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Coati Optimization Algorithm for Detecting Pediatric Kidney Abnormalities using Ultrasound Images

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Abstract

This study aimed to classify pediatric ultrasound images as normal or abnormal by identifying the optimal number of image texture features for analysis and developing an effective classification system using selected features. The experiment identified a successful feature selection and classification algorithm with a good performance. This study introduced a new approach for computer-assisted ultrasound image classification. Initially, a Gaussian median filter enhances the image quality and removes noise. For feature extraction, various features, including first-order derivatives, Gray Level Co-Occurrence Matrix (GLCM), Gray Level Run Length Matrix (GLRLM), Gray Level Dependence Matrix (GLDM), Gray Level Size Matrix (GLSZM), and Neighbouring gray tone difference matrix (NGTDM), were extracted using the Pyrandiomics Python package. The Coati optimization algorithm (COA) was employed as a feature selection technique. The Classification was performed using Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), K-nearest Neighbor (KNN), Naïve Bayes (NB), and Extreme Gradient Boosting (XG-Boost) algorithms. Therefore, this study proposed a new machine learning classifier, the Extreme Gradient Neighborhood classifier (XGNC), using NB, KNN, and XG-Boost, with a classification accuracy of 97.91%, which outperformed the other classifiers mentioned in the study. The results indicated that the optimal feature selection and classifier choice yielded the most accurate computer-aided diagnosis of kidney abnormalities.

Keywords: Coati Optimization Algorithm (Coa), Extreme Gradient Neighborhood (Xgnc), Feature Selection, Kidney, Machine Learning (Ml), Ultrasound (Us).

Introduction

Maintenance of good kidney health is a global priority. Kidney failure occurs when the filtering abilities of the kidneys decline, leading to the buildup of waste, fluids, and electrolytes in the body, often without notice until significant damage has already occurred. The early detection of renal abnormalities in children is crucial, and pediatric Ultrasound (US) imaging plays a vital role in achieving this goal (1). In the past decade, the affordability of ultrasound imaging relative to Magnetic Resonance Imaging (MRI) has driven its widespread adoption. US imaging is a prevalent diagnostic tool for identifying kidney abnormalities, including tumors, stones, and cysts (2). However, the interpretation of US images is challenging due to variability in radiologists' assessments (3). Research on ultrasound image-based computer-assisted diagnosis (CAD) systems has significantly intensified. CAD systems typically comprise four primary modules: pre-processing, feature extraction, feature selection, and classification. This study concentrates on the extraction and selection of features. The optimal feature set should include information that clearly distinguishes normal from abnormal images. The extracted features are commonly derived from texture, shape, and intensity. Considering the various feature extraction methods such as Gray level Co-Occurrence Matrix (GLCM) features, Gray level size zone matrix (GLSZM) features, Gray level run Length matrix (GLRLM) features, Neighbouring gray tone difference matrix (NGTDM) features and Gray level difference matrix (GLDM) features and First Order derivatives based on statistical descriptors, they remain among the top choices (4). Images, particularly US, possess an abundance of features from which only the relevant ones should be chosen to attain a specific objective. Furthermore, some characteristics that may be pertinent provide the same information, and are thus redundant (5). Considering irrelevant factors and, to a lesser extent, extraneous information can negatively impact the accuracy of image classification and the effectiveness of

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diagnostic procedures. The most effective way to improve classification is feature selection, where only the most significant features are selected. The aim of this approach is to remove unnecessary or irrelevant attributes, thereby improving the performance and efficiency of the model (6). According to recent studies researchers have concentrated on the combing machine learning, optimization algorithms to predict and diagnose kidney abnormalities as described in Table 1, while table describes the focus of the study, methodology used. Despite examining the literature review limited researchers have focused on capturing detailed spatial variation of the pixel intensity of the tissue in kidney that aid in the classification of kidney ultrasound images. Recent developments in artificial intelligence have highlighted the potential of metaheuristics for addressing optimization challenges, particularly in the field of medical image analysis. Utilizing artificial intelligence for feature selection can enhance the classification process and aid in diagnostic interpretation, especially when dealing with intricate features derived from ultrasound data. This research employs the Coati Optimization Algorithm (COA), which is inspired by the intelligent foraging behavior of coatis and has emerged as a leading swarm-based metaheuristic. It is renowned for its balanced approach to exploration and exploitation, coupled with minimal computational demands, making it highly efficient for feature selection (7). While COA has been utilized in several engineering and medical fields, its application in medical imaging, particularly for classifying pediatric renal ultrasounds, remains unexplored. This study marks one of the initial efforts to assess COA for radiomics feature selection within the realm of pediatric nephrology. The following research aims to recognize research gaps in ultrasound images classification using texture features. Many prior models have used a limited number of texture features to classify kidney abnormalities, and our work seeks to identify the most important factor that influence predictions and provide deeper insights into the underlying data that is the texture of the images.

