

RESEARCH ARTICLE

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KIDNEY STONE PREDICTION USING OPTIMIZED FEATURE SELECTION AND MULTI-LAYER PERCEPTRON WITH EXPLAINABLE AI

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ARTICLE INFO

Article History

Received: February 10, 2026

Reviewed: April 17, 2026

Accepted: May 17, 2026

Published: June 30, 2026

Keywords:

Kidney stone prediction,
Feature selection,
Multi-Layer Perceptron,
Evolutionary optimization,
SHAP.

ABSTRACT

Kidney stone disease is a frequent urology condition that occurs from a combination of complex biochemical and physiological factors. This study incorporates a composite decision-support framework combining deep learning and several different feature selection methods to develop an effective kidney stone prediction model. The study used a clinical dataset consisting of 15756 patient records collected from a clinical laboratory. Furthermore, systematic analysis was conducted to determine the most predictive clinical features using three different approaches including: filter-based feature engineering, embedded feature engineering and evolutionary feature engineering. Subsequently, a Multi-Layer Perceptron (MLP) was constructed using only the most predictive features to classify whether there were kidney stones, but also to provide an estimated risk score associated with determining if a patient had kidney stones. SHapley Additive exPlanations (SHAP) was used as a method to enhance model interpretability and clinical trust in the model's output by providing additional context for making individual patient predictions. Experimental results show that the new Genetic Algorithm feature selection approach for the MLP was able to produce a superior level of classification accuracy, with an overall prediction accuracy of 98.3 percent. Thus, this proposed framework provides a reliable, interpretable, accurate decision-support tool to predict the outcome of kidney stones at the onset of a patient's condition prior to the development of later-stage complications such as acute kidney failure.



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I. INTRODUCTION

Kidney stones affect the urinary tract system due to an imbalance of urinary solutes like calcium, uric acid, etc. Conventional approaches to diagnosing kidney stones (such as CT scans) are expensive, time-consuming, rely on expert interpretation, and need efficient data-driven diagnostic support. To facilitate this, optimization-based feature selection methods (e.g., Improved Genetic Algorithm (IGA) and Particle Swarm Optimization (PSO)) are applied to achieve effective identification of compact and informative subsets of features used to train a Multi-Layer Perceptron (MLP) based classification model (IGA identifies compact and informative subsets of features when utilized with Mutual Information (MI)). In addition, the MLP generates instance-level explanations of diagnostic results by providing SHapley Additive exPlanations (SHAP). The research team also developed an easy-to-use diagnostic application that allows users or doctors to enter patient parameters and receive predictions and explanations for each prediction using various optimization-based feature selection techniques (random selection, MI, LASSO, PSO, and GA). The development of the diagnostic application was enhanced by a Tkinter-based graphical user interface (GUI). Ultimately, the contributions of this research are: (i) A comparative study of various feature selection methods; (ii) An optimized GA-based feature subset consisting of seven clinical features; (iii) The creation of an MLP-based kidney stone prediction model using the optimized features; and (iv) The development of an explainable and user-friendly diagnostic application.

II. THEORETICAL REFERENCE

By [1] introduced a model based on a DNN architecture to predict the occurrence of kidney stones. They focused their model on input parameters, including urine pH, calcium, oxalate, and uric acid levels, among other clinical characteristics. The authors concluded that DNNs provide a more accurate prediction of future stone occurrences than traditional classifiers due to their ability to capture complex interactions between input, or feature variables. In summary, the work done by Gulhane et al. serves as the foundational study for the research presented. However, because their model used the complete set of features as inputs without evaluating if any of the features were redundant or without considering interpretability of the model outputs, this limited the ability of their model to provide clinical utility. Other studies in the literature have also explored the use of machine learning for the prediction of kidney stones and their associated recurrent events through the use of large datasets. Yanase et al. utilized both clinical and biochemical data to generate machine learning models for the prediction of recurrent stones in patients following endoscopic combined intrarenal surgery. They also highlighted the need for careful feature selection when using machine learning algorithms to predict future events. [2]. Similarly, Doyle et al. employed the data contained in electronic health records (EHR) to develop machine learning models that predict symptomatic recurrence of kidney stones. In their study, the authors pointed out problems associated with feature redundancy and data imbalance, which are issues commonly found in the application of machine learning to real-world clinical datasets. [3]. The research area on machine learning techniques has included developing predictive models for determining kidney stones' characteristics and therapeutic interventions.

