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Technological Trend Analysis for Surgical Operation Duration Estimation

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Abstract: Surgical procedures are complex in nature and operative time is subject to variability influenced by many factors. Accurate estimation of the surgical operation duration not only helps to maximize Operation rooms' efficiency, but also helps to optimize hospital resources which are a crucial factor in planning surgical procedures. In this regard, Al techniques such as machine learning and deep learning promise to significantly improve the duration estimation by identifying hidden factors and make more accurate prediction. They achieve this success by identifying latent factors which are generally hard to be explored by human intelligence. Eventually, accuracy in time estimation added to a good scheduling optimization leads to make more efficient utilization of hospital resources by better aligning Operation Room, relevant equipment, and human resources. This study addresses the recent trends in research on surgical operations duration estimation, considering the relevant factors.

Keywords: Surgical procedure duration, Time estimation, Operating room scheduling, Operation room optimization, Scheduling

Introduction

The duration of a surgery is expressed in terms of the time a patient spends in the operating room, regardless of whether the operation has started or not (Wang et al., 2021). In the literature, studies on the prediction of surgery duration have shown that the target parameter, the surgery duration, depends on various factors such as the type of surgery, the performing surgeon's experience, and the surgical team's proficiency (Wang et al., 2021, Rath et al., 2021). These factors can either reduce the surgery duration compared to the predicted time or extend it further.

Although studies focusing on predicting surgery durations hold a significant and popular place in medical literature, this process is complex and challenging to implement. Surgery procedures inherently possess a multi-layered and variable structure, leading to different approaches in the literature regarding this subject. When studies and applied methods on operating room planning and scheduling in the medical literature are examined on a daily, weekly, and yearly basis, a continuous process of method improvement is observed. Hospitals' approaches to surgery-time management involve not only online and offline planning but also strategic and tactical planning.

Due to the performance of various types of surgeries in operating rooms, harmonious long-term planning can be established among different surgical groups on a yearly basis. Additionally, medium-term planning on a weekly level can also be applied. Another method is to plan the surgeries of non-urgent patients within a predetermined date range (Kroer et al., 2018). In this approach, the surgery dates of patients can be planned according to specific rules or based on surgical priorities. The aim is to optimize the utilization of available resources in the healthcare facility where the operation will take place, ensuring that the needs and productivity of healthcare professionals are not compromised by avoiding unfavorable conditions.

In addition to this method, there is an approach focusing on the analysis and control of a planned surgery during its operational process. At this level, the emphasis is on anticipating and providing responses to unforeseen circumstances that may arise during the planned procedure to ensure the smooth progression of subsequent operations. Controlling the pre-operative and post-operative needs of patients, preparing the equipment to be used during the surgery, managing the participation of healthcare workers in the surgery, and organizing the operating room for the surgical procedure are crucial at this level (Erwin et al., 2012).

Literature Review

Various studies in the literature focus on resource optimization in surgical processes. Researchers often concentrate on mathematical modeling at this point. Decisions that need to be made in accordance with varying needs, depending on the problem definition, are modeled to yield the outcome of the decision. The complexity imposed by operating room conditions has prompted researchers to develop different methods to achieve better results.

In the study conducted by Master et al. (2016) various prediction models for Surgical Duration Estimation were investigated, each offering different levels of automation and utilization of input from surgeons. Some models provided automated predictions, leveraging features available in electronic records without the need for additional input from surgeons. On the other hand, semi-automated models utilized electronic record features but also incorporated valuable insights from surgeons. Most particularly, tree-based prediction methods, such as decision tree regressor, adaptively boosted regression trees, and random forest regressor were employed in the analysis. The dataset encompassed 4475 distinct procedures, serving as a substantial foundation for the model training process. Post-training, it was evident that the random forest regressor and adaptively boosted regression trees exhibited superior accuracy among the evaluated methods.

Contrary to findings in the existing medical literature, the study's models showcased remarkable performance, outperforming currently used algorithms and, in certain instances, even rivaling human experts in Surgical Duration Estimation. These findings signify the potential of their proposed models to enhance surgical duration prediction practices, paving the way for more effective and informed decision-making in medical settings.

