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Predictors of Outcomes in Liver Transplantation

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Predictors of Outcomes in Liver Transplantation

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Resumo

Introdução

O transplante hepático é uma terapêutica de resgate final, permanecendo um desafio nomeadamente, devido à grande disparidade entre a necessidade e a escassez de órgãos. O desenvolvimento de modelos preditores pode auxiliar na estratificação de risco e monitorização destes doentes.

Objetivo:

Este estudo tem como objetivo o desenvolvimento de um modelo, baseado na tecnologia de inteligência artificial, que possa prever a taxa de sucesso do transplante hepático, após um ano. Esta foi definida pela sobrevida do doente e pelo tempo de vida útil do órgão. O impacto de variáveis individuais de cada doente foi também avaliado recorrendo a este modelo.

Material e Métodos

Uma análise retrospetiva dos registos anestésicos de doentes adultos que receberam transplante de fígado de junho de 2006 a agosto de 2019 no Centro Hospitalar Universitário do Porto, foi a base para o desenvolvimento de um modelo de inteligência artificial. Foram utilizadas variáveis como, as características demográficas do doente (idade, sexo e IMC), dados pré-operatórios (score MELD, creatinina, albumina, bilirrubina, sódio, lactato, hemoglobina, INR), dados intra-operatórios (duração da cirurgia, perda de sangue, transfusão de sangue, uso de hemoderivados e aminas; valores de lactato, hemoglobina e INR, hemorragia) e dados de doadores (idade, sexo, peso e dias de internação na unidade de UCI). Os resultados do modelo desenvolvido previram a sobrevida doente e a vida útil do órgão, após 1 ano. Esses resultados foram comparados com os obtidos na base de dados. O impacto das variáveis individuais, no sucesso do transplante, foi também avaliado utilizando o mesmo modelo.

Resultados:

Durante o período do estudo, 811 transplantes foram realizados em 690 doentes. O modelo desenvolvido foi capaz de prever a sobrevida dos doentes com alta precisão (81,3% usando dados pré-operatórios e 84,6% usando uma combinação dos dados pré-operatórios com dados intra-operatórios) e alta sensibilidade (98,2% utilizando dados pré-operatórios e 97,5% associando estes a dados intra-operatórios). O modelo também prevê quais os órgãos com vida útil superior a 1 ano com idêntica precisão (82,1% usando dados pré-operatórios e 81,8% quando combinando dados pré-operatório com dados intra-operatórios) e sensibilidade (95,5%

usando dados pré-operatórios e 96,0% quando combinando dados pré-operatório com dados intra-operatórios). As variáveis que demonstraram maior impacto na sobrevida de ambos, doente e órgão, foram valores de sódio e bilirrubina no pré-operatório, duração da cirurgia e necessidade de transfusão de sangue assim como características do dador (idade e dias de internamento em UCI).

Conclusão:

O modelo desenvolvido foi capaz de detetar implicações relevantes entre as variáveis clínicas e o sucesso do transplante hepático. Métodos de inteligência artificial podem melhorar o processo de seleção do doente para transplante em tempo útil. Posterior investigação será necessária para confirmar estes resultados preliminares.

Palavras chave: Transplante hepático, Modelos de inteligência artificial, Fatores preditores, Sucesso do transplante hepático, Doença hepática terminal

ABSTRACT

Background:
Liver transplantation is a lifesaving therapy but also a challenge mainly due to the overwhelming disparity between the need for liver transplant and the shortage of donor organs. The development of predicting models could improve the selection and monitorization of these patients.

Objectives:
To develop a model based on artificial intelligence technology that could predict liver transplant success rate defined by, patient´s overall survival and time of organ lifespan, leading to re-transplantation, after 1 year. The impact of individual patient's variables on the outcome was also evaluated.

Methods:
A retrospective analysis of anesthetic records from adult patients that received liver transplant from June 2006 to August 2019 at Centro Hospitalar Universitário do Porto was the base for the development of the artificial intelligence model. As inputs, demographic characteristics (age, gender and IMC), pre-operative (MELD score, creatinine, albumin, bilirubin, sodium, lactate, hemoglobin, INR), intra-operative data (duration of surgery, blood transfusion, use of hemoderivatives and amines; lactate, hemoglobin and INR values, hemorrhage) and donor data (age, gender, weight and days as in-patients in ICU unit) were used. The study's outputs were the patient's overall survival and organ lifespan after 1 year. Those outcomes were verified on the database and compared with the results of the predicting model. Individual patient´s variables impact on the same outcomes, were also evaluated using the same model.

Results:
During the study period, 811 transplants were performed in 690 patients. The developed model was able to predict patient survival with high accuracy (81.3% using pre-operative data and 84.6% using pre-operative combined with intra-operative data) and high sensitivity (98.2% using pre-operative data and 97.5% using pre-operative combined with intra-operative data). The model also predicts which organs have a lifespan of more than 1 year with similar accuracy (82.1% using pre-operative data and 81.8% using pre-operative combined with intra-operative data) and sensitivity (95.5% using pre-operative data and 96.0% using pre-operative combined with intra-operative data).

The variables that proved to have a bigger impact on the survival of both, the patient and the organ, were patient´s sodium and bilirubin pre-operative, duration of surgery and the need of blood transfusion as well as donor characteristics(age and in-patients in ICU).

Conclusion:

The developed model was able to detect relevant implications between clinical variables and outcomes. Patient selection for liver transplant timely decision may improve with the use of artificial intelligence methodologies, but further studies are necessary to confirm these preliminary results.

Keywords:

Liver transplantation, Artificial intelligence models, Predictive factors, Outcomes for liver transplant, End-stage liver disease.

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Introduction

Liver transplant is a lifesaving surgery used as a last resort therapy. This procedure should be considered in any patient with end-stage liver disease, in whom the liver transplant would extend life expectancy beyond what the natural history of underlying disease would predict (1). Starzl *et al* on the 1st of March of 1963, reported the first liver transplant surgery and since then this procedure has been continuously under improvement (2). In the first 5 years that this surgery was performed, no patient lived more than 23 days as all patients evolved to hepatic failure or sepsis due to rejection or ischemia. Since then, development of surgical technique, graft preservation, use of immunosuppressors and anesthetic management had a determining positive impact on the liver transplantation outcomes (3). The success of liver transplantation is usually evaluated by the patient survival after 1 year presenting nowadays 96% in Europe (4).

Currently, one of the main challenge within the transplant community is the rate of patient death on the waiting list (1). The persistent shortage of donor organs comparing with the needs has motivated efforts to find predictor indexes post-transplant outcome, maximize survival benefit, and encourage the appropriate allocation of donor organs. This has increased pressure on organ allocation programs, demanding more predictive tools for the optimal patient selection. Predictors are important in medicine since they can alert us to situations in which a different approach or care is needed to have a positively impact on the patient's outcome.

European guidelines have been published and updated regularly where indications, transplant evaluation process and contraindications are established (5). Although, in Europe there are no uniform rules or systems for organ allocation (1).

