**S220 – Optimizing Surgical Efficiency: Predicting Case Duration of Common General Surgery Procedures Using Machine Learning**

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**ABSTRACT**

**Background:** Accurate prediction of surgical duration is critical to optimizing use of operating room resources. Currently, cases are scheduled using subjective estimates of length by surgeons, relying heavily on prior experience.This study aims to develop and compare various predictive models—from conventional statistics to machine learning-based algorithms—to accurately and objectively predict case duration for common elective general surgical procedures.

**Methods:** Electronic health record data across three academic tertiary centers were used to train models to predict “case time duration”, defined as the time between patient entry to and departure from the operating room. Model performance was evaluated based on predictive accuracy as well as residual analysis, and ultimately benchmarked against “scheduled duration”, defined as case time estimated preoperatively by primary surgeons.

**Results:** Predictive models, including simple linear regression, Ridge regression, Lasso regression, Support Vector Regression, Random Forest, Gradient Boosting Machine, XGBoost, and Artificial Neural Network (ANN), were trained on a cohort of 16,159 patients [mean age, 56.85 ± 15.95; 47.48% male] having undergone 17,246 elective general surgery procedures. The ANN model demonstrated the superior predictive accuracy (Root Mean Squared Error, 49.7 minutes [95% CI 47.5 to 52.0]; Mean Absolute Error, 31.8 minutes [95% CI 30.6 to 33.0]). Residual analysis showed that the ANN resulted in an average residual of -0.37 minutes [95% CI -40.42 to 39.68, *p* = .34], while the scheduled duration produced an average residual of -18.52 minutes [95% CI -55.24 to 18.2, *p* < .01], demonstrating that the ANN provided a more accurate case time estimation by more than 18 minutes.

**Conclusions:** The ANN model estimates of case time were meaningfully more accurate than provider knowledge-based estimates. By eliminating the subjective bias and dogma inherent in the traditional scheduling methods, future applications of machine learning to predict case duration may improve healthcare resource utilization.

**Keywords:** machine learning; case duration prediction; case scheduling; general surgery; elective surgery

**1 INTRODUCTION**

Optimizing operating room (OR) efficiency is vital to the delivery of high-quality and timely surgical care [1]. To this end, accurate predictions of case duration are necessary to extract maximal value from limited OR resources [2]. Inaccurate estimates lead to both under and over-utilization of OR time—resulting in idle time, overtime wages, frequent delays, case cancellations and postponements—that reduce surgical throughput, incur additional operational costs and, ultimately, impact patient care [1].

Current industry standards for predicting case duration rely either on subjective surgeon estimates or on historical averages from electronic medical records (EMR), and often overlook patient, procedural, anesthetic and systemic factors that impact operative time [3]. These approaches have been shown to have limited accuracy, significant variability, and predictive inconsistency, highlighting the need for a more reliable method of estimation [3].

Recent advancements in Machine Learning (ML) present promising alternatives to existing methods of case scheduling [4]. ML has demonstrated potential in improving the accuracy of case duration predictions, which could enhance OR scheduling and decision-making processes [5,6]. By integrating ML with EMR systems, healthcare providers can better manage surgical workflows and address the backlog, ultimately leading to more efficient and effective OR utilization [7].

This study aims to develop advanced predictive models using a large dataset of common general surgery procedures from our institution’s EMR to enhance the accuracy of case-time duration estimates. We hypothesize that an ML model, incorporating a wide range of clinical variables beyond those considered in traditional methods such as patient characteristics, procedural details, and personnel information will offer more precise predictions.

# **2 MATERIALS & METHODS**

This retrospective cohort study was approved by the Research Ethics Board of Western University (London, ON, Canada), and is here reported in accordance with the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD-AI) guidelines [8].

## **2.1 Data Sources & Setting**

Existing de-identified EMR (Cerner, North Kansas City, USA) data were retrospectively collected for surgical cases that took place across 3 tertiary care academic hospitals in the London Health Sciences Center (London, ON, Canada) over a 5-year period. All data was housed on a secure university-based server for analysis, model development, and internal validation.

