Predictive modeling of delayed graft function after kidney transplantation using machine learning methods

Alexander Decruyenaere[1,*], Philippe Decruyenaere[1,*], Patrick Peeters[2], Frank Vermassen[3], Tom Dhaene[4] and Ivo Couckuyt[4]

[1] Third Master in Medicine, Ghent University, Belgium
[2] Department of Nephrology, Ghent University Hospital, Belgium
[3] Department of Thoracic and Vascular Surgery, Ghent University Hospital, Belgium
[4] Department of Information Technology (INTEC), Ghent University - iMinds, Belgium

INTRODUCTION AND AIMS

- Kidney transplantation is the preferred treatment for patients with ESRD, improving survival, cardiovascular comorbidity, QoL and costs.
- Delayed graft function (DGF):
  - Early postoperative graft dysfunction due to ischemia/reperfusion injury
  - Usually defined as the need for dialysis within the first week after transplantation
  - Deleterious short-term and long-term consequences:
    - Prolonged hospitalization and higher transplantation costs
    - Increased rate of acute rejection
    - Reduced long-term graft function
    - Long-term graft loss
    - Reduced recipient survival
  - 4 predictive models have been developed using logistic regression.
- Logistic regression can be poorly suited for complex interactions or pattern recognition in the data, which is important due to the multifactorial characteristics of DGF.
- Aim: we want to evaluate the value of machine learning methods in the prediction of DGF.

METHODS

- Retrospective cohort study of 497 adult kidney transplantations from deceased donors between 2005-2011
- Observed incidence of DGF is 12.5%.
- Feature elimination procedure results in 20 selected parameters (24 parameters after conversion to indicator parameters) out of 55 parameters.
- 6 types of predictive models are fitted: logistic regression (LR), linear discriminant analysis (LDA), support vector machines (SVM; linear and radial basis kernel functions), random forest (RF) and stochastic gradient boosting (SGB)
- Performance after 10-fold stratified cross-validation:
  - Sensitivity and specificity
  - Discrimination: area under the receiver operating characteristic curve (AUROC)

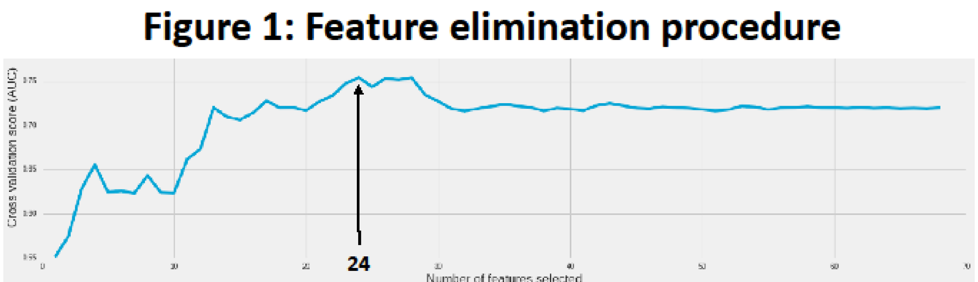
Table 1: Baseline characteristics

Donor	Age (year)	42.6 ± 14.8
	Male (%)	60.4
	BMI (kg/m²)	24.9 ± 4.2
	DBD (%)	90.3
Recipient	Age (year)	52.8 ± 11.7
	Male (%)	66.6
	BMI (kg/m²)	25.9 ± 4.7
	Duration of dialysis (year)	2.7 ± 1.7
Preservation	Cold ischemia time (hour)	14.2 ± 4.3
	Warm ischemia time (min)	22.3 ± 7.1

Abbreviations: BMI, body-mass index; DBD, donation after brain death.

