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Application of machine learning and conventional techniques in the detection of renal calculi: A comparative study

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Abstract
This paper presents a dynamic comparative study on current machine learning (ML) applications and other state of the art techniques in the detection of renal calculi. Compared to other obstacles in the physiological system, the occurrence of kidney stones will not cause a high rate of mortality but may result in high morbidity around the world. Both Non-ML and ML techniques discussed in this paper are based on imaging techniques, *viz.* Ultrasound (US), magnetic resonance imaging (MRI), and computed tomography (CT) for detection of kidney stones. Multiple issues, *viz.* low-quality image, analysis of size over time, and kidney stone similarity are the hindering factors in the detection of renal calculi. In order to select the appropriate technique to make detection easier, a detailed analysis of several ML and non-ML algorithms has been carried out. Both techniques were found to have advantages and disadvantages. The decision for an effective treatment strategy for kidney stone detection was made easy by introducing the developing ML techniques, which still require additional improvements in advanced diagnostics, early detection, and innovative methodologies. A variety of scientific articles have been collected and reviewed to provide support for developing a real-time system. Perhaps it is very important to exploit the methods that provide accuracy in detecting kidney stones.

Keywords: Machine learning, ultrasound scan, Ct scan, kidney stone, renal calculi

1. Introduction
The kidney is a vital excretory organ in the human and animal body. Kidney stones have been a widespread problem in recent years. The minerals reaching the kidney for excretion form solid pieces of materials resulting in Kidney stones. Normally these minerals are excreted through urine. A combination of genetic and environmental factors leads to the deposition of these minerals in the kidney leading to illness. Drinking insufficient water, being overweight, eating certain foods, and using certain medicines predispose to the condition. All races of people irrespective of culture and geographic location are prone to this condition. Blood tests, urine tests, and scans are all utilized to diagnose this condition. Detecting renal calculi early will help to avoid surgical procedures for its correction. For its proper detection, image processing is very important. Ultrasonography has traditionally lesser sensitivity and accuracy than computed tomography (CT), but it does not involve radiation use. These imaging modalities, on the other hand, were shown to have equal diagnostic accuracy when compared to a randomized controlled experiment. CT scans, Ultrasound scans, MRI and Doppler scans all utilize exclusive techniques (Verma *et al.*, 2017) [15]. Additionally, several mathematical approaches were previously utilized to identify kidney stones using ultrasound images (Sudharson and Kokil, 2021) [13] among all the approaches for detecting kidney stones, image processing has the most advantages since it analyzes the stone with great precision. Currently, computed tomography (CT) is the established benchmark for diagnosing patients suspected of having stone disease. Nevertheless, CT scans come with the drawbacks of radiation exposure and significant cost. In contrast, ultrasonography (US) is an affordable and radiation-free alternative for patients, making it a safer and more cost-effective choice (Vijayakumar *et al.*, 2018) [17]. Nowadays, automated machine learning techniques are being employed in the medical industry to analyze foreign materials or tumors in internal organs like the kidney and gallbladder (Shobana *et al.*, 2022) [10]. Inaccurate images or inadequate algorithms may give rise to many issues in automation. The contributions of various researchers are being reviewed based on the accuracy of detection from images by ML and non-ML techniques.

2. Materials and Methods
All methods in the diagnosis of kidney stone condition are aimed at timely detection and finding the location of the calculi, for alleviating pain or distress to the affected patients. Earlier, clinical symptoms and tests involving blood and urine were the only techniques available to detect the condition. Fast developments in the medical field and the advancements in imaging techniques led to the implementation of imaging technology in disease diagnosis. Computer Tomography scans, Ultrasound scans, Doppler scans, and Magnetic Resonance Imaging scans are the commonly used imaging methods. Clinicians depend highly on these imaging techniques for disease diagnosis, nowadays. There lies the importance of the accuracy of imaging techniques in the field of disease diagnosis. Direct analysis of the images or scans might cause errors that may lead to dangerous situations in terms of precision. The artifacts, *viz.* Noises, absence of sufficient contrast, and difficulty in locating the edges of the foreign body or lesions will affect the success of detection adversely. Image processing techniques use algorithms for removing the noises in the image thus enhancing the contrast and further helping in 'region of interest extraction'. ML techniques could be used effectively to classify and segment kidney stones from the processed images. Thus a drastic improvement in the accuracy and specificity regarding analysis of the images was brought in.

