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iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 20 No. 5 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v20i05.43257

PAPER

Flexible Ureteroscopy Lithotripsy Operative Time Prediction Model for the Treatment of Kidney Stones

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ABSTRACT

Effective time and resource management is crucial not only in the operating room but also in healthcare supply chains. Healthcare supply chains involve the movement of medical supplies, equipment, and medications from manufacturers to healthcare providers. Effective management is crucial to ensuring that patients receive the care they need promptly. In the operating room, it is essential to have an information process in place to effectively manage time and resources during the current surgical procedure. This paper focuses on developing a predictive model for the operating time of flexible ureteroscopy for kidney stones. The model can forecast surgical and preoperative time based on patient characteristics and surgeon experience. The model can assist in planning ureteroscopy procedures and preventing surgical complications, which is crucial not only for the operating room but also for healthcare supply chains. The paper presents a study that compares different feature selection methods and regression techniques. The study found that sequential backward selection combined with the extra tree regressor was the most effective approach.

KEYWORDS

machine learning (ML), flexible ureteroscopy lithotripsy, kidney stones, surgical time prediction, healthcare supply chains

1 INTRODUCTION

Healthcare supply chains play a critical role in ensuring the timely and efficient delivery of medical supplies, equipment, and medications to healthcare providers. Effective management of these supply chains is crucial to ensuring that patients receive the care they need promptly. In the context of the operating room, accurate prediction of surgical time is crucial for efficient resource allocation and effective time management. However, current estimates of surgical duration are frequently inaccurate, resulting in delays, longer patient waiting times, and decreased operating room efficiency. In this context, the motivation behind this manuscript is to develop

Baidada, C., Aatila, M., Lachgar, M., Hrimech, H., Ommane, Y., Houlali, A. (2024). Flexible Ureteroscopy Lithotripsy Operative Time Prediction Model for the Treatment of Kidney Stones. *International Journal of Online and Biomedical Engineering (iJOE)*, 20(5), pp. 101–119. https://doi.org/10.3991/ijoe.v20i05.43257

Article submitted 2023-07-18. Revision uploaded 2023-12-18. Final acceptance 2023-12-18.

a predictive model for the operating time of flexible ureteroscopy in the treatment of kidney stones, using advanced machine learning techniques and comprehensive feature selection methodologies. The proposed model aims to improve the accuracy of surgical time prediction, enabling more efficient planning of operating rooms, reducing patient waiting times, and enhancing the quality of care. Furthermore, the study aims to investigate the influence of surgeon characteristics, including age, experience, gender, and team composition, on procedure times. This will provide valuable insights into the factors affecting operating duration in ureteroscopy. The manuscript presents a comparative analysis of various feature selection methods and regression techniques, emphasizing the transition from conventional approaches to more advanced, data-driven methodologies. The proposed model, which combines the extra tree regressor with sequential backward selection, demonstrates superior performance in predicting ureteroscopy operating durations compared to traditional linear regression models. The study's findings underscore the critical importance of accurately predicting the duration of the ureteroscopy procedure and its significant implications for patient safety, surgical outcomes, and resource utilization.

Operating rooms are one of the most expensive surgical resources in hospitals. When healthcare budgets are limited, efficiency improves as more surgeries can be completed within the available time in operating rooms. Precise prediction of case length helps in the efficient planning of operating rooms, reducing patient waiting times and downtime for medical and other staff, thereby improving the quality of care. As a result, medical services will be provided in other areas of the hospital.

The ability to accurately forecast the duration of medical procedures is crucial for efficiently planning operating room schedules in hospitals. This study examines the influence of surgeon characteristics, such as age, experience, gender, and team composition, on procedure timeframes. In this context, the work presented in this article is relevant, as it proposes a flexible model for predicting operation times for ureteroscopy lithotripsy in the treatment of kidney stones.

Urinary stones affect approximately 12% of the global population [1]. In some instances, they can vanish spontaneously and do not necessitate any treatment [2] [3]. However, they can also be complicated by pain and infections and, in some cases, impair kidney function. An intervention is necessary.

The treatment of kidney and ureteral stones can be performed using various techniques. Among these treatment methods, extracorporeal shock wave lithotripsy is one of the most commonly used treatments. Nevertheless, some stones, due to their size, location, symptomatic character, or the risks they pose, may require treatment by a natural method called ureteroscopy. Figure 1 clearly illustrates the locations of kidney stones in the urinary system.

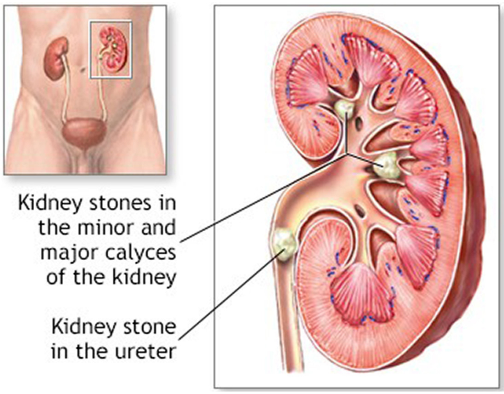

Fig. 1. Kidney stone locations in the urinary system (adapted from HIE multimedia – kidney stones, s. d.)

In recent years, there has been a significant increase (251.8% over the past two decades, according to [4]) in the use of ureteroscopy (URS) due to its minimally invasive technique, which does not alter the renal parenchyma. Additionally, recent flexible ureterorenoscopes allow natural access to the renal cavities and enable the treatment of stones in situ.

The intervention involves inserting a device called a ureteroscope into the ureter. This optical instrument allows for work under visual control. It contains a functional channel through which various instruments are introduced. Some ureteroscopes are rigid (URSR), semi-rigid (URSSR), suitable for treating ureteral stones, or flexible (USSR), suitable for kidney stones. The urologist will make the instrument selection based on various parameters [5].

The intervention is most often performed under general anesthesia. The ureteroscope is naturally introduced into the bladder and then into the ureter, where a wire guide has been previously placed. The ureteroscope may be able to see the renal cavities, depending on the location of the stone or the lesion to be treated. In certain situations, it may be necessary for technical reasons to utilize an additional instrument known as a working sheath. The fragmentation of the stones can be carried out in situ by ballistic waves or ultrasound in the case of the URSR and by pulsed laser radiation (Holmium: YAG laser) in the case of the USSR. Fragmented stones can also be removed using extraction forceps. At the end of the procedure, a double J stent (JJ catheter) can be placed to ensure drainage of the ureter.