By [4] classified the composition of urinary calculi using endoscopic images, while [5]. used an integrated approach to improve kidney stone prediction accuracy leveraging clinical and radiomics features together with LASSO-based feature selection methods. Other investigators, such as Fan et al., showed that combining feature selection with machine learning (ML) improves complication prediction following percutaneous nephrolithotomy (PCNL); the findings reaffirm that reducing data dimensionality is essential in urology research [6]. Medical prediction tasks involving very large dimensionality clinical datasets require careful preprocessing of the data, and feature selection represents a critical preprocessing task. One of the most common types of preliminary feature ranking technique(s) is filtering based upon mutual information and correlation analyses [7]. Embedded methods, including LASSO regression, provide feature selection during the model training process, contributing to better prediction performance due to improved model generalization, while simultaneously reducing overfitting [8]. Evolutionary algorithms such as particle swarm optimization (PSO) and genetic algorithms (GA) have been applied to biomedical classification tasks and have produced very promising results in identifying optimal subsets of features for prediction [9], [10]. Currently, there are very few comparative evaluations of multiple types of feature selection methods available on the prediction of kidney stones. Deep learning approaches, specifically Multi-Layer Perceptron architectures, have previously performed well on structured clinical datasets when applied [1], [11].

The advantages of using an MLP architecture for structured tabular data in medicine are numerous as they are computationally efficient. However, a significant drawback of using MLPs in the clinical setting is their lack of inherent interpretability, which has limited their use in many clinical environments where the need for explainable AI solutions is critical. As researchers continue to address the challenges posed by the black-box nature of ML and DL algorithms, more and more researchers are applying Explainable AI (XAI) methodologies to their model development. Among the various XAI techniques, SHapley Additive exPlanations (SHAP) has provided reliable, theoretically-based explanations of why a certain prediction was made throughout the quantification of the importance of each feature used in a given prediction [12]. Many studies have used the combination of SHAP with ML and DL models to predict diseases, including chronic kidney disease progression, the risk of postoperative complications, and the potential outcome of the patient [13-18]. These studies illustrate how SHAP can be used to create a more trustworthy model and enhance clinician's confidence in the model. In conclusion, the existing body of literature has shown that ML and DL methods are effective for predicting kidney stones; however, there are shortcomings in the comparison of feature selection methods as well as the use of explainable deep learning models. The current study builds upon these previous research efforts by providing a comprehensive assessment of the use of multiple feature-selection techniques, the application of an MLP classifier, and the implementation of SHAP-based explainability to create an accurate, interpretable decision-support tool for use by healthcare providers when assessing the risk of kidney stone disease.

III. MATERIALS AND METHODS

III.1 DATASET DESCRIPTION

The investigational dataset comprises clinical and biochemical characteristics associated with the development of kidney stones. The dataset features urine pH, Specific Gravity, Urine Calcium, Urine Oxalate, Urine Uric Acid, Serum Calcium, Serum Uric Acid, Serum Creatinine, Urine Conductivity, and Urine Citrate as the associated characteristics. Data preparation techniques included missing value treatment, encoding of categorical attributes, and the use of normalizing methods such as standardizing numerical values. Upon completion of the data preparations, the dataset was then partitioned into an 80% training set and a 20% test set. By employing these methods during training will result in a more stable and consistent set up for the resulting model. Below is a schematic of the proposed model.

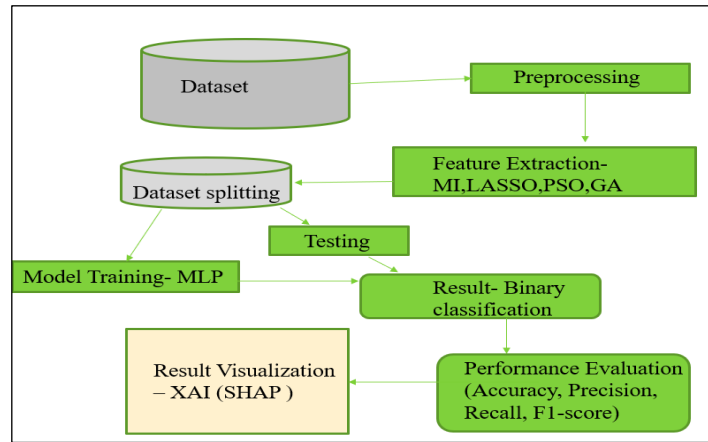


Figure 1: Block Diagram.

