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Kidney Stone Detection using Butterfly Optimization Algorithm

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Abstract

A kidney stone is a solid object made of molecules found in urine. Uric acid, cystine, struvite, and calcium oxalate are all possible causes of kidney stones. Typical symptoms include severe pain, blood in the urine, nausea, vomiting, fever, and chills. Every year, about 1.5 million people seek medical care for kidney stone problems. Kidney stones affect around 11% of men and 9% of women. Individuals with conditions such as high blood pressure, diabetes, and obesity are more susceptible to developing kidney stones. The objective of the proposed study is to detect the presence of kidney stones in Computed Tomography (CT) images of kidneys. The dataset is collected from the Kaggle website which contains 12446 CT images of kidneys. The film artefact is removed in the pre-processing stage. The pre-processing is divided into two steps: The median filter is used initially, and erosion is performed using structuring elements of three different sizes (3 x 3, 4 x 4, and 5 x 5). Better results are obtained for the 3x3 structuring elements. For image segmentation, the gradient vector flow method and the soft organ and bony skeleton removal approach are used. The features that are extracted from the segmented data include mean, standard deviation, contrast, correlation, energy, homogeneity, skewness, kurtosis, and entropy. The Butterfly Optimization Algorithm (BOA) is used for feature selection, while classification is done with the XG Boost supervised machine learning method.

Index Terms - Kidney stone detection, butterfly optimization algorithm, machine learning.

I. INTRODUCTION

A kidney stone is a crystal that forms in the kidneys, ureters, bladder, and urethra. In most cases, kidney stones are undetectable unless they cause severe stomach pain or have an unusual color in the urine. In most cases, there is a subsequent stone development as well. The existence of kidney stones and their recurrence can lead to Chronic Kidney Disease (CKD) and mortality [1]. In India, kidney stones are a significant public health issue. A study found that 12% of Indians suffer kidney stones, and that among them, 50% are losing renal function. There are approximately 100 lakh people who have kidney stones, and the number is increasing [18]. According to the World Health Organization, Myanmar has one of the highest rates of CKD in the world. In 2017, there were 26.20 deaths from CKD per 100,000 inhabitants in Myanmar. In the same year, Indonesia and Japan were rated 54 and 137, respectively. One year after the first stone, the recurrence of renal stones is 14% in Myanmar [2]. A survey found that there were more than 1.3 million kidney stone cases in the US in 2009. Fortunately, most kidney stone diseases can be cured by choosing the appropriate course of treatment and avoiding stone recurrence [12].

Researchers have taken efforts to enhance the visual quality of medical images and to improve the accuracy of their findings about the size and location of kidney stones [3]. In recent years, computer-aided diagnosis has become increasingly dependent on 3D medical image processing.

Assessing medical images or identifying unusual characteristics in an image can help the radiologist to make decisions. Kidney stone disease is diagnosedwith conventional testing methods such as blood tests, urine tests, biopsies, and imaging modalities such as ultrasound, CT, and Magnetic Resonance Image (MRI). CT has become the most popular diagnostic technique since it provides slice-by-slice images and three-dimensional information [4]. The CT scanner uses X-ray beamsto scan the targeted area in order to generate a cross-sectional image [11].

The purpose of this work is to detect the presence of kidney stones from the CT images of kidney. This paper is organized such that Section II initially reviews the related works, Section III describes the flow diagram, and Section IV draws a conclusion based on the classification results.

II. Related Works

A study has shown the effectiveness of three pre-processing methods for removing noise from CT images of kidney and these methods were based on size, shape, and hybrid thresholding algorithms [1]. In [2], the intensity-based thresholding, hypodense and isodense zones are first removed. The bones in the abdomen are removed in the second stage using a technique called size-based thresholding. To reduce the number of false positives, thresholding based on geometric features is developed in the third stage. To establish the image outlines of the kidney stone area and estimate variation in stone measurement, the Gradient Vector Flow (GVF) model was used. [3]. Unwanted area removal is accomplished using three thresholding techniques, including soft-organ, bony skeleton, and bed-mat [4]. For the classification of medical data, a revolutionary oppositional-based learning technique called Oppositional Based Learning Butterfly Optimisation Algorithm - Multilayer Perceptron (OBLBOA-MLP) had been developed, which combined the Multilayer Perceptron (MLP) and the Butterfly Optimization Algorithm (BOA). Pre-processing, classification, and parameter tuning are the three stages of the operation for the presented OBLBOA-MLP model [5].

