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Prediction Methodologies to Detect Kidney Stones using Deep Learning

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Abstract

Under the condition known as nephrolithiasis, unwanted sediments accumulate in the kidneys, interfering with normal urinary system function and, in certain circumstances, obstructing urine flow, causing excruciating pain. Thus, the capacity to identify kidney stones via medical imaging is essential for administering treatment in a timely and efficient manner. Detecting objects in photos may be done with accuracy using Deep Learning techniques. The percentage of errors that are currently caused by human error will be reduced with the use of deep learning techniques in kidney stone identification. In this work, the presence or absence of kidney stones in CT scan pictures has been determined using four distinct deep learning techniques. The four algorithms that are employed are InceptionNetV3, ResNet50V2, MobileNetV2, and VGG16. These kidney stone detection algorithms were constructed using a dataset including 1799 kidney CT scan pictures. A combination of accuracy, precision, and recall metrics were used to evaluate each of the four models' categorization performance. For classification, the InceptionNet neural network yielded the highest results in terms of recall, accuracy, and precision. It yielded results of 0.8331 for recall, 0.866 for precision, and 0.862 for accuracy. These measurements are higher by 11%, 10.5%, and 2.9%, respectively, than the comparable values for the other three models. Therefore, this study validates that, among the four methods under evaluation, InceptionNet should be used for kidney stone diagnosis that occurs automatically.

Keywords

CT-Scan, deep learning, kidney stones, transfer learning, VGG-16

1. Introduction

The human body is made up of a complex web of interconnected chemical components that are essential to carrying out various processes including blood circulation and digestion. Two organs known as the kidneys are vitally responsible for controlling these chemicals and their levels in the human body. Beneath each side of the rib cage are the bean-shaped kidneys. In addition, the kidneys regulate the synthesis of red blood cells, eliminate waste products as urine, and directly affect blood pressure. Nephrons, which are numerous filtering units found in each kidney, eliminate undesirable molecules while retaining only the chemicals that are needed. External variables like diabetes and high blood pressure might affect how well the kidneys function. Kidney stones are tiny lumps of undesirable mineral

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deposits, and they are a major contributing reason to urinary system dysfunction. renal stones, which are tiny lumps of material in the kidneys, are the most common cause of renal dysfunction. Kidney stones are hard deposits that form in the urinary tract as a result of excess minerals and salts that occasionally remain in the urine tract over time. When these particles grow to a considerable size, they can cause urine blockage, which can lead to kidney malfunction. When these stones are small, the kidneys may not be impacted. This is quite painful for the back, thus early detection of these kidney stones is essential to helping those who are experiencing this rare condition feel less agony.

Nowadays, undesired kidney sediments can be found using a range of imaging methods. Imaging modalities used for kidney stone identification include computed tomography (CT), ultrasound, and X-ray imaging. Of the three methods, the CT scan approach is the one that is most frequently employed [1]. The radiologists are in charge of deciphering the scans and figuring out whether the kidneys contain stones. It has been found that the error rate in clinical radiology is 4% [2]. 4% might not seem like much, but when we take into account all of the scans that are done globally, it adds up to a substantial amount of errors. Owing to the greater amount of computing power available nowadays, deep learning techniques are increasingly frequently employed to complete the task of precise object identification. Because deep learning techniques have been demonstrated to produce accurate results, the amount of mistakes can be significantly decreased when kidney stones are detected using deep learning algorithms [3]. Our project aims to investigate if deep learning algorithms can reliably identify kidney stones, hence removing the need for radiologists to diagnose kidney stones. For this categorization work, KUB (Kidney Ureter and Bladder) type computed tomography pictures will be used. In order to attempt to address the issue of kidney stone detection from CT scan pictures, this study uses four deep learning algorithms: ResNet50V2, InceptionNetV3, VGG16, and MobileNetV2. Our study aims to bridge the research gap by aiming to identify a solution for kidney stone identification utilising these approaches, as the proposed algorithms have never been used for kidney stone diagnosis. In the field of kidney stone detection, our research adds value by using these relatively new deep learning methods for Nephrolithiasis.

