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StackSHAP for the Explainability and Prediction of Urinary System Diseases

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ABSTRACT

Different urinary tract conditions often exhibit overlapping symptoms such as a strong urge to urinate, burning sensations, abnormal urine output and fever, making diagnosis and treatment challenging and time-consuming. Traditional diagnostic methods are inefficient, time consuming, expensive to practice and involve the use of a domain expert and finally increase the rate of immortality for those affected. Additionally, a significant issue with AI models is their black-box nature making it difficult for a reliable and trustworthy AI system. Therefore, this study proposed a StackSHAP dependable AI machine learning models to predict two urinary system diseases: acute nephritis of the renal pelvis (ANRP) and inflammation of the urinary bladder (IUB). StackSHAP values are used to address the black-box nature for interpretability. StackSHAP tools are employed to demystify the model, providing transparency and identifying key features influencing predictions. Additionally, this paper handled the issue of the data imbalance by employing support vector machine synthetic minority over-sampling technique (SVMSMOTE) is employed.

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Additionally, our work is investigated with twelve different machine learning techniques and checkmated with various evaluation metrics, thereby achieving an excellent prediction score across the evaluation metrics. This proposed model ensures the ethical adoption in healthcare by addressing transparency, casuality and interpretability in urinary disease diagnosis, thus providing valuable insights and making our study clinically relevant.

Keywords: StackSHAP, interpretability, Machine learning, urinary system diseases, acute nephritis, urinary bladder inflammation.

1. INTRODUCTION

The urinary system maintains the body's chemical balance by filtering waste products from the blood and producing urine to expel them from the body [1]. The urinary system primarily consists of the kidneys, the bladder, and the urethra. Renal pelvis is a funnel-shaped structure located in the kidney, which transmits urine to the ureter, and its infection causes acute nephritis of renal pelvis [2]. The indicated symptoms of acute nephritis of renal pelvis were nausea, abnormal urination, and fever were observed [3]. The inflammation of urinary bladder, known medically as cystitis, is usually caused by a bacterial infection and is associated with bad habits and improper cleaning. Generally, the simple case of cystitis typically presents with a low-grade fever, painful urination with a burning sensation [4]. However, similar symptoms may also occur in other diseases of the urinary system, which increase the difficulty of diagnosis. Traditional diagnosis of urinary diseases often relies on bacterial culture and elective procedures such as ureteral intubation, which are not only expensive and bring patients uncomfortable experience, but also a longer diagnosis time may lead to prolonged symptoms and even more serious conditions [5] – [6].

Relevant researches on machine learning models for the two urinary diseases, namely: acute nephritis of renal pelvis (ANRP) and inflammation of urinary bladder (IUB). Dzuho et al., [1] applied artificial neural networks, emphasizing the model's high accuracy. Kahramanli et al., [6] employed a back propagation algorithm with adaptive learning coefficients, achieving an accuracy of 95%. Rosly et al., [7] analyzed the performance of various classifiers like SVM and KNN, achieving 98% accuracy, although the model faces overfitting issues. Lango et al., [8] proposed multi-class and feature selection extensions of roughly balanced bagging for imbalanced data, achieving 94% accuracy. Linusson et al., [9] introduced conformal prediction, achieving 93% accuracy. Additionally, Guo et al., [10] focused on logistic discrimination for imbalanced learning, achieving 92% accuracy, but lacks external validation. Further research by Lochotinunt et al., [11] implemented ML models for the prediction of the two diseases, achieving high accuracy rates, and finally, Ros et al., [12] compared different ML approaches, and the LogitBoost achieved the highest accuracy of 97%. These studies demonstrate significant progress in the medical diagnosis of the acute inflammation using ML models, but they generally lack a focus on interpretability and transparency, which is crucial for clinical applications.

The main contributions of this paper include:

- The novel StackSHAP for the prediction and interpretability of the urinary disease diagnosis. This proposed model helps to demystify the black-box nature of ML models, offering transparency and understanding of how individual features impact predictions.
- Employing technique to handle the issue of imbalance dataset by generating synthetic samples near the decision boundary, enhancing the training dataset's balance and improving model performance.
- By incorporating StackSHAP values, this study not only achieves high accuracy but also ensures ethical adoption of AI in healthcare.

The transparency provided by StackSHAP values allows for better understanding and trust in the diagnostic models, which is crucial for their acceptance and use in real-world clinical settings.

The subsequent sections of this study are organized as follows: Section 2 provides the materials and methods employed for the proposed framework. Section 3 presents the experimental results and analysis, and lastly Section 4 provides the conclusion, limitation and future trends.

2. MATERIAL AND METHODS

2.1. Dataset Description

The UCI repository acute inflammatory dataset [13] is gotten from 120 patients with six features and two prediction classes if diagnosed with IUB or ANRP diseases. ANRP case has 50 patients were diagnosed with nephritis (Class1) and 70 without nephritis (Class 0) whereas for the IUB case, 59 patients are diagnosed with inflammation (Class 1) and 61 without inflammation (Class 0). The data is cleaned and has no missing values, noise and outliers. Table I displays the detailed data attributes, and it should necessary to be noted that this study employed all attributes from the original dataset for a good accuracy prediction.