In [6], a method that employs morphological procedures to cut out unnecessary skull and ribcage pieces is developed. This approach also lowers the number of false positives in subsequent processing steps. The Weighted Butterfly Optimization Algorithm (WBOA) is used to find the optimal features in order to maximise classification accuracy while anticipating and evaluating the COVID-19 parameters. An Adaptive-Neuro Fuzzy Inference System (ANFIS) classifier is used to categorise people who are at risk of infection based on the selected characteristics [7]. In order to deal with complex optimization issues, the Butterfly Optimization Algorithm (BOA), a new algorithm inspired by nature that imitates the food-seeking and mating behaviours of butterflies, has been introduced [8]. As part of routine ureteroscopies, endoscope-captured images of the four most commonforms of urinary calculi were used to test the kidney stone recognition capabilities of three deep-learning architectures and six shallow machine learning methods [9]. Using data from electronic health records, a machinelearning model eXtreme Gradient Boosting (XG Boost) has been developed to forecast 24-hour urine abnormalities. A Logistic Regression model (LR) and the machine learning model are investigated. An ensemble model (EN) that combines the XG and LR models are also assessed. The Area Under the Receiver Operating Curve (AUC-ROC) has been used to assess the performance [10].

Researchers acquired and interpreted a sum of 12,446 CT images, including complete abdominal areas and urogram images, to build an AI-based diagnostic system for kidney issues. Six machine learning models are used, three of which (EANet, CCT, and Swin) are based on decreasing versions of Vision Transformers, while the remaining three are well-known deep learning models that are updated in the final layers (ResNet, VGG16, and Inception v3) [11]. A plan to decrease false positives for stone detection and also to retrieve useful structural information for kidney stone diagnosis is proposed and experimentally evaluated. To segment the target object (a stone), Otsu's thresholding approach and morphological operation are applied first. Second, the parameters for stone detection based on 3D morphological traits are measured [12]. The hybrid Butterfly Optimization Algorithm - Ant Lion optimizer (BOA-ALO) method is devised. Using the best collection of characteristics selected by BOA-ALO, three classifiers—Artificial Neural Networks (ANN), ANFIS, and Support Vector Machine (SVM)— predict whether breast tissue is harmless or aggressive [13]. In Hybrid Particle Swarm Optimization - Butterfly Optimization Algorithm (PSO-BOA), three techniques are presented to improve the fundamental BOA. As a result, a nonlinear parameter control strategy is used, with the initialization of BOA using a cubic one-dimensional map. Additionally, the PSO technique is used with BOA to enhance the fundamental BOA for global optimization [14]. The adaption form is the foundation for recently reviewed and summarised research that uses the BOA to address optimization challenges. All the examined studies are divided into three primary categories: original, modified, and hybridised [15].

III. Materials and Methods

A CT kidney dataset consisting of 12,446 images which are categorized as normal, cyst, tumor, and stone are collected from Kaggle database. The structuring elements with different sizes (3x3, 4x4, and 5x5) are used in conjunction with a median filter for the removal of noise. The denoised images are segmented using the GVF method and the soft organ and bony skeleton removal method.

Features like mean, standard deviation, contrast, correlation, energy, homogeneity, skewness, kurtosis, and entropy have been extracted from the segmented images. The feature selection is done using the BOA. The XG Boost algorithm is trained to find the presence of kidney stones using the selected features. The proposed methodology is illustrated in Fig.1.

