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A Regression Analysis for Predicting Surgical Complications

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Abstract**—** A surgical complication is any undesirable and unexpected result of an operation. Surgical complications could be fatal to a patient if they are not detected earlier. One of the factors that could affect the severity of the complication is the time between a patient's diagnosis and the surgery. The patient might be at risk if the doctor misdiagnoses them or concludes that the patient has no severe symptoms. This paper aims to study the correlation between post-surgical conditions & time duration with possible surgical complications. Using regression analysis, the research intends to evaluate predictive possibilities of early discovery of these complications. The results reveal that the Gradient Boosting Regressor performs with minimal error rate and predicts almost all complications in line with the original data, measured across MAE, RMSE and R2 with scores of 0.07, 0.11 and 0.98 respectively. In comparison to Random Forest Regressor and Decision Tree Regressor, Gradient Boosting Regressor performs 70-80% efficiently across the three major aforementioned metrics on average. Thus, presenting itself as a valuable tool for finding the correlations in surgical data and early intervention of possible surgical complications.

Keywords**—** surgical complication, medical, diagnosis time, predictive modelling, regression

I. Introduction

As the medicinal field and its research progresses throughout human history, patients are bound to experience complications. There are several types of complications, some of them being disease or medical-related. In other words, true or avoidable yet unwanted complications respectively. Complications such as pain, fever and infections can be experienced at any time in between the doctor's diagnosis and the time for the actual surgery. By observing the patients' conditions after their diagnosis, before and after surgery, the data collected during this delicate process is vital in determining the severity or presence of complications that may endanger or cause unnecessary discomfort toward the patient. Doctors must strive to improve from past medicinal conventions and find innovative ways, such as via machine learning, to perform medical procedures on their patients [1-2].

By educating themselves on how to detect accurate and early pre-operation complications, doctors are able to educate the patients on the issues they are facing. Though not quite proven, it is greatly hypothesised that in doing so, this might reduce or alleviate their fears regarding the surgery itself and help with handling post-operation procedures that pop up [3-4].

In relation, from what we have researched, the use of new technology in surgical matters enables the patients to recover quite quickly and without further problems barring any unexpected situations. Thus, detection or prediction of surgery complications in patients can be an essential process in the medical field that might be able to reduce any form of casualties resulting between diagnosis until before and after surgery. If surgical complication detection is done incorrectly or late, adverse consequences may affect the patient and trigger other side effects. Hence, by using machine learning to perform analysis on data regarding post or pre-operation complications, the quality of patient-care will be improved and losses can be minimised [5-7]. Therefore, this study aims at the following:

- To find the complications that have a strong connection with the time of diagnosis to surgery
- To understand trends in the given data on finding possible correlation in between complications
- To determine the possibility of predicting the future complications based on the time between diagnosis and surgery

Based on the aforementioned aims, the study addresses the following significances:

- A prediction model that predicts surgical complications can prevent severe complications by providing care at the earliest possible stage
- Identifying surgical complications can help the doctor to plan ahead a treatment plan for the patient
- Identifying high risk complications may help to minimise mortality with a quick approach of proper treatment

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II. Related Work

Research on the diagnosis to surgery complications can be analysed using various features such as the time from diagnosis to surgery and the patient's complications. Application of deep machine learning methods to predict severe complications such as mortality, renal failure with a need for renal replacement therapy, and postoperative bleeding leading to operative revision during critical care in real time after cardiothoracic surgery has been explored in [8]. A range of common performance metrics like positive predictive value (PPV), negative predictive value, sensitivity, specificity, and area under the curve were implemented in assessing the predictive performance of their model. Wilcoxon signed-rank test is used to compare the accuracy levels of the clinical reference tool against the RNN-based predictions. The deep learning methods showed accurate predictions immediately after patient admission to the intensive care unit as it yields accurate predictions with the following PPV scores of 0·90 and sensitivity scores of 0·85 for mortality, 0·87 and 0·94 for renal failure, and 0·84 and 0·74 for bleeding.