2.2. Model Architecture

For the prediction of the proposed StackSHAP, we have employed twelve different ML models for the classification of IUB and ANRP by ensuring a strong comparison and highlighting the strengths and weaknesses in predicting urinary diseases. These models were optimized in order to achieve a good prediction performance and they include: support vector machine (SVM), k-nearest neighbors (KNN), decision tree (Tree), quadratic discriminant analysis (QDA), extreme gradient boosting (XGBoost), light gradient boosting (LGB), voting, bootstrap aggregating (bagging), adaptive boosting (AdaBoost), gradient boosting decision tree (GBDT), random forest (RF) and stacking.

2.3. Dataset Balance

It is observed that ML model encounter issues of underfitting and overfitting, therefore, to alleviate this issues and biases in the datasets, this study balances the dataset by generating new synthetic samples by adopting the vector machine SMOTE technique. This approach generates synthetic samples to increase the number of minority class samples to balance the dataset. More so, this research employs data normalization to ensure both the original and synthetic samples conform to the same data distribution, which is vital for distance-based algorithms such as KNN and SVM to efficiently and effectively learn from the data.

Table 1. Dataset Description.

Parameter Name	*Attribute Description*	*Type*	*Domain*	*Symbol*
Temperature	Temperature of patient	Numeric	$35^{o}C$ - $42^{o}C$	a1
Nausea	Occurrence of nausea	Nominal	yes, no	a2
Lumbar_pain	Lumbar pain	Nominal	yes, no	a3
Urine_pushing	Urine pushing	Nominal	yes, no	a4
Micturition_pains	Micturition pains	Nominal	yes, no	a5
Bu_su_ic	Burning of urethra, itch, swelling of urethra outlet	Nominal	yes, no	a6
inf_uri_bladder	Inflammation of urinary bladder	Nominal	yes, no	d1
Inf_neph_pelv	Nephritis of renal pelvis origin	Nominal	yes, no	d2

2.4. Model Explainability

For model explainability, StackSHAP values are used to explain the contribution of each feature to the model's predictions. StackSHAP Plots such as waterfall, force, summary, dependence plots are used to provide insights into how the individual features impact the predictions. The proposed StackSHAP model presented in Figure 1 shows the full architectural design of our study for the prediction of the urinary disease. The process starts with the collection of the dataset, handling the data preprocessing steps such as imputation of missing values, dataset standardization, rescaling, and encoding. The data split ratio to validate our proposed model using both the 10-fold cross-validation and the 80%-20% train-test split. Thereafter, ten different machine learning models are applied to predict urinary disease, and the performance is evaluated using various metrics, such as accuracy, precision, recall, sensitivity, F1-score, specificity, ROC-AUC, and confusion matrix. More so, SHAP is applied to interpret the predictions made by the models, producing summary plots, dependency plots, force plots, and waterfall plots, which gives insights into the impact of each feature on the model's predictions.