The primary activities included in the research are collecting data, preparing the data (which includes pre-processing photos, image augmentation, and deep neural network model development), and assessing the performance of the models. The tests are conducted using a dataset of 1799 CT scan images, and because there are just a small number of source images, there may be bias in the results. Therefore, in order to expand the amount of source photographs, image augmentation is done.

Hence the research question of the paper appears to be as; which of the following deep learning algorithms, MobileNetV2, VGG16, InceptionNetV3, and ResNet50V2, yields the best results for kidney stone recognition from computed tomography images in terms of accuracy, precision, and recall?

The following is a roadmap for the paper's extra sections: The research's aims are listed in Section 1. Section 2 offers a critical evaluation of earlier studies in the field of kidney stone diagnosis through data analysis techniques. A thorough explanation of the technique used to accomplish the research objectives is given in Section 3. A summary of the research's design specification is provided along with a list of implementation strategies is provided in Section 4. In Section 5, many experiments are enumerated along with an analysis of the evaluation parameter values for each experiment. It also offers a description of the outcomes that came from the assessment procedure. Section 6 provides a final summary of the research findings along with recommendations for future improvements. The first table outlines the research's aims.

Table 1: List of Objectives

S.No	Description	Metrics
1	Review of Kidney Stone Detection using various ML and DL techniques	Sensitivity and specificity
2	EDA Analysis to gain powerful insights on kidney stone detection	Confusion matrix
3	Deployment of MobileNetV2 for CNN and evaluation of kidney stones	Accuracy and recall
4	Deep learning model for prediction of kidney stones using VGG-16	Accuracy and recall
5	Usage of InceptionNetV3 to evaluate performance of kidney stone detection	Precision

2. Related Works

Deep learning and machine learning techniques have been widely used in the past ten years to achieve precise object detection and image classification. In a short length of time, these methods can be applied in medicine to diagnose a variety of defects or illnesses. Unwanted deposits in the urinary system that impede urine flow are known as kidney stones. An analysis of the methods and strategies employed in earlier kidney stone detection research is given in this section.

The XResNet-50 deep neural network was utilised in [4] to locate and detect kidney stones from Computed Tomography images. To identify kidney stones, a cross-residual network is comprised of the XResNet-50 algorithm. Furthermore, augmentation methods like rotation and zooming are employed to get around the over fitting issue that arises when a model learns to memorise the input data. The parameters of the XRestNet-50 model were also adjusted using the Adam Optimizer and the Cross Entropy Loss Function. The Grad-CAM method was also applied during categorization to identify the regions of focus. 1800 photos from more than 500 patients in two distinct classes—Kidney Stone and Normal—with 790 and 1009 photos in each category—make up the dataset that was utilized to train the algorithm. Several criteria have been used to assess the model's performance, including sensitivity and specificity, which were determined to be 95% and 97%, respectively. Four normal photos were incorrectly assessed as having kidney stones by the model. The kind of scan images that were used to model the data is the primary cause of the misclassification. Because the images were of the coronal CT kind, the scan also included images of the belly, thorax, and pelvis, among other regions. By segmenting the source image data to concentrate more on the kidney region in the source CT scan, the performance of this classification approach might have been further improved.

An efficient deep learning technique for kidney stone identification is the convolutional neural network. The CNN algorithm was notably employed in [5] to identify ureteral stones. Unwanted obstructions called ureteric stones develop in the ureters, which are elongated, muscular tubes that carry urine from the kidneys to the bladder. They are around ten metres in length. 465 male and female CT scan photos were used to create the fake model. The method uses a pixel/voxel-based machine learning strategy to learn directly from raw data, instead of using extracted features. The pre-processing method was the Connected Components approach, whose two steps are binarization and grouping all pixels together. The sensitivity was set at 100 percent, and the connected components approach's main drawback is that no images without ureteral stones were included in the dataset when training the model; consequently, the performance metric appears skewed because the source data lacks significant subsets of data that can be available in real-time. Additionally, the number of images that have been used to train the model is small—there are only 465 total. By using the sensitivity parameter to gauge the model's performance, it was discovered that the sensitivity was 100%. The main finding of this study is that it focuses only on ureteral stones, which are more difficult to detect than kidney stones because their target area is smaller. This makes the research particularly noteworthy.

