Predictive Analytics on Scheduled Surgery Cases in Forecasting the Operating Theatre Utilisation

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Article history
Received: 15 May 2021

Received in revised form:
27 May 2021

Accepted:
15 June 2021

Published online:
26 June 2021

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Abstract

The scheduled surgery cases, allocation of clinical provider, machine, equipment, preparation time, surgery performance, and patient recovery give the big impact on operating theatre (OT) utilization. Low OT utilization due to no show patient and scheduling bottleneck interrupt patient flow in clinical process. It also decreases the admission to the OT and wastage of resources. In order to improve the capacity of OT, the logical solution need to be carried out is utilization audit. The trend of scheduled surgery cases has identified, and element affect the OT capacity have used to predict the OT optimization for future planning. The purpose of this study is to investigate efficiency of OT utilization in healthcare institution and the application predictive analytics on its daily operational data. OT contribute to the revenue for the hospital and workload. This project use machine learning in identify which model can use to predict the decision of admission to which facility after the surgery. The model has been going through a few mathematical reasoning to getting the usage efficiency on the dataset. The result shows that Support Vector Machine (SVM) got the highest accuracy in test data rather than Logistic Regression (LR) and Random Forest Classifier. SVM used to predict the admission decision, which contribute to the surgery scheduling in OT. This project can be extended to the admission decision with the factor or severity of patient condition to undergo any intervention in outpatient.

Keywords— predictive analytics, machine learning, schedule surgery cases.

1. Introduction

Operating theatre is one of the health service facilities that provide the high volume, fast-paced operating lists in a potentially stressful and pressured Environment [1]. The operating theatre is use for surgery case. Marinus [2] mention that 60% of patients treated in operating room. Surgery case is series of operation conducted by medical practitioner of single patient, in a single operating room over the course of the day [3]. While, OT utilization. While, OT utilization can be defined as a time taken in performing the surgery within a scheduled session. The surgical patient can be assuming as job waiting to be processed, the provider such as surgeon, anesthetist, nurse, facility and surgical apparatus as a machine in process the job [4]. In order to achieve the optimum cost-benefit, the healthcare organization must nurture the scientific and efficient management of an OT [5]. Talati [5] also mention better OT utilization was measure by availability of healthcare provider and resources, attitude and good practice. There are many ways to improve the utilization of operating room such as reduce the surgery duration, anesthesia technique and making a better schedule technique [6]. One measure to evaluate the OT utilization is surgery procedure time taken to the total [7]. Time utilization can be start, and end time of patient undergo the surgery by available resource [3]. However, the utilization time taken does not meant for how effective the time is. Any deep analysis towards the OT utilization must consider the efficiency, effectiveness, productivity and complexity in planned surgery against actual, late start or no show and arrangement of resource within the OT facility.

The scheduling needs to match with the resource availability to cater the demand of the service. The OT resource is operating room, availability of surgeons and anesthesiologists; nurses, allied health, support team and equipment [4]. In order to harness the healthcare industry, predictive analytics used to identify the probability of show and no-show patient arriving. Predictive analytics answering the how and why questions will reveal specific patterns to identify that detection when outcomes are about to occur. Better arrangement of procedure estimation may optimize surgery scheduling [8]. Predictive analytics builds upon the diagnostic analytics to look for these patterns and see what will happen. Through prediction, the organization can forecast the necessary inventory to meet the demand of health services. Machine learning also applied to continuous learning as new patterns emerge. Advance analytics use text, data and web mining to make the prediction.

