters of each of these predictors using the GridSearch hyperparameter tuning method. We report the mean and standard deviation of the AUC score and precision of the classifiers when a transplant is received, and the RMSE and MAPE scores of regressors in Table 1.

Table 1: Classification and regression results for status of transplant and time to allocation, respectively.

	Metrics	SVM	Bagging	Random forest	ANN
Classification	AUC score	0.91 (0.01)	0.90 (0.00)	0.90 (0.008)	0.90 0.01)
	Precision	0.97 (0.00)	0.96 (0.00)	0.96 (0.00)	0.97 (0.01)
Regression	RMSE	193.29	193.62	208.61	856.4
	MAPE	80.31	89.01	190.39	91.49

4 CONCLUSION AND DISCUSSION

The classifiers, especially the decision tree ensemble classifiers (bagging and random forest) achieve over 95% precision for patients receiving a transplant. The regressors clearly require significant improvement. The bagging ensemble tree regressor yielded the best results.