Several researchers have worked on various methods in Machine Learning (ML) techniques for the analysis of images. These methods have been discussed based on preprocessing techniques and the models used

2.1 Preprocessing techniques
2.1.1 CT Scan Images
Machine Learning techniques were used by Yildirim *et al.* (2021) [19] in analyzing CT scans for renal calculi, where they fed raw images into the XResNet-50 model. No preprocessing techniques were used to clean the images. The datas*et al*.so lacked diversity as images were only collected from one hospital and hence the model suffered in accuracy and sensitivity as compared to a similar model proposed by Baygin *et al.* (2022) [1] where they resized CT images to a resolution of 224x224 pixels. The images were also split into non-overlapping patches of size 28x28 blocks and both the resized image and patches were fed as input to the Darknet19 model. This was necessary to make the images compatible with the Darknet19 model, which required an input size of 224x224 pixels. Division of the image into patches also helped the model for effective feature extraction. Because of the complexities in their models, the authors did not consider image enhancement techniques using DSP filters.

On the other hand, Soni and Rai (2020) [11] applied the histogram equalization technique to enhance the contrast of the CT images. In their study, they also used directional embossing which essentially moves a horizontal and vertical convolutional kernel, for edge detection operations. This improved kidney stone visibility to a great extent. This preprocessing technique enabled the proposed model to achieve results at par with models having high complexity.

Anisotropic Diffusion Filtering was performed on 3-D U-Net segmented images by Elton *et al.* (2022) [4] to reduce noise in the CT images. Denoising was performed iteratively until the number of connected components was less than 200. This lowered the computational burden for the CNN network applied in later steps. The authors used a 130 HU as the threshold for connected component analysis, which was determined to be the optimal value for their data set to segment the kidney stones from the surrounding tissue. 'Region growing' was used to fill in any small gaps in the kidney stone segmentation masks. Even after performing preprocessing techniques, the model faced difficulty in dealing with a large amount of image noise. In addition to the excessive computational intensity of the model, the image-processing techniques exacerbated the complexity of the proposed method.

A less intensive preprocessing technique for a similar model was proposed by Li *et al.* (2022) [6], adjusting the range of intensity between -135 to 215 HU to highlight particular structures and alter the appearance of the images. Min-max normalization was employed to normalize HU intensities. To ensure uniformity in the data input, the z-axis spacing between cases was adjusted to 1.25 mm. The images were resized to (256, 256) in order to match the input of the 3D U-Net.

2.1.2 Ultrasound and MRI
One of the main issues with ultrasound images compared to CT scan images and MRI is that it is prone to speckle noise (Rahman and Uddin, 2013) [9]. Nithya *et al.* (2020) [8] in their work, proposed noise removal from ultrasound pictures using the median filter. By supplanting the pixels of a kernel with the value of the center pixel, speckle noise could be eradicated without diminishing the sharpness of the picture. Lack of diversity in the training set used hinders the technique from being effectively evaluated with other models.

Instead of directly applying filters to remove speckle noise, Viswanath and Gunasundari (2014) [18] put forward a three-step procedure to process ultrasound images before kidney stone detection. The first step involved reducing degradations caused during image acquisition by using the level set function. Images were extrapolated using plane curve motion and curve smoothers. The next step was employed using the Gabor filter which acted as a bandpass filter to optimize spatial and frequency domain resolution. The final step enhanced the image contrast by using Histogram Equalization by modifying the pixel intensities to be uniformly distributed in the image. Once the image was segmented by the level set segmentation, the segments were applied to a wavelet processing block which consisted of Daubecheis Symlets and Biorthogonal filters. Each of these filters generated features which were then evaluated by succeeding neural network models. On using a Naive Bayes classifier instead of a MLP-BP classifier, the model resulted in poor outputs, indicating that those preprocessing techniques could not be generalized for all models.