Properly structured of operating theatre is needed to ensure it fulfil the demand of chronic care service [9]. Case cancellation, no show patient and scheduling bottleneck is the main issues in operating theatre utilization. The current data can be used to identify the opportunity of improvement and to synchronize with the changes of administration and facility. Predictive analysis is the fast-evolving practice. The predictive analytic offers the inter data connection and turn the raw data into meaningful insights. The one year daily operational data on OT is used to validate the reasonableness of the data. The key pattern of data is analysing to get the changes of the data and hypothesis is made as initial analysis on predictor variable. Moreover, another motivation of this project report is enhancing the resources usage by the heart centre through the prediction analysis. The resource that can be improved through this project report is capacity planning, clinical provider scheduling, patient scheduling, bed management, surgery equipment and medical supplies. The motivation of this project report is to make a prediction analysis to the intended user about the OT utilization in hospital. Predictive analysis is the fast-evolving practice. The predictive analytics offers the inter data connection and turn the raw data into meaningful insights. The one-year daily operational data on OT used to validate the reasonableness of the data. The key pattern of data is analysing to get the changes of the data and hypothesis has made as initial analysis on predictor variable. Moreover, another motivation of this project report is enhancing the resources usage via prediction analytics. The resource that can be improve through this project report is capacity planning, clinical provider scheduling, patient scheduling, bed management, surgery equipment and medical supplies.

The study on scheduling bottleneck found that there is no specific measure or rules in patient schedule for surgery [10]. This measure is on how the hospital segregate the patient according to the condition, severity and procedure characteristic. Procedure characteristic such as procedure duration are depending on the surgeon experience, surgery team member, patient's condition and type of anesthesia. Devi [11] has done the project report on predicting the procedure duration by applying the Multiple Linear Regression Analysis, Adaptive Nero Fuzzy Inference Systems and Artificial Neural Networks. The result does not address the problem stated because she used limited number of dataset and only emphasize one department only. There are many departments involved during surgery such as sterile department, pharmacy, Anaesthesiology and nursing. Accuracy in estimating procedure time is important in surgery scheduling planning and management. This approach is decision analysis for the building decision models [12].

2. Research Backgrounds

One of the crucial and significant elements of surgical is the OT. OT is a clinical facility which surgery takes place in an aseptic environment. In the hospital, usually the operating theatre booking inclusive with the medical equipment, human resource and sterile. The excellence management of the operating theatre is needed to satisfy the necessities of patients, surgeon, anesthetist, perfusionist, nurses and operating theatre staff. In order to ensure the smooth process of operating theatre, tertiary care teaching hospital in Pakistan documenting the current OT utilization by capturing it trend with time of different specialties and surgeries performed [13].

In the hospital, OT utilization is the sub-indicator for Key Performance Indicator (KPI). This OT utilization indicator is narrow down into cancellation of scheduled cases in intensive care unit (ICU) and OT list. This indicator also had been practicing in National Health Service (NHS) hospital in United Kingdom (UK) [14]. In NHS hospital, they tend to minimize the waiting time patient to undergo surgery less than 18 weeks. This strategy is to enhance the capacity of OT. The project report identifies the validity of OT utilization with the scheduled cases. Bouguerra [15] proposed the mathematical model to maximize the utilization of OT. The mathematical model helps manager in arrange the optimal OT room scheduling. The model takes surgeon availability and OT opening hour. The objective for optimal scheduling is to ensure OT efficient usage during their current opening hour. The strategy is due to complex problem they are having in arranging the systematic surgical discipline and elective surgery to the OT. Outcome from the session, the optimal usage have been take place in a specific time during a day. Mohan [16] also use a model to assess the OT efficiency. Factor of OT efficiency is utilisation rates, over-running of list and cancellation rates to name. The efficiency of emergency OT usage is asses to identify the issues that improve OT utilization. The number of each point such as arrival of patient, anesthetist procedure, surgery start and end time are recorded. The time recorded are compared with the issue arise in OT to get the OT efficiency. Value stream mapping (VSM) used to recognize the factor affect the OT efficiency in Khan [6] by assessing the current state, identify the area improvement and select the action plan. VSM is an aid in identifying the waste in production [17]. Through the assessment, the OT utilization can be improved by post-operative debrief tracking system, regional anesthetist blocks and reduces turnover time Joint Commission International (JCI) is international standard that advocate the patient safety and accrediting health care service to ensure they gain the patient trust on their services. The heart surgery center is JCI accredited standard. Inomata [18] mention that the improvement of pre-anesthesia after the JCI implementation due to introduction of International Patient Safety Goal (IPSG) chapter to improve the communication between the patient and medical staff.