Surgery durations have been attempted to be predicted using statistical methods such as standard deviation and coefficient of variation, as well as machine learning-based approaches, which have also started to be preferred by researchers (Fairley et al., 2019). Predictions based on patients' past hospital records and the professional experience of the performing surgeon play a significant role in statistically estimating surgery duration. Data from all types of factors that are believed to influence surgery duration are collected and interpreted with a statistical distribution as part of the prediction approaches. In particular, the Log-Normal Distribution (Zhang et al., 2020) and Empirical Distribution (Cappanera et al., 2014) are among the most popular methods in the literature. Surgical operation durations, which have multi-factorial uncertainty, can be better comprehended, and more effectively channeled into real-life problems with the help of uncertainty sets.

Method

In this study, systematic mapping (Petersen et al., 2015) has been conducted by compiling the existing surgical duration estimation papers in the literature along with the methods used in these papers and their respective results. This section summarizes the systematic mapping study conducted in the field of Surgical Operation Duration Estimation. As a result of the publication searches carried out in the popular databases mentioned in Table 1, a total of 351 candidate articles were identified in the Surgical Operation Duration Estimation domain. These candidate articles were meticulously evaluated based on the inclusion and exclusion criteria provided in Table 2 and Table 3. Consequently, following the evaluation process, 24 final articles were selected, and the research continued with these articles.

During the systematic mapping study, the following search string was employed:

((“surgical duration” OR “surgery time”) AND (“estimation” OR “prediction” OR “forecasting”))).

This search string aimed to ensure the efficiency and comprehensiveness of the research. Focusing on studies related to the prediction of surgical durations, it facilitated the identification of potentially relevant articles. The results obtained in this study are intended to serve as an important resource for understanding the current state of research in the Surgical Operation Duration Estimation domain and identifying potential areas of opportunity for future research.

Table 1. Database sources

Literature Database	Direct Link
Science Direct	https://www.sciencedirect.com/
IEEE Xplore	https://ieeexplore.ieee.org/
Springer Link	https://link.springer.com/
Pubmed	https://www.ncbi.nlm.nih.gov/pmc/
Google Scholar	https://scholar.google.com/

Table 2. Inclusion criteria of the systematic mapping

Inclusion criteria
The publications directly related to surgical duration estimation are included.
The publications containing the utilized methods, evaluation metrics, and results are included.
The publications available as full text in the literature are included.

Table 3. Exclusion criteria of the systematic mapping

Exclusion criteria
Publications not directly related to surgical duration estimation have been excluded.
Publications that are not written in the English language have been excluded.
Publications that are not in the form of academic journals or conference papers in the literature have been excluded.

The following research questions are considered to shed light on significant topics related to Surgical Duration Estimation:

RQ1) How frequently are machine learning, deep learning, and statistics-based methods used in the studies conducted in the field of surgical duration estimation?

RQ2) What evaluation metrics are preferred by researchers in the literature to assess the reliability of the employed methods?

RQ3) After applying inclusion and exclusion criteria, in which years was an increasing trend observed in the number of studies conducted in the field of Surgical Duration Estimation?

Data Creation

After the systematic mapping process, a total of 24 final papers were selected and subjected to a detailed data extraction procedure. During the data extraction phase, comprehensive information was retrieved from each paper, encompassing the author's details, publication years, employed methodologies, descriptions of the utilized datasets, and, finally, the reported results. The extracted data from all the papers have been compiled and presented in Table 4.

The data extraction phase is a crucial step in the research process, as it allows for the synthesis and organization of relevant information from the selected papers. By meticulously extracting and collating key details, Table 4 provides a comprehensive overview of the literature on Surgical Duration Estimation. The extracted data serves as a valuable resource for gaining insights into the research landscape, identifying prevailing trends, and discerning the various methodologies employed by researchers in the field.