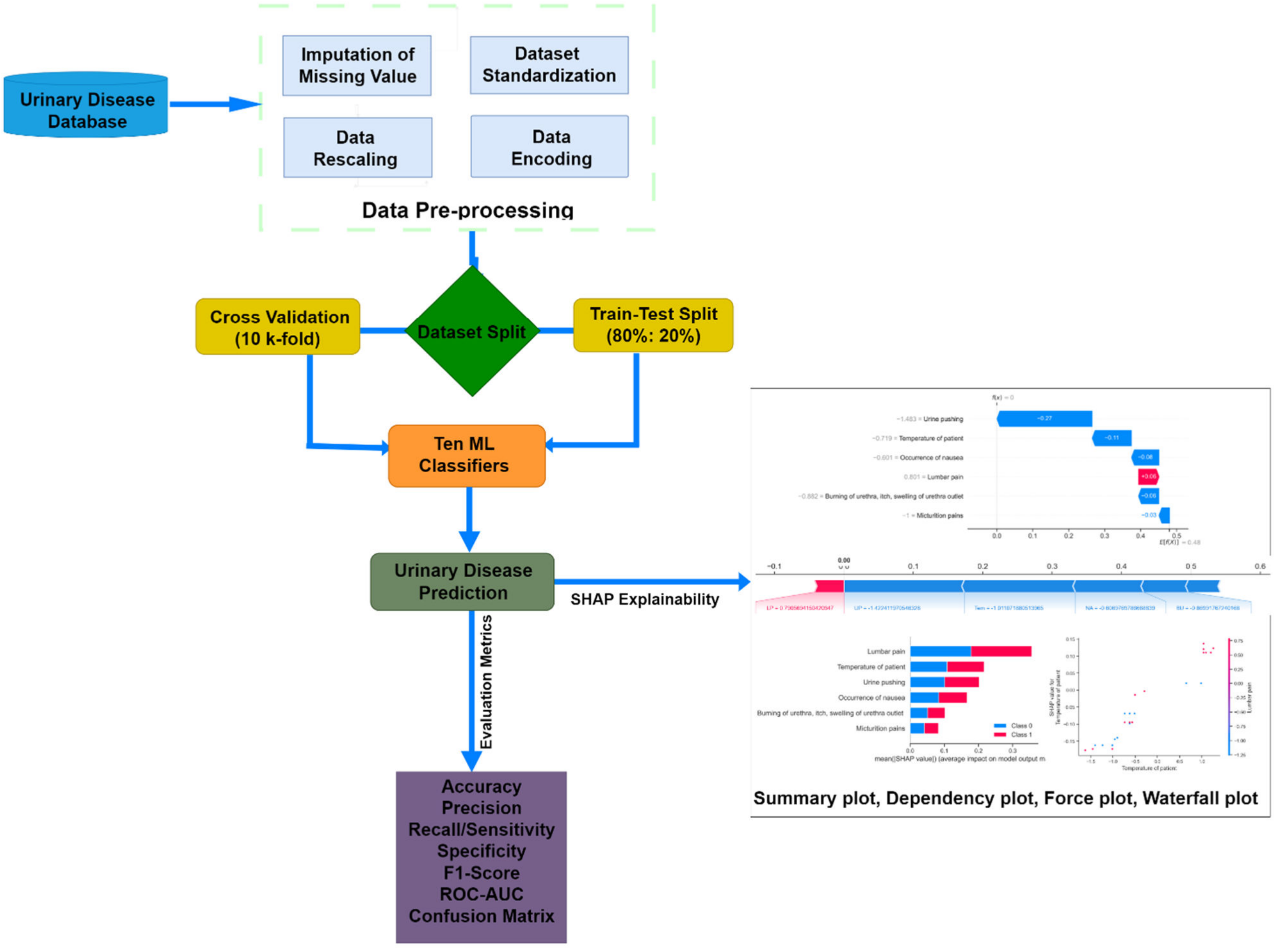

Figure 1. The Proposed StackSHAP Architectural Pipeline.

2.5. Dataset Split

In order to checkmate the proposed model performance, this study utilized both the train-test split and k-fold cross validation methods. For the train-test split, the data ration is set as 80% for training set and 20% for testing set. Additionally, the shuffle-split with 10-fold is used for cross-validation as nine subset is utilised for training set while the remaining one is for validation set.

2.6. Model Evaluation

In this study, we have employed standard evaluation metrics to checkmate the performance of our investigations, which include: accuracy, precision, recall, f1-score, ROC-AUC, cross-validation accuracy in Mean ± standard deviation, and confusion matrix. Their respective mathematically formulas are as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-score} = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

$$\text{ROC-AUC: } \frac{TP}{TP+FN} \text{ on y-axis \& } \frac{FP}{FP+TN} \text{ on x-axis} \tag{5}$$

$$\text{Confusion Matrix} = \begin{bmatrix} \text{TN} & \text{FP} \\ \text{FN} & \text{TP} \end{bmatrix} \tag{6}$$

Where TP, TN, FP, and FN represent true positive, true negative, false positive and false negative respectively.

2.7. Experimental Environment Setup

The model implementation for this research is carried out utilizing the necessary ML libraries from scikit learn and others, using the Python programming language, with a hardware configuration of 64GB RAM, 8GB GPU, and an 11^{th} Generation Intel Core I7-11800H Processor at 2.30GHZ on a Windows 11 OS.

3. RESULT AND ANALYSIS

3.1.Stackshap Interpretability For Anrp Prediction

StackSHAP summary plot in Figure 2, shows the impact of different features on the prediction of urinary disease classification. The features are ranked based on their mean SHAP value, indicating the relative importance of each feature. "Lumbar pain" is shown to have the highest impact on the prediction for Class 1 represented in red, followed by features such as "Temperature of patient" and "Urine pushing." Class 0 in blue has lower SHAP values for most of these features, implying they are more critical for identifying Class 1. Also, the StackSHAP dependency plot in Figure 3, explores how the "Temperature of patient" affects the model output for urinary disease prediction. The dots represent individual predictions, and their color gradient (from blue to pink) represents the feature "Lumbar pain." As the temperature increases, the SHAP value for the temperature also increases, demonstrating that higher temperatures positively contribute to the prediction, particularly when "Lumbar pain" is present, which is indicated by the pink points.

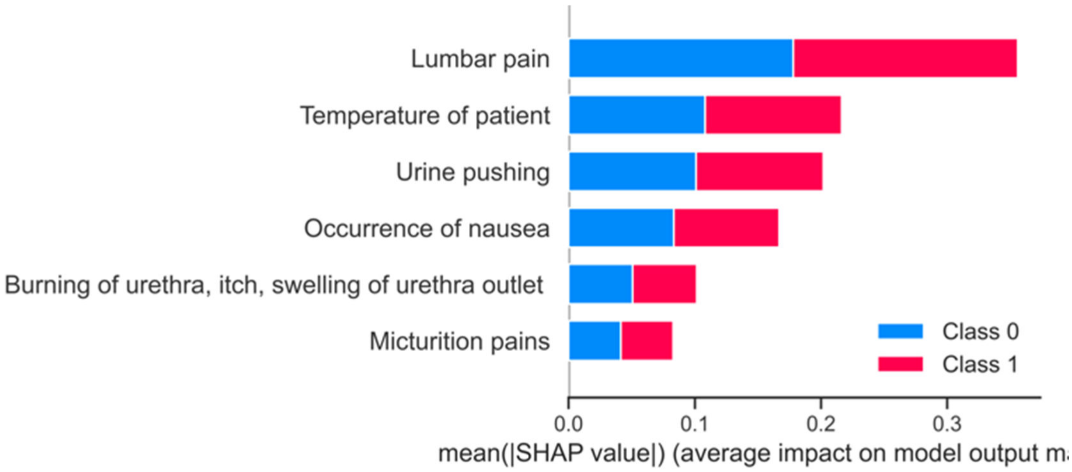

Figure 2. StackSHAP Summary plot for ANRP.

