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Kidney Stone Detection from CT scan Using CNN

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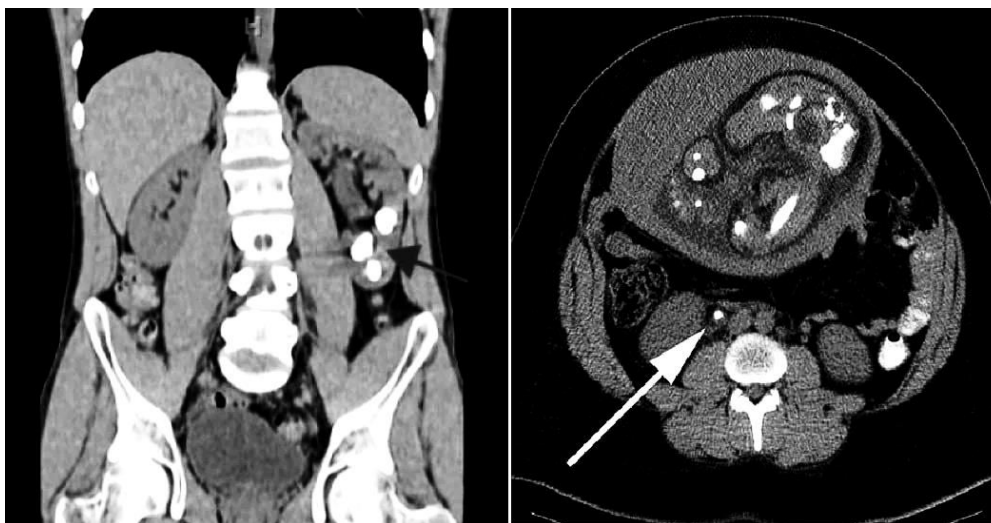
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Abstract: A non-contrast computed tomography scan of the abdomen that uses deep learning may be able to assist in the detection of stones by doing away with the necessity of manually measuring the stone's volume. When it comes to kidney stones, the volumetric measurements provide more accurate and reproducible results than the linear measurements. The early detection and accurate measurement of renal calculi are essential for both the prevention and treatment of severe cases of renal stone disease. Images obtained from CT scans can be of great assistance in diagnosing kidney lesions. They are able to pinpoint the exact location of lesions and provide an estimate of their size in a variety of medical settings. Testing that requires a lot of work and takes a lot of time is essential in the medical field. Today's clinical diagnosis cannot function without the use of CT scans that can automatically detect lesions. As a result of our research, we have developed a method for the detection of lesions utilizing Cascade RCNNs and an intersection over union (IOU) threshold (CNN), and we have discovered that the medical testing efficiency can be improved by combining four Cascade CNNs with two morphology convolution layers in a faster CNN and modified pyramid neural networks (FPN) to improve the detection of small lesions (1–5mm) and stabilize the network. Pytorch served as the platform on which we trained our modified CNN by providing us with DeepLesion CT kidney images from the institution's image archive and communication systems. To put it another way, the proposed detector that we developed had an accuracy of 0.988, which placed it among the most accurate and precise tools available for locating lesions in CT scans.

I. INTRODUCTION

The expansion of a computer-aided automatic detector for urethral stones is the primary goal of this project. Nephroliths, also known as renal calculus, and nephroliths are the two forms that kidney stones can take (renal calculus). If kidney stones grow large enough, they can obstruct the ureter and cause urinary tract infections. In addition to a high fever, nausea, vomiting, and painful urination, patients may also experience symptoms such as blood or pus in their urine. Depending on the nation, the likelihood of a person developing kidney stones during the course of their lifetime ranges anywhere from 10 percent to 25 percent. Each year, there are approximately 0.5 percent [2-3] of new cases that are filed.

Numerous factors, such as genetics, obesity, the consumption of particular foods or medications, and an inadequate intake of fluids, can all contribute to the formation of kidney stones. The mineral make-up of kidney stones as well as their location are taken into consideration when classifying the various types of kidney stones. The diagnosis was arrived at after considering the patient's symptoms, as well as the results of urine tests, blood tests, X-ray images, and CT scans (computed tomography). The ultimate decision regarding the diagnosis is made by an imaging specialist called a radiologist. Considering that the current procedure calls for the expertise of a specialist to determine whether or not a urethral stone is present and its precise location, the creation of an automatic urethral stone system would be more time and money efficient.

**Figure 1:** Kidney Stone detection from CT Scan

When it comes to treating urethral stones, factors such as the size of the stone, its composition, and its location are all important considerations. It is sufficient to treat the pain with medication and drink a lot of fluids in order to facilitate the passage of small stones out of the body. Treatment options for larger stones include laser lithotripsy, shock wave lithotripsy, ureteroscopy, and percutaneous nephrolithotomy (which uses a laser to break or remove the stone). Ureteroscopy is another alternative (removing the stone by using a small surgery).

In this particular study, a computed tomography, or CT, scan was all that was required to determine whether or not a patient had a stone and where the stone was located. The process of creating cross-sectional images of the patient using computed tomography (CT) involves combining multiple x-ray images of the patient taken at different angles (slices). A three-dimensional representation of an area's topography is now possible to create. It is a grayscale 3D image in which the value of each pixel is directly linked to the type of material that occupies that particular pixel. It is possible for the number of pixels occupied by a kidney stone to have a wide range of values due to the variety of components that make up kidney stones. This particular group of materials is used in the construction of a great deal of the human body. Pixel values for bone and various other materials are comparable to those of kidney stones.