However, the duration of the operation can impact the surgical outcome, particularly the complications of flexible ureteroscopy (FURS) [6]. Several significant preoperative and postoperative complications, such as sepsis, perforation, and massive bleeding, can occur with endourologic procedures such as URS or percutaneous nephrolithotomy (PCNL) [7] [8]. According to a previous study, serious adverse outcomes following URS were associated with longer operative times and fewer URS procedures performed in hospitals [9]. As a result, it is critical to understand the preoperative clinical factors that contribute to the duration of FURS operations. Significant factors, such as surgeon experience level, stone volume, Hounsfield units (HU), and preoperative stenting, have been previously documented to help predict the operative time for FURS [10]. However, a more precise model for predicting operating times based on these parameters still needs to be developed. The development of a predictive model will significantly aid surgeons by enabling them to plan surgeries more accurately, predict the likelihood of additional FURS surgeries, provide better information to patients, and prevent surgical complications.

To maximize the use of the operating room, an accurate estimate of the procedure's duration is necessary. Current projections are inaccurate because prior models used data that was not readily available for planning. Our objective was to utilize a comprehensive retrospective dataset to develop statistical models that would enhance the prediction of case duration in line with current standards.

The remainder of this paper is organized as follows: Section 2 presents the related works. Section 3 describes the methodology adopted for predicting operative time in FURS lithotripsy. The simulation results are presented and explained in Section 4. Section 5 discusses the experimental results. Finally, Section 6 presents conclusions and perspectives for future work.

2 RELATED WORKS

A close study of the literature reveals that the duration of the operation is closely associated with the outcomes of ureteroscopy and the treatment of kidney stones.

Secondly, some research has utilized ML algorithms to predict the duration of various operating procedures.

During endourological procedures for stone management, it is evident that the operating time significantly impacts the results of the operation. Studies have shown that preoperative and postoperative complications are associated with a longer operating time. The study in [9] demonstrates that lithotripsy and ureteroscopy can sometimes lead to serious complications, such as septic shock. There is also empirical evidence indicating a relationship between longer operative times and complication rates. In the study of [11], a longer duration of ureteroscopic intervention is strongly associated with ureteral perforation. A retrospective study concluded that a longer duration of surgery is a significant risk factor [9]. The authors in [12] reported a significant correlation between operative time and ureteral lesions. In a systematic review conducted by [13], it was found that a longer procedure time is significantly correlated with a higher risk of post-ureteroscopic complications. Table 1 sheds light on studies correlating operative times with the outcomes of ureteroscopy and stone treatment.

Table 1. List of studies examining the association between operation times and the results of ureteroscopy and stone treatment

Paper	Total No. of Patients	Stone Size	Complications Rate	Comments
[14]	736	12.3 mm (3–100 mm)	4.1% (35)	The longest operating times are associated with infectious complications ($p < 0.001$)
[15]	1332		12.0% (127)	increased operating time ($p < 0.0001$) is a predictor of the presence of hydronephrosis after ureteroscopy
[16]	494	182.4 mm^3 and 161.3 mm^3	3.2% (16) Haemorrhage, thermal injury, perforation	Infectious problems were substantially linked to longer operating times (65.3 vs. 47.8 min $p = < 0.001$)
[17]	224	mean 12.6 mm vs. 9.9 mm	–	–
[18]	3298	–	–	Procedures with postoperative fever (POF) or systemic inflammatory response syndrome complications had a longer median duration of surgery (57 vs. 49 minutes, $p < 0.01$)
[19]	604	20 mm	6.7% (41) UTI	Preoperative polymicrobial urine culture ($p < 0.001$) and increased operative time ($p = 0.02$) were associated with postoperative urinary tract infection
[20]	304	–	–	An operation time following URS was found to be an independent risk factor for febrile urinary tract infection ($p < 0.001$) by multivariate analysis. The operating time limit for a higher risk of febrile UTI was 70 minutes
[21]	11885	–	7.4% (874) Bleeding, fever, UTI, lung embolism, CVA, sepsis, acute abdomen, AMI, pain, urinary retention, stent placement, nausea and vomiting, respiratory, and allergy.	Patients who had intra- or postoperative problems typically required procedures that were at least 10 minutes longer (50 (33–75) vs. 40 (25–60))
[22]	1256	–		operative time is associated with post-ureteroscopic sepsis ($p = 0.041$ median operative time was 45 minutes) with other factors

(Continued)

Table 1. List of studies examining the association between operation times and the results of ureteroscopy and stone treatment *(Continued)*

Paper	Total No. of Patients	Stone Size	Complications Rate	Comments
[23]	550	–	15.5% (91)	Found statistically significant increase in unplanned return to the hospital rates in patients who had operating times > 120 min (p = < 0.001)
[24]	462	< 125 mm³, 125 – 1000 mm³ and > 1000 mm³	–	There was no significant association between the duration of the operation (more than 70 minutes) and postoperative infection: OR 1.89, 95% CI 0.82–4.36, p = 0.14
[25]	266	–	–	Among the significant prognostic factors of acute postoperative pyelonephritis, the duration of the operation 70 minutes) (p < 0.005)
[26]	233	425 mm³, [op time < 90 mins versus 934.6 mm (> 90 mins)]	6.4% [15] High-grade fever, ureteric strictures requiring balloon dilatation	Significantly longer operating times were seen when stone volume increased (p < 0.001) and operator experience decreased (p < 0.001). Operative time had no effect on the rate of post-operative readmission.
[27]	2010	7 mm	14.3% (298) Bleeding, extravasation, ureteral perforation, mucosal injury, UTI, hydronephrosis, ureteric avulsion, and sepsis	Complications were substantially linked with longer operating times (34 (20–60) vs. 45 min. (25–76) p = < 0.001).
[28]	227	2.06 cm vs. 1.66 cm	8.37% (19) Fever and rigors, SIRS and sepsis	Long times of operations were significantly correlated with complication rates (99.42 min ± 19.08 vs. 73.37 min ± 19.37 p = 0.000 (Mann-Whitney U test)
[9]	12372	–	2.39% (296)	Positive correlation found between increasing length of surgery and the occurrence of adverse post-operative events. (p = < 0.001)
[29]	213	11.3 mm (renal) 7.7 mm (ureteric)	3.3% (7) Pain, retained stent, stent migration, ureteral stricture	Renal stones took a considerably longer operating time (112 minutes) than did ureteral stones (70 minutes; p < .001). These cases had a higher preoperative stenting rate (55% vs. 37%, p = .014) and a significantly larger renal stone size (11.3 vs. 7.7 mm, P.001).
[30]	4512	9.4 mm (2.3; 5–20) 10.9 mm (3; 4–22)	6.67 %	Major intraoperative problems are significantly correlated with longer surgery times. (p = < 0.001)