Reference [9] presents prediction about complications of diabetes mellitus using advanced machine learning algorithms. According to the paper, deep learning approaches based on recurrent neural network (RNN) long short-term memory (LSTM) and RNN gated recurrent unit (GRU) were developed and compared to classic models based on random forest and multilayer perceptron. The accuracy of selected complications' prediction was then examined in three settings corresponding to the least number of hospitalizations between diabetes diagnosis and the diagnosis of complications. The outcomes of the study have been documented in the paper in which the RNN GRU model produced the best results, followed by the RNN LSTM model. The prediction accuracy of the RNN GRU model ranged from 73% (myocardial infarction) to 83% (chronic ischemic heart disease), while traditional models ranged from 66% to 76%.

The goal of [10] was to develop a machine learning (ML) system that could predict the likelihood of severe complications following bariatric surgery. They used data from 37,811 patients who underwent bariatric surgery in Sweden between 2010 and 2014 to train and compare 29 supervised machine learning algorithms. In both the training and test sets, the majority of the ML systems demonstrated high accuracy (>90%) and specificity (>90%). In the test data, however, none of the algorithms attained an acceptable sensitivity.

DeepDRG aims at Real-Time Prediction of Diagnosis-Related Groups. The purpose of this study is to predict the primary diagnosis in order to ensure proper reimbursement and improve hospital performance. Due to the enormous workload, poor documentation quality, and lack of computer support, the rate of inaccurate DRGs is constantly high. Therefore, this research was developed using the Deep Learning Model. Based on this study, the area under the receiver operating curve, precision, recall, and F1 score were used to evaluate the Deep Learning models' performance. The GRU technique outperformed the other two DL models in terms of predicting the principal diagnosis (AUC: 0.99, precision: 83.2 percent, and recall: 66.0 percent). The performance of the ANN model for DRG prediction, on the other hand, was AUC 0.99, accuracy 0.82, and recall 0.57. The findings suggest that DL algorithms, particularly GRU, can be employed to construct DRG prediction models for effectively identifying main diagnoses [11].

In reference [12], the researchers built an interpretable machine-learning-based model, K-Means Clustering that incorporates patient demographics, surgery-specific variables, and intraoperative blood pressure data for properly predicting problems after paediatric congenital heart surgery. The findings show that cardiac complication prediction has a higher AUC of 0.946, whereas lung complication prediction has a lower AUC of 0.785. This prediction model achieved higher accuracy and sensitivity compared to risk adjustment models. Integration of abundant preoperative data, such as thorough laboratory findings of patients, into the prediction model would be a future upgrade for this research.

Machine learning was used to predict bleeding and thrombosis using an ECMO dataset in [13]. Their hypothesis was that machine learning will accurately predict these events and find unique factors that would not have been identified by standard biostatistical methods or expected clinically. In this study, the authors compared chi-square to five supervised classification and regression machine learning models which are random forest, recursive feature elimination, decision trees, k-nearest neighbours and logistic regression. The results show that the models to predict haemorrhage performed better (accuracy of 58–80%) than the models for thrombosis (40–64%).

Reference [14] focuses on the research of risk factors for early postoperative complications after bariatric surgery. The purpose for this study is to seek a better understanding of the complications that might have a significant effect on the outcome of a bariatric surgery procedure. This research also contributed to recognizing predictive factors of the complications to reduce patient's burden after the surgery. The complications were categorised according to the Clavien-Dindo classification method based on the severity of the complication. Binary logistic regression was utilised to detect the independent risk factors of surgical complications. The independent risk factors that have been studied include male gender, open and revisional surgery,

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hypertension and hypoalbuminemia. The findings from the research are that hypoalbuminemia had significant relationships with the frequency of deep surgical site infection and leak. Meanwhile, open surgery had associations with the frequency of superficial and deep surgical site infection and respiratory complications.