Very little research has been done on using MRI-scanned images for kidney stone detection. Issac (2014) [5] proposed that MRI-scanned images were treated to discrete wavelet transform and concluded that applying discrete wavelet transform decomposed the input image into high-pass and low-pass components using the high-pass and low-pass filters. The image was decomposed into four subbands LL, LH, HL, and HH. The LL sub-band contained most of the information. Further detection and classification were performed on the LL sub-band. This technique lacked in many aspects as the authors did not clearly exhibit the performance of the model with existing techniques.

2.2 Models Used

2.2.1 CT Scan Images

A study on XResNet-50 for kidney stone detection was done by Yildirim *et al.* (2021) [19], where the model was trained from scratch on raw CT images. To prevent overfitting, data augmentation techniques such as rotation and zooming were applied. XResNet-50 architecture consisted of four stages, with image resolution reduction in Stem and Max Pooling layers. Optimization was done using the Adam algorithm, and cross-entropy loss was used for parameter adjustment. The model provided both the output class and identified the region of interest for accurate diagnosis, both using the XResNet-50 alone. The authors suggested that certain inaccurate predictions could be attributed to the proximity of the rib tip to the lower pole of the kidney. They proposed that this issue could be mitigated by focusing training solely on the specific regions of interest within the coronal NCCT section, encompassing the entire abdomen, pelvis, a portion of the thorax, and the lower extremities.

While a single ML technique was used by Yildrim *et al.* (2021) [19] to perform both prediction and localization, Baygin *et al.* (2022) [1] devised a novel approach employing two architectures. The first architecture was the 'ExDark19' where CT images were segmented and resized into patches and analyzed by Darknet19 to generate feature vectors. The dimensionality of these vectors was then efficiently reduced by a factor of ten through the application of Incremental Non-linear Component Analysis (INCA). The INCA used two parameters: (i) loss/error value calculator and (ii) range of iteration to automatically choose the best feature vector. The second architecture: the kNN classifier, came into play after essential features were determined. The hyperparameters of the classifier were tuned using a Bayesian optimizer. Subsequently, classification of the feature vectors was performed using a k-NN classifier, incorporating Bayesian optimization techniques to tune the hyperparameters of the classifier. Since the model did not use intelligent segmentation, stones might be present in more than one patch, sometimes making it difficult to show the location of kidney stones.

In search of an intelligent segmentation algorithm, Elton *et al.* (2022) [4] chose 3D U-NET to segment kidney stones and then injected only the denoised segmented parts into a CNN model for detecting stones. The 3D U-Net was trained on 56 cases with ground truth segmentations. The image was denoised using gradient anisotropic diffusion denoising techniques. A 13-layer convolutional neural network classifier was then applied to distinguish kidney stones from false positive regions. While employing a slightly different approach, a comparison between different segmentation models was presented by Li *et al.* (2022) [6] differentiating 3D U-Net, Res U-Net, SegNet, DeepLabV3+, and UNETR specifically for unenhanced abdominal CT images. The approach consisted of two stages: (i) Coarse kidney segmentation which extracted just the sections with kidney and (ii) Fine kidney and kidney stone segmentation which utilized the first stage outputs and original image for kidney stone detection and segmentation. The difficulty of using two segmentation algorithms was that errors tended to accumulate as the features moved through various layers.

Soni and Rai (2020) [11] adopted a distinctive approach for stone segmentation in CT images. They eschewed the use of an intelligent segmentation algorithm and instead employed a thresholding operation. This operation involved replacing low-intensity pixels with non-active pixels and high-intensity pixels with active pixels. This innovative approach significantly reduced the computational complexity of the model. A nonlinear SVM classifier was then used to classify the stone in the segmented image by clustering analogous types of data into a particular class. After computing entropy from the SVM, if the entropy was superior to the threshold value, it indicated that the selected kidney image might have a stone or lump otherwise the system would declare it as a healthy kidney.

