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*Original Article*

# A machine learning approach to predict types of bariatric surgery using the patients first physical exam information

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## Abstract

**Background and aim:** According to the IFSO worldwide survey report in 2014, 579517 bariatric operations have been performed in a year, of which nearly half the procedures were SG followed by RYGB. This procedure is a proven successful treatment of patients with morbid obesity which induces considerable weight loss and improvement of type 2 diabetes mellitus, insulin resistance, inflammation, and vascular function. In the present study, we aimed to build a machine based on a decision tree to mimics the surgeon's pathway to select the type of bariatric surgery for patients.

**Methods:** We used patient's data from the National Bariatric Surgery Registry between March 2009 and October 2020. A decision tree was constructed to predict the type of surgery. The validation of the decision tree confirmed using 4-folds cross-validation.

**Results:** We rich a decision tree with a depth of 5 that is able to classify 77% of patients into correct surgery groups. In addition, using this model we are able to predict 99% of bypass cases (Sensitivity) correctly. The waist circumference less than 126 cm and BMI equal to or more than 43 kg/m2, age equal to or greater than 30 years old, and being hypertensive or diabetes are the most important separators.

**Conclusion:** The effects of all nodes have been studied before and the references confirmed the relations of them and surgery type.

**Keywords:** Bariatric surgery, Machine learning, Roux-en-Y Gastric Bypass, Sleeve Gastrostomy, Mini-gastric Bypass/One-Anastomosis Gastric Bypass

## Introduction

Bariatric surgery is a proven successful treatment of patients with morbid obesity which induce considerable weight loss and improvement of type 2 diabetes mellitus, insulin resistance, inflammation and vascular function (1). This surgery consists of several surgical procedures, including restrictive, mal-absorptive or combination of restrictive and mal-absorptive components (2). Roux-en-Y gastric bypass (RYGB) becomes more widely accepted as a combination surgical treatment (3). As well, one anastomosis gastric bypass-mini gastric bypass (OAGB-MGB) is considered as a restrictive and mal-absorptive surgical option (4). Furthermore, sleeve gastrectomy (SG) is defined as a restrictive bariatric technique (5). As a note, according to the IFSO worldwide survey report in 2014, 579517 bariatric operations have been performed in a year, of which nearly half of the procedures were SG followed by RYGB (6). Although, all these bariatric surgeries are effective way to lose weight and to improve obesity-related diseases, patient selection criteria for each surgical method in an effort toward the personalized bariatric procedure (7) should be considered by multidisciplinary team.

In the recent years, the tendency to apply information-based techniques in the area of health challenges and progressing medical investigating increase among researchers. From this point of view, machine learning (ML) methods are more common and applicable among them. Different algorithms in ML like artificial neural networks, decision trees (8), Bayesian networks (9), and support vector machines (10), have been broadly applied to recognizing key features and patterns of the medical datasets. Using these patterns, we are able to predict or diagnosis various types of outcomes for new patients. For instance, ML calculations have recently been utilized to classify skin cancer using pictures with comparable precision to a trained dermatologist (11) and to anticipate the movement from prediabetes to type 2 diabetes utilizing routinely-collected electronic health record information (12).

The predictions help us to prepare for future situations that our patients may confront. We could prevent lots of side effects or subsequences using inexpensive and safe treatments in the right early time. The treatments should not only be a serious medical intervention or even a surgery. Informing patients on time about a simple protective behavior or the cares of a surgery may be effective as hospitalizing them (13).

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A Medical decision usually consists of a hierarchical series of classification. It starts from a primary symptom or condition and the physicians follow a pathway to find out other common symptoms. Finally, after several steps, they ensure that a specific disease or treatment is almost correct to be chosen. A similar approach exists in the context of machine learning called decision trees also known as classification trees.

Classification trees apply to data where the outcome usually is a binary classification label, such as the disease status of a patient, and the medical decision creator would like to construct a decision rule that predicts the outcome using available dependent variables (14). In this study, we aimed to build a machine based on a decision tree to mimics the surgeon's pathway to select the type of bariatric surgery for patients. Our result could be seen as a recommendation system that patients or even surgeons interact with and use as an extra informative device.