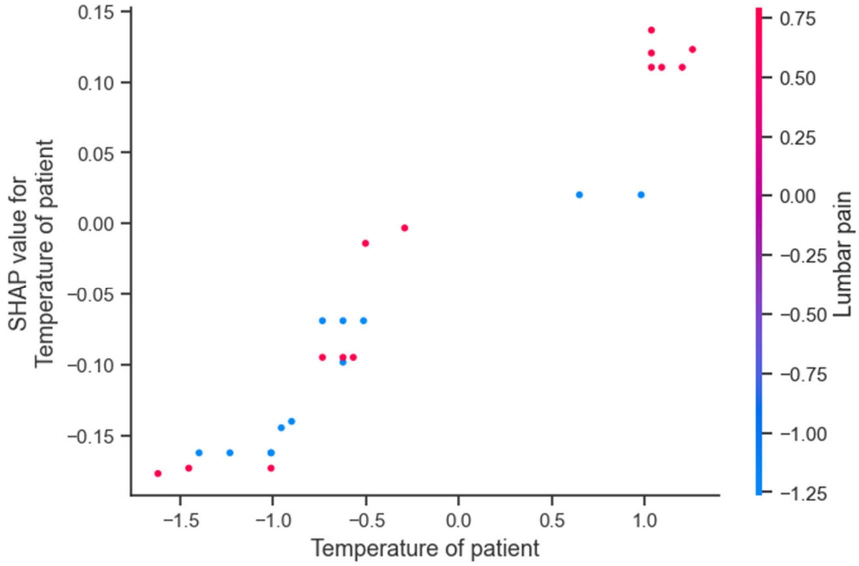

Figure 3. StackSHAP Dependency plot for ANRP.

Additionally, the StackSHAP waterfall plot in Figure 4 demonstrates how each feature contributes to the prediction for a specific instance. It breaks down the impact of "Urine pushing" and "Temperature of patient" which are negative contributions and "Lumbar pain" and other features which are positive contributions to the final predicted value.

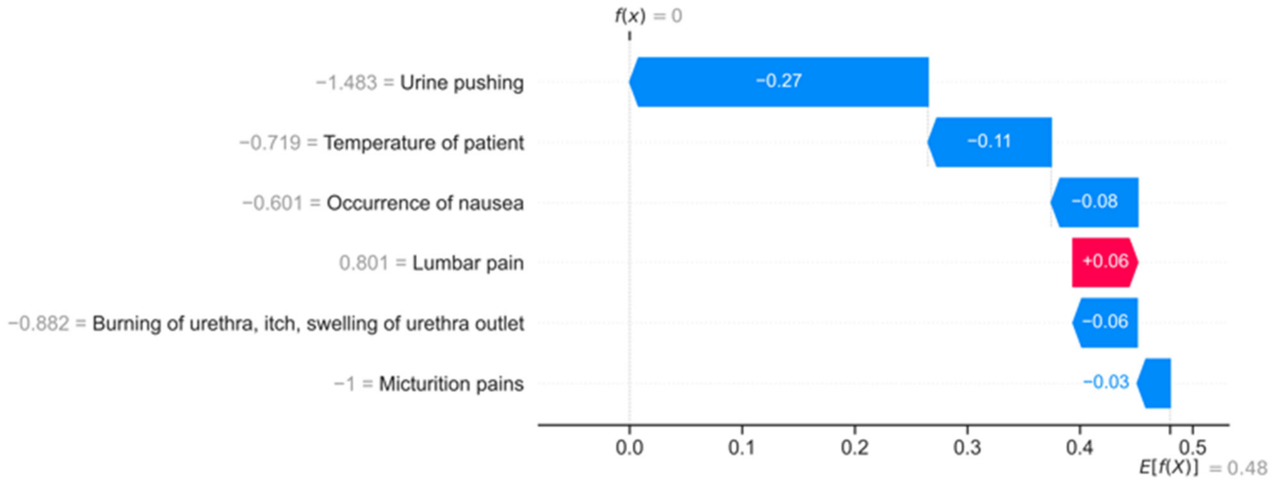

Figure 4. StackSHAP Waterfall plot for ANRP.

Lastly, the StackSHAP force plot in Figure 5 visually shows the cumulative effects of each feature—both positively and negatively—towards the final prediction. The "Lumbar pain" (LP) feature pushes the prediction towards Class 1, while others like "Urine pushing" (UP) and "Burning of urethra, itch, swelling" (BU) contribute less or negatively, helping explain the model's decision for the specific case.

