A Machine Learning Prediction Model for Immediate Graft Function After Deceased Donor Kidney Transplantation

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Background. After kidney transplantation (KTx), the graft can evolve from excellent immediate graft function (IGF) to total absence of function requiring dialysis. Recipients with IGF do not seem to benefit from using machine perfusion, an expensive procedure, in the long term when compared with cold storage. This study proposes to develop a prediction model for IGF in KTx deceased donor patients using machine learning algorithms. **Methods.** Unsensitized recipients who received their first KTx deceased donor between January 1, 2010, and December 31, 2019, were classified according to the conduct of renal function after transplantation. Variables related to the donor, recipient, kidney preservation, and immunology were used. The patients were randomly divided into 2 groups: 70% were assigned to the training and 30% to the test group. Popular machine learning algorithms were used: eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine, Gradient Boosting classifier, Logistic Regression, CatBoost classifier, AdaBoost classifier, and Random Forest classifier. Comparative performance analysis on the test dataset was performed using the results of the AUC values, sensitivity, specificity, positive predictive value, negative predictive value, and F1 score. **Results.** Of the 859 patients, 21.7% (n = 186) had IGF. The best predictive performance resulted from the eXtreme Gradient Boosting model (AUC, 0.78; 95% CI, 0.71–0.84; sensitivity, 0.64; specificity, 0.78). Five variables with the highest predictive value were identified. **Conclusions.** Our results indicated the possibility of creating a model for the prediction of IGF, enhancing the selection of patients who would benefit from an expensive treatment, as in the case of machine perfusion preservation.

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INTRODUCTION

Kidney transplantation (KTx) is the best treatment for end-stage kidney disease, and the majority are performed with kidneys from deceased donors.[1,2] These kidneys evolve in different ways: from excellent immediate graft function (IGF) to delayed graft function (DGF) with the need for dialysis.[3,4]

Although definitions for DFG, based on dialysis and serum creatinine levels, exist the most widely used definition is the need for dialysis in the first week after transplantation.[5] However, these 2 immediate renal outcomes do not include patients with slow graft function (SGF), who usually do not require dialysis. For this reason, some authors define 3 different outcomes: IGF, SGF, and DGF.[6-10]

DGF is associated with a higher occurrence of acute rejection, reduced graft survival, and increased hospital length of stay and costs.[11-18] In addition, there is evidence that patients with SGF, even if they do not require dialysis, have similar outcomes to those who require dialysis.[8,9,18,19]

There are models with the objective of identifying the risk of patients who developed DGF after KTx, built using classical statistics, most of which use risk factors.[20-23] These models performed well in the dataset in which they were developed, with a few being generalizable.[24-26] Some studies did not reveal the same results

in the validation cohorts as those in the development cohort and consider that some models overestimate the incidence of DGF.[27,28]

Another modeling approach recently used in the healthcare field involves the use of artificial intelligence or, more specifically, machine learning (ML), in which algorithms learn patterns from a dataset without being explicitly programmed with prespecified rules.[29] Artificial intelligence has been used more frequently in medicine and specifically in transplantation in the last decade, with an increase in publications in the last 2 y.[30-33]

There are ML models that predict allograft survival,[34,35] DGF,[36-39] immunosuppressive dose optimization,[40] rejection diagnosis,[41] and waitlist time for KTx.[42] Although models based on ML can improve the prediction in various clinical situations compared with classic statistics, in the case of DGF prediction, the ML models did not significantly improve performance compared with that in classical regression models.[39,43]

The prediction of DGF after transplantation is difficult because the definition of DGF is mostly based on the need for dialysis. The indication for dialysis in the first week after transplantation has only a few absolute indications like hyperpotassemia and excessive hypervolemia, but many others are subject to medical discretion, such as the removal of volume gain after transplantation without respiratory discomfort and blood urea nitrogen (BUN) concentrations, for example. This may cause a large variation in the dialysis rates in the first week after transplantation. On the contrary, the definition of IGF is not questionable, as it is easy to determine which patients present good diuresis and a daily drop-in serum creatinine, with rapid recovery of renal function. The incidence of IGF varies between centers.[6,7,9,44,45] In our center, it has varied between 21% and 25% in recent years.

Therefore, we consider that the prediction of IGF may be more accurate than the prediction of DGF. By identifying, with certainty the group with IGF, interventions such as machine perfusion (MP), only in patients who are prone to develop SGF or DGF could then be carried out. MP is an expensive procedure that requires special logistics and should be more cost-effective in patients with a higher risk of developing DGF (or SGF).

This study proposes the development of a prediction model for IGF in recipients of a first KTx, from deceased donors, using several ML algorithms.

