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A Machine Learning-based Model to Recognize Kidney Stone Diseases

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Abstract

Background: Kidney stones significantly raise healthcare expenses due to the requirement for specialized treatments and frequent hospital visits. Kidney stones lower workforce productivity because affected individuals frequently miss work or are less efficient due to pain and the necessity of treatment. In society, kidney stones lead to reduced productivity and quality of life, affecting both individuals and the broader economy.

Objectives: The primary objective of this study is to analyze the influence of urine-based biochemical and physical parameters on kidney stone formation and to develop a high-accuracy machine learning model for early kidney stone prediction.

Methods: In this paper, data analytics methods are used to investigate kidney stones based on urea analysis and uncover valuable insights from the relationship between various factors. Additionally, a predictive model is developed by integrating deep learning with Particle swarm optimization (PSO) algorithms, where PSO is utilized to tune the model hyperparameters.

Results: This model boasts an impressive 98.1% accuracy in predicting kidney stones. Such a proactive approach can significantly enhance patient outcomes by preventing the onset of painful and debilitating kidney stones.

Conclusion: In this research, it was shown that early prediction allows for timely medical intervention, reducing symptom severity and preventing complications like urinary tract infections or kidney damage. Consequently, the need for emergency treatments and hospitalizations is minimized, lowering healthcare costs.

Keywords: Deep Learning, Healthcare, Kidney Stone, Metaheuristics

1. Background

Kidney stones represent a significant health issue, affecting millions of individuals worldwide and leading to substantial healthcare costs.[1] These crystalline formations in the kidneys can cause severe pain, urinary tract infections, and even kidney damage if not treated promptly.[2] Kidney stones, or nephrolithiasis, can substantially affect the economy. In 2021, the annual expense for managing kidney stones in the United States was approximately $9 billion.[3] This figure encompasses both direct medical expenses and indirect costs such as reduced worker productivity. For instance, privately insured adults may need to take time off work due to kidney stones, resulting in an estimated annual cost of $775 million.[3] Therefore, recognizing the important factors and signals of kidney stones to prevent further damage is necessary.

The health industry has prioritized the early detection and treatment of kidney stones to mitigate these adverse effects.[4] Machine learning (ML) is emerging as a powerful tool in this realm, enhancing diagnostic accuracy and treatment personalization.[5] By analyzing large datasets from medical records, imaging studies, and genetic profiles, ML algorithms can predict the likelihood of stone formation, identify underlying risk factors, and suggest individualized prevention strategies.[6] This technological advancement not only enhances patient outcomes but also decreases the overall burden on healthcare systems by preventing recurrent stone events and unnecessary interventions.

Urine analysis is a critical component in the diagnosis and management of kidney stones.[7] Determining the composition and concentration of various substances in urine can provide valuable insights into the type and causes of kidney stones, aiding in more targeted treatment approaches.[8] ML plays a pivotal role in refining this diagnostic process. By leveraging ML algorithms, clinicians can analyze complex patterns in urine samples that may not be apparent through traditional methods.[9] These algorithms can identify early markers of stone formation, predict future risk, and monitor treatment efficacy with high precision.[10] Consequently, integrating

machine learning with urine analysis enhances the ability to detect kidney stones early, tailor treatments to individual patients, and potentially prevent the occurrence of stones altogether, leading to better patient care and resource optimization in the health industry.[11]

Some of the literature focused on the role of machine learning in kidney stone disease. Kazemi et al.[10] developed a model for predicting the type of kidney stones using 42 features derived from patients' medical records. Abraham et al.[12] proposed an XGBoost algorithm to recognize the composition of kidney stones based on clinical information and urine data, and their model showed 91% accuracy. Kavoussi et al.[13] utilized urine samples and clinical data to forecast urinary abnormalities and kidney stones. The three most influential variables in training their prediction models were age, gender, and body mass index. Shabaniyan et al.[14] employed Fisher's Discriminant Analysis for kidney stone problems, achieving an accuracy of 94.8%. Qadri[15] utilized a random forest algorithm to predict the kidney stones, and the model showed 90% accuracy.