## Methods

**Study Setting:** In this study, we used data from the National Bariatric Surgery registry (obesitysurgery.ir) that include severe or morbid obese patients who were candidates for bariatric surgery and referred to the obesity clinic of Hazrat-e Rasool General Hospital (Center of excellence of the European Branch of the International Federation for Surgery of Obesity), Tehran or other surgeons in the country.

Several surgeons are collaborating with this center but we limited the information to patients of two of them, because of preventing a variety of minor surgical techniques and reducing inter-observer bias. They are highly experienced which most of surgeries was done by them.

The most common types of bariatric surgery are Roux-en-Y Gastric Bypass (9.0%), Sleeve Gastrostomy (7.2%), and Mini-gastric Bypass/One-Anastomosis Gastric Bypass (14.3%). Because of the similarity of the procedures, preoperative cares and postoperative care of bypass surgery types, we combined them. Therefore, we compare bypass versus Sleeve surgeries in our study. Other types of surgery with lower frequency were dropped from analysis.

The duration of study is between March 2009 and October 2020. Hence, patients with the first visit and conducting surgery in this period were included in the analysis. Finally, the data on 6567 eligible patients were drawn from the Iran National Obesity and used in model building.

**Variables Selection:** The variables asked of a patient in the first visit were the candidate for including in model building. Also, there was an important condition for variable selection, that all patients should be able to answer the related questions, without any professional knowledge in medicine. This condition guarantees the application of the final results of our machine, especially for all patients as the end-users.

There was a comprehensive list of drugs and medicines in the database that we prefer to eliminate them in model building. There were several reasons for considering this choice. Drugs, comorbidities and risk factors usually have relation which cause collinearity in statistical models. Also, a non-familiar user could be confused whenever uses our product. Therefore, we ignored this part for simplifying the model.

Finally, a trimmed dataset with 32 variables prepared for training the model. This includes variables in categories of demographic, Nutrition Habits (sweet eater, volume eater, emotional eater or snacker/nibbling), anthropometric (weight, height, blood pressure, waist and hip circumference), history of using an alternative approach (diet or exercise), comorbidities (type 2 diabetes, dyslipidemia, hypertension, cardiovascular diseases, hyperthyroidism, sleep apnea, etc.), and family history of these comorbidities.

**Statistical analysis:** Continuous variables were described as mean±SD and compared using Student's t-test or Mann–Whitney U-test according to whether the distribution of the variables was normal or non-normal. The normality of variables was explored using the Shapiro-Wilk test and Q-Q plot. The difference between groups in the distribution of categorical variables was tested by chi-square Pearson chi-square statistics and described as number and percent. All analyses were performed with R software (http://www.R-project.org) and a P value of less than 0.05 was considered as statistically significant.

A decision tree was constructed as the predictor machine using "rpart" package in R core 2019. The validation of the decision tree confirmed using 4-folds

Table 1. Characteristics of patients across surgery type groups

| Characteristic | Bypass (n = 5023) | Gastric Sleeve (n = 1544) | P values |
|---|---|---|---|
| Female | 4021 (77.3) | 1180 (22.7) | 0.002* |
| Males | 1002 (73.4) | 364 (26.7) | |
| Non-Hypertensive | 4217 (78.5) | 1154 (21.5) | <0.001* |
| Hypertensive | 806 (67.4) | 390 (32.6) | |
| Non-Diabetes | 4033 (73.8) | 1432 (26.2) | <0.001* |
| Diabetes | 990 (89.8) | 112 (10.2) | |
| Age | 40.36 (11.0) | 37.21 (11.1) | <0.001* |
| BMI | 44.96 (6.7) | 44.17 (6.7) | <0.001* |
| Waist circumference | 168.75 (287.9) | 174.19 (226.5) | 0.451 |
| Hip circumference | 182.09 (286.5) | 194.04 (338.1) | 0.223 |

