Original Article

Can Machine Learning Revolutionize Post-Retrograde Intrarenal Surgery Urosepsis Prediction? A Single-Center Study

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Abstract

Background: One of the main surgical methods for upper urinary stones is retrograde intrarenal surgery (RIRS). Urosepsis is a serious complication of RIRS that threatens patients and confronts clinicians. To construct a valid predictive model for post-RIRS urosepsis, a dataset including demographic and pre-operative factors from 260 patients who underwent RIRS was used.

Objective: The aim of this research was to create a machine learning (ML) model as a novel solution to predict high-risk patient populations for urosepsis after retrograde intrarenal surgery (RIRS).

Methods: This retrospective analysis involved 260 patients who were treated with retrograde intrarenal surgery (RIRS) without pre-stenting at Pakistan Kidney and Liver Institute & Research Center from September 2018 to August 2024. Demographic, clinical, and preoperative data were retrieved to construct a predictive model for post-RIRS urosepsis. Supervised machine learning algorithms, i.e., Support Vector Machine, Gaussian Naïve Bayes, Logistic Regression, Decision Tree, and k-nearest Neighbors, were utilized. Model performance was assessed by accuracy, precision, recall, and Area Under the Receiver Operating Characteristic Curve.

Results: The machine learning models were able to predict post-RIRS urosepsis based on preoperative demographic and clinical features. Of the algorithms used, Support Vector Machine (SVM), Logistic Regression, and k-Nearest Neighbors (KNN) classifiers performed best in terms of predictive accuracy, and SVM had the best overall accuracy. The findings prove that ML-based methods are capable of predicting high-risk patients before surgery effectively.

Conclusion: This algorithm encompasses the potential to detect and prevent the development of urosepsis in RIRS patients and creating proper care plans through machine learning models.

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Introduction

In the last 20 years, the incidence of renal stones has varied between 1 and 19 percent globally, with a rising rate of incidence.[1,2] Renal stones are treated with shock wave lithotripsy (SWL), percutaneous nephrolithotomy (PCNL), or retrograde intrarenal surgery (RIRS).[1] The operations related to urolithiasis are rising due to the increasing prevalence of the disease and the rapid development of endourology.[2] Five years after lithotripsy, nearly 50% of patients have a recurrence of kidney stones.[3] PCNL has up to 95% stone-free status but is more suitable for larger stones.[4] For patients with renal stones smaller than 2 cm, RIRS with a flexible ureteroscope is advised as the primary option.[5,6]

Retrograde intrarenal surgery (RIRS) is a novel and successful treatment for kidney stones because it dramatically influences the development of endoscopy in urology and the advancement of minimally invasive surgery in urology.[7] According to EAU recommendations, 9–25% of RIRS procedures result in complications.[8] The treatment is typically considered safe.[9] Although there are still significant complications, the most critical ones are bleeding, cardiovascular events (such as stroke or pulmonary embolism), ureteral avulsion or perforation, stricture of the ureter, vascular or enteric fistula formation, acute urinary tract infection (UTI) and sepsis, and death.[10] Mortality rates from sepsis range from 17.3% in the general population to 35.5%.[11] Additionally, the high treatment costs associated with critical care place a significant financial strain on the healthcare system.[12]

Nonetheless, as a surgical modality, RIRS is relatively safe; however, adverse events such as acute urinary tract infection and sepsis are sometimes life-threatening and cause multi-organ dysfunction. Urosepsis, sepsis caused by infection of the urogenital tract, is the most serious complication of RIRS.[13] The risk of urosepsis development should be identified as early as possible to implement appropriate preventive measures, lower risk-related costs, and have a better prognosis.[14] Preoperative screening of such patients enables clinicians to use individual care plans and avert serious postoperative adverse events.[14]

Machine learning (ML) is now often used in healthcare to be able to anticipate and handle a variety of chronic and acute health problems. Due to its ability to analyze datasets, identify patterns and create exclusive forecast models, it can potentially support clinical decisions.[15] Patients undergoing retrograde intrarenal surgery (RIRS) can be classified into two categories: those who encounter urosepsis and those who do not. It is still hard for physicians to identify individuals who will experience complications prior to their arrival. ML may be used to classify patients into risk categories based on measurements drawn from their files prior to surgery.[16] They may be used in models that attempt to predict the likelihood of postoperative complications such as urosepsis. To have prediction tools available in clinical use may guide pre-surgery preparation for patients as well as follow-up on them, enabling physicians to make rapid interventions when needed.[17]