RESULTS

Figure 1: Feature elimination procedure



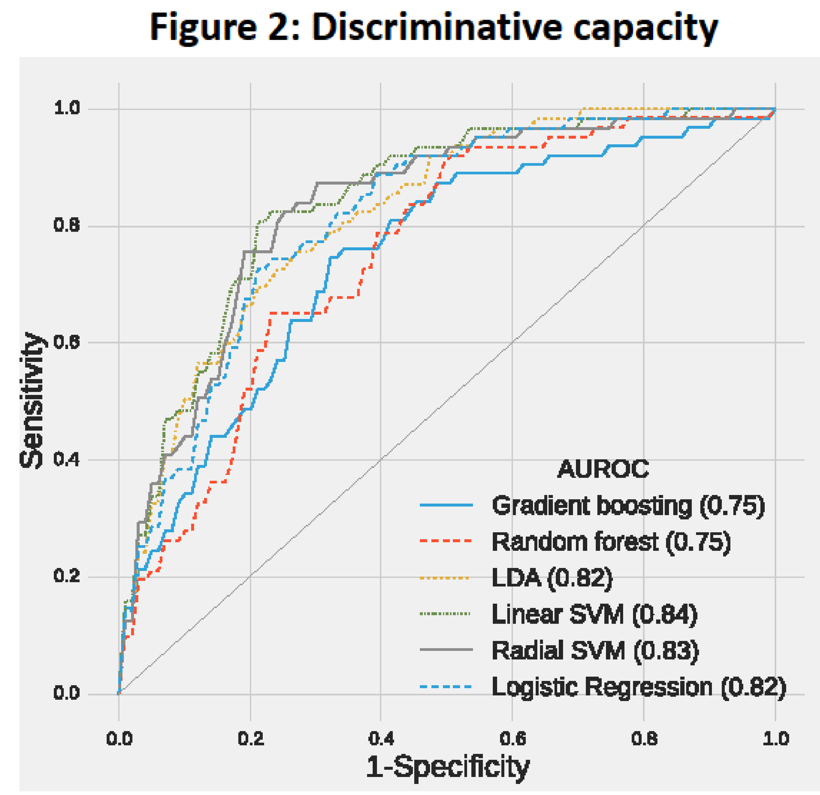
- **Donor:**
  - Age
  - Body mass index
  - Terminal serum creatinine
  - Subtype
  - Diabetes mellitus
  - History of hypertension
  - Hypotensive episodes during pre-explantation period
- **Preservation/operation:**
  - Preservation method
  - Preservation solution
  - Perioperative graft reperfusion
  - Male donor-to-female recipient
- **Recipient:**
  - Body mass index
  - Duration of dialysis
  - Panel reactive antibodies at time of transplantation
  - Peak panel reactive antibodies
  - Acute calcineurin inhibitor toxicity
  - Iliac artery atheromatosis/stenosis
  - Reduced cardiac function
  - Impaired circulating volume
  - Urinary tract obstruction

Table 2: Performance of the statistical methods after 10-fold cross-validation

Statistical method	Sensitivity (%)			Specificity (%)			AUROC (%)
	No DGF	DGF	Overall	No DGF	DGF	Overall	
Gradient boosting	98	18	88	89	53	84	75
Random forest	100	0	88	88	0	77	75
LDA	95	27	86	90	42	84	82
Linear SVM	72	84	73	97	30	89	84
Radial SVM	58	89	62	97	23	88	83
Logistic regression	65	85	68	97	26	88	82

Abbreviations: AUROC, area under the receiver operating characteristic curve; DGF, delayed graft function; LDA, linear discriminant analysis; SVM, support vector machine.

Figure 2: Discriminative capacity



Abbreviations: AUROC, area under the receiver operating characteristic curve; LDA, linear discriminant analysis; SVM, support vector machine.

CONCLUSIONS

- SGB and RF are mainly sensitive in identifying recipients without DGF, resulting in an inferior discriminative capacity compared with the other methods.
- LDA, and especially SVMs and LR are also sensitive in identifying recipients with DGF, resulting in a strong discriminative capacity.
- SVMs perform slightly better than LR in the prediction of DGF.

Corresponding authors: Alexander.Decruyenaere@UGent.be and Philippe.Decruyenaere@UGent.be

* Both authors contributed equally to this study.

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Alexander Decruyenaere
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