

A Deep Learning Approach to Kidney Stone Detection

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Abstract:

The kidney is commonly evaluated using ultrasound scanning as a diagnostic tool to detect various abnormalities, including stones, cysts, urine blockages, congenital anomalies, and cancerous cells. Nephrolithiasis, a prevalent kidney stone disease in the western population, can lead to significant morbidity if left untreated, particularly in cases of large stones. To address this issue, Convolutional Neural Networks (CNNs or ConvNets) have been developed as complex feed-forward neural networks with a hierarchical structure that aid in accurate image classification and recognition. The network architecture resembles a funnel, processing input data at each level until the output is generated from a fully connected layer where all neurons are interlinked.

Keywords—KidneyStone, Nephrolithiasis, Deep Learning, Convolutional Neural Networks (CNNs or ConvNets), Medical Imaging, Ultrasound Scanning, Diagnosis, Computed Tomography

I. INTRODUCTION

When hard mineral and acid salt deposits accumulate in the kidneys, they can form calcium stones, a prevalent type of kidney stone that can cause pain during their passage through the urinary tract. The process of stones moving through the urinary tract can lead to considerable discomfort and intense pain, typically felt on one side of the abdomen and accompanied by nausea. However, kidney stones usually do not result in permanent harm. The standard treatment for kidney stones involves pain relief medication and increasing fluid intake to aid in the stones' passage. Drinking plenty of water is particularly helpful for this condition. The formation of kidney stones occurs when minerals and salts such as calcium and uric acid accumulate in the urine due to inadequate fluid intake. When the body lacks fluids, it accumulates waste and increases the likelihood of kidney stone formation. Medical intervention may be necessary

to remove or break up larger stones. To diagnose kidney stones, several methods are available, including urine and blood tests, CT scans, and MRI scans. However, producing results for a large amount of data through human inspection and operator is impractical.

Accurately identifying the location and presence of kidney stones is crucial during surgical procedures. Ultrasound imaging is one of the imaging techniques that can be used to diagnose kidney abnormalities. It is a non-invasive and safe method that utilizes high-frequency sound waves to produce images of the kidneys, allowing doctors to detect and locate kidney stones with precision.

In recent years, the field of automation has emerged and is being applied in the medical industry. However, this has led to a number of common issues related to automated analysis, including the need for accurate and precise outcomes and the use of appropriate algorithms. Clinical analysis is a

complex and intricate process that can be challenging to navigate due to its inherently fuzzy nature.

Complex feed-forward neural networks known as Convolutional Neural Networks (CNNs) are gaining popularity for their ability to process large amounts of data, particularly in the area of medical diagnosis. One of the benefits of using a neural network approach like CNNs is the ability to analyze disease by first learning and then detecting on a partial level, through the process of feature extraction. This approach can help to identify patterns and correlations that might not be immediately apparent through traditional methods.

II. LITERATURE REVIEW

[1] This proposed preprocessing technique for segmenting kidney stones will be helpful in identifying kidney stones. The proposed segmentation methodology is straightforward and simple to comprehend due to the usage of thresholding approaches based on the past information of the image. [2] In this paper, they suggest a noninvasive, inexpensive, and cost-effective computerized classification method for diagnosing kidney illness based on clinical history, physical examinations, and laboratory tests. The sensitivity, specificity, and accuracy metrics of the SVM classifier with linear kernels have been studied in order to determine the performance measures with the highest scores. [3] Every year, an increasing number of people are given a kidney stone diagnosis. Therefore, very precise techniques for stone detection and identification are constantly required. This study suggests a deep learning model-based automated approach for the precise diagnosis of kidney stones. [4] The current research is aimed at automating the procedure of ultrasound stone analysis. The system comprises of feature extraction and classification of features, where extraction of the data and the image data set have been performed on the ultrasound picture. [5] This paper proposes an image processing technique to identify kidney stones automatically without human intervention. This report also presents the literature review and comparative study of varied algorithms available within the

existing literature for urinary calculus detection in human bodies. [6] This paper explains the real-time implementation via interfacing it with the scanning machine's captured kidney photograph can be subjected to the proposed set of rules to become aware of the affected vicinity and for accurate classification of kidney stone.

