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IJIEMR Transactions, online available on 25th Dec 2023. Link :http://www.ijiemr.org/downloads.php?vol=Volume-12&issue=Issue 12

10.48047/IJIEMR/V12/ISSUE 12/02

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Volume 12, ISSUE 12, Pages: 08-15

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Kidney Stone Detection in Ultrasound and/or CT Scan Images Using Image Processing and Machine Learning

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Abstract

Kidney stones, also known as renal calculi, are a prevalent medical condition affecting millions worldwide. The kidney stone detection has several valuable applications in the medical field. Firstly, it can assist radiologists and urologists in accurately identifying kidney stones from CT scan images, reducing the time required for manual analysis and improving diagnostic accuracy. Secondly, early detection of kidney stones can lead to more effective treatment plans and better patient outcomes. Moreover, the approach can be integrated into computer-aided diagnosis (CAD) systems, enhancing the overall efficiency of medical image analysis and supporting healthcare professionals in their decision-making process. Existing methods for kidney stone detection often rely on manual inspection by radiologists, which can be time-consuming and subjective. Some automated approaches use traditional image processing techniques, such as thresholding and edge detection, but they may struggle with accurately identifying kidney stones in complex CT scan images due to variations in stone size, shape, and intensity. Additionally, traditional regression methods might struggle with noise and artifacts commonly present in medical images, leading to reduced accuracy. This work presents a novel approach for kidney stone detection in CT scan images, leveraging the combined power of image processing and machine learning techniques. The integration of image processing and machine learning techniques addresses the drawbacks of existing methods and provides a reliable, efficient, and automated solution for early detection and diagnosis.

Keywords: CT imaging, Kidney stone detection, machine learning, decision tree classifier.

1. INTRODUCTION

Kidney stone detection in ultrasound and CT scan images is a critical aspect of modern medical imaging, playing a crucial role in the diagnosis and treatment of patients with renal calculi, a condition characterized by the presence of solid mineral deposits in the kidneys. Ultrasound and CT scans are the primary imaging modalities used for this purpose due to their ability to provide detailed images of the urinary tract and kidneys.

Ultrasound imaging, which uses high-frequency sound waves, is often the initial screening tool for kidney stone detection. It is non-invasive, cost-effective, and does not expose patients to ionizing radiation. In ultrasound images, kidney stones typically appear as hyper-echoic structures with acoustic shadowing, making them distinguishable from the surrounding tissue. Sonographers and radiologists analyze these images to locate and characterize the stones' size and position.

CT (Computed Tomography) scans, on the other hand, offer superior sensitivity and specificity in identifying kidney stones, making them the gold standard for diagnosis. CT scans provide detailed cross-sectional images, which can reveal the precise location, size, and composition of kidney stones. They are particularly useful for detecting smaller stones that might be missed on ultrasound or for

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assessing the degree of obstruction they may be causing. Additionally, CT scans can help determine the potential complications associated with kidney stones, such as infection or obstruction of the urinary tract.

The detection process involves advanced image processing and analysis techniques, including the use of computer algorithms and artificial intelligence. These tools can assist radiologists and healthcare professionals in identifying and quantifying kidney stones with greater accuracy and efficiency. Machine learning algorithms can be trained on large datasets of ultrasound and CT images to enhance their ability to recognize different types of kidney stones and distinguish them from normal renal tissue.

So, kidney stone detection in ultrasound and CT scan images plays a vital role in the diagnosis and management of renal calculi. Ultrasound serves as an initial screening tool due to its safety and accessibility, while CT scans provide a more detailed and accurate assessment. The integration of advanced imaging technologies and computer-assisted analysis methods continues to improve the accuracy and speed of detection, ultimately leading to better patient outcomes and more efficient healthcare delivery in the field of nephrology.

