Modelling the length of hospital stay after knee replacement surgery through Machine Learning and Multiple Linear Regression at “San Giovanni di Dio e Ruggi d’Aragona” University Hospital

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ABSTRACT

Knee arthroplasty is one of the most commonly performed procedures within a hospital. The progressive aging of the population and the spread of clinical conditions such as obesity will lead to an increasing use of this procedure. Therefore, being able to make the process related to this procedure more effective and efficient becomes strategic within hospitals, subject to increasingly stringent clinical and financial pressures. A useful parameter for this purpose is the length of stay (LOS), whose early prediction allows for better bed management and resource allocation, models patient expectations and facilitates discharge planning. In this work, the data of 124 patients who underwent knee surgery in the two-year period 2019-2020 at the San Giovanni di Dio and Ruggi d’Aragona university hospital were studied using multiple linear regression and machine learning algorithms in order to evaluate and predict how patient data affect LOS.

CCS CONCEPTS

• **General conference proceedings, Health informatics, Health care information systems, Statistical software, Machine learning approaches**;

KEYWORDS

Knee Replacement Surgery, Length of Stay, Multiple Linear Regression, Machine Learning

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1 INTRODUCTION

Hip and knee prostheses are the best solution for people suffering from terminal arthritis. This procedure has been shown to be highly effective in the treatment of pain and immobility, leading patients to a significant improvement in the quality of life [1, 2]. For this reason, the number of procedures performed is constantly increasing. Population aging and the growing obesity epidemic are just two examples of contributing causes [3, 4]. In Italy, a country of interest for this study, 181,738 joint replacement surgeries were performed in 2015, 4% more than the previous year, of which 38.6% in the knee [5]. The interventions mainly concern the age group 65-74, and among these it is the women who most characterize the sample. As a result of this growth, the number of review procedures is also expected to increase [6]. Among the causes that lead to the revision of the knee prosthesis, the main one is infection in 27.1% of cases, followed by painful prosthesis for 15.9% of cases, up to causes more closely related to the prosthesis, such as wear of the materials and implant rupture (4.9%) and instability (3.8%) [5].

In consideration of the growing costs in the healthcare sector and the quality requirements in this field, the detection of the main processes and variables that can alter its standard execution, or in

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accordance with the patient's expectations, is becoming increasingly important. Specifically, for the intervention studied, there will always be a fixed amount of expenditure linked to the plant to which a variable component linked to hospitalization and other hospital costs is added [7].

In this, data analysis becomes an indispensable tool for characterizing a process. Several studies and different techniques have been applied with great success to the healthcare world, starting from the use of innovative management methods, such as the Lean Six Sigma paradigm [8–16] or the Health Technology Assessment [17–19], up to advanced processing techniques, such as Machine Learning [20–23] and Data Mining [24–28].

A parameter particularly used in literature and in application practice is the length of stay (LOS) [1, 7, 8, 29, 30]. Being able to manage the length of stay is useful not only in economic terms, but also in operational terms. In fact, it is designed to evaluate both the quality of care and the ability to plan a health facility. Furthermore, it is a good representation of the amount of resources used, in terms of both beds and human and technological resources and is closely related to patient satisfaction [31].

The following work fits into this perspective. The purpose is precisely to analyze which of the variables provided in input are those that most affect the output, in this case represented by the overall patients' LOS. This analysis will be conducted on the data extracted from the QuaniSDO hospital computer system on the activity of the "San Giovanni di Dio e Ruggi d'Aragona" University Hospital, using first the Linear Multiple Regression and then the Machine Learning algorithms. The latter made it possible to identify the optimal solution that would allow the construction of a classifier that will facilitate the planning phases within the department.

2 METHODS

The analysis involves the data obtained by the Complex Operative Unit (C.O.U.) of Orthopaedic and Traumatology of the "San Giovanni di Dio e Ruggi d'Aragona" University Hospital of Salerno (Italy). The information of 124 patients who underwent a procedure for the insertion or review of knee prostheses in the two years period 2019-2020. The following information were extracted from the hospital information system (QuaniSDO):

- gender (male/female);
- age;
- presence of comorbidity, like hypertension, diabetes and obesity (yes/no);
- complications during surgery (yes/no);
- date of admission;
- date of surgery; and
- date of discharge.

These data were analysed in order to build a Multiple Linear Regression Model (MLR) and a Machine Learning (ML) classifier to predict the total LOS. IBM SPSS Statistics 26 Software was used to perform the MLR, instead KNIME Analytics Platform for the ML algorithms.

2.1 Multiple Linear Regression

MLR was used to find a functional relationship between the output variable y, in this case the total LOS, and the independent variables, that is age, gender, presence of comorbidity, complication during the surgery and pre-operative LOS. The equation, reported below, describe the model implemented:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5$$

Where y represents LOS, xk the input variables, β0 the intercept and βk the regression coefficient.

Before the implementation of the model, the following conditions were verified:

- The linear relationship between the independent and dependent variable.
- Absence of multicollinearity in the data.
- Independence of residual values.
- Constancy in the variance of residuals.
- Normally distributed residual value.
- There are no influential cases that affect the model.

2.2 Machine Learning

With the ML algorithms it can be possible the construction of a smart system that increase the knowledge starting from the elaboration of the input data. In this work, the ML algorithms were used to classify and predict the target value (LOS) influenced by the input variables. Starting from the knowledge acquired through the analysis of initial set of data called training, the model was built. For this reason, the dataset was divided into training (80%) and test (20%) sets.