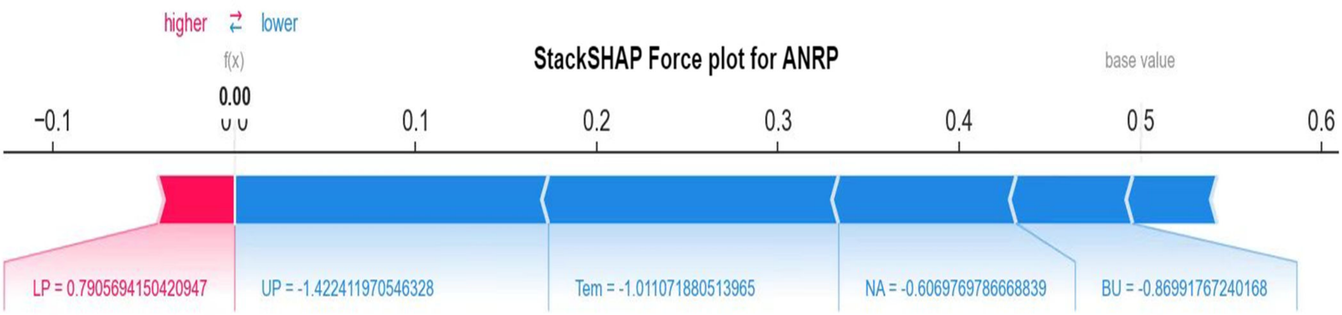

Figure 5. StackSHAP Force plot for ANRP.

3.2. Stackshap Interpretability For Iub Prediction

The StackSHAP summary plot in Figure 6 shows the average impact of each feature on the model output, separating contributions for Class 0 (in blue) and Class 1 (in red). "Urine pushing" has the most significant positive impact on Class 1 predictions, while features like "Lumbar pain" and "Occurrence of nausea" also contribute meaningfully to both class outcomes. Class 0's contributions are reflected mostly for "Urine pushing," with less impact from other features. Also, the StackSHAP dependency plot in Figure 7, analyzes the interaction between the "Temperature of patient" feature and the model predictions. The color represents "Urine pushing," showing a clear relationship where the SHAP values for "Temperature of patient" vary depending on the presence of "Urine pushing." High temperatures correlate with higher predictions for Class 1, particularly when "Urine pushing" is also present (represented in pink).

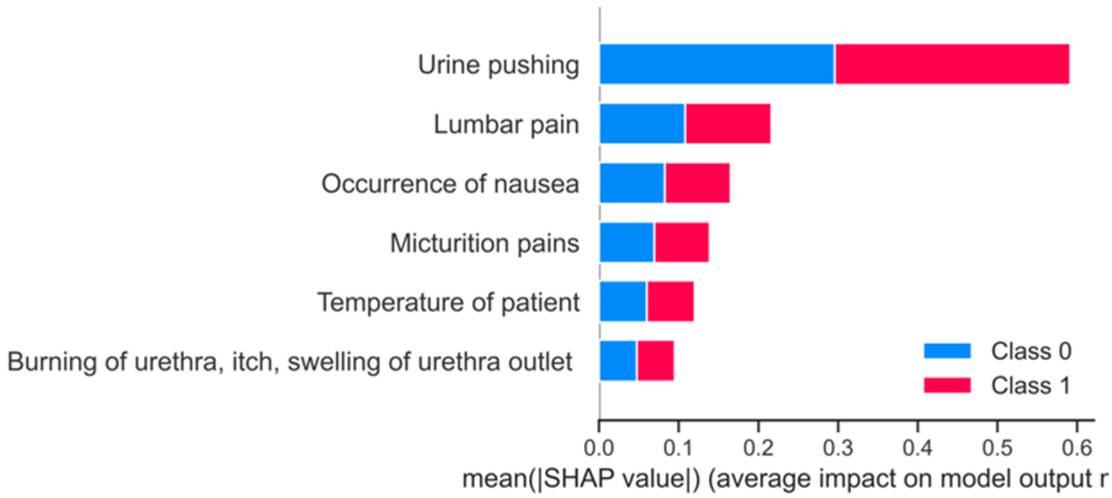

Figure 6. StackSHAP Summary plot for IUB.

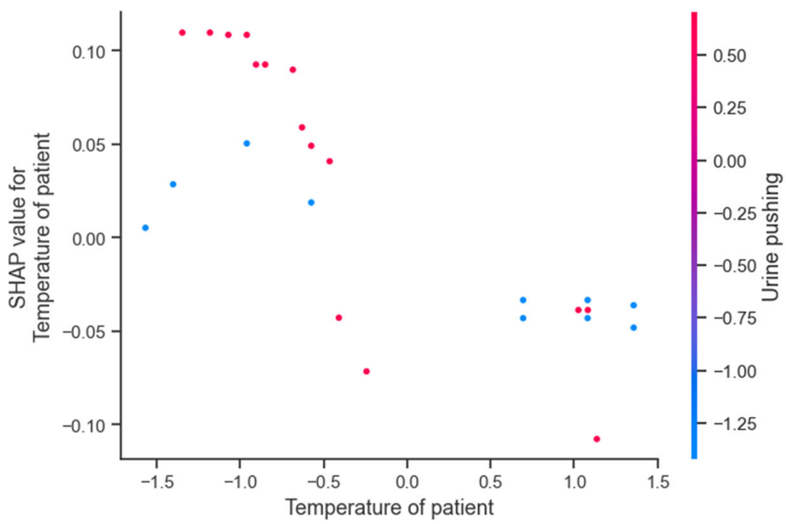

Figure 7. StackSHAP Dependency plot for IUB.