**2.2 Study Population**

From this dataset, a cohort of adult (age ≥ 18) patients undergoing select general surgery procedures scheduled between January 1, 2015, and January 1, 2020, was identified. To focus on the most commonly performed procedures, included cases were limited to the following operations: appendectomy, non-radical cholecystectomy, colectomy, gastric bypass, non-hiatal abdominal hernia repair, ileostomy closure, liver resection, mastectomy, parathyroidectomy, thyroidectomy, and Whipple procedure. Cases were included based on regular expression codes, and not limited to procedures performed under the General Surgery service. Urgent and emergent non-elective cases were excluded. Cancelled cases were also excluded. Cohort selection is outlined in Figure 1.

## **2.3 Data Preparation & Pre-processing**

To ensure transparency and reproducibility, a comprehensive description of final variables and applied pre-processing steps are presented in Supplementary Table 1. Cases with missing values were removed rather than imputing missing values to avoid introducing bias. Outliers were identified based on clinical parameters (age ≥ 130; BMI ≤ 5, ≥ 200) and removed. Continuous features were scaled using min-max normalization. Categorical variables with rare categories (defined as those with frequency ≤ 1%) were merged into a generalized “Other” category. All categorical variables underwent one-hot encoding or ordinal encoding. Additional features were derived from existing date-time data. The final pre-processed dataset, consisting of 17,246 examples, was generated using structured query language (SQL; Joint Technical Committee of the International Organization for Standardization and International Electrotechnical Commission [ISO/IEC]) and Python programming language version 3.9 (Python Software Foundation) code.

**2.4 Model Development**

The primary study outcome and predictive output was “case time duration”, defined as the time between patient entry to and departure from the OR. Models were designed to make predictions at the time of case scheduling by the primary surgeon; to prevent data leakage, all inputs were restricted to information available in the pre-operative period. Initial feature selection was informed by clinical field expertise as well as a review of the existing literature. Ten-fold cross validation was used for model training and testing, detailed in Figure 2. The previously described data preparation and pre-processing steps were applied separately to each fold to prevent data leakage. A data dictionary of all variables used in this study is provided in Supplementary Material eTable 1.

Traditional multivariate and machine learning supervised machine learning models were trained: simple linear regression, Ridge regression, Lasso regression, Support Vector Regression (SVR), Random Forest, Gradient Boosting Machine (GMB), XGBoost and Artificial Neural Network (ANN). For each model type, hyperparameters were tuned using the Tree-structure Parzen Estimator algorithm9, a variant of Bayesian optimization particularly effective in handling high-dimensional space, illustrated in Supplementary Material eFigure 1. Ranges for hyperparameter optimization are described in further detail in Supplementary Material eTable 2. Overall, the model development process is illustrated in Supplementary Material Figure 2.

### **2.5 Model Evaluation**

Predictive models were benchmarked against “scheduled duration”—the estimated case time booked by the primary surgeon. Model performance was evaluated via Mean Squared Error (MSE)10, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE)11, Mean Absolute Percentage Error (MAPE) and Coefficient of Determination (*R*2), calculated across each fold of cross-validation.12 RMSE reflects predictive accuracy in minutes, while penalizing larger errors more harshly compared to MSE. MAE presents average error in minutes, while MAPE reflects the error as a percentage of true case duration.

**2.6 Statistical Analysis**

Statistical analysis was designed to compare models by testing for significant differences across performance metrics. Levene’s test was first conducted to confirm the assumption of equality of variances held true for each metric. To reduce the risk of Type I errors from performing multiple t-tests, Analysis of Variance (ANOVA) was used to compare groups of models against “scheduled duration”, and significant results were followed by Dunnett’s test post-hoc. Analysis of residuals—the differences between actual and predicted outputs—was also performed to assess whether any models exhibited consistent bias. One-sample t-tests were performed to evaluate whether model residuals were significantly different from zero, with residuals not significantly different from zero indicating unbiased predictions.