2.1.Predictive Analytics

Predictive analysis is statistic approach combines the historical data and algorithm technique to forecast the future event. Time series approach is part of predictive analysis. Time series analysis comprises methods for analysing time series data to extract meaningful statistics and other characteristics of time series data. It focuses on comparing values of a single time series or multiple dependent time series. Predictive analytics broadly use in healthcare, manufacturing, retail, energy etc. In order to improve patient care, the patient's record used to process the healthcare information and make a prediction on upcoming epidemics, expected therapeutic, improve life and avoid deaths. While for manufacturing used predictive analytic on optimizing the factor in steps and input to improve the efficiency. Retail used predictive to identify the preferences of customer on their product, identify their behavior and influence to drive actions that influence outcomes that are more profitable. Business company focus on producing energy collect data for geology interpretation, new oil well and well optimization. They also apply predictive analytics for predictive maintenance and optimal use of assets to reduce capital expenditures. Predictive analysis contributes to the organization's strategy and survival in their business. Predictive analysis controls the impact form the business. Predictive analysis influences their decision-making. Diagnostic analytics offer to look the patterns and see what will happen on existing data to predictive analysis. Diagnostic analytics answer what and how things happen while predictive analysis predicts what will happen in future based on diagnostic findings. The statistical approach from data mining, predictive modelling and machine learning process the historical trend to create accurate prediction. However, not only prediction, predictive analysis can solve the operation issue because the process occurs on daily base [19]. The element of predictive analytics is data, statistic and assumption.

In order to ensure the right forecast, the right data and useful information is crucial to answer the early question. The relevant data on transaction history can be dependable on the right information provider. The hectic task not only on tracking the data but also data storage. Usually organization use data warehouse for storage so that the tracking became easier. Statistic technique especially regression analysis are formulated for predictive analysis in order to identify the relationship between independent variables and dependent variable. After trial and error of correlation between the dataset, the process comes up with regression equation to see how much variable affect the result. The equation can be use in assumption element. The assumption will use the findings from the statistic. Any variation of the variable affects the validity of the prediction equation.

Predictive techniques are categorize into numerical prediction and categorical prediction. Regression is type of numerical prediction. Regression analysis is modelling the relationship between variable [20]. The analysis recognizes how the variable reacts when the predictor is changes. Classification prediction is the analysis identify the new findings are owned by which category based on the attempt of training data. This analysis is supervised method, which target known grouping. However, for clustering, the categorical will be naturally grouping based on their nature.

2.2.Model Selection

For the model selection, based on the literature the following models selected to the data analysis which are Logistic Regression, Support Vector Machine (SVM) and Random Forest Classifier. These models selection based on its capability to do a classification prediction [21] [22]. Basic predictive measures used such as accuracy, precision, and recall to assessing the model capability in predicting. Logistic regression is predictive algorithm that used on categorical of dependent variable. Logistic regression is the best machine-learning model in predicting the probability of dependent categorical of dataset variable. Processing data in logistic regression model required the data to be coded as 1 (Yes, Present etc.). However, in this prediction, the Logistic Regression not the best in predicting categorical of discharge decision in the dataset due to the lower accuracy regarding other models.

Support vector machine (SVM) identify the pattern trend. This machine-learning algorithm can be use in regression and classification task. SVM work well on unstructured data, semi structured data and structured data. SVM strength is on its kernel. Kernel is useful during the set of training data is not linear. Kernel will be mapping the dataset into higher dimensional dataset until the hyperplane met for separation purpose. Hyperplane is a decision surface. This model is data nodes that are close to the hyperplane. SVM functioned as maximizing the margin or also called as street between nodes to hyperplane. Below equation show the nodes that touch the hyperplane and under hyperplane expectation. This SVM show the most accuracy among the three models but not in precision and recall.Random Forest Classifier can be used for both categories, either classification or regression. Random Forest is easy to obtain the relative importance of prediction measure. The computational process of Random Forest Classifier measures the importance features after training. The result form the Random Forest Classifier is very straightforward because this model is easy to use.

3.Methodology

The research decides to use simple random sampling. The project covers the OT report list, which comprises the post-operative dataset that determine discharge decision after the surgery. The data analysis and model building is process by using Jupyter Notebook with Python Language. The use of Jupyter Notebook makes it easy to show the result visually and manage the whole experiment. Python provides many libraries suited for data analysis and machine learning. In this experiment, three primary analysis libraries has been used which are pandas for data manipulation, scikit-learn for model bulding and machine learning and Weka for information gain.