Child-Pugh-Turcotte classification takes into account bilirubin, albumin levels, international normalized ratio (INR), presence of ascites and encephalopathy. Since 2002 Model of End-stage Liver Disease (MELD) score has been establishing patient priority (6). MELD is calculated based on creatinine, bilirubin and (INR). MELD score proved to be a good model to predict short-term pre-transplant mortality risk. Patients at end stage liver disease and MELD>15 should be listed for transplantation. However, it does not provide prediction for mortality following transplant except for MELD very high >35 (5). The integration of serum sodium (MELD-Na) and patient age in MELD score (integrated MELD) increase mortality prediction (7).

At this moment there isn't a single score that predicts which patient will benefit most of the transplant. There is a need for a robust model to categorize high-risk transplants in order to

identify those more prone to complications and those that will benefit the most from a specific organ. This will allow to further improve liver transplant selection criteria.

Machine learning, a branch of statistics and computer science has revolutionized the analysis of large and complex data sets. Not only have machine-learning algorithms been used to develop the technology for Google Home, Siri, and self-driving cars, they have also been used to predict hospitalization in patients with heart failure, remission in patients with inflammatory bowel disease, and graft failure after solid organ transplantation(8–10). Artificial Neuronal Network (ANN) has been applied for designing diagnostic and prognostic models in different health conditions, such as the detection of cirrhosis in hepatitis B patients (10). They achieved sensitivity of 87,5% and specificity of 92%. In another study, an ANN based model was constructed to successfully predict the mortality risk of patients with cirrhosis (11). The objective of neural networks is to perform those cognitive functions similar to our brain like problem-solving and being teachable. The neural network itself has many small units called neurons and these neurons are grouped into several layers. Layers are columns of neurons that are connected to each other through their neurons. Each neuron is connected to another layers' neuron through connectors called weighted connections. Neural network can be used to extract patterns from complicated data and detect trends in huge amounts of data that could not be recognized otherwise.

Objectives

The aim of this study was to develop a model, based on artificial intelligence, that could predict liver transplant success rate defined by, patient´s overall survival and organ failure leading to re-transplantation after 1 year using an established data base. The impact of individual patient's variables on the outcome was also investigated.

Methods

Study area and design

A retrospective analysis was performed using a database with collected data of the adult liver transplants realized in Centro Hospitalar Universitário do Porto between June 2006 and August 2019. Centro Hospitalar Universitário do Porto, currently with 1000 beds, is part of a national liver transplant program since 1995. About 60 hepatic transplants are performed each year. On 2006 a data base of liver transplant recipient patients was created and is continuously updated. This study was approved by the ethic commission of the hospital (234-CE).

Data collection

A fully clinical registry using EpiData was started by the anesthetic department of the Hospital, allowing audits and comparisons both historical, internally, and between different centers. Records from the last 13 years were scrutinized in order to record pre and intra-operatory data from the patients; re-transplants patients were excluded. The type of organ, donation, including brain death grafts and live donors was recorded. Live donors were from a domino transplant program; patients with Familial Amyloidotic Polyneuropathy that receive liver from cadaveric donors and give their liver, with a normal structure, to recipients with extended indications (i.e. alcoholic with cirrhosis).

The anesthetic protocol used was generally the same during the study period, as well as the surgical technique.

The data recorded and used as inputs on the ANN model includes:

- Demographic characteristics: sex, age and body mass index (IMC);
- Underlined disease that result in liver failure
- Pre-operative variables: primary diagnosis, CHILD score, ASA score, MELD score, cold ischemia time, INR, serum albumin, hemoglobin, creatinine, lactate levels, bilirubin, sodium;
- Intra-operative variables: consumption of blood derivatives (platelets, red blood cells), epinephrine, norepinephrine and other vasoactive drugs, fluid intake (crystalloid and colloid), tranexamic acid, hemorrhage, surgical time duration, albumin, fibrinogen, diuresis and presence of ascites, also at the end of surgery levels of hemoglobin, INR and lactate were recorded;
- Donor characteristics: sex, weight, age, days in intensive care and type of donor (living or dead)

- Patients survival after 1 year
- Organ failure that lead to re-transplantation after 1 year.

Data analysis

The outputs of the model were the survival of the patient and the lifespan of the organ (y= 1) or dead (y= 0) after 1 year of the transplant date. A group of patients was randomly selected to train the model (n=541) and another to test the model (n=149). Accuracy (the number of correct predictions divided by total predictions), sensitivity (the proportion of actual positives which are correctly identified), specificity (the proportion of actual negatives which are correctly identified) and precision (how closely a test result is reproduced) of the model were obtained. The discriminatory power was measured by area under curve (AUC) of the ROC plot to evaluate the model. The AUC is a measure of a model's discriminatory power. An ideal model would have an AUC of 1.0 and thus having the highest sensitivity and specificity (100%).

Results

During the study period 811 liver transplants were performed in 690 patients. Some patients received a second (n=111) and even a third liver transplant (n=10). Only data from the first transplant was included and analyzed. The underlining diseases that lead to liver transplant are represented on the Table I.

Most of the patients received a graft from a brain-dead patient (81.2%). Most were male (65.8%), with a mean of age of 51 years old (the youngest had 18 years and the oldest 73 years old) and the mean of IMC was 25.3kg/m^2 with standard deviation of 4.18.

Most patients presented an ASA score of III or IV (55.4%, 42.5% respectively); the Child score more frequent was 2, representing 49% of the patients, followed by 27.6% with a score of 1 and 22.6% with a score of 3. Regarding MELD score, the majority presented a mean value of 15.25 (std dev. 8.34).

The mean values of albumin, creatinine, sodium, bilirubin and lactate evaluated in the pre-operative study are represented on Table II.

The consumption of blood products during surgery and intra-operative variables are also represented on Table II. More than half of the patients received blood transfusion, 11.5% received platelet transfusion and 22.8% of patients received fresh frozen plasma. Other intra-operative parameters, such us duration of procedure, hydric balance, diuresis, ascites, hemorrhage, noradrenaline administered, hemoglobin values, lactate and INR are also recorded on Table II. The mean value of cold ischemia time was 436 min with a Std of 168.8 min. Regarding the use of amines they were used in 93.6 % of the cases.

Regarding patient donor, 64% were male, with a mean age of 55 years old (std. dev. 17.5), a mean weight of 72 kg (std. dev. 10.6), and a mean of 7.5 days stay in the intensive care unit (std. dev. 21). Few missing data was found in these group.

Eighty-four percent of patients lived more than one year after the transplant. Twenty-one percent of them presented organ failure leading to liver re-transplantation during study follow-up time.

The ANN model was used to evaluate liver transplant success, analyzing separately patient's survival and re-transplantation rate after 1 year.

ANN results for patient's survival after 1 year:

Using only pre-operative variables as the input of the model, the accuracy to predict the survival of the patient after 1 year was 81.3%, with 98.2% of sensitivity, 81.5% of precision and of 21.9% specificity. Using both pre and intra-operative variables as the input, the accuracy of the prediction for survival of the patient was 84.6%, 97.5% of sensitivity, 85.2% of precision and 35.5% of specificity. The ROC curve obtained show the model's Discriminatory Power (Figure 1).