MATERIALS AND METHODS

Study Design and Patients

In this study, data from patients undergoing their first deceased donors KTx at our Transplant Service between January 1, 2010, and December 31, 2019, were used. Children (<18 y old), retransplant, panel reactive antibody levels >10%, missing panel data, preemptive KTx, multiorgan transplants, and patients who lost their grafts or died within 7 dafter KTx were excluded. Patients were classified into 3 groups according to the recovery of renal function after KTx:

- IGF: reduction in serum creatinine levels ≥10% on 2 consecutive days (1st to 2nd and 2nd to 3rd day after KTx).
- SGF: reduction in serum creatinine levels <10% on 2 consecutive days but without the need for dialysis in the first week.
- DGF: need for dialysis in the first week after KTx. Patients who underwent dialysis only on the first day after transplantation due to hypervolemia or hyperkalemia were classified as SGF.

This study was conducted following the Declaration of Helsinki and was approved by the Ethics Committee for Research of the Institution (CAPPesq # 4,403 231). The need for informed consent was waived due to the retrospective nature of the study.

The outcome variable of interest was the presence of IGF after KTx, with collected variables of the recipient, donor, organ preservation, and transplant immunology.

The included parameters were as follows:

- Donor: age, sex, ethnicity, body mass index (BMI), type of donor, length of stay in the intensive care unit, terminal serum creatinine levels, initial serum creatinine levels, blood type, history of hypertension and diabetes mellitus, brain death cause, terminal urine output, reversed cardiac arrest, mean arterial pressure, pretreatment with norepinephrine, Kidney Donor Risk Index (KDRI), and Organ Procurement Organization of origin.
- Recipient: age, sex, ethnicity, BMI, chronic kidney disease etiology, modality, duration of dialysis, and drug used in induction therapy.
- Organ preservation: preservation solution and cold ischemia time (CIT).
- Immunology: HLA mismatches in loci A, B, DR.

Popular ML algorithms were used for structured data: eXtreme Gradient Boosting (XGBoost),[46] Light Gradient Boosting Machine,[47] Gradient Boosting classifier,[48] Logistic Regression, CatBoost classifier,[49] AdaBoost classifier,[50] and Random Forest classifier.[51] The logistic regression model was built without regularization following the same procedures as the other algorithms.

The patients were randomly divided into 2 groups: 70% for training and 30% for testing. The test set was composed of data not seen by the algorithms during model development. All the results of the predictive performance of the study were about calibrated models using the sigmoid method.

Because of the unbalanced nature of the positive outcome, which accounts for only about 21% of cases, balancing techniques were performed by applying the undersampling method edited nearest neighbor in the training dataset,[52] leaving the test set unchanged. Edited nearest neighbor rebalances the dataset by excluding training examples from the majority class considered noisier when they were distinct from their nearest neighbors. The hyperparameters of each model were optimized by 10-fold cross-validation in the train set through Bayesian optimization (HyperOpt),[53] optimizing the area under the receiver operating characteristic curve (AUC-ROC). After that, the models were trained with the best hyperparameters using the training set in its entirety.

Comparative performance analysis of the test dataset was performed using the area under the receiver operating characteristic (AUC) values. In addition, sensitivity (recall), specificity, positive predictive value (PPV), negative predictive value (NPV), and F1 score were also reported. The

number of true positives among 20% of individuals with the highest predicted probability of having IGF after KTx was reported.

To provide interpretability of the results, graphs from SHapley Additive exPlanations (SHAP)[54] and density graphs were plotted for the best-performing model, allowing visualization of variable importance and discrimination of classes performed by the model.

An additional analysis was performed. We verified the results of the models built with the algorithms by making 5 random seed draws from the first selected seed.

We also tested the Boruta variable selection algorithm,[55] using the first tested seed, which removes the variables that do not significantly improve the predictive performance of the model.

All analyses were performed using the Python programming language, with the libraries Pandas,[56] Scikit Learn,[57] NumPy,[58] Matplotlib,[59] and SHAP,[54] following the Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) guidelines.[60]

RESULTS

Descriptive Analysis

A total of 1610 deceased-donor KTxs were performed at our institution during the study period, and 751 patients were excluded according to the exclusion criteria already described. Thus, a total of 859 patients were analyzed (Figure 1). Of the 859 patients, 186 (21.65%) developed IGF, 248 (28.87%) developed SGF, and 425 (49.48%) developed DGF.

Table 1 presents a descriptive analysis of the database (n = 859) in relation to the recipient, donor, organ preservation, and immunology.

Algorithmic Performance

Table 2 shows the results separately obtained from the test dataset for all the algorithms. XGBoost achieved the best overall performance of the AUC-ROC (AUC, 0.78; 95% CI, 0.71–0.84; recall, 0.64, specificity, 0.78; PPV, 0.44; NPV, 0.92).