More so, the StackSHAP waterfall plot In Figure 8 explains how each feature pushes a specific prediction towards Class 1. "Urine pushing" and "Micturition pains" contribute significantly to pushing the prediction towards 1, while "Lumbar pain" and "Burning of urethra" have negative impacts, pushing the prediction towards 0. The individual contributions of the other features further explain the prediction dynamics.

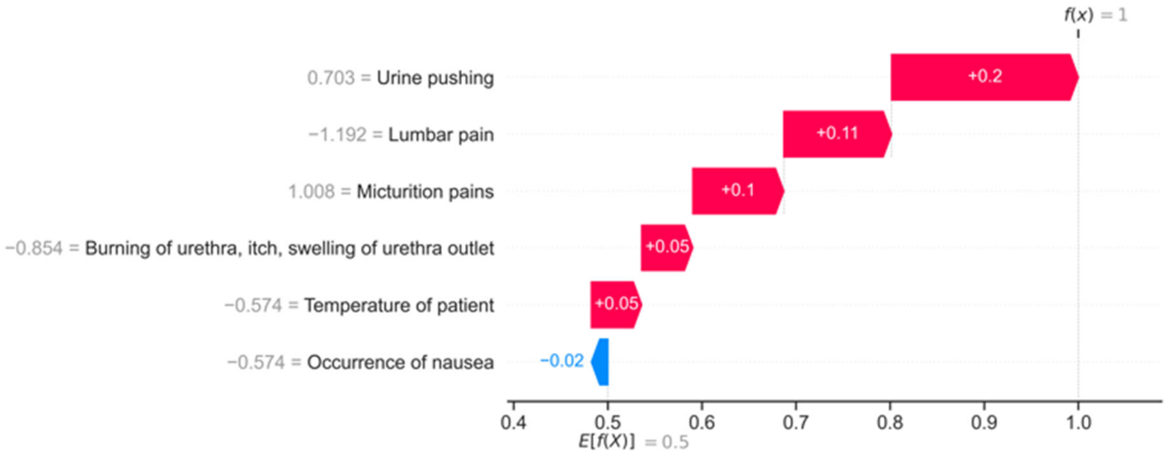

Figure 8. StackSHAP Waterfall plot for IUB Explainability.

Lastly, the SHAP force plot in Figure 9 breaks down the cumulative contributions of different features for a specific instance in the prediction process. "Burning of urethra, itch, swelling of urethra outlet" (BU) and "Urine pushing" (UP) negatively influence the prediction, while "Micturition pains" (MP) and "Lumbar pain" (LP) push the prediction towards Class 1. This visualization helps demonstrate how each feature's contribution interacts with the overall model output.

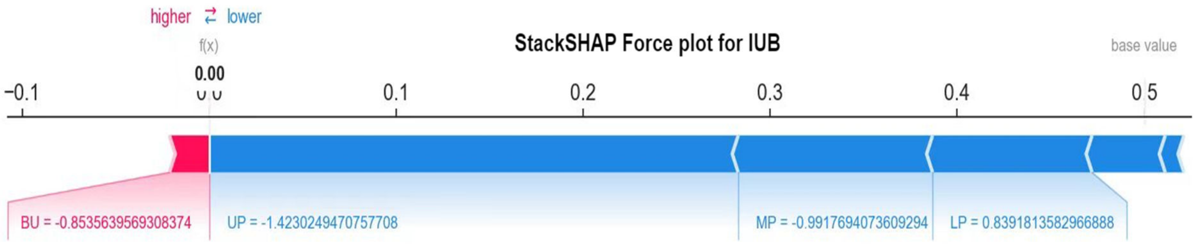

Figure 9. StackSHAP Force plot Interpretability for IUB Explainability.

3.3. Anrp Prediction Using Proposed Stackshap With Other Ml Classifiers

The proposed StackSHAP model outperforms all other machine learning classifiers in Table 2 based on different performance metrics achieving 100% across all metrics in accuracy, specificity, precision, recall, and F1-score, indicating that it perfectly classifies all instances with no negatives or false positives score. Additionally, it maintains consistent cross-validation accuracy of 100%, with a low standard deviation of ±0.00, which demonstrates its robustness and reliability across different subsets of the data. In comparison, while models like SVM, KNN, and QDA also achieve high individual performance, some have longer processing times (e.g., QDA taking 5.962 seconds) or lower CV-ACC values (e.g., QDA with 83.64 ± 13.36). The StackSHAP model, although requiring slightly more time (2.534 seconds), offers a balanced trade-off between computational efficiency and perfect prediction results, making it the most optimal model for ANRP (Acute Non-Responsive Pain) prediction in this comparison. The use of stacking combines the strengths of multiple classifiers, thus offering superior predictive performance and generalization over individual models.

Table 2. Anrp Performance Evaluation Metrics Using Stackshap With Other Ml Classifiers.