Several research studies have been conducted to predict the duration of surgical operations, aiming to optimize the accuracy of case duration, pre-surgical resource utilization, and patient waiting time without increasing surgeons' wait times between cases. In [31], the authors investigated the potential correlation between the duration of surgery and factors associated with the surgeon, such as age, experience, gender, and the composition of the team. The researchers concluded that the significance of surgeon factors depends on the type of operation, with team composition, expertise, and time of day being the most frequently considered significant elements. In [32], the authors endeavored to enhance the accuracy of predicting the total procedure time by employing linear regression models that incorporate the estimated time controlled by the surgeon and other pertinent variables. The proposed model outperformed both the fixed ratio model and the separately anesthesia-controlled time prediction method. Additionally, in [33], the authors developed models to predict the duration of cases using linear regression and some supervised ML techniques to enhance surgical management and planning. The authors in [34] propose comparing various ML techniques to estimate the duration of surgical interventions using a large dataset of surgical recordings. This not only allows for a comparison of techniques but also enables exploration of the potential variables and factors influencing the duration of surgery. The authors in [35] found that using ML-generated surgical case length forecasts could increase the accuracy of case duration, the utilization of preoperative resources, and the waiting time for the patient without increasing the waiting time between cases for the surgeon. Table 2 presents the sizes of the datasets and the algorithms that performed well in each of the works mentioned above.

Table 2. Summary of the work carried out to predict the operations duration

Paper	Year	Dataset Size (Number of Observations)	Used Model
[31]	2010	30.000	ANOVA models
[32]	2017	79.983	Linear regression
[36]	2018	472	Linear regression
[33]	2019	38880	XGBoost ML surgeon-specific models
[34]	2021	206587	Bagged Trees
[35]	2021	683	Not specified

Most of the work presented enables the prediction of the duration of surgical procedures based on common characteristics. The duration of a surgical intervention varies from one operation to another [31], depending on the type of surgery and the organ being operated on. It is time to focus on each type of operation and analyze patient data, resource availability, surgeon experience, and the optimal time of day to perform the operation. This will help determine the variables that affect the duration of each type of operation. Flexible ureteroscopy operative lithotripsy is a unique procedure that requires analysis of several characteristics, including stone volume, external diameter, and patient positioning during the operation. These characteristics vary between operations and are not consistent across all cases.

It is essential to propose a new approach that accurately predicts the operating time before surgery. This will help us understand the various factors that extend the operating time of FURS interventions. In this context, the authors [36] proposed the first model to predict the duration of a preoperative operation based on patient characteristics and surgeon experience. This model incorporates six characteristics: stone volume, maximum HU, operator experience, gender, preoperative stenting, and ureteral sheath diameter. In this article, Shapley values are used to investigate the impact of variables on prediction.

3 METHODOLOGY

Figures 2 and 3 depict the overall process described in this article. First, a pre-processing step is applied to the data. This is done to identify any missing values and remove redundant data. This step also helps to organize and standardize the dataset and convert target attributes into factor attributes. In the next step, the most important parameters are extracted using feature selection techniques. Regression techniques are applied to the selected critical, optimized features by splitting the dataset into training and testing phases. To predict the operation time, the regression algorithm is trained using unknown samples from the training data. The final step is to select an appropriate model and assess the results using the R-squared metric. The analysis identifies the most effective method for feature selection and the most suitable technique for regression.

Data pre-processing is a necessary initial step before applying to any ML project. Its objective is to simplify the training and testing process by appropriately transforming and normalizing all datasets. Data pre-processing consists of several steps, such as data cleaning and transformation, which are used to eliminate outliers and standardize the data into a format that can be easily used to create a model.

Feature selection is the process of choosing the most relevant features and reducing the number of input variables for the predictive model under development. Feature selection involves extracting the most important signals from our data while ignoring the noise. The main reasons for utilizing feature selection are to (i) speed up machine learning algorithm training, (ii) reduce model complexity, and (iii) facilitate interpretation [37]. Additionally, it minimizes overfitting and improves the model's accuracy when selecting the appropriate subset. Filters, wrappers, and embedded methods are the three categories of feature selection methods used in the attribute selection step [38].