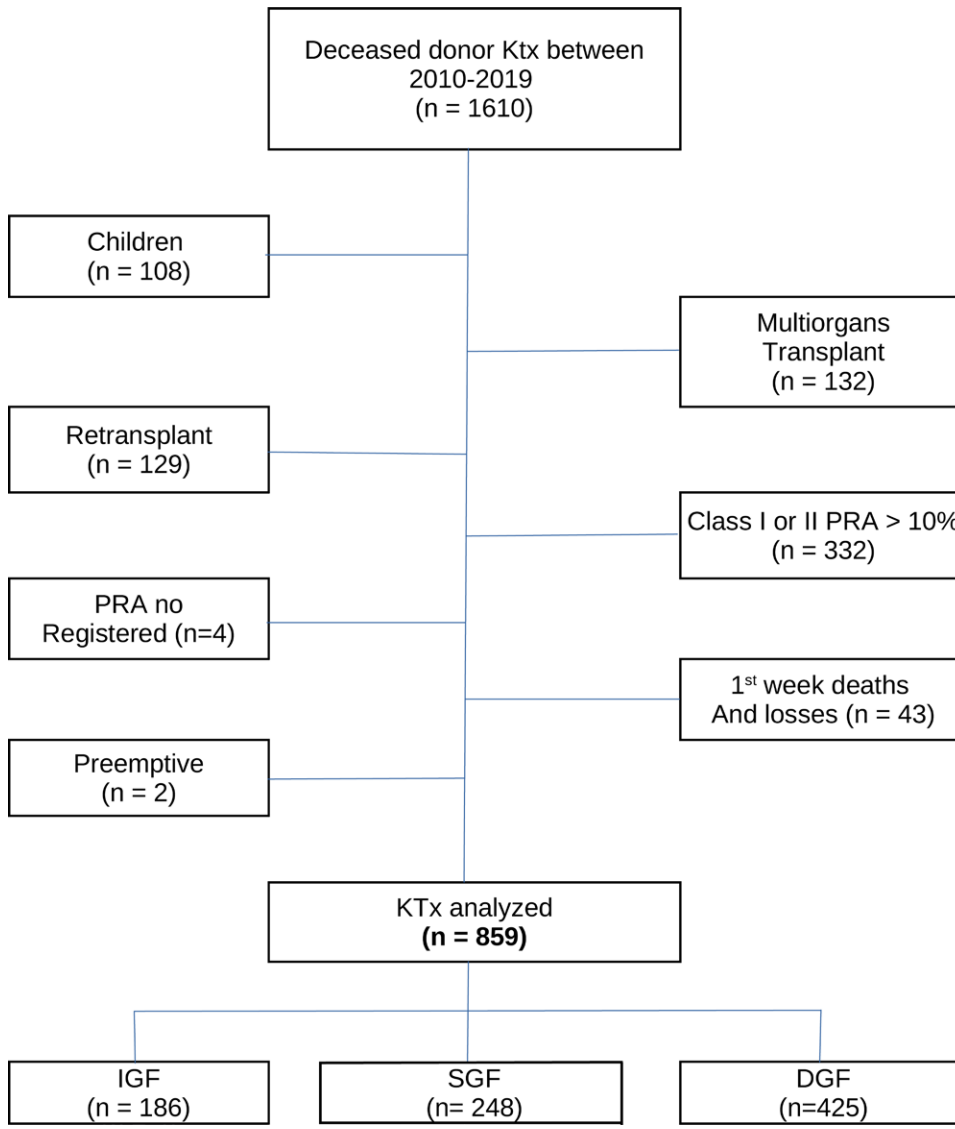

FIGURE 1. Flowchart. DGF, delayed graft function; IGF, immediate graft function; KTx, kidney transplantation; PRA, panel-reactive antibody; SGF, slow graft function.

TABLE 1.