Table 1: Existing Literature Review

Ref	Objective	Feature Extracted	Feature Selection	Methods	Contribution
(8)	Classify stages of CKD, Normal, mild, moderate	19 texture features (GLCM)	-	ANN	Developing a method that leverages texture analysis and Neural network for classification of CKD stages
(9)	Develop a method for detection and segmentation for kidney abnormalities	22 feature type from GLCM	CSA	ANN	Introduces a hybrid methodology using ANN and multi kernel k-means for segmentation and improved classification accuracy
(10)	Create an AI model employing DL to automatically detect pediatric kidney abnormalities	Using CNN	-	Resnet50	Develop an automated screening method for pediatric ultrasound images
(11)	Automated system for categorizing kidney ultrasound images using an ensemble model	Using CNN	-	ResNet 101, ShuffleNet, and MobileNet v2.	overcome the limitations of manual interpretation, which often lacks high accuracy
(12)	Developing a focused approach for extracting features from ultrasound images	GLCM	PCA	ANN	Categorize features in different classes that is normal kidney, kidney stone, cystic kidney, and kidney tumor

(13)	Classifying kidney US images using texture analysis	GLCM	grasshopper opposition optimization algorithm	Neural Network	Proposed an approach to extract and select optimal features for increasing the classification accuracy.
(14)	Novel classification approach for predicting and diagnosing chronic kidney disease	GLCM -22 type features	Oppositional grasshopper optimization algorithm	ANN	Developed a technique for classification of kidney disease in ultrasound to increase the classification accuracy.
(15)	Automatic feature selection and classification of kidney ultrasound images	first-order and second-order gray-level statistics, Gabor filters, DFT, and multiscale differential Gaussian features	Fruit Fly optimization algorithm	SVM and multilayer Perceptron	Early detection, segmentation and classification of CKD was presented using Internet of Medical Things(IoMT)

Our proposed method, the Coati Optimization Algorithm (COA) is used as feature selection technique, that helps to eliminate redundant features that lack significant value and enhance classification accuracy. We also aim to determine the best-performing machine learning model for the dataset, proposing a stacked-based ensemble model, the Extreme Gradient Neighborhood Classifier (XGNC), to classify kidney ultrasound images with improved accuracy. Additionally, we will evaluate the performance of our proposed approach against existing models. The main contribution of the paper is: A set of texture features were extracted from the kidney ultrasound images to characterize their texture and intensity properties, resulting in a total of 94 texture features. To identify the most effective feature among the 94 extracted features, a feature selection process utilizing COA was implemented. The goal was to minimize the feature subset, computational complexity and execution time while improving the classification accuracy during the use of the classifier. To assess the effectiveness of the chosen features, we employed six machine learning algorithms: Random Forest (RF), Decision Tree (DT), Naive Bayes (NB), XG-Boost, Support Vector Machine (SVM) and K-Nearest Neighbour (KNN). We developed an ensemble model called Extreme Gradient Neighborhood Classifier (XGNC) by combining the best and worst performing classifiers. This ensemble approach enhanced the classification accuracy of kidney US images.

The rest of the paper is structured as follows: Section 2 introduces the suggested approach; Section 3 showcases the results and discussion; and lastly, Section 4 concludes the paper.

Methodology

The methodology described in this paper for classifying pediatric US images of kidney relies on the extraction of texture and first-order derivatives using statistical measures. We employ the COA for feature selection to determine the most significant set of features. Our approach utilized 340 US images, as depicted in Figure 1, which illustrates the comprehensive process.

Data Acquisition and Pre-Processing

To evaluate the usefulness of the proposed method for classifying pediatric ultrasound images, a dataset comprised of 340 images, including both normal and abnormal images, was obtained from the publicly available repository (16). This study is mainly focused on pediatric kidney images from the age group of 3 weeks to 7 years old. After acquiring the images, preprocessing was conducted for image quality enhancement and noise removal. For this, a Gaussian median filter was used. For edge detection, a Sobel operator was employed. Additionally, background artifacts were removed, and the images were resized to a 225x225 size to ensure optimal preprocessing.