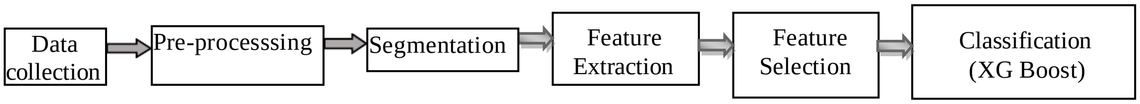


Fig. 1 Flow Diagram of proposed methodology

Image pre-processing

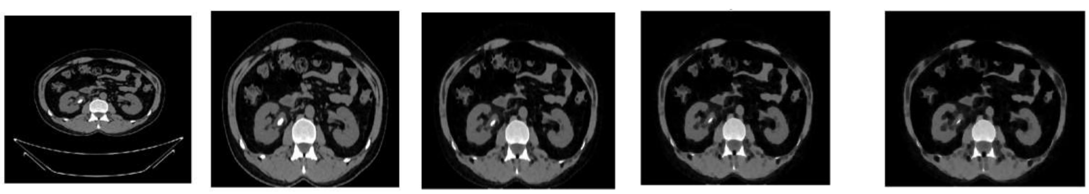
The purpose of pre-processing is to enhance the quality of the image. The CT images are largely composed of film artefacts. The median filter is employed in pre-processing along with the structuring elements 3x3, 4x4, and 5x5 to eliminate those film artefacts. To evaluate the quality of the denoised images, metrics such as Signal to Noise Ratio (SNR), Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM) were computed using eqns. 1–4. The input image and the pre-processed images are shown in Fig 2.

$$\mathrm{SNR} = 20 \log 10(\frac{\mathrm{S}}{\mathrm{N}}) \tag{1}$$

$$\mathrm{MSE} = \sum_{\mathrm{M,N}} [\mathrm{I1}(\mathrm{m},\mathrm{n}) - \frac{\mathrm{I2}\ (\mathrm{m},\mathrm{n})]^2}{\mathrm{M} * \mathrm{N}} \tag{2}$$

$$\mathrm{PSNR} = 20 \log 10\ (\frac{\mathrm{MAX}}{(\mathrm{MSE})^{\frac{1}{2}}}) \tag{3}$$

$$\mathrm{SSIM}(x,y) = \frac{(2\mu x\ \mu y + c1)(2\sigma xy + c2)}{(\mu x^2 + \mu y^2 + c1)(\sigma x + \sigma y + c^2)} \tag{4}$$



(a) (b) (c) (d) (e)

TABLE 1 Evaluation metrics of pre-processing

Test image 1				**Test Image 2**		
	3x3	**4x4**	**5x5**	**3x3**	**4x4**	**5x5**
SNR	**16.755**	14.059	12.399	**6.6438**	5.492	4.7657
MSE	**0.1691**	0.3146	0.4611	**0.4942**	0.6443	0.7616
PSNR	**25.849**	23.152	21.493	**21.192**	20.04	19.314
SSIM	**0.9464**	0.8925	0.8497	**0.7941**	0.7373	0.6975

Table 1 shows the evaluation metrics of pre-processing for square shaped structuring elements of 3x3, 4x4 and 5x5. The parameters used for assessing the performance are SNR, PSNR, MSE, and SSIM. From the evaluation metrics, it is observed that the structuring element 3x3 performed better than 4x4 and 5x5.

A Segmentation

Medical image segmentation is extremely important in providing details about parts of human body that help doctors to make accurate diagnoses and decide whether to perform radiotherapy or surgeries [3]. The pre-processed image has been segmented using two distinct techniques, such as the soft organ and bony skeleton removal method and GVF approach. The accuracy, sensitivity, specificity, and F1-score of these techniques are compared.

Soft-organ removing

The removal of soft organs from the abdominal cavity is the initial stage in the segmentation procedure. One of the CT's best features is its ability to distinguish between soft and hard organs based on significant intensity differences. Compared to other organs, soft tissues have low intensity ratings. Additionally, kidney stones can range in Hounsfield scale (HU) from 200 HU to 2800 HU. The soft organs in the image are therefore eliminated by using intensity-based thresholding with two critical values, Ta and Tb [1].

Bony skeleton removing

Several high-intensity areas, such as thebedmat, bone, vascular calcification, stones, and noise, remain following the removal of soft organs. Kidney stones have the potential to get as big as golf balls. The size of a bony skeleton varies widely from the size of a kidney stone. Additionally, it is removed by identifying the area of objects in the image [1]. Fig 3 illustrates the segmented images using soft organ removal and bony skeleton removal, as well as the fused image of these two methods.

(a) (b) (c)

Fig 3 (a) Soft Organ Removing, (b) Bony Skeleton Removing and (c) Fused Image

Gradient vector flow (GVF) Technique

The majority of earlier segmentation techniques have issues in diagnosing the size and location of the stones by inaccurately detecting the boundaries of kidney stones. Active contours have a high degree of convergence with concave objects with various types of limits. Professionals utilises GVF active contours which converge to deep and thin concavity boundaries [3]. It is commonly used for object tracking, form recognition, segmentation, and edge detection in image analysis and computer vision applications. The output image of the GVF method is shown in the Fig 4.