Characteristics of patients who underwent kidney transplantation

Variable	IGF (n = 186)	Non-IGF (n = 673)	*P*
Recipient			
Sex, n (%)			0.123
Female[a]	77.0 (41.4)	241.0 (35.8)	
Male	109.0 (58.6)	432.0 (64.2)	
Ethnicity, n (%)			0.129
Non-White[a]	64.0 (34.4)	209.0 (31.1)	
White	122.0 (65.6)	464.0 (68.9)	
Age, median ± SD, y	52.0 ± 14.4	54.0 ± 13.3	0.261
Time on dialysis, median ± SD, mo	37.5 ± 34.3	42.0 ± 42.5	0.069
CKD etiology, n (%)			0.855
Diabetes mellitus	40.0 (21.5)	177.0 (26.3)	
Hypertension	28.0 (15.0)	66.0 (9.8)	
CGN	41.0 (22.0)	169.0 (25.1)	
ADPKD/Alport	15.0 (8.1)	47.0 (7.0)	
Tubulointerstitial disease	9.0 (4.8)	38.0 (5.6)	
Urological/malformation	4.0 (2.2)	14.0 (2.0)	
Unknown	46.0 (24.7)	151.0 (22.4)	
Others	3.0 (1.6)	11.0 (1.6)	
BMI, median ± SD, kg/m^2	24.3 ± 4.5	25.1 ± 4.7	0.002
Drug used for induction, n (%)			0.815
Basiliximab	122.0 (65.6)	476.0 (70.7)	
ATG	62.0 (33.3)	94.0 (28.8)	
Methylprednisolone	2 (1.1)	3.0 (0.4)	
Modality of dialysis, n (%)			0.517
PD[a]	24.0 (12.9)	43.0 (6.4)	
HD	162.0 (87.1)	630.0 (93.6)	
Donor			
Type of donor, n (%)			0.026
SCD[a]	149 (80.1)	469.0 (69.7)	
ECD	37 (19.9)	204.0 (30.3)	
Sex, n (%)			0.732
Female[a]	75 (40.9)	273.0 (40.6)	
Male	110 (59.1)	400.0 (59.4)	
Ethnicity, n (%)			0.968
Non-White[a]	92.0 (49.5)	309.0 (46.9)	
White	94.0 (50.5)	364.0 (54.1)	
Age, median ± SD, y	43 ± 14.0	49.0 ± 13.1	0.000
BMI, median ± SD, kg/m^2	25.4 ± 4.5	26.0 ± 4.7	0.015
Blood type A, n (%)	73.0 (39.4)	247.0 (36.8)	0.511
Blood type B, n (%)	24.0 (13.0)	82.0 (12.2)	0.738
Blood type AB, n (%)	10.0 (5.4)	19.0 (2.8)	0.158
Blood type O, n (%)	78.0 (42.2)	323.0 (48.1)	0.935
Length of stay in the ICU, median ± SD, d	4.0 ± 3.9	4.0 ± 4.5	0.032
Mean blood pressure, median ± SD, mm Hg	91.0 ± 15.2	88.0 ± 17.3	0.076
Reversing cardiac arrest, n (%)			0.762
No[a]	159.0 (85.5)	573.0 (85.1)	
Yes	27.0 (14.5)	100.0 (14.9)	
Use of norepinephrine			0.834
No,[a] n (%)	24.0 (12.9)	88.0 (13.1)	
Yes, n (%)	162.0 (87.1)	586.0 (86.9)	
KDRI, median ± SD	1.0 ± 0.4	1.2 ± 0.5 (0.010)	
Diabetes mellitus, n (%)			0.802
No[a]	176.0 (94.6)	631.0 (93.8)	
Yes	10.0 (5.4)	42.0 (5.2)	

Continued next page

TABLE 1. (Continued)

Variable	IGF (n = 186)	Non-IGF (n = 673)	*P*
Hypertension, n (%)			0.194
No[a]	134.0 (72.0)	436.0 (65.1)	
Yes	52.0 (28.0)	235.0 (34.9)	
OPO, n (%)			0.012
OPO 1	37.0 (19.9)	175.0 (26.0)	
OPO 2	70.0 (37.6)	194.0 (28.9)	
OPO 3	19.0 (10.2)	147.0 (21.8)	
OPO 4	37.0 (19.9)	102.0 (15.2)	
OPO 5	13.0 (7.0)	30.0 (4.5)	
OPO 6	10.0 (5.4)	24.0 (3.6)	
Brain death cause, n (%)			0.003
Stroke	100.0 (54.9)	439.0 (65.9)	
Head trauma	70.0 (38.5)	205.0 (30.8)	
Anoxia	2.0 (1.1)	3.0 (0.5)	
CNS tumor	1.0 (0.5)	7.0 (1.0)	
Others	9.0 (4.9)	12.0 (1.8)	
Initial Cr level, median ± SD, mg/dL	0.9 ± 0.5	0.9 ± 0.8	0.272
Final Cr level, median ± SD, mg/dL	1.1 ± 0.6	1.6 ± 1.6	0.000
Diuresis, median ± SD, mL/kg/h	1.3 ± 1.4	1.1 ± 1.2	0.003
CIT, median ± SD, h	25.0 ± 6.0	27.0 ± 5.7	0.004
Preservation solution, n (%)			0.087
Euro-Collins[a]	148.0 (78.6)	490.0 (72.8)	
Others	38.0 (20.4)	183.0 (27.2)	
Immunology, n (%)			
HLA mismatch – locus A			0.875
0	26.0 (14.0)	86.0 (12.8)	
1	89.0 (47.8)	312.0 (46.4)	
2	71.0 (38.2)	275.0 (40.8)	
HLA mismatch – locus B			0.021
0	38.0 (20.4)	95.0 (14.1)	
1	97.0 (52.2)	367.0 (54.5)	
2	51.0 (27.4)	211.0 (31.4)	
HLA mismatch – locus DR			0.362
0	108.0 (58.1)	405.0 (60.2)	
1	58.0 (31.2)	151.0 (22.4)	
2	20.0 (10.8)	117.0 (17.4)	

