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AUTOMATIC KIDNEY LESION DETECTION FOR CT IMAGES USING MORPHOLOGICAL CNN

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Abstract: The CT scan is the best tool for diagnosing and finding injuries in the kidney. It can provide precise information about the location and size of lesions in many medical applications. Manual and traditional medical tests work and time-consuming. The automatic detection of injuries in CT is now an integral task for clinical diagnosis. To develop and improve the efficiency of medical testing computer-aided diagnosis (CAD) is needed. However, the existing low accuracy and incomplete detection algorithm remain a tremendous challenge. The proposed lesion sensor is based on morphological cascaded convolutional neural networks using a multi-intersection threshold (IOU) (CNNs). To increase network stability and morphology co-detection layers and amended pyramid networks in the faster RCNN and combine four IOU threshing thresholds with cascade RCNNs and for better detection of small lesions (1-5 mm). In addition, the experiments have been conducted on CT deep-lesion kidney pictures published by photos and communication systems of hospitals (PACSs

Keywords:Kidney Lesion, Convolution Neural Network, Morphological Operations, CT Images.

I. INTRODUCTION

The main objective of this paper is to create an automated computer-assisted stone sensor for kidneys. The kidney stones are mineral and salt deposits within your kidneys (also known as renal calculi, nephrolithiasis, or urolithiasis). They could hinder the ureter when kidney stones get big enough. Genetics, excess weight, food and medication consumption, and the absence of sufficient water are all risk factors for kidney stones. The most diverse forms of cancer that can be explained by economic and social factors can be found in developing countries. The structure and position of kidney stones are determined by using minerals. The diagnosis is symptomatic, urinary, blood test. The tailing of urethral stones is dependent on their size, composition, and position. With no care except for pain relief and plenty of water, small stones are expelled. Shock-wave lithotripsy (which breaks into pieces) ureteroscopy and percutaneous nephrolithotomy are used for the treatment of larger pillars (removing the stone by using a small surgery).

The tumors of the kidneys may be categorized into two different classes into benign and malignant tumors. Although benign tumors do not normally have pain, some symptoms, like muscle and hematuria, can be caused. Malignant tumors are both toxic and dangerous. Deep education approaches in the medical sector with ever more frequent medical segmentation have become more effective in recent years. However, when segmentation is involved with kidney and kidney tumors, there are few algorithms in the literature. Further research on the application of deep learning processes in kidney tumors is therefore necessary. The efficiency of CNN has been highlighted in the recent computation.

The only data used for this analysis were CTscans (computer tomography) for the patient to find out whether a patient has a stone or not. Computer tomography incorporates multiple x-ray pictures from different angles to produce cross-sectional images of the patient (slices). A 3D image of a given area is then generated. There are various components in a human body, however, which make up this particular collection of materials. In the same range as kidney stones, bones and other content amounts have pixel values. There are various components in a human body, however, which make up this particular collection of materials.

The computer-assisted algorithm is used in MATLAB. The procedure is based on a modified form of an Artificial Neural Network.

A. *Related Work*

Certain work is being done by auto-detection systems to detect a kidney stone based on CT scans. The texture characteristics include average and standard intensity deviations of a segmented individual, a local binary model, and a histogram. The design features include the ability of the candidate, two-dimensional proportions of the height, length, and breadth, and the distance of the candidate from his kidney. The SVM classification includes the functions form and texture.

The design features include dispersion, convex hull depth, and lobulation, another task that uses the features you have removed to detect kidney stones. The internal textures include edge density, skewness, histogram variance (DHV), and matrix time in the grey level. An artificial neural network (ANN) is trained and the ROC is analyzed to determine the exactness to the diagnoses of the shape and the texture.

