Aiding treatment decisions through effective predictions can alleviate the situation of renal disease patients in India, but such efforts are hindered by data scarcity

Industry: Kidney transplantation networks in India

Market Size: 220,000-275,000 new ESRD patients requiring renal transplantation / dialysis in India every year

Treatment Options: Renal transplantation established as more efficacious to dialysis in improving patient survival rates

Problems: Shortage of donated kidneys, Long waitlists

Trends:
- The rate of deceased donation has increased by more than 3 times since 2012
- Patients and doctors remain uninformed of expected timelines, leading to inefficient diagnoses and uninformed decisions

Proposed Solution: Inform patients at the time they seek admission, enabling informed decisions about whether they should wait, seek treatment elsewhere, or by other means.

Objective: to develop capabilities for end-stage renal disease patients to make better-informed treatment decisions at the time of their registration to the kidney transplantation waitlist.

We obtain distributions for the following parameters through available literature and govt organ sharing websites:

Operational Parameters
Patient inter arrival time
District origin of patient
Age
Blood Group
Donor Inter-Arrival Time
Donor Blood group
District in which organ originates
Number of kidney retrieval probability

Clinical Parameters
Time on Dialysis
Removal time
PRA Level
Probability of a previous IMGF
Failed all AV Fistula sites
Failed AV Graft after all failed AVF sites

Aggregated as the KAP score of the patient

Proposal

- Develop a simulation model to generate waitlist data, using the operational and clinical parameters.
- Utilize the waitlist data to train a prediction model to obtain accurate real-time predictions.

Source: Indian Journal of Urology

We show that a simulation + prediction framework can be used to generate accurate real-time predictions for kidney transplantation networks in India

Simulation Flow

INPUT: patient-related and organ-related parameters

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SIMULATION: programmed in Python and runs for 30 years (with 12 years warm-up) and 100 replications

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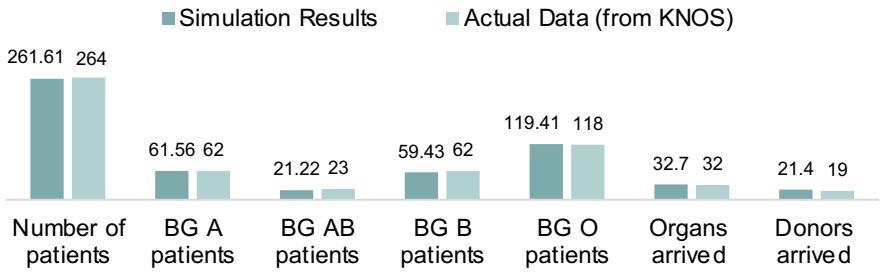
OUTPUT: year-on-year probabilities of receiving a transplant, drilldowns, and waitlist data

VALIDATION OF SIMULATION OUTCOMES
(values per year)



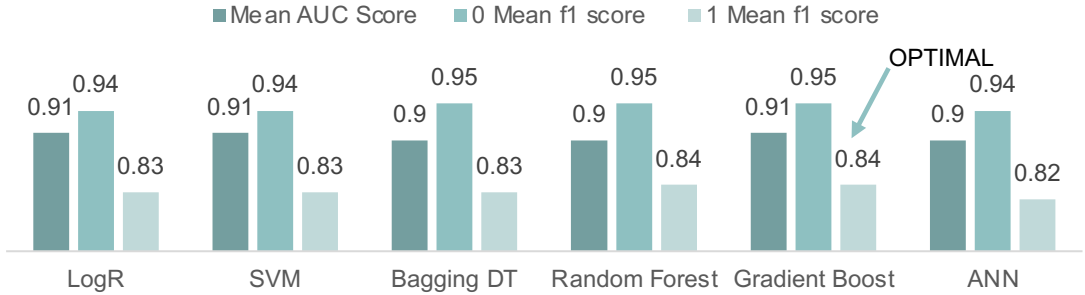
INSIGHTS:

- The simulation agrees with real-world data, producing statistically similar results overall
- Further study reveals influence of the patient's blood group and the type of hospital (govt/private) a patient registers

Prediction (Classification) Specifics

- Target variable: status (whether a patient receives a transplant), and drilldowns for year-wise and blood-group-wise probability
- Extensive data preprocessing is performed, including balancing of the dataset due to its intrinsic skewedness.
- Performance Metrics: ROC-AUC and f1 scores (range 0-1). We prefer models with high AUC and f1 scores.

PERFORMANCE OF CLASSIFICATION MODELS



INSIGHTS:

- Classification across methods achieves an AUC score > 90%
- Further improvements using DT ensembles enable AUC scores > 95%.

Patients can thus be confident in the predictions obtained and make their treatment decisions accordingly.

Source: Kerala Network for Organ Sharing Abbreviations: BG– Blood Group, LogR – Logistic Regression, SVM – support vector machine, DT – decision tree, ANN – Artificial Neural Network