Feature Extraction

Features are defined as the relevant information that can be used to accomplish computing tasks related to a specific application. Various feature extraction algorithms are available, each with its own principles. Transforming an image into relevant features is crucial in image processing, allowing the extraction of characteristics like texture, shape, and color for further analysis, that are essential for effectively analysing and treating medical images (5). In this study, kidney US images features were extracted using first-order derivates and second order derivates (Gray Level Co-Occurrence (GLCM), Gray Level Run Length Matrix (GLRLM), Gray Level Dependence Matrix (GLDM), Gray Level Size Matrix (GLSZM), Neighboring Gray Tone Difference Matrix (NGTDM)). While, GLCM, provides information on the frequency with which a specific combination of pixel intensity values appears in an image. GLSZM is determined by tallying the count of regions comprised of interconnected pixels with consistent color values in any direction. GLDM calculates the number of pixels at a specific distance that is influenced by a particular shade of gray. NGTDM quantifies a pixel's average deviation from its neighbors' gray tones within a specified radius. First Order ignores spatial linkages and bases decisions only on the values of individual pixels. The extracted features help in identifying the abnormal patterns associated with the disease, identifying the irregular tissue texture, intensity and density while using the texture and statistical features. The Pyrandiomics, Python library, is crucial for extracting radiological features from medical images using texture and shape-based statistical methods and have been used to extract the features (17).