The arrangement of values according to condition and stability of patient after operation. Since the aim of the project is to identify the schedule surgery for OT utilization, it is useful to identify the condition of patient either to send into the ICU or not so that the management can prepare the slot for OT. All the attributes in the dataset converted to binary for the ease of training and modelling. Based on the selection and features derivation, we ended up with eight features having 91 observations. The feature selection is important to develop a feasible model. Features selection is process to select the relevant subset or variable in model selection building. Feature selection identify the variable and predictor. Features techniques used for simplifying the model, quick process of training time, avoid curse of dimensionality and reducing overfitting. For this project dataset, entropy analysis is process in Weka machine learning. In Weka, Info Gain function is used. The following table show the attribute processed in Weka.

Table 1. Features Selection

Feature	Information Gain
Internal temperature	0.1155
Surface Temperature	0.1132
Oxygen Saturation	0.104
Stability Core Temperature	0.0843
Comfort	0.0243
Last Measurement Blood Pressure	0.0166
Stability of Patient	0
Patient Blood Pressure	-0.0742

4.The Results and Discussion

The project results begin with the gathering of the data and select fit features to be analyse suing machine learning. The best three algorithm model from the literatures is selected for analysis on predictive scheduled cases for OT utilization. The model had been assessed through their accuracy, precision and recall identifying the model quality.

Table 2. Performance Matrix Comparison

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	37.04%	40.0%	50.0%	44.0%
Random Forest	37.04%	55.56%	83.33%	0.067%
Support Vector Machine	55.56%	40.0%	50.0%	44.0%

Based on the table above, the performance metrics is showing the behavior and quality of each model. This table shows the accuracy, precision and recall metrics based on the confusion matrix result. Accuracy and precision identify the correctness and precise the model to predict the positive which referring to the actual positive. While recall calculate the number of Actual Positive of the test model count as Positive label. Recall is a metric to identify the high cost best model associate with False Negative. F1 Score is output from the combination of output Precision and Recall. F1 Score shows the balance between the Recall and Precision. F1 Score is a best measure because it emphasizes the large number of Actual Negative. The highest accuracy score among the three-model shown by SVM, followed by Random Forest Classifier and Logistic Regression, which is hold the same lowest value. The accuracy of SVM is highest rather than the rest because it has highest true negative value. True negative value shows the actual positive (predicted as true).

5.Conclusion

The research has identified which the algorithm can function well with the operative data specifically for post-operative data. The most accurate predictive analytics, SVM in predicting the number of patients, which admitted to the ICU or General Wards. This number of patients from OT contribute the bed preparation on ICU [23]. ICU play an important role in post-surgery activity. Patient that undergo the surgery will admit to the ICU for rehabilitation and recovery. Transfer from the OT to ICU need the clear communication regarding to the patient information because patient at the vulnerable stage. These predictive analytics help critical care management to prepare and plan the admission for ICU facility. The availability of bed in ICU is a benchmark of OT planning. This project report contributes the patient characteristic that mostly sent to the ICU after the surgery. It predicts which patient condition that are fit to the ICU; so that the application of predictive model within the post-operative dataset is good strategy to plan for the OT scheduling.

Predictive model enlightens which attributes in the dataset that should be take action to improve the outcome but not provide on how to do it. In this project, the dataset did not include the time series as plan in the early project methodology. The predictive application only applied on condition of patient that influences the discharge decision. Analyzing the dataset through the predictive analytics model require familiarity by the analyzer. The predictive analysis not only use the basic measure such as accuracy, recall, precision and F1 but also learning rate, number of epoch and number of cells.

The minimal number of instances affect the predictive analytics. The dataset only contains the 90 instances. The sample of data may under fitting because the data did not enough due to poor performance of the training and testing data through the selected model. The sources of data from public data may adjusted and not appropriate for the analysis. There is missing attribute in predicting the dataset, which is surgery date, length of stay in Critical Care Unit (CCU). This attribute assist in predicting the OT utilization by measuring the duration of patient stay in ICU.

6. References

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