In previous works, the overall accuracy is 88%. Furthermore, extracted directly from the created classifiers. A loss and non-use of part of data in the photos are the biggest drawbacks of using the features derived from photographs rather than the pixels themselves. Greenspan et al. proposed an early detection of acute renal transplant rejection using diffusion-weighted MRI[1].Moreover, the classification output depends heavily on the selection of steps. These characteristics are selected at random and require experts to determine which characteristics to use. To improve the classifier efficiency according to time and effort, new features must be selected. Compared to the last study, a contribution. One addition to this study is that the pi compared to previous works. Jiang et al‘s[2] approach to fixing structure and training procedure can be applied to resolve the medical problem. Noll et al.[3] utilized basic kidney shape information to detect the kidney position. Moon et[4] al. developed automated breast ultrasound images based on multiple image detection. Li[5] presents GPN’s for the detection of lesion bounding ellipse. Cuingnetet[6] al. proposed an automatic detection of kidneys using 3D CT images with a random forest algorithm. Zhang et al.[7] proposed for the identification of small blobs from medical images to relevant images. Zhou and Qi [8] focus on the adaptive imaging Ben-Cohen et al. [9] detected in CT examinations, using both a global context with an FCN for lesion detection.

A modified artificial neural network is a type of algorithm for automatic image learning (CNN). The main advantage of this artificial neural network type is that the number of parameters is not directly linked and can be much lower than the input variables.

Recent works use CNN as input into applied medicine with CT scans, but not in the detection of kidney stones. A random forest classifier is selected first as input to the CNN. These areas are then used to train the CNN on different scales using a series of bounding boxes in each region. The assessment is based on CT pictures of 82 patients. They achieve a precision of 83.6%. The segment lesions in the liver of CT images are presented using an automatic process based on coevolutionary neural networks. First of all, Gaussian filters are used for noise reduction. The second is to normalize the images and then to train the CNN.

Some recent works use CNN with CT scans, but not the identification of kidney stones as an input in applied medicine. At first, the CNN entry is selected as a random forest classifier. They are then used to train the CNN on different scales across the country with several border boxes. The evaluation is based on 82 CT images of patients. The precision is 83.6%. The segment injuries in the livers of CT images are shown in an automated networking system. Gaussian smoothing filters are the first way of minimizing noise. The second is the normalization of the images and then the CNN's preparation. 30 CT images will be analyzed experimentally

II. METHOD

The approach to the thesis is summarized. The urethral stone detection and location algorithm are based on a neural network and several pre-processing subcycles. The system architecture diagram is shown in Fig. 1. The main focus of pre-processing subsystems is to reduce the number of data to be used as the classification subsystem by the convolutions neural network. CNN structures have to be summarized in the history and basic philosophical principles behind the use of CNN's. SoftMax, the last layer, categorizes the applicants. The input of the system is the CT scans. The first step of the system is to resample the data, then the images are binarized to calculate the centroid of each connected component and, finally, the regions around the objects that can be stoned are used as input in the CNN, which extracts some features used to classify the candidates of the CNN.

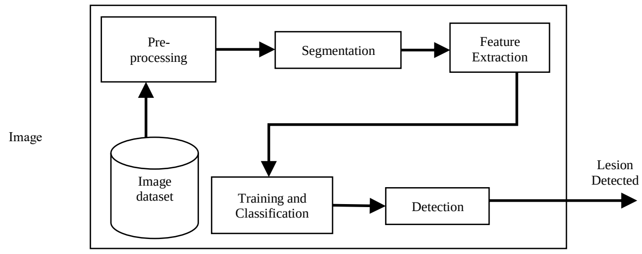

Fig 1. System architecture Diagram of Kidney Lesion Detection.

A. *Input data*

The system's input data is a series of CT scans. A 3D grayscale picture of a patient may represent a CT scan. A 3D grayscale image reflects the application to the image of a natural number of three natural numbers (position of each pixel).

The $I \in N^3$ represents the intensity c in pixel position *i,j,k*by $I_{ijk} = c$ where $c = [-1024\ 3072]$

The entire CT Scan is used as the device input, but the CNN classifies only some volumes around stones. The subsystems before the CNN choose these volumes. Sufficient data must be provided to train classifiers so that the neural network has adequate examples. There are only a few examples and the amount of data available is quite limited. With the number of instances, the network is more accurate. The model is not good for recent, unreported examples when the training set is limited relative to the level of parameters in the network.