When using computer-aided urethral stone detection methods, it can be challenging to differentiate between real stones and fake stones.

The accuracy of the system is directly proportional to its overall performance. It is simple to identify a false positive in the images, whereas a false negative may have catastrophic results. Because of this, stone sensitivity plays such an important and crucial role in the application of the system. As a direct consequence of this, the primary purpose of the system is to accurately and carefully classify stones. This thesis on automatic kidney stone detection also addresses the massive amount of data that is contained in a CT scan.

A single computed tomography (CT) scan of the abdomen contains close to one hundred million individual pixels. To put it another way, the input of the system includes a significant number of variables, which indicates that the algorithm's parameters, which are used to process the data, will also be significant in number. In order to perform well and achieve a high level of accuracy, the required number of training examples rises in direct proportion to the number of parameters that are being learned.

II. LITERATURE SURVEY

Both individuals and academic institutions are showing an increased interest in researching medical image detection as it becomes an increasingly popular research topic. In order to deal with the challenges posed by medical imaging, each of them modifies their strategies to better suit the new environment. Jiang et al. [2] developed a medical imaging repair structure as well as a training procedure to go along with it. In order to lessen the impact of speckle noise and improve the quality of the image, Rahman, Tanzila, and Mohammad Uddin (2013) made use of a gabor filter in conjunction with histogram equalisation. Both cell segmentation and region-based segmentation[1] were utilised in the process of isolating the various kidney regions. An ultrasound database was developed by Hafizah, Wan, and Eko, along with Yusmy and Jasmy, by utilising features extracted from images of kidney ultrasounds (2012). In order to extract

features, we made use of the grey level co-occurrence matrix, also known as the GLCM, as well as five intensity histogram features [2].

In 2011, P. Gladis, V. Rath, and S. Palani developed a method for the detection of tumours in the human brain. This method was published in the journal *Neurology*. The Hierarchical Self-Organizing Map, abbreviated as HSOM, is used to partition images into sections that can then be analysed separately (HSOM). Artificial neural networks and Wavelet packets were used in the process of determining the type of anomaly and the spectrum of the abnormality. [4] Researchers Bommanna Raja K., Madheswaran Muthusamy, and Thyagarajah, K. (2007) identified significant content descriptive feature parameters and classified kidney disorders with the help of an ultrasound scan. The sensitivity of feedforward neural networks to weight errors was researched by Maryhelen Stevenson and her colleagues [5].

Noll and colleagues were the ones who figured out where the kidneys should be located. [3] utilising information regarding the kidney's primary anatomical structure. Zhang et al. [4] have developed a Hessian-based HDog (Difference of Gaussian) detection method. Greenspan et al. [5] proposed the use of diffusion-weighted magnetic resonance imaging (MRI) for the early detection of acute renal transplant rejection. The processing of kidney ultrasound images was accomplished by Akkasaligar and Biradar [6] through the use of wavelet thresholding and wavelet decomposition. [7] Van Ravesteijn et al. presented a computer-aided diagnosis (CAD) system that prioritises polyps according to their clinical significance.

Arnaud and his colleagues [17] were able to characterise and locate lesions by employing a procedure that was entirely automated. Deep Neural Networks were utilised by Kolachalama et al. [18] in order to identify pathological fibrosis in the kidneys. Danae and her colleagues were able to make improvements to a cancer detection tool [19]. The only form of polycystic kidney disease that was looked at in this research was [20]. Ben-Cohen and his colleagues [21] were the first to use a global context and a fully convolutional network in their discovery of computerised tomography, also known as CT exams (FCN). Random forests were used by Cuingnet et al. [22] for the detection and segmentation of kidneys in 3D CT images. [Citation Needed] Zhang et al. [23] were able to identify and quantify clinically relevant characteristics in small structures by using medical images (blobs). It is now possible to automatically detect diseased tissues by utilising an algorithm that was developed by Mahapatra et al. [24]. [Citation needed]

Because there is no network that is capable of resolving the issue of small and sparse lesions in the kidney while simultaneously producing a high-precision and comprehensive detector, none of these methods are suitable for locating kidney lesions. Standard image classification and object detection are simplified by the use of medical image detection of the kidney, which resolves a plethora of additional problems [25]. Only those individuals who have received specialised training are able to assign labels to the images because there is no comprehensive database of images that have been annotated. Because deep learning now also encompasses the processing of images, computer-aided design (CAD) has emerged as the most popular and intriguing hot area to keep an eye on.

Grigorescu et al. [8] proposed a new method for the automated detection and segmentation of all large lesions. This method makes use of a local protrusion measure in conjunction with geodesic distance clustering. Adaptive imaging is the primary focus of Zhou and Qi's [9] research, which aims to detect lesions. Moon et al. developed a multi-scale image detection-based automated breast ultrasound image (ABUS) analysis system. ABUS stands for automated breast ultrasound image. A Gaussian Proposal Network, which was proposed by Li [11], is able to identify ellipses that represent lesion boundary regions. (GPNs). Zhang et al. [12] made an accurate prediction of the spread of a tumour. Using a novel framework that was proposed by Khalifa et al. [13], it is possible to differentiate between the status of rejection and nonrejection in renal transplants. Zheng et al. [14] came up with the idea of using a CNN-based method to make the detection of nodules more accurate.