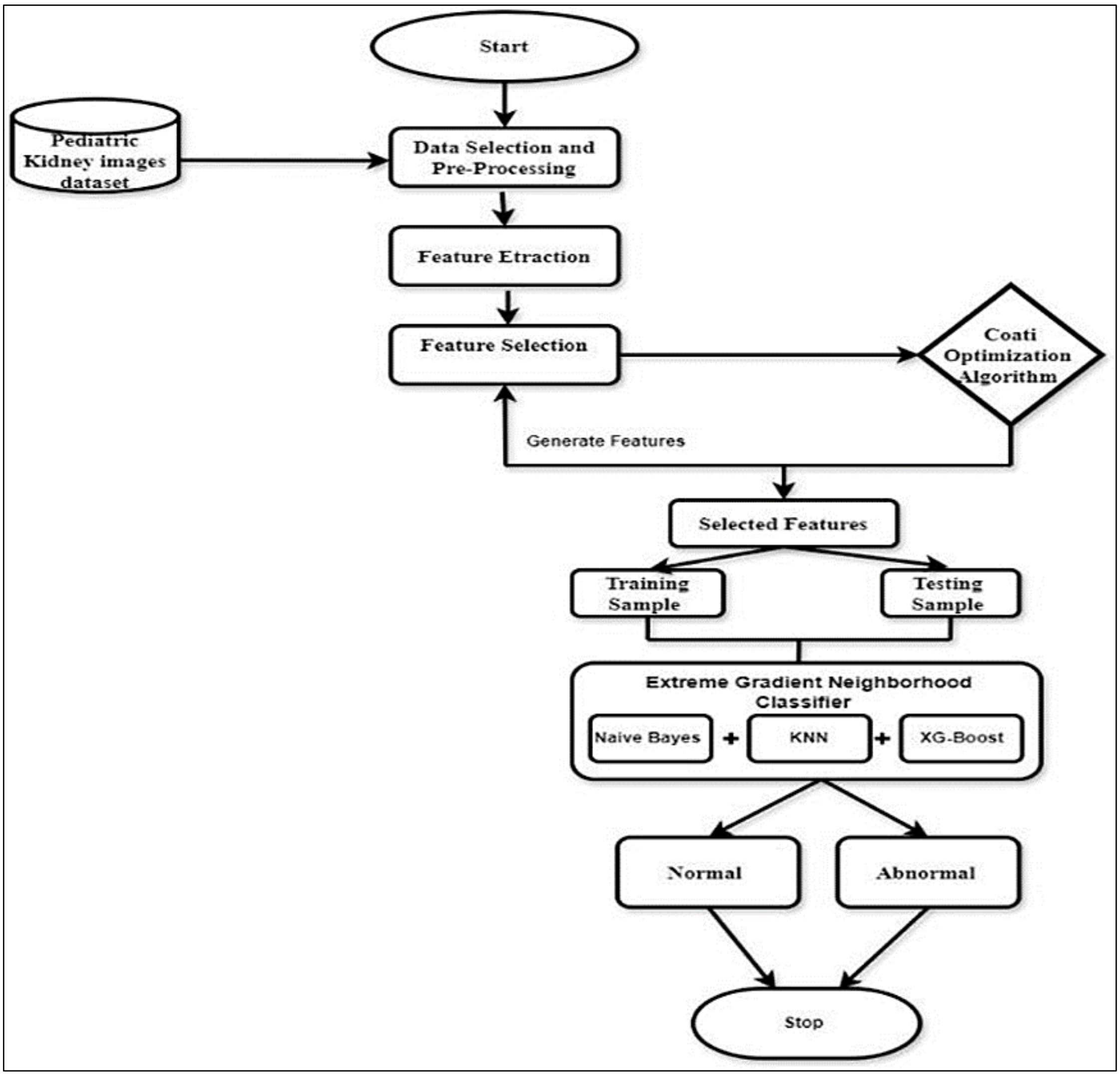


Figure 1: Overall Workflow of the Proposed Approach

Feature Selection

Feature selection (FS) seeks to identify the most significant features from the original 94-feature vector. FS aims to choose the smallest essential feature set to optimize classification accuracy (18). The COA is employed to identify the most relevant feature subset from the extracted texture and statistical features, enhancing the performance of the US paediatric kidney classification system. The COA is inspired by nightlife coatis in the United States. These animals were comparable to those of large domestic cats. Being omnivorous, coatis consume a variety of prey, including insects, small mammals, birds, reptiles, and alligator eggs. They use a combination of tactics to hunt for green iguanas. The COA replicates the intelligent escape and hunting techniques of coatis, reflecting their intelligent behaviour (19, 20).

During the COA Initialization Phase, each coati is designated to represent a population member. The position of each coati in the search space corresponds to the value of decision variable, which serves as a solution. Initially, the coati is randomly assigned according to the following Eq. [1]

$$X_i: x_{ij} = lb_j + r.(ub_j - lb_j), i = 1,2,\ldots\ldots,C, \quad j = 1,2,\ldots.,d \qquad [1]$$

where X_i denotes the position of the ith coati, x_{ij} represents the value of the jth decision variable, C is the total number of coatis, d is the number of decision variables, r is a random number in the interval [0,1], and lb_j and ub_j are the lower and upper bounds of the jth decision variable, respectively.

The population matrix$X$, representing coati positions, is defined in Eq. [2]:

$$X = \left(x_{1,1} \cdots x_{1,d} \vdots \ddots \vdots x_{C,1} \cdots x_{C,d}\right)_{C\times d} \qquad [2]$$

The objective function values for the different solutions are represented by the vector F, as shown in Eq. [3]:

$$F = [F_1 \vdots F_i \vdots F_C] = [F(X_1) \vdots F(X_i) \vdots F(X_N)]_{Nx1} \qquad [3]$$

In the first phase, COA uses the coatis' method of hunting iguanas. Coatis work together by raising trees to scare away iguanas, while others wait below to catch them. This approach allows for exploration, allowing coatis to search for prey around the world. Once the coati identifies an iguana, the group's behavior changes in climbing and waiting. A mathematical model of the climb can be found in Eq. [4].

$$X_{P1i}: x_{p1ij} = x_{ij} + r.\left(Iguana - I.x_{ij}\right), \ i - 1,2,\ldots.,\left[\frac{C}{2}\right], \ j = 1,2,\ldots,d \qquad [4]$$

The positions were updated based on the random placement of the fallen iguana, as outlined in Eq. [5] and [6], respectively.

$$Iguana: Iguana_{Gj} = lb_j + r.\left(ub_j - lb_j\right), \ j = 1,2,\ldots.,d \qquad [5]$$

$$X_{P1i}: X_{P1i} = \{x_{ij} + r.\left(x_{ij} - r.\left(Iguana.\left(x_{ij} - G_J.Iguana - I.x_{Gj,j}\right)\right)\right), \ if\ Iguana < F_i\, x_{ij} + r.\left(X_{ij} - Iguana_{Gj}\right), \ else \qquad [6]$$

If the new position results in an improvement in the objective function value, it will be accepted; otherwise, the coati will retain its previous position, as indicated in Eq. [7].

$$X_i = \{X_{P1i}, \quad if\ F_{P1i} < F_i\, X_i, \qquad [7]$$

Phase 2: Exploitation Through Predator Evasion

In the second phase of their behaviour, COA models simulate the actions of coatis when trying to evade predators. Coatis aim to locate new positions that are close to their current positions and seek safety in this manner. To capture this local search process, Eq. [8] and [9] were utilized.

$$lb_{localj} = \frac{lb_j}{t} \ , ub_{localj} = \frac{ub_j}{t} \ , t = 1,2,\ldots,T \qquad [8]$$

$$X_{P2i} = x_{p2i,j} = x_{ij} + (1 - 2r)\left(lb_{localj} + r.\left(ub_{localj} - lb_{localj}\right)\right), \quad i = 1,2,\ldots.,C, \quad j = 1,2,\ldots,d \qquad [9]$$

According to Eq. [10], If the new position results in a better value than the objective position, it will be accepted; Otherwise, the coati remains in its previous position.

$$X_i = \{X_{P2i}, \quad if\ F_{P2i} < F_i\, X_i, \qquad [10]$$

The COA algorithm goes through an iterative process involving the repositioning of all coatis in the search space during the first and second runs. This process, as expressed in equations [4] to [10], continues until the last iteration of the algorithm is completed. When the algorithm is completed, the best solution obtained from all the iterations is selected as the final solution. A comprehensive explanation of the specifics has been provided in the research paper (20).