Moreover, the extracted results provide a clear representation of the findings reported in the literature, enabling further analysis and comparison among the studies. This compiled information will aid in shaping a comprehensive understanding of the advancements made in Surgical Duration Estimation research and contribute to the identification of potential research gaps and opportunities for further investigations in the domain.

Table 4. Extracted data of the 24 main papers from the systematic mapping results.

Study	Year	Method	Data Detail	Results
Hinterwimmer et al.	2023	Extreme Gradient Boosting (XGBoost) Algorithm	864 cases were collected at Klinikum rechts der Isar (Munich) from 2016 to 2019	Accuracy of 92.0%, Sensitivity of 34.8%, Specificity of 95.8%, and Area Under the ROC Curve (AUC) of 78.0%
Gabriel et al.	2023	Multivariable Linear Regression (MLP), Random Forest (RF), Bagging, and Extreme Gradient Boosting (XGBoost)	A total of 3189 surgeries were examined	XGBoost performed best scores with a variance score of 0.778, R-Square of 0.770, Root Mean Square Error (RMSE) of 92.95 minutes, and Mean Absolute Error (MAE) of 44.31 minutes
Jiao et al.	2022	Artificial Neural Network (ANN)	70,826 cases were collected from eight hospitals	Accuracy of 89%
Chu et al.	2022	Extreme Gradient Boosting (XGBoost), Random Forest, Artificial Neural Network (ANN), 1-dimensional Convolution neural network (1dCNN)	124,528 records from January 2015 to September 2019 from Shin Kong Wu Huo-Shih Memorial Hospital	XGBoost model with the values 31.6 min, 18.71 min, 0.71, and 28% for Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R-Square), Mean Absolute Percentage Error (MAPE), respectively
Abbas et al.	2022	Mean Regressor, Linear Regression, SGD Regression, Elastic Net, Linear SVM, KNN, Decision Tree, Random Forest, AdaBoost, XGBoost, Scikit-learn Multilayer Perceptron (MLP), PyTorch MLP	A total of 302,300 patients were analyzed	Mean Squared Errors (MSEs) of PyTorch MLP for the duration of surgery and length of stay are 0.918 and 0.715, respectively.
Ito et al.	2022	Random Forest (RF)	9567 surgical cases from the National Cancer Center Hospital East, between April 2015 and March 2018 are collected.	Mean Absolute Error (MAE) of 39.94, R-Square value of 0.80, and adjusted R-Square value of 0.77
Martinez et al.	2021	Linear Regression (LR), Support Vector Machines (SVM), Regression Trees (RT), and Bagged Trees (BG)	The dataset is consisting of 206,587 records of the university hospital in Bogotá, Colombia between	Root Mean Squared Error (RMSE) value of 26 min. for BG