Source: Authors, (2026).

III.2 FEATURE SELECTION METHODS

Significant features are used to identify the most informative subset of attributes contributing to kidney stone prediction. The following methods are evaluated:

III.2.1 Mutual Information

Mutual Information (MI) is one of the key methods for feature selection based on Information Theory's fundamentals. MI measures how much the input feature is dependent on (or is explained by) the output (the target class variable). MI scores are obtained for each of the clinical input features with respect to their individual binary class label, (i.e., ACT or Non-ACT) and the clinical input features are then ordered based on their MI score (from highest to lowest) to determine each feature's importance. As a result, a subset of available clinical features, (i.e., Urine Oxalates, Serum Uric Acid, Urine Uric Acid, Urine pH, Urine Calcium, Specific Gravity, and Serum Calcium) will provide the greatest amount of information to classify accurately to either of the two classes, while those clinical input-feature candidates with less information may be excluded from use in the descending order of MI score, thereby assisting in reducing the dimensions of the feature vector and to help reduce the noise within the data set. Using only the most informative biochemical input-feature candidates enhances the ability of downstream classifiers, (e.g. Multi-Layer Perceptron (MLP)), to provide stable classifier performance on test data.

III.2.2 Lasso Regression

Using LASSO for selection of features based on a regularization method is an approach used to select the most significant clinical variables associated with the prediction of kidney stone disease. The use of an L1 penalty term in the loss function of LASSO limits the size of the coefficients of the model which results in forcing the coefficients of less relevant features to shrink to exactly zero. Therefore, by simultaneously performing feature selection and model regularization, LASSO reduces dimensionality and reduces overfitting. When predicting kidney stones, LASSO selectively retains those clinically pertinent features (i.e., w) while discarding redundant or weakly correlated features. The reduced subset of features is then used as the input to a Multi-Layer Perceptron (MLP) classifier, which leads to improved model stability, faster convergence, and greater predictive accuracy.

III.2.3 Particle Swarm Optimization

The method of Particle Swarm Optimization (PSO) [19] looks to find a good subset of features to reduce dimensionality and maximize classification performance. Each particle is an array of binary numbers (1 for selected features and 0 for excluded features) that represent a feature subset. Each particle starts out randomly placed in the feature space and will move towards the best solution (pBest) and the best solution overall (gBest), and will be updated on a velocity basis to their location using their current velocity. The pre-defined objective function will be evaluated for the fitness of each particle on the chromosome, typically combining the classification accuracy and the number of features selected; therefore, over multiple updates, the particles will converge to feature subsets (i.e.: urine pH, urine calcium, urine oxalate, serum calcium, urine uric acid and serum uric acid) that produce better predictive performance and with fewer dimensions.

III.2.4 Improved Genetic Algorithm

Using operations inspired by biological evolution - selection, crossover and mutation - the Improved Genetic Algorithm (IGA) creates an optimal subset of features for dimensionality reduction. Each chromosome is a binary representation of a subset of clinical features, with '1' indicating that the feature is included, and '0' that the feature is excluded from the feature subset. Initially, some number of chromosomes are created and evaluated using a fitness function that is normally based on classification success with an added penalty for larger feature subsets. The chromosomes with higher fitness values are also selected as the parent chromosomes for the purpose of creating child chromosomes through crossover, while the mutation function adds a controlled amount of randomness in order to provide genetic diversity within the population. This evolutionary process converges to an optimized and discriminative feature subset, thus enabling the reduction of dimensionality while preserving predictive accuracy for future MLP classification.