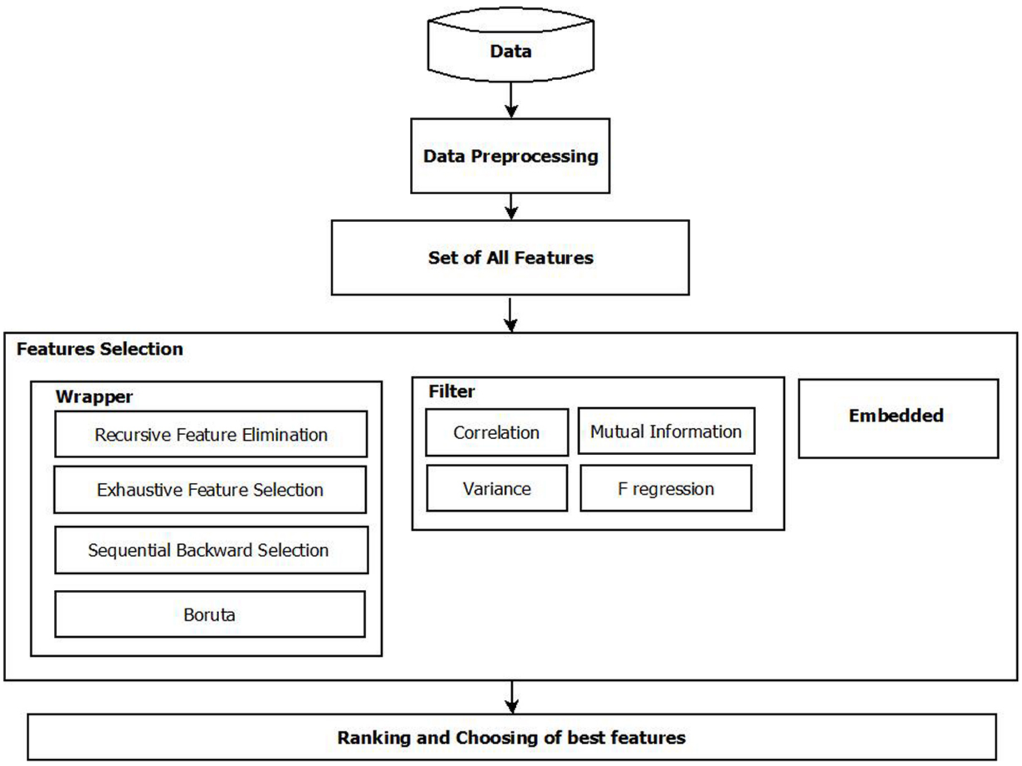

Fig. 2. Feature selection model

i) **Filter methods** identify the most relevant features by analyzing the data itself. In other words, features are scored based on the inherent characteristics of the data, without the use of clustering algorithms. Filtering methods are distinguished by their speed and scalability [39]. Typically, filter methods are used in the pre-processing stage [40]. Below are some of the filtering techniques:

Variance algorithm calculates the variance of multiple features. It identifies the features with variances greater than or equal to a specified initial threshold.

Correlation filter-based methods measure the strength of the relationship between two features. It is useful for feature selection because highly correlated features or those that are not correlated with others at all can be filtered out. In any case, it is a multivariate feature selection method, specifically bivariate.

F-regression method is a fuzzy regression technique that uses fuzzy input and output with clear parametric dependencies between them. The use of a similarity measure between a model and a fuzzy point is the central feature of f-regression [41].

Mutual information (MI) allows for the measurement of the dependence between two or more random variables [37]. A high MI suggests a significant reduction in uncertainty, while a zero MI indicates that two random variables are unrelated [42].

ii) **Wrapper methods** allow for the selection of feature subsets that contribute to improving the quality of the clustering algorithm results used for the selection. Wrapper methods have a main disadvantage in that they frequently incur a high computational cost and are limited to use with specific clustering algorithms [39]. The concept behind wrapper methods is relatively simple: evaluate various subsets of features on the ML model and select the one that attains the highest score in a predefined objective function.

There are a variety of wrapper techniques available, including those listed below:

Boruta is based on the random forest algorithm and is used as a wrapper for the feature selection step. It is simple and quick to process and assess the degree of importance of the attributes. This algorithm is evaluated using the mean accuracy and standard deviation of the results. Boruta considers it to be the most important factor in this feature selection [43].

Recursive feature elimination (RFE) is a popular feature selection technique for datasets with small sample sizes. It follows a model, removing weak properties until all the required features are met.

Sequential backward selection (SBS): This process starts with all features included and removes one feature at a time.

Exhaustive feature selection (EFS): This technique evaluates all possible combinations of features to select the best subset of relevant variables.

iii) **Embedded methods** utilize both filter and wrapper techniques and have their own process for selecting attributes [38]. Embedded methods proceed to select the most relevant characteristics while executing the modeling algorithm. As a result, these methods are either standard or enhanced functionalities in the algorithm [44].

3.1 Regression methodology

The regression problem is a generalization of the classification problem. In regression, the model provides a continuously valued output rather than just an output from a finite set. A regression model evaluates a multivariate function with continuous values. In the following, a detailed presentation of the regression algorithms used in this study will be provided. Figure 3 below illustrates the adopted methodology in this study.

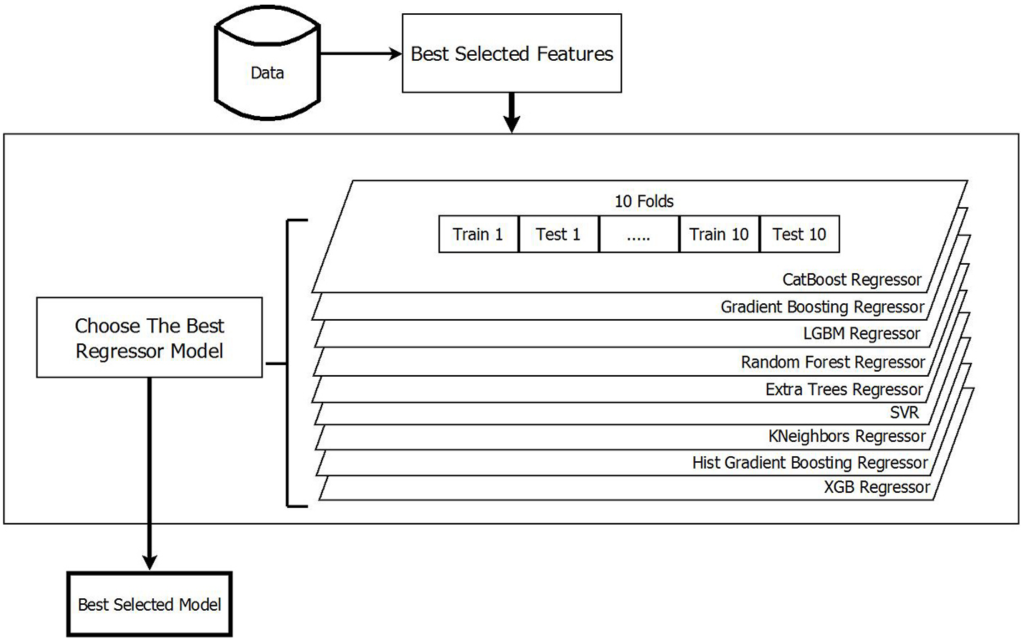

Fig. 3. Outline of the work

4 EXPERIMENTAL RESULT ANALYSIS

4.1 Dataset description

The clinical data analyzed in this study are the same as in [36]. In total, 472 FURS procedures for the treatment of kidney stones were retrospectively analyzed. All treatments were conducted at Ohguchi East General Hospital between December 2009 and December 2014.