In this article, a machine learning-based predictive model for the prediction of urosepsis among RIRS patients has been proposed. The major risk factors for urosepsis during the postoperative course after RIRS for urolithiasis are also discussed. SVC, Gaussian Naïve Bayes, Decision Tree Classifier, KNN Classifier, and Logistic Regression were applied. These models were selected because of their versatility in carrying out classifiers pertaining to linear or non-linear in the data sets. This machine learning algorithm seeks to identify and define an easy, efficient, and effective way for allowing clinicians to detect risky patients prior to surgery. The performance of the models is measured with reference to using accuracy and AUROC.

Methods

The overall approach to carry out this study is as follows: Numbers need to be removed and subheadings can be kept as requested by authors but in italics.

i. Data Collection:

The above-mentioned retrospective study was performed at Pakistan Kidney and Liver Institute and Research Center (PKLI & RC) between September 2018 and August 2024. The goal was to construct a predictive model for urosepsis in patients with retrograde intrarenal surgery (RIRS) without preoperative stenting. 260 patients were enrolled, and inclusion criteria like the preoperative ureteral stent free status, 9.5 Fr re-access ureteric sheath use, and availability of detailed medical records were fulfilled. The patients who received other stone managing procedures or emergency cases of RIRS were excluded based on exclusion criteria. Data were collected retrospectively using a structured form that captured demographic, clinical, and postoperative outcome information.

The dataset included variables like age, BMI, stone size and location, and preoperative blood biomarkers, which were used in the predictive model to assess urosepsis.

ii. Problem-specific Pre-processing

We did the following pre-processing according to the problem:

- Only the pre-operative features were included to develop a predictive model
- Records with incomplete data for patients were filtered

iii. Numerical Encoding

Numerical encoding or Label encoding is a technique typically used in machine learning to convert categorical data into numerical data.[18] The dataset had both categorical and numerical features. Therefore, 'Label Encoder' translated all non-numeric features into numerical values. For example, for the post-operative complication, the data was labeled as 1 for the presence of urosepsis and 0 for no complication, Out of 260 patients, approximately 30 (11.5%) developed urosepsis following RIRS, while 230 (88.5%) experienced no postoperative complications.

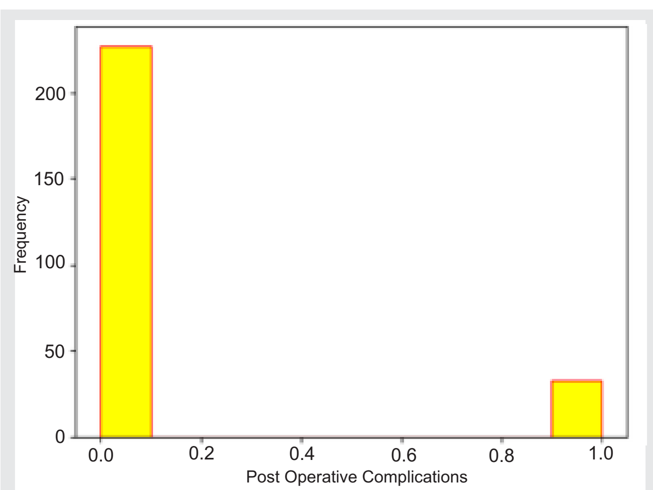


Figure 1: Frequency of Post Operative Complications

i. *Normalization:*

Normalization is used to re-scale all the data points on a common scale.[19] We used min-max scaler to normalize features and limit values in the 0, 1 range.

ii. Data Sampling:

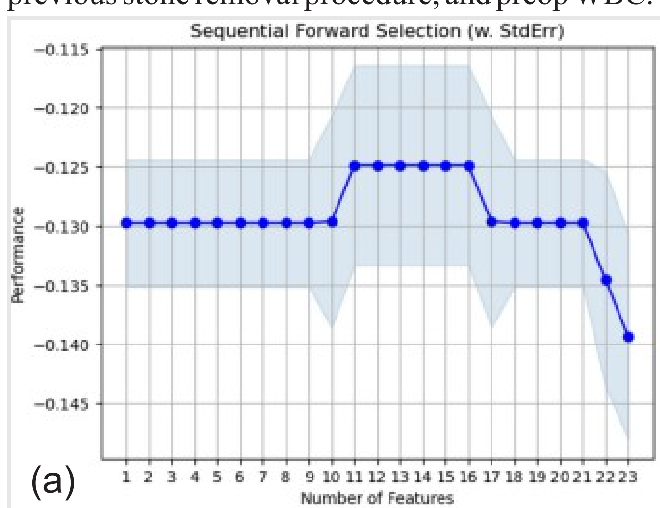
The dataset was split into 80% training set, 10% test set, and 10% validation set.