Some research uses computerized tomography images and machine learning to predict kidney stones. Parakh et al.[16] employed convolutional neural networks to detect kidney stones based on computerized tomography images, and their model had 95%. De Perrot et al.[17] introduced a machine learning model that was trained using the Adaboost algorithm to detect kidney stones based on computerized tomography images. Their model showed 85.1% accuracy. Caglayan et al.[18] utilized the XResNet50 algorithm to build a deep learning model to detect kidney stones based on computerized tomography images, and the accuracy of the model was 93%. Zhu et al.[19] worked on the prediction of kidney stones based on radiomic features using a logistic regression algorithm, and the model had 86% accuracy.

2. Objectives

The primary objective of this study is to analyze the influence of urine-based biochemical and physical parameters on kidney stone formation and to develop a high-accuracy machine learning model for early kidney stone prediction.

This paper provides an analytical method to study the interrelationships among some major factors in urine analysis, including urea concentration, calcium concentration, osmolarity, conductivity, specific gravity, and pH, in relation to the formation of kidney stones. Moreover, this study also develops a highly accurate predictive model based on deep learning optimized by PSO for identifying individuals at risk of kidney stone disease. This proactive approach can greatly improve patient outcomes by preventing the development of painful and debilitating kidney stones. Also, it can reduce healthcare costs.

The remainder of the paper is organized as follows: Section 3 describes the deep learning and PSO algorithms, Section 4 presents the numerical results, Section 5 mentions the discussion, and Section 6 provides the conclusion.

3. Methods

This section introduces the metaheuristic algorithm used for tuning the hyperparameters of the machine learning model, the machine learning algorithm itself, and the evaluation metrics employed.

3.1. Problem Definition

Given the significant impact of kidney stone problems on individuals, community healthcare costs, and workplace productivity, our objective is to thoroughly analyze the various characteristics linked to these conditions. Acknowledging the complex nature of kidney stone problems, we intend to investigate crucial factors based on urine analysis. Through detailed examination, we aim to uncover the intricate relationships among these variables and their potential effects on an individual's health. Our goal is to harness the power of machine-learning techniques and metaheuristic algorithms to develop a predictive model capable of accurately classifying different types of factors that affect kidney stones. This approach is expected to aid in treating and preventing the problem, enhance workplace efficiency, and reduce healthcare costs.

The dataset used in this study was collected from individuals with and without kidney stone disease and contains urine analysis records. It includes six independent urinary variables: urea concentration, calcium concentration, osmolarity, conductivity, specific gravity, and pH, along with one dependent categorical variable for the presence or absence of a kidney stone.

The dataset is from an existing clinical database.[20] The data were anonymized for analysis. The urine samples were collected in the course of routine clinical investigations following the standards and practices of a conventional laboratory. Personal identifying information was not a part of the dataset. The data were employed purely for research purposes and were analyzed in accordance with ethical research standards.

First, the dataset was checked for missing values and outliers, after which the appropriate preprocessing techniques, such as the StandardScaler method, were performed before model development. The dataset was then divided into training and testing subsets such that 80% of the data was used for model training and 20% for performance evaluation.

The specific features of the dataset to be used in this study are outlined in Table 1.

The six physical properties of urine include: (1) specific gravity, which measures urine density relative to water; (2) pH, representing the negative logarithm of hydrogen

Table 1. Factors of the Dataset

Variable	Type	Role
Conductivity	Numerical	Int*
CC*	Numerical	Int
Osmolarity	Numerical	Int
SG*	Numerical	Int
UC*	Numerical	Int
pH	Numerical	Int
Kidney stone	Categorical	Dt*

*Note: Int = Independent, Dt = Dependent, UC = Urea concentration, CC = Calcium concentration, SG = Specific gravity

ion concentration; (3) osmolarity, a biological and medical unit indicating the concentration of molecules in solution; (4) conductivity (mmho), where one mho equals the reciprocal of an ohm, and conductivity corresponds to the concentration of charged ions in solution; (5) urea concentration, expressed in millimoles per liter; and (6) calcium concentration, also measured in millimoles per liter.

3.2. Metaheuristic Algorithm

PSO is a metaheuristic optimization algorithm inspired by the collective behavior of birds and fish. Recognized for its efficiency and flexibility in tackling optimization challenges, PSO models a social system in which individuals, represented as particles, collaborate to find the optimal solution within a search space.[21] The effectiveness of PSO is based on a core set of principles that direct its functioning.