			December 2004 to April 2019	
Ramos et al.	2021	Backward stepwise linear regression modeling	Data were collected from 14 cases.	Mean Absolute Error (MAE) of 3.7 minutes (±41.1)
Yuniartha et al.	2021	K-Nearest Neighbors (kNN), Decision Tree, Support Vector Machine (SVM), Stochastic Gradient Descent (SGD), Random Forest (RF), Linear Regression (LR), AdaBoost	Historical data of Hospital A and Hospital B	Hospital A: Linear Regression with a Mean Absolute Error (MAE) of 25.143 min. Hospital B: Random Forest with a Mean Absolute Error (MAE) of 23.038 min.
Jiao et al.	2020	Bayesian statistical method (Bayes), Decision Tree (DT), Gradient Boosted Decision Tree (GBT), Mixture Density Network (MDN), Random Forest (RF)	53,783 cases performed during 4 year-period at a tertiary-care pediatric hospital	Continuous Ranked Probability Score (CRPS) of 18.1 minutes for MDN
Soh et al.	2020	Linear Regression (LR)	First Synthetic Dataset, Second Synthetic Dataset, and Third Synthetic Dataset	Root Mean Squared Error (RMSE) values of First Synthetic Dataset, Second Synthetic Dataset, and Third Synthetic Dataset are 6.72 mins., 13.46 mins, and 4.91 mins., respectively.
Zhao et al.	2019	Multivariable Linear Regression (MLR), Ridge Regression (RG), Lasso Regression (LR), Random Forest (RF), Boosted Regression Tree (BRT), and Neural Network (NN)	500 cases from January 1, 2014 to June 30, 2017, are examined.	Root Mean Squared Error (RMSE) of 86.8 min for MLR, RMSE of 82.4 min for RG, RMSE of 81.3 min for LR, RMSE of 81.9 min for RF, RMSE of 80.2 min for BRT, RMSE of 89.6 min for (NN)
Bartek et al.	2019	Linear Regression (LR) and Extreme Gradient Boosting (XGBoost)	46,986 scheduled operations performed between January 2014 to December 2017	Mean Absolute Percentage Error (MAPE) of 26 min for Surgeon-specific XGBoost and 74% Accuracy for Surgeon-specific XGBoost
Twinanda et al.	2019	Convolutional Neural Network (CNN) and Long-Short Term Memory (LSTM)	Cholec120 Dataset and BYPASS170 Dataset	Mean Absolute Error (MAE) of 7.7 ± 5.2 min for TimeLSTM Model and MAE of 15.6 ± 7.9 min for RSDNet Model
Bodenstedt et al.	2019	Convolutional Neural Networks (CNN)	Publicly available Cholec80 dataset is used	Mean Absolute Error (MAE) of 2093 ± 1787 seconds Baseline Type Model.

Shahabikargar et al.	2017	Generalized Linear Model (GLM), Multivariate Adaptive Regression Splines (MARS) and Random Forests (RF) algorithms	60362 data collected between 01/07/2008 to 30/06/2012 from HBCIS and ORMIS	Mean Absolute Percentage Error (MAPE) of 0.38 for RF
Spangenberg et al.	2017	Linear Regression (LR), Decision Tree (DT), Random Forest (RF), Multilayer perceptron (MP)	Data consists of 15 surgeries of two different surgery types.	Mean Absolute Error (MAE) of 17.52±15.17 for LR, Root Mean Squared Error (RMSE) of 23.14 for LR, Mean Squared Error (MAE) of 535.34 for LR, and R-Square value of 0.88 for LR
Master et al.	2017	Decision Tree Regressor (DTR), Random Forest Regressor (RFR), Gradient Boosted Regression (GBR)	Electronic medical records from hospital information systems	Overall R-Square values of DTR, RFR, and GBR are 0.28, 0.38, and 0.44, respectively.
Edelman et al.	2017	Linear Regression	Data was collected from a Dutch benchmarking database that encompassed all surgeries conducted in six academic hospitals in The Netherlands between 2012 and 2016.	Mean Absolute Error (MAE) of 29.2 minutes and a Mean Squared Error (MSE) of 2,320.7 minutes for the predictions made between 2012 and 2015. For the predictions made in 2016, the MAE was 31.3 minutes with a MSE of 2,366.9 minutes.
Shahabikargar et al.	2014	Linear Regression (LR), Multivariate Adaptive Regression Splines (MARS), and random forests (RF)	The research utilized administrative and perioperative data spanning four years (from 1st July 2008 to 30th June 2012) obtained from a prominent teaching hospital in Queensland, Australia.	Root Mean Square Error (RMSE) of 28.12 for LR, Mean Absolute Percentage Error (MAPE) of 0.68 for RF, and R-squared value of 0.65 for RF
Kayıs et al.	2014	Bootstrap-enhanced least absolute shrinkage operator	The cases within two years (2010-2011) in the seven main operating rooms at a large children's hospital in the US is analyzed. 10292 surgery data is collected.	R-Square of 0.64 and Mean Absolute Deviation (MAD) of 39.98 ± 0.58.
Devi et al.	2012	Adaptive Neuro Fuzzy Inference Systems (ANFIS),	Data from 100 surgeries each of	ANFIS: Root Mean square Error (RMSE)