The identification of lesions is accomplished through the use of mask RCNN-based hard negative example mining, as suggested by Tang et al. [15]. Shin et al. [16] utilised natural image data sets in order to train CNN models for medical image tasks. [Citation needed] The diagnosis of lesions is one of the most common types of medical research. It has been demonstrated that convolutional neural networks, or CNN, can be used for a variety of computer vision tasks. One of these tasks is the detection of medical imaging, which is required for the algorithm to accurately and thoroughly diagnose. The workload of the radiologist is decreased because, in comparison to conventional CT diagnosis methods, this method is both more accurate and requires less time to detect the lesion.

III. PROPOSED METHODOLOGY

Figure 2 depicts a block diagram for kidney stone detection that was created through the use of the back propagation method. The images obtained from the MRI of the kidney are used for the method that has been proposed. Utilizing the preprocessing and feature extraction capabilities of DWT and GLCM data, the fuzzy C-means algorithm is applied to the task of segmenting kidney stones. The utilization of a convolutional neural network in conjunction with a variety of preprocessing subsystems is what allows for the detection as well as the localization of urethral stones. One of the primary objectives for the classification subsystem, which is a convolutional neural network, is to lessen the quantity of data that it is required to use as input. We are going to take a look at the systems that existed before the CNN, in addition to the fundamental theory that underpins their application.

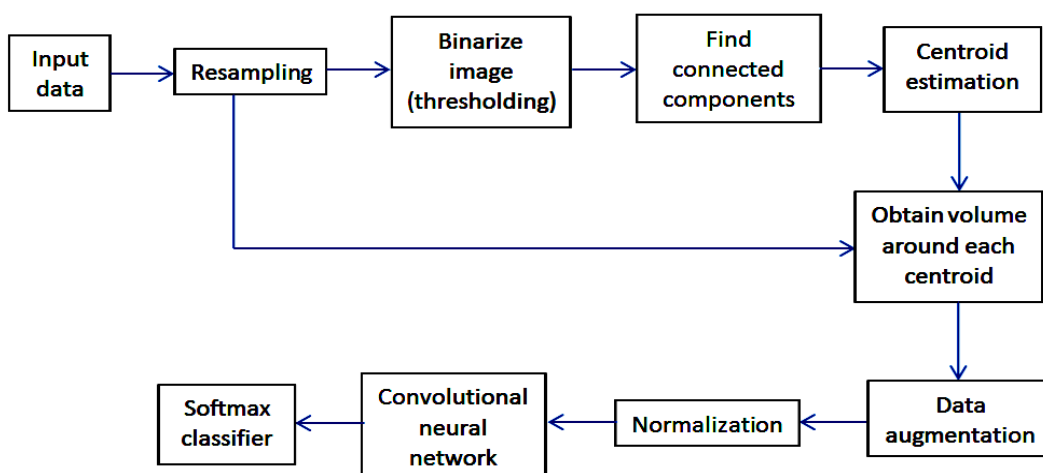


Figure 2. Proposed methodology

3.1 Input image

The system's input data, which consists of a series of CT scans, is depicted in Figure 3. A CT scan will produce a grayscale three-dimensional image of a patient that can be used for diagnostic purposes. This image can be used in a variety of ways. Multiplying three natural numbers (representing the position of each pixel) by a natural number that stands for the intensity of the image's grayscale results in the creation of a three-dimensional grayscale image. The value I_{N3} stands for the intensity c at the pixel positions i, j and k of the image I_{N3} .



Figure 3. Input Image

The CNN analyses only the regions surrounding possible stones after receiving the entire CT scan as input into the system. These volumes are determined by the subsystems that come before the CNN. When training classifiers, sufficient amounts of data are required so that the neural network can be provided with a sufficient number of examples from which to learn the behaviour of the classifier. There are only a few different kinds of stones that can be examined, and there is an absence of data. The accuracy of the network improves in tandem with the amount of data it has stored

as examples. If there are more parameters in the network than there are data points in the training set, the model will not be able to generalize well to new data points.

3.2 Preprocessing

The Discrete Wavelet Transform is used to perform preliminary preprocessing on the input test image. Image enhancement is the process of removing noise and enhancing brightness in an image (also known as pre-processing). Wavelets are intended to convert an image into a series of wavelets, which can be stored in a manner that is more space and time efficient than pixel blocks. Through the utilisation of high-pass and low-pass filters, the discrete wavelet transform is able to segment the input image into high-pass and low-pass components respectively. The image has been segmented into four subbands, which are denoted by the letters LL, LH, HL, and HH respectively. Higher order bands contain edges in a variety of orientations, including vertical, diagonal, and horizontal, while lower order bands contain the majority of the information.