In the context of problem optimization, the PSO algorithm starts by randomly positioning a population of particles within the solution space.[22] Each particle's position represents a potential solution, and its movement is guided by two key factors: its own past performance and the performance of the best particle in its neighborhood. By iteratively adjusting their positions, the particles strive to move closer to the global optimum, balancing exploration and exploitation. This collaborative approach allows PSO to effectively search the solution space in a decentralized manner. The movement of particles is determined by calculating the change in velocity using Equation (1).[23]

$$\vec{V}_{ij}(h+1) = \varphi_1 e_1 \left(\vec{z}_{ij}(h) - \vec{x}_{ij}(h)\right) + \varphi_2 e_2 \left(\vec{z}_{gi}(h) - \vec{y}_{ij}(h)\right) + W\,\vec{V}_i \quad (1)$$

In this context, $\vec{V}_{ij}(h)$ represents the velocity of particle i during the h-th iteration, while $\vec{y}_{ij}(h)$ denotes the position of particle i at the same iteration. The variables e_1 and e_2 are random numbers between 0 and 1, and φ_1 and φ_2 are constants. Additionally, $\vec{z}_{ij}(h)$ indicates the best position of an individual particle, and $\vec{z}_{gi}(h)$ signifies the best position of the entire swarm. The constant W remains unchanged. The new position of a particle is calculated using Equation (2).

$$\vec{y}_{ij}(h+1) = \vec{y}_{ij}(h) + \vec{V}_{ij}(h+1) \quad (2)$$

This paper employs PSO to optimize the hyper-parameters of a machine learning model, with the goal of improving task performance accuracy. Figure 1 presents the flowchart of the PSO algorithm.

3.3. Deep Learning

Deep learning is a category of machine learning algorithms distinguished by its diverse architectures, such as deep neural networks (DNNs).

A DNN is employed to create the predictive model. This DNN is an artificial neural network algorithm that comprises multiple hidden layers. The DNN model presented in this study features four hidden layers. Figure 2 illustrates the proposed algorithm structure.

The DNN model is developed using Stochastic Gradient Descent through the following process:

1. The weights start with small, randomly chosen values that are near zero;
2. Each feature is assigned to a separate input node in the input layer.
3. Forward propagation is executed: neurons are activated according to the weights, constraining each neuron's activation. This process continues until convergence is achieved for the prediction *y*.
4. The error is computed through comparison of the predicted value with the actual value.
5. Backpropagation is performed: the weights are adjusted based on their contribution to the error, with the magnitude of adjustment determined by the learning rate.
6. Steps 1 to 5 are repeated, with weight updates occurring after each batch of data is processed.
7. Upon completing this process, one epoch concludes; additional epochs are executed to enhance model training.

Each layer possesses its own biases and weights, and the computations along with the application of activation functions for each layer are described in Equations (3) to (7):

$$h_i^{(1)} = f^{(1)}\left(\sum_j w_{ij}^{(1)} X_j + b_i^{(1)}\right) \quad (3)$$

$$h_i^{(2)} = f^{(2)}\left(\sum_j w_{ij}^{(2)} h_j^{(1)} + b_i^{(2)}\right) \quad (4)$$

$$h_i^{(3)} = f^{(3)}\left(\sum_j w_{ij}^{(3)} h_j^{(2)} + b_i^{(3)}\right) \quad (5)$$

$$h_i^{(4)} = f^{(4)}\left(\sum_j w_{ij}^{(4)} h_j^{(3)} + b_i^{(4)}\right) \quad (6)$$

$$y_i = f^{(5)}\left(\sum_j w_{ij}^{(5)} h_j^{(4)} + b_i^{(5)}\right) \quad (7)$$

In this context, y_i represents the prediction, W denotes the weight, f is the activation function, and $h_i^{(N)}$ are the units in the N-th hidden layer. The input data are denoted by X_j. The rectified linear unit (ReLU) is employed as the activation function across four hidden layers, as described by Equation (8):