iii. Feature Selection:

Feature selection is used to find the best or optimal set of features out of all the variables in the original dataset.[20] This is essential for the optimization of machine learning models because only relevant data is fed into them. We employed Sequential Forward Selection (SFS) and Sequential Backward Selection (SBS), as depicted in Figure. 2, to determine the optimal selection of features for the machine learning algorithms. Sequential Forward Selection (SFS) is a feature selection algorithm that begins with an empty initial feature set and includes the most important feature in each iteration cumulatively. This process is carried out until the addition of additional features no longer enhances the model's performance or until a termination point is reached. This technique assists in choosing the best possible features while minimizing computational complexity.[21]

Sequential Backward Selection (SBS) is a feature selection technique that begins with all features and removes the least important feature in each iteration cumulatively. The procedure is repeated until further feature reduction degrades the performance of the model, or some convergence criterion is met. This technique proves useful in removing unnecessary or meaningless features, thus enhancing model efficiency and interpretability.[21] Features provided by SBS were considered for the next analysis and all other features were rejected.

The SBS gave age, gender, family history of kidney stones, BMI numerical value, BMI category, UTI, diuretics antacids, geographic location, pre-stent, previous stone removal procedure, and preop WBC.



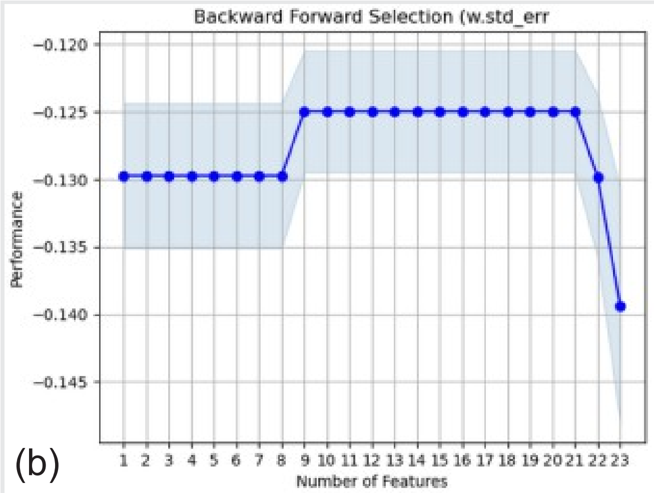


Figure 2: *(a) The Sequential Forward Selection Method gives the optimal result on a set of 16 feature, (b) The Sequential Backward Selection Method gives the optimal result on a set of 11 features.*

i. Machine Learning Models:

The following machine learning algorithms were used to develop the predictive model. Jupyter Notebook was used for coding in Python. The scikit learn build in models were used for analysis.

Support Vector Machine Classifier

SVM is a supervised learning algorithm that determines the best hyperplane to divide data points into different classes. It is suitable for both linear and non-linear classification with kernel functions and performs well in high-dimensional spaces.[22]

Gaussian NB Classifier

It is a Bayes' theorem-based probabilistic classifier that assumes features are Gaussian (normally) distributed. It is fast, easy, and suitable for independent feature problems and hence suitable for text classification and medical diagnosis.[22]

Decision Tree Classifier

A tree-based model that classifies data points by splitting data into branches depending on feature values to make a classification decision. It is easy to interpret, can handle numerical and categorical data, and is susceptible to overfitting if not pruned.[22]

KNN Classifier

A non-parametric algorithm that classifies data points according to the majority class of their k-nearest neighbors. It is easy and effective for small datasets but computationally intensive for large datasets.[22]

Logistic Regression

A statistical model applied for binary classification that predicts the probability of an instance belonging to a specific class based on a sigmoid function. Although simple, it is effective for linearly separable data and a baseline for most classification problems.[22]

Results

This paper focused on creating machine learning prediction model that can forecast the risk of urosepsis after retrograde intrarenal surgery (RIRS). We used models such as Support Vector Classifier (SVC), Gaussian Naive Bayes, Decision Tree Classifier, K-Nearest Neighbours (KNN) Classifier, and Logistic Regression. The models were evaluated using performance metrics like precision, recall, F1-score, accuracy, and Area Under the Receiver Operating Characteristic Curve (AUROC). Table 1 gives the summary for each model's precision, recall, F1-score, accuracy, and AUROC.