2. LITERATURE SURVEY

The kidneys are intricate organs that serve as a filter system of the human body. The kidneys remove acids produced by body cells and maintain the balance of salts, minerals, such as calcium, sodium, potassium, and phosphorus, and water in the blood [1]. Stones form in the kidneys when urine comprises crystal-forming constituents, such as uric acid, oxalate, and calcium. Concurrently, when urine lacks substances that prevent these crystals from joining together, there exists a chance for the development of an optimal environment for kidney stone formation. When a stone in the kidney becomes blocked in the ureters, it might block urine flow and result in kidney swelling. This also results in ureter contraction. This could be painful. Thus, it is crucial to prognosticate kidney stones. When such a circumstance is left untreated, it could block the ureters or narrow them [2]. This would enhance infections, or urine might build up, adding strain to the kidneys. These issues are rare as kidney stone treatments are accomplished before complications occur. However, conventional techniques of gathering and testing urine infections seem to be a cumbersome process. This might also affect the treatment level.

Moreover, following the reports claimed in [3], nearly 50% of women suffer from urinary infections in their lifetime. Thus, identifying such infections is crucial. As conventional process seems to be time consuming, adopting data-driven technologies, such as IoT assisted by AI and ML [4], has revolutionized the medical sector by affording effective healthcare solution wherein kidney stone prediction is no longer an exception [5]. The IoT includes a collection of connected devices with transmission abilities and data collection by wireless media [6]. Such devices could generate huge amounts of health-related patient-centric data. Processing these data demands third-party cloud data centers.

Nevertheless, transferring huge data volumes to the cloud demands huge bandwidth. Besides, various cloud computing challenges, including location unawareness, less security, high latency, and downtime, make it infeasible for sensitive applications. Hence, a computing archetype has evolved, namely fog computing, that exists as a backbone of sensitive applications for affording users with services in real time [7]. Moreover, conventional works have tried to regard various dimensions to prognosticate kidney stones by considering ML and AI.

The study [8] evaluated the differences amongst profiles of chemistries in the initial period of kidney stone formers and controls. High resolution-1H NMR (Nuclear Magnetic Resonance) spectroscopy relying on metabolomic evaluation was undertaken using 24 h urine samples. Covariance was utilized for determining the relationship of the status of stone formers with urinary metabolites or chemistries after adjustment, while correcting for FR (False Rate). In addition, GBM (Gradient Boosting Machine) with nested cross-assessment was employed for identifying the status of stone formers. Though NMR-quantified metabolites did not enhance discrimination, various urine metabolic summaries were found that might enhance the comprehension of the development of kidney stones. To construct the WISQOL-MLA (Wisconsin Stone Quality of Life–Machine Learning Algorithm) for prognosticating the health quality of urolithiasis patients based on clinical data, symptomatic and demographic data were gathered using the WISQL questionnaire, and a HRQoL computation tool was designed for patients having kidney stones. The data were gathered from 3206 patients from sixteen centers. DL (Deep Learning) and gradient boosting frameworks were utilized for predicting HRQoL scores. The dataset was split with formal training and testing ratios. The regression performance was assessed with Pearson's correlation. The classification performance was assessed with AUROC (Area under Receiver Operating Characteristic) curve. In addition, Gradient Boosting attained 0.62 as a test correlation.

Furthermore, multivariate regression accomplished correlation at a rate of 0.44. Quintile stratification in the WISQOL dataset attained an average value of 0.70. The suggested model worked better in finding the high and low quintiles of the HRQoL. Evaluating the feature significance exposed that the model weights were associated with factors used to compute the HRQoL, such as BMI (Body Mass Index), age, and symptomatic status [9].

In addition, a retrospective study was undertaken by considering 358 patients who underwent SWL for prognosticating urine stones. Probable prognostic features were assessed inclusive of the patient population, characteristics of the urinary stone, etc. DT (Decision Tree)-based ML algorithms, including RF (Random Forest), LightGBM (Light Gradient Boosting), and XGBoost, were utilized. The accuracy rates were exposed to be 86%, 87.9%, and 87.5%. Among all the considered models, LightGBM had better accuracy rate [10].