III.3 CLASSIFICATION USING MULTI-LAYER PERCEPTRON

The MLP is used to create the main prediction model for determining whether or not someone has kidney stones based on optimally chosen clinical features. The operational flow within the MLP consists of five main functions: data pre-processing, forward propagation, error computation, backpropagation and optimization of parameters. Initially, the clinical features selected from feature selection techniques - Mutual Information, LASSO, Particle Swarm Optimisation, Improved Genetic Algorithm - were then normalised to provide a uniform feature scale as well as to ensure stability when training the MLP. The Normalized features were then presented as input into the MLP network. Each neuron in each of the hidden layers computes an aggregate of its weighted inputs and then applies a nonlinear activation function to that value before sending an output signal to the next layer. By doing so, the MLP is able to create complex and nonlinear mappings that relate to the clinical data associated with kidney stones. In forward propagation, the input signals move through at least one hidden layer and subsequently output signals, which have been progressively transformed into higher representations based on feature representation. A sigmoid activation function is used in the output layer to create a probability score that indicates how likely it is for kidney stones to be present and thus will be compared to the ground truth label, with the prediction error being calculated using a binary cross-entropy loss function.

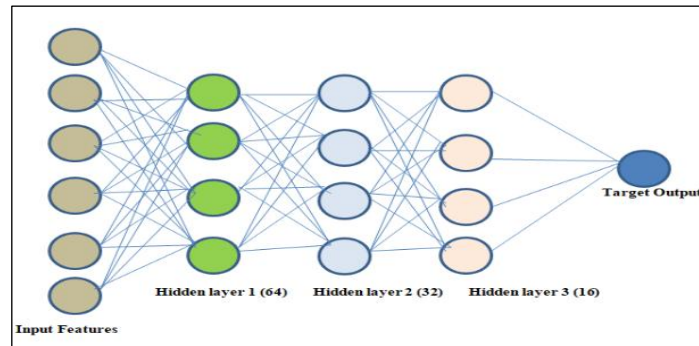


Figure 2: Architecture of MLP network.
Source: Authors, (2026).

An error will be obtained from the use of back-propagation algorithms in a neural network through back-propagating errors across multiple hidden layers, thus enabling error calculations according to the chain rule for loss functions have to be made for each weight and bias based on the hidden layers. Once all of the parameters of the neural network models have been determined, they will be updated through an iterative process by back-propagating the error until the predictions are made. The training phase will continue until either of the primary stop criteria for training goals (i.e., convergence achieved through minimal loss or reaching a specified number of epochs) are met. In order to determine future kidney stone probability, we will implement the multi-layered perceptron (MLP) model to make predictions on the risk of a patient developing kidney stones based on previously unseen patient records. We will use a threshold value of 0.5 for binary classification of detected and non-detected kidney stones based on the predicted output probabilities obtained using the classification model. Kidney stone-risk prediction can be obtained directly by transforming the probabilistic output of the trained MLP classifier $P(i)$ into a percentage likelihood of developing a urinary tract outlet obstruction (UTSO). Let $P(i) = p$ = the probability for individual patient i having a UTSO, and the kidney stone-risk prediction is given by:

$$R(i) = P(i) \times 100 \quad (1)$$

To improve clinical interpretability of continuous risk scores, these scores can be divided into low/medium/high-risk groups based on predefined probability intervals. The estimated risk scores' reliability and validity can be assessed with standard performance metrics (accuracy, precision, recall, and F1-measure). In addition, SHAP (SHapley Additive exPlanations) can be used to assess how much each of the individual clinical input features contributed to the predicted outcomes, which will improve both the model's transparency and trust in clinical use.

III. 4 EXPLAINABILITY USING SHAP

Using SHAP (SHapley Additive exPlanations) for MLP Classifier (Multi-layer Perceptron) will provide a better understanding of the Kidney Stone prediction model (KSpM). Deep Learning models have very high accuracy with their predictions, but due to their Black Box nature this limits their use within Clinical settings. SHAP addresses this limitation by providing a transparent and trustworthy explanation for each of the models predictions. For each patient instance, SHAP helps quantify how much a feature's value is increasing or decreasing the chance of the creation of a kidney stone in comparison to that of the model's predictive baseline for the patient(s)[20]. If the SHAP value is positive, then it means that the feature is increasing the likelihood that a kidney stone will occur, and if it is negative it means the feature is providing some degree of protection from the creation of a kidney stone or is reducing risk. The magnitude of the SHAP value reflects the degree of contribution to the prediction provided by the feature. Using SHAP will help provide a clearer understanding for the Medical Professional(s) to recognize deviations from standard Clinical thresholds, and to identify significant Biochemical characteristics related to the prediction of kidney stones. The provision of clear and patient-specific explanations through SHAP will improve the Clinical value, accountability, and degree of confidence associated with Clinical decision-making of the proposed Decision-Support System.