The Support Vector Classifier model achieved a high recall value of 0.98, accurately diagnosing most urosepsis cases. The model demonstrated precise diagnostics by achieving 0.88 precision, which implies that it predicted positive cases with few erroneous outcomes. The F1-score value of 0.94 effectively demonstrates how well the model

Table 1: *Model Performance Overview of each machine learning model*

Model	Precision	Recall	F1-Score	Accuracy	AUROC*
SVC	0.88	0.98	0.94	0.88	0.6957
GaussianNB	0.56	0.52	0.49	0.5	0.7391
Decision Tree	0.87	0.87	0.87	0.77	0.4348
K-Nearest Neighbors	0.88	0.99	0.94	0.88	0.5942
Logistic Regression	0.88	1	0.94	0.88	0.6087

** AUROC (Area Under the Receiver Operating Characteristic Curve)* balances its precision and recall numbers proportionally. The SVC model demonstrated 88% accuracy, marking a leading position among the reported study participants. The 0.6957 AUROC score, given in Figure. 3 (b) demonstrates the model's good performance yet reveals further potential for development to advance its ability to differentiate between classes. The confusion matrix in Figure. 3 (a) shows that the model performs well in identifying class 0, correctly classifying 23 instances with no false positives. However, it fails to identify class 1, misclassifying all three instances as class 0, resulting in zero true positives. This suggests a strong bias toward class 0, potentially due to class imbalance. While the model has high recall for class 0, its poor recall for class 1 makes it ineffective for tasks where detecting class 1 is crucial.

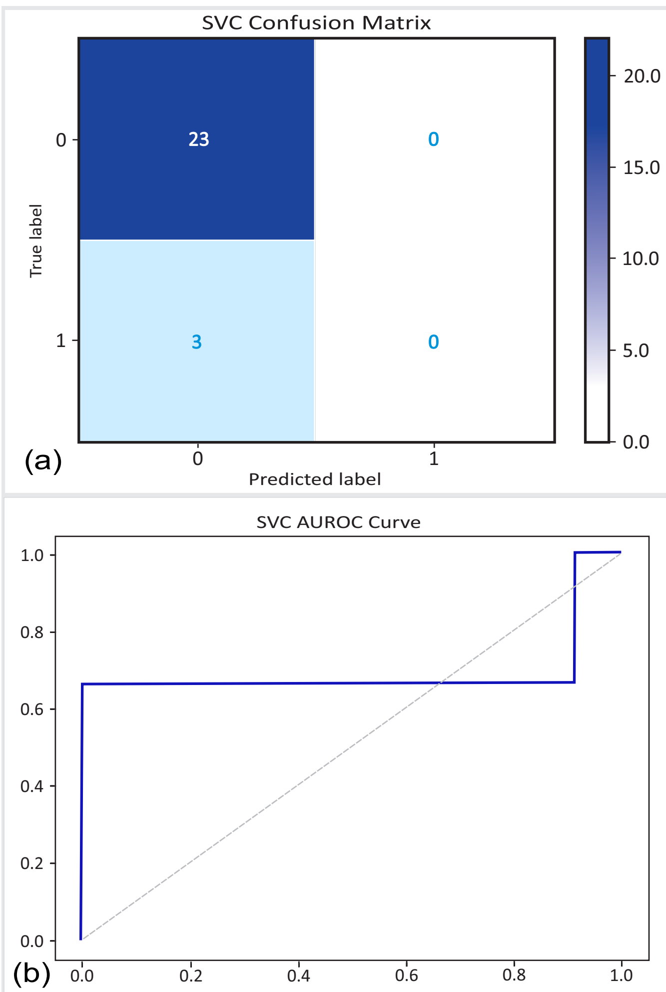


Figure 3: *This figure shows the performance of Support Vector Machine Classifier through (a) Confusion Matrix (b) AUROC*