4.2 Performance metrics

In machine learning, utilizing performance metrics can provide concrete data to support evaluation. In this study, the results are evaluated using the R-squared metric:

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{1}$$

1. R-squared is determined by dividing the sum of the regression model residuals squares (SSres) by the total sum of error squares (SStot) from the average model and then subtracting it from 1.

4.3 Technical specifications of the used calculator

In this study, all the prediction models under investigation are implemented in Python using the Jupyter program. We use a Lenovo T460 running Windows Professional 8.1 64 bits, equipped with an Intel(R) Processor Core (TM) i5-6300U CPU @ 2.40GHz, and 8.0 GB of RAM to conduct all simulations.

4.4 Simulation results

Data distribution analysis. Figure 4 shows that the data used in this study are normally distributed and closely aligned along the main diagonal (Henry's line). This indicates that the dataset can be approximated using a normal distribution.

To better assess the data distribution, skewness and kurtosis coefficients are calculated for the data being used. The obtained values are –0.019 and –0.844 for skewness and kurtosis, respectively. Since the skewness value is between –1 and 1, the distribution is less flattened but closer to a normal distribution. This is indicated by the kurtosis value, which is closer to 0.

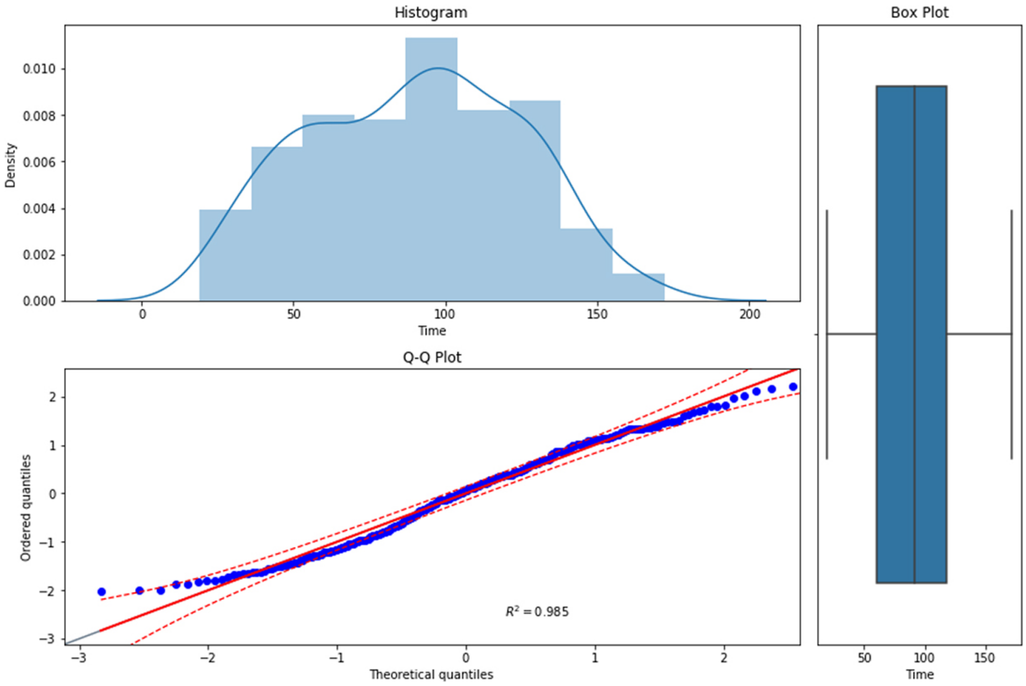

Fig. 4. Data distribution

Obtained results. Table 3 represents the results obtained in terms of R^2-score, using different studied regression algorithms for all features of the used dataset and combining them with different feature selection algorithms as previously mentioned.

Table 3. Performance evaluation results of different models using different features selection algorithms (R^2-score)

	Cat Boot Regressor	Gradient Boost Regressor	LGBM Regressor	RF Regressor	Ada Boost Regressor	Extra Trees Regressor	SVR	KNeighbors Regressor	Hist Gradient Boost Regressor	XGB Regressor
Mutual information	0.4709	0.3613	0.3905	0.4625	0.4536	0.4841	0.1575	0.2662	0.4369	0.4489
F regression	0.3621	0.1766	0.3695	0.3918	0.4123	0.3843	0.1598	0.2703	0.3314	0.3406
SBS	**0.5062**	0.3928	0.4084	0.4794	0.4654	**0.5163**	0.1559	0.2654	0.4301	0.4436
SBS correlation	0.4984	0.3785	0.4237	0.4802	0.4840	**0.5303**	0.1563	0.2662	0.4324	0.4578
Embedded	0.4841	0.3441	0.4174	0.4780	0.4698	0.4795	0.0868	0.2223	0.4331	0.4640

(Continued)

Table 3. Performance evaluation results of different models using different features selection algorithms (R^2-score) *(Continued)*

	Cat Boot Regressor	Gradient Boost Regressor	LGBM Regressor	RF Regressor	Ada Boost Regressor	Extra Trees Regressor	SVR	KNeighbors Regressor	Hist Gradient Boost Regressor	XGB Regressor
Embedded correlation	0.4858	0.3858	0.4381	0.4751	0.4622	0.4734	0.1538	0.2673	0.4595	0.4508
HRFE	0.4787	0.3871	0.4454	0.4784	0.4869	0.4733	0.0830	0.2263	0.4415	0.4560
HRFE correlation	0.4732	0.3776	0.4271	0.4709	0.4985	0.4715	0.1580	0.2683	0.4598	0.4410
RFE	0.3841	0.2097	0.2857	0.4235	0.4056	0.4059	0.0696	0.2296	0.2870	0.3451
RFE correlation	0.4674	0.3854	0.4065	0.4735	0.4617	**0.5013**	0.0704	0.2296	0.4461	0.4346
Boruta	0.4894	0.3767	0.4301	0.4879	0.4819	0.4894	0.0868	0.2223	0.4503	0.4725
Boruta correlation	0.4894	0.3767	0.4301	0.4879	0.4819	0.4894	0.0868	0.2223	0.4503	0.4725
EFS	0.4821	0.4332	0.3567	0.4813	0.4672	0.4971	0.0885	–0.0133	0.4572	0.4317
All features	0.4884	0.4195	0.4266	0.4780	0.4529	0.4712	0.0671	0.2296	0.4339	0.4340

Figure 5 illustrates a comparison of the obtained R^2-score of different regression algorithms using all features (A) and the mutual algorithm of feature selection (B).