Classification

The COA was used to create a subset of texture features, which are then used by several classifiers for kidney US image classification, such as XG-boost, KNN, SVM, DT, NB and RF. SVM is a supervised learning technique that forms a hyperplane in an N-dimensional space to classify data whose dimensions are equal to features. It classifies points by their location relative to this hyperplane, focusing on key features, SVM is advantageous in large data spaces, especially for texture analysis, and can accurately predict complex texture with proper regularization and its efficient with small dataset. Naïve Bayes (NB) is a likelihood- based classifier that uses Bayes 'theorem, which is capable of handling high-dimensional feature space common in texture analysis (21). This method predicts probabilities, providing insights into classification confidence (22). Despite the potential texture feature dependencies, Naïve bayes remains effective due to its robustness. Decision Tree (DT) captures complex nonlinear data patterns without the need for visualization thresholding or reduction and efficiently handles similarities and distribustions.it works as a predictive model by comparing data and statistics (23). Developing decision-making algorithms involves classifying elements to improve decision-making rules for kidney ultrasound image classification. Random Forest (RF) is mainly utilized for feature selection, retaining optimal features, minimizing redundancy, and enhancing outcomes. By extending bagging methods and incorporating feature randomness, it constructs an uncorrelated forest of decision trees, effectively improving regression and classification accuracy as tree numbers rise (24). This technique employs bootstrapped training data samples and random feature subset to boost diversity and explore various feature selection combinations in classification. K-Nearest Neighbor (KNN) classifies or predicts information based on proximity, using the most frequent class among its k nearest neighbors in the feature space, it can process dataset of different texture features and handle both numerical and categorical information (25). The algorithm relies on observations close to a given point and is adaptable to diverse classification tasks. XG-Boost is a popular machine learning algorithm that excels in classification and regression tasks. It uses iterative decision tree to resolve errors and capture complex information patterns. XG-Boost handles large, high-quality datasets with high accuracy and speed compared to most algorithms. Its ability to reveal the significance of features assists researchers in identifying key features of data (26). Furthermore, its expertise in managing large amount of data is useful for analysing complex data.

Proposed Model

The use of stacked classifiers has been investigated to improve CKD detection. Initially various machine-learning algorithms, including SVM, RF, DT, NB, KNN, and XG-Boost, were evaluated for their effectiveness, and all showed exceptional results, except for NB and KNN, which performed slightly worse. To improve the classification accuracy of machine learning, then the idea of stacking ensemble classifiers was proposed using the strengths of the inferior KNN and Naïve Bayes classifiers, and the exceptional performance of XG-Boost (27). This approach has been found to increase reliability and performance across a wide range of datasets, with KNN being particularly effective in handling complex decision boundaries and Naive Bayes providing probabilistic insights. In addition, the ability of the stacked ensemble to reduce overfitting and its high computational power make it a reliable option for various classification tasks. Figure 2 shows the combined method used in the proposed model.

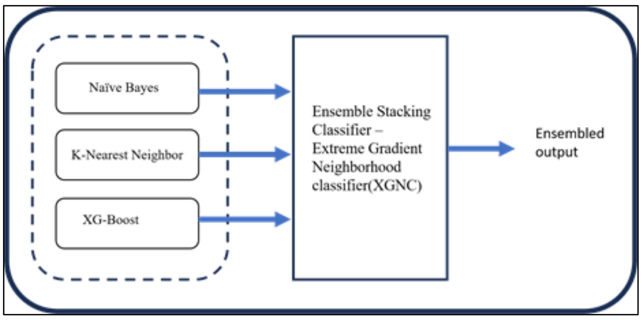


Figure 2: A Proposed Approach based on the Ensemble-Extreme Gradient Neighborhood (XGNC) Classifier

Table 2: Confusion Matric and other Performance Measure used in the Study

Predicted		True class		
Class		P	N	
	Y	True Positive (T_p)	False Positive (F_p)	$Accuracy = \frac{T_P+T_n}{T_p+T_n+F_p+F_n}$ $Precision = \frac{T_p}{T_p+F_p}$
	N	False Negative (F_n)	True Negative (T_n)	$Specificity = \frac{T_n}{T_n+F_p}$ $Sensitivity = \frac{T_p}{T_p+F_n}$ $F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$

For Performance Evaluation this research applied four evaluation metrics to evaluate the proposed methods: accuracy, precision, recall, sensitivity, specificity, F1 score, and AUC. The confusion matrix in Table 2 was used to calculate these metrics. The area under the receiver operating characteristic (ROC) curve, determined by the AUC, illustrated the relationship between sensitivity and specificity rates (25).