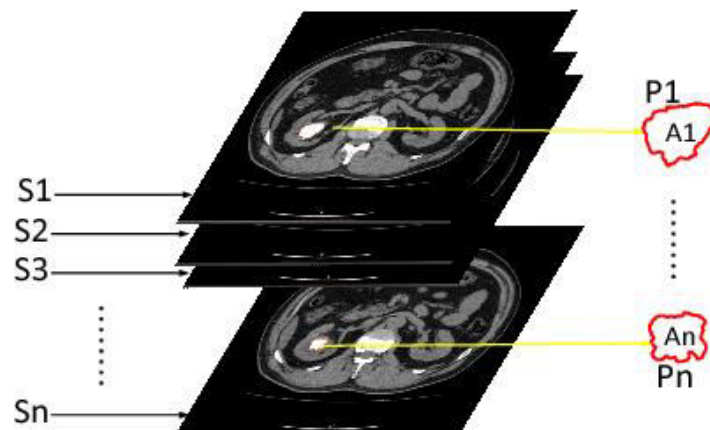


Figure 3. Pre processing

3.3 Data augmentation The neural network contains a greater number of parameters than the amount of data that was examined in this study. In the extensive assortment of things that are not stones that each patient possesses, there is just one instance of a stone for them to look at. Because of the extremely high level of accuracy that results from having such a large sample size, a neural network that has been trained using all of the data will be able to correctly identify every object as a non-stone. In order for the neural network to learn the characteristics that differentiate one class of objects from another, the network needs to see a significant number of examples from each class. The network needs a large number of CT scans taken from patients in order to arrive at an accurate diagnosis; however, it only has a limited number of examples from which it can learn. On the other hand, there is not enough evidence to back up this assertion.

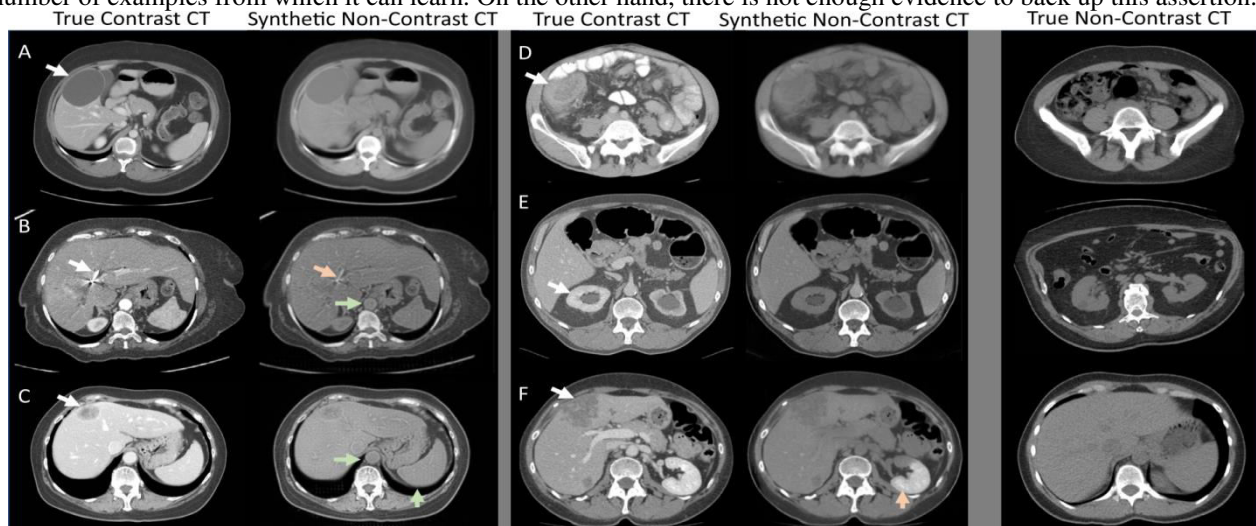


Figure 4. Data Augmentation

In order to solve this issue, the training of the network was done with multiple copies of the stones that were available. Alterations were made in order to increase the number of stone examples that could be obtained compared to what was previously available. Additional examples can be obtained by turning the images around and slightly translating them. The centre of each pixel has been moved to the left by one pixel so that it takes into account all of its immediate neighbours, which total 26 in total. As a result of rotating each of these copies by a total of 90 degrees twice, a total of 24 copies have been produced. It is possible to produce 1300 copies of a stone from its original using this technique, which results in a significant quantity of stones. It is not necessary to make copies of non-stone objects because each patient already contains a large number of samples.

3.4 Convolutional Neural Network

The Convolutional Neural Network, which is the primary subsystem, calls for a significant amount of computational and memory resources. The process of classification is accomplished by teaching an artificial neural network which aspects of an image are most interesting, and then making use of that knowledge in a subsequent classification task. Neurons in one layer of a Convolutional Neural Network are not connected to each and every one of the neurons in the layer that comes before it; rather, the neurons in that layer are only connected to a predetermined number and region of the neurons in the layer that comes before it. A loss function (shown in Fig. 5) and a Softmax classifier are both components of the Convolutional Neural Network.