2.2.2 Ultrasound images and MRI scans

Unlike CT scan techniques that utilize CNN for segmentation and detection, ultrasound imaging cannot employ the same approach due to its illegible and noisier images. The gray-level Co-occurrence Matrix is a statistical method used in image processing and computer vision to analyze the spatial relationship between pixel values in an image. The GLCM quantifies how often different combinations of pixel intensity values occur in a given image and can also be used to extract texture information from an image. One such approach to tap feature vector was introduced by Nithya *et al.* (2020) [8], where they utilized preprocessed images to create twenty-two GLCM features. Subsequently, they employed the Crow Search Optimization algorithm to select only the most crucial features, with accuracy as the fitness function. The selected features were input into a neural network whose output was a single decimal value that could be used to classify whether the image was of a normal kidney, stone, or tumor based on threshold values. The authors also presented a comparison study between different combinations of kernels for performing segmentation using multi-kernel k means clustering, out of which, used a combination of linear and quadratic kernels was found to be the most effective.

Instead of relying on machine learning methods for stone area segmentation, the level set segmentation method proposed by Viswanath and Gunasundari (2014) [18], consisted of two modified gradient descent methods. The first was using a momentum term and the second was based on the resilient propagation (Rprop) term. After feature extraction through wavelet processing, for the model to predict renal calculi, a multi-layer perceptron was employed. Comparing the performance of the MLP-BP with the Naive Baeyes classifier, the authors found MLP-BP to outperform the Naive Baeyes classifier. The work also showed promises for hardware implementation in FPGA.

Vinayagam *et al.* (2019) [16] worked on the preprocessing technique for MRI images proposed by Issac (2014) [5]. The authors proceeded to extract GLCM features from the processed image to obtain five properties, Contrast, Correlation, Energy, Homogeneity, and Entropy. Those features were fed into a back propagation neural network. Once the BPNN identified a stone, the image was sent for segmentation using the Fuzzy C means algorithm. The authors also presented a comparative study of the Fuzzy C means algorithm with the Watershed algorithm for stone segmentation.

2.3 Non-ML Processing Techniques

These techniques do not use Machine Learning to decide whether the segmented images were stones. The final decision was taken by an expert clinician. Hence results are prone to more error as compared to ML methods.

2.3.1 CT Scan Images

Thein *et al.* (2018) [14] proposed a three-stage CT image processing technique. Soft organs in the scan had low intensity values compared to kidney stones having intensity values between 200 HU and 2800 HU. To remove a bony skeleton, the area of each 3D object was calculated by evaluating the number of voxels in an object and then removing the object with the maximum area i.e. (bony skeleton). The bed mat region in a CT scan image was the region of the image that contained the patient's bed and the mattress. The bed-mat region was always found to lie behind of the bony skeleton region, hence it was removed using the location-based thresholding method. The resulting image after processing segmented out regions were suspected to be kidney stones.

The performance of a research photon-counting detector (PCD) CT scanner was compared to a dual-energy CT scanner for the detection and characterization of renal stones in human participants with known stones by Marcus *et al.* (2018) [7]. Dual-energy CT is a type of CT imaging that uses two different X-ray energies to create images. PCD CT was a newer type of CT imaging that used photon-counting detectors to detect X-rays. Photon-counting detectors were found more sensitive than traditional CT detectors, which allowed them to produce images with lower radiation doses and higher image quality.

2.3.2 Ultrasound Scan Images

From a study regarding kidney stones based on Ultrasound scan images Dai *et al.* (2019) [3] highlighted the potential of twinkling artifacts caused by the reflection of sound waves from the different surfaces of a stone, as a non-invasive and accurate method for the detection and characterization of kidney stones. The authors also stated that the shadow width was a more accurate measure of true stone size than a direct measurement of the stone in the ultrasound image. The shadow technique worked by measuring the width of the acoustic shadow behind a kidney stone. The acoustic shadow was caused by the inability of sound waves to penetrate the stone. The wider the acoustic shadow, the larger the kidney stone was likely to be. The shadow technique was a simple and non-invasive way to size kidney stones. This claim was also supported by Brisbane *et al.* (2016) [2] who stated that twinkling artifacts could help to identify kidney stones and make ultrasound more accurate by distinguishing stones from other echogenic structures by utilizing B-mode and Doppler ultrasound images. In addition, Sorensen *et al.* (2013) [12] claimed that S-mode ultrasonography performed better than conventional ultrasonography in humans.