$$f(X) = max(0, X) \quad (8)$$

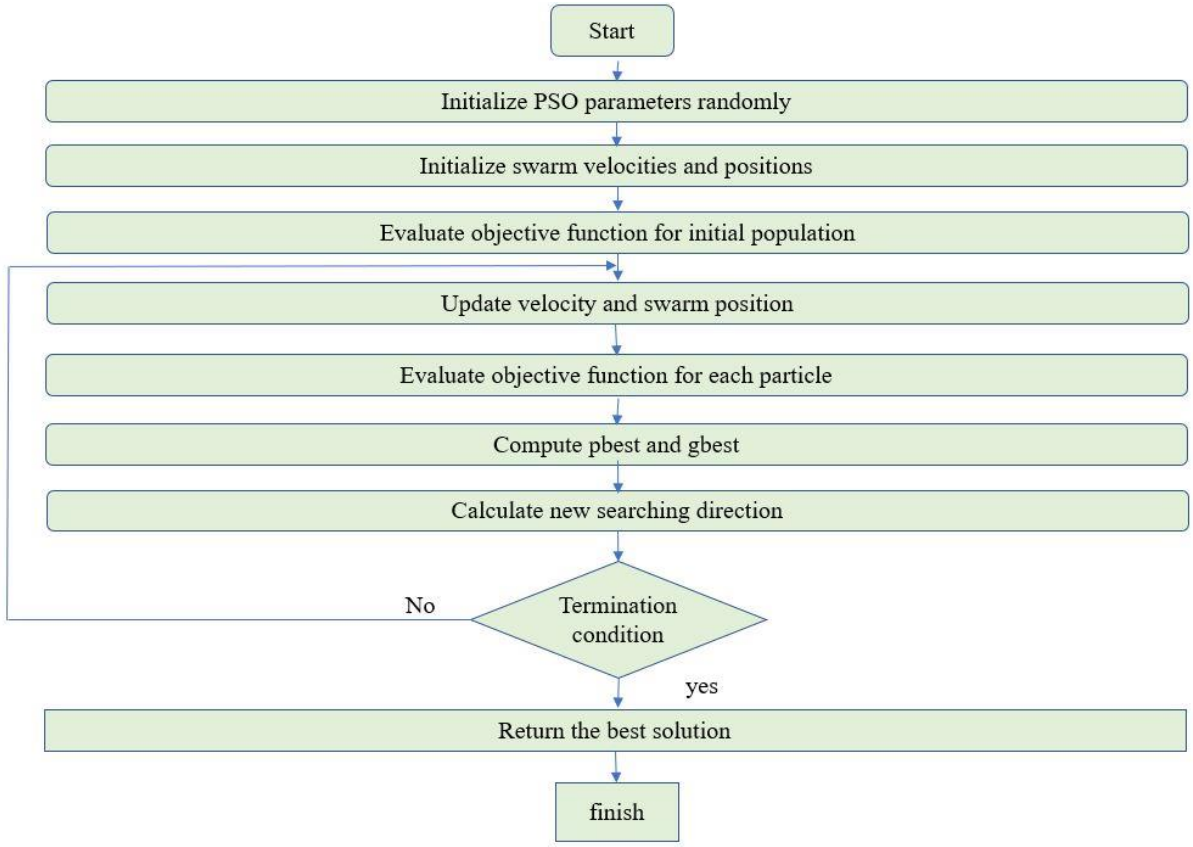

Figure 1. Flowchart of the PSO.

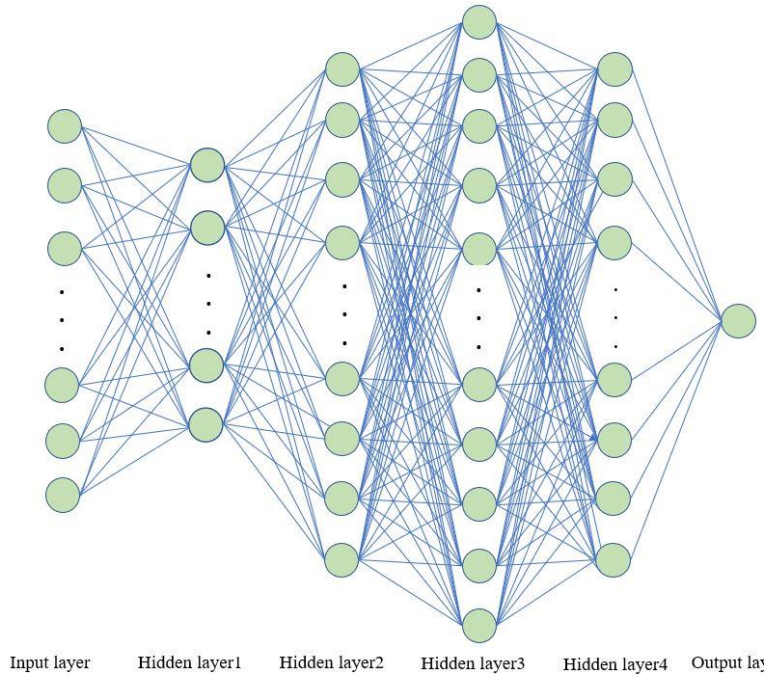

Figure 2. DNN Structure.