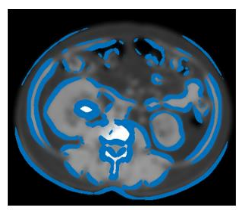


Fig 4 Output of GVF method

Table 2 shows the comparison of performance metrics of soft organ and bony skeleton removing method and GVF method. The evaluation metrics are Accuracy, Sensitivity, Specificity, and F1 Score. The proposed GVF method achieved the better performance when compared to soft organ and bony skeleton removing method.

TABLE 2 Evaluation metrics of segmentation

Metrics	Accuracy	Sensitivity	Specificity	F1 Score
GVF	**0.998**	**0.98**	**0.97**	**0.997**
Soft organ removing	0.85	0.84	0.87	0.91
Bony organ removing	0.75	0.73	0.75	0.79
Fused image	0.86	0.86	0.88	0.90

B Feature extraction

The features extracted from the segmented images are mean, standard deviation, contrast, correlation, energy, homogeneity, skewness, kurtosis and entropy.

C Feature selection

A common pre-processing procedure called feature selection seeks to separate out the important featuresfrom the irrelevant ones. In this manner, the dimensionality of the data can be reduced without reducing the performance. Due to these traits, feature selection is a popular research subject that is frequently used to solve real-world problems. It mostly pertains to classification, but it can also be used in regression and other domains [17]. In this work, BOA is used for feature selection.

Butterfly Optimization Algorithm (BOA)

The BOA for feature selection mimics behaviour of the butterfly food-seeking. BOA uses butterflies as search agents to carry out optimization. The intensity of fragrance production is related to fitness, and as a butterfly fly from one area towards another, its best solution will alter accordingly. The fragrance will travel through distance, and other butterflies will be able to detect it, which is how the butterflies can exchange private information and create a network of shared social knowledge. A butterfly will migrate towards the other butterfly when it detects its odour, and the BOA refers to this phase as global search. The phase in which a butterfly flies randomly because it is unable to recognize fragrance in its environment is known as "local search" in the BOA technique. Initialization, iteration, and finalisation are the three processes that compose a BOA [8]. The output graph fig 5 shows the fitness value for every iteration

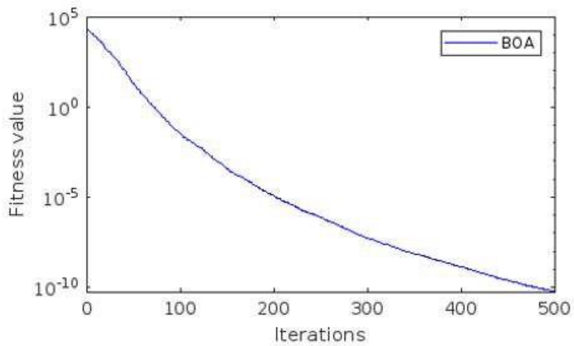


Fig 5 Fitness value for each Iteration

D ***Classification***

A supervised-learning technique for regression and classification on large datasets is called XG Boost. The decision tree-based algorithms are thought to perform well when dealing with tabular or structured data. One of the remarkable algorithms initially chosen for structured data is XG Boost. Boosting merely refers to an ensemble strategy where new models correct flaws in older ones. These models are continuously added until no further progress is seen. Gradient boosting is a technique in which new models are made, the error in the prior model is computed, and the remainder is then added to get the final forecast. It is known as a "gradient boosting algorithm" as it uses the gradient descent algorithm. The working flow of the XG Boost is shown in the Fig. 6.