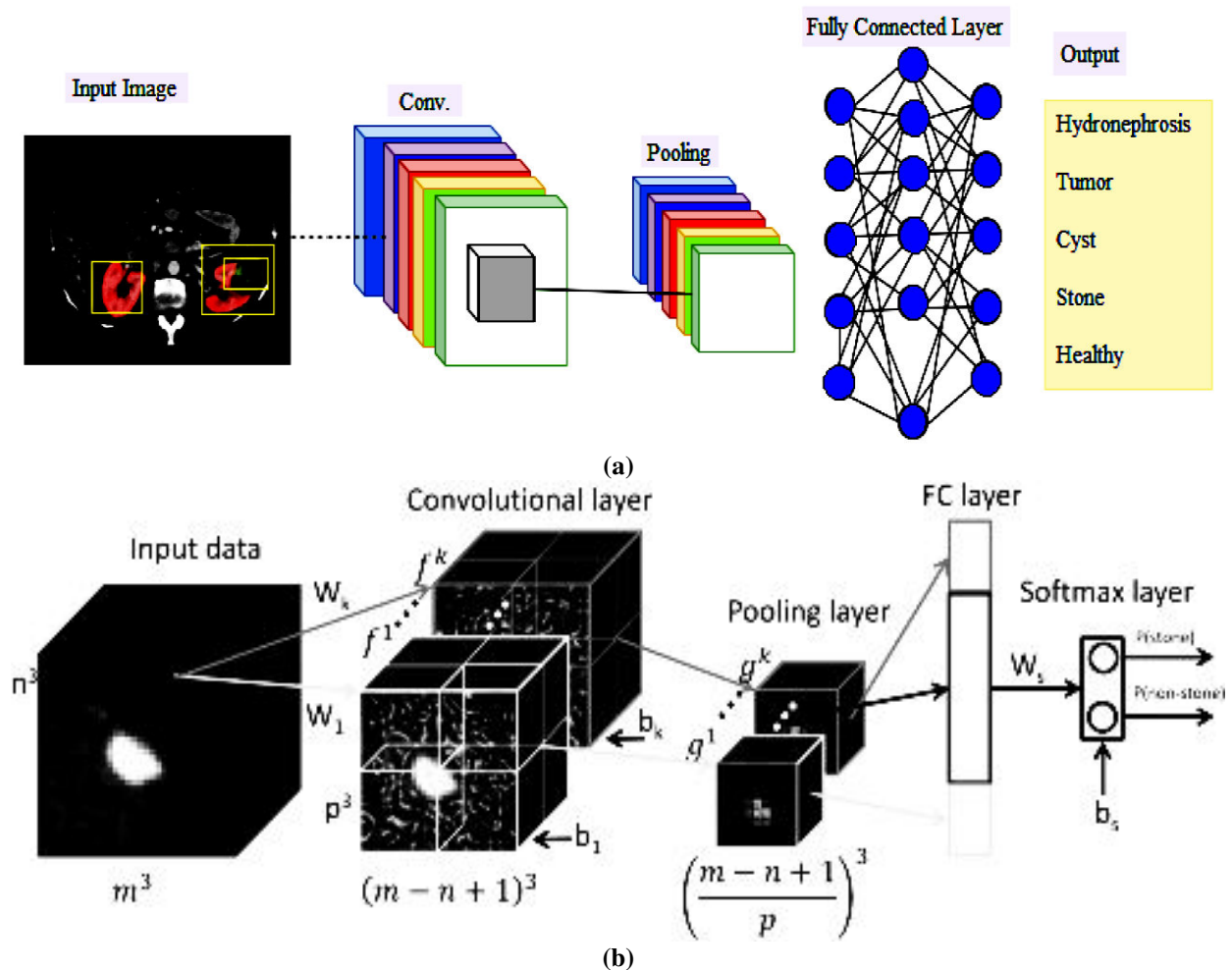


Figure 5. Convolutional Neural Network

3.4.1 Background

Convolutional neural networks are a type of machine learning algorithm that was named after their biological inspiration (CNNs). Convolved patterns of cell distribution can be observed in the visual cortex. The cells have the ability to detect relatively small portions of the visual field, but this ability extends across the whole visual field.

Utilizing the spatial correlation present in the images, the cells perform the function of local filters across the input space. There are two broad classifications that can be applied to cells: Complex cells, on the other hand, are able to respond to a wider variety of stimuli and are unaffected by the location of the stimulus within the receptive field. Complex cells are also known as multi-potent cells. The capacity of the animal processing system to act in a manner similar to that of the animal being processed is the primary motivation for doing so. The majority of classification methods and algorithms do not take into account the spatial distribution of the input data; instead, they correlate all of the information in the same way. In other words, they are unable to distinguish between pixels that are located a significant distance apart and those that are located relatively close to one another. Taking into account the proximity of pixels is beneficial for the current project, where the input data is obtained from images and there is a correlation between pixels that are close together.

Convolutional neural networks make use of the spatial structure of the images they process. Because the spatial relation is already incorporated into the structure of convolutional neural networks, the process of training these networks is significantly accelerated. Because the number of parameters required is determined by the number and size of filters used rather than the amount of input data, one of the most significant benefits of convolutional neural networks is that they require far fewer parameters to train than Artificial Neural Networks do for large amounts of input data. This is one of the most significant advantages of convolutional neural networks. It is possible to construct classification algorithms utilising the information that can be gleaned from the input data.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 198, 198, 32)	320
max_pooling2d (MaxPooling2D)	(None, 99, 99, 32)	0
conv2d_1 (Conv2D)	(None, 97, 97, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 48, 48, 32)	0
conv2d_2 (Conv2D)	(None, 46, 46, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 23, 23, 64)	0
conv2d_3 (Conv2D)	(None, 21, 21, 64)	36928
max_pooling2d_3 (MaxPooling2D)	(None, 10, 10, 64)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	73856
max_pooling2d_4 (MaxPooling2D)	(None, 4, 4, 128)	0
conv2d_5 (Conv2D)	(None, 2, 2, 128)	147584
max_pooling2d_5 (MaxPooling2D)	(None, 1, 1, 128)	0
flatten (Flatten)	(None, 128)	0
dense (Dense)	(None, 512)	66048
dense_1 (Dense)	(None, 4)	2052
Total params: 354,532		
Trainable params: 354,532		
Non-trainable params: 0		

Figure 6. Max Polling and Output Shapes in CNN

After the bias in the convolutional layer, it is common practice to apply nonlinear functions such as a hyperbolic tangent, sigmoid function, or RELU function [17]. As a result of this, the output of the convolution layer can better

approximate and adapt to nonlinear functions by incorporating a nonlinear function into its output. This is done through the use of a nonlinear function. The use of hyperparameters allows for control over the output of a convolutional neural network as well as the number of parameters that are learned by the network. The receptive field size of the neuron, also known as the filter size, is the first hyperparameter that needs to be considered (F). The following stage of the design process involves making a decision regarding the optimal size of the filter (D). This value of two was used for 2D images, while this value of three will be used for 3D images. The third hyperparameter is called filtering (N), and it refers to the number of neurons that are connected to a single input. The stride hyperparameter is the fourth one (S).