This study addresses a binary classification problem; hence, the sigmoid function is used as the activation function for the output layer. The formulation of the sigmoid is given in Equation (9):

$$f\,(X)\ =\ \frac{1}{1\ +\ e^{-X}} \tag{9}$$

Backpropagation is utilized to update the weights in order to minimize the loss function. This process involves comparing the probabilities of the actual values with the predicted values to reduce the cost function and enhance the performance of the DNN model. The cost function used here is the cross-entropy function, formulated as shown in Equation (10).

$$Cost\ =\ -\frac{1}{m}\sum_{i=1}[\,\bar{y}_i\ log\ (y_i)\ +\ (1\ -\ \bar{y}_i)\ log\ (1-\ y_i)] \tag{10}$$

A DNN was chosen in this paper because of its high capacity to model complicated and non-linear inter-dependencies between a number of physiological variables. The parameters of urine analysis are frequently interrelated, as well as non-linear relationships that may not be successfully represented by classical machine learning models. The multi-layer structure of DNN can realize the feature learning in a hierarchical manner, to automatically learn informative representations from the input data and enhance classification.

PSO was selected as the hyperparameter tuning methodology due to its ease of use and context as an effective global optimizer for continuous problems. Contrary to gradient-based optimizers or exhaustive searches, PSO does not use an explicit gradient and can thus easily escape from local optima through a population-based search. PSO has been shown to be an effective optimization strategy for determining deep learning hyperparameters in medical/health applications, especially in the case of a complex and non-convex search space.

The combination of DNN and PSO can make use of the prediction ability of deep learning and the global searching ability of PSO, which helps to achieve better model performance with stability rather than singular deep learning or classical optimization methods.

3.4. Evaluation Metrics

Various metrics can be used to assess a machine learning model, and some of them are outlined below:

$$Precision\ =\ \frac{TP}{TP\ +\ FP} \tag{11}$$

$$Recall\ =\ \frac{TP}{TP\ +\ FN} \tag{12}$$

$$Accuracy\ =\ \frac{TP\ +\ TN}{TP\ +\ TN\ +\ FP\ +\ FN} \tag{13}$$

$$F1-score\ =\ \frac{TP}{TP\ +\ \frac{1}{2}(FP\ +\ FN)} \tag{14}$$

A true positive (TP) occurs when a model correctly predicts a positive outcome. In contrast, a true negative (TN) occurs when the model accurately predicts a negative outcome. False positives (FPs) happen when the model predicts a positive outcome incorrectly, and false negatives (FNs) occur when the model incorrectly predicts a negative outcome.

A confusion matrix is a widely used tool in machine learning for assessing the accuracy of a classification model.[24] It displays a table of the model's predictions against the actual outcomes in a dataset, divided into four quadrants: TP, TN, FP, and FN.[24] By examining these values, we can calculate metrics like accuracy, precision, recall, and the F1 score, which offer a comprehensive insights into the model's performance across various classes. The confusion matrix is a valuable diagnostic tool that helps identify areas where the model performs well or needs improvement, thereby guiding refinement and optimization efforts.[25]

3.5. Confidence Interval

The confidence interval is a statistical technique used to quantify and assess the uncertainty associated with a prediction. It helps evaluate the predictive model's performance and improve its robustness. The width of the confidence interval indicates the accuracy of the assessment: a narrower interval provides a more accurate measurement. Equation (15) calculates the margin of error for the model's accuracy and error.

$$W\ =\ Z\ \times\ \sqrt{\frac{P\ \times\ (1\ -\ P)}{n}} \tag{15}$$

$$W\ =\ Z\ \times\ \sqrt{\frac{R\ \times\ (1\ -\ R)}{n}}$$

Here, W represents the radius of the confidence interval, n denotes the sample size, R stands for the error, P signifies accuracy, and Z corresponds to the standard deviation value derived from the Gaussian distribution.