		Artificial Neural Networks (ANN) and Multiple Linear Regression Analysis (MLRA)	corneal transplant surgery, cataract surgery, and oculoplastic surgery (total of 300 data), performed by the same surgeons and anesthetists.	of 0.0697 for cataract surgery. ANN: Root Mean square Error (RMSE) of 0.1427 for cataract surgery. Regression: Root Mean square Error (RMSE) of 0.1768 for cataract surgery.
Schneider et al.	2011	Log-Linear Mixed Regression Model (LLMRM) and Univariable Random Effect Model (UREM)	Historical data of 312 patients	Prediction Error: 17.5 min for LLMRM and 21.6 min for UREM
Eijkemans et al.	2010	Linear Mixed Modeling	17,000 operation cases are analyzed.	Overestimation: 2.8 min Underestimation: 6.6 min

Results and Discussion

As a response to the first research question, in the context of studies related to Surgical Duration Estimation in the literature, researchers exhibit varying preferences for the methodologies employed. According to the Figure 1, analysis of the data reveals that Machine Learning stands out as the most favored approach, accounting for 45.8% of the studies. It appears to be a popular choice due to its ability to process and learn from large datasets, enabling the development of predictive models for surgical duration. Machine Learning methods used in papers can be seen in Figure 2. Statistics, constituting 16.7% of the studies, also retain their significance, offering traditional and well-established methods for data analysis and inference. Statistical methods used in papers can be found in Table 5. Surprisingly, Deep Learning, with a preference rate of 12.5%, emerges as a relatively less frequently utilized method, despite its widespread application in various fields. Overall Deep Learning methods used in papers can be seen in Figure 3. Interestingly, a subset of studies (4.2%) adopts a comprehensive approach, combining Machine Learning, Deep Learning, and Statistics, likely to harness the complementary strengths of these methodologies.

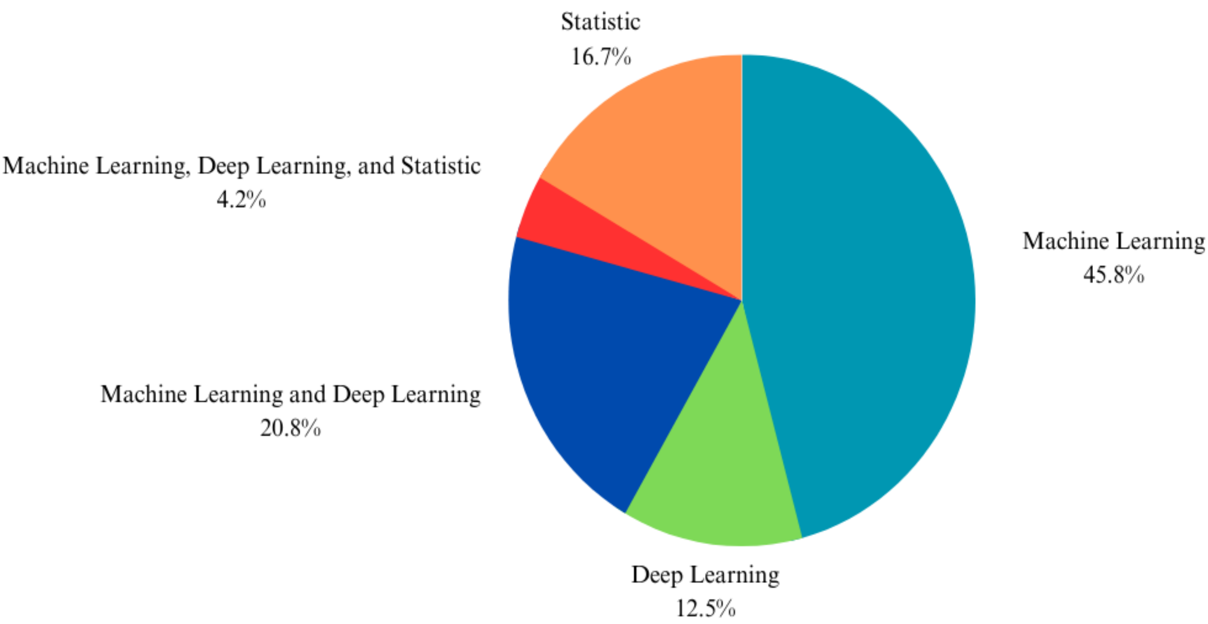

Figure 1. Chart showing the distribution of the methods used in the studies.