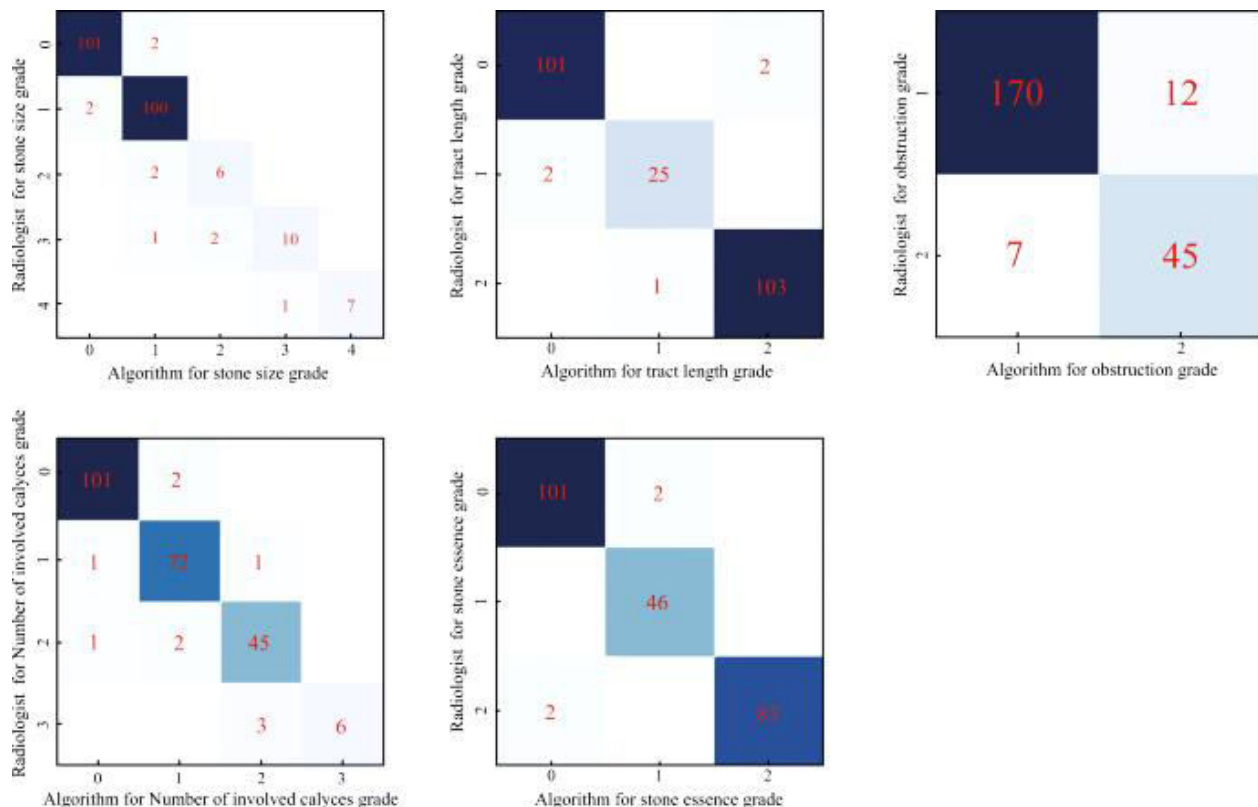


Figure 7. Kidney Stone Diagnosis based on grade prediction

Within the pooling layer, non-linear subsampling is applied with the purpose of condensing more relevant data into a smaller number of variables. The different convolutions produced by the various filters are not connected to one another in any way because the pooling process can be applied to the output of each filter on its own. Generally speaking, the mean or maximum of a collection of convolutional regions that either overlap or do not overlap is what constitutes a pooled value (Fig 7). Each of these data blocks is comprised of sections of equal length (F2). The pooling layer makes use of two hyperparameters: the region size, which is denoted by "F2," and stride, which is the pixel-based distance between each region (S2). In regions where there is no overlap, the size of the stroke and the area are identical. Because the regions being overlapped are of a smaller size, the stride that is required to traverse between them must be shorter. The pooling layer has no influence on the parameters of the neural network because it is responsible for carrying out a fixed operation that is unaffected by any of the parameters. A typical value is either the mean or the maximum for each data region. In the final layer, we implement a Softmax classifier. This type of classifier employs a standard artificial neural network to predict each class (in this case, between stone and no stone) based on the output of the layer that came before it, which pools the data.