4. Results

Out of 400 patients referred to the clinic, 281 (70.3%) were women and 119 (29.7%) were men. Table 1 shows the In this section, we propose conducting exploratory data analysis (EDA) to gain insights into the variables and their relationships. Subsequently, a predictive model will be trained based on these insights.

4.1. EDA

Certain analyses are performed to reveal the relationships between factors, aiding decision-makers. This information helps them make informed choices and develop effective strategies.

The correlation matrix of the urine analysis variables is presented in Figure 3. The results indicate a significant positive relationship between osmolarity and urea concentration, osmolarity and conductivity, specific gravity and osmolarity, as well as specific gravity and urea concentration. These relationships are physiologically relevant, as urinary concentration and ion composition are directly related to the propensity for kidney stone formation.

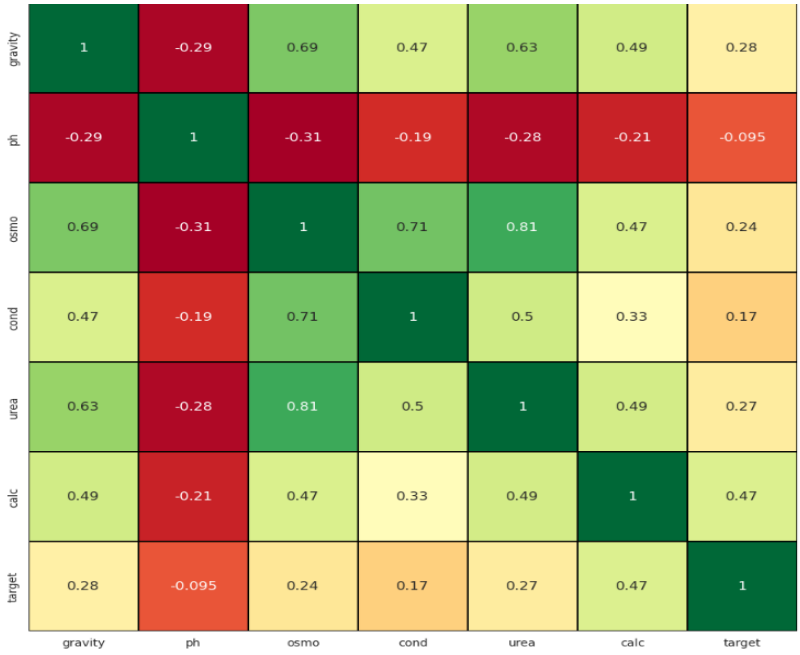

Figure 3. Correlation Analysis.