The Gaussian Naive Bayes proved to achieve worse results than other models in analysis. The method demonstrated a poor ability to detect actual urosepsis cases through its low precision score of 0.56 and recall score of 0.52. The precision and recall relationship are evaluated as F1 score of 0.49, indicating an undesired performance imbalance. The model demonstrated a moderate ability to classify patients based on their susceptibility to urosepsis according to the AUROC score value of 0.7391, given in Figure. 3 (b) despite having lower precision and recall scores. The confusion matrix given in Figure. 3 (a) indicates that the model struggles with correctly classifying class 0 (urosepsis) but performs slightly better for class 1 (normal). It correctly identifies only one instance of class 0 while misclassifying 22 cases of class 0 as class 1, leading to a high false positive rate. However, it correctly classifies three cases of class 1 and does not misclassify any of them as class 0. This suggests that the model is biased toward predicting class 1, possibly due to the feature distribution assumptions of Gaussian Naïve Bayes

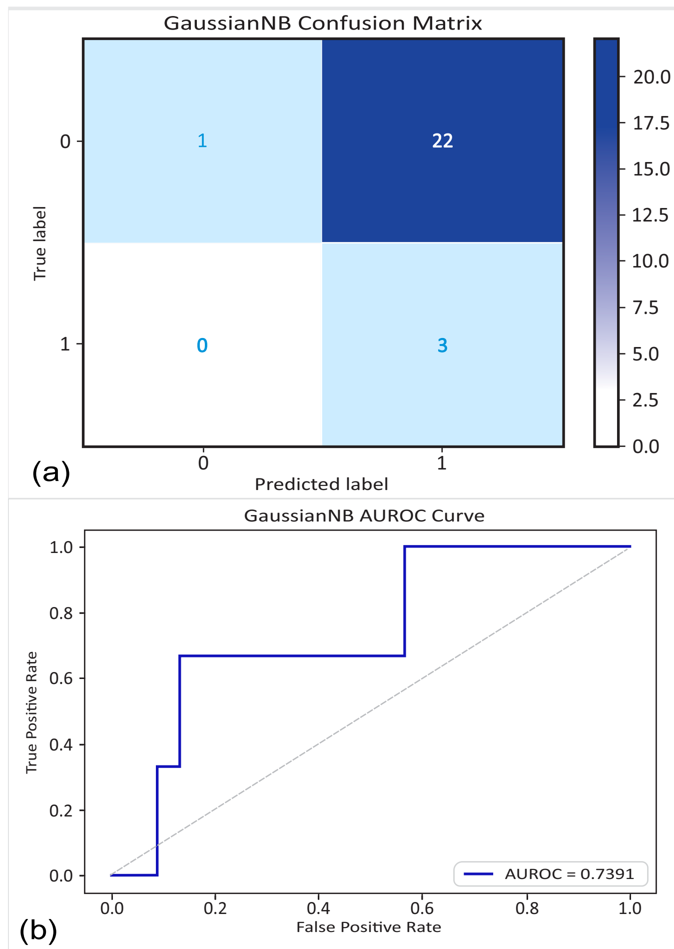


Figure 4: *This figure shows the performance of Gaussian Naïve Bayes Classifier through (a) Confusion Matrix (b) AUROC.*

The decision tree model showed good performance through a precision value of 0.87 and recall value of 0.87, which indicated equal efficiency in detecting true positives and minimizing incorrect predictions. The model achieved an accuracy level of 0.77, lower than both SVC and KNN. The AUROC score of 0.4348 indicates the poor performance in distinguishing among classes. The confusion matrix for shows that the model performs well in identifying urosepsis cases (class 0), correctly classifying 20 instances, with only three false negatives (urosepsis cases misclassified as non-urosepsis). However, it fails to identify non-urosepsis cases (class 1), misclassifying all three instances as urosepsis, resulting in zero true positives. This suggests the model is biased towards predicting urosepsis, likely due to data imbalance or overfitting.