P-values of continuous variables were calculated by the Mann–Whitney test. *P*-values of categorical variables were calculated by the chi-square test.
[a]Reference dummy.
ADPKD, autosomal dominant polycystic kidney disease; ATG, antithymocyte globulin; BMI, body mass index; CGN, chronic glomerulonephritis; CIT, cold ischemia time; CKD, chronic kidney disease; CNS, central nervous system; Cr, creatinine; ECD, extended criteria donor; HD, hemodialysis; ICU, intensive care unit; IGF, immediate graft function; KDRI, Kidney Donor Risk Index; OPO, Organ Procurement Organization; PD, peritoneal dialysis; SCD, standard criteria donor.

TABLE 2.

Predictive model performance with full set of predictor variables

Algorithm	AUC (95% CI)	Recall	Specificity	PPV	NPV	F1	k-tops
XGBoost	0.78 (0.71-0.84)	0.64	0.78	0.44	0.92	0.53	46.2%
LightGBM	0.76 (0.70-0.83)	0.57	0.76	0.40	0.87	0.47	44.6%
GBC	0.76 (0.69-0.83)	0.52	0.83	0.45	0.86	0.48	44.6%
LR	0.75 (0.69-0.82)	0.70	0.72	0.41	0.90	0.52	39.3%
RF	0.76 (0.69-0.83)	0.52	0.83	0.44	0.86	0.48	42.9%
CatBoost	0.72 (0.65-0.80)	0.52	0.78	0.40	0.87	0.45	39.3%
Adaboost	0.76 (0.69-0.82)	0.38	0.85	0.41	0.83	0.39	37.5%

AUC, area under the receiver operating characteristic; CI, confidence interval; F1, F1 score; GBC, gradient boosting classifier; LightGBM, light gradient boosting machine; LR, logistic regression; NPV, negative predictive value; PPV, positive predictive value; Recall, sensibility; RF, Random Forest; XGBoost, eXtreme Gradient Boosting.

Table S1, SDC, http://links.lww.com/TP/C674, shows a comparison of the different ML algorithms on the test set in 5 different seeds for IGF.

Table S2, SDC, http://links.lww.com/TP/C674, shows the predictive performance of models with variables selected to the Boruta algorithm for IGF.

Figure 2 shows the ROC curve for each of the different algorithms. Figure 3 shows the distribution of the risk score and class discrimination for the XGBoost algorithm. The distribution of probability densities in blue represents patients who did not develop IGF and in red those with IGF after KTx. The results show that, albeit not perfect, the XGBoost algorithm was able to discriminate patients who developed IGF from those who did not.

The top 5 variables with the greatest predictive importance according to the Shapley value are shown in Figure 4. The variables are ranked in descending order of importance. Low levels (represented in blue) of final donor serum creatinine levels had a positive impact on the IGF prediction results, with similar results noted for donor age, especially with younger age. Regarding the mean blood pressure and diuresis of the donor, higher values (in red) had an overall positive impact on posttransplant IGF prediction.

DISCUSSION

This single-center, retrospective study analyzed a homogeneous population of 859 unsensitized patients undergoing their first KTx with kidneys from deceased donors and compared several ML algorithms for the prediction of IGF. An ML model was developed that identified patients who will develop IGF after KTx.

Popular algorithms were used to develop the model. When all available variables were used, the algorithm that presented the best prediction of IGF was XGBoost (AUC, 0.78; sensitivity, 0.64; specificity, 0.78; PPV, 0.44; NPV, 0.92). The other algorithms had similar AUCs, which demonstrates the predictive ability of the dataset, even if with a lower NPV. It is important to emphasize that ML models are capable of learning complex relationships between variables. XGBoost is a learning-by-set method that brings together decision trees as building blocks to construct a strong "learner" that can discover nonlinear relationships between predictors and the outcome. Recently, XGBoost has been shown to have a better predictive performance than that in other ML algorithms in various contexts.[61-63]

Several predictive models developed by conventional statistics have been published with good performance in the population in which they were developed.[20-23] However, in validation studies, these models were not generalizable, with the exception of the model developed by Irish et al. [24-26] However, this is a complex nomogram that uses many variables not frequently available and may not be applicable in clinical practice.[20] More recently, studies developed by ML were published compared with those of classic statistics models to predict DGF and concluded that ML was superior.[37,38]