[7] In this paper, the proposed work is advantageous for recognizing kidney stones from CT scan pictures with less processing instant and achieves great accuracy. [8] In this paper, the survey of different algorithms and classifications are analyzed followed by the detection of stone present in the kidney. From this implementation, the existing system limitations are inferred and a new design is proposed to address the limitations. [9] This paper explains that pre-processing the ultrasound image, segmenting it, and then performing morphological analysis on the resulting picture are all part of the proposed methodology for detecting the existence of stones generated in the kidneys. [10] In this paper, BPN is used to detect stones in MR images of a kidney. The two-stage detection process namely the feature extraction and classification has eventually detected the stone in the kidney.

III. COMPARATIVE ANALYSIS

Comparative analysis involves evaluating two or more objects, processes, documents, or data sets to identify similarities and differences. Through this analysis, patterns can be observed, filters can be applied, and decision trees can be created. As an example, a comparison table is presented below that evaluates four machine learning algorithms based on various parameters. This analysis can assist in identifying which algorithm may be best suited for a particular task based on its strengths and weaknesses.

Table I. Comparison of different machine learning algorithms

Parameters	ANN	CNN	RNN	MLP
Data	Tabular	Image	Sequence	Tabular
Parameter Share	No	Yes	Yes	No

RecurrentConnections	No	Yes	No	No
SpatialRelationship	No	Yes	No	No
Vanishing	Yes	Yes	Yes	Yes
ExplodeGradient	Yes	Yes	Yes	Yes
FixedLength	Yes	Yes	No	No

IV. CNN ALGORITHM

CNN is a type of neural network model which allows us to extract higher representations for the image content. Unlike the classical image recognition where you define the image features yourself, CNN takes the image's raw pixel data, trains the model, then extracts the features automatically for better classification.

A. The First Block

The distinctive feature of this neural network is the first block that acts as a feature extractor. Its main function is to perform template matching by applying convolution filtering operations. The initial layer filters the image with multiple convolution kernels to produce "feature maps", which are further normalized using an activation function and resized if necessary. This process can be repeated several times by filtering the feature maps obtained with new kernels, which generates new feature maps that are normalized and resized. Finally, the last feature maps' values are concatenated into a vector, which defines the first block's output and serves as input to the second block.

To improve the accuracy and quality of the feature extraction process, the process can be repeated multiple times. With each repetition, the obtained feature maps are filtered with new kernels, resulting in new feature maps that are normalized and resized. This process can be repeated several times until the desired level of feature extraction is achieved. Once the feature extraction process is complete, the final output is obtained by concatenating the values of the last feature maps into a vector, which then becomes the input

of the second block.

B. The Second Block

The second block in a convolutional neural network (CNN) differs from other layers as it serves as the final step for classifying input data. During this stage, the input values undergo linear transformations and activation functions, generating a new vector as the output. The vector's length corresponds to the number of classes, with

each element indicating the probability of the input belonging to a particular category. These probabilities are determined by the last layer of the network, which utilizes either a logistic or SoftMax function as an activation function for binary or multi-class classification, respectively. Notably, the sum of all probabilities equals one, with each element ranging between zero and one.

Similar to traditional neural networks, CNN layers' parameters are determined using gradient backpropagation during the training phase to minimize cross-entropy. However, unlike regular neural networks, CNN parameters relate to specific image features.

1) The convolutional layer

The convolutional layer is an essential building block in convolutional neural networks and typically serves as the first layer. Its primary objective is to identify a particular set of features present in the input images. To achieve this, the convolutional layer implements a convolutional filtering mechanism. It involves sliding a window that represents the desired feature across the image and computing the convolution product between the filter and each portion of the scanned image. The convolutional layer accepts multiple input images and performs convolution with each filter. The filters correspond precisely to the features that we intend to detect in the input images.

2) The pooling layer

The pooling layer is typically inserted between two convolution layers, where it takes in multiple feature maps and performs pooling operations on each of them. The primary objective of the pooling operation is to decrease the image size while maintaining their crucial features. By doing so, the pooling layer effectively

ely reduce the network's parameters and computations, which improves overall network efficiency and helps prevent overfitting.

3) *The ReLU correction layer*

ReLU (Rectified Linear Units) is a non-linear function that is defined by $ReLU(x) = \max(0, x)$. The ReLU activation layer serves to replace any negative input values with zeros. This correction layer effectively acts as an activation function within a neural network.

4) *The fully connected layer*

The fully-connected layer is a standard component of a neural network, including convolutional neural networks, where it always serves as the final layer. Its primary objective is to accept an input vector and produce a corresponding output vector by performing a linear combination of the input values, potentially followed by an activation function. In the case of a classification problem, the last fully connected layer provides an N-size vector, where N represents the number of classes. Each element of this vector corresponds to the probability of the input image belonging to a particular class.