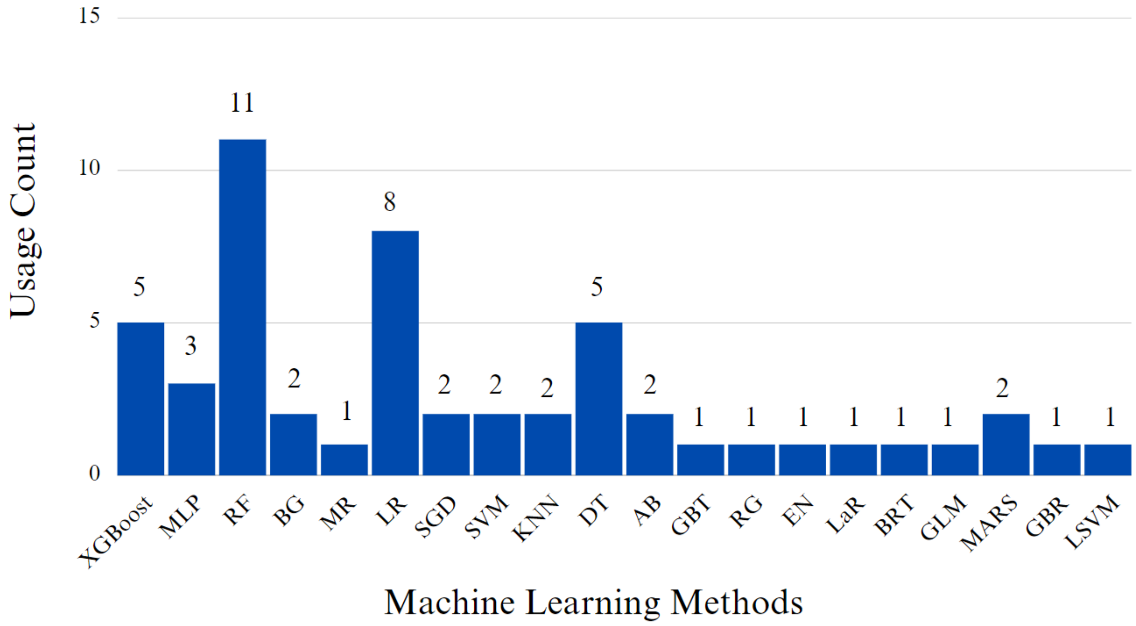

Figure 2. Usage numbers of machine learning methods used in papers.

(XGBoost: Extreme Gradient Boosting, MLP: Multivariable Linear Regression, RF: Random Forest, BG: Bagged Trees, MR: Mean Regressor, LR: Linear Regression, SGD: Stochastic Gradient Descent Regression, SVM: Support Vector Machine, KNN: K-Nearest Neighbors, DT: Decision Tree, AB: AdaBoost, GBT: Gradient Boosted Decision Tree, RG: Ridge Regression, EN: Elastic Net, LaR: Lasso Regression, BRT: Boosted Regression Tree, GLM: Generalized Linear Model, MARS: Multivariate Adaptive Regression Splines, GBR: Gradient Boosted Regression, LSVM: Linear Support Vector Machine)