ANN results for re-transplantation rate after 1 year:

Using only pre-operative parameters, the accuracy was 82.1%, 95.5% of sensitivity, 84.1% of precision and 31.0% of specificity. Including pre-operative and intra-operative variables, it was possible to predict the need of re-transplantation after 1 year with 81.8% of accuracy, 96.0% of sensitivity, 82.9% of precision and 35.5% of specificity. ROC curve obtained shows the model's Discriminatory Power (Figure 2).

Analysis of each individual variable was performed to understand the contribution of each one in both the patient's survival and the need for re-transplantation. Variables showing most impact on the outcome are shown on table III and IV. A variable with a negative correlation means a bad outcome. Our results reinforced the importance of some variables already established, such as blood transfusion and platelets transfusion. It also brings to light new variables, such as the negative impact (-0.516) of donor's data like their age and the number of days the donor had been and in-patient in ICU care. Intra-operatory variables such as the fluid balance after surgery and surgery duration showed an important negative correlation (-0.45 and -0.40 respectively).

Discussion

This study used artificial intelligence to find a predictive model for success evaluation of liver transplant patients and organs. The model took profit of numerous clinical data that already exist in hospitals almost impossible to deal with traditional methods. Only those informatic tools allow the investigation and correlation between so many variables at the same time.

The results obtained from our study are extremely promising and could help clinician to label high-risk patients for liver transplantation. High accuracy and sensitivity were obtained using only patient´s intra-operative alone both on patient´s survival and organ lifespan evaluation. Adding intra-operative variables to the pre-operative data to the model, does not represented a great increase on its accuracy or sensitivity.

Similar results were achieved when predicting patient´s survivor than organ lifespan. Donor data were often incomplete, which could impact on the discriminatory power of the test and should be added.

The developed model showed low specificity value probably due to the difference in size of the population that survive after 1 year (84%) vs the population that died (16%); the same happened with the sample size in case of evaluation of organ lifespan above 1 year (79%) vs the ones that died (21%). If more equilibrated population were considered, the specificity of the test will increase. Increasing the time of the study, the size of the samples will increase allowing an improvement on the model.

Regarding the correlation of patients individual variables on clinical outcome, comparisons among other studies can be difficult since different clinical endpoints have been measured, recipients had different underlying liver disease and because donors are often selected based upon recipient characteristics (12–15).

Our results agree with previous studies regarding the impact of creatinine, bilirubin and INR values (13). Intra-operatory variables like the use of hemoderivates (blood and platelet transfusion) were shown to have a negative impact similar to other studies (16–19). Time of surgery, fluid balance after surgery and hemorrhage were found to have an impact on patient/organ survival. Recipient variables were shown to be more relevant than any other donor characteristic (20) although, we found a negative impact on the age of the donor and number of days in ICU, as previously suggested(14).

Using predictive models, we can label high-risk patients and identify those that require more resources. ANN promises a big impact on research and medicine practice, but applications are still in their infancy.

Limitations

There was some missing data, as the data base has been updated and several parameters included through time. Despite a big number of patients were included in this work, those informatic instruments needs a lot of data to be robust. It will be very interesting to include on this model patients from other hospitals, being aware of the difficult of its distinct data base.

Key Learning Points

In this study an artificial intelligence model was created allowing the labelling of high-risk patients for liver transplant that will die in 1 year from the surgery. With 81.3% of accuracy and 98.2% of sensitivity it was possible to predict the outcome using only pre-operative variables; with an accuracy of 84.6% and a sensitivity of 97.5% it was possible to predict the outcome using pre and intra-operative variables. Similar results were obtained when the survival of the organ for less than one year; 82.1% of accuracy and 95.5% of sensitivity when only pre-op data were used and 81.8% of accuracy and 96.0% of sensitivity using pre and intra-operative data.

Additionally, this model allowed the detection of individual variables that affect the outcome of the transplant.

Conclusion

Artificial intelligence model proved to be an excellent tool to labeling high-risk transplants patients leading to better organ selection and better patient management as well as highlight some variables which impact on the outcome. A lot of clinical data have been stored lately on hospitals almost impossible to use without informatic tools. The use of this new tools showed to be powerful in bringing great progress on management of liver transplantation.

There is a need for medical community to brainstorm about how to use this information in order to improve patients care.

Future Perspective

- Construction of a national or European database of liver transplant patients to increase the statistic power of those new informatic tools that could impact on medical decisions.
- Develop an ANN for re-transplant patients as they should not be analyzed together with the studied population.
- Develop predictor factors for additional periods of time such as less than 3 months and 5 years.
- Inclusion of data from donors would improve model power.

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Tables and Figures

Table I- Underlined diseases of the studied patients that lead to liver transplant

Cause of Liver Failure	**Number of patients that underwent Liver transplant**
Alcoholic cirrhosis	213
Familial Amyloidotic Polyneuropathy	141
Primary Biliary Cirrhosis	19
Secondary Biliary Cirrhosis	4
Wilson disease	3
Fulminant hepatitis	47
Other hepatic disturbances	11
Hepatic cystic disease	9
Primary sclerosing cholangitis	12
Congenital hepatic fibrosis	1
Alfa 1 anti-trypsin deficit	8
Budd-Chiari syndrome	1
Congenital biliary abnormalities	2
Inherited metabolism errors	7
Auto-immune cirrhosis	18
Nonalcoholic cirrhosis	9
Hepatic carcinoma	131
Cirrhosis B or C virus	54
Total	**690**

Table II- Patient variables (pre and intra- operatory) distribution on studied patients and blood products administrated to the patient during surgery

Pre-operative Variables	**Mean**	**Standard Deviation**
Albumin	3.57	0.74
Creatinine (mg/dL)	0.91	0.55
Bilirubin (mg/dL)	3.53	5.88
Sodium (mmol/dL)	142.07	60.63
Lactate (mmol/dL)	2.18	0.89
Hemoglobin (g/dL)	12.0	2.3
INR	1.66	3.45
Intra-operative data	**Mean**	**Standard Deviation**
Duration of Surgery (min)	240.5	54.80
Haemorrhage (mL)	3279.8	3347.66
Diuresis (mL)	367.8	506.70
Balance (mL)	1100.4	1866.76
Ascites (mL)	1907.1	4015.98
Noradenaline (mg)	8.4	63.33
Lactate after surgery (mmol/L)	3.6	3.92
Haemoglobin after surgery (g/dL)	9.3	2.2
INR after surgery	2.6	7.02
Use of Blood Products during surgery	**Mean**	**Standard Deviation**
Hemoderivatives (mL)	1410.3	2245.74
Blood Transfusion (U)	2.7	3.97
Transfusion of Platelets (pools)	0.84	7.09
Fresh Frozen Plasma (U)	1.36	7.27

Table III- Impact of variable on the outcome of patients. A variable with a negative correlation means that leads to a bad outcome

Variables	**Pre-op**
Meld	-0.176
Donor Age	-0.165
Pre-op lactate	-0.146
Creatinine	-0.136
Bilirubin	-0.136
Sodium	-0.136
Type of donor liver	-0.125
Variable	**Pre and Intra-op**
Duration of Surgery	-0.497
Blood Transfusion	-0.464
CaCl administration	-0.361
Hemorrhage	-0.347
Colloid	-0.346
Bicarbonate	-0.294
Usage of albumin	-0.282
Administration of platelets	-0.272
Diuresis	-0.272
Pre-op Creatinine	-0.220