V. PROPOSED WORK AND IMPLEMENTATION

In this particular study, we have leveraged the tremendous advancements made in the field of computer science through the use of deep learning (DL) techniques. Specifically, we have employed convolutional neural networks (CNNs), with an emphasis on the Xception Model, to autonomously detect kidney stones using coronal computed axial tomography (CT) images. Our analysis has been conducted using Python in conjunction with the Keras deep learning framework, and the CNNs have been pre-trained on the ImageNet database. Deep learning, a subset of machine learning, involves the use of neural networks to enable computers to "learn" from massive amounts of data. While these neural networks are designed to mimic the functioning of the human brain, they are not as powerful as the human brain. In essence, a typical neural network consists of three layers: the

input layer, the hidden layer, and the output layer. Although a single-layer neural network may produce only rough predictions, additional hidden layers can be added to improve accuracy and refine predictions. A CT scanner, short for "computerized axial tomography scanner," is a medical imaging device that uses x-ray technology to create detailed cross-sectional images, or "slices," of the body. During a CT scan, a patient is positioned on a table and passed through a narrow x-ray beam that rotates around their body. The signals generated by the beam are processed by a computer to generate the tomographic images, which are more detailed than traditional x-rays. This non-invasive imaging technique is commonly used in the diagnosis and monitoring of various medical conditions. Each CT machine produces one slice of the following type for each calculation made; these slices are then digitally combined to create a three-dimensional image of the patient's anatomy. This allows for easy identification and segmentation of important structures as well as any tumors or abnormalities that may be present.

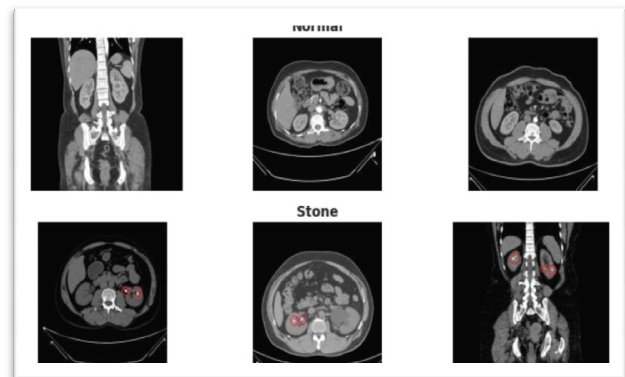


Fig. 1. Dataset Image

A computed tomography (CT) scanner operates by rotating an X-ray emitter around a patient's body to create a three-dimensional image. The CT machine has a circular opening in its center and a platform on which the patient lies still. Unlike traditional X-rays that use a high-energy radiation tube, a CT scanner employs a low-powered X-ray source. As the platform slowly moves through the circular opening, the scanner rotates around the patient, emitting tiny X-ray beams into the body. The X-rays that pass through the body are detected by multiple

radioactivity detectors located on the opposite side of the body from the radiation source. The detectors convert the detected X-rays into electronic signals that are then processed by a computer to construct the final 3D image of the patient's body.

Kidney CT scans are a more comprehensive diagnostic tool compared to standard kidney, ureter, and bladder X-rays. By providing a more detailed view of the organs, CT scans can aid medical professionals in identifying kidney injuries and diseases. CT scans of the kidneys can be utilized to detect a variety of conditions, such as tumors or lesions, obstructive conditions such as kidney stones, congenital anomalies, polycystic uropathy, fluid accumulation around the kidneys, and abscess locations when evaluating one or both kidneys.

VI. RESULTS AND DISCUSSIONS

This part summarizes the project's outcome and provides a summary of the user interface and functionalities.



Fig.2. Mainpage

The second step is to submit any patient's CT scan pictures by selecting a file and uploading it.



Fig.3. Files Uploaded

The third stage is to show the results; it indicates whether or not the kidney stone is predicted to be present in the provided images. When a kidney stone is found, the program displays the outcome as "Alert! Stone Detected," but if there is no stone, the program displays

"No Kidney Stone."



Fig.4. Result Prediction

VII. CONCLUSIONS

To identify kidney stones, it has been proposed to use a convolutional neural network (CNN) to create a model, train it, and then examine the picture it produces. The generated picture was used to pinpoint the exact position of the stone. The suggested method is able to accurately predict 98.50% of the results. The suggested method of identifying kidney stones has been realized using CNN Algorithm and Keras, image net assisted by its figure preprocessing, and finally performing exception act in line with the produced picture. The crucial fusion of these three methods has been demonstrated to be a repeatable process for renal stone detection.

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