On the contrary, DL-based methods have also been used for predicting kidney stones. Accordingly, the study [11] assessed the recall of the DL technique for the automatic detection of compositions of kidney stones. Overall, 63 kidney stones were attained from the laboratory, comprising CO monohydrate, uric acid, cystine stones, MAPH (Magnesium Ammonium Phosphate Hexahydrate), and CHPD (Calcium Hydrogen Phosphate Dihydrate). Deep CNN (Deep Convolutional Neural Network)-ResNet-101 was employed as a multi-classification framework. The overall prediction rate was exposed to be 85%. Thus, the issues of conventional urine testing and preference for quick prognostication of kidney stones require an immediate need for analyzing urine in an IoT-fog environment.

Though conventional research has endeavored to accomplish this, most of the studies have not employed the suggested methods in an IoT-fog environment. In contrast, others have lacked a focus on kidney stone prognostication. Though some studies have considered their research work in this aspect, they have been deficient regarding accuracy rate. Hence, there is a scope for enhancement in this area. Moreover, different IoT-permitted sensors embedded in toilets exist to gather information related to urine in real time. Thus, this study proposes a smart toilet monitoring framework that gathers urinary information and evaluates it with real-time data to accomplish early prognostications of kidney stones based on the below objectives.

3. PROPOSED SYSTEM

Implement post-processing steps if necessary to refine the results, such as removing false positives or false negatives. Integrate the trained RFC model into clinical workflows, allowing healthcare professionals to make more accurate and efficient diagnoses. Continuously monitor the model's performance in clinical practice and gather feedback from healthcare professionals to make necessary adjustments and improvements. Validate the model's real-world effectiveness by conducting clinical trials and comparing its performance with existing diagnostic methods. This research methodology combines advanced image processing techniques with machine learning to develop a reliable and efficient system for kidney stone detection in ultrasound and CT scan images, ultimately benefiting patient care and healthcare processes. Figure 4.1 shows the proposed system model. The detailed operation illustrated as follows:

Step 1. Data Collection and Preprocessing:

- Gather a diverse dataset of ultrasound and CT scan images containing examples of kidney stones of various sizes, shapes, and compositions, along with images of healthy kidneys.
- Ensure that the dataset is properly annotated with information such as stone locations, sizes, and composition.
- Preprocess the images, which may include resizing, noise reduction, and standardization to ensure consistent data quality.

Step 2. Image Processing for Feature Extraction:

- Apply image processing techniques to extract relevant features from the ultrasound and CT scan images. These features may include texture, intensity, shape, and location characteristics.
- Segment the kidney stones from the surrounding renal tissue using segmentation algorithms like thresholding, region growing, or contour-based methods.
- Extract additional features that describe the internal properties of the stones, such as density variations in CT images or echo characteristics in ultrasound images.

Step 3. Data Splitting:

- Divide the preprocessed dataset into three subsets: a training set, a validation set, and a test set. The training set is used for model training, the validation set for hyperparameter tuning, and the test set for model evaluation.

Step 4. RFC Model Training:

- Implement a Random Forest Classifier (RFC) algorithm using libraries like scikit-learn in Python.
- Utilize the training dataset to train the RFC model. The model should learn to classify images into two categories: kidney stones present and kidney stones absent.
- Experiment with different hyperparameters, such as the number of trees in the forest and maximum tree depth, using the validation set to optimize the model's performance.

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Step 5. Model Evaluation:

- Assess the RFC model's performance on the test dataset using various evaluation metrics such as accuracy, sensitivity, specificity, precision, and F1-score.
- Generate a confusion matrix to visualize the model's ability to correctly classify kidney stone presence or absence.
- Analyze any misclassifications to identify common sources of errors.

Step 6. RFC Prediction for New Images:

- Once the RFC model demonstrates satisfactory performance on the test dataset, it can be used to predict kidney stone presence in new, unseen ultrasound and CT scan images.
- Apply the trained RFC model to the entire dataset, including images not used during training or validation, to identify kidney stone cases in clinical practice.