Table IV- Impact of variable on the outcome of organ lifespan. A variable with a negative correlation means that leads to a bad outcome

Variables	**Pre-op**
Donor age	-0.516
Days of donor in ICU unit	-0.516
Sodium	-0.487
Bilirubin	-0.487
Creatinine	-0.487
Lactate	-0.476
Previous Abdominal Surgery	0.411
Variable	**Pre and Intra-op**
Fluid balance after surgery	-0.451
Hemorrhage	-0.405
Surgery Duration	-0.400
Crystalloid	-0.356
Bicarbonate	-0.360
CaCl administration	-0.346
Blood Transfusion	-0.333
Noradrenaline	-0.298
Colloid	-0.271
Creatinine	-0.249
Final INR	-0.249
Sodium	-0.249
Final Lactate	-0.249
Final Hemoglobin	-0.249

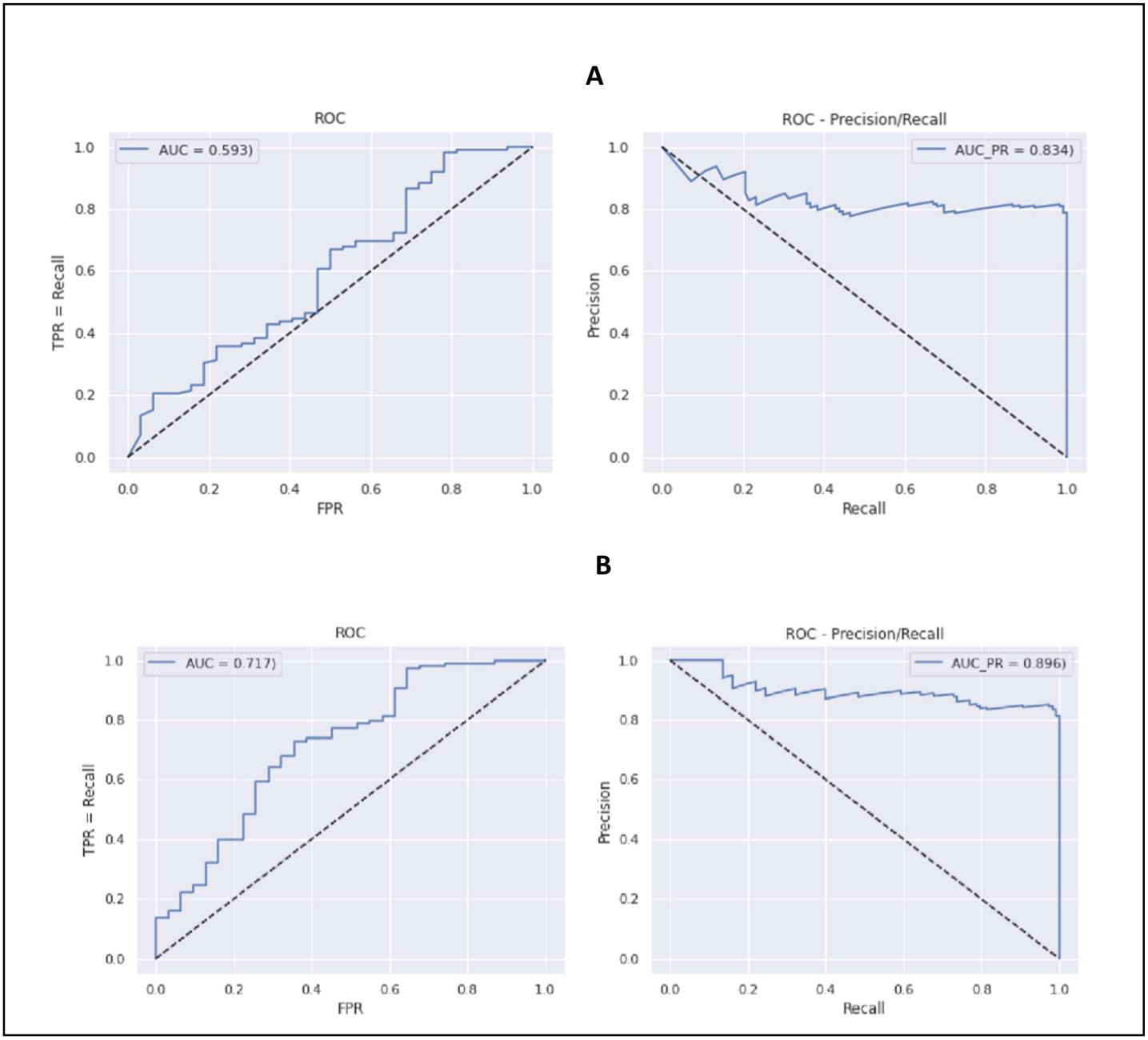


Fig 1. Results obtained using the predictive model and the real firstly only pre-operative variables (A) and then using pre and intra-operative variables(B) for patient´s survival in 1 year. ROC Curve Shows the Model's Discriminatory Power. AUC-area under the curve; on the left side: true positive rate (TPR-recall) *versus* false positive rate (FPR); on the right side: Precision (positive predictive values) *versus* TPR-recall.