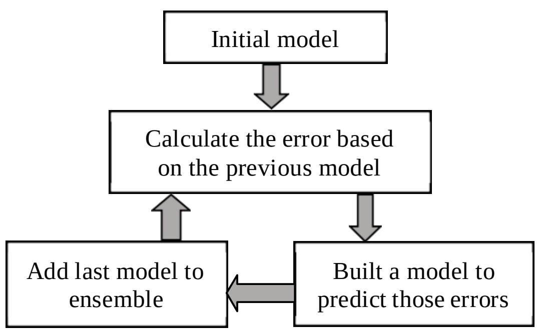


Fig 6 Working flow of XG Boost

IV. Results and Discussion

The goal of the proposed research is to detect the presence of kidney stones in a CT image. The dataset includes 12446 kidney-related CT images that were taken from the Kaggle platform. Film artefacts are typically present in the CT image. The pre-processing step is used to get rid of the film artefact. There are two stages in the pre-processing: Applying the median filter is the first step, followed by erosion using a square structuring element made up of 3x3, 4x4, and 5x5. The pre-processing algorithm yields an effective result for 3x3 structuring elements. In segmentation, the GVF method and the soft organ and bony skeleton removal method are compared. GVF method outperformed the soft organ and bony skeleton removal methods in segmentation procedures. Mean, standard deviation, contrast, correlation, energy, homogeneity, skewness, kurtosis, and entropy are the features that are extracted from the segmented images. Using these extracted features, the BOA was implemented to optimise the features. The optimal features for the classification process have been determined using the fitness values for each iteration. XG Boost, a supervised machine learning method, is used to perform the classification. The classification model shows good accuracy in detecting the presence of kidney stones in a CT image. Fig. 7 displays the confusion matrices of the proposed method using 3000 training images and 300 test images. Fig. 8 displays the confusion matrices of the XG Boost classifier for the same images.

Table 3 displays the evaluation matrices for the proposed method, which are compared with the XG Boost classifier. To evaluate the effectiveness of the proposed technique, accuracy, sensitivity, specificity, and the f1 score have been calculated using eqns. 5–9.

$$\mathrm{ACCURACY} = \mathrm{TP} + \frac{\mathrm{TN}}{\mathrm{TP+TN+FP+FN}} \quad (5)$$

$$\mathrm{SENSIVITY\ (OR)RECALL} = \frac{\mathrm{TP}}{\mathrm{TP}} + \mathrm{FN} \quad (6)$$

$$\mathrm{PRECISION} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (7)$$

$$\mathrm{SPECIFICITY} = \frac{\mathrm{TN}}{\mathrm{TN+F}} \quad (8)$$

$$\mathrm{F1\ SCORE} = \frac{\mathrm{2TP}}{2(\mathrm{TP})} + \mathrm{FP} + \mathrm{FN} \quad (9)$$

Fig. 7 Results of XG Boost classifier and BOA

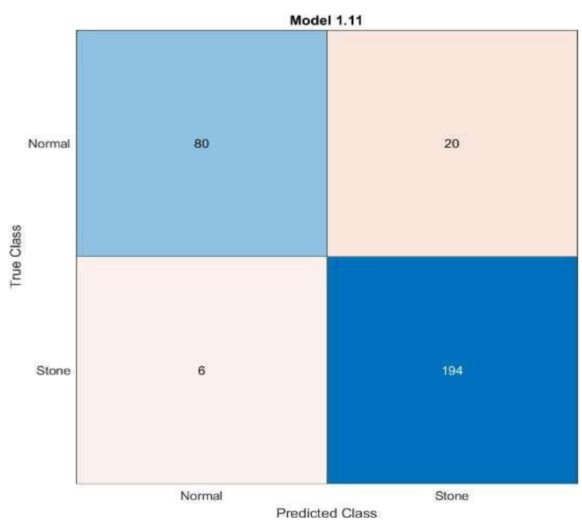


Fig. 8 Result of XG Boost classifier

TABLE. 3 Evaluation metrics of XG Boost + BOA and XG Boost

Algorithm	Accuracy	Sensitivity	Specificity	F1 Score
XG Boost	91.33	80	97	86.02
BOA + XG Boost	**98.00**	**97.9**	**98.01**	**96.96**

The proposed algorithm (BOA + XG BOOST) detects the presence of kidney stones with 98% accuracy. The proposed algorithm performed better than XG Boost for detecting the presence of kidney stones, with greater accuracy (98% vs. 91.33%), sensitivity (97.9% vs. 80%), specificity (97% vs. 98.01%), and F1 score (86.02 vs. 96.96%).

V. CONCLUSION

A novel BOA combined with XG Boost model for medical data classification is proposed in this paper. The proposed work involves six stages of operations, such as dataset collection, pre-processing, segmentation, feature extraction, feature selection, and classification. The dataset is collected from Kaggle in the first stage, which contains a total of 12446 CT kidney images. The images are then pre-processed using a median filter, followed by square-shaped structuring elements of 3x3, 4x4, and 5x5. The effectively denoised image is segmented by comparing two different algorithms, such as the GVF method and the soft organ and bony skeleton removal method. Due to the outperformance of the GVF method, its features are extracted. The extracted features are fed to the process of feature selection using the BOA. XG Boost, a supervised machine learning method, is used to perform the classification with the best solution from the BOA. Deep learning architectures can be used in future extensions to improve classification performance.