* Significant at alpha level = 0.05

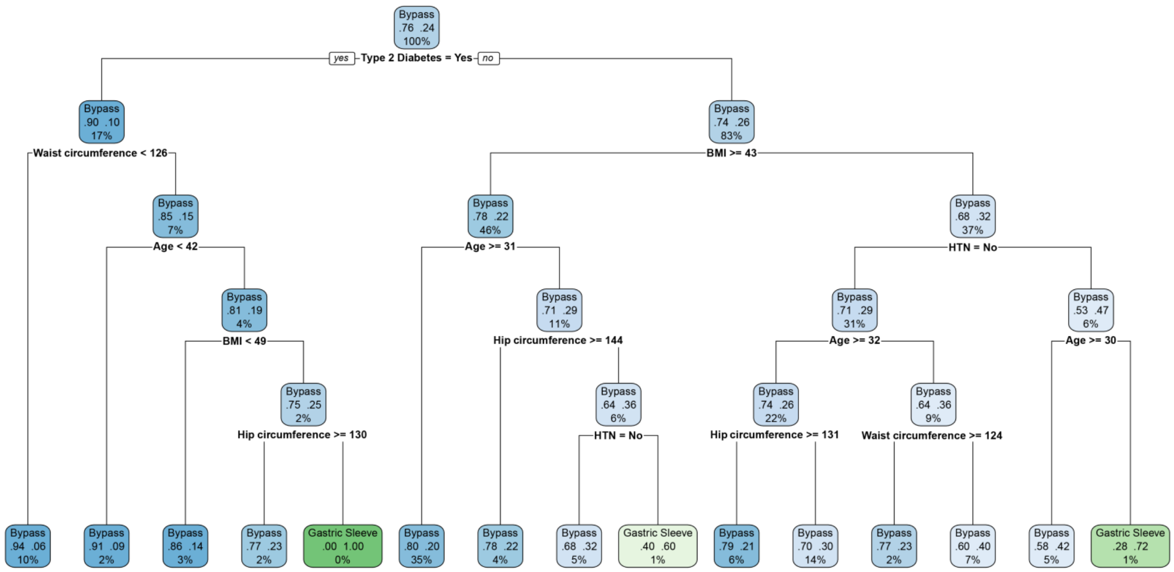


Fig. 2. Structure of decision tree for predicting surgery type in bariatric patients

cross-validation. Sensitivity, specificity, and accuracy values of the tree were also calculated.

## Results

Table 1 summarizes the characteristics of patients in surgery type groups. The prevalence of bypass surgeries in the female is 77.31% versus 73.4% in males which is statistically significant (p=0.02). Hence bypass surgery is more likely in females. In addition, the prevalence of bypass surgery is 67.4% and 78.5% in hypertensive and non-hypertensive patients respectively (p<0.001). On the other hand, bypass surgery is more prevalent in diabetes with 89.8% versus 73.80% in non-diabetics (p<0.001). Although, the difference between BMI in the 2 groups is statistically significant (p< 0.001), the absolute value of the difference is not relatively high (0.79). Finally, the mean age is 40.36 and 37.21 for the both types of bypass and gastric Sleeve groups respectively (p<0.001).

Figure 1 shows the structure of the decision tree in order to categorize the surgery types. The depth of the tree is 5 and its accuracy is 0.77. It means that we can classify 77% of patients into correct surgery groups. In addition, using this model we are able to predict 99% of bypass cases (Sensitivity) correctly. Figure 2 also depict the ROC curve of model with the area under curve equal to 0.66.

The first discriminant variable is type 2 diabetes. The diagram shows that diabetes patients are most likely to receive bypass surgery rather than gastric Sleeve. The second level consists of waist circumference less than 126 cm and BMI equal to or more than 43 kg/m$^2$. Age equal or greater than 30 years old and being hypertensive are the next level classifiers. The other classifier in the last two levels is hip circumference and almost all variables except type 2 diabetes repeat several times to perform more accurate classifying.

Finally, the leaves show the ability of the classifier by reporting the prevalence of surgery types. The greener density color is in favor of gastric sleeve and the blue one is for Bypass. Because bypass is more prevalent, only 3 leaves are green.