The presence of speckle noise in a medical image might significantly affect the classification accuracy. The Artificial Neural Network approach was used in [6] to identify kidney stones after speckle noise was removed using the median filter. Furthermore, to reduce complexity and increase classification accuracy, a specialist optimization method known as the crow search optimization algorithm has been used. One hundred ultrasound pictures make up the dataset that was utilised to create the model. The model achieved 100% sensitivity, 90% specificity, and 93.45% accuracy in classification. Following classification, the multi kernel k-means technique was used to segment the pictures that were determined to contain kidney stones. The main flaw with this strategy is that not a lot of photos were used to train the model. Given the over fitting effect, the classification accuracy is dubious because only 99 photos were employed.

Another technique is referred to as an ensemble method when two or more approaches are joined to carry out a specific job with the aim of improving performance. CNN and threshold-based algorithms were used in [7] to detect kidney stones and ascertain their size and effect. A cascaded application of the 3D U-Net technique was employed for the segmentation process on a total of 625 computed tomography scan photos used in the investigations. Two-step segmentation eliminated the likelihood of classification errors caused by the presence of many organs in the original image by providing the classifier with a clean image that focused only on the target region. It was discovered that the segmentation accuracy was 0.97 and the post-classification accuracy was 91%. Kidney photos with notable abnormalities were not included in this study, which is a limitation since it could affect the model's performance if these images were included.

Medical image object recognition can also be accomplished with modified artificial neural networks. The Heterogeneous Modified Artificial Neural Network has been utilized in [8] to detect renal calculi. 640 ultrasound pictures were used for this study, and they underwent a variety of processing including contrast enhancement, image restoration, sharpening, and speckle noise removal. On these processed images, the Grey Level Co-occurrence matrix is then used to extract features, which is followed by segmentation. The classifier's accuracy was discovered to be 98%, and the modified neural network's performance was contrasted with that of other methods including SVM, Backpropagation networks, and multilayer perceptrons. Compared to other techniques, the HMANN was found to have the best classification results. The results of this study have demonstrated the significance of the segmentation procedure in enhancing classification accuracy.

Transfer learning is the process of storing and applying the knowledge and insights obtained from solving one problem to another that is related to the first. In [9], kidney stone detection is performed by a cascaded convolutional neural network that has been pre-trained with ImageNet. The model was trained using 535 CT scan images of the abdominopelvic region and pre-processing techniques like segmentation, normalisation of the image orientation, and multi-window encoding. Training with pre-available datasets can significantly increase classification accuracy. The inner CNN performs nephrolithiasis, while the first CNN measures the urinary tract's depth. The suggested model achieved 94% sensitivity and 96% specificity in classification. Pretraining the model with ImageNet and GrayNet has been done in order to get over the underlying dataset's small amount of photos. This study demonstrates that object detection in medical photos may be accomplished with cascaded networks; nevertheless, the main disadvantage of this method is the little amount of training material (less than 600 images).

Accurate object detection can be achieved by combining deep learning models with optimisation strategies. An ideal probabilistic neural network and a spider monkey optimizer were used in [10] to conduct renal calculilocation in ultrasound pictures. The raw photos have been treated with the median filter to remove noise because ultrasound images have a substantial amount of speckle noise in them. The classifier's performance is then improved by extracting features from these photos. The Spider Monkey Optimizer is used to determine the classifier's weight in the best possible way. It was discovered that the OPNN classifier had a 93% accuracy rate. One significant disadvantage of this approach is that the research does not explore the details of the number of photos in the source dataset, which could potentially bias the conclusions based on the size of the source dataset.

A convolutional neural network with weights changed to minimise mistakes from the loss function, lower the error rate, and improve model reliability is called a back propagation network (BPNN). In [11], kidney stone identification was accomplished through the use of a back propagation network. The dataset used to construct the model contained renal magnetic resonance images. Prior to classification, pre-processing procedures including feature extraction using Principal Component Analysis were carried out. The primary flaw in this study is that the assessment metric used to gauge how well the classification performed and the total number of photos in the dataset are not stated clearly.