B. *Data Argumentation*

In this work, the amount of data in the neural network is not large enough in comparison with the number of parameters. There are thousands of examples of artifacts not stones in every patient, although only one example of stone is present. When the neuronal network is trained with all the data, any object can be classified as no stone because the class imbalance makes it extremely accurate. A close number of examples from every class is necessary so that the neural network can find the characteristics that define every class of objects. Building on the small number of CT scans by patients, the network does not have the right examples to learn and the precision falls when stones of each patient and the same number of items that are not stones are used. However, not enough data is available.

The available stones were copied several times to train the network to solve this problem. However, the data has been copied to obtain more stone examples than current ones with several variations. The method used to achieve further examples is based on the rotation and slight translation of the images.

C. *Binarizing image*

The device input is a CT scan that is a 3D grey image. The presence and location of the stones are generally not possible by the pixels found in a CT scan. In addition, not even inside the body are several of them. In the CT scan, the pixel value is linked to the type of material in this location. A variety of minerals that have several levels in the CT scan are made up of kidney stones. This classifies the neural network as a stone or not stone, rather than any volume in the CT scanner, just the areas around pixels of strength within this range. [3] The input variables in the CNN are greatly reduced. The histogram of the intensity values of a CT scan and the intensity values in 7x7x7 pixels around every stone. As can be observed, the pixels around the stone centers, vary entirely from the distribution of pixels in the CT scan, take up a specific range and distribution. The volumes inside the CT scan that is likely to stone are calculated using a series of operations. First of all the pixels with a value within the range of urethral stone values are white (1), and pixels that are not in mineral range take a coloration of Black The first step of this procedure is to binarize the picture (0). A radiologist expert suggested the threshold values used and a binary 3D image is the outcome of this process. A binary image is an image that can be black or white for each pixel c = {0, 1}.

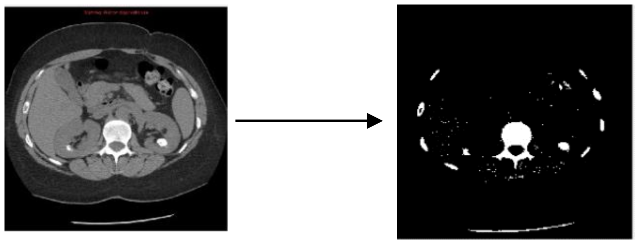

Fig 2. Binarizing process. In the left a slice of a CT scan before binarizing, in the right the same slice converted to a binary image.

In the Fig.2 there is an example of slice of a CT scan before and after binarizing. The white pixels in the binary image belong mostly to bones, stonesand calcifications.

D. *Connected Components*

Following the binarization procedure, you must separate each of the connected components with a white colour in the binary picture. The aim is to distinguish possible objects from the whole picture, which can be stones. This would decrease the number of pixels which are to be classified by the CNN. Although the related components are known, they are not included, because they are bones or noise, in volume larger or smaller than a given threshold. After a histogram was built of the items known as stones and those not stones, the threshold was fixed. The position of each of the stones is known (it is part of the information got by the hospital), so, the components that are placed in those positions are stones, while the objects that occupy other regions are not stones. Connected component labelling is used to detect connected areas in the binary digital images in computer vision applications. The aim in this thesis is to find and distinguish the regions that could be stones from the 3D image.

E. *Centroid Estimation*

The third step involves the calculation of the centroid of each linked part (the ones that have a volume between the thresholds used). The center of the center, so that the areas of interest can be marked as stones or as no stones (volume around the middle of the components). Also, if one of these items is categorized as stone, the stone location (centroid) is known immediately, and no additional calculus is required to locate the stone position. The center of a volume is the average location of all volume points. It can be calculated using the coordinates of all the points in the region by: $C = \sum_{(i=1)}^{K} \frac{x_i}{K}$, where is the centroid of the volume, K is the number of pixels in the volume and x_i is the position of a given point in a global coordinates frame.