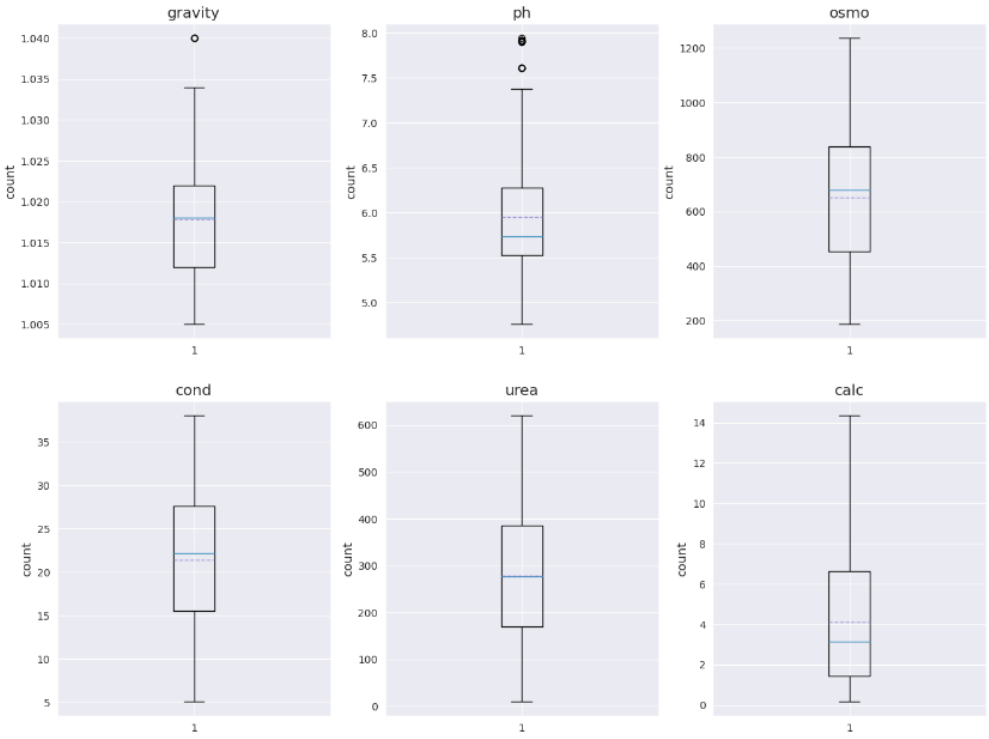

Figure 4. Correlation Analysis.

The distribution of the variables from urine analysis methods is shown in Figure 4 through boxplots. The dots indicate the existence of outliers, especially in specific gravity and pH. It is important to identify such outliers for training a robust model, and preprocessing for prediction modeling was conducted.

4.2. Deep Learning Model

After examining how certain variables relate to kidney stones, the predictive model was developed using the independent variables. This process involved applying various preprocessing techniques to the dataset, which was then divided into a training set and a test set, with 80% of the data allocated to the training set and 20% to the test set.

Some classification algorithms are employed to build the machine learning and deep learning models, and the outcomes are presented in Table 2.

Furthermore, in Table 3, the DNN is evaluated based on the other metrics.

Table 2. Evaluation's Outcome and Algorithms Comparison

Algorithm	Accuracy (%)
Logistic regression	78.31
Decision Tree	83.3
K-Nearest Neighbors	89.5
XGBClassifier	85.6
Gradient Boosting	84.1
DNN	96.4
DNN + PSO	98.1

Table 3. Evaluation Results for DNN

Class	Metrics		
	Precision (%)	Recall (%)	F1-score (%)
Positive	98.2	98.4	98.3
Negative	96.9	97.8	97.3

Additionally, a feature importance analysis is performed to identify the influence of each variable on the kidney stone variable following the model training. The findings are displayed in Figure 5.

The radius of the confidence interval for the DNN and PSO model is determined using Equation (15) to achieve more reliable results. Four standard significance levels can be chosen to enhance the robustness of the predictions. The results are presented in Table 4.

Confidence interval analysis provides insight into the reliability and robustness of the proposed DNN-PSO model. From Table 4, it can be observed that even at a 99% significance level, the lower bound of the accuracy remains above 94%, meaning that the model maintains its strong predictive performance under different confidence levels. The relatively narrow confidence interval reflects low variability in prediction accuracy, indicating that the performance of this model is stable and not highly sensitive to fluctuations in sampling. This provides further support for the reliability of the proposed approach for predicting kidney stones using urine analysis data.

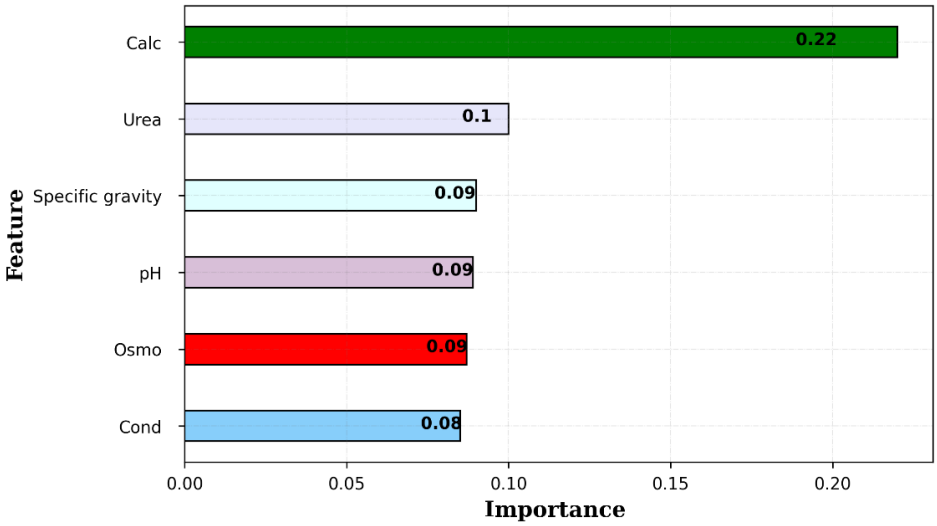

Figure 5. Feature Importance.

