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Assessment of Performance Capability of Machine Learning Methods in Predicting Postoperative Outcomes of PCNL Surgery in Patients of Kidney Stone Disease

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Abstract: *Kidney stone disease is everywhere in urology, and figuring out what'll happen after surgery is a big deal for both doctors and patients. For years, people have relied on scoring systems like the Guy's Stone Score and the CROES nomogram to predict how things will go after an operation. But honestly, those tools have their flaws. They only look at a handful of factors, and a lot depends on how each doctor interprets the results.*

Now, with all the data piling up in medicine, machine learning is starting to change the game. These algorithms can sift through massive, complicated datasets—think details about the stones themselves, patient histories, lab results, scans—and spot patterns we just can't see with traditional methods.

New research shows machine learning models aren't just a little bit better; they're nailing predictions about who'll be stone-free after surgery, who'll need a second procedure, and who might run into trouble like bleeding or infection. Some models hit accuracy rates over 90%. The best part? They keep getting smarter as more data comes in.

In our study, we're taking a close look at how well different machine learning approaches predict outcomes for patients undergoing percutaneous nephrolithotomy. We're stacking them up against the old-school scoring systems to see which does a better job. The goal is to figure out if machine learning can actually help doctors make better choices, plan treatments more effectively, and, in the end, get better results for people dealing with kidney stones.

Keywords: CROES nomogram, Percutaneous nephrolithotomy (PCNL), Machine learning, Predictive modeling, Postoperative outcomes

I. INTRODUCTION

Kidney-stone disease is recognized as one of the most prevalent and economically burdensome conditions globally [1]. Among the available surgical options, percutaneous nephrolithotomy (PCNL) is widely utilized for the management of large renal calculi and remains a standard intervention in such cases [2]. Since the initial introduction and clinical reporting of this technique, PCNL has gained broad acceptance due to its effectiveness in treating complex and sizable kidney stones [3]. It is considered the benchmark procedure for the treatment of stones measuring 2 cm or more, owing to its superior clearance rates compared to other modalities [4]. Reported success rates of PCNL vary considerably across different studies, ranging from 56% to 96%, reflecting the influence of patient-specific and procedural factors on surgical outcomes [5] [6] [7].

Successful stone clearance following PCNL depends on several parameters, such as stone size, anatomical location, stone multiplicity, the degree of hydronephrosis, and the surgeon's level of expertise. To enhance outcome prediction, multiple scoring systems have been developed, including the Guy's Stone Score, the S.T.O.N.E. nephrolithometry system, the CROES nephrolithometry nomogram, and the S-ReSC score [8]. While each scoring model presents distinct strengths and limitations, existing evidence indicates that their predictive accuracy for stone-free status remains broadly comparable [9].

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In recent years, machine learning (ML) methods have gained significant traction within clinical medicine, particularly for constructing advanced predictive models. Studies in the field of urology and oncology have consistently demonstrated the superiority of ML algorithms over traditional statistical approaches for analyzing complex clinical datasets and identifying outcome patterns [10] [11] [12]. These predictive models offer promising potential for improving clinical decision-making, optimizing patient selection, and supporting preoperative counseling by providing more individualized and data-driven outcome predictions.

II. LITERATURE REVIEW

Machine learning (ML) Machine learning (ML) techniques have been increasingly utilized to predict postoperative outcomes in patients undergoing PCNL, with several studies highlighting their potential to outperform conventional assessment methods [13] [14] [15]. These predictive models serve as valuable tools for clinicians, supporting improved decision-making and enabling more personalized patient counseling. Although significant technological advancements have been made in the field of urinary stone surgery, selecting the optimal treatment strategy and providing accurate preoperative counseling continue to present challenges. Numerous studies have examined the prognostic value of preoperative factors in predicting outcomes such as stone-free rate (SFR) and the likelihood of requiring additional procedures [14] [16] [17]. Effective preoperative prediction models can therefore play a crucial role in assisting urologists with patient selection, treatment planning, and individualized counseling.

Kadlec et al. developed an artificial neural network (ANN) to forecast outcomes following various endourologic interventions [16]. Using data from 382 renal units, their model predicted SFR—defined as the absence of residual stones on KUB or <4 mm on CT—with a sensitivity of 75.3% and specificity of 60.4%. For secondary procedure prediction, the model achieved 30% sensitivity and 98.3% specificity, with corresponding positive and negative predictive values of 60% and 94.2%.

Aminsharifi et al. created another ANN using pre- and postoperative data from 200 PCNL patients and validated it on an additional 254 cases [14]. Their system demonstrated 81.0%–98.2% accuracy in predicting SFR, transfusion requirements, and ancillary interventions, with stone burden and morphometry identified as key predictive variables.

In a further study, Aminsharifi et al. developed a machine-learning–based software platform incorporating more than 20 variables to predict SFR and ancillary procedure requirements after PCNL [15]. This system showed superior performance, achieving an AUC of 0.915 compared with 0.615 for GSS and 0.621 for CROES.

Choo et al. designed an ML-driven decision-support model for predicting shock wave lithotripsy outcomes in ureteral stone patients, demonstrating 92.3% accuracy using 15 clinical variables [17]. Stone volume, length, and Hounsfield units were among the most influential predictors.