Prior to classification, the medical images should undergo pre-processing to enhance image quality. Three distinct pre-processing techniques are used on a dataset of 500 ultrasound pictures in [12]. First, speckle noise and other defects that have deteriorated the image are removed from the source photos through restoration. Next, the image is smoothed and texture-based features are extracted using the Gabon filter. Following that, the photos undergo Histogram Equalization processing, which enhances the contrast of the image. The target areas are then determined using the level set segmentation technique. After that, the energy levels are obtained and used to train the Multi-Layer Perceptron and Back Propagation Artificial Neural Network. The accuracy of the classifier was discovered to be 98%. This model does not apply any augmentation techniques to the original photos, which could have affected and enhanced the model's performance. In this section, previous research publications that employed deep learning techniques to identify kidney stones were assessed, and via this analysis, the different object detection algorithms that were available as well as the most popular assessment metrics were comprehended. It was shown that neural networks that used the transfer learning strategy were the most often used deep learning techniques for kidney stone diagnosis. For this reason, transfer learning is used by all four of the deep learning networks in this study to classify images.

Conventional machine learning algorithms can also be used for object detection in medical images; some prior studies that have used these techniques for kidney stone detection are discussed in this section. These techniques are less common than the number of studies using deep learning for classification, but they provide an option to the resource-intensive yet incredibly powerful deep learning techniques.

Kidney stone identification in [13] was accomplished with the application of Support Vector Machine and K-nearest Neighbour classification algorithms. Before using the classifiers, a feature extraction approach is used to perform the reduction of multi-dimensional data space mapping to lower dimensions, Principal Component Analysis. Although the precise number of ultrasound images in the dataset is unknown, it is present. To improve the classifier's accuracy, morphological and entropy-based segmentation techniques are also used. For KNN and SVM, the corresponding classification accuracy was 89% and 84%, respectively. This paper's main finding is that machine learning techniques are less accurate than their deep learning equivalents. It is unclear how many photos are in the collection, which begs the question of how trustworthy the research's conclusions can be.

The main drawback of using ultrasound for medical imaging is that speckle noises can readily alter the images, which can have a direct impact on how well a model performs when it uses these images as input. To remove speckle noise, in [14] employed an adaptive mean median filter technique. Using 250 ultrasound pictures, the Support Vector Machine learning algorithm detects kidney stones. Techniques like dilatation and erosion are used to remove the unwanted portions of the image. The k-means segmentation technique has been used to carry out additional segmentation. SVM is used for classification, with the help of Particle Swarm Optimization to identify the ideal hyper-plane. It was discovered that 98% of the classifications were accurate. This method's main benefit is that it takes care of non-Gaussian speckle noises, which have a negative impact on SVM classifier performance.

The Support Vector Machine is a frequently employed classification tool. In order to identify kidney stones in the urinary tract, the SVM classifier was utilisedin [15]. The algorithm achieved a 98 percent accuracy rate after being trained on 156 CT scan samples. A technique called Histogram Equalization was applied to the source photos to enhance their contrast. The improved photos were embossed to make edge and object identification simpler. By adding a layer to the original image that resembles a mask, embossing facilitates the identification of stones. A directional differential filter including both vertical and horizontal kernels was employed in the embossing process. After embossing, the SVM classifier is employed to guarantee accurate categorization. The primary drawback of this approach is that there are only 190 images in the source data, which is insufficient for the model to be properly trained and leads to an over-fitted model. An effective and capable model that could perform classification on new data would have been produced if augmentation techniques to increase the number of data to be used for training had been applied.

Thus, the part before this one included a summary of research that employed conventional machine learning techniques to identify kidney stones. These methods demonstrated the range of approaches available for kidney stone detection. This review makes it evident that while kidney stones may be identified from medical photos using machine learning techniques, doing so requires more time than using deep learning approaches. The selection of deep learning techniques for kidney stone identification was made possible by this finding.