Results and Discussion

In this study, 340 pediatric US images were collected and pre-processed. Noise removal was performed using a Gaussian median filter, and image quality and contrast were enhanced using a median filter. The Sobel operator was used for edge detection. The data were split into training and testing sets in a ratio of 80:20. The proposed method's block diagram is shown in Fig. 1. Utilizing the Pyrandiomics package in Python, ninety-four features were extracted from each image, derived from GLCM, GLRLM, GLDM, GLSZM, NGTDM, and first-order derivatives. Feature optimization was conducted using the COA, and the experiment was executed with 30 iterations, 100 Epochs and a population size of 50 for the COA. The COA selected 30 out of 94 features. Classification algorithms employed included RF, KNN, SVM, DT, NAÏVE BAYES, and XGBOOST. This research study aims to classify pediatric kidney ultrasound images using a proposed texture feature selection method across various classification algorithms.The model's effectiveness was assessed using various classification metrics: accuracy, precision, sensitivity, specificity, F1 score, and AUC-ROC. Table 3 shows that analysing texture features of pediatric ultrasound images without feature selection yielded specific results, RF and XG-Boost achieved the highest accuracy, with RF reaching 97.92% and XG-Boost 97.92%. RF surpassed XG-Boost with an ROC AUC of 99.57%. DT performed well with an accuracy of 88.54%, a precision of 84.31%, but had lower sensitivity at 93.48%, indicating a higher rate of false positives. KNN showed better performance in identifying negative cases with a specificity of 78%, higher than its sensitivity. In contrast, the SVM demonstrated poor performance with a specificity of 48%. NB had the lowest performance among the classifiers, with an ROC-AUC of 61.57%, indicating weak discriminative capability.

Table 3: Texture Feature Classification Results without Feature Selection Using Machine Learning

	Without Feature Selection					
Classifier	**Accuracy**	**Precision**	**Sensitivity**	**Specificity**	**F1Score**	**ROC-AUC**
Random Forest	0.9792	0.9783	0.9783	0.9800	0.9783	0.9957
Decision Tree	0.8854	0.8431	0.9348	0.8400	0.8866	0.8874
Naïve bayes	0.5938	0.5854	0.5217	0.6600	0.5517	0.6157

KNN	0.7292	0.7381	0.6739	0.7800	0.7045	0.8061
SVM (RBF)	0.6042	0.5667	0.7391	0.4800	0.6415	0.6448
XG-Boost	0.9792	0.9783	0.9783	0.9800	0.9783	0.9874

While table 4 describes the classification result of different classifier for texture feature classification using COA for feature selection, XG-Boost achieved the highest scores across all metrics with accuracy 100%, indicating the most effective classifier for this dataset, followed by RF with ROC-AUC: 97.91%. SVM showed strong performance, Precision: 95.83%, Sensitivity: 93.47%, F1 Score: 95.55%, with a slight bias towards false positives. DT exhibited excellent class separation with ROC-AUC: 95.91%. KNN achieved an F1 score of 93.02%, balancing precision and sensitivity. NB showed good performance with F1 Score: 87.91%, Precision: 88.88%, Sensitivity: 86.95%, Specificity: 89.66%, balancing false positives and negatives. The Figure 3(A) and 3(B) shows analysis highlighting the importance of feature selection in improving classification accuracy and reliability.