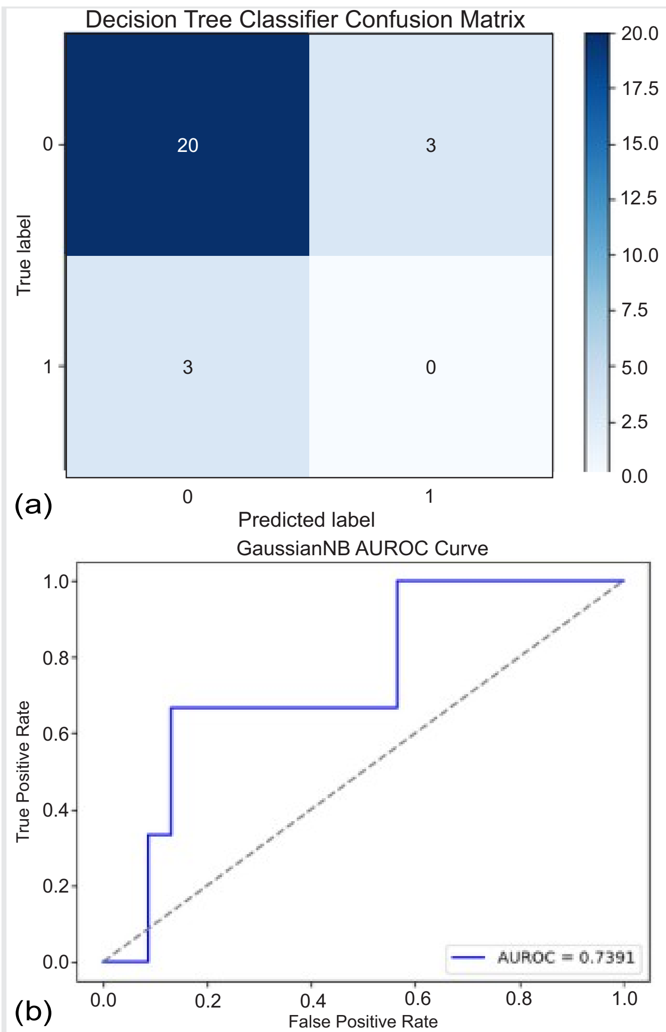


Figure 5: *This figure shows the performance of Decision Tree Classifier through (a) Confusion Matrix (b) AUROC*

The KNN model showed high reliability (0.99) in correctly identifying true urosepsis cases; the model demonstrated a precision of 0.88, indicating that most of its positive predictions were accurate. This model achieved an 88% accuracy. The model demonstrated reduced capability in accurately ranking patient urosepsis risk levels according to an AUROC score of 0.5942. The confusion matrix given in Figure. 6 (a) indicates that the model performs well in identifying urosepsis cases (class 0), correctly classifying 23 instances with zero false positives. However, it fails to detect non-urosepsis cases (class 1), misclassifying all three instances as urosepsis, resulting in zero true positives. This suggests that the model is highly biased towards predicting urosepsis, possibly due to class imbalance or the choice of K value in KNN.

