Predicting Kidney Stone Size using Computed Tomography Images using VGG16 Architecture

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Abstract. Kidney stone is crucial medical disease that require prompt identification and accurate assessment for effective treatment. Their development is greatly influenced by environmental variables, especially climate, with extreme heat, high humidity, and increased sweating increasing the risk. A deep learning-based technology is used in the methodology to increase learning efficiency and automate kidney stone identification using Computed Tomography(CT) scans.The methodology incorporates dropout layers, the Adam optimizer, data augmentation, and the VGG16 model. The modular approach using OpenCV for size estimation and stone feature analysis, offers a strong foundation for precise measurements. Even the smallest stones can be approximately identified by CT scans, which is well known for its great sensitivity and specificity. Accurate diagnosis and well-informed treatment planning are made possible by insights from axial and coronal view of kidney evaluations. The procedure is enhanced by the Kidney Stone Size Prediction (KSSP) algorithm, which measures stone sizes precisely, with testing and validation accuracy of 97.53% and 97.20%, respectively,using VGG16 model and a precision of 97.68% on the training dataset. The inclusive method facilitates better patient outcomes in kidney stone management, speeds up clinical workflows, and increases diagnostic accuracy. The model's accuracy increases with the number of epochs it experiences.

Keywords: Deep Neural Networks· Kidney Stone · VGG16

1 Introduction

Kidney stones are solid mineral and salt deposits that form in the kidneys due to concentrated urine, causing the crystallization of calcium, oxalate, and uric acid. Kidney stones are more common in urban areas and in places with hot, humid weather, where the risk of stone development increases during periods of intense heat and is greatly influenced by factors such as increased humidity and perspiration. According to studies, men are more likely than women to have kidney stones [1]. Predicting the size and position of stones accurately allows effective treatment planning by determining the probability of spontaneous stone passage.

Every year on the second Thursday in March, World Kidney Day is celebrated. The goal of this international effort is to increase awareness of the critical role that healthy kidneys play in general health. Due to environmental and regional factors, the prevalence of kidney stone disease, a serious health risk, varies greatly. The occurrence in Northern India is around 15% [2]. Globally, occurrence varies by location, with rates ranging from 9.3% in North America[3] to 3.96% in South America[4], 4.7 to 6. 8% in Europe[5], and 1.9 to 17. 6% in Asia[6]. Interestingly, Iran, with its arid climate, has the highest worldwide search interest for kidney stones, outperforming all other countries. This variation is the result of regional lifestyle and environmental factors.

Creating a model that can precisely identify kidney stones and gauge their sizes addresses a major demand for better diagnostic techniques in the medical industry. Through the use of sophisticated deep learning algorithms and image processing technologies, the methodology seeks to improve prediction accuracy while insisting on accurate size measurements. Predictions are based on normal and stone CT images, using KSSP algorithm which incorporates VGG16 architecture for efficient stone recognition and modular approach using OpenCV being used for precise size estimate.

The model is sensitive to change in image quality or preprocessing methods, as well as its difficulties in generalizing across various datasets, are some of its shortcomings. Using data augmentation techniques, the method overcomes these obstacles by strengthening the model's resilience and enhancing its capacity to generalize to new data. Increasing accuracy and decreasing overfitting can be achieved by fine-tuning the VGG16 architecture on a larger and more diverse data set. Ensemble approaches also improve prediction reliability, and ongoing clinical expert feedback guarantees that the model satisfies real-world diagnostic needs, which eventually results in more precise and reliable identification of kidney stones and sizes.

Fig. 1: VGG16 Architecture

The architecture retains its convolutional layers, which identify edges, textures, and shapes essential for CT scan analysis, and uses the pre-trained VGG16 as a feature extractor. Robust, broadly applicable features are guaranteed by the frozen VGG16 layers. A dropout layer guards against overfitting, a dense layer discovers intricate patterns unique to kidney stones, and a GlobalAveragePooling layer streamlines feature maps. The model is accurate and effective for medical imaging tasks because the last softmax layer produces kidney stone classification probabilities.

The structure of the paper is as follows: A concise review of the literature is given in Section II, with an emphasis on the more recent related publications. The problem statement, objectives, context, and suggested methodology are described in Section III. The findings are shown in Section IV, which also provides a thorough analysis of the implementation procedure. Finally, the paper is concluded in Section V.