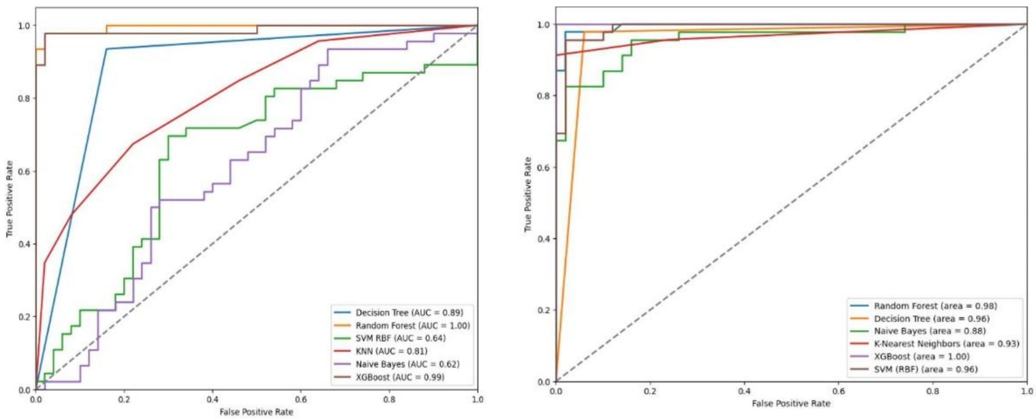
Feature selection for NB and KNN revealed poor performance when compared to other classifiers used for the classification with feature selection, as they compute distance assuming feature independence, leading to suboptimal results. To address this, an ensemble model combining these classifiers with XG-Boost was employed. This method merges weak learners into a strong learner, enhancing performance and mitigating overfitting.

Table 4: Texture Feature Classification Results with Feature Selection Using Machine Learning

	With Feature Selection					
Classifier	**Accuracy**	**Precision**	**Sensitivity**	**Specificity**	**F1Score**	**ROC-AUC**
Random Forest	0.97916	0.9782	0.9782	0.98	0.9782	0.9791
Decision Tree	0.9583	0.9375	0.9782	0.94	0.9574	0.9591
Naïve bayes	0.8854	0.8888	0.8695	0.90	0.8791	0.8791
KNN	0.9375	1.0	0.8695	1.0	0.9302	0.9347
SVM (RBF)	0.9583	0.9583	0.9347	0.98	0.9555	0.9573
XG-Boost	1.0	1.0	1.0	1.0	1.0	1.0

Table 5: Texture Feature Classification Results with Feature Selection Using Extreme Gradient Neighborhood Classifier

Classifier	**Ensemble**					
	Accuracy	**Precision**	**Sensitivity**	**Specificity**	**F1Score**	**ROC-AUC**
Naïve bayes	0.8333	0.8750	0.7608	0.9000	0.8139	0.8304
KNN	0.9479	1.0	0.8913	1.0	0.9425	0.9456
XG-Boost	0.9895	1.0	0.9782	1.0	0.9890	0.9891
XGNC (Proposed Model)	0.9791	0.9782	0.9782	0.98	0.9782	0.9791



(A) (B)

Figure 3: Texture Feature classification (A) Without Feature Selection (B) With Feature Selection

Table 6: Comparative Study with the Existing Work and Proposed Approach

Ref	Feature Extraction	Feature Selection	Accuracy
(8)	GLCM	-	95.4%
(12)	GLCM	PCA	77.8%
(13)	GLCM	Oppositional Grasshopper optimization (OGOA)	95.8%
(15)	Gray level statistics, Gabor filter, Discrete Fourier Transform (DFT)	Dragonfly Optimization Algorithm	95%
Proposed Approach	First Order, Second Order features (GLCM, GLSZM, GLDM, GLRLM, NGTDM)	Coati Optimisation Algorithm	97.91%

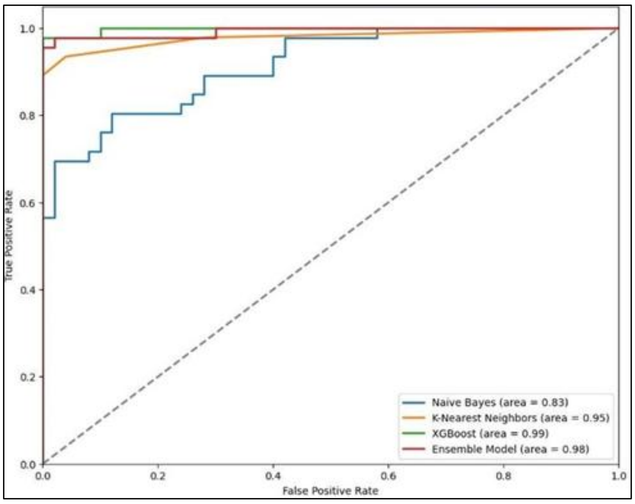


Figure 4: Texture Feature Classification ROC-AUC with Feature Selection Using Extreme Gradient Neighbourhood Classifier

Classification results are detailed in Table 5, with a graphical ROC-AUC representation in Figure 4, offering insights into feature importance and aiding selection. KNN, which does not assume any underlying data distribution and provides a probabilistic classification framework, is beneficial for uncertain or incomplete data. It performs well with independent features, simplifying the model as shown in Figure 5 illustrates the top-selected feature via the XGNC.