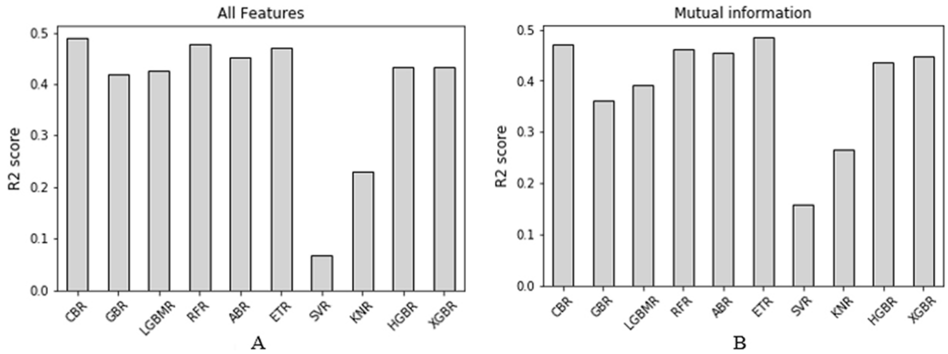

Fig. 5. Regression algorithms comparison using all features (A) and Mutual Information of features selection (B) considering provided R^2 score

The Figure 6 represents a comparison of the obtained R^2-score of different regression algorithms using feature selection algorithms of Boruta (A), Boruta combined with correlation (B), embedded (C), and embedded combined with correlation (D).

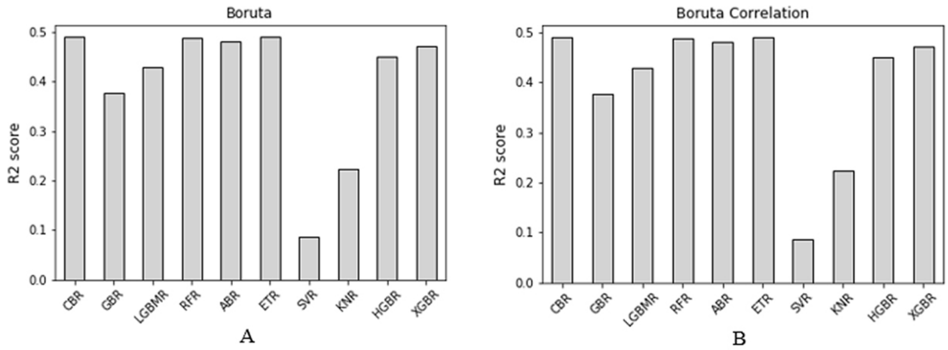

Fig. 6. *(Continued)*

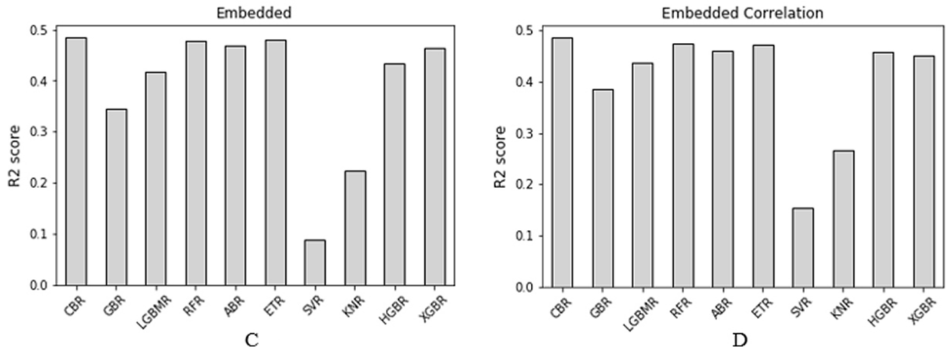

Fig. 6. Algorithms comparison using Boruta (A), Boruta with correlation (B), embedded (C) and embedded with correlation (D) algorithms of features selection considering provided R^2 score

The Figure 7 represents a comparison of the obtained R^2-score of different regression algorithms using feature selection algorithms of HRFE (A), HRFE combined with correlation (B), SBS (C), and SBS combined with correlation (D).

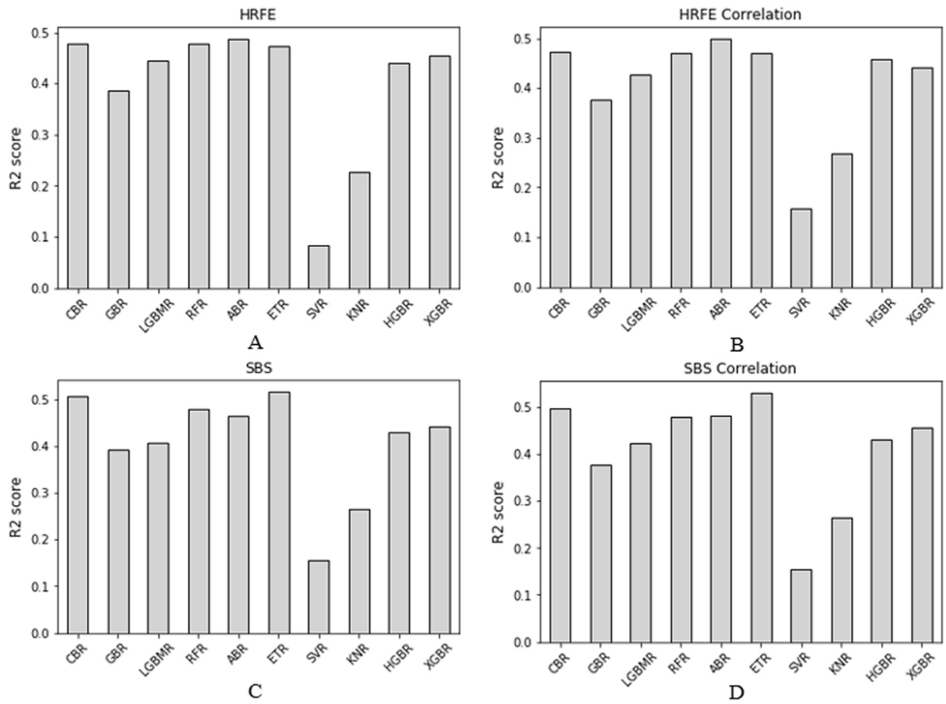

Fig. 7. Algorithms comparison using HRFE (A), HRFE with correlation (B), SBS (C) and SBS with correlation (D) algorithms of features selection considering provided R^2 score