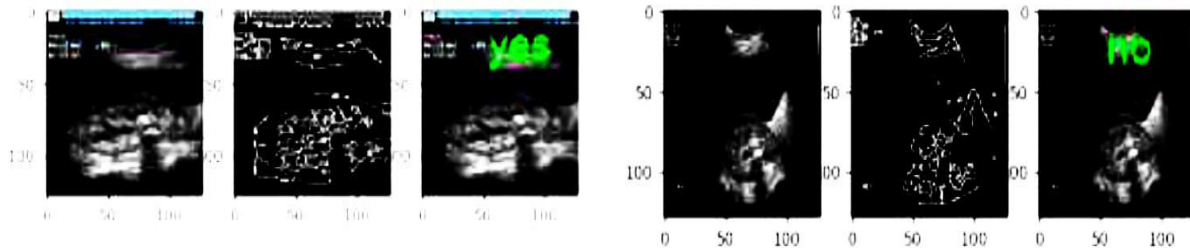


Figure 8. Prediction of Kidney Stone with Label indication

IV. RESULT ANALYSIS

When developing a CNN, it is necessary to take into account a number of hyperparameters, including the number of convolution layers and the number of pooling layers. In order to make a fair comparison between the CNN and the softmax classifier, it is assumed that both use the same total number of features in their training sets. Alternating between convolution layers and pooling layers is the most effective way to maintain a smaller size for both the filter and the pool. As an illustration, because of this new rule, the network will have a lower total number of parameters.

For the purpose of determining the degree to which classification models are accurate, a ROC curve makes a comparison between the number of true positives and the number of false positives. The ROC curve draws attention to the sensitivity of the model. True Positive Rates and False Positive Rates are the two operational characteristics that are measured by ROCs. ROCs are also known as "relative operating characteristic curves" due to their relationship to one another. For the purpose of evaluating the effectiveness of a classifier, we make use of metrics such as accuracy, precision, recall, and loss (Table I). A classifier that is perfect will have a ROC that has a true positive rate of one hundred percent but will have no false positives at all. On the other hand, as the number of incorrect positive classifications increases, our standard practise is to monitor the number of correct positive classifications.

Table I: Result Analysis based on Accuracy, Precision, Recall, Loss

Result Analysis	Efficiency
Accuracy	0.988
Precision	0.979
Recall	0.976
Loss	0.977

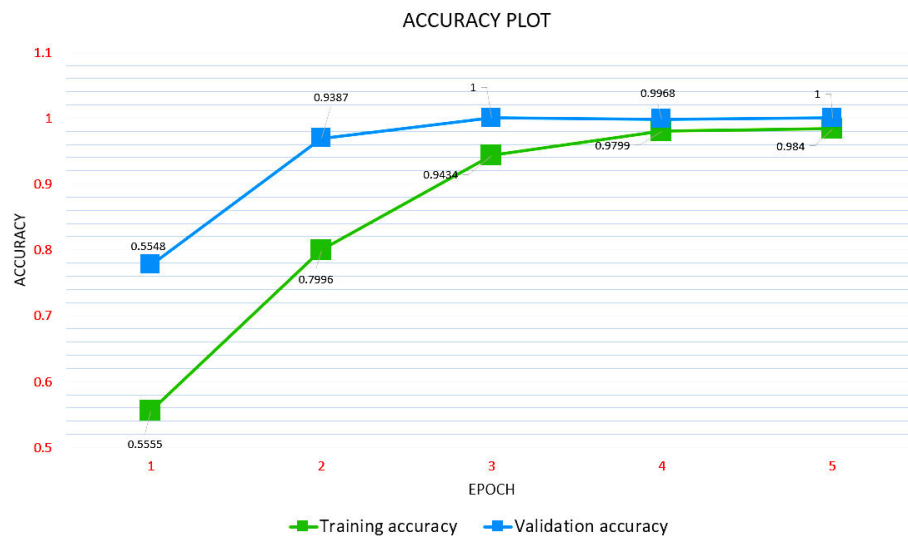


Figure 9. ROC Curve based on Accuracy Metrics

There are many different probability threshold measures that can be used in order to optimise a model so that it produces the greatest number of accurate positive results while producing the fewest number of erroneous negative results. If you use ROC curves, you will be able to determine the probability threshold measure that provides the optimal balance between the number of true positive results and the number of false positive results. If the data in each class is distributed evenly, it is best to use ROC curves to analyse the data. Figures 9, 10, 11, and 12 each contain a ROC curve that represents accuracy, precision, loss, and recall respectively.