Different standard criteria for assessing classification performance rates, such as accuracy, precision, recall, and F1 scores, will be used to evaluate the performance of the proposed pedestrian level of service (LOS) prediction model. A comprehensive evaluation of classification performance can be performed using these criteria, particularly in terms of their ability to handle class imbalance and minimize erroneous predictions; these two aspects are both critical to making effective clinical decisions. Experimental evidence has also shown that compared to using the complete feature set, performing feature selection prior to classification results in an improvement in accuracy of predictions about 90%. The improvement in prediction accuracy is attributed to removal of features that provide little or no information about the output variable, resulting in less overfitting of the model and improved generalization properties. In comparing numerous feature selection methods on the basis of their performance as compared with the Improved Genetic Algorithm (IGA)–based feature selection method, the IGA–based method consistently provides the best classification results on all performance measures. The IGA performs well in exploring the feature space and is effective at capturing complex nonlinear relationships among the biochemical/biophysical variables, resulting in a set of clinically relevant features that have been optimized. The other methods of feature selection for Very Long Vehicle (VLV) classification, i.e., Mutual Information and LASSO, also show considerable improvement in classification; however, the nature of selection methods as filter-based (MI) and linear (LASSO) limits their ability to identify higher-order relationships between feature sets.

Table 1: Comparison of Evaluation Metrics.

ALGORITHM	Accuracy	Recall	Precision	F1 score
Mutual Information	98.2	97.1	95.4	96.2
LASSO	97.6	94.8	95.0	94.9
PSO	80.4	65.6	77.8	71.7
Improved GA	98.3	96.0	96.5	96.3

Source: Authors, (2026).

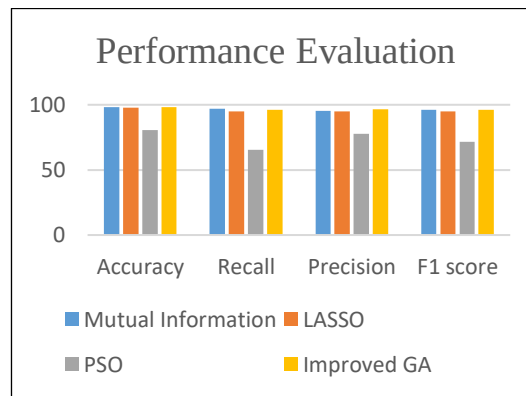


Figure 3: Comparison graph.

Source: Authors, (2026).

Integrating SHapley Additive exPlanations (SHAP) allow us to understand better how our model works and how we can explain its behaviour [21]. For example, the SHAP analysis of kidney stone formation shows that these stones form as a result of the interaction of many biochemical characteristics – not just one dominant biochemically-based characteristic. For example, urine pH, calcium concentration, oxalate level, uric acid and many different biochemical characteristics together create the prediction outcome. In addition, visualizing the SHAP value of each individual instance using instance-level SHAP will enhance clinical transparency by providing an easy way to see how variation in each feature affects the prediction outcome. The predictions generated from the model will be presented using a Tkinter-based GUI.

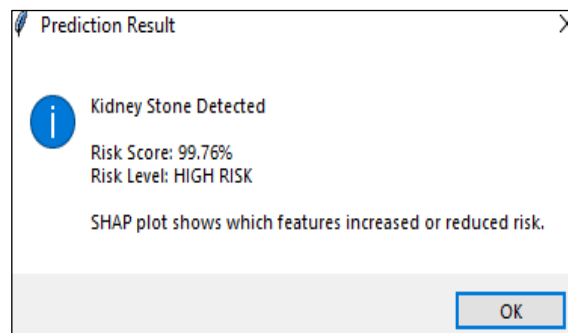


Figure 4: Prediction result.