F. *Normalization*

The pixel values in the CT scans range from 1024 to 3072. The areas chosen as possible are standardized to values between 0 and 1. This improves the consistency of the classification system. For this purpose the maximum and minimum is estimated in each area and the values are scaled to these values:

$$Normalisedvalue_{value} = \frac{value - value_{min}}{value_{max} - value_{min}}$$

G. *Convolution Neural Network*

The Convolution Neural Network is the system's key subsystem and requires more computer power and memory. It is an updated ANN edition, which extracts features from images through the learning that are interesting and uses them to identify the various images. Instead of connecting the neural neurons in the previous layer to all the neurons in the previous layer, the principal distinction between an ordinary neural network and a Conventions neural network is that the neurons are only bound to the species in the previous layer. The CNN has a loss function or error function, so that the parameters (weights and b) are learnt. The CNN contains a loss function or error function, which is used to learn the parameters (weights and partialities) of the structure and a SoftMax classifier.

H. *Structure*

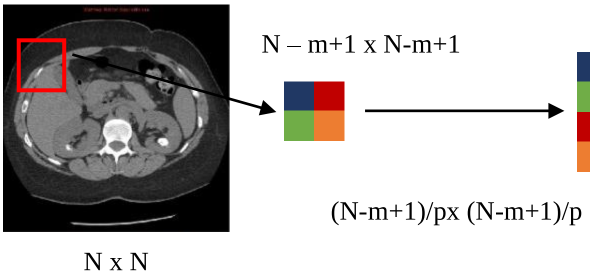

Fig 3. Example of convolution layer and pooling layer in two dimensions with an input of size N, one filter of size m and a pooling layer of size p.

An artificial neural network is an inspired pattern for the development of biological neural networks. They have neurons with weights and biases that are learning. Every neuron in the network receives such inputs and increases their weight by an optional non-linear transformation (activation function). The neurons are layer structured and can be classified as input nodes, hidden nodes and output nodes. All the nodes in one layer are linked to all the nodes in the following layer in an ordinary neural network, while in a CNN only each neuron is connected to a small number of neurons in the previous layer.

A Convolution Neural Layer Network builds on three layers: convolutionlayers, bundling layers and completely linked layers (ordinary neural network). The first two layer forms alternate as much as the neural neuronal network requires and the last layer is a completely connected layer. Different weight and bias values are dependent on the convolutionlayers and completely connected layers, while a pooling layer often performs the same role so that no parameters must be known. The effect of the application of a convolutionlayer and a pooling layer in two dimensions to the input data is shown in fig. 3.

III. EXPERIMENTAL RESULTS

The test results of CNN will be overviewed in this segment. The first step is to choose the best combination of CNN parameters to get the best setup. The results of the classification will then be analysed and compared to various kinds of ANNs which use features from the CT scans previously collected and those which explicitly use the pixels.

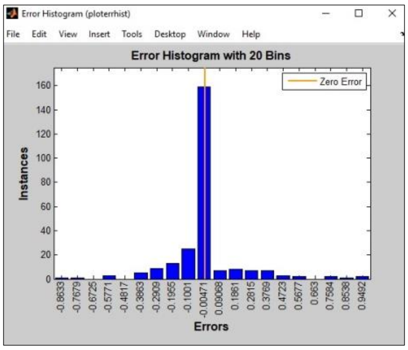

Fig 4. Output Error histrogram with 20 Bins.

The Fig.4 shows the error occurred in each epocs, while the maximum times the error occurred is plotted using Hitrogram.

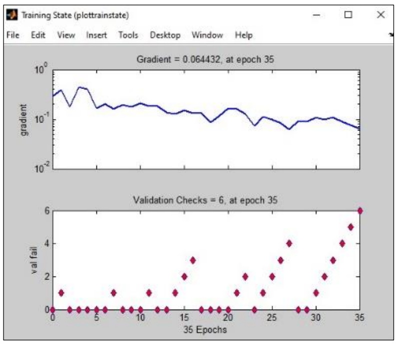

Fig 5. Training State of each epocs.