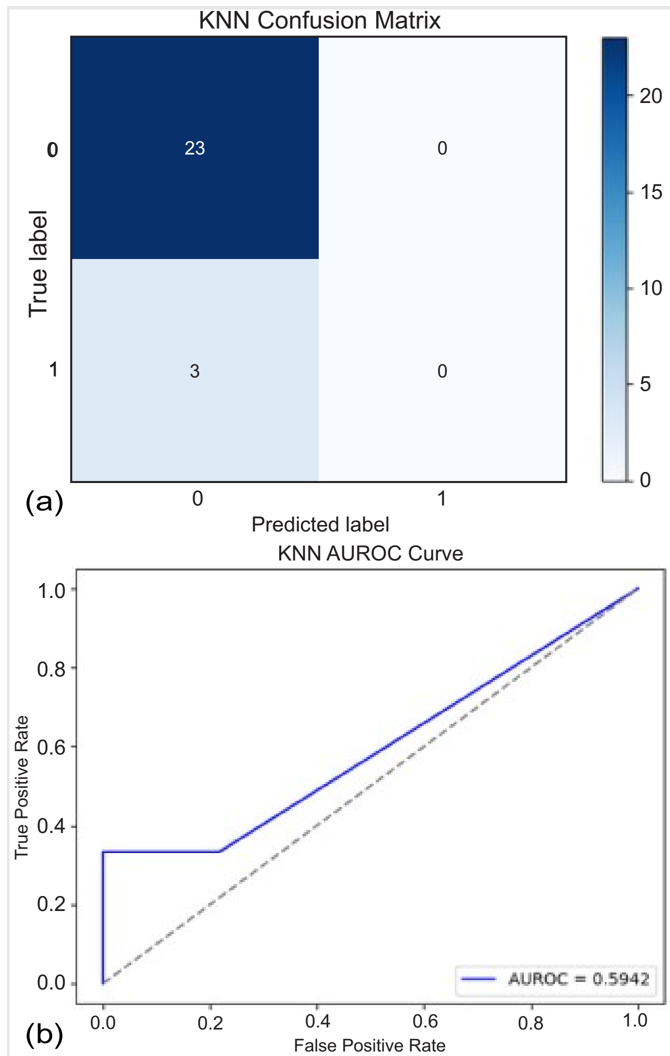


Figure 6: *This figure shows the performance of KNN Classifier through (a) Confusion Matrix (b) AUROC*

The Logistic Regression model correctly recognized all actual urosepsis cases, achieving a perfect recall result of 1.00. The precision value of 0.88, aside from the F1-score value of 0.94, matched those of KNN and SVC models. The model successfully detected true urosepsis cases yet struggled with separating the classes across all patient data based on its AUROC score of 0.6087. The confusion matrix shows that the model is highly skewed towards predicting urosepsis (class 0). It correctly classifies 23 cases of urosepsis with zero false positives, indicating perfect specificity. However, it completely fails to identify non-urosepsis cases (class 1), misclassifying all 3 instances as urosepsis, resulting in zero true positives. This suggests a strong bias toward predicting urosepsis, which may be due to class imbalance or model limitations in distinguishing features of non-urosepsis cases.

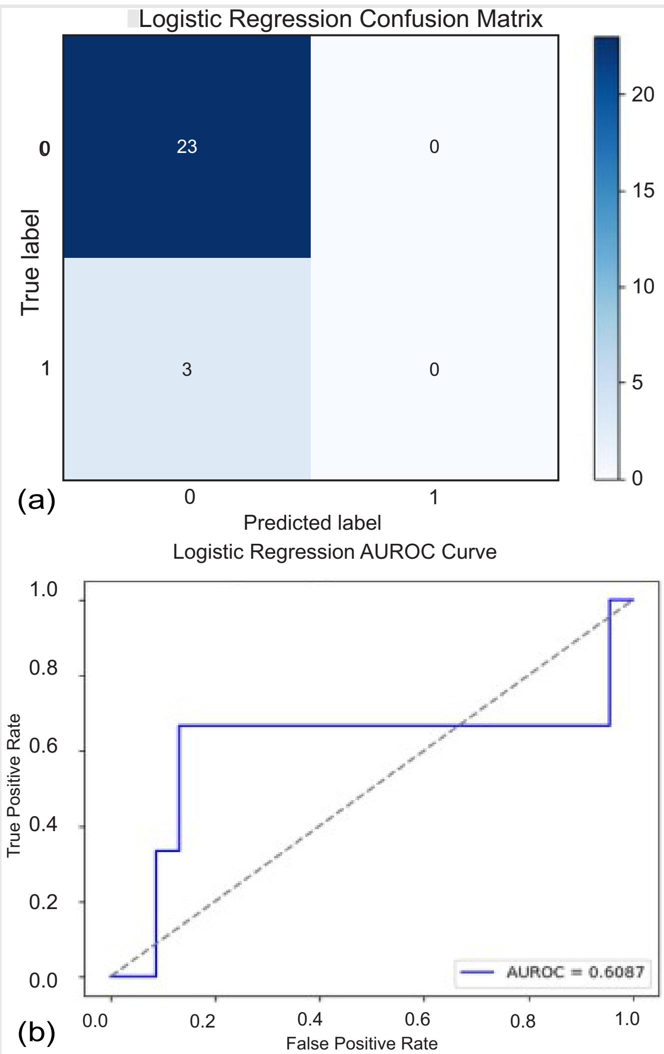


Figure 7: *This figure shows the performance of Logistic Regression through (a) Confusion Matrix (b) AUROC*

The three models, Support Vector Classifier and K-Nearest Neighbours and Logistic Regression demonstrated exceptional results based on precision rates and recall and F1-score performance and accuracy metrics. The KNN and SVC models demonstrated a superior ability to recall urosepsis cases while minimizing inaccurate positive results along with other tested models. The Gaussian Naive Bayes model delivered the poorest results because it was not adapted to this dataset, as shown by its poor precision score, recall rate, and F1 score. The Decision Tree model showed adequate performance levels in precision and recall measurements yet had insufficient AUROC results, indicating poor class discrimination. The developed ML models, particularly SVM and KNN, offer practical clinical value by enabling early identification of patients at high risk for post-RIRS urosepsis. This enables targeted preoperative interventions, closer monitoring, and enhanced patient outcomes.