**3 RESULTS**

**3.1 Descriptive Analysis**

A cohort of 16,159 patients having undergone 17,246 elective general surgery procedures were identified to train and internally validate predictive models. With regards to surgical features, the most frequently scheduled cases were abdominal hernia repairs (33.92%), non-radical cholecystectomies (20.00%) and thyroidectomies (11.99%), followed by gastric bypasses (4.85%), liver resections (4.75%), parathyroidectomies (4.62%), mastectomies (1.86%) and appendectomies (1.07%), largely performed with open (62.68%) and laparoscopic (37.16%) approaches. With regards to clinical history, patients were largely of ASA Class III (47.98%) and II (35.86%), and most responsible indications for surgery included digestive pathology (56.77%), malignant neoplasms (19.74%), endocrine pathology (11.92%). With regards to systemic factors, the majority of procedures were performed by the General Surgery service (83.35%), on an outpatient (83.35%) basis. Additional patient and surgical case characteristics of the study population are described in Table 1.

**3.2 Model Performance**

As seen in Tables 2 and 3, the ANN outperforms all other models. Compared to “Scheduled duration” (RMSE 49.9 ± 2.0 minutes), ANN demonstrates comparable predictive accuracy (RMSE 49.7 ± 2.3 minutes; p < .05) compared to “Scheduled duration” (RMSE. “Scheduled duration” performs comparably to the ANN with an RMSE of 49.9 ± 2.3 minutes, and is in fact superior to all traditional statistical models which have higher RMSE values. The average error of ANN can be interpreted as 0.26 ± 0.01 percent (p <.05) of true case duration, significantly outperforming primary surgeon predictions, which have larger error of 0.34 ± 0.01 percent. For all models, including ANN, the large difference between RMSE and MSE reflect that outliers impact performance to a marked degree; however, R2 values show that variability is well captured. “Scheduled duration”, however, does consistently perform equivalentrly or outperform traditional statistical models across evaluation metrics.

## **3.3 Residual Comparison**

As shown in Table 4, the ANN model is the only one that does not have a significant difference from zero (*p* = 0*.*337), suggesting that it provides more accurate predictions with less bias. In contrast, other models, including the Scheduled Duration, show significant differences from zero (*p <* 0*.*05), indicating potential biases in their predictions. When comparing the mean and median residuals, the Neural Network model demonstrates a mean residual close to zero (-0.37 minutes) and a median of -3.69 minutes, further underscoring its superior performance in minimizing prediction errors compared to other models, where the Scheduled Duration shows a larger mean residual of -18.52 minutes.

# **4 DISCUSSION**

This study presents compelling evidence that machine learning models, particularly Artificial Neural Networks (ANN), provide more accurate predictions of case time duration than conventional methods. Traditional methods, predominantly reliant on surgeon intuition and historical averages, often result in substantial discrepancies between scheduled and actual surgical durations [9]. By leveraging a comprehensive dataset of 17,246 elective surgical procedures, our findings indicate a clear advancement in predictive accuracy that could enhance OR management.

The superiority of the ANN model over other conventional regression models and machine learning approaches is noteworthy. The ANN model demonstrated a mean residual close to zero (-0.37 minutes) whereas the scheduled duration showed a larger mean residual of -18.52 minutes, resulting in a more accurate and unbiased case time estimation by over 18 minutes. This discrepancy underscores the limitations of relying on historical averages or personal experience for scheduling, which can lead to inefficient OR usage and extended patient wait times. Other previous studies have also demonstrated that machine learning models, particularly ANNs can provide superior predictive accuracy, reducing the mean absolute error significantly compared to conventional approaches [10].

Before the development of ANN models, previous research utilized linear statistical models to evaluate the importance of relevant input variables and predict case time durations [11].11 Patient and clinical characteristics were the most utilized predictors of surgery duration, such as the algorithms developed to predict the duration of laparoscopic cholecystectomies [12]. However, one important disadvantage with this strategy is the inability of these type of models to handle numerous input variables. Studies have found that consideration of temporal factors like surgical setting, rank of case, day, week or month of surgery should be considered to improve prediction [13,14].