## Discussion

Several studies have investigated utilizing Machine learning strategies to predict the risks after bariatric surgery. Razzaghi et al (15) assessed 6 of the foremost popular classification methods to anticipate 4 common results (diabetes, angina, heart failure, and stroke) utilizing 11,636 patients from the Premier Healthcare

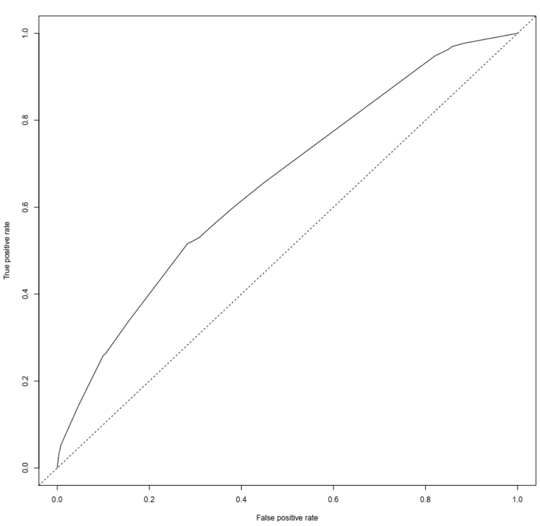


Fig. 1. The ROC curve of decision tree

Database of the United States. The project also accomplished the Smote technique to handle the imbalance issue in the data, and the conclusions demonstrated that random forest and bagging methods outperform other methods (15). However, the research did not test methods using external unseen data. Subsequently, the real performance of the methods of this study is controversial.

Thomas et al (16) anticipated the long-term weight status after bariatric surgery in 478 patients using 8 neural networks. Their neural networks yielded an AUC of 0.77 to 0.78 in predicting weight loss success. However, the types of performed neural networks were not mentioned. It seems as if the authors only utilized 1 neural network but with different variables as input. Yang Cao et al (17) registered patients who underwent a bariatric procedure between 2010 and 2015. They concluded that deep neural network has the potential to improve the accuracy in predicting the severe postoperative complication among bariatric surgery patients. The ensemble algorithms outperform base algorithms. In spite of the fact that several ensemble algorithms, such as random forest, gradient regression tree, and bagging k nearest neighborhood, represented favorable performance, the overfitting problem was clear (17).

In this study, we considered Roux-en-Y and Mini-gastric bypass methods as bypass methods. Therefore, bypass and Sleeve entered the model. Also, indicators such as BMI, waist circumference, hip circumference, etc. were examined which according to the studies have shown a significant impact on the choice of surgery. We also concluded from this study that women are more likely than men to benefit from bypass surgery. In addition, people with high blood pressure underwent less bypass surgery than people without blood pressure, and sleeve surgery seems to be more popular with patients with high blood pressure.

Although the difference in BMI is statistically significant, there was a little difference between the BMI of the two groups and it can be inferred that BMI was not an important factor in choosing the type of surgery. The mean age in the group of people who underwent sleeve surgery was statistically significant, so age can affect the choice of surgery, although it is suggested that in future research, the age variable should be further studied. It means that, usually age confounding the effect of comorbidities on outcomes.

It is also clear from the diagram that people with diabetes are more likely to have bypass surgery than sleeve surgery, and therefore bypass seems to be a better option for them.

The national database of bariatric surgery (obeitysurgery.ir) covers all pre-/and post-operative demographic data, co-morbidities, anthropometric measurement, nutrition habits, biochemical parameters and body composition features of patients with morbid obesity which were recorded in this database by several surgeons. As an opportunity, we applied our idea to this nationwide database. Using such information adds generalizability to our results.

In addition, this is one of the first studies to use machine learning for analyzing type of bariatric surgery. As mentioned previously, Thomas et al (10) and Yang Cao et al (11) used surgical data in their works but their aims and approach were completely different.

## Conclusion

We aimed to build a machine that able patients to interact with, without any limitation. This idea forced us to eliminate some important variables like laboratory results. In addition, as a routine procedure, specialists and surgeons find out lots of information in their visits which patients are not aware of themselves. We can also point to the fact that machine learning and artificial intelligence are still a long way from mimicking physicians and surgeons in the health area.

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