Investigation of risk factors and predict complications in deep brain stimulation surgery with machine learning algorithms was conducted by [15]. The aim of this study is to find clinical risk factors of deep brain stimulation surgery and to build machine learning models that are able to predict surgery outcomes. Logistic regression was used to predict the risk factors by training and validating the algorithms 70% and 30% respectively. Then, the performance of the model was evaluated by using area under curve (AUC), sensitivity, specificity and accuracy. The model showed that the risk of complications related to the operating institution yielded 0.44 of OR, confidence interval of 0.25-0.78. Meanwhile, BMI achieved 0.94 OR and CI of 0.89-0.99. On the other hand, diabetes has 2.33 OR and 1.18-4.60 CI. The model demonstrated a decent performance when predicting any complication with AUC of 0.86, a 12-months gap of complication achieved 0.91 AUC, those returning to the operating room attained 0.88 AUC and infection complications with AUC of 0.97.

The discussion about applications of Surgical Data Science when discussing patient care and interventional surgery has been conducted by [16]. Through the general implementation of machine learning algorithms, data obtained from several stages of a surgery is analysed to formulate improvements or solutions. It can also be used to decide whether or not the patient requires interventional surgery before their situation becomes worse by observing data about their conditions. Said data can be obtained from medical professionals, the patients or caregivers via the use of sensors, medical records or observation and survey. Improvements in terms of planning, prevention, assessment and training of nurses or caregivers will bring about tremendous positive impacts on the quality of patient care. When data is analysed accurately, caregivers or the patients themselves are able to make more-informed decisions regarding the risks or issues that might occur in the future.

The use of a Black Box in the Operating Room and a surgical Control Tower being adopted during an operation has been discussed in [17]. Both of these methods help in detecting complications during surgery and provide ways for medical professionals to deal with the issues in real-time. These smart technologies being incorporated into the OR have provided a largely positive impact on current medical procedures and processes. By acquiring a large amount of data in real time alongside the usage of artificial intelligence to analyse them, doctors and nurses are able to be assisted effectively and strive to study the limitations of such a system for future improvement. Though there are apprehensions and obstacles preventing these technologies from being commonplace in a medical setting, researchers of both the Data Science and Medical fields are using the Black Boxes and Control Towers as a way to show the positive applications of Surgical Data Science on the topic of surgical care.

III. Methods & Implementation

Ensuring high quality data is being used during the analysis process is a vital step in order to boost the decision-making process and improve the data analysis efficiency. This can be done through the data cleaning process where we will be dealing with missing and duplicates data and the amending or removing incorrect or superfluous data, as well as checking for incompleteness or inconsistencies before we begin analysing the data. The research used three regression algorithms for the prediction process – Decision Tree, Gradient Boosting and Random Forest. These algorithms are often used for predictive analysis in the medicine field [18].

Spearman's correlation test has been applied in this study to find the correlation between the variables. A change in the magnitude of one variable is connected with a change in the magnitude of another variable, either in the same (positive correlation) or opposite (negative correlation) direction in correlated data. A Spearman correlation can be employed as a measure of monotonic relationship for non-normally distributed continuous data, ordinal data, or data containing important outliers. The correlation coefficients are scaled from −1 to +1, where 0 implies no linear or monotonic link and the relationship grows stronger and eventually approaches 1 and vice versa [19]. The Spearman's rank correlation is given by:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

IV. Exploratory Analytics

This section is divided into two parts –the first section deals with findings from the data through exploratory analysis about the relation between surgery and complications in patients. The second section presents comparative performance of the prediction models used in this work.

A. *Exploratory Analysis*

The data reveals that the most common complication seen in patients is pain, high blood pressure, fever, thrombosis and infection. The average time taken between the doctor's diagnosis and the actual surgery for an infection to occur in patients averages at 54.28 hour. This is an

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indication that, on average, a little bit over two days would be the window of time when a patient should be observed in the case of an infection. Figure 1 shows the Spearman's Rank Correlation Coefficient which is a measure of monotonic correlation between two variables. Figure 2 shows the correlation matrix which is the correlation coefficient between variables related to diagnose time and surgery complications. The correlation matrix is used to understand the relationship between two variables. From the correlation matrix, the value shows that the time between diagnosis and surgery positively correlates with fever, infection and confusion which means the longer the time between the surgery, the higher chances the patient will experience fever. On the other hand, the value shows that the time between diagnosis and surgery negatively correlates with the rest of the complications which are bleeding, heartburn, pain, nausea, high blood pressure, shock and thrombosis. This indicates that the longer the time between diagnosis and surgery, the lesser the possibility to experience those complications. From this result, it is assumed that the time in between diagnosis and surgery have quite a significant impact on getting more complications.