Machine learning algorithms leverage vast amounts of data and complex variables that encompass patient demographics, case complexity, and provider experience, enabling a more nuanced understanding of predictive factors [15]. One of the most significant implications of our findings is the reduction of subjective bias associated with provider-based estimates. The ANN model’s mean residual was close to zero, indicating that its predictions were unbiased and reliable. This not only highlights the potential for improved accuracy but also the elimination of biases inherent in human judgment [16]. This suggests that integrating machine learning into surgical scheduling could mitigate the variability inherent in surgeon or staff estimations. As surgical procedures become increasingly complex, employing data-driven models like the ANN could enhance the precision of time predictions, ultimately leading to better OR efficiency and patient throughput [17].

There are some limitations that should be acknowledged in this study. First, the study’s reliance on retrospective data from a single academic institution may limit the generalizability of the results. Variability in surgical practices, patient populations, and institutional resources could impact the applicability of the model to other settings [18]. Furthermore, the algorithm’s performance could be influenced by the quality of the input data, including missing values or inaccuracies within electronic medical records. Future studies should explore multi-center data validation to assess the robustness of machine learning models across diverse healthcare environments [19]. We acknowledge that some important clinical variables, such as past medical history, were not captured in the initial dataset curation, while others were unsuitable for model development. Specifically, primary case status, a collected variable meant to capture whether the patient had previous surgery in the same anatomical area, was excluded due to significant class imbalance, likely secondary to incorrect data entry. Additionally, while machine learning models can improve prediction accuracy, they do not account for real-time intraoperative variables, such as unexpected complications or variations in surgical techniques. These factors can significantly influence case durations and may not be captured in preoperative data [20]. Developing adaptive models that can incorporate real-time data could further enhance predictive capabilities and operational efficiency.

Clinically, the implications of implementing machine learning algorithms are profound. Improved accuracy in predicting surgical case time allows for better scheduling, optimizing the use of surgical suites and personnel [21]. This could lead to reduced costs and enhanced patient satisfaction due to reduced cancellations and more efficient care delivery [22]. Moreover, machine learning could facilitate the identification of cases at risk of extended durations, allowing for preemptive adjustments in scheduling and resource allocation. While this study focused on elective general surgical procedures, the framework developed here could be adapted to other surgical specialties, potentially leading to widespread improvements across the healthcare system.

**5 CONCLUSIONS**

In conclusion, our study demonstrates that machine learning, specifically the ANN model for predicting surgical case time duration, provides a significant advantage in predicting surgical case durations compared to traditional estimation methods. By minimizing bias and improving accuracy, these advanced predictive models can optimize OR scheduling, potentially leading to more efficient use of healthcare resources. Continued exploration of this technology will be crucial in further refining surgical processes and improving overall patient outcomes. The next stage of research will explore whether integration of these prediction tools in the EMR can provide significant cost savings and enhance patient care by reducing case cancellations.

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**7 FIGURE LEGENDS**

**Figure 1: Cohort Selection Flowchart.** Cohort selection via application of inclusion/exclusion criteria to arrive at training dataset.

1. Selected procedures: appendectomy, cholecystectomy, colectomy, gastric bypass, abdominal hernia repair, ileostomy closure, liver resection, mastectomy, parathyroidectomy, thyroidectomy, Whipple procedure.
2. Selected procedures: hiatal hernia, diaphragmatic hernia, paraesophageal hernia, radical cholecystectomy, exploratory laparotomy.

**Figure 2: K-fold Cross Validation.** Schematic of the 10-fold cross validation methodology used in this study for model training and testing. Application of pre-processing steps, hyperparameter tuning and calculation of evaluation metrics were performed indpdently for each fold.

Abbreviations: represents evaluation metrics (i.e., MSE, mean squared error; RMSE, root mean squared error; MAE, mean absolute error; MAPE, mean absolute percentage error; and *R*2, coefficient of determination) calculated across fold

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