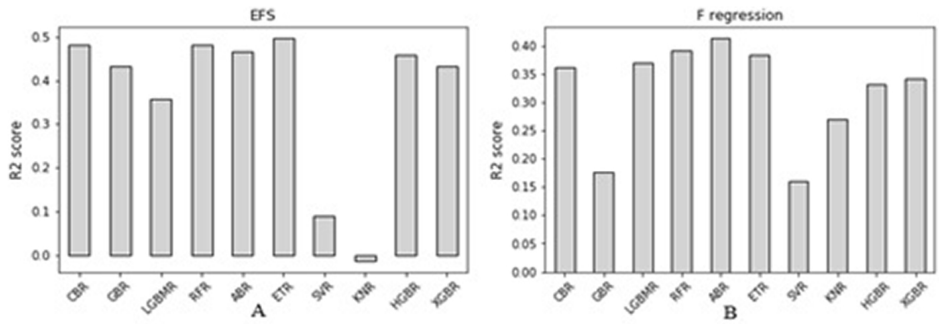

Fig. 8. *(Continued)*

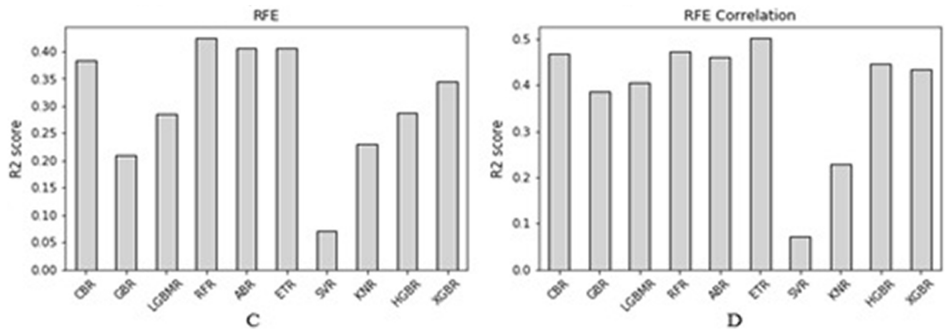

Fig. 8. Regression algorithms comparison using EFS (A), F Regression (B), RFE (C) and RFE with correlation (D) algorithms of features selection considering provided R^2 score

Figure 8 represents a comparison of the obtained R^2-score of various regression algorithms using feature selection algorithms such as EFS (A), F Regression (B), RFE (C), and RFE combined with correlation (D).

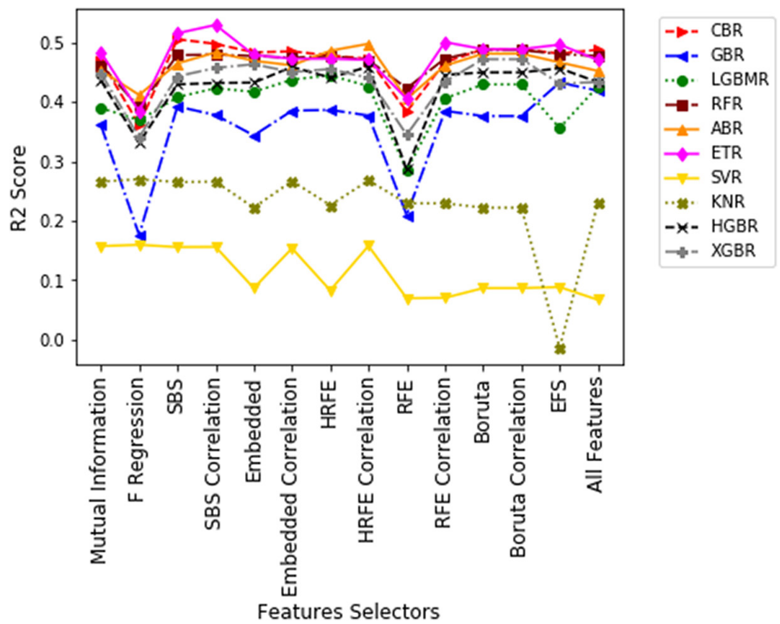

Fig. 9. Performance of different regression models based on R^2-score, using different features selection and all features

Figure 9 represents the performance of various regression algorithms based on R^2-score, utilizing different feature selection methods and all features from the dataset.

5 DISCUSSION

Longer operative time for flexible ureteroscopy with lithotripsy could potentially be one of the risk factors for serious complications, such as septic shock, cardiovascular events, and blood loss [36].

The proposed approach aims to establish a predictive system for the duration of FURS with lithotripsy procedures to mitigate the risks of complications and improve operational planning. Various ML techniques, combined with several algorithms for feature selection, were compared in this study to develop a robust predictive system.

As illustrated in Table 3 and Figure 9 above, the outcomes of this study clearly demonstrate that algorithms based on decision trees and boosting techniques (ETR, ABR, RFR) have yielded favorable results compared to other methods (SVR, KNR).

When utilizing all variables in the dataset, various ML models, with the exception of the Cat Boot Regressor, Extra Trees Regressor, and RFRegressor, achieved an R^2-score of 0.4884, 0.4780, and 0.4712, respectively, which could not exceed 0.45 as a result. However, by using feature selection techniques, these models were able to achieve results that surpassed this value, reaching 0.5303 when combining the Extra Trees Regressor model with the SBS and correlation technique for variable selection.

The high precision of the obtained results can be attributed to the benefits of utilizing various techniques for selecting the features. This includes a combination of a filter, represented by the correlation method, and a wrapper, specifically the SBS. Additionally, the regression model employed, the Extra Trees Regressor, is founded on an ensemble technique that enhances the predictive performance of the final model.

