Kidney Stone Detection

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Abstract

Background and Objectives: Kidney stones have been a significant issue lately. If not caught early, they can lead to problems that may require surgery to remove the stone. Research indicates that measuring the volume of kidney stones is more practical and consistent than using linear measurements. Deep learning algorithms, which rely on non-contrast abdominal CT scans, could be helpful in spotting stones and reducing the manual effort needed for detection. We use a collection of CT scans, some showing kidney stones marked manually and others without. To find kidney stones, we apply CNN and Random Search to the dataset. **Material & Methods**: This study sought to address the crucial issue of kidney stone diagnosis and utilized a comprehensive dataset of non-contrast abdominal CT scans. The dataset included annotated cases of kidney stones as well as scans without any such conditions. To effectively identify and detect kidney stones, Convolutional Neural Networks (CNN) were employed, leveraging their ability to learn hierarchical features from the provided CT images. In addition to CNN, the study also utilized the Random Search algorithm to enhance the model's overall performance. This methodological approach was aimed at establishing a robust and automated system for identifying kidney stones in CT scans, with the potential to significantly minimize the manual effort traditionally required for such detection processes.

1 Introduction

The incidence of kidney stone disease is increasing, with renal calculi, or kidney stones, being solid masses forming in the kidneys. Anyone, including children, can be affected, often going unnoticed unless there is severe abdominal pain or unusual urine color. Symptoms may include fever, discomfort, and nausea, and complications like infection and renal failure can worsen an obstructing stone. While small ureteral stones can pass on their own, larger ones may need interventions like extracorporeal shock wave lithotripsy or endoscopic lithotripsy. Early detection is crucial as kidney stone disorders may go unnoticed until later stages, causing harm to the kidneys. Conditions like diabetes, hypertension, and glomerulonephritis are major causes of kidney failure, emphasizing the need for early detection to prevent complications and death. Kidney stones are categorized based on location as kidney (nephrolithiasis), ureter (ureterolithiasis), and bladder (cystolithiasis).

In the realm of biological and clinical research, imaging plays a vital role. Medical imaging creates visual representations of internal organs, aiding clinical research and interventions. Options like Ultrasound (US), Noncontrast Computed Tomography (NCCT or CT-Scan), Magnetic Resonance Imaging (MRI), and X-ray are now available. NCCT is widely used for diagnosing acute flank pain. Automating stone detection in CT images can leverage image processing to yield precise results without human intervention.

Traditionally, radiologists manually detect stones in CT images, contributing to increased CT usage for urolithiasis but also leading to higher workload, longer turnaround times, and hospital admissions. This study developed a semi-automatic kidney screening tool using KUB CT scans, employing digital image processing and analysis.

Deep learning algorithms have proven successful in medical image analysis and physiological signal interpretation. These models, used in various medical applications, excel in tasks like segmentation, classification, and detection. In urology, DL techniques automate the detection of ureteral and kidney stones.

CT scan data, presented as grayscale 3D images, associates each pixel's value with the substance occupying that location. Kidney stones have a distinct chemical composition, reflected in pixel values. However, other body components may share this composition, requiring advanced image analysis techniques to differentiate them from kidney stones.

2 Literature Survey

1. Title: Kidney Stone Detection Using Image Processing and Deep Learning.(ULTRASOUND IMAGES)Year: The paper is published in May 2023.The authors of the paper areNeha Khandelwal, Raju Kamble, Sonam Rani, and Sarvesh Mamidwar from the Department of E&TC at SKNCOE, SPPU Pune.Methods used:- Dataset Preparation, Data Processing,CNN Training,Trained Module.The paper showed experimental outputs indicating whether a kidney stone was present or not. It used a classification approach with [0,1] indicating no stone and [1,0] indicating a stone. The paper mentioned that the system was working correctly with proper accuracy, but it didn't provide specific accuracy figures.

2. Title: Detection of kidney stone using digital image processing: a holistic approach.Year: The paper is published in September 2022.The authors of the paper are Angshuman Khan, Rupayan Das, and M C Parameshwara . Methods used:- Image Collection,Feature Extraction, Image Enhancement,Image Adjustment. Image Segmentation, Morphological Analysis.It involves digital image processing method, which includes image enhancement, median filtering for noise reduction, thresholding for segmentation, and morphological analysis, is effective in detecting kidney stones in ultrasound images.

3. Title: Kidney Stone Detection with CT Images Using Neural Network Year: The paper is published in May 2020.The authors of the paper are Riya Mishra, Avik Bhattacharjee, M. Gayathri, and C. Malathy.•Discrete Wavelet Transform (DWT) for preprocessing, Gray Level Co-occurrence Matrix (GLCM) for feature extraction •, Back Propagation Neural Network (BPN) for classification, •Fuzzy C-Means clustering for segmentation.