The date infers the most common complications experienced by patients that are going through pain are high blood pressure, fever and an infection. Patients that experienced the complication of pain would also be likely to experience these three complications. Knowing this, a doctor would be able to observe their patients and prepare for any eventualities. The correlation coefficient shows that pain has a positive relationship with bleeding, heartburn, infection, confusion and high blood pressure. This indicates that if the patient has already experienced pain from the surgery, the patient will most likely experience these complications too. The Spearman's correlation between confusion and pain is 0.872 which is the highest compared to the other complications that we can draw from the correlation matrix. This indicates that the patient who experiences confusion is more likely to experience pain too. From the result, the Spearman's correlation between high blood pressure and thrombosis is 0.872 which means the probability of getting high blood pressure after experiencing thrombosis is quite high.

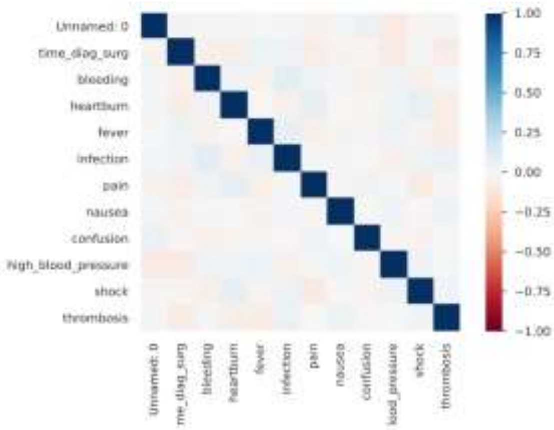
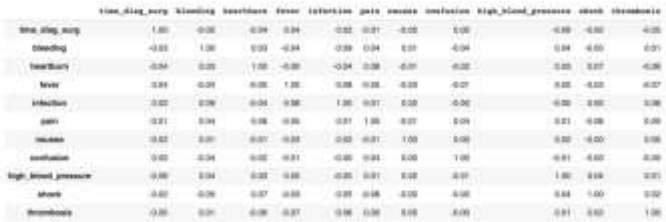


Fig. 1 Spearman's rank correlation coefficient



	time_diag_surg	bleeding	heartburn	fever	infection	pain	nausea	confusion	high_blood_pressure	shock	thrombosis
time_diag_surg	1.00	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
bleeding	[illegible]	1.00	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
heartburn	[illegible]	[illegible]	1.00	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
fever	[illegible]	[illegible]	[illegible]	1.00	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
infection	[illegible]	[illegible]	[illegible]	[illegible]	1.00	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
pain	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.00	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
nausea	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.00	[illegible]	[illegible]	[illegible]	[illegible]
confusion	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.00	[illegible]	[illegible]	[illegible]
high_blood_pressure	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.00	[illegible]	[illegible]
shock	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.00	[illegible]
thrombosis	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.00

Fig. 2 Correlation matrix

In conclusion, the time in between diagnosis and surgery has a quite significant impact on the complications experienced by the patients especially for the fever, infection and confusion. There are also some complications that will most likely to occur if the patients experience other complications like high blood pressure will most likely to occur with thrombosis and confusion will most likely to occur with pain.

B. *Predictive Performance*

The predictive performance has been presented in Table I and Fig 3-5.