2 Literature Survey

The literature review offers a vital foundation for understanding the advances and challenges in the classification and detection of kidney stones using computer vision and machine learning techniques. This paper examines previous research to identify significant methodologies, datasets, and algorithms that have aided in the accurate segmentation and analysis of medical images of kidney. By examining this research, we intend to offer a distinct framework for developing a solid solution that closes the gaps and provides a method to improve diagnostic precision.

Sumit *et. al.,*[7] proposed a coronal CT scans with Random Forest (RF), Logistic Regression (LR), or a combination of the two to automatically diagnose kidney stones. The ensemble model yields lower FPR(False Positive Rate) and FNR(False Negative Rate) of 2.04% and 3.92% and the greatest accuracy of 97% with TPR(True Positive Rate), TNR(True Negative rate) of 96.07%, and 97.95%. High accuracy and efficient feature selection are benefits noise issues and the requirement for huge datasets are drawbacks.Soman *et. al.,*[8]suggests a deep learning model, namely VGG16, for kidney stone detection that is automated. Using the Grad-CAM technique to identify the area of interest, the model successfully detects kidney stones with an accuracy of 99%. Great accuracy and efficient Grad-CAM detection are advantages nevertheless, overfitting may occur because of the great accuracy attained on the training set. This implies that the model's performance in practical applications may suffer if it is unable to generalize adequately to fresh, untested data.Hemalatha *et. al.,* [9] proposed a deep learning model for automated kidney stone detection using VGG16. The model achieves an accuracy of 99% and effectively detects kidney stones using the Grad-CAM technique to identify the area of interest.One benefit of preprocessing techniques, such as the application of filters, is that they aid in lowering noise and enhancing image quality however, there are drawbacks as well. Some medical facilities may not be able to afford the model's high processing requirements for training and inference.

Bülent *et. al.,*[10]proposes using CT images to assess the effectiveness of many deep learning techniques used to kidney stone illnesses. With test accuracy of 98.52, sensitivity of 95.34%, and specificity of 100%, the Inception-V3 model attains the highest results. High accuracy, efficient feature extraction, and technical assistance for radiologists are among the benefits nevertheless, drawbacks include the accuracy of the model may be impacted by noise in CT scans, necessitating efficient preprocessing methods. Bingding *et. al.,* [11] suggests deep segmentation networks to identify kidney stones and segment kidneys in unenhanced abdominal CT scans. The model offers an open-source dataset for additional study and demonstrates great accuracy in both 2D and 3D segmentation tasks. High precision and the availability of an open-source dataset are benefits, while drawbacks include the lengthy and skilled procedure of annotating the CT scans can be a hindrance to the production of sizable, high-quality datasets.

The literature review highlights the progress of image-based diagnostic approaches, namely in the identification and description of kidney stones. Previous studies, from traditional image processing techniques to advanced deep learning models, have emphasized the need of accurate segmentation, feature extraction, and classification in achieving improved diagnostic results. The review's findings emphasize how important it is to combine precise preprocessing methods with optimal CNN architectures.In particular, CNN architectures like VGG16 and contemporary preprocessing techniques are emphasized as means of enhancing kidney stone characteristic prediction. These findings pave the way for future advancements in medical image processing and predictive diagnostics by facilitating the creation of innovative methods that satisfy existing standards and get around limitations.

Table 1: Assessment of Stone Detection Techniques from the Literature in 2024

Author	**Methodology**	**Performance Parameter**	**Gaps Identified**
Sagar *et. al.,* [12]	YOLOv8	Precision of 85.76%, recall of 75.28%, F1 score of 75.72%.	The requirement for a bigger and more varied dataset.
Sohaib *et. al.,* [13]	InceptionV3	Accuracy of 98.84%, Precision (PRC) StackedEnsembleNet 100%, PSOWeightedAvgNet 98.79%.	Limited data affects model generalization,combining multiple models can capture more features.
Hanife *et. al.,* [14]	VGG19	Accuracy of 98.15%, recall of 0.991%, specificity of 0.974%, precision of 0.966%, F1-measure of 0.978%, kappa statistic of 0.962%, and weighted-F1 score of 0.981%.	The use of complex transfer learning models like ResNet101 requires significant computational resources, which may not be feasible for all healthcare settings.

3 PROPOSED METHODOLOGY

Solid mineral deposits called kidney stones, develop in the kidneys as a result of the crystallization of chemicals such as uric acid, calcium, and oxalate in concentrated urine. Patients' pain levels and consequences are influenced by their size. Stone formation is caused by a number of factors, including genetic predisposition, nutrition, and hydration. Because CT scans have a high sensitivity and specificity for identifying kidney stones, they are frequently utilized in clinical settings. Choosing the best course of therapy, which may include conservative management or surgery, depends on knowing the size of these stones. Efficient medical care depends on precise measurement and detection.