4. Title: Kidney CT Image Analysis Using CNN Year: The paper is published in July, 2023. Harshit Mittal, Department of Computer Science and Engineering, Maharaja Agrasen Institute of Technology, New Delhi, India.Method used are CNN Architecture: Six convolutional layers (32, 64, 128 filters, 3x3 size), max-pooling (2x2), two fully connected layers (256, 128 neurons), and an output layer (four neurons).Training: TensorFlow, Adam optimizer, categorical cross-entropy loss, 5 epochs, batch size 112.Regularization: Dropout and L2 regularization.Evaluation: Test set with 6,223 images, metrics: accuracy, precision, recall, F1-score.

5. Title: Kidney Tumor Segmentation and Classification using Deep Neural Network on CT Images.Authors:Md Humaion Kabir MehediDepartment of Computer Science and Engineering, Brac University, Dhaka. Method used are

Annotation the process of identifying and describing the subject matter of a picture. Second is segmentation Both manual and model based automated kidney segmentation are used in our work to segment the kidney from CT images. Then comes classification which Target Labeling with the help of cnn.The accuracy of UNet is 97.58% and SegNet is 96.38%. For the loss function value, UNet has less which is 4.01%, and SegNet has 10.01%. IoU value of UNet is 98.57%, whereas, SegNet is 97.30%. Calculating the dice coefficient, there is a significant difference between the two models. UNet has a score of 54.40% but SegNet has much less, 31.91%. The precision value has been calculated as 59.52% for UNet and 37.11% for SegNet.

3 Methodology

3.1 Data-Set

The process of gathering the dataset depends upon the type of problem we are trying to solve. As this project is mainly focused on Image Classification, we need to acquire the required resources from open-source websites such as Kaggle, Github etc.

The dataset comprises over 1609 images acquired from patients who were suspected of having a medical condition. Their CT scans were performed and analyzed by experienced laboratory professionals. This dataset is categorized into two distinct groups: one consisting of individuals with kidney stones and the other without kidney stones.

3.2 Pre-Processing

3.2.1 Data Pre-Processing

Data preprocessing plays a vital role when working with image datasets. Given the variable sizes of the images, it's essential to standardize them to a fixed size. The dataset comprises two folders, namely "Kidney_Stone" and "Normal." Since the images lack explicit labels, we leverage these folder names to categorize them for training the Deep Learning Model. All images are resized to a uniform dimension of 128 x 128 pixels. Following this, we transform each image into a Numpy array, incorporating the corresponding class label. The dataset is then divided, allocating 90% for training the model and 10% for testing purposes.

3.2.2 Image Processing

Image Processing is divided into 2 modules:

1. Image Pre-processing

This task is fundamentally important due to the potential presence of noise in CT scan images. During this process, we employ techniques such as the Median filter and utilize histogram equalization or Power Law Transformation to enhance and filter the images.

- **Median Filter:** The cv2.medianBlur() function in Python's OpenCV is designed for image blurring using a median kernel. This non-linear filtering method is particularly adept at eliminating impulse noise and salt-and-pepper noise. The operation involves taking the median of all pixels within the specified kernel area and substituting the central element with this calculated median value. The syntax for this function is illustrated in Figure 4.1:

  Syntax: cv2.medianBlur(image, ksize)

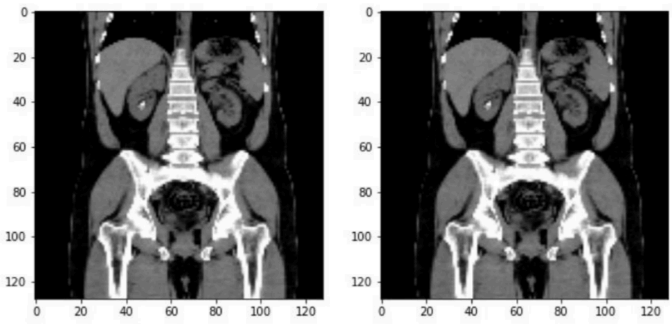

Figure 3.1: Median Filter

- **Histogram Equalization:** The Histogram Equalization technique is employed to adjust the intensities of an image. The resulting image may exhibit lower quality, prompting the need for image enhancement to improve its overall quality. In this process, the intensity of each pixel is adjusted. If the image tends towards darker tones, this method stretches the intensity distribution towards the brighter side, effectively enhancing the image.
- **Power law Transformation**: This method is better option for image enhancement. Here, the value of constant should be assumed on the basis of trial-and-error method. Gamma correction is useful when you want to change the contrast and brightness of an image.