Source: Authors, (2026).

In the above figure, the prediction results tell about the risk score of 99.76%, the integration of SHAP will give a chart that describes which feature contributes more to the presence or absence of kidney stone for an individual.

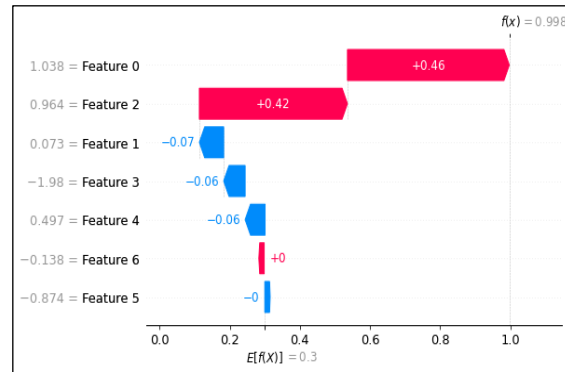


Figure 5: SHAP chart.
Source: Authors, (2026).

Overall, the findings endorse the effectiveness of the proposed framework in delivering accurate, interpretable, and clinically meaningful kidney stone predictions.

IV. CONCLUSIONS

This research is aimed at implementing a kidney stone prediction framework that uses deep learning and evaluates a systematic selection method of modelling and selection of features used in the model. The use of Evolutionary optimisation techniques and in particular Improved Genetic Algorithms, has provided experimental evidence that non-linear relationships between clinical and biochemical parameters can be captured successfully leading to improved prediction accuracy, reduced redundancy of features, and reduced model complexity. The addition of SHapley Additive exPlanations (SHAP) improves the interpretability of the model by providing explanations for each prediction's feature contributions at an instance level. This facilitates more informed and transparent clinical decision-making. In summary, the proposed framework is capable of producing accurate, interpretable and clinically useful decision support systems for the prediction of kidney stones, and has the potential for broad future implementation in terms of using large scale multi-centre datasets, multi-class stone classification, integrating real-time health monitoring, and conducting longitudinal studies on the risk of developing kidney stones.

V. AUTHOR'S CONTRIBUTION

Conceptualization: V.Dhivya, D.Sivaganesan, N.Senthil Madasamy, A. Noble Mary Juliet, N.Suba Rani and J.Bhavithra.

Methodology: V.Dhivya, D.Sivaganesan, N.Senthil Madasamy, A. Noble Mary Juliet, N.Suba Rani and J.Bhavithra.

Investigation: V.Dhivya, D.Sivaganesan, N.Senthil Madasamy, A. Noble Mary Juliet, N.Suba Rani and J.Bhavithra.

Discussion of results: V.Dhivya, D.Sivaganesan, N.Senthil Madasamy, A. Noble Mary Juliet, N.Suba Rani and J.Bhavithra.

Writing – Original Draft: V.Dhivya, D.Sivaganesan, N.Senthil Madasamy, A. Noble Mary Juliet, N.Suba Rani and J.Bhavithra.

Writing – Review and Editing: V.Dhivya, D.Sivaganesan, N.Senthil Madasamy, A. Noble Mary Juliet, N.Suba Rani and J.Bhavithra.

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Supervision: V.Dhivya, D.Sivaganesan, N.Senthil Madasamy, A. Noble Mary Juliet, N.Suba Rani and J.Bhavithra.

Approval of the final text: V.Dhivya, D.Sivaganesan, N.Senthil Madasamy, A. Noble Mary Juliet, N.Suba Rani and J.Bhavithra.