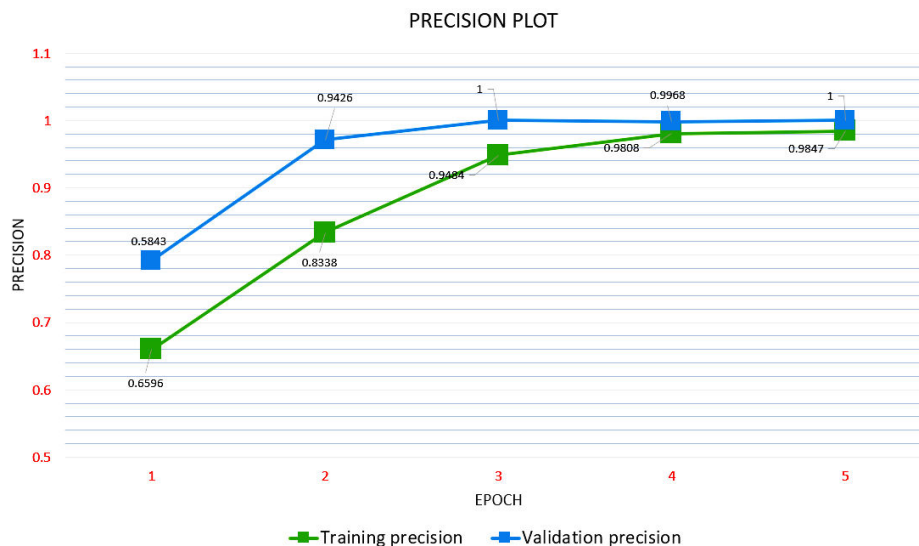


Figure 10. ROC Curve based on Precision Metrics

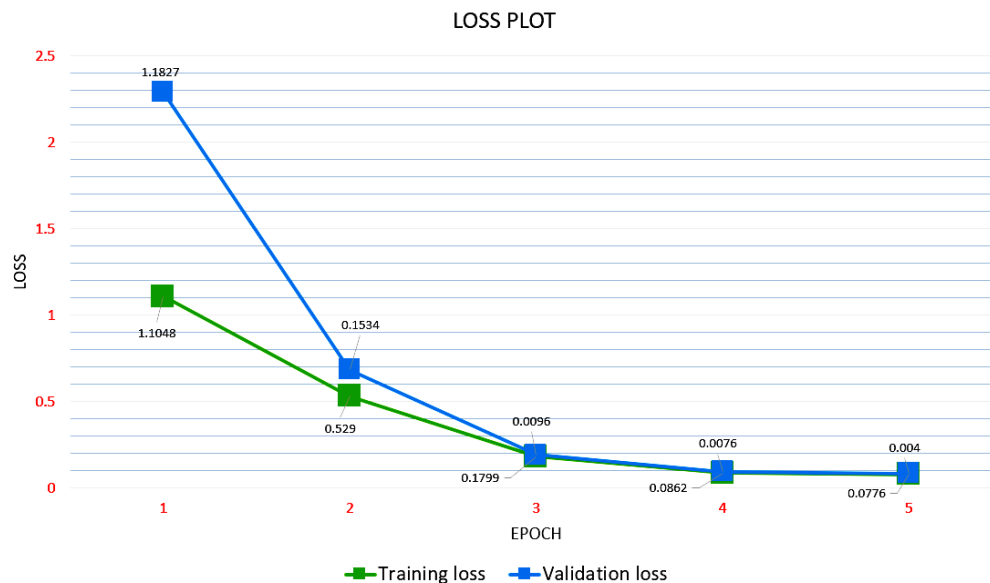


Figure 11. ROC Curve based on Loss Metrics

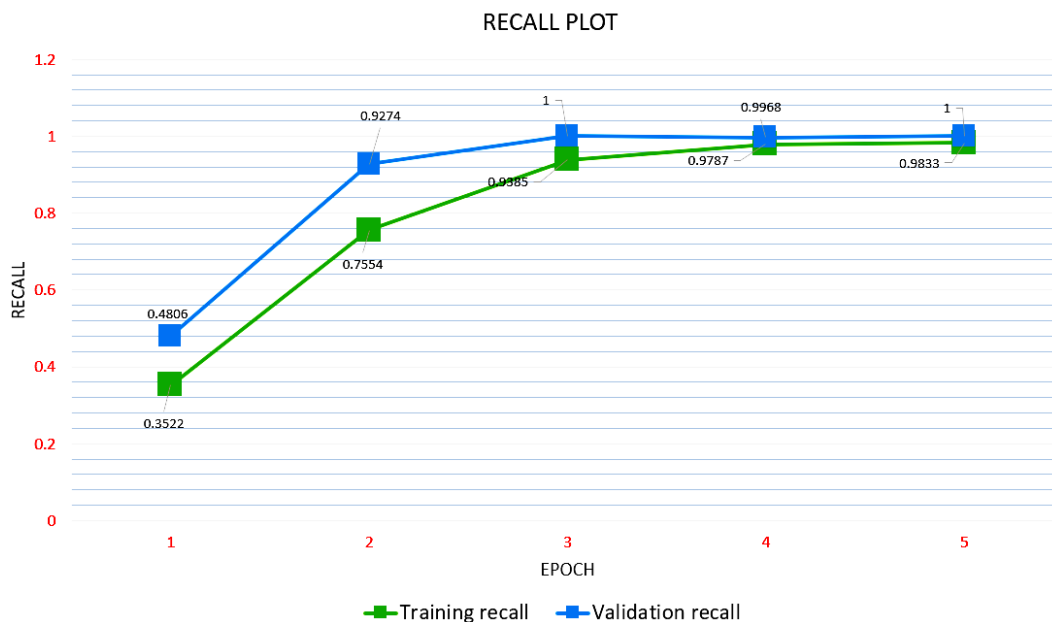


Figure 12. ROC Curve based on Recall Metrics

V. CONCLUSION

When using CNN lesion detection, the amount of time and effort required to locate and analyse lesions on medical images is significantly reduced. Deep learning has been demonstrated to be a potentially useful strategy in the past, but it does not meet the requirements for accuracy and comprehensiveness. This has been demonstrated by prior research. We were able to detect kidney lesions in CT scan images with a high degree of accuracy and robustness by using morphological cascade convolutional neural networks. A two-layered FPN is capable of carrying out two different morphological operations. The first thing that needs to be done is to raise awareness of and make it simpler to spot smaller goals. The second step is to use our anchor sizes and ratios to generate different-sized feature maps for the overall location and classification of goals. These maps will be created by using our anchor sizes and ratios. For the purpose of high-precision detection, a four-IOU threshold cascade CNN was designed and developed. The cascade

CNN was put to the test using CT images, and it was discovered to be successful in locating lesions. On the other hand, when it comes to detecting other lesions and organs, our modified network is a detector that is both effective and accurate.

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