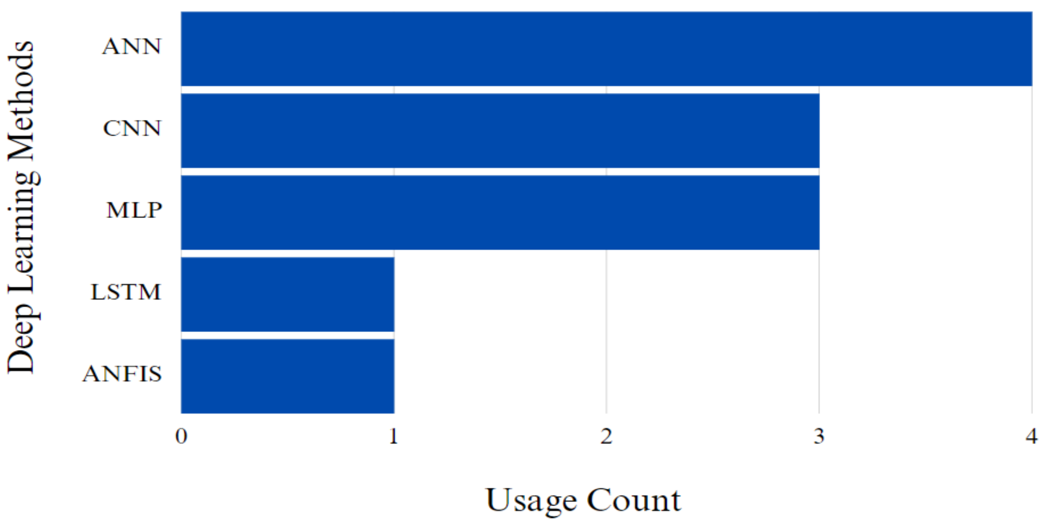

Figure 3. Usage numbers of deep learning methods used in papers.

(ANN: Artificial Neural Networks, CNN: Convolution Neural Networks, MLP: Multilayer Perceptron, LSTM: Long-Short Term Memory, ANFIS: Adaptive Neuro Fuzzy Inference Systems)

Table 5. Usage numbers of Statistical Methods used in papers.

Statistical Methods	Usage Count
Backward stepwise linear regression modeling	1
Bayesian statistical method	1
Bootstrap-enhanced least absolute shrinkage operator	1
Log-Linear Mixed Regression Model	1
Univariable Random Effect Model	1
Linear Mixed Modeling	1

For the second research question, in the realm of Surgical Duration Estimation research, researchers utilize various evaluation metrics, Table 6, to assess the accuracy and performance of the employed methods. The analysis of the literature reveals a discernible preference for certain metrics over others. Specifically, Mean Absolute Error (MAE) emerges as the most favored evaluation metric, with 9 instances of usage, highlighting its significance in quantifying the average absolute difference between predicted and actual surgical durations. Following closely is Root Mean Square Error (RMSE), which yields 8 instances, serving as an essential indicator of the model's predictive accuracy by measuring the square root of the average squared differences between predictions and actual values. R-Square (R2) is another frequently employed metric, observed in 7 instances, acting as a valuable measure of the model's performance of fit and its ability to explain the variance in surgical duration data. While Mean Absolute Percentage Error (MAPE) and Accuracy were conducted as 4 and 3 instances, respectively, they also exhibit a significant presence in the literature, reflecting their relevance in evaluating the relative percentage error and overall predictive correctness. In contrast, evaluation metrics such as Mean Squared Error (MSE), Adjusted R-Square, Continuous Ranked Probability Score (CRPS), Sensitivity, Specificity, and Area Under the ROC Curve (AUC) demonstrate limited prevalence, each with only one instance of usage, indicating their less frequent adoption in assessing the accuracy of the employed methods.

Table 6.Evaluation metrics used in the papers and their frequencies of usage.

Evaluation Metrics	Usage Count
Mean Absolute Error (MAE)	9
Root Mean Square Error (RMSE)	8
R-Square (R2)	7
Mean Absolute Percentage Error (MAPE)	4
Accuracy	3
Mean Squared Error (MSE)	2
Adjusted R-Square	1
Continuous Ranked Probability Score (CRPS)	1
Sensitivity	1
Specificity	1
Area Under the ROC Curve (AUC)	1

The third research question refers that the analysis of the literature on Surgical Duration Estimation, following the application of inclusion and exclusion criteria, revealing significant years, Figure 4A, showcasing an increasing trend in the number of conducted studies. Specifically, the years 2017, 2019, and 2022 stand out, each featuring four studies in the field. This surge in research activity during these periods indicates a growing interest and recognition of the significance of Surgical Duration Estimation as a subject of investigation. The observed trend suggests an expanding body of knowledge and a potential emphasis on exploring novel methodologies and technologies to enhance the accuracy and efficiency of surgical duration predictions. The consistent rise in the number of studies during these years underscores the field's dynamic nature, encouraging further exploration and advancement in this critical domain of medical research.