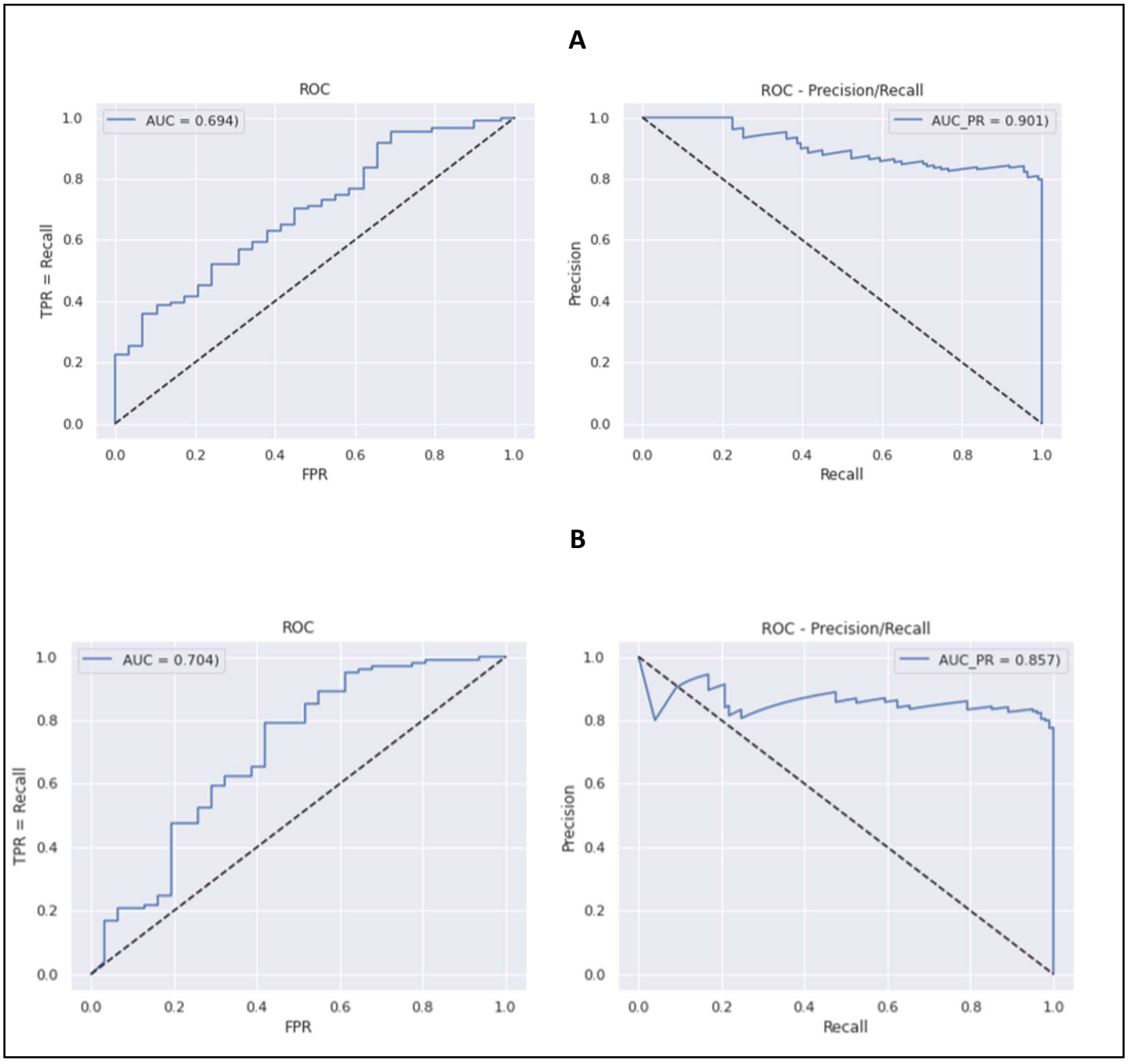
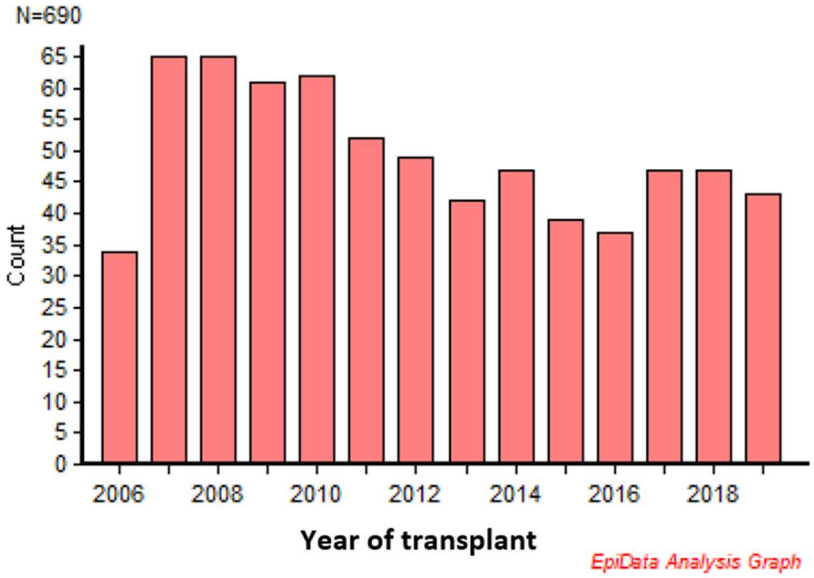


Fig 2. Results obtained using the predictive model and the real firstly only using pre-operative variables (A) and then using pre and intra-operative variables (B) for the survival of the organ in 1 year. ROC Curve Shows the Model's Discriminatory Power. AUC-area under the curve; on the left side: true positive rate (TPR-recall) *versus* false positive rate (FPR); on the right side: Precision (positive predictive values) *versus* TPR-recall.

Annexes



Year of Transplant	Number
2006	34
2007	65
2008	65
2009	61
2010	62
2011	52
2012	49
2013	42
2014	47
2015	39
2016	37
2017	47
2018	47
2019	43
Total	690

Fig.A- Distribution of number of liver transplants at Centro Hospitalar Universitário do Porto between 2006-2019

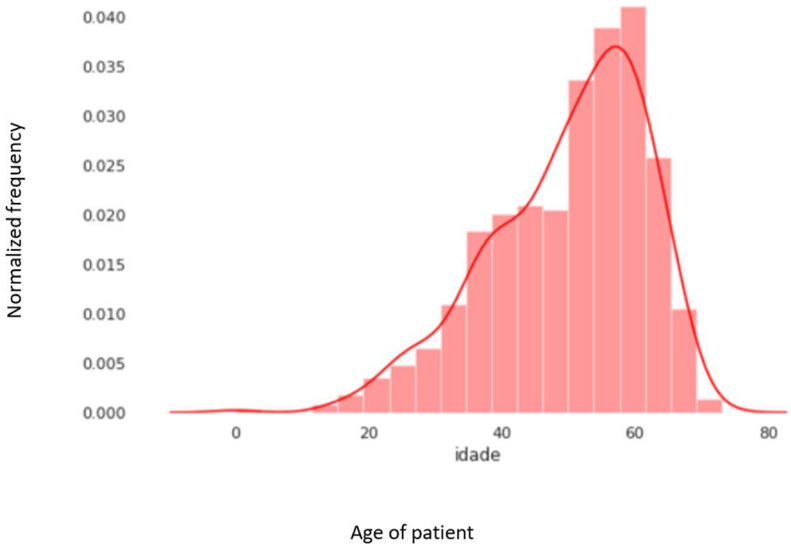


Fig. B- Distribution by age of the studied liver transplant patients (mean-51 years old)