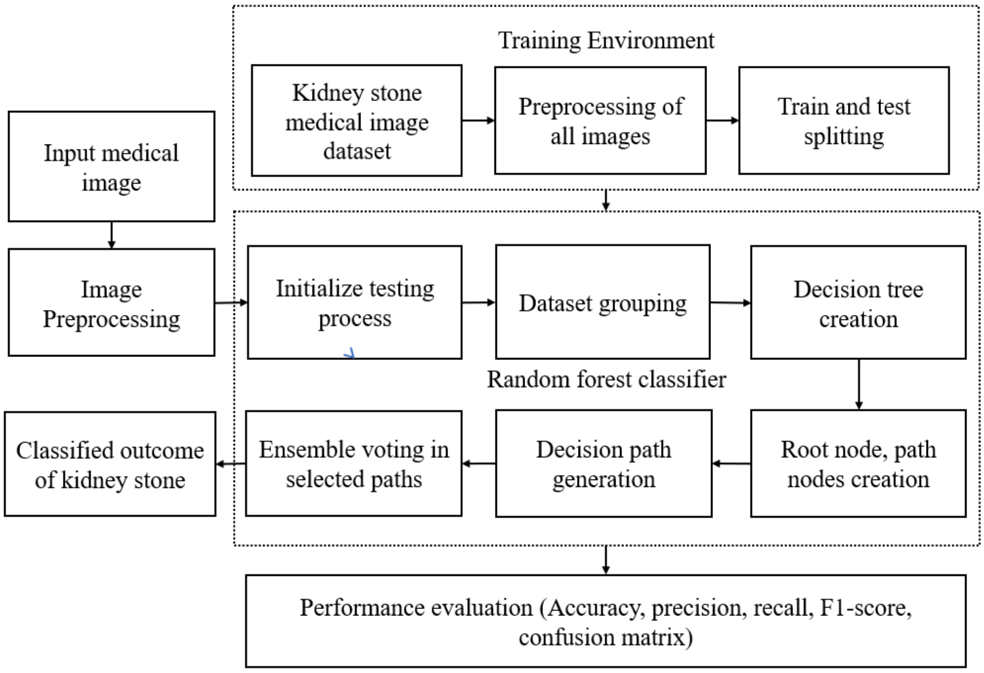

Figure 1: Proposed methodology.

4. RESULTS AND DISCUSSION

Figure 2 showcases a collection of sample images also taken from the dataset, this time representing the "Stone" class. These images offer a tangible visual representation of kidneys that are afflicted with kidney stones, offering valuable insight into the characteristics of the "Stone" class within the dataset.

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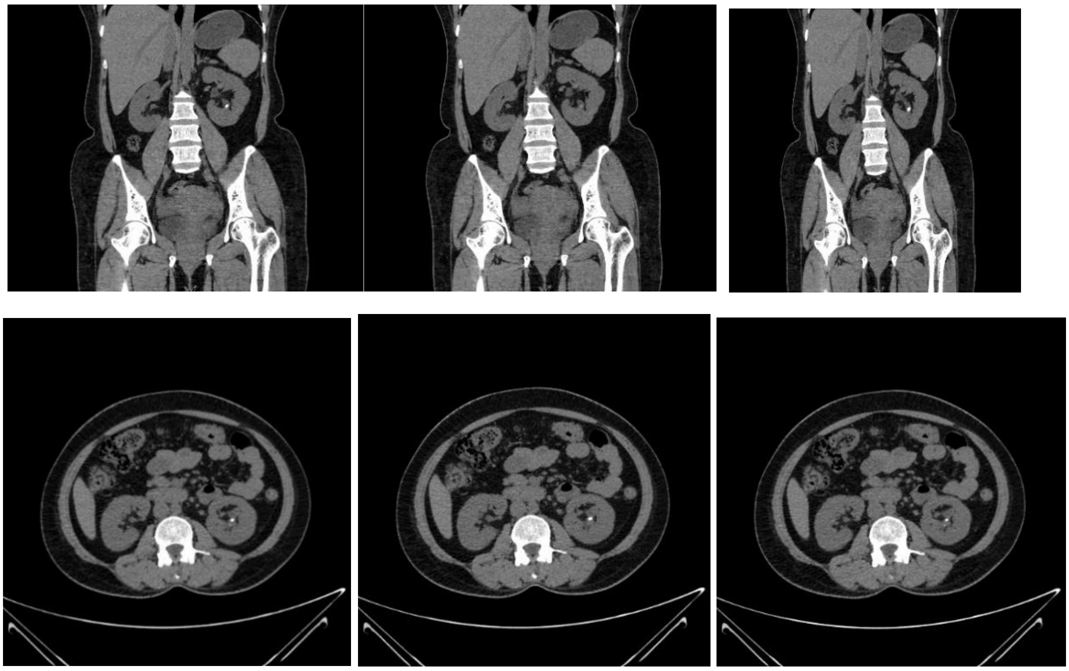