3. Results and Discussion

3.1 CT Scan Images

3.1.1 ML Techniques

The experimental results of Baygin *et al.* (2022) [1] for CT images demonstrated a superior accuracy of 99.22% and a sensitivity of 98.35% when using kNN classifier and Bayesian optimization for classification. Substituting the kNN classifier with a Neural Network classifier resulted in a drop in accuracy to 86.33%. Tuning hyperparameters using grid search function instead of Bayesian decreased the accuracy to 98.94%. Compared to the work of Yildirim *et al.* (2021) [19] utilizing the XResNet-50 model which achieved an accuracy of 96.82% and sensitivity of 95.76%, the latter’s approach lacked image segmentation into patches and INCA feature reduction, thereby lowering specificity by 3%. But at the same time reducing resource utilization and time consumption. It was clear from the results that Darknet19 was a better choice than different versions of the ResNet model, namely ResNet18, ResNet50, and ResNet101.

The automated system for kidney stone detection from CT images by Elton *et al.* (2022) [4] using 3D-UNet achieved an impressive AUC of 0.95 for patient-level classification, with a substantial improvement in sensitivity (0.52 to 0.86). The detector was capable of identifying 85% of E4 stones, and 78% of E3 stones. While denoising it was found that some small stones were lost and therefore never fed into the CNN resulting in lower accuracy for E3 stones.The observed false positive rate of 0.5 per scan, while marginally exceeding the acceptable threshold, suggested that the model might be better suited for its segmentation capabilities in medical applications, rather than its role as a detection model. On the contrary, According to Li *et al.*(2022) [6] Res U-Net was found to perform best among SegNet, DeepLabV3+, 3D U-Net, UNETR, and Res U-Net, with an accuracy of 99.95%, Specificity of 99.97%, and a Sensitivity of 96.61%. This suggests that preprocessing techniques also play a major role in improving the accuracy and efficiency of the model.

Out of the 156 CT images tested by Soni and Rai (2020) [11], the Support Vector Machine classifier achieved an accuracy of 98.71%, Sensitivity of 100%, and specificity of 97.5%. While the architecture doesn't incorporate intricate CNN structures, its performance is comparably strong, akin to the models previously mentioned. However, the model still suffers from a limited diversity and abundance of training data.

3.1.2 Non-ML Techniques

In the study conducted by Thein *et al.* (2018) [14], their image processing technique was put to the test using actual CT scan data from 30 patients. The results showed that the algorithm successfully identified 60 true positive cases while missing only 3 cases, resulting in a high sensitivity rate of 95.24%. Additionally, the algorithm generated clear output images for segmentation, although it did exhibit some instances of false positives. This approach can be utilized when there is a scarcity of data for training machine learning models.

Results from the research work of Marcus *et al.* (2018) [7] presented photon-counting-based CT (99.4%, Specificity: 98.6%, Accuracy: 99.0%) to outperform dual-source dual-energy CT (Sensitivity: 95.0%, Specificity: 94.9%, Accuracy: 96.6%.) in all three categories. That was found especially true for the detection of small stones, where photon-counting–based CT has a sensitivity of 45% compared to 25% for dual-source dual-energy CT. However, photon-counting-based CT comes at a higher cost and demands advanced hardware that may not be accessible in many locations.

3.2 Ultrasound and MRI

3.2.1 ML Techniques

The neural network model for Ultrasound images, proposed by Nithya *et al.* (2020) [8] performed best when the number of hidden neurons was 20, achieving an accuracy of 93.45%, a specificity of 90%, and a sensitivity of 100%. The segmentation using multi-kernel k means clustering method achieved an accuracy of 99.61%. A noticeable disparity in accuracy is evident when comparing ultrasound images to CT scans, suggesting that CT images outperform ultrasound in the context of kidney stone detection and segmentation.

Results from Viswanath and Gunasundari (2014) [18] revealed that the Bayes and MLP-BP classifications for Ultrasound images achieved an accuracy of 79.1% and 98.8%, respectively, in determining stone types. This leads to the clear selection of the MLP-BP classifier for stone segmentation in ultrasound images, while the kNN classifier proved more effective for CT scans.
Gray-Level Co-Occurrence Matrix (GLCM) together with the Discrete Wavelet Transform (DWT) proposed by Vinayagam *et al.* (2019) [16] had shown great potential in feature extraction leading to a high accuracy of 98.8% classification rate. However, the study does not include information regarding the model's sensitivity or specificity, which results in a significant absence of critical details.