The goal is to create a model that can precisely identify kidney stones and gauge their sizes, meeting a medical demand for better diagnostic techniques. The goal of the proposed paper is to use image processing tools to obtain accurate size measurements and improve prediction accuracy through sophisticated deep learning algorithms.The proposed paper seeks to accomplish the following objectives:

- To develop pre-trained model for precise kidney stone detection in CT scan images.
- To improve diagnostic capabilities by implementing modular approaches for accurate kidney stone size measurement.

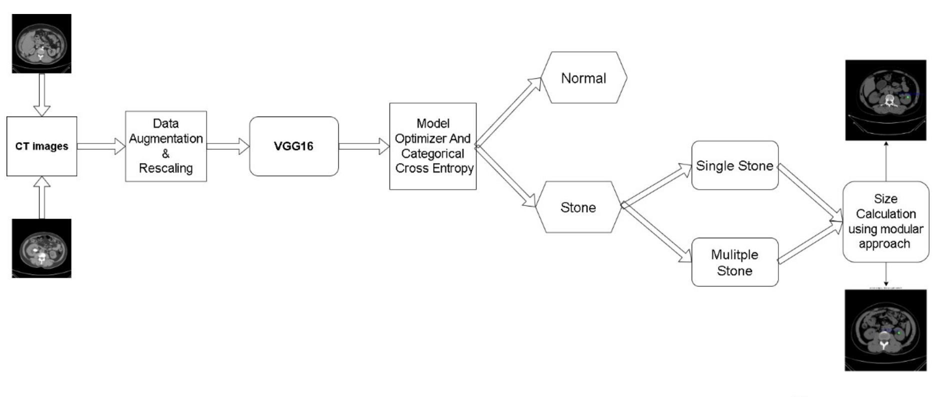


Fig. 2: Proposed Approach for Identifying and Measuring Kidney Stone Size

In Fig.2,the model offers a deep learning pipeline for the detection of kidney stones and the estimation of their size using CT scans. Starting with data preprocessing, the procedure involves enhancing the dataset using methods such as uniform image rescaling and zooming. VGG16, a pre-trained convolutional neural network renowned for its precision in images classification, is used by the pipeline to improve detection skills. The kidney stone dataset is used to refine the model during training by applying a binary cross-entropy loss function and an optimizer such as Adam. When kidney stones are found, the trained model analyzes the photos and determines their size. The classification results and size estimations are included in the final output, which offers insightful information for better diagnostic techniques.The accuracy of kidney stone detection and size estimation in clinical situations is improved by this pipeline's effective combination of cutting-edge deep learning algorithms.The detailed steps for proposed methodology are represented in Algorithm 1(KSSP)

Algorithm 1 Kidney Stone Size Prediction (KSSP)

Input: CT-Scan images of the kidney (axial view, coronal view)
Output: Prediction of kidney stone presence and size

1. Initialization: Preprocess the input images: Resize to target dimensions and normalize pixel values.

2. Load Pre-trained Model: Load the pre-trained VGG16 model excluding the top layer. Compile the model using the Adam optimizer and binary cross-entropy as the loss function.

3. Model Training: Train the model with early stopping and model checkpointing to save the best weights. Evaluate model performance on validation and test datasets (accuracy and loss).

4. Prediction: For each input image, predict class probabilities using the trained model. Extract the class with the highest probability (Stone or Normal). If the prediction is Normal, output Normal and break. Otherwise, extract the DPI of the image. Compute the conversion factor for kidney stone size using:

$$\text{Conversion Factor} = \frac{25.4}{\text{DPI}} \tag{1}$$

Preprocess the region of interest (ROI): Convert to grayscale, apply Gaussian blur, set thresholds, and detect relevant coordinates. Compute the kidney stone size using:

$$\text{Length}_{px} = \max(\text{width}, \text{height}) \tag{2}$$

$$\text{Length}mm = \text{Length}px \times \text{Conversion Factor} \tag{3}$$

Annotate the input image with the detected stone and its size in mm.

Output: Prediction:Stone with annotated size (in mm).

Kidney stones are detected and their sizes are estimated from CT scans using the VGG16 architecture of the model. Data preprocessing, which includes scaling and data augmentation to improve model resilience. The Adam optimizer and binary cross-entropy loss are used to train the model, while early stopping and checkpointing are used to avoid overfitting. It categorizes CT images as Normal or Stone after training.In clinical settings, it provides useful outputs for increased diagnostic accuracy by estimating sizes for images with stones based on image dimensions and DPI conversion factors.