Figure 2: Sample images from dataset with Stone class.

Figure 3 showcases sample predictions generated by a Random Forest Classifier model when applied to test data. These predictions illustrate how the model classifies test images into either the "Normal" or "Stone" categories, offering a practical glimpse into its performance in real-world scenarios.

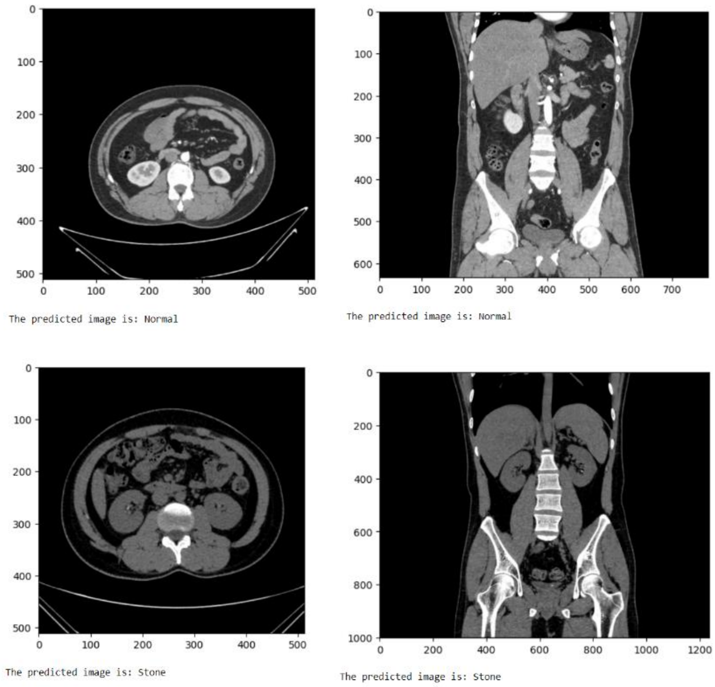

Figure 3: Sample prediction on test data using Random Forest Classifier model.

Table 1 provides an overview of the overall performance comparison of the machine learning (ML) models for kidney stone detection, namely the Random Forest and Decision Tree (DT) classifier models.

Table 1: Overall performance comparison of proposed ML models.

Model name	Accuracy (%)	Precision (%)	Recall (%)	F1-score
Random Forest	100	100	100	100
DT classifier	99	99	99	99

5. CONCLUSION

In conclusion, the research methodology outlined for kidney stone detection in ultrasound and CT scan images through image processing and Random Forest Classifier (RFC) model integration represents a significant advancement in the field of medical imaging. It offers a comprehensive solution to the challenges of accurately and efficiently diagnosing kidney stones, leading to improved patient care, streamlined healthcare workflows, and reduced radiation exposure. The methodology's ability to enhance diagnostic accuracy, ensure consistency, and support remote healthcare services underscores its transformative potential. Furthermore, its educational and research applications pave the way for ongoing improvements in diagnostic techniques and the development of a well-trained healthcare workforce. Overall, this research methodology has the potential to revolutionize the diagnosis and management of nephrolithiasis, ultimately benefiting both healthcare providers and patients.

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