VI. REFERENCES

- [1] R. Gulhane, S. Patil, and A. Deshmukh, "Integrative approach for efficient detection of kidney stones based on improved deep neural network architecture," *Biomedical Signal Processing and Control*, vol. 92, pp. 105–118, 2024.
- [2] K. Yanase *et al.*, "Machine learning-based prediction of kidney stone recurrence following endoscopic combined intrarenal surgery," *Journal of Clinical Medicine*, vol. 14, no. 12, pp. 4037–4049, 2025.
- [3] M. Doyle *et al.*, "Predicting symptomatic kidney stone recurrence using machine learning and electronic health records," *Urology*, vol. 186, pp. 102–110, 2024.
- [4] Y. Zhu *et al.*, "Machine learning prediction of kidney stone composition using endoscopic image data," *BMC Urology*, vol. 24, no. 1, pp. 1–11, 2024.
- [5] Z. Guo *et al.*, "Radiomics and clinical feature fusion for kidney stone composition prediction using machine learning," *European Radiology*, vol. 34, no. 2, pp. 987–997, 2024.
- [6] Y. Fan *et al.*, "Explainable machine learning for predicting urosepsis after percutaneous nephrolithotomy," *Biomedical Engineering Online*, vol. 24, no. 1, pp. 1–18, 2025.
- [7] H. Peng, F. Long, and C. Ding, "Feature selection based on mutual information criteria," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 8, pp. 1226–1238, 2005.
- [8] Y. Wang, B. Zou, J. Xu, C. Xu, and Y. Y. Tang, "ALR-HT: A fast and efficient Lasso regression without hyperparameter tuning," *Neural Networks*, vol. 181, art. no. 106885, 2025. doi:10.1016/j.neunet.2024.106885.
- [9] A. K. Singh and A. Kumar, "Multi-objective hybrid particle swarm optimization with firefly algorithm for feature selection with Leaky ReLU," *Discover Artificial Intelligence*, vol. 5, art. 192, Jul. 2025.
- [10] S. Deng *et al.*, "Genetic algorithm-based feature selection with deep neural networks for medical diagnosis," *Comput. Biol. Med.*, vol. 170, art. no. 107930, 2024.

- [11] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Networks*, vol. 61, pp. 85–117, 2015.
- [12] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," *Advances in Neural Information Processing Systems*, vol. 30, pp. 4765–4774, 2017.
- [13] X. Li *et al.*, "Explainable machine learning for predicting postoperative complications in urology," *International Urology and Nephrology*, vol. 57, no. 3, pp. 521–531, 2025.
- [14] A. K. Tjoa and C. Guan, "A survey on explainable artificial intelligence (XAI): Toward medical XAI," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 11, pp. 4793–4813, 2021.
- [15] M. Nedbal *et al.*, "Machine learning prediction of ureteroscopy outcomes in pediatric kidney stone patients," *World Journal of Urology*, vol. 43, pp. 1–10, 2025.
- [16] S. Rasheed *et al.*, "Explainable deep learning models for clinical risk prediction," *BMC Medical Informatics and Decision Making*, vol. 25, no. 1, pp. 1–15, 2025.
- [17] Verma S, Singh P. K, Kaur G, Vashistha A, Pansari S. Non-Invasive Kidney Stone Prediction using Machine Learning: An Extensive Review. *Biomed Pharmacol J* 2025;18(March Spl Edition). Available from: <https://bit.ly/4bg38Rs>.
- [18] V. Dhivya, D. Sivaganesan, S. S. Prabhu, B. Suganya, C. Devipriya and T. Kanagasabapathy, "Personalized Kidney Stone Prediction: Review and Analysis," 2025 International Conference on Intelligent Computing, Information and Control Systems (ICOIICS), Lalitpur, Nepal, 2025, pp. 1763-1768, doi: 10.1109/ICOIICS67115.2025.11390651.
- [19] Alqahtani, A.; Alsubai, S.; Binbusayyis, A.; Sha, M.; Gumaie, A.; Zhang, Y.-D. Optimizing Kidney Stone Prediction through Urinary Analysis with Improved Binary Particle Swarm Optimization and eXtreme Gradient Boosting. *Mathematics* 2023, 11, 1717. <https://doi.org/10.3390/math11071717>
- [20] Pietro Manuel Ferraro, Eric N. Taylor, and Gary C. Curhan „24-Hour Urinary Chemistries and Kidney Stone Risk., *Am J Kidney Dis.* 84(2):164-169. Published online April 5, 2024. doi: 10.1053/ j.ajkd.2024.02.010
- [21] Khan, I. U. (2022). Explainable Artificial Intelligence (XAI) Model for the Diagnosis of Urinary Tract Infections in Emergency Care Patients. *Mathematical Modelling of Engineering Problems*, 9(4).