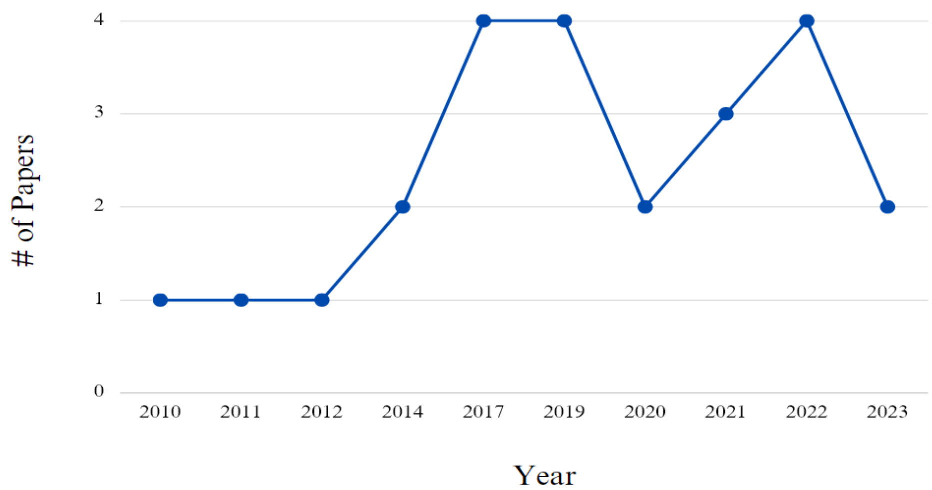

Figure 4.The number of articles changing over the years.

Conclusion

This study has provided an analysis of the methodologies, evaluation metrics, and temporal trends in the field of Surgical Operation Duration Estimation. The comprehensive analysis of 24 selected papers has shed light on the prevailing trend methodologies in the field. The insights derived from this study can inform future research endeavors, inspire the development of novel methodologies, and aid in improving the accuracy and efficiency of surgical duration prediction models.

The first research question highlighted the varying preferences of researchers regarding the employed methodologies. Machine Learning emerged as the most favored approach, accounting for 45.8% of the studies, owing to its capacity to handle large datasets and develop predictive models for surgical duration. Statistics also retained significance, constituting 16.7% of the studies, while Deep Learning, with a preference rate of 12.5%, appeared less frequently utilized despite its widespread applications.

The second research question delved into the evaluation metrics used to assess the accuracy of the employed methods. Mean Absolute Error (MAE) emerged as the most favored metric, followed by Root Mean Square Error (RMSE) and R-Square (R2). While MAPE and Accuracy were also prevalent in the literature, other metrics such as MSE, Adjusted R-Square, CRPS, Sensitivity, Specificity, and AUC were less frequently adopted

Lastly, the third research question addressed the temporal trends in Surgical Duration Estimation research. The years 2017, 2019, and 2022 exhibited a notable increase in research activity, indicating a growing interest and recognition of the importance of this domain. This trend signifies the dynamic nature of the field and suggests ongoing efforts to explore novel methodologies and technologies for more accurate surgical duration predictions.

All in all, this systematic mapping study has provided valuable insights for researchers, practitioners, and decision-makers in the medical field. The findings contribute to a comprehensive understanding of the current state of research, prevailing methodologies, and preferred evaluation metrics in Surgical Duration Estimation. The observed trends can serve as a guide for future research endeavors, encouraging the development of innovative approaches to enhance surgical planning and resource allocation, and ultimately improve patient outcomes in the domain of surgical care.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

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