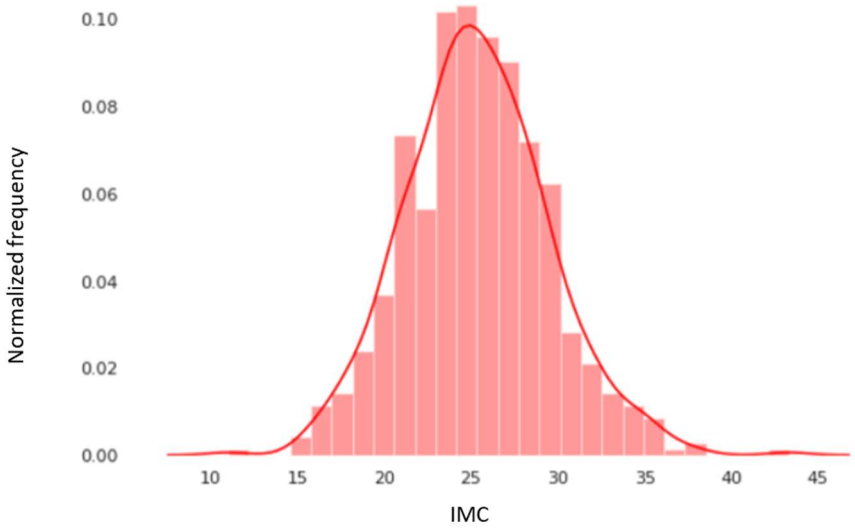
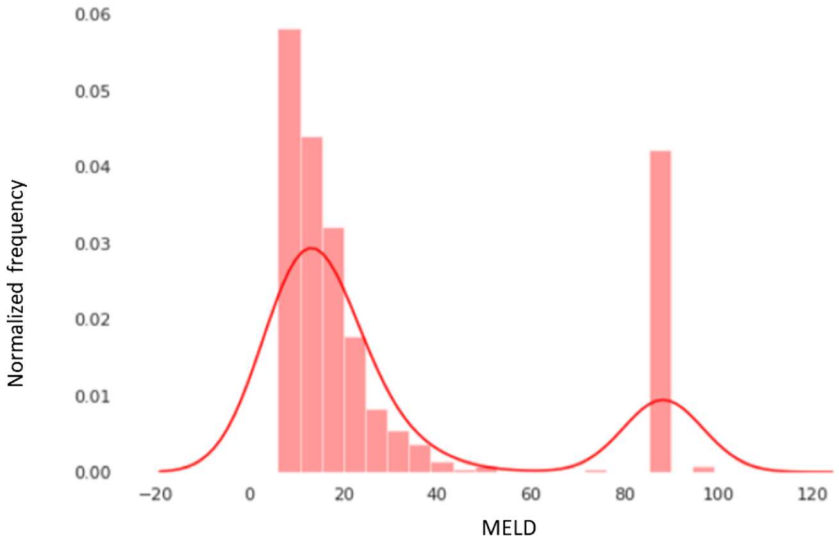


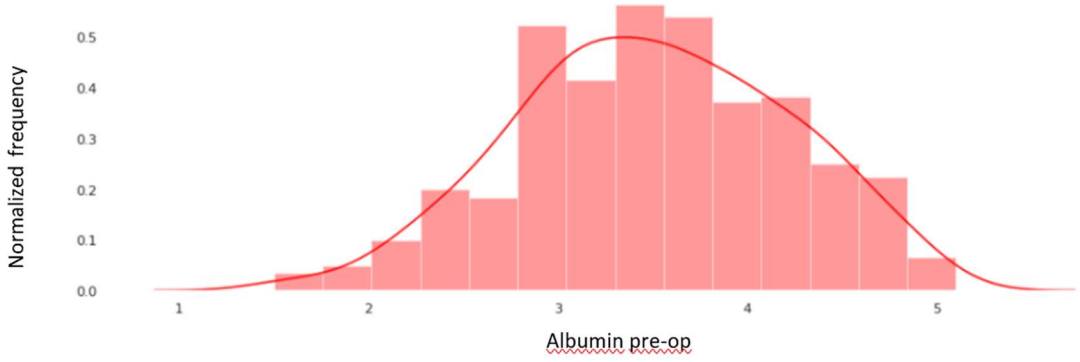
Fig. C- Distribution of the Body Mass Index (IMC) of the studied liver transplanted population.



MELD

Obs.	Sum	Mean	Variance	Std Dev	(95% CI	mean)	Std Err	
544	8297.0	15.25	69.58	8.34	14.55	15.95	0.36	
Minimum	p5	p10	p25	Median	p75	p90	p95	Max
6.00	6.00	7.00	9.00	14.00	19.00	26.00	31.75	72.00

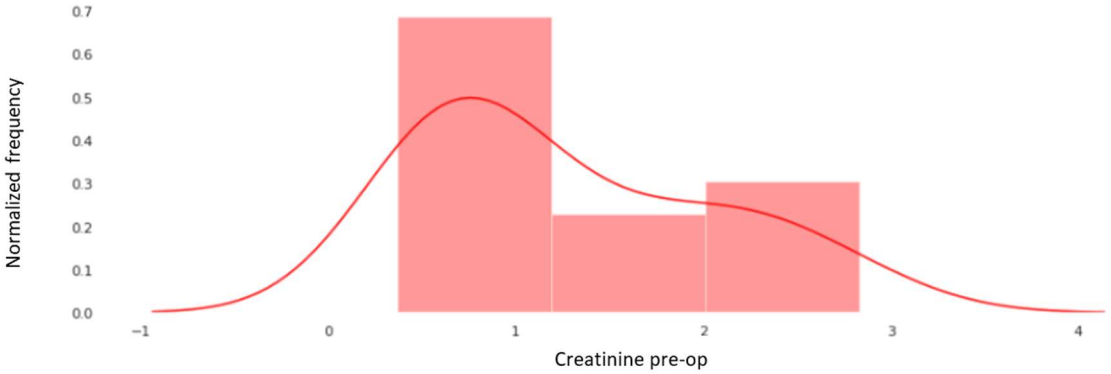
Fig. D- MELD score distribution of the studied liver transplant patients



Albumin pre-op(xx.x g/dL)

Obs.	Sum	Mean	Variance	Std Dev	(95% CI	mean)	Std Err	
686	2446.90	3.57	0.556	0.746	3.51	3.62	0.03	
Minimum	p5	p10	p25	Median	p75	p90	p95	Max
1.50	2.34	2.60	3.08	3.60	4.10	4.50	4.70	9.80

Fig. E- Pre-operative albumin value distribution of the studied liver transplant patients



Creatinine pre-op(xx mg/dL)

Obs.	Sum	Mean	Variance	Std Dev	(95% CI	mean)	Std Err	
203	185.19	0.912	0.298	0.546	0.837	0.988	0.04	
Minimum	p5	p10	p25	Median	p75	p90	p95	Max
0.290	0.512	0.550	0.660	0.790	0.980	1.34	1.67	6.47

Fig. F- Pre-operative creatinine value distribution of the studied liver transplant patients

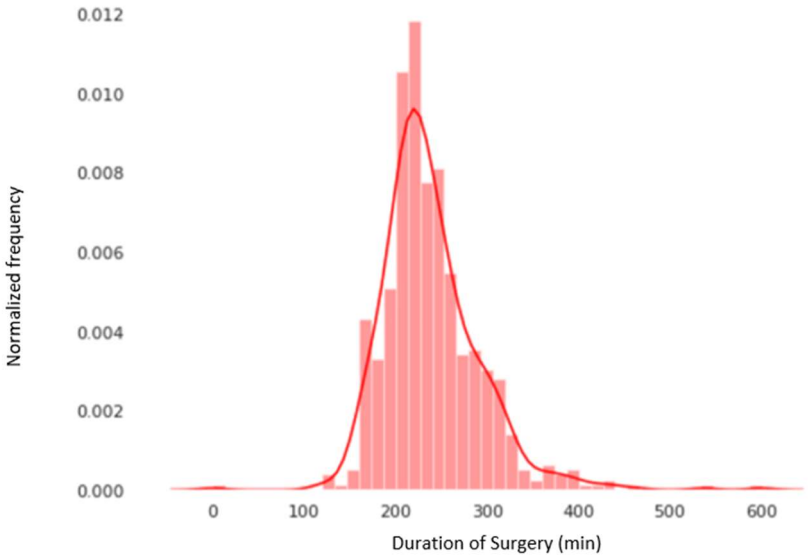


Fig.G- Duration of liver transplant surgery on studied patients

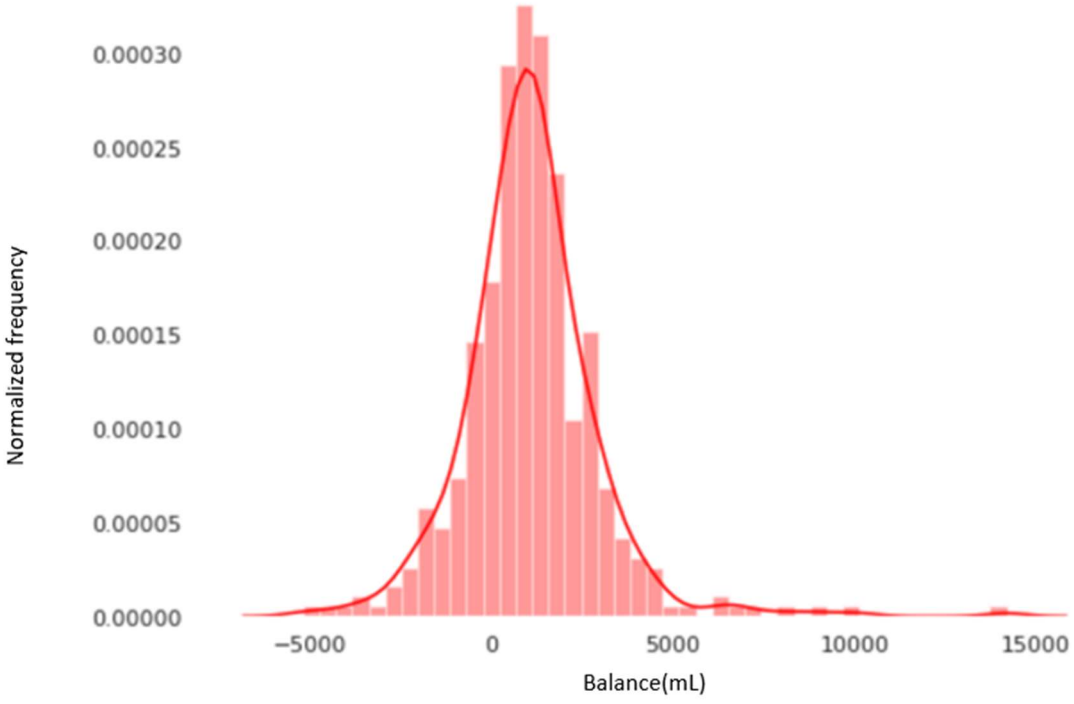


Fig.H- Hydric Balance after surgery on studied patients

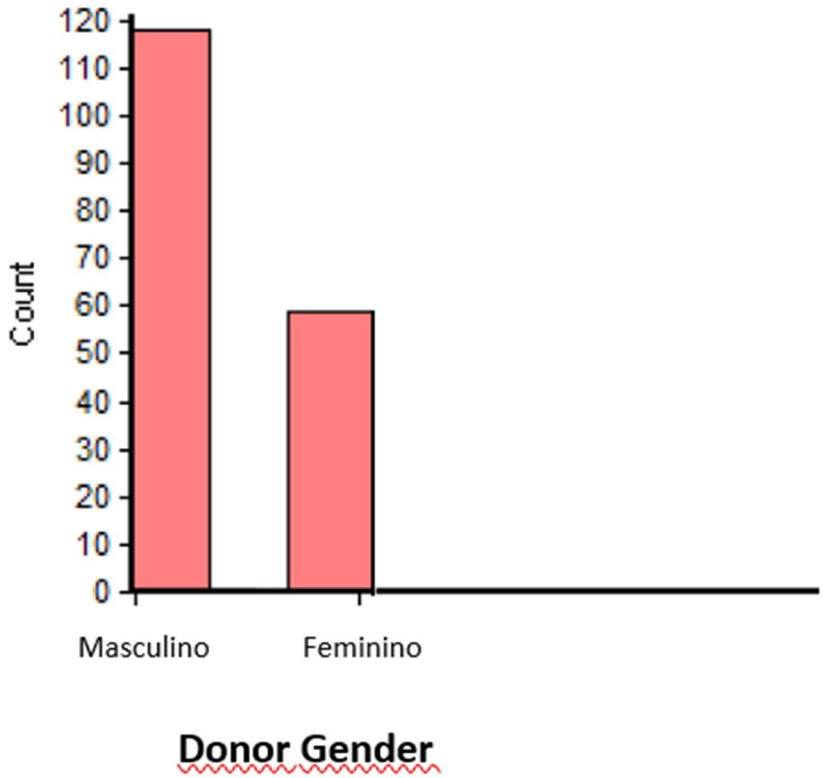


Fig. I- Liver donor gender distribution on studied patients

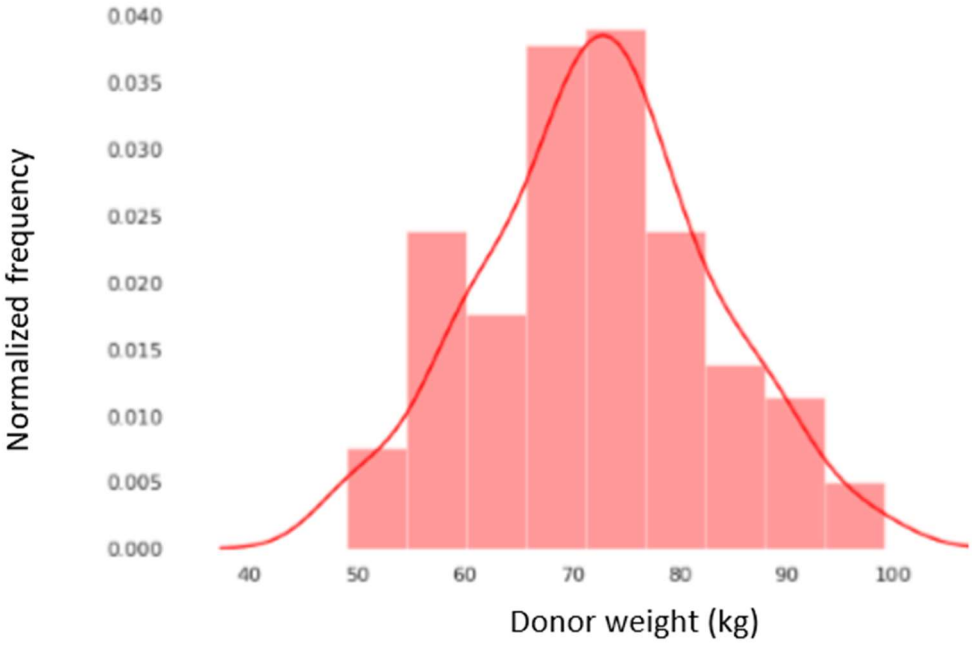


Fig. J- Liver donor weight distribution on studied patients

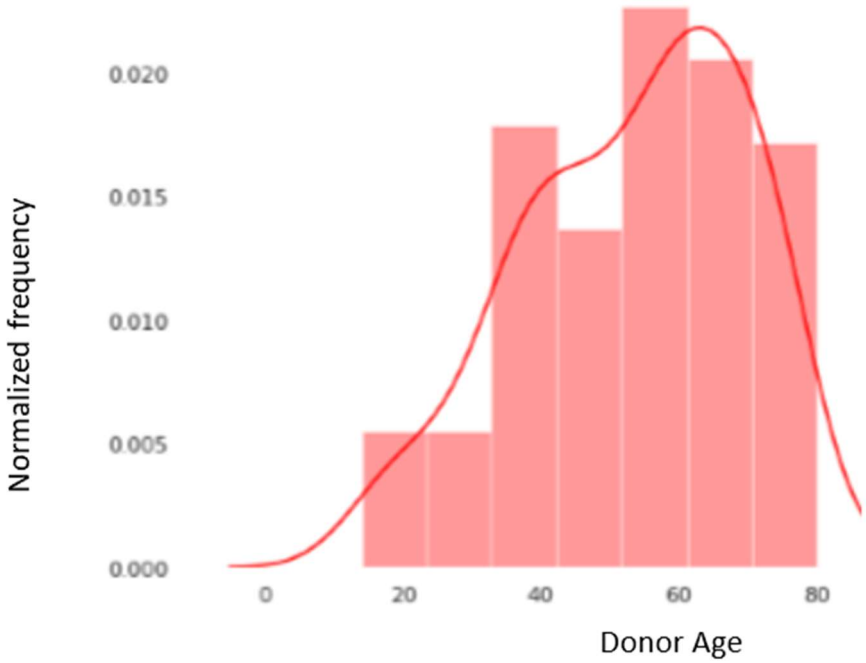


Fig. K- Liver donor age distribution on studied patients

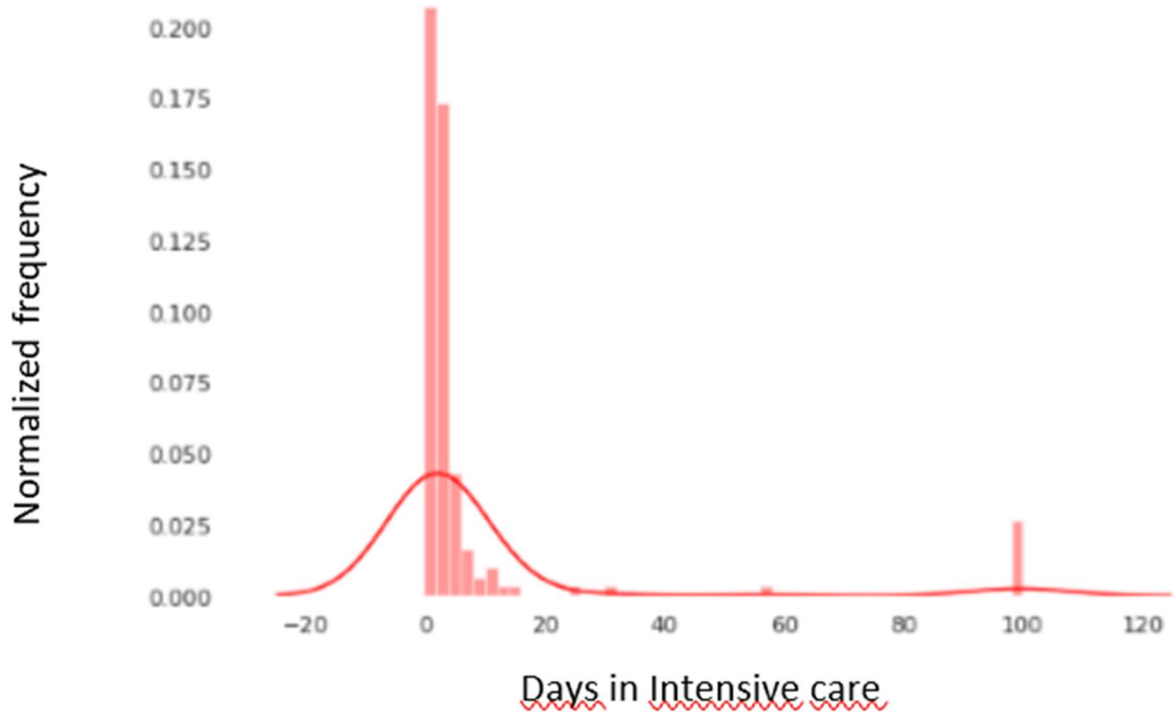


Fig. L-Liver donor in-patient days in intensive care unit

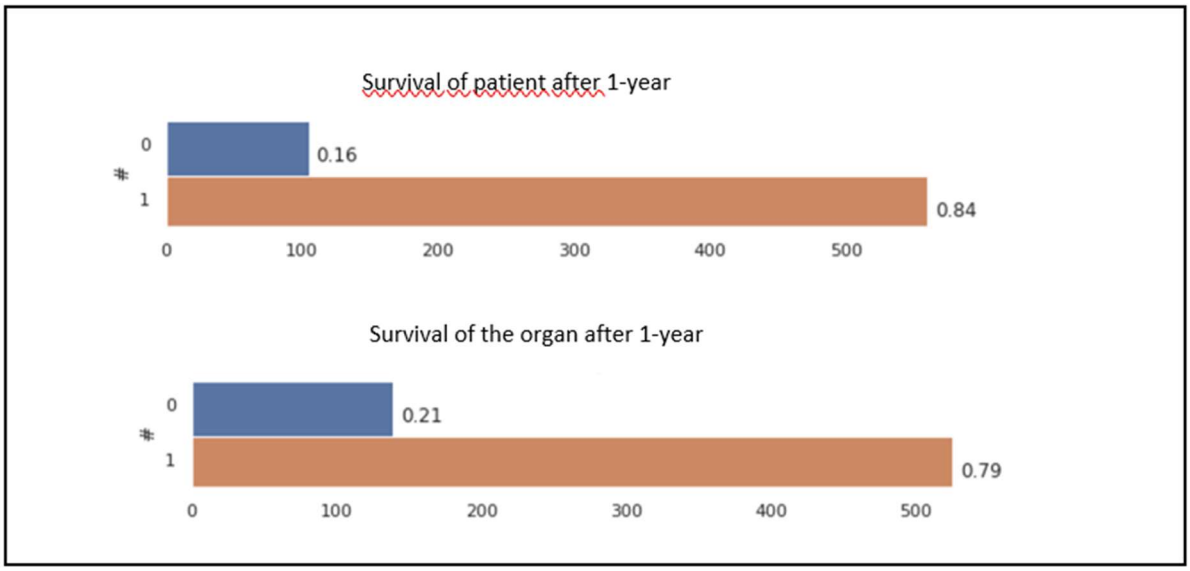


Fig. M- The time of survival of the patients and organ after one year. Blue representing the death of the patient or organ failure before 1 year; Brown representing patient or organs that survive more than 1 year.