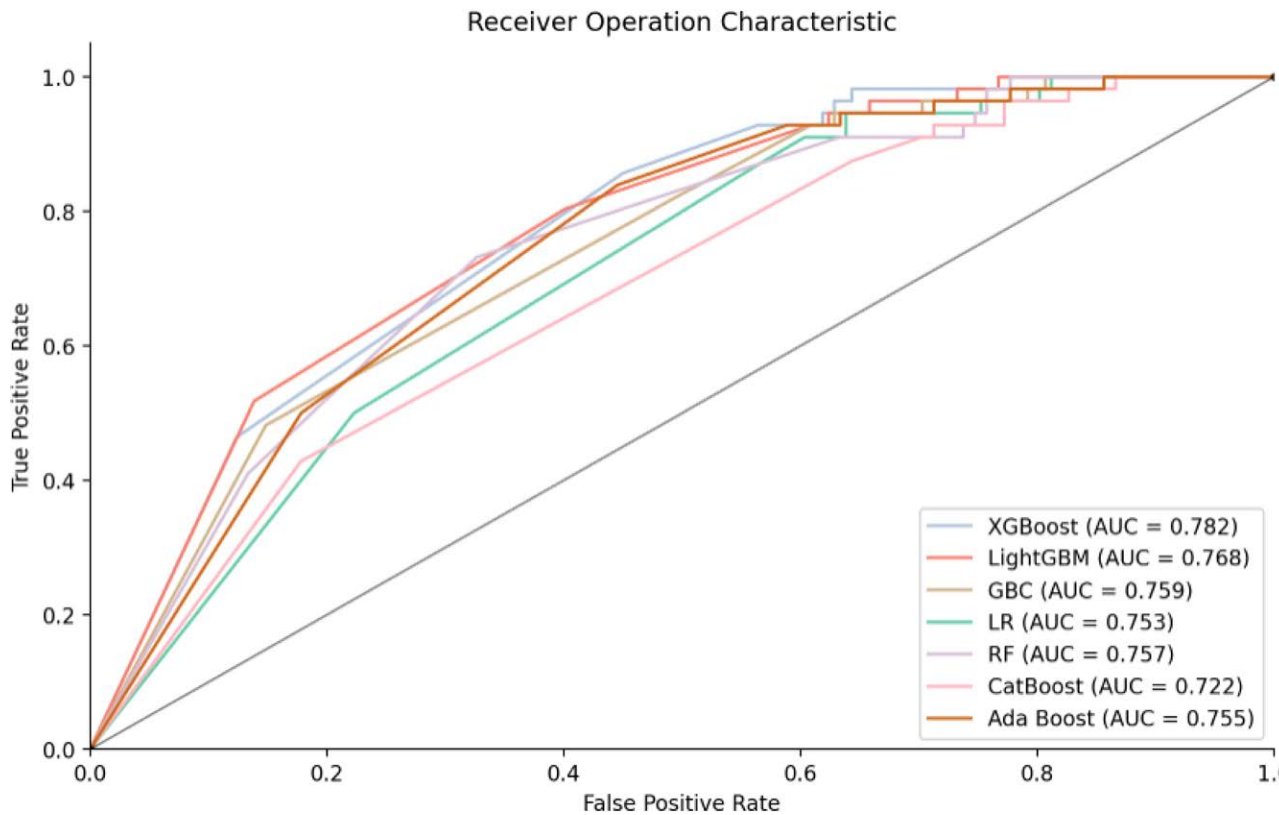

FIGURE 2. Comparison of the different machine learning algorithms on the test set. AUC, area under the receiver operating characteristic; GBC, gradient boosting classifier; LightGBM, light gradient boosting machine; LR, logistic regression; RF, Random Forest; XGBoost, eXtreme Gradient Boosting.