Before the elaboration, LOS was normalized in weeks, in order to simplify the discussion of the results, and only the two classes most represented were considered. The ML algorithms implemented are Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM) and Gradient Boosted Trees (GBT). DT, RF and GBT use the tree structure as the base technique for the classification. In particular, DT uses tree structure, where each node is a specify condition and, depending on the value assumed, the flow proceeds to another node through a specific branch. At the last level, the final decision will be made. RF and GBT extend this simple structure, the first is based on the aggregation of multiple decision trees and the second create a strong predictive model starting from the set of weak predictive models, as DT. In both cases, the performance improves compared to the single tree, but the complexity increases. The last one, SVM doesn't use the previous structure but it is based on a hyperplane, which is of a higher dimension than the dimension of the variables and enables the separation between the different identified classes.

3 RESULTS

Firstly, the six assumption of the MLR model have been evaluated. Linear relationships between the varibales have been assessed by means of scatter plots. The absence of collinearity was verified through a Tolerance greater than 0.2 and the Variance Inflation Factor (VIF) less than 10 for each input variable. The Durbin-Watson test, used to study the correlation between residuals, return 1.913 and so a value between the acceptable range of [1.5; 2.5], demonstrating the independence. Homoschedasticity (i.e. homogeneity of the variance of the residuals) and normality distribution of the

Table 1: Model summary

	R	R^2	R^2 adjusted	Std. Error of the Estimate
MLR Model	0,646	0,418	0,393	2,186

Table 2: Regression coefficients, t-test results and level of significant.

	Regression coefficients Bk	Coefficients Std. Error	Regression coefficients βk	t	Sig.
Intercept	2,017	2,144	-	0,941	0,349
Age	0,059	0,026	0,165	2,263	0,025
Gender	-0,111	0,464	-0,018	0,240	0,811
Pre-operative LOS	1,127	0,137	0,594	8,257	0,000
Presence of comorbidities	0,001	0,501	0,000	0,002	0,999
Presence of complications	2,474	1,298	0,136	1,905	0,059

Table 3: Accuracy, Error and all statistical parameters for each ML algorithms implemented

Algorithms	Accuracy(%)	Error (1-Accuracy)(%)	Class	Precision(%)	Sensitivity(%)	Specificity(%)	F-measure(%)
DT	87.5	12.5	1	76.92	100.00	78.57	86.96
			2	100.00	78.57	100.00	88.00
RF	87.5	12.5	1	81.82	90.00	85.71	85.71
			2	92.31	85.71	90.00	88.89
SVM	66.67	33.33	1	100.00	20.00	100.00	33.33
			2	63.64	100.00	20.00	77.78
GBT	79.16	20.83	1	72.73	80.00	78.57	76.19
			2	84.62	78.57	80.00	81.48

residuals have also been checked graphically through a residual-vs-predicted values plot and a quantile-quantile (Q-Q) plot respectively. Visual assessment allowed to confirm that both the homoscedasticity and variance homogeneity assumptions were met. Then, the Cook’s distance for each sample is less than 1 and ensure the absence of outliers. After the validation of the MLR assumptions, the model has been implemented. Table 1 shows the goodness of the model obtained.

Despite the modest value of the determination coefficient of the model, it seems interesting and somewhat representative (R^2>0.5), thus giving a rough but still useful and indicative estimate of the robustness of the model. Further helpful indications can be obtained looking at the coefficient of the model. Indeed, Table 2 reported the regression coefficients, the t-test results and the significant (the test result is significant if Sig. <0.05).

For age and pre-operative length of stay, the t-test return a significant result and, in particular, the second have the higher coefficient in agreement with the definition of LOS.

Finally, the performances of the four selected ML algorithms were analyzed. Table 3 shows the results obtained.

With DT and RF, the best performance has been obtained. For DT algorithms, the F-measures for the class 1 is equal to 86.96 and for the class 2 is equal to 88.00 while for RF are 85.71 and 88.89 respectively. In this case, the best algorithm selected has been DT for its simple structure compared with RF. The confusion matrix of DT algorithm has been reported in Table 4

Table 4: The confusion matrix of the DT algorithm

Real / Predicted	1	2
1	10	0
2	3	11

The Cohen’s kappa coefficient is equal to 0.727 demonstrating a good agreement.

4 DISCUSSION AND CONCLUSIONS

This study analyzed the data of 124 patients who underwent knee replacement surgery in the two-year period 2019-2020 at the "San Giovanni di Dio e Ruggi d’Aragona" University Hospital in Salerno. Age, gender, pre-operative LOS, comorbidity and presence of complications was used as independent variables to predict the total LOS. Through both the MLR and the Machine Learning, promising results are obtained. However, the MLR model showed that only two factors appear to significantly affect the LOS, namely age and preoperative LOS, thus suggesting that a more standardized preoperative management and the introduction of dedicated pathways based on the patient's age could improve the quality of the care process and possibly reduce the LOS. The low value of the determination coefficient of the MLR model also suggest that a more robust models is needed to study the LOS. More appealing results have been achieved by means of the machine learning algorithms. Indeed, through the DT algorithm it was possible to create a predictor that is simple to understand and that works with an accuracy of more than 87%. When compared to the relevant literature in the field, despite the most of the works focus on the use of machine learning to predict clinical outcome and preoperative variables [32, 33], such results are promising since other works that proposed models to study the LOS after knee arthroplasty report an Area Under the Curve (AUC) ranging from 0.710 to 0.766 [34, 35], which is still far from optimal values (0.95 - 1). However, a direct comparison between our study and other literature works since the selected predictors are different and the size of the dataset are not comparable.

The future developments of this work are manifold. The observation period and the variables considered will certainly be extended. More comorbidities will be analyzed in order to obtain a more accurate characterization of the classes of patients who undergo the surgery. Through management tools, for example Lean Six Sigma, it will be possible to analyze the situation and evaluate the possibility of implementing fast-track surgery paths within this hospital structure [11, 12].

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