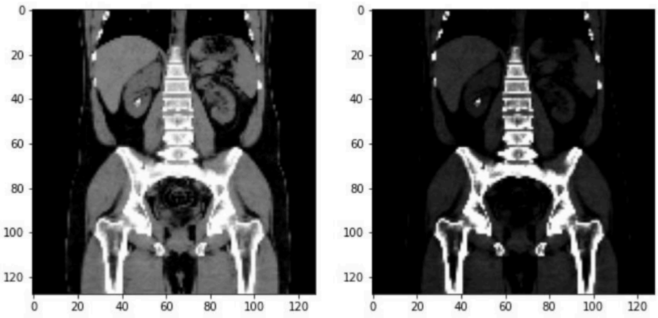

Figure 3.2: Power law Transformation

2. Image Segmentation:
Image segmentation involves dividing an image into distinct regions to extract pertinent information. This process is crucial in medical imaging, facilitating the visualization of medical data and the diagnosis of various diseases. The Thresholding Method is applied to the image, which has undergone gamma adjustment, enabling the segmentation of the foreground (stone and bones) and background. The thresholding value is determined by the pixel intensity, causing intensities below this level to be set to zero.

3.3 Model Architecture

3.3.1 Convolutional Neural Networks(CNN): The most crucial step in the project involves building a model to process the collected data, and we have opted for Convolutional Neural Networks (CNN) as our algorithm of choice. CNNs, inspired by the visual cortex of the human brain, are a category of deep neural networks designed for handling structured arrays of data, especially images. Widely utilized in Computer Vision, CNNs stand at the forefront of technology for tasks such as Image Classification.

```
model.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 126, 126, 64)      640

 max_pooling2d (MaxPooling2  (None, 42, 42, 64)        0
 D)

 conv2d_1 (Conv2D)           (None, 38, 38, 32)        51232

 max_pooling2d_1 (MaxPoolin  (None, 12, 12, 32)        0
 g2D)

 flatten (Flatten)           (None, 4608)              0

 dense (Dense)               (None, 80)                368720

 dropout (Dropout)           (None, 80)                0

 dense_1 (Dense)             (None, 1)                 81

=================================================================
Total params: 420673 (1.60 MB)
Trainable params: 420673 (1.60 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig 3.4: Figure showing the detailed architecture of proposed CNN model

3.3.2 Hyperparameter Turning:: Hyperparameter Tuning is the process of modifying the model architecture to fit the available space. This is nothing more than looking for the suitable hyperparameter to achieve great precision and accuracy. There are various parameter tuning methods, the most popular ones are:

- Grid Search
- Random Search

Grid Search: Grid search is a method for determining the optimal collection of hyperparameters for a given model. Hyperparameters are not model parameters, and finding the optimal set from training data is impossible. When we use something like Adam, RMSprop etc. to optimize a loss function, we learn model parameters during training. We just generate a model for each combination of hyperparameters and test each model in this tuning process.

Random Search: Random search is a method for finding the optimum solution for the model by using random combinations of hyper-parameters. It's similar to grid search, but it is better in terms of performance. The only limitation of random search is that it generates a lot of variance during computation. Because the parameters are chosen at random and no intelligence is applied to sample these combinations, we cannot guarantee for optimal parameters.

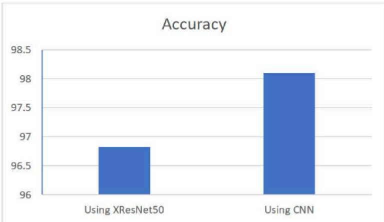

Fig. 3.5: **Accuracy Comparison**

4 Results

Metrics helps in analyzing, measuring the performance quality of machine learning models in different areas such as efficiency and error proneness by using Accuracy, Precision, Recall, F1 score and specificity values.Firstly, before learning about these metrics we classify the results into four different labels:

- **True Positive (TP):** Predicted value is True and True is actual value.
- **True Negative (TN):** Predicted value is False and False is actual value.
- **False Positive (FP):** Predicted value is True but False is actual value.
- **False Negative (FN):** Predicted value is False but True is actual value.

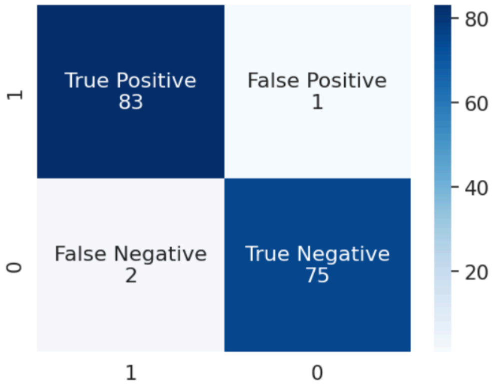

Figure 4.6: Confusion matrix

4.1 Confusion Matrix: The confusion matrix is an N x N matrix employed to evaluate the performance of a model in addressing classification problems, applicable to both binary and multiclass scenarios. Figure 6.1 provides a visual representation of the fundamental aspects of a confusion matrix.

In our project, after splitting the dataset into train and test, we performed testing on 161 unseen images and the results are shown in the below table

4.2 Accuracy Value: Accuracy is a common evaluation metric for classification problems. It's the number of correct predictions made as a ratio of all predictions made. The percentage of correct predictions for the test data is known as accuracy.

$$Accuracy = (TP + TN) / TP + FP + FN + TN$$

Accuracy value for our project after testing it on unseen data is as follows:

$$Accuracy = (83+75)/(83 + 1 + 2 + 75) = 0.981$$

4.3 Precision, Recall, F1-Score, IoU: Precision, recall, F1-score, and Intersection over Union (IoU) are key metrics used to evaluate the performance of machine learning models, particularly in the context of object detection and classification tasks. Precision measures the proportion of correctly identified positive cases out of all cases predicted as positive, emphasizing the model's accuracy. Recall quantifies the proportion of actual positive cases that were correctly identified by the model, focusing on the model's ability to capture all positive cases. The F1-score represents the harmonic mean of precision and recall, providing a balanced assessment of a model's performance. Lastly, IoU measures the overlap between the predicted bounding box and the ground truth box