Seckiner et al. developed an ANN to predict SWL outcomes in 203 patients, achieving 99.3% accuracy in the training set and over 85% accuracy in the validation and test cohorts [18].

Hong et al. evaluated four ML methods—Lasso logistic, random forests, SVM, and Naïve Bayes—against Guy's and S.T.O.N.E. scoring systems for predicting SFR after PCNL in 222 patients. All ML models yielded higher AUCs (0.803–0.879) and superior accuracy compared to conventional scoring tools, with Lasso logistic demonstrating the best performance [19].

Overall, ML algorithms such as random forests, decision trees, ANNs, Bayesian learning, and deep learning each present unique advantages. Collectively, they have shown strong potential in predicting post-PCNL stone-free outcomes, frequently surpassing traditional scoring systems in predictive accuracy.

Table 1 Applications of Machine learning in kidney stone surgery

Author	Year	Journal	AI / ML Method	Patients	Outcome Prediction Accuracy / Key Findings
Kadlec-et al.	2014	Urolithiasis.	Predictionmodel for outcomes in SWL, URS, PCNL	382 Renal-units	SFR prediction showed 75.3% sensitivity, 60.4% specificity, 75.3% PPV, and 60.4% NPV. Secondary procedure prediction achieved 30% sensitivity, 98.3% specificity, 60% PPV, and 94.2%

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					NPV.
Aminsharifi et al.	2017	Journal of Endourology	ANN for predicting PCNL outcomes	200 patients (training) + 254 (validation)	Overall SFR 76.4%. Ancillary procedures in 21.3% (SWL 5.9%, URS 10.6%, repeat PCNL 4.7%). Prediction accuracy and sensitivity ranged 81%–98.2%.
Choo et al.	2018	Journal of Urology	Machine learning (Decision Tree) for SWL success	791 ureteral stone patients	Model achieved 92.29% accuracy and AUC 0.951 for single-session SWL success prediction.
Seckiner et al.	2017	International Brazilian Journal of Urology	ANN for predicting SFR after SWL	203 renal stone patients	Prediction accuracy: 99.25% (training), 85.48% (validation), 88.70% (testing).
Aminsharifi et al.	2020	Journal of Endourology	SVM for PCNL outcome prediction	146 renal stone patients	SFR 72.6%. Prolonged urine leakage: 8.2%. Transfusion: 7.5%. Ancillary procedures needed in 27.4% (31 SWL, 11 repeat PCNL).
Hong et al.	2022	Frontiers in Pharmacology	LL, RF, SVM, Naïve Bayes	222 PCNL patients	Overall SFR 50%. AUCs: LL 0.879, RF 0.803, SVM 0.818, Naïve Bayes 0.803. All models outperformed Guy's score (AUC 0.800) and S.T.O.N.E. score (accuracy 0.788%).

Table Note:
AI – Artificial Intelligence; ML – Machine Learning; PCNL – Percutaneous Nephrolithotomy; SWL – Shock Wave Lithotripsy; URS – Ureteroscopy; SFR – Stone-Free Rate; ANN – Artificial Neural Network; SVM – Support Vector Machine; LL – Lasso Logistic Regression; RF – Random Forest; AUC – Area Under the Curve (Receiver Operating Characteristic); PPV – Positive Predictive Value; NPV – Negative Predictive Value..

III. ANALYSIS

A comprehensive search of various research databases was conducted, and a total of six journals were consulted to complete this review. The available literature indicates that substantial work has been undertaken globally on predicting postoperative outcomes of PCNL surgery in patients with kidney stone disease. However, there is a notable scarcity of studies from the Indian context. At present, no published data or analyses assess the performance of these predictive models specifically in Indian patients.

Given this gap, the present study aims to evaluate machine learning methods for predicting key treatment outcomes—such as stone-free rate, postoperative infection, and the need for blood transfusion—in patients with kidney stone disease undergoing PCNL in an Indian clinical setting. This assessment may help determine the applicability and reliability of existing ML-based predictive tools for the Indian population and support better clinical decision-making in the region.

IV. CONCLUSION

We reviewed the existing literature on the application of machine learning techniques across various domains of urology. Machine learning is now being widely investigated in multiple urological conditions, including kidney cancer, prostate cancer, bladder cancer, benign prostatic disease, and kidney stone disease, as well as in associated imaging and pathological evaluations. These techniques are being explored for their utility in assisting clinicians with disease diagnosis, correlating imaging findings with clinical symptoms, predicting treatment outcomes, assessing pathological results, estimating survival rates, and supporting overall clinical decision-making.

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Within this expanding field, we identified a specific area of interest related to the management of kidney stone disease using endoscopic surgery, particularly percutaneous nephrolithotomy (PCNL). The success of this procedure is commonly assessed using several outcome parameters, such as stone-free rate, postoperative infection, and the need for blood transfusion. A limited number of machine learning approaches have been reported in the literature for predicting these outcomes, with the aim of developing reliable models to support clinical practice. These predictive tools can potentially assist clinicians in preoperative counseling, informing patients about expected outcomes, evaluating the risk of postoperative complications, and selecting the most appropriate treatment strategies.

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