ML Classifiers	ACC (%)	SPE (%)	PREC (%)	REC (%)	F1-S (%)	Time (s)	CV-ACC (Avg ± std)
SVM	97.8	100	100	100	100	0.030	100 ± 0.00
KNN	99.89	100	98.90	100	99.20	0.013	100 ± 0.00
Tree	96.15	95.5	100	87.5	93.33	0.017	96.15 ± 0.00
RF	95.15	94.5	100	97.5	93.33	2.002	96.15 ± 0.00
QDA	100	100	100	100	100	5.962	83.64 ± 13.36
Voting	100	100	100	100	100	9.442	100 ± 0.00
Bagging	96.15	95.5	100	87.5	93.33	0.076	96.15 ± 0.00
AdaBoost	96.15	95.5	100	87.5	93.33	1.683	96.15 ± 0.00
GBDT	96.15	96.5	100	87.5	93.33	0.514	96.15 ± 0.00
XGBoost	96.15	96.5	100	87.5	93.33	0.023	96.15 ± 0.00
LGB	96.15	95.5	100	87.5	93.33	0.358	96.15 ± 0.00
Stack	100	100	100	100	100	2.534	100 ± 0.00

3.4. Iub Prediction Using Proposed Stackshap With Other Ml Classifiers

In Table 3, the StackSHAP model once again proves to be the most optimal classifier for IUB prediction when compared to other ML classifiers achieving perfect scores in all performance metrics of 100%. Additionally, the cross-validation accuracy remains in100% with zero variation, maintaining the model's consistency and generalization capability. Nevertheless, other models like KNN, SVM, and Random Forest perform well, with varied time efficiencies. For instance, the RF model takes 1.818 seconds, while StackSHAP takes slightly longer time of 2.215 seconds. Howbeit, the 100% perfect performance amongst all the evaluation metrics, makes StackSHAP the most dependable and robust model for IUB prediction. The little increase in computational time is an acceptable trade-off for its superior predictive power and interpretability, justifying it as the best model selected.

Table 3. Iub Performance Evaluation Metrics Using Stackshap With Other Ml Classifiers.

ML Classifiers	ACC (%)	SPEC (%)	PREC (%)	REC (%)	F1-S (%)	Time (s)	CV-ACC (Avg ± std)
SVM	100	99.80	100	100	100	0.030	100 ± 0.00
KNN	100	100	100	100	98.17	0.015	100 ± 0.00
Tree	100	100	100	100	88.89	0.012	100 ± 0.00
RF	100	100	100	100	88.89	1.818	100 ± 0.00
QDA	92	91.33	100	83.33	90.91	0.016	94 ± 4.90
Voting	100	100	100	100	100	4.009	100 ± 0.00

Bagging	100	100	100	100	88.89	6.565	100 ± 0.00
AdaBoost	100	100	100	100	88.89	0.023	100 ± 0.00
GBDT	100	100	100	100	88.89	1.521	100 ± 0.00
XGBoost	100	100	100	100	88.89	0.345	100 ± 0.00
LGB	100	100	100	100	88.89	0.184	100 ± 0.00
Stack	100	100	100	100	100	2.215	100 ± 0.00

Figures 10 and 11 display the AUC-ROC-AUC curves for ANRP and IUB predictions respectively and these curves evaluate the model's ability to differentiate between the negative and positive instances within numerous classification thresholds. Both curves in Figures 10 and 11 exhibit an AUC value of 1.000 representing a perfect model performance. AUC of 1.000 depicts that the model is capable to perfectly separate positive from negative classes with no false negatives or positives, showcasing optimal classifier behavior. The sharp curves seen around the top left corner further highlight this perfect performance, showcasing that the StackSHAP model is highly efficient and effective at making accurate predictions for both IUB and ANRP cases.

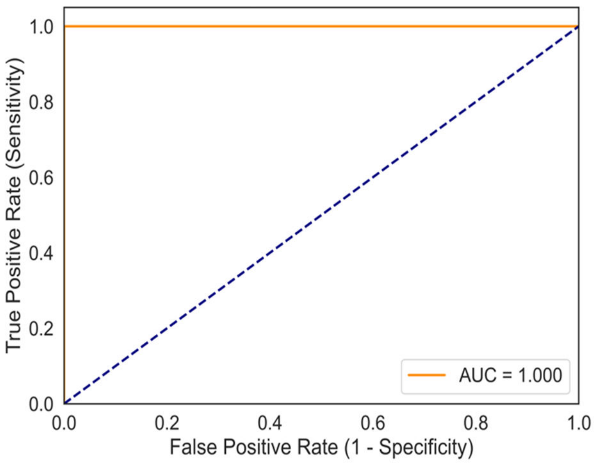

Figure 10. AUC-ROC Curve for ANRP Prediction.

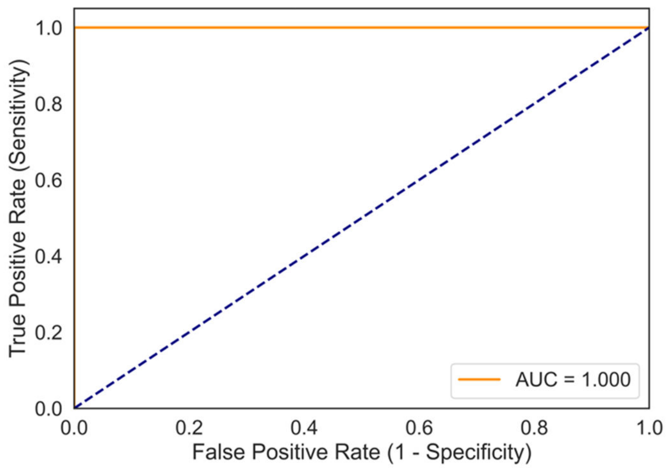

Figure 11. AUC-ROC Curve for IUB Prediction.