This shows that an appropriate combination of feature selection techniques and boosting techniques can make a learning system more efficient.

According to Table 3, employing the Extra Tree Regressor model on the chosen data using the SBS method in conjunction with correlation yielded the best outcome, achieving an R^2 value around 0.5303 compared to alternative data selection methods and regression algorithms. However, the results obtained by this combination exceed even those obtained by using all the data in the dataset. This highlights the significance of variable selection algorithms in removing data for learning systems.

In addition, the Figure 10 below illustrates the impact of the selected parameters on the operation time using the SBS method with correlation and the Extra Tree Regressor.

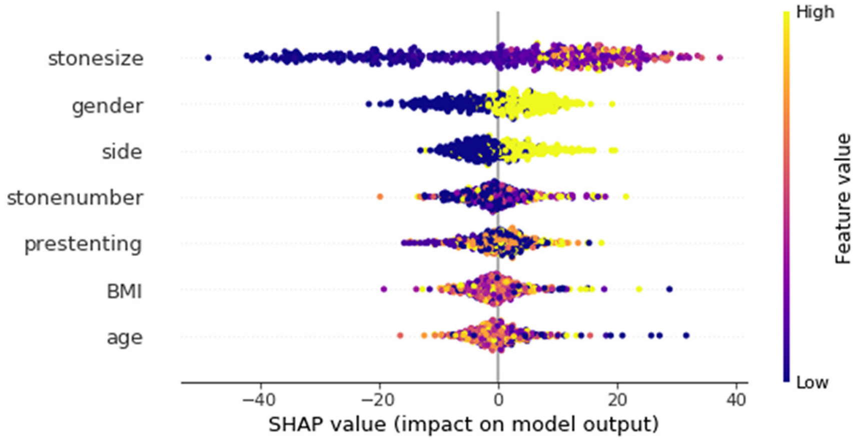

Fig. 10. The SHAP variables importance

Figure 10 illustrates the overall importance of the variables as calculated by the values of SHAP [45]. Thanks to the fact that the values are calculated for each example in the dataset, it is possible to represent each example as a point. This provides additional information about the variable's impact based on its value. For example, the size of the stone, which is the most important variable, has a negative impact when the value of this variable is high. Yellow dots represent high values of the variable, while purple dots represent low values of the variable.

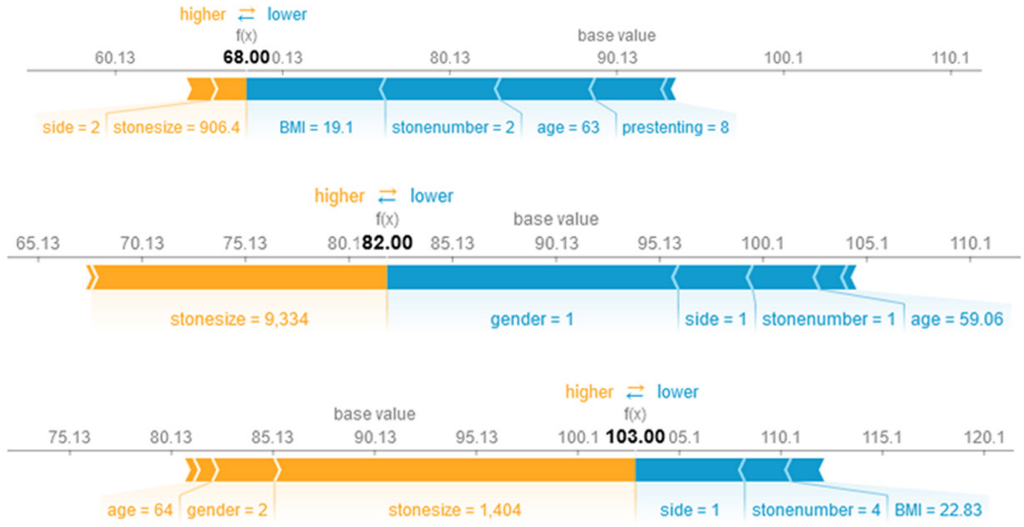

Fig. 11. Impact of variables for three different datasets

Figure 11 illustrates the impact of the variables for three examples from the dataset. In orange are the variables that have a positive impact, contributing to the prediction being higher than the base value. In blue, those factors have a negative impact (they contribute to the prediction being lower than the base value). The baseline value of the dataset is 90.13 minutes (average operation time). The predicted median surgery durations are 68 minutes in the first observation, 82 minutes in the second, and 103 minutes in the third. The figure also illustrates the impact of the feature on the model; the larger the arrow, the greater the impact.

In line with previous studies that aimed to predict the operative time of URS lithotripsy, such as [36] and [46], the present study clearly demonstrates that the most significant factor affecting the operation time is the volume of the stone. The predicted operative time is proportional to the stone volume; as the stone volume increases, the operative time also increases significantly. Therefore, achieving a more accurate prediction of the operating time relies on a precise calculation of the volume of the stone to be extracted.

Yet, Table 4 shows that the proposed model outperforms the approach published in [36], which also utilizes the same dataset.

Table 4. Comparison of the proposed model against the existing approach on the same dataset

Paper	Year	Used Model	R^2
[36]	2018	Linear regression	0.319
Proposed Model	2023	Extra Trees Regressor + SBS	0.5303

6 CONCLUSION

This paper focuses on developing a FURS lithotripsy operation time prediction model for treating kidney stones. This model can assist in planning the operation in stages to prevent surgical complications. This study conducts a comparative analysis of various feature selection methods and regression techniques. The findings indicate that SBS combined with the Extra Trees Regressor was the most effective approach. The article also emphasizes the influence of surgeon characteristics, such as age, experience, gender, and team composition, on procedure times. The study aims to assist surgeons in planning operations more accurately, predicting the need for additional FURS sessions, better informing patients, and avoiding surgical complications.

The results of this study can be used to enhance the quality of care and decrease costs in hospitals. They can be achieved by enabling more operations to be completed within the available time in the operating room, thereby reducing waiting times for patients and minimizing downtime for doctors and other staff.

Our future work will focus on developing a new approach to predicting the potential complications of URS. We also plan to develop a new prediction-based platform to assist doctors in making informed decisions prior to surgery.

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