4 Results and Discussion

A machine with Windows 11 with an Intel(R) Core(TM) i5-10210U CPU running at 1.60GHz and 8GB of RAM is used for the testing. Python is the main programming language used in the development of the deep learning model, which makes use of TensorFlow and Keras. Libraries like NumPy and Pandas are used for data processing and analysis. OpenCV, NumPy, and Matplotlib are among the tools used for image processing and analysis; images are first loaded in grayscale. Gaussian blur is employed to smooth the images and reduce noise.Binary thresholding is used to successfully separate kidney stones from the background . For precise measurement, this approach sharpens the attention on important areas.

The dataset includes 6,454 images including both normal and kidney stone images. Each picture provides a thorough look of the kidney's anatomy by showing a horizontal cross-section of the organ. A healthy kidney's cross-section is depicted in 5,077 scans that are categorized as normal. The sample images are shown in Fig. 3.The dataset has 1,377 images that are classified as kidney stones each image depicts a cross-section of a kidney having stones in it. Fig. 4, shows samples of both types of images. Every image in the collection is of 224 x 224 pixel resolution.

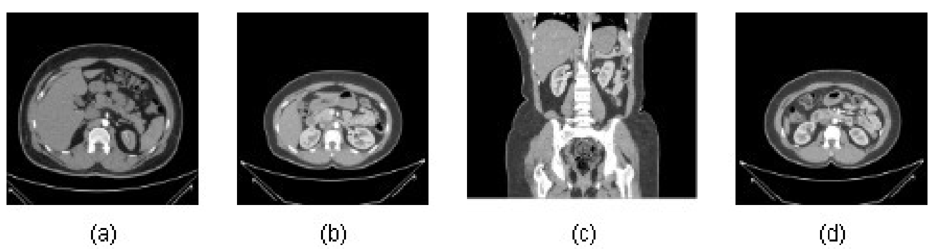


Fig. 3: Sample CT scan images of Normal Kidney

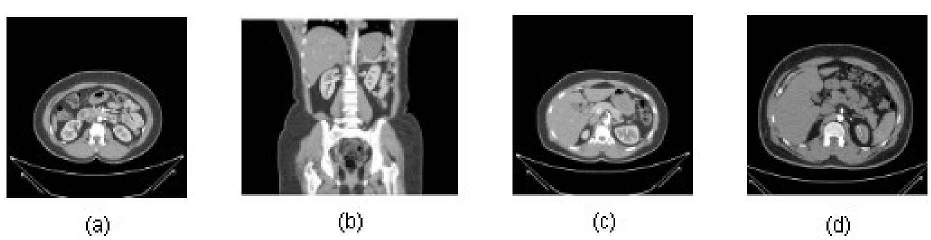


Fig. 4: Sample CT scan images of Kidney Stones

The model is trained on 224x224 pixel-scaled photos across 25 epochs with a learning rate of 0.001 and a batch size of 32. The loss function is the binary cross-entropy, and the pixel values are rescaled by 1/255 to augment the data. All layers of the VGG16 base model are first frozen to avoid overfitting, and it is enhanced with a custom classifier. By lowering the learning rate and selectively unfreezing individual layers, fine-tuning improves model performance and makes it more adaptive to the particular dataset. The global average pooling layer (2D) in the VGG16 model is used to extract hierarchical features from the input images. Fully connected neural networks intended for classification make up the next layers, and dropout is used at a rate of 0.5 to reduce overfitting. To further help with overfitting, a dense layer is also used. The loss function for classification tasks is binary cross-entropy, and the Adam optimizer is used for effective gradient descent. The dataset is divided into two parts: 20% is set aside for testing and 80% is used for training.