3. Methodologies Used

The purpose of this study is to evaluate the effectiveness and applicability of the four deep learning networks in identifying kidney stones from CT scan pictures. This study investigates whether these four distinct neural networks are suitable for classifying kidney stones using the CRISP-DM data mining technique. The CRISP-DM strategy is an iterative, cross-industry standard procedure for data mining that consists of a series of steps such business understanding, Knowledge of data, preparation of data, modelling, assessment, and deployment. Because of its affordability and consistency in project planning and management, the CRISP-DM technique is the most popular methodology for managing data mining initiatives. The research's CRISP-DM approach went through the following stages:

A Research Methodology

The detailed identification and description of the issue, as well as methods for gauging the degree to which the goal has been attained, are all part of the business understanding phase. Radiologists in the medical field are in charge of determining whether kidney particles are present from medical imaging. Using a dataset of CT scan pictures, deep learning models are built in this study to automate the detection procedure. Through the use of deep learning techniques in modelling, the research effectively reduces

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human error in kidney stone identification. The models were constructed using four distinct deep learning techniques that include transfer learning, and they were evaluated using several measures like accuracy, recall, and precision. An early and error-free identification of kidney stones via medical imaging will assist treat the individuals under consideration appropriately and promptly. It will also help lessen the pain associated with the occurrence.

B Dataset Used

The goal of the data understanding phase is to critically evaluate the data that will be utilised in the modelling process. This phase also makes it possible to identify any potential issues that could develop in the subsequent phase and affect the methodology's outcomes. In this stage, data access and exploratory analysis are conducted to evaluate the current data's quality. The research utilised a dataset that was sourced from Github for the modelling method. The dataset includes 1799 CT scan images from 500 patients, divided into two classes: Normal and Kidney_Stone. Images showing kidney stones are categorised under the Kidney_Stone class. The photos in the collection are all of different resolutions and are all in the.png format.

C Data Understanding

All of the tasks involved in creating the final dataset from the original dataset in order to accomplish effective modelling are included in the data preparation phase. The various photos used in our research are first transformed to the same resolution. The pixel values in these images are then adjusted by rescaling or normalisation to fit the required format required for constructing the deep neural network. After that, the images are enhanced using various factors, such flipping and rotation, to boost the reliability and capacity for prediction of the models that will be built.

D Resolution of the image

Since the raw photos for a deep learning network will be processed in batches, it is important that they all have the same resolution. Figure 1 illustrates the 25 distinct resolutions in which the photos are available within the dataset. While the other three versions require photographs to be in the 240*240 resolution, the MobileNet model just requires images to be in the 160*160 resolution. The keras API's built-in functions are used to modify the resolution of the source images. The resolution of the input photos fed into the deep learning model is specified by the input_shape parameter; in this study, the resolution of 240*240 has been utilised as the standard value for all models. Because the MobileNet model expects the resolution to be in 160*160 by default, it has been fed input images with a resolution of 160*160. For this reason, MobileNet was given a resolution of 160 x 160, whereas other models received a resolution of 240 x 240.

E Rescaling of the image

Since pixels represent samples of the image under consideration, each pixel in an image contains meaningful information about the image. Images are made up of these components, called pixels. Matrix representation of pixels is done using values in the matrix whose structure varies based on the colour of the image. Pixel values typically fall in the range of 0 to 255. The conversion of such pixel values into a standard format in the range of 0–1 is the process of scaling, or normalisation. This method's main benefit is that it shortens the time needed to train the deep learning models. To achieve normalisation, divide each pixel value by 255. This process is carried out for every channel. The pixel values have been normalised through the usage of the ImageDataGenerator function in the Keras API.

4. Implementation Details

Github provided the dataset that will be used in the modelling process. Python was the programming language of choice for creating the deep neural network models. Deep Learning network modelling and development demand a significant amount of processing power. A web-based Integrated Development Environment called Google Collaboratory was thus used to frame the Python code base.

Google Collab makes it possible to connect to powerful GPUs via the cloud, making it possible to model even the most complicated neural networks with ease. An NVIDIA GPU with 27.3 GB of RAM available was used in this study's model construction. A high-level neural network library called Keras has been employed in the study to facilitate easy prototyping and processing. Tensorflow framework has also been utilised in addition to keras. The dataset was uploaded to Google Drive in order to be accessed through Google Collaboratory.

The photos to be utilised for the Training and Testing phases are organised into two folders, Train and Test, within the source dataset. Using Keras APIs like flow_from_directory and ImageDataGenerator, the validation dataset is created from the training pictures. Additionally, the ImageDataGenerator makes it possible to specify the rescaling option, which is used to conduct Image Normalisation.