Table 4. Confidence Interval Radius

Significance Level (%)	Z	Radius (%)	Accuracy Range (%)
90	1.64	2.5	(95.6, 100)
95	1.96	3.01	(95.09, 100)
98	2.33	3.57	(94.53, 100)
99	2.58	3.96	(94.14, 100)

5. Discussion

These results establish the pragmatic use of machine learning techniques for early prediction of kidney stones, leveraging biochemical and physical parameters through

urine. The deep learning model proposed in this study, optimized with PSO, provided an accuracy of 98.1%, which outperformed several traditional machine learning classifiers such as logistic regression, decision trees, k-nearest neighbors, and gradient boosting. This performance improvement underscores the benefit of combining deep learning with metaheuristic optimization for the purpose of hyperparameter tuning.

Comparative studies to previous works show that the performance of the proposed approach is competitive and, in many aspects, superior. For instance, Abraham et al.[12] reported an accuracy of 91% using XGBoost for kidney stone composition prediction, while that of Shabaniyan et al.[14] was 94.8% using Fisher's Discriminant Analysis. Deep learning approaches based on imaging have also been associated with high accuracy, ranging from 85% to 95%; however, such methods are computed tomography image-based, which is costly and exposes patients to radiation. The present study is solely based on data from routine urine analysis; hence, it is non-invasive, low-cost, and accessible.

The feature importance analysis shows that kidney stone prediction depends significantly on urine-related parameters, such as urea concentration, osmolarity, and specific gravity. These findings are in tune with the literature, in which abnormal urinary concentration and composition are known to lead to the formation of stones. The positive correlation among urea concentration, osmolarity, and conductivity also justifies the physiological relevance of the selected features, thereby reinforcing the validity of the proposed model.

These findings have immense implications from the clinical perspective. The identification of kidney stone risk early and with a great degree of accuracy allows healthcare providers to implement certain prevention strategies, which include modifications to diet, hydration management, and closer clinical monitoring. These may minimize the painful episodes of passing stones, reduce the chances of developing serious complications such as urinary tract infections or damage to the kidneys, and decrease the need for emergency interventions and hospitalizations. Moreover, the use of routine laboratory data makes the proposed approach suitable for large-scale screening and integration into clinical decision support systems.

Despite these promising results, an important limitation must be acknowledged. The investigation was performed only on a limited set of urine analysis features. The inclusion of additional clinical variables, such as age, body mass index, diet, and genetic background may lead to further improvements in the performance.

6. Conclusion

Kidney stone disease places a significant burden on the healthcare system and impairs patients' quality of life. Herein, various urine-based biochemical and physical parameters were analyzed to identify their relationship with kidney stone formation; further, a deep neural network optimized with the PSO algorithm was developed to propose a predictive model.

The proposed DNN–PSO model showed the best performance with an accuracy of 98.1%, well ahead of most machine learning algorithms. Thus, it is established that routine urine analysis data can effectively be used for early and accurate predictions of kidney stones, eliminating the need for expensive or invasive diagnostic techniques. It also underlines the importance of factors such as urea concentration, osmolarity, and specific gravity in assessing the risk of kidney stones.

From a practical point of view, this approach opens up possibilities for the early identification of at-risk persons, enabling timely preventive measures that may possibly reduce complications, hospitalizations, and related healthcare costs. Given that laboratory data are widely available, this model has strong potential for integration into clinical decision support systems. Validation using much larger and more diverse datasets and including additional clinical features will be part of further enhancement of both predictive performance and generalizability.

Research Highlights

What Is Already Known?

- Kidney stones significantly raise healthcare expenses and lower workforce productivity.
- Kidney stones lead to reduced productivity and quality of life, affecting both individuals and the broader economy.

What Does This Study Add?

- The proposed DNN–PSO model showed the best performance with an accuracy of 98.1%, well ahead of most machine learning algorithms.
- Routine urine analysis data can effectively be used for early and accurate predictions of kidney stones, eliminating the need for expensive or invasive diagnostic techniques.

Author Contributions

Authors contributed equally to this work.

Conflict of Interest Disclosures

All authors declared that they have no conflict of interest.

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