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Effect of Clinical and Demographic Variables on the Hospital Stay of Patients Undergoing Total Knee Arthroplasty

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Abstract. The knee is the joint most affected by osteoarthritis and in its severe form can significantly affect people's physical and functional abilities. The increased demand for surgery leads to greater attention by health care management to be able to keep costs down. A major expense item for this procedure is Length of Stay (LOS). In this study, several Machine Learning algorithms were tested in order to construct not only a valid predictor of LOS but also to know among the selected variables the main risk factors. To do so, activity data from the Evangelical Hospital "Betania" in Naples, Italy, from 2019-2020 were used. Among the algorithms, the best are the classification algorithms with accuracy values exceeding 90%. Finally, the results are in line with those shown by two other comparison hospitals in the area.

Keywords. Total knee arthroplasty, Length of stay, Machine Learning

1. Introduction

Osteoarthritis (OA) of the knee is a major cause of disability [1]. To counteract the adverse effects caused, it is recommended to perform surgery, Total knee arthroplasty (TKA) [2]. In Italy, the reference country for this study, knee prosthetic surgery suffered a significant setback during the COVID-19 pandemic, being performed mainly as elective surgery. In order to ensure continuity of care, OA and its treatment are one of the largest contributors to health care-related economic costs [3]. Length of Stay (LOS) is an important component of TKA, so it is necessary to be able to reduce LOS without affecting the physical and functional outcomes of the procedure [4]. To date, several analytical and no analytical techniques are available that are providing significant support to global healthcare. Additive Manufacturing [5-7] and sensor technology [8-9] are making significant strides in helping physicians and patients. In actuality, it is the data analysis techniques that have had the greatest impact. Statistical analysis [10-12], Fuzzy Logic [13,14], advanced mathematical models [15,16] or management approaches

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[17,18] are helping not only in the diagnosis and treatment of diseases but also in reorganizing healthcare processes.

Indeed, in this study, we want to use different Machine Learning algorithms to build models that can predict the LOS of patients undergoing revision or total knee replacement. The data are those of the two-year period 2019-2020 of the Evangelical Hospital "Betania" in Naples (Italy). This work is part of a line of research initiated by the same group in 2021 on data from two other similar hospitals in southern Italy [1, 2].

2. Methods

In this study, data from 304 patients who underwent revision and total knee replacement in 2019-2020 at the Evangelical Hospital "Betania" in Naples, Italy, were processed. The information source is the QuaniSDO, which collects all discharge records of patients admitted to the hospital. From these, the 4 dependent variables (Age, Gender, Preoperative LOS and Comorbidity) and the dependent variable (LOS) were obtained.

2.1. Machine Learning Algorithms

LOS is first treated as a continuous variable and analyzed through a multiple linear regression (MLR) model. The model searches for the linear relationship that exists between the dependent variable by finding an appropriate set of coefficients with smaller error. Through the coefficients used and the use of the t-test with a 95% confidence level, it is also possible to investigate which of the identified variables is a risk factor for LOS. Before proceeding, it is necessary to test a set of hypotheses, as shown in the Table.

Table 1. Hypotheses underlying the MLR Model.

Hypotheses	Used Methodologies	Threshold [19,20]
Multicollinearity absence	Tolerance and Variance Inflation Factor (VIF)	Tolerance > 0.2, VIF < 10
Independence of residuals	Durbin-Watson test	(2; 4)
Absence of outliers	Cook's Distance	< 1

IBM SPSS ver. 27 was used for the implementation. After, LOS was divided into two homogeneous groups and analyzed with classification algorithms. Among those available in the literature [19,20], in agreement with previous studies [1, 2], three algorithms exploiting decision tree prediction (Decision Tree (DT), Random Forest (RF) and Gradient Boosted Tree (GBT)) were used, to which Support Vector Machine (SVM) was added, which is based on the identification of an optimal hyperplane separation between classes. Eighty percent of the dataset was used for training, while the remaining 20 percent was used for performance testing. To augment the dataset, SMOTE was used to create additional samples based on the available data. The KNIME Analytics platform was used for these.

3. Results

First, the MLR was implemented. Assumptions allowing the use of linear models were first tested. According to the literature [19,20], Durbin-Watson test and Tolerance, VIF (see Table 2) and Cook's distance were for each observation within the range of acceptability given in Table 1. At this point, the model was implemented. The result of the test and the performance of the model are shown in the following Table.

Table 2. Tolerance, VIF, MLR model and t-test results

MLR Model		Independent Variables	Tolerance	VIF	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
					B	Std. Error	Beta		
R	0.703	Intercept	-	-	2.610	0.375	-	6.954	**0.000**
R^2	0.494	Pre-Operative LOS	0.961	1.041	1.022	0.064	0.670	15.964	**0.000**
Adjusted - R^2	0.487	Comorbidities	0.957	1.045	0.497	0.174	0.120	2.850	**0.005**
Std. Error	0.720	Age	0.995	1.005	0.006	0.005	0.052	1.261	0.208
Durbin-Watson	1.761	Gender	0.990	1.010	0.012	0.091	0.005	0.130	0.897

Looking at the value of R^2, often used to evaluate performance [19,20], it can be seen that a simple linear model did not give good results. Table 2 details the coefficients to analyze the risk factors. Except for preoperative LOS, the variable that has a significant impact on LOS is the presence of comorbidities. Next, the implementation of the classification algorithms was performed. Among the selected algorithms, RF showed the best performance reaching an accuracy of almost 92%. The details of the results are shown in Table 3.

Table 3. Results (%) of classification algorithms.

	ACC	Error	Class	Precision	Recall	Sensitivity	Specificity	F-measure
DT	90.16	9.84	1	85.44	96.70	96.70	83.70	90.72
			2	96.25	83.70	83.70	96.70	89.53
RF	91.26	8.74	1	86.41	97.89	97.80	84.78	91.75
			2	97.50	84.78	84.78	97.80	90.70
SVM	69.40	30.60	1	77.78	53.85	53.85	84.78	63.64
			2	65.00	84.78	84.78	53.85	73.58
GBT	89.07	10.93	1	84.47	95.60	95.60	82.61	89.69
			2	95.00	82.61	82.61	95.60	88.37

4. Discussion and conclusion

In this study, data from patients undergoing total knee replacement surgery in 2019-2020 at the Evangelical Hospital "Betania" in Naples, Italy were analyzed. Among the algorithms tested to predict LOS, the MLR model did not show very good performance obtaining an R^2 value just below 0.5. Different discourse for the classification algorithms. The best was RF with an accuracy of just under 92%. Comparing the results obtained with what has been reported in the literature for the two structures in the same area, it can be seen that for all of them the best algorithm is decision tree with a performance in line with those already recorded (91.2% VS 87.5% [1] and 92.5% [2]). However, the result for the regression algorithm is different, where the low performance in this study is actually in the middle between the R^2=0.418 of the first study [1] and the excellent value R^2=0.942 obtained in the second [2]. Our work has several limitations including a small number of analyses, patients and the lack of a validation dataset. In addition, the other hospitals are used only for comparison; merging the datasets will allow validation of the conclusions.

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