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5. Results

The purpose of this study is to determine whether kidney stones can be detected from CT scan pictures using the four deep neural networks: VGGNet, MobileNet, ResNet, and InceptionNet. A useful summary of each model's performance across all classes is given by its accuracy. Both the overall number of guesses and the number of accurate predictions are considered. An elevated Accuracy metric value signifies that the model generates precise classification for every class being examined. From Figure 7, it can be seen that the accuracy of the InceptionNet model is greater than all other models built using the unmodified dataset without cropping by an average percentage value of 20%. The accuracy of the InceptionNet model without cropping is measured as 0.66.

For the adjusted dataset, the accuracy values for ResNet, MobileNet, and VGGNet are 0.56, 0.59, and 0.59, respectively. Therefore, when compared to other models, InceptionNet performs the best overall in terms of accuracy. The intricacy of the dataset—each image represents a CT scan of a human body—is the reason for the poor accuracy values. These scan images not only provide information about the kidneys but also about other organs such the lungs, rib cage, spinal cord, and thorax. Therefore, manual cropping of the source photographs is done in order to reduce the target area for the models.

As Figure 2 makes clear, the models that were constructed utilising the cropped photos as the base dataset achieved higher classifications. It was found that the MobileNet model outperformed all other models for both the unmodified and cropped dataset, yielding an accuracy value of 0.92 for the cropped pictures dataset.

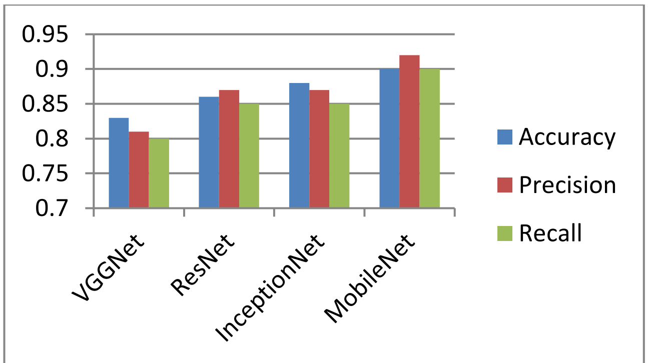

Figure 2: Comparison of algorithms used

The ratio of True Positives to all Positives is used to compute the precision metric. It gives an indication of how many samples the model accurately identified as having kidney stones. Therefore, a high Precision value is needed in this study. Among models constructed on both unmodified and cropped datasets, the InceptionNet model has the highest precision value of 0.866, as shown in Figure 2.

Recall is a metric used to assess a model's ability to accurately identify positive samples; higher recall values suggest that more positive samples were successfully identified. The InceptionNet model has the highest recall value, which is consistent with the findings found in terms of Precision and Accuracy. It can be concluded that, among ResNet, MobileNet, VGGNet, and InceptionNet, the InceptionNet model is the most suitable deep learning neural network since it yields the greatest results in terms of Accuracy, Precision, and Recall.

It is clear from Figure 2 that all four models' classification performance improved significantly after cropping, on average by 15% across all criteria. In all four trials, the cropping procedure was done manually, which took a significant amount of time. In subsequent studies, the cropping process will be done automatically using code. This represents a constraint of the study. Only 1800 photos make up the dataset utilised in this study; by using a dataset with additional photographs, the classification performance can be further enhanced.

6. Conclusions and Future Works

The goal of the project is to identify kidney stones from CT scan pictures using deep learning models and assess the effectiveness in terms of recall, accuracy, and precision. The InceptionNet model performs the best across all metrics taken into consideration, according to the findings of the four experiments. By manually trimming the models to concentrate on the desired areas, the models' performance was enhanced, leading to increased precision, recall, and accuracy values. Thus, all of the suggested goals listed in Section 1 were accomplished by this research. The results of this study suggest that, when CT scan pictures are supplied as system input, kidney stones can be automatically detected by an end-to-end system built using the InceptionNet model. The work that can be done in the future using the research findings is this interactive system. With the use of this method, kidney stone identification can be done automatically, eliminating the need for radiologists in the process.

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