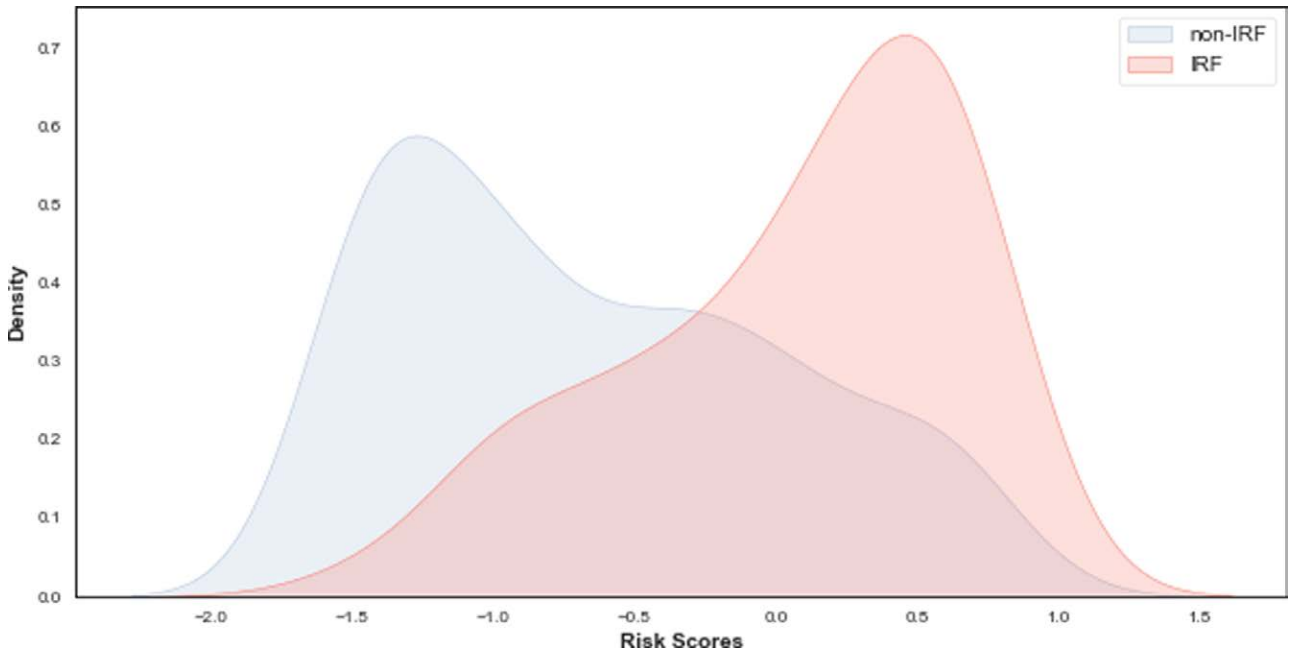

FIGURE 3. Probability density distributions for predicting immediate graft function for XGBoost algorithm. IRF, immediate renal function; XGBoost, eXtreme Gradient Boosting.

The novelty of our study lies in the prediction of IGF instead of DGF. The models described in the literature, either using conventional statistics or ML, used the DGF as an outcome. The prediction of DGF can be complex because of different definitions, but most of them are based on the need for dialysis in the first week after KTx.

Universal indications for dialysis are few (extreme hypervolemia, severe hyperkalemia, and very high BUN levels). However, several indications may change according to the nephrologist's discretion. The indication according to the BUN level varies among centers. Economic issues also exist, such as dialysis fees or limiting it due to the maximum number of dialysis that can be reimbursed by the health system. In addition, the incidence of dialysis in the first week also varies if dialysis is performed in the morning of the 8th day instead of the night of the 7th day due, for example, to the availability of the dialysis facility, only to mention a few. For these reasons, models described in the literature do not perform well when applied to other centers.

Conversely, IGF defined as patients presenting good diuresis from the beginning, with a daily drop in SCr levels and rapid renal function recovery adds no margins for doubts, despite the nephrologist who evaluates the patient or the logistic conditions of the hospital. Besides, it seems that there is no long-term (3-y) improvement in graft survival by machine perfusion in patients who do not develop DGF.[64]

According to the importance of variables reported as a result of SHAP in the complete model (Figure 4), as well as for the analysis of a minimum set of variables with Boruta's variable selection algorithm (described in **Table S2, SDC**, http://links.lww.com/TP/C674) the most relevant variables for predicting IGF were donor final serum Cr, KDRI, donor mean blood pressure, donor 24-h diuresis and donor age. In the literature, there are several predictive models for DGF, but we did not find any reference to the prediction of IGF. Younger donors and lower CIT are described in a