TABLE I
PREDICTIVE PERFORMANCE

Model	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	R-Squared (R2)
Gradient Boosting Regressor	0.07	0.11	0.98
Random Forest Regressor	0.18	0.35	0.92
Decision Tree Regressor	0.16	0.42	0.88

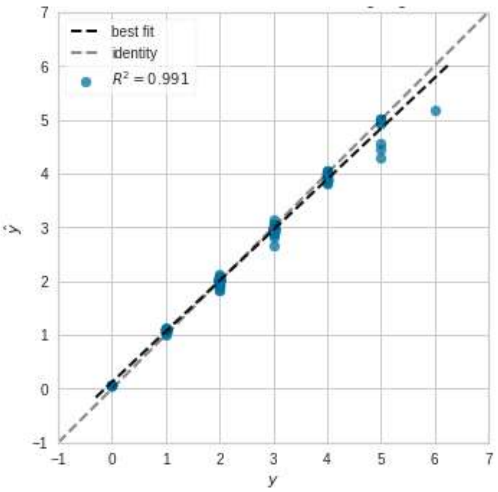


Fig. 3 Prediction Error – Gradient Boosting Regressor

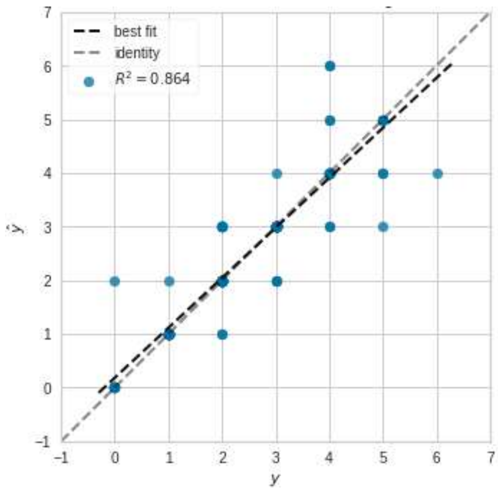


Fig. 5 Prediction Error – Decision Tree Regressor

V. Discussion & Conclusion

The exploratory analysis reveals that the amount of time between diagnosis and surgery has a substantial impact on the complications that patients experience particularly fever, infection and confusion. These results show that the doctors and patients must be prepared for these complications during and after the surgery. Surgical complications are a leading cause of morbidity and mortality, and they can result in an extended stay in the hospital, repeat surgery, further medical care, legal concerns and higher costs. Although there are many other factors that could lead to surgery complications, the time between diagnosis and surgery is one of the essential factors that the medical teams need to be alert of. The patients should also be prepared for other complications because most probably they will experience more than one complication during and after the surgery [20].

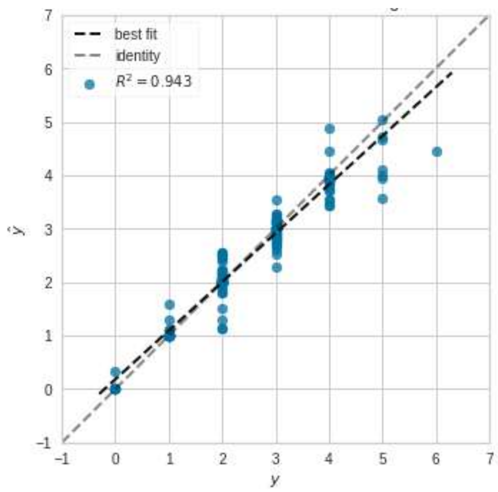


Fig. 4 Prediction Error – Random Forest Regressor

The predictive performance reveals that GBR outperforms RFR and DTR for the regression problem at hand. Grand Boosting outperformed both the predictive models across all the three metrics, being the closest to the actual data with a prediction of 0.98. Although the other two models aren't far behind lagging around by 10% with regards to mean absolute error but this is still high in critical domains such as healthcare. The predictive capability of Random Forest is quite close to the dot plot of actual data at 92% while Gradient Boosting outperforms with an accuracy of 9 out of every 10 predictions, with a higher level of confidence, which is presented in Fig 3 – 5 by plotting the actual and predicted outcomes by the various algorithms used in this study. As is evident, the most of the predicted data points align itself on the actual Gradient Boosting Regressor curve while as the prediction points for Random Forest Regressor and Decision Tree Regressor sway far away from the best fit prediction curve.

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Conflict of Interest

The author(s) declare that there is no conflict of Interest

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