Fig 6. Confusion Matrix

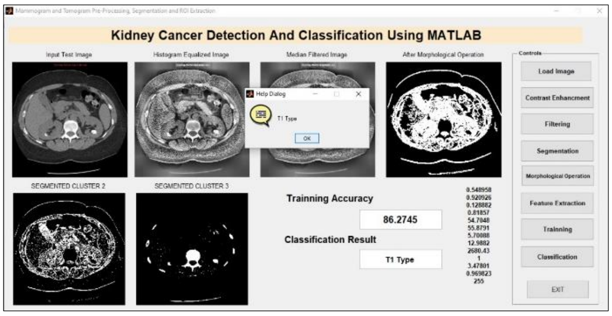

Fig 7. Final output

The Fig.7 shows the final output with Training accuracy and number od intermediate results. If the dilog box shows retived the value as 'Type 1', then the kindey damaged is high. The system is desiged to identify 3 types, T1, T2 and T3, indicating T3 as null or less leison found.

A. *Design of the CNN*

A volume is obtained as a CNN input around each centroid of items classified. There are also multiple instances of linked components used for network training for any CT scan, the majority of which are not stones and the stones are repeated with minor variations to provide more examples. A binarized image is determined from the centroid of any object that may be a stone. The CNN input is the original resampled image, however, as it contains many more data. A number of hyperparameters must be selected for the CNN. The first hyperparameter to choose from is that the overall structure of the CNN is the sum of convolutionlayers and pooling layers. The comparison shall be carried out considering that the input characteristics in the softmax classification should be the same. Therefore, if more layers are used, the size of filters and pools will be less than if less layers of each kind are used.

The benefit of multiple convergence layers alternating before the use of one layer is that the number of neural network parameters can be reduced. The issue of the use of a number of convolutional and pooling layers in front of each form is that the amount of memory required for background spreading is larger. Because the application's key bottleneck is the memory used during the training phase, one layer of each form has been selected.

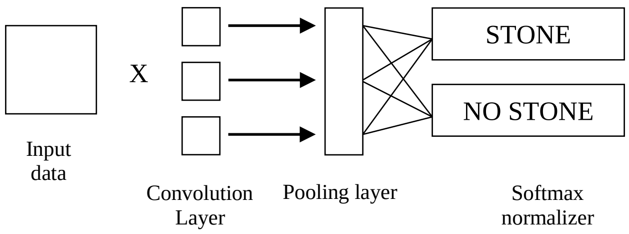

Fig 8. CNN design patterns.

The second judgement is the activation feature to be included in the convolutionary layer. A neural network's power source is the activation mechanism. The activation function selection has an enormous influence on network efficiency. They provide a quantitative comparison over ten different data sets of different widely used activation functions.

The findings show that the sigmoid function exceeds the other activation functions in respect of an error, while it is much faster to measure the linear activation function since its derive is simple. The function sigmoid is known as:

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

The real number is needed and saturated into a range from 0 to 1. It has a clear connection to the fire in a neuron: from the shooting to the fire. However, it has a significant inconvenience: when the function output is almost nil or nil, the gradient is almost nil. The derivative of the activation function is multiplied by the error gradient of the output during back propagation. In case the activation function derivative is near zero, a very small number is set to multiply the two terms and almost no signal passes through the network. In all, the activation feature chosen was because training time was not a significant problem in system design and the gradient was near zero only if the firing of the neuron or no firing was learnt after many examples (The initialization of the parameters is random around 0).

B. *Performance*

This segment provides a greater dataset for the best configurations of the CNN to achieve their efficiency and pick the best. Due to their precision, sensitivity and training time, the various settings are compiled, but the best settings based on the F1 score will be chosen. The F1 scoring blends sensitivity and accuracy in an output metric. It is used as sensitivity is a crucial parameter in this task but it has to be verified manually or by another algorