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Forecasting Consent in Organ Donation: Early Assessment of Machine-Learning Techniques

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***Abstract*—Accurately predicting whether consent for organ donation will be granted is essential for optimizing timing and resource use in donor management. This study develops and evaluates machine learning models to estimate the likelihood of obtaining consent based on donor and contextual factors. The goal is to support early clinical decision-making by identifying cases where consent is more or less likely. Using real-world data from a regional transplant center operating under an opt-in system, we conduct data preprocessing, feature selection, and model training with various algorithms. Model performance is assessed using standard classification metrics, and key predictors of consent outcomes are identified. Results show accuracy levels exceeding 80%, highlighting the importance of including information about the relatives responsible for the decision. We also find that prediction accuracy varies with donor nationality, being higher for non-Italian donors. These findings demonstrate the value of predictive analytics in improving organ procurement efficiency and reducing unnecessary costs.**

***Index Terms*—Health care, Modeling and prediction, Machine learning, Decision support**

I. Introduction

ORGAN transplantation remains the most effective and economically viable treatment for patients with end-stage organ failure. However, despite ongoing efforts to raise awareness and increase donor registrations, a persistent and critical gap remains between the demand for and supply of transplantable organs [1], [2]. Among the key barriers contributing to this shortage is the high rate of opposition to organ donation, particularly when consent must be obtained post-mortem from next-of-kin.

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The acquisition of consent is a pivotal step in the organ donation process. In systems where explicit authorization is required—such as the *opt-in* framework in place in many regions—the inability to secure timely consent can lead to lost donation opportunities, unnecessary delays, and avoidable costs. Even in jurisdictions with *opt-out* legislation, in practice, healthcare professionals often still seek family confirmation, making the consent process a practical and ethical bottleneck.

In this paper, we propose a data-driven approach to support and optimize the consent acquisition phase through predictive modeling. Specifically, we develop and evaluate machine learning models aimed at forecasting the likelihood of obtaining consent for organ donation. By leveraging available demographic, clinical, and contextual data, our models seek to provide early estimates of consent probability, offering valuable decision support for clinicians involved in donor management.

As it is better discussed in Section III-B, this predictive capability has the potential to significantly enhance operational efficiency. For example, if a high probability of consent is anticipated, preparatory clinical activities can be initiated earlier, minimizing the time to transplantation and reducing organ deterioration risks. Conversely, in cases where consent is unlikely, healthcare teams may choose to delay or forego certain cost-intensive procedures, thus conserving resources.

Our study contributes to the field of healthcare information systems by introducing a predictive tool for estimating the likelihood of consent or opposition in organ donation. The practical relevance of such predictions lies in their integration into transplant logistics, where they can support informed decision-making and improve both clinical efficiency and cost-effectiveness.

The main contributions of the paper are as follows.

- We develop predictive models based on established machine learning algorithms to estimate the likelihood of family consent (or opposition) to organ donation, with a focus on the Italian opt-in system.
- We present a context-specific analysis using real-world data from the Lazio region, contributing the first known predictive study on consent acquisition in Europe.
- We compare various machine learning algorithms and identify the most effective approaches for consent prediction under data scarcity conditions.
- We highlight differences in predictive performance across different nationality groups.

The remainder of the paper is organized as follows. In Section II, we review the relevant literature. In Section III, we describe the donor management process, with a particular focus on the critical role of consent acquisition. The input data used in this study, along with the preprocessing and transformation procedures (including feature deletion, grouping, and refinement), are presented in Section IV. In Section V, we outline the predictive modeling methodology, detailing the algorithms, performance metrics, and selected features. The results of the predictive analysis are reported and discussed in Section VI. Finally, conclusions and future research directions are presented in Section VII.

II. Related literature

Organ donation consent is a critical component of the transplantation process, with direct implications for timing, cost, and overall success rates. As highlighted in the introduction, delays in consent acquisition can lead to suboptimal organ preservation and increased process costs [3]–[6]. In this section, we review the literature across three main areas: (i) barriers and refusal patterns in consent acquisition, (ii) strategies and policy frameworks aimed at improving consent rates, and (iii) the use of artificial intelligence and predictive analytics in organ transplantation.

A number of studies have investigated the sociocultural and procedural factors that hinder the acquisition of post-mortem consent. For example, the refusal rate in South Korea was examined in [7], where the authors identified structural and cultural barriers to obtaining consent. The intersection of ethics, religion, and policy was found to influence organ donation practices in South Asia [8]. Similarly, Lewis et al. discussed general barriers to organ donation across different populations [9]. In the Italian context, Grossi et al. found that refusal rates were significantly higher among immigrant populations compared to native citizens, highlighting the importance of demographic and cultural variables in consent prediction [10].

Efforts to proactively increase donation rates and consent have also been widely studied. In [11], hospitals were benchmarked based on their consent rates, with key influencing factors including donor age and ethnic background. A number of studies [9], [12], [13] have compared opt-in and opt-out systems, with opt-out systems generally associated with higher donation rates. However, these studies also acknowledge the complex ethical and political considerations surrounding such transitions. The role of family members in the final consent decision is emphasized in [14]–[16], even in jurisdictions with presumed consent. Additionally, many studies have revealed that one of the most influential issues is the expertise of the person approaching the family to obtain consent for organ donation. For instance, [17] highlighted the crucial influence of healthcare professionals' engagement and communication skills in facilitating positive consent outcomes, while [18] reviews studies on differences in consent rates based on the type of professional doing the asking. Expanding on these findings, [19] presents the practices adopted by Spanish transplant coordinators during consent requests for Irreversible Cessation of Circulatory and Respiratory Functions (ICOD). The study outlines the sequence of preparatory steps coordinators follow prior to engaging families in decision-making. Many of these steps are not only rooted in a structured and empathetic communication approach but are also recognized as best practices in broader organ donation contexts. This method has been associated with a notably low rate of family refusals, reinforcing the importance of professional training and protocol in achieving favorable consent outcomes. Additionally, some studies explore effective strategies for obtaining consent from families. For example, [19] presents the practices adopted by Spanish transplant coordinators when requesting consent for Irreversible Cessation of Circulatory and Respiratory Functions (ICOD). The study outlines the sequence of steps coordinators follow before engaging the family in decision-making. Many of these steps are recognized as best practices in broader organ donation contexts and are associated with a notably low rate of family refusals.

Broader applications of AI in organ donation and transplantation have also been explored. In [20], a comprehensive review was conducted on the use of artificial intelligence across various stages of the transplant process, including organ allocation, process optimization, and clinical decision support. However, the application of AI specifically to predict consent outcomes remains largely unexplored.

While the importance of timely consent acquisition in organ donation is widely acknowledged, research employing predictive modeling in this context remains limited. Notable exceptions include the studies by Khan et al. [2] and Tutun et al. [21], both of which apply machine learning techniques to forecast consent outcomes. In particular, the methodologies proposed by Khan et al. [2] demonstrate high levels of accuracy, indicating that such approaches are both viable and effective. Ultimately, they have the potential to increase consent rates and thereby save more lives among individuals on organ transplant waiting lists.

In [2], the authors develop a predictive framework that integrates machine learning and network science to estimate the likelihood of family consent in organ donation. Their model is designed not only to predict outcomes but also to uncover the most influential factors driving family decisions. The basic goal is to provide Organ Procurement Organizations (OPOs) and hospital staff with actionable insights that support more effective communication strategies during consent discussions. This work emphasizes the role of predictive models as expert systems to improve consent rates and, by extension, help mitigate the persistent mismatch between organ supply and demand.

Similarly, Tutun et al. [21] propose a responsible AI framework that merges network science with machine learning to enhance consent prediction. Their study leverages a large dataset collected from approximately 1,500 consent discussions across 92 hospitals in New York, recorded between January 2016 and March 2018. Results indicate that incorporating network-based features significantly improves the performance of traditional ML algorithms. The study highlights how algorithmic insights can support ethical and effective approaches to organ procurement.

Despite their relevance, both studies above differ from our work. First, their primary objective is to reduce the rate of family refusal, with a strong focus on optimizing the approach strategies of healthcare professionals. In contrast, our goal is to develop a predictive framework that provides a probabilistic estimate of consent likelihood, which can be integrated into transplant logistics and used to inform cost-effective and timely decision-making throughout the donor management process. Second, the methodological approaches vary considerably. While [2] and [21] rely on extensive sets of features and large datasets—enabling more complex models and improved predictive performance—our study operates on a significantly smaller dataset collected in Italy. This naturally constrains model complexity but provides a novel, context-specific perspective.

This context-specific perspective builds on previous investigations of the Italian case study [22], [23]. In [22], a probabilistic model was developed to estimate the time required to obtain consent, using real-world data from successful organ donation cases in the Lazio region, where an opt-in consent system is in effect. However, that study focused on modeling the timing of consent acquisition, rather than predicting the binary outcome of whether consent would be granted. The same case study was further explored in [23], where the pre-transplant process was modeled and simulated to identify time-critical activities through critical path analysis. Building on that work, [24] conducted a cost-benefit analysis to evaluate management strategies aimed at balancing time efficiency and cost-effectiveness throughout the pre-transplant phase.

To the best of our knowledge, our study is the first to address consent prediction using real-world data from Italy, and more broadly, among the first of its kind in Europe. This regional focus enables us to explore consent dynamics within the specific legal and procedural framework of an opt-in system, offering valuable insights for local policy and process optimization.

III. Overview of Donor Management and Consent Dynamics

Transplant centers worldwide generally follow a hierarchical structure, with a national coordinating authority and regional and local healthcare facilities. This is also the case in the center we consider here. Namely, we focus on the Italian Transplant System, involving the National Transplant Center (NTC), Regional Transplant Centers (RTCs), and local hospital units. Organ transplantation is a complex process involving many phases and actors. In this paper, we are interested in the process leading to consent acquisition. In this section, we describe the donor management process and the relevance of the timeliness of consent acquisition for the overall efficiency of the process.

A. The organ donor management process

The organ donor management process is a structured set of activities that begins with the identification of a potential donor and ends with the retrieval of organs and their allocation to compatible recipients. Its primary aim is to ensure the quality and availability of transplantable organs while safeguarding recipient health.

This work focuses on the process currently implemented at the RTC of the Lazio region in Italy. The UML (Unified Modelling Language) diagram in Figure 1 represents a sketch of the donation process, which begins when a potential donor is identified. The identification of a donor starts with the recognition of the brain death status of a patient, which qualifies him/her as a potential donor. A six-hour period is required for Brain Death Assessment (BDA). After BDA, two parallel streams of activities are triggered:

- Acquisition of consent for organ donation;
- Initial clinical and diagnostic evaluations.

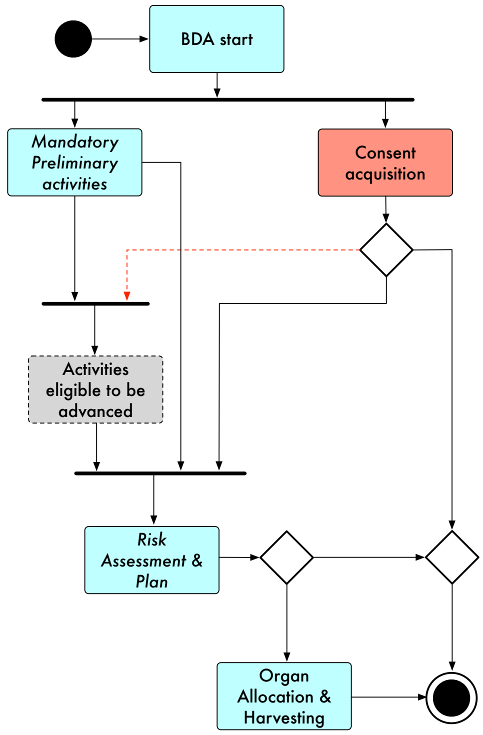

Fig. 1: Compact UML diagram of the process.

The following phases involve a comprehensive assessment of donor suitability, including laboratory analyses, virological testing, and instrumental diagnostics. Although there are no strict technical constraints, higher-cost exams are generally performed only after consent is obtained, in order to avoid unnecessary expenses when the transplant cannot proceed due to a lack of consent. If consent arrives in due time, it allows the medical staff to proceed with all the medical tests needed to properly carry out the transplant. If consent is denied, any further medical test for transplant is cancelled. Some activities are susceptible to be advanced, i.e., carried out even if consent has not arrived yet, so as to reduce the overall process time. Those activities are shown as *advance-eligible* in Fig. 1. Dashed arrows indicate precedence relations that are not mandatory. After the examinations are carried out to assess the clinical suitability of the potential donor, a risk level is defined—sometimes following consultation with the Second Opinion team appointed by the National Transplant Center (NTC). If the evaluations indicate that the donor presents an unacceptable risk to recipients, the process is immediately stopped. Once the donor's risk level has been defined, the process moves into the Organ Allocation and Harvesting phase. In this stage, potential recipients are identified and matched based on clinical compatibility and logistical considerations, through coordinated efforts involving the NTC, Regional Transplant Centers (RTCs), local transplant teams, and logistics services, ensuring timely and efficient organ retrieval and distribution.

B. *Impact of Consent activity on process time and cost*

If a potential donor has not expressed their wishes regarding organ donation while alive, the responsibility for releasing consent is transferred to their relatives. The Consent acquisition phase becomes a critical crosspoint in the donation process—regardless of whether consent is ultimately granted or denied by those legally empowered to decide. This phase significantly affects both the duration and cost of the process.

To illustrate, imagine that the family or other authorized individuals communicate their decision at some unknown time point T after the donation process begins. By that time, a possibly empty subset S of activities (eligible to be initiated before the consent is given) may already have been started or completed. Let c_S denote the cumulative cost of these activities. If consent is not granted, then a cost c_S is effectively wasted.

This would suggest a conservative strategy: delaying costly actions until consent is confirmed to keep S, and thus c_S, minimal. However, such caution comes at a price. Postponing action until the decision time T prolongs the process—especially in cases where consent is eventually given. The more activities completed before T, the more progress has been made by the time consent is secured, allowing transplantation to proceed more quickly. Since organs are perishable and their viability deteriorates over time, any delay can compromise the success of the transplant.

This tension calls for a cost-benefit analysis to guide decision-making, weighing the trade-off between minimizing wasted costs and maximizing time efficiency in cases where consent is ultimately granted (see [24]). In short, cost-efficiency favors deferring activities until consent is certain, while time-sensitivity and organ viability argue for initiating tasks early—even at the risk of incurring unrecoverable costs if consent is later denied, particularly when T is large. If we indicate the process times as T_{adv} and $T_{\mathrm{del}} > T_{\mathrm{adv}}$, respectively, when activities are advanced or postponed with respect to consent acquisition, we can summarize the time-cost trade-offs in the matrix shown in Fig. 2, where each bracket contains the time needed to complete the process and the wasted cost.

In this context, a predictive tool that can estimate the likelihood of consent with reasonable accuracy would be highly valuable. High confidence in a positive outcome justifies starting preparations sooner, improving both patient outcomes and resource utilization. Conversely, if the predicted probability of denial is high, delaying

Outcome \ Strategy	Advancing	Delaying
Consent	$(T_{\text{adv}}, 0)$	$(T_{\text{del}}, 0)$
Opposition	(NA, c_S)	$(\text{NA}, 0)$

Fig. 2: Trade-offs in donor management process strategy

costly tasks becomes the prudent course, helping to avoid unnecessary expenditure.

IV. Dataset

We collected and analysed a dataset concerning potential donors at the Regional Transplant Center for the Lazio region in Italy. In Italy, the opt-in regulation applies where the potential donor may have given or denied his/her consent to transplant when they were alive. In the case the potential donor did not express their decision concerning organ transplant during their life, it is up to the family members to decide after the potential donor's brain death. The decision about donation as well as the personal details of the potential donor and their relatives are recorder. In this section, we describe the dataset including that information.

Our data collection took place over four years, from 2021 to 2024. We can first see how the consent information is distributed over the years in Table I. A significant growth year-on-year can be observed, with a CAGR (Compound Annual Growth Rate) of 6.7%. The overall number of instances is 867 (the data for 2024 do not cover the whole year). However, the dataset is heavily imbalanced, with the *Silent* group (i.e., those not expressing their opinion during their lifetime) being the large majority (80.2% of the total). The overall dataset has been processed through Bootstrap and 10-fold cross-validation to get the final dataset to be fed to the algorithms described in Section V-A for training and testing. Since our focus is to predict consent for potential donors after brain death (DBD), we are not interested in those donors expressing their consent during their lifetime. Actually, for those potential donors, the donor management process either starts with all the medical tests to be carried out as soon as possible, or does not start at all. Hence, in the following, we will focus on the silent potential donors. After examining the dataset, we removed those instances where most features are absent. The overall number of silent donors has then reduced to 653, which is the reference number we will consider in the following.

In addition, in order to examine how the nationality of the donor may influence the decision and may be predicted with larger or lesser accuracy, we considered the following subsets of potential donors:

- European donors;
- Italian donors;
- non-Italian donors.

TABLE I: Consent expression in the dataset

Year	Consent	Opposition	Silent	Total
2021	18	18	196	232
2022	32	14	202	248
2023	34	28	202	264
2024	23	5	95	123
Total	107	65	695	867

TABLE II: Number of silent donors by nationality

Nationality	Numerosity
European	585
Italian	542
non-Italian	111

The numerosity of the three subsets is shown in Table II. As can be seen, Italians make up roughly 90% of the whole set of European potential donors, as expected.

We can see in Fig. 3 how nationality influences the decision about organ donation during lifetime. While we see a balanced distribution for European and South American potential donors, the distribution is heavily imbalanced for the other continents. The culture of donation is quite widespread in North America, where just a small minority opts for opposing donation. On the other end of the spectrum, we find Asia and Africa, where oppositions largely outnumber consents.

For each potential donor, 67 features have been collected. Those features may be subdivided into six groups:

1) General;
2) Personal data;
3) Information on relatives;
4) Risk level;
5) Organ information;
6) Consent.

Group 1 contains information related to the death of the potential donor, including time and cause of death. Group 2 includes all personal data pertaining to the donor: name, surname, age, gender, date of birth, place of birth, place of residence, height, and weight. Group 3 provides data necessary to determine the degree of kinship of the relatives involved in the consent process (e.g., parents or siblings). Group 4 comprises information regarding the donor's risk profile, based on second opinions obtained by the medical staff during the organ compatibility assessment. Finally, Group 5 is

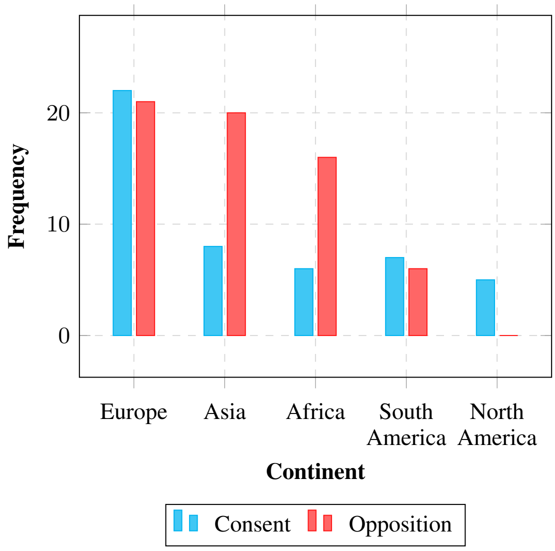

Fig. 3: Frequency of support and opposition by continent

included only if consent has been obtained, and contains specific details about the organ that may be considered for transplantation.

It is to be noted that Group 6 actually includes the target variable (whether Consent has been released), but also information on the source of consent (the donors themselves or their relatives).

V. Methodology

The problem of consent prediction has been modelled as a binary classification one, where the two classes are Consent or Opposition (Consent denial) and the potential features are the 67 mentioned in Section IV. In this section, we describe the classification algorithms that we have employed, the performance metrics that we have adopted to assess the algorithms, and the feature selection process.

A. Algorithms and tools

We have employed the following established classification algorithms:

- Decision Tree;
- Logistic Regression;
- AdaBoost;
- Feedforward neural network.

Each method in this selection has its own characteristics.

Decision Trees split data into subsets using feature thresholds, creating a tree-like structure where each node represents a feature condition, and leaves represent class labels. They are easy to interpret, but are prone to overfitting, especially on small datasets like ours.

Logistic Regression is a linear model where the probability of a class is predicted by using a logistic function. Regularization is achieved through LASSO (L1 Regularization) by adding a penalty term to reduce overfitting and performing feature selection by shrinking some coefficients to zero. It is simple, interpretable, good for high-dimensional data with irrelevant features. It has been chosen since we have a relatively large number of features (we are considering non-image data) many of which may prove to be not relevant. It has limited capacity for complex relationships.

AdaBoost (Adaptive Boosting) is an ensemble method that combines multiple weak learners (often decision stumps) by iteratively focusing on previously misclassified examples. It should be more accurate than single models like decision trees or logistic regression and works well with less data (as in our case). However, it is sensitive to noisy data and outliers.

Finally, feedforward Neural Networks represent a very simple type of deep learning model where data flows through multiple layers of interconnected nodes (neurons) from input to output. They are powerful for modeling complex, non-linear relationships. However, they require large datasets, which we do not have at present, and are less interpretable.

In the following we describe the configuration details for each classification algorithm.

For decision trees we have employed a general (non-binary) structure, where splitting was carried out just for nodes with at least five instances. The maximum tree depth was kept at 50 and pruning was employed for nodes where the majority class includes more than 95% of the instances.

Logistic Regression was employed with LASSO regularization with L1 norm and the classification threshold set at 0.5 probability..

In AdaBoost 60 trees were used as base estimators, with the learning rate set to 1.

A multilayer network with 100 neurons per hidden layer was employed with a feedforward structure. A logistic sigmoid function was chosen as the activation function used, and ADAM was selected as solver, based on the gradient descent algorithm for calculating weights during the training phase [25]. The maximum number of iterations (stopping condition) was set to 200.

B. Performance metrics

Our aim is to identify the cases where consent to donation is obtained. We have then a binary classifier, where we label as Positive the cases where consent is actually obtained. With the usual 4-cell confusion matrix, we have then the following possible outcomes: True and False Positives (TP and FP, respectively) as well as True

TABLE III: MOST SIGNIFICANT FEATURES

Feature	Overall	European	Italian	non-Italian
Donor's hospital	✓	✓	✓	✓
Nationality	✓	✓		
Birthplace region	✓	✓	✓	
Continent	✓			✓
Cause of death	✓	✓	✓	✓
Region of residence	✓	✓	✓	✓
Donor's age	✓	✓	✓	✓
Size of birth city	✓	✓	✓	
Donor gender	✓	✓	✓	✓
Year of death	✓	✓	✓	✓
Donor blood type	✓		✓	
Size of city of residence	✓	✓	✓	✓
Part of Italy (residence)	✓	✓	✓	✓
Country of birth				✓
Country of residence				✓

and False Negatives (TN and FN, respectively). We adopt the following extablished performance metrics [26]:

- Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$
- Precision = $\frac{TP}{TP+FP}$
- Recall = $\frac{TP}{TP+FN}$
- F1 Score = $2\frac{1}{\frac{1}{\text{Precision}}+\frac{1}{\text{Recall}}}$

C. Features

Though we have a large number of potential features (67), most of them have proved to be of small significance for the performance. For that reason, we have chosen a subset of significant features by employing three metrics: the information gain, the gain ratio, and the Gini index. The choice of features depends on the subset of interest, so that we have selected the most relevant features for each data subset. In Table III, we show the selection for the full dataset and the three subsets investigated in this paper. Some features appear to be significant for all the sets, namely: Donor's hospital, Cause of death, Location of residence, Donor's age, Year of death, and Size of city of residence.

VI. RESULTS

We have examined our dataset by employing all the four algorithms described in Section V-A. We first consider the results obtained for the whole set of silent donors, i.e., those potential donors who did not express their consent (or denial) during their lifetime, so that the decision has been left to their relatives. Then we examine the results for the nationality subsets defined in Section IV.

In Table IV, we show the major performance metrics. Linear Regression is by far the worst performer, exhibiting figures below 70% on all four metrics. We see a significant improvement by roughly ten percentage points with decision trees. However, if we abandon the intrinsic explainability of decision trees, both ensemble techniques (AdaBoost in this case) and neural networks

TABLE IV: MODEL PERFORMANCE USING BOOTSTRAP ON THE SILENT DATASET

Technique	Accuracy	F1 Score	Precision	Recall
Tree	0.76	0.76	0.76	0.76
LASSO	0.66	0.64	0.65	0.66
AdaBoost	0.85	0.85	0.85	0.85
Neural Net	0.82	0.82	0.82	0.82

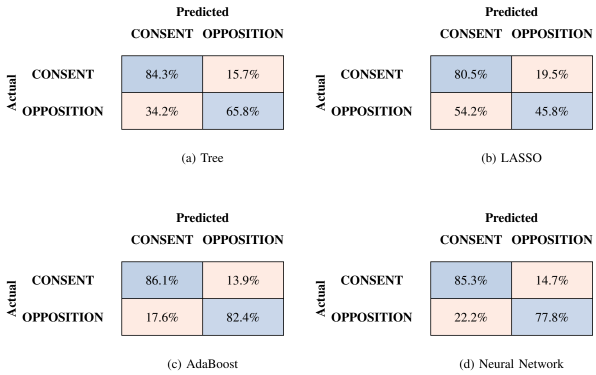

Fig. 4: Confusion matrices (percentages) using Bootstrap on the silent dataset

(though in their simple feedforward configuration) allow us to reach good performances achieving figures well beyond 80% on all metrics. AdaBoost appears the best overall performer.

We can take a closer look at the performance by examining the confusion matrices in Fig. 4. Linear regression (LASSO) shows the worst imbalance in performance, being good in recognizing Consent decisions, but failing by misclassifying a major portion of Opposition decisions (performing even worse than a random classifier). The imbalance in performance decreases but is still significant in decision trees (though the majority of oppositions is now classified correctly). The per-class performance improves significantly with AdaBoost and neural networks. The imbalance across classes is very small for AdaBoost and a bit larger for neural networks. In both cases, the imbalance works against oppositions, which are classified correctly in less than 80% of the instances with neural networks.

Summing up, Adaboost appears as the best classifier, both overall and over either class, exhibiting well-balanced performances.

We can now examine the performances on the subsets described in Section IV, considering European, Italian, and non-Italian potential donors.

In Table V, we show the performance metrics for European donors. The performance is quite similar to what we have obtained on the overall dataset, though a bit better. This may suggest that European donors may

TABLE V: MODEL PERFORMANCE USING BOOTSTRAP ON EUROPEAN DONORS

Technique	Accuracy	F1 Score	Precision	Recall
Tree	0.78	0.78	0.78	0.78
LASSO	0.67	0.66	0.66	0.67
AdaBoost	0.84	0.84	0.84	0.84
Neural Net	0.85	0.85	0.85	0.85

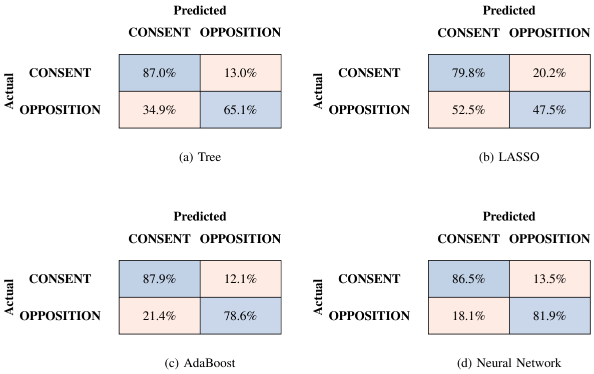

Fig. 5: Confusion matrices (percentages) using Bootstrap on the European dataset

be predicted more reliably than non-European donors.

Similarly to what we did for the whole dataset, we can examine the performance metrics on either class by looking at the confusion matrices in Fig. 5. We see again that decision trees have similar performances as the best performing algorithms for the Consent class. It is the performance on the Opposition class that brings the overall accuracy down. The imbalance between the performance for the two classes is high for the LASSO regression. Neural networks appear as the most balanced algorithm for this subset.

If we focus on Italian donors, which are, as expected, the largest nationality subgroup by far, we obtain the results shown in Table VI. We do not see significant changes with respect to the results that we have already shown. The pertaining confusion matrix is shown in Fig. 6.

What removes some doubts about the reliability of predictions for nationals is the examination of Table VII, where the performance improves significantly. We can conclude that, though AdaBoost and neural networks provide accuracy values over 80% in any case, predictions are more accurate for non-Italian potential donors than for Italian ones. though the size of the non-Italian subsample is not very large, it appears that the features that we have employed give much clearer indications for non-Italian donors.

Finally, we have examined the possibility of improving the forecasting accuracy by introducing features related to family members. The results in Table VIII clearly show a significant improvement for the worst performing algorithms (decision trees and LASSO regres-

TABLE VI: MODEL PERFORMANCE WITH BOOTSTRAP ON ITALIAN DONORS

Technique	Accuracy	F1 Score	Precision	Recall
Tree	0.77	0.76	0.77	0.77
LASSO	0.69	0.67	0.68	0.69
AdaBoost	0.81	0.81	0.81	0.81
Neural Net	0.83	0.83	0.83	0.83

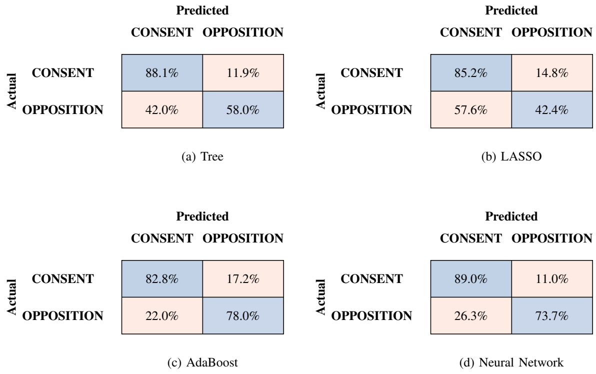

Fig. 6: Confusion matrix (percentages) for Neural Network using Bootstrap on the Italian dataset

TABLE VII: MODEL PERFORMANCE WITH BOOTSTRAP ON NON-ITALIAN DONORS

Technique	Accuracy	F1 Score	Precision	Recall
Tree	0.71	0.71	0.71	0.71
LASSO	0.71	0.71	0.71	0.71
AdaBoost	0.86	0.86	0.86	0.86
Neural Net	0.85	0.85	0.85	0.85

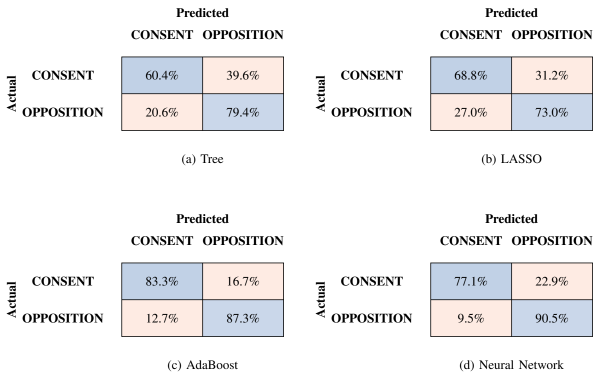

Fig. 7: Confusion matrices (percentages) using Bootstrap on the non-Italian dataset

TABLE VIII: MODEL PERFORMANCE WITH BOOTSTRAP BY ADDING INFO ON FAMILY MEMBERS

Technique	Accuracy	F1 Score	Precision	Recall
Tree	0.80	0.79	0.80	0.80
LASSO	0.79	0.79	0.79	0.79
AdaBoost	0.88	0.88	0.88	0.88
Neural Net	0.86	0.86	0.86	0.86

sion) and a small improvement for the best-performing algorithm (AdaBoost and neural networks). For the latter algorithms, the accuracy gets closer to 90%. The addition of that information, though notoriously difficult to get, is then highly recommended.

VII. CONCLUSIONS

This study has demonstrated the feasibility and effectiveness of using machine learning techniques to forecast consent outcomes in the organ donation process. By leveraging a comprehensive set of socio-demographic, clinical, and contextual features, our models—particularly AdaBoost and neural networks—achieved strong predictive performance, with accuracies exceeding 85% and well-balanced classification across both Consent and Opposition cases. These results affirm the value of predictive modeling in addressing one of the most critical and uncertain phases of organ donation: the acquisition of consent.

The practical implications of this work are substantial. In a process where timing is critical and resources are constrained, early estimation of the likelihood of obtaining consent enables healthcare professionals to tailor their actions. High predicted probabilities of consent support the early initiation of cost-intensive diagnostic and preparatory procedures, thereby minimizing delays and reducing the risk of organ deterioration. Conversely, low predicted probabilities can help avoid unnecessary expenditures and optimize allocation of staff and equipment. The integration of such predictive tools into clinical decision support systems can therefore enhance both operational efficiency and cost-effectiveness in transplant logistics.

Looking ahead, several promising directions could further extend this research on consent prediction in solid organ transplantation. First, integrating additional qualitative and behavioral data—such as prior interactions with healthcare staff or known family attitudes—may enhance predictive accuracy and provide deeper contextual understanding. Second, the development of real-time, interpretable models tailored for clinical settings would improve usability and foster trust among healthcare professionals, potentially leveraging more advanced and explainable forecasting architectures [27].

Third, conducting cross-regional studies with data from multiple transplant centers would allow for broader validation and support the generalization of findings, thus laying the groundwork for national or even international implementation of consent prediction tools within organ donation systems.

Finally, we believe that embedding the proposed model within a comprehensive decision-support framework—capable of optimizing various components of the donor management process, including logistical challenges such as organ transportation [28]–[31]—could significantly improve the overall performance and efficiency of the system (see, e.g., [32]).

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