To further assess the models' effectiveness, the proposed approach's results were compared with existing literature in Table 6. When contrasted with state-of-the-art methods, the findings show superior performance in classification and feature reduction rate. Notably, focusing exclusively on texture features for feature extraction validates our approach, which achieved outstanding outcomes when COA was implemented on FS, decreased the number of features utilized, resulting in faster training times and enhanced classification accuracy. These findings validate the effectiveness of COA in managing the radiomics domain for classifying pediatric kidney ultrasounds. The current outcomes lay a solid foundation for expanding this framework. While the proposed model demonstrated encouraging outcomes in classifying pediatric renal ultrasound images through COA-based feature selection, the research was conducted on a dataset of moderate size, potentially restricting the applicability of the findings to wider clinical populations. Additionally, the method did not include anatomical segmentation of the kidney structure. All radiomic features were derived from the entire kidney area, which might miss localized abnormalities that segmental analysis could better identify. The primary aim of the research was to assess the independent performance of COA. Future research will involve comparing it with other metaheuristic algorithms and investigating hybrid models that integrate selected COA features with deep learning-based features to boost performance and clinical applicability with larger dataset.

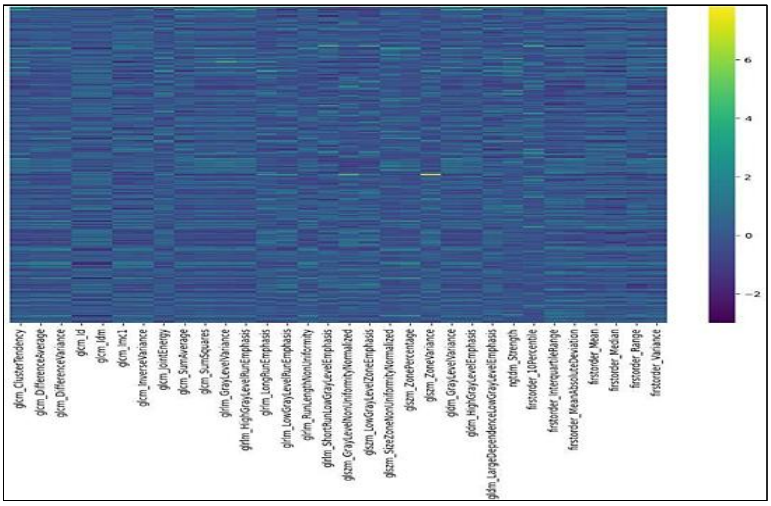


Figure 5: Best Selected Texture Feature using Feature Selection

Conclusion

This study presents a novel application of Coati Optimization Algorithm for feature selection in pediatric kidney ultrasound image classification. By evaluating the standalone impact of COA on feature dimensionality reduction and classifier performance, the research establishes its relevance in medical image analysis, particularly for pediatric diagnostics tasks. Utilizing the optimal number of features extracted from pediatric kidney ultrasound images, this research aimed to classify them into normal and abnormal categories. To achieve this, the COA was employed for optimal feature selection, followed by the use of RF, KNN, SVM, DT, NAÏVE BAYES, and XGBOOST classifiers. Additionally, a new ensemble machine learning model called the Extreme Gradient Neighborhood Classifier (XGNC) was proposed. XGNC combines the strengths of multiple classifiers using bagging, boosting, and stacking techniques. The results of this study show that optimal feature selection and classifier selection can significantly increase the accuracy of computer-aided diagnosis of ultrasound images. The research utilized publicly available medical data, which facilitated comparison without requiring significant hardware resources. Manual feature selection is challenging, necessitating an understanding of the dataset to choose meaningful features before applying machine learning algorithms. Feature selection critically affects model accuracy; The finding indicate that COA can effectively identify discriminative radiomics features, improving classification accuracy and reducing model complexity. This work sets the stage for future comparative evaluations, segmentation- based diagnosis, and integration with AI -assisted clinical decision tools. The proposed approach demonstrates the potential of nature inspired optimization methods in advancing in diagnostics intelligence, encouraging further research and adaption in related healthcare applications by employ deep learning classifiers and hybrid optimization techniques to explore feature combinations that may enhance classification accuracy.

Abbreviations

None.

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Author Contributions

Fizhan Kausar: Conceptualization, Methodology, Software, Validation, Resources, Data Curation, Writing—original draft preparation, Writing—review and editing, Ramamurthy B: Formal analysis, Investigation, Visualization, Supervision.

Conflict of Interest

The authors declare no conflict of interest.

Ethics Approval

Not applicable.

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