Discussion

This section presents the previous studies that have been done to develop predictive models for urosepsis. Pietropaolo et al. - 2021 used the ML model to determine potential correlates of severe urosepsis in ICU patients. Patients were retrospectively collected from nine high-volume European centers: 57 patients with urosepsis (Group A) and 57 matched controls without urosepsis (Group B). The random forest model was used, and the accuracy obtained was 81.3%, and sensitivity and specificity were 0.80 and 0.82, respectively, with an area under the curve of 0.89. Other outcomes were proximal stone location, stent duration, stone size, and operative time.[23]

Bunn et al. - 2021 utilized machine learning techniques to predict postoperative sepsis following appendectomy. Pretreatment predictors of sepsis were evaluated using logistic regression, support vector machines, random forest decision trees, and extreme gradient boosting. There was a comparable performance between logistic regression, random forest, and gradient boosting with an AUC of 0.70; 95% CI, 0.68–0.73, while support vector machine had a significantly lower AUC of 0.51; 95%CI, 0.50–0.52. The results showed that machine learning approaches could reasonably perform postoperative sepsis risk assessment to minimize morbidity through early detection and intervention.[24]

Su et al. - 2022 developed an ML model based on biomarkers of patients with urosepsis. Retrospective analysis enrolled 157 patients with urosepsis, for whom laboratory data of biomarkers, such as procalcitonin, D-dimer, and C-reactive protein, were obtained. Five of the six machine learning models developed got above 80% accuracy, with the ANN yielding the highest prediction.[25] Hong et al. – 2023 developed an early risk assessment model for urosepsis in upper urinary tract calculi patients. A retrospective analysis of 1,716 patients (10.8% cases, 89.2% controls) identified eight key variables: sex, age, body temperature, diabetes history, urine leukocyte, nitrite, glucose, hydronephrosis, etc. The ANN model exhibited excellent performance based on the high accuracy score of the validation set, which generated an AUC of 0.945, while the training set gave an AUC score of 0.992.[26]

Chen et al. - 2022 developed a model incorporating radiomics and deep learning to predict sepsis after PCNL in patients with proximal ureteral calculi. The radionics model has an internal validation AUC of 0.881 and an external validation AUC of 0.783. Implementing the DNN model increased prediction accuracy by 7 %, with internal validation of AUC 0.920 and external 0.874.[27] Chen et al. - 2022 developed a machine-learning model to identify infection stones preoperatively in 462 urolithiasis patients. The random forest classifier (RFC) outperformed logistic regression, achieving an AUC of 0.951 with high sensitivity and specificity.[28]

Therefore, it is essential to derive a model suitable for our specific local population using region-specific data. Ideally, such a model would be tailored to identify unique demographic, clinical, and environment-based factors contributing to sepsis in the patients undergoing RIRS.

Conclusion

The clinical adoption of this prediction model can start by utilizing SVC, KNN, and Logistic Regression because they demonstrate the best performance in risk assessment for urosepsis following RIRS. Such a predictive model can enable doctors to recognize high-risk preoperative patients by analysing their clinical and demographic features, allowing for timely interventions such as administering prophylactic antibiotics, opting for delayed surgery, or increasing postoperative monitoring to improve patient outcomes. The detection of urosepsis before its development enables patient-specific care strategies that decrease serious complications and health expenses related to postoperative infections. The validation of these models on clinical patient populations representing various demographic backgrounds must occur in real-world settings to evaluate their capability of maintaining effectiveness. Implementing predictive models into clinical decision support systems should be thoroughly explored since they boost providers' data-based choices during postoperative care.

Ethical Approval: The Intuitional Review Board of Pakistan Kidney and Liver Institute and Research Center has approved the study vide letter Ref No PKLI-IRB/AP/00142025.

Conflict of Interest: None

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Authors' Contribution:

AR, NBN, SM, NZ, SI: Conceptualization, study design, supervision of data collection, and critical review of the final draft

AT, SI: Analysis & interpretation of results, critical revisions, and finalization of the manuscript

AY, AH, AA, MA, AC: Acquisition of data and critical revisions to the manuscript

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