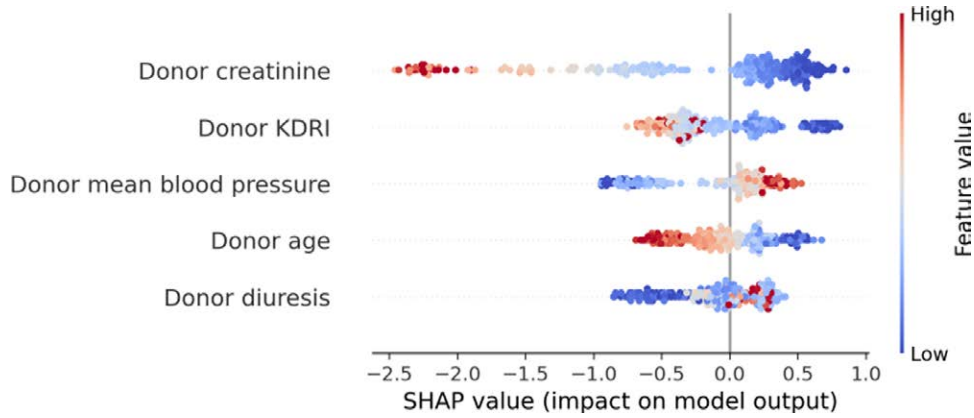

FIGURE 4. Top 5 feature contributions to predict immediate graft function with XGBoost algorithm. KDRI, Kidney Donor Risk Index; SHAP, SHapley Additive exPlanations; XGBoost, eXtreme Gradient Boosting.

study published by Siénko et al, which describes factors associated with IGF.[65] On the other hand, although not described in the literature as factors associated with IGF, donor serum creatinine, donor mean blood pressure, and diuresis reflect maintenance conditions before organ procurement.

By identifying patients with a possible outcome of IGF, patients with a higher chance of developing either DGF or SGF were combined. It seems that patients with SGF have long-term outcomes comparable to those of the DGF group.[8-10] Therefore, both SGF and DGF groups may be considered unique groups that may need special assistance to improve their outcome, for example, with the use of hypothermic MP.

MP is an expensive procedure (the cost in Brazil is US $2000.00/kit). Besides requiring special logistics, MP is a high-cost procedure, especially for developing countries like Brazil, where MP is not reimbursable by the health system.

The idea, therefore, is to use MP only in kidneys with a higher chance of developing DGF/SGF. Specifically, in this condition, there is a need to present to the health authorities that this extra expense is cost effective, reducing hospital stays, days at the intensive care units, exams, biopsies, etc.[18] With MP, it has been reported that cost reduction was approximately US $2626 per procedure.[66]

A Brazilian collaborative, randomized study of kidney recipients from the same deceased donor showed a 16% reduction in DGF (61% versus 45%) with MP versus cold storage (CS).[67]

Another major study comparing CS with MP in kidneys from the same donor showed a small reduction (5.7% with marginal statistical significance, $P = 0.05$) in the incidence of DGF with no differences in the duration of DGF, creatinine clearance, acute rejection episodes, and length of hospital stay.[68]

In a 3-y analysis of the same cohort, overall, 3-y graft survival was better for machine-perfused kidneys (91% versus 87%; adjusted hazard ratio for graft failure, 0.60; $P = 0.04$). However, when evaluating survival in patients who did not develop DGF, there were no differences in the 3-y graft survival.[64]

Therefore, the results of MP in terms of DGF rate and costs are not striking to introduce the procedure worldwide. Including kidney transplant recipients who possibly will develop IGF (around 20%–25% of patients) in the MP studies may reduce the power of these studies in demonstrating a cost-effective benefit of MP in brain-dead kidney donors. By excluding patients with a higher chance of IGF, the statistical results of studies comparing MP with CS may be enriched. This is the next step after developing our model.

The recorded incidence of DGF in our country is high, with rates much higher than those reported in other countries. In this study, the incidence of DGF was 49%, higher when compared with the rates described in the United States and Europe, but comparable to what has been described in Brazil and even lower when compared to the incidence of some Brazilian centers that describe rates of up to 82% and 87.7%.[69]

The exact reason for the high incidence of DGF in Brazil is not known, but it is likely to be related to the maintenance of the potential donor before organ procurement and prolonged CIT due to procurement and organ distribution in a large country.[36]

Our study has several limitations. This study was conducted at a single center with a very "homogeneous" population (first KTx, nonsensitized patients) designed to avoid biases that could increase the incidence of DGF. For this reason, it is possible that the model may not be generalizable to the entire transplant cohort, which includes sensitized recipients and retransplants. Although access to data from another research center could be used to test the generalization of the model, there would be a need to retrain the model with local data given the change in the distribution of variables, which would lead to inadequate extrapolation. For this reason, it is possible that the model cannot be directly extended to the entire transplant population including sensitized recipients or retransplants. However, a single-center–based model may be more accurate and practical for clinical applicability in its specific population. The small number of patients can also be considered a limitation when compared with other ML models recently published in the literature[38,39] and thus, the high NPV found for this study could be different in centers with low DGF prevalence. Nevertheless, it can be looked at as a pilot study to develop a larger analysis at a multicenter level.

In summary, an ML model was developed to identify transplanted patients with a higher chance of developing IGF after KTx. By excluding them, a prospective study comparing CS and MP in patients with a higher chance of developing DGF will be developed to demonstrate a higher cost-effective benefit of MP, which might largely overcome the costs of the MP procedure.

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