REFERENCES

[1] Thein, N., et al., “A Comparison of Three Pre-processing Techniques for Kidney Stone Segmentation in CT Scan Images”, Biomedical Engineering International Conference (BMEICON), IEEE, pp. 1-5, 2019, November.

[2] Myint, L. Y., et al., “Removal of Unwanted Object in 3D CT Kidney Stone Images and 3D Visualization”. In 2020 24th International Computer Science and Engineering Conference (ICSEC) (pp. 1-5). IEEE, 2020.

[3] Mosa, Q.O., “Improved Kidney Stone Detection from Ultrasound Images Using GVF Active Contour”, Journal of Al-Qadisiyah for Computer Science and Mathematics, Vol.14, Issue-1, pp. 24-31, 2022.

[4] Thein, N., et al., “An Image Pre-processing Method for Kidney Stone Segmentation in CT Scan Images”, International Conference on Computer Engineering, Network and Intelligent Multimedia (CENIM) IEEE, pp. 147-150, 2019 November.

[5] Yogananda, P., et al., “Oppositional Butterfly Optimization Algorithm with Multilayer Perceptron for Medical Data Classification”, Turkish Journal of Computer and Mathematics Education, Vol.12, Issue-10, pp.2721-2731, 2021.

[6] Patil, S. and Udupi, V.R., “Pre-processing to be Considered for MR and CT Images Containing Tumors”, IOSR journal of electrical and electronics engineering, Vol.1, Issue-4, pp.54-57, 2019.

[7] Sundaravadivel, T. and Mahalakshmi, V., “Weighted Butterfly Optimization Algorithm with Intuitionistic Fuzzy Gaussian Function Based Adaptive-Neuro Fuzzy Inference System for COVID-19 Prediction”, Materials Today: Proceedings, Elseiver, Vol.56, pp.3317-3324, 2022.

[8] Arora, S. and Singh, S., “Butterfly Optimization Algorithm: A Novel Approach for Global Optimization”. Soft Computing, Springer, Vol.23, Issue-3, pp.715-734, 2019.

[9] Ochoa-Ruiz, et al., “On the In Vivo Recognition of Kidney Stones using Machine Learning”, arXiv preprint arXiv: 2201.08865, Elsevier, pp.1-17, 2022.

[10] Kavoussi, N.L., et al., “Machine Learning Models to Predict 24 Hour Urinary Abnormalities for Kidney Stone Disease”. Urology, Elsevier, Vol.169, pp.52-57, 2022.

[11] Islam, M.N., et al., “Vision Transformer and Explainable Transfer Learning Models for Auto Detection of Kidney Cyst, Stone and Tumor from CT-Radiography”. Scientific Reports, Vol.12, Issue-1, pp.1-14, 2022.

[12] Thein, N., et al., “Automated False Positive Reduction and Feature Extraction of Kidney Stone Object in 3D CT Images”. International Journal of Intelligent Engineering and System, Vol.12, Issue-2, pp.62-73, 2019.

[13] Thawkar, Set al., "Breast Cancer Prediction Using a Hybrid Method Based on Butterfly Optimization Algorithm and Ant Lion Optimizer". Computers in Biology and Medicine, Elsevier, Vol.139, pp.104968, 2021.

[14] Zhang, Met al., "A Chaotic Hybrid Butterfly Optimization Algorithm with Particle Swarm Optimization for High-Dimensional Optimization Problems". Symmetry, Vol.12, Issue-11, pp.1800-1827, 2020.

[15] Makhadmeh, S.N., et al., O.A., "Recent Advances in Butterfly Optimization Algorithm, Its Versions and Applications". Archives of Computational Methods in Engineering, pp.1-22, 2022.

[16] Thombare, M. R. S., & Bonde, M. G, "Image Processing for Brain Tumor Segmentation and Classification". Image, 6(12), 2019.

[17] Bolon-Canedo, V., & Remeseiro, B, "Feature selection in image analysis: a survey. Artificial Intelligence Review", 53(4), 2905-2931, 2020.

[18] *Dr. Saurabh Mittal*, "Poor dietary habits backed by sedentary lifestyle are the major reason for Kidney stones" 2022.