3.2.2 Non-ML Techniques
According to Dai *et al.* (2019) [3], clinical studies revealed that twinkling artifacts could improve the detection of kidney stones. In patients with acute renal colic, twinkling artifacts had a sensitivity of 83% and a positive predictive value of 94%, compared to a sensitivity of 80% and a positive predictive value of 65% for gray-scale ultrasound alone.
Sorensen *et al.* (2013) [12] concluded that Ultrasonography techniques continued to evolve, but the version of S-mode ultrasonography performed better than conventional ultrasonography in humans, with a sensitivity of 80%, specificity of 90%, a positive predictive value of 76%, and a negative predictive value of 92%

Table 1: Table of Techniques under review

References	Methods	Performance	Dataset
Yildrim *et al.* (2021) [19]	Implemented XResNet-50 for detection	Accuracy: 96.82% Sensitivity: 95.76%	1799 CT images coronal CT images
Baygin *et al.* (2022) [1]	Used Darknet19 to generate feature vectors. Dimensionality of the vectors was then efficiently reduced through the application (INCA)	Accuracy: 99.71% Sensitivity: 99.39%	1799 CT images belonging to 790 kidney stones and 1009 healthy classes
Elton *et al.* (2022) [4]	3D U-Net model was employed to segment the kidneys, A CNN classifier was then applied to distinguish kidney stones from false positive regions	AUC of 0.95 for patient-level classification, sensitivity improvement from 0.52 to 0.86	91 CT colonography scans with kidney stones with 89 CTC scans without kidney stones
Soni and Rai (2020) [11]	A nonlinear SVM classifier was used to classify the stone in the segmented image	Accuracy: 98.71%, Sensitivity: 100% Specificity: 97.5%.	156 CT images
Thein *et al.* (2018) [14]	Three-stage CT image processing technique: Soft organ scan, remove a bony skeleton, bed-mat region removal	Sensitivity: 95.24%. Gave clear output image for segmentation	CT scan image of 30 patients. Each patient has between 500 slices and 600 slices
Marcus *et al.* (2018) [7]	Compared Dual-energy CT with PCD CT	PCD CT (Sensitivity: 99.4%, Specificity: 98.6%, Accuracy: 99.0%) outperformed Dual-energy CT (Sensitivity: 95.0%, Specificity: 94.9%, Accuracy: 96.6%)	CT scan images
Nithya *et al.* (2020) [8]	GLCM features from which only essential features were selected using the CSOA. Segmentation using multikernel k means clustering	Detection Accuracy of 93.45%, Specificity of 90%, Sensitivity of 100%. Segmentation achieved an accuracy of 99.61%	100 Ultrasound images out of which 40 are normal 30 are tumor and 30 are stone image
Viswanath and Gunasundari (2014) [18]	Stone segmentation by level-set segmentation approach, Multi-Layer Perceptron (MLP) and a Naive Bayes classifier for stone-type classification	Bayes classifier accuracy of 79.1% and MLP-BP classifier accuracy of 98.8%	500 US kidney images of both normal and abnormal kidney
Vinayagam *et al.* (2019) [16]	Extracted GLCM features. Features were fed into BPNN. Segmentation using the Fuzzy C means algorithm	Accuracy: 98.8%	Set of 20 MRI images consisting of normal and abnormal kidney
Dai *et al.* (2019) [3]	Twinkling artifacts for the detection and characterization of kidney stones	Sensitivity of 83% and a positive predictive value of 94%	Doppler mode Ultrasound images

4. Conclusion
In the realm of research comparing machine learning (ML) and non-ML techniques, there exist distinct pros and cons related to factors such as radiation exposure, cost-effectiveness, and analysis complexity. ML methods stand out for their ability to minimize human errors when it comes to identifying kidney stones, ultimately achieving exceptional precision.
When evaluating different imaging modalities, it becomes clear that the use of CT scans for detecting renal calculi yields superior accuracy, sensitivity, and specificity when contrasted with ultrasound and MRI assessments. However, it's important to note that CT scans come with a drawback - they involve a higher level of radiation, which can be a limiting factor in their broader acceptability.

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