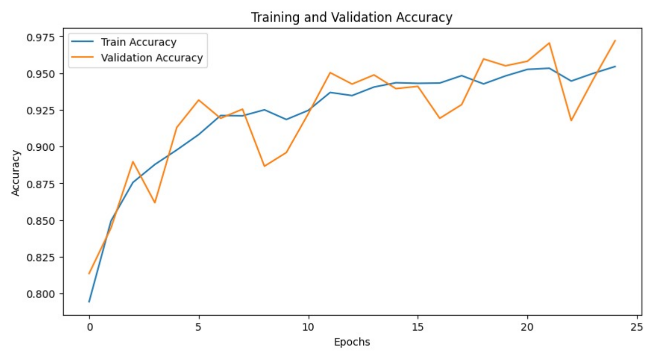


Fig. 5: Accuracy of VGG16 for stone prediction

Fig. 6: Loss of the VGG16 Model during Kidney Stone Prediction

The model's accuracy increases with the number of epochs it experiences. The VGG16 model achieves 97. 68% precision in the training data set, as shown by the training versus validation accuracy curve in Fig. 5. The model achieves 97.53% accuracy on the testing dataset and 97.20% accuracy on the validation dataset. The VGG16 model's binary cross-entropy loss function in Fig.6 demonstrates a consistent drop in loss as the number of epochs increases, suggesting successful learning. The Fig. 7.shows confusion matrix, the model properly detects 509 normal photos and diagnoses 123 kidney stone images. It also highlights the fact that no ordinary images are incorrectly labeled, despite 16 stone images being misclassified.

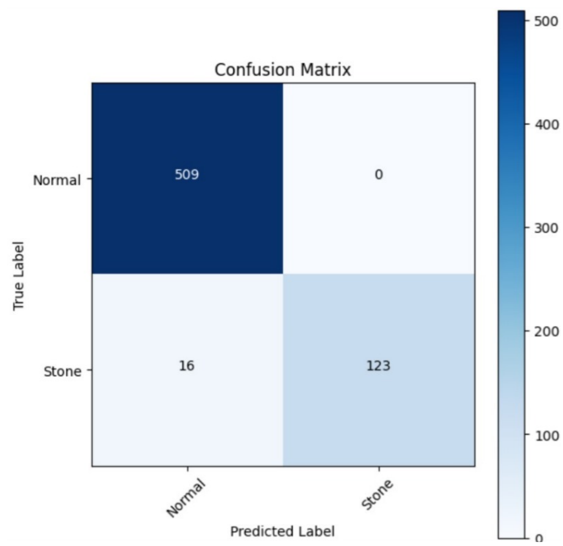


Fig. 7: Confusion Matrix for the Performance of the Kidney Stone Prediction

The Table 2 shows kidney stone images with size calculated using Algorithm 1(KSSP).It shows axial and coronal view of images of kidney stones used for stone size prediction ,it is observed that predicted kidney stone sizes are displayed in last column of table 2.With this information, medical experts can more accurately evaluate the disease and decide whether surgery is necessary or if a stone can pass spontaneously. Natural passage is about 80% likely for stones smaller than 2 mm. The chance of passing is about 60% for stones that are between 4 and 10 mm. Surgery like ureteroscopic lithotripsy (URSL), retrograde intrarenal surgery (RIRS), or percutaneous nephrolithotomy (PCNL) is usually required for stones greater than 10 mm.

5 Conclusion

The paper shows how the VGG16 architecture can be used to detect kidney stones and estimate their size using CT scans. The model produces reliable predictions by improving learning and reducing overfitting through the use of data augmentation, dropout layers, and the Adam optimizer. Medical experts can make well-informed treatment recommendations based on stone size by analyzing axial and coronal images of kidney. The study emphasizes how deep

Table 2: Size Prediction of Kidney Stone

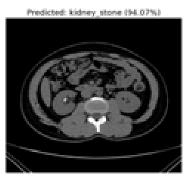
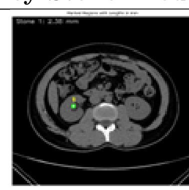
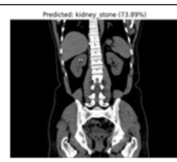
Sno	Original Image	Kidney Stone Prediction	Stone Sizes
1.			Stone 1: 2.38 mm
2.			Stone 1: 1.85 mm Stone 2: 2.12 mm Stone 3: 1.06 mm
3.			Stone 1: 1.06 mm Stone 2: 2.38 mm

Table 3: QUANTITATIVE COMPARISON WITH METHODS

Parameters	**Sagar *et. al.,* [12]**	**Reimer *et. al* [15]**	**Proposed Model (VGG16)**
Model	YOLOv8	virtual non-contrast reconstructions (VNC)	VGG16
Accuracy	82.52%	87.9%	97.53%

learning can improve clinical procedures for kidney stone care and increase diagnostic accuracy. In order to improve clinical decision making and prediction accuracy, future studies might concentrate on incorporating cutting-edge methods like transfer learning and real-time image processing, as well as broadening the data set to encompass a variety of demographics of patients and types of kidney stones.

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