Figures 12 and 13 explain the confusion matrices for ANRP and IUB predictions, respectively. The confusion matrix summarizes the model performance by showcasing the following score for the true positives, true negatives, false positives, and false negatives. In Figure 12, the confusion matrix for ANRP shows 18 true negatives and 8 true positives, with zero false positives or false negatives. Likewise, in Figure 13, the confusion matrix for IUB reviews 13 true negatives and 12 true positives, again with zero errors. Furthermore, these matrices reinforce that the proposed StackSHAP model prediction accuracy is absolutely correct, thus achieving perfect classification for both conditions.

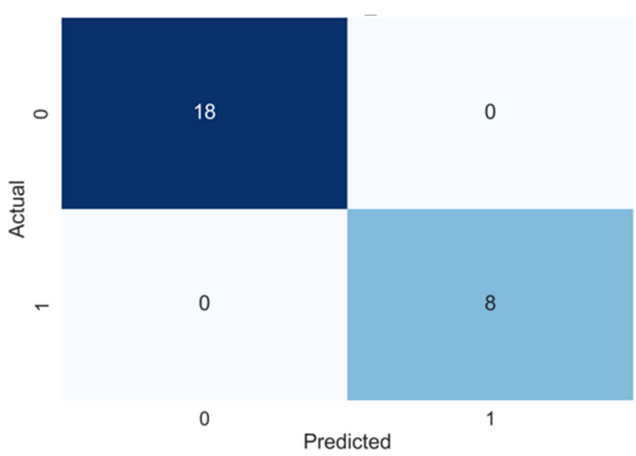

Figure 12. Confusion Matrix for ANRP Prediction.

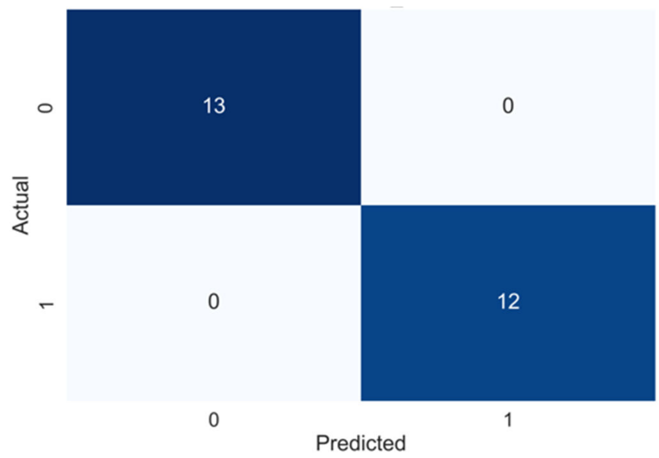

Figure 13. Confusion Matrix for IUB Prediction.

4. CONCLUSION AND FUTURE WORK

This paper proposes a StackSHAP model in predicting two critical urinary system diseases: Acute Nephritis of the Renal Pelvis (ANRP) and Inflammation of the Urinary Bladder (IUB). By investigating the StackSHAP model, we not solely achieved highly accurate predictions but also addressed the issue of the black-box nature of traditional AI models by providing interpretability and transparency making the system a dependable AI. The utilization of SHAP values permitted us to recognize and elucidate on the main features influencing each classifier's prediction, enhancing the trustworthiness of the AI system in a healthcare domain. Additionally, the SVMSMOTE was employed to handle the issue of data imbalance, which improved the model's performance and robustness amongst numerous evaluation metrics. Our proposed model significantly decreases diagnostic issues, contributing to faster, efficient, effective and dependable urinary disease detection. This proposed model offers a reliable AI-based technique, fostering ethical and clinically relevant implemented in healthcare settings by handling the vital factors of interpretability, transparency, and causality. Aside the amazing and promising results, our study comes with few limitations. First, the dataset applied to investigate the performance of the proposed model is relatively few, which may restrict the generalizability of the model to larger, more vastly populated cases. While the SVMSMOTE approach might address the issue of data imbalance, future advanced techniques may still benefit from richer datasets with larger range of urinary cases. More so, the current study focuses on two specific urinary diseases, IUB and ANRP, and did not consider how well the model might fit other related. Finally, as the StackSHAP values provide interpretability, the computational cost of the proposed model still remains higher than simpler models, which is likely to pose problems for real-time diagnostic applications in limited resources situations.

Future study will focus on extending the dataset by accommodating larger range of urinary system diseases, enhancing the model's generalization and robustness to more complicated scenarios. Integrating additional clinical data, like patient historical data or even genetic markers could further improve the diagnostic prediction accuracy and personalization. Additionally, incorporating the StackSHAP model into real-time clinical AI-based systems could aid healthcare experts with immediate and interpretable diagnostic assistance, especially in scenarios where access to medical professionals is limited or restricted. Future works will also analysis on optimizing the computational cost of the proposed model and making the model more implementable to real-time settings.

Lastly, further validation analysis including broader clinical trials and real-world deployment are required to ensure the fusion of both the ethical and clinical reliability of the model into existing clinical infrastructures.

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