```
Precision: 28.666666666666668
Recall: 25.333333333333332
F1-score: 52.666666666666664
IoU: 0.6674815380697733
Dice Coefficient: 0.3529518193588301
```

Figure 4.7: Output Values

4.3 Testing on Unseen Data

We separated 18 images from the original dataset before feeding them to the model for training. These images will be used for testing. Fig 4.7 and 4.8 .

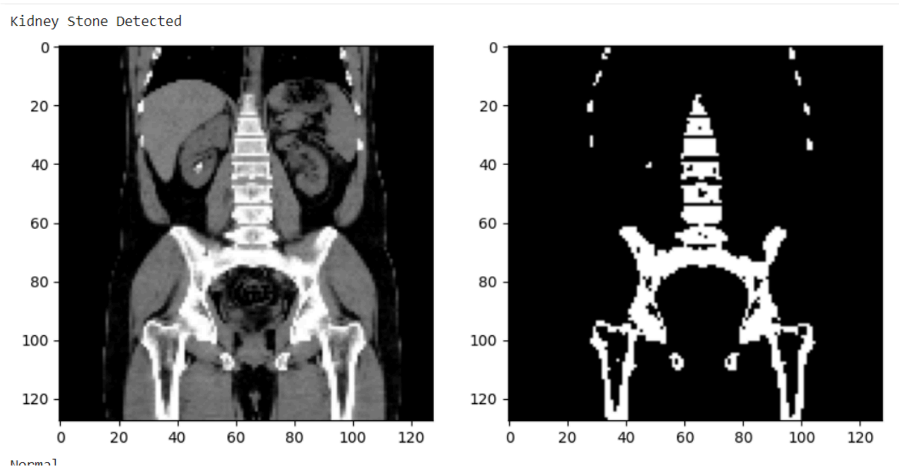

Figure 4.7: Output 1(Kidney Stone Detected)

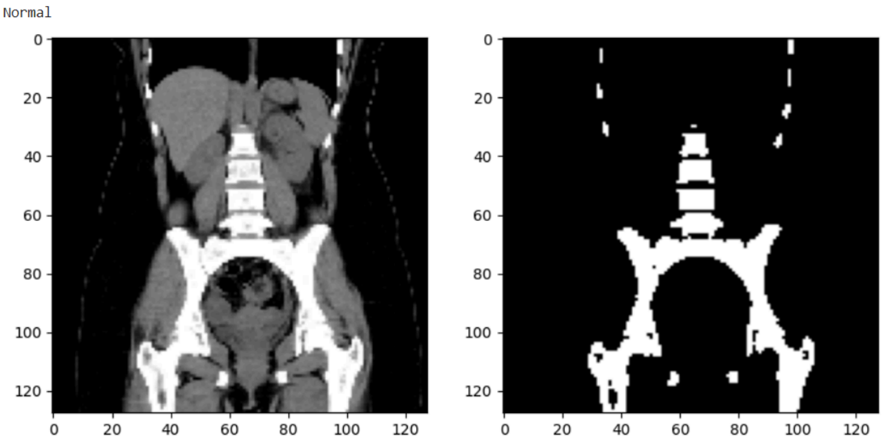

Figure 4.8: Output 2(Normal)

5 Conclusion

An efficient machine learning based detection system has been developed for identification of Kidney Stones. Convolutional Neural Network is used in designing of the system. Thus, another innovative touch of our project is that with help of image processing important features are extracted for classification thus it helped to reduce the processing time of the detection system. The model has acquired an accuracy of around 90% for test data. Thus, with the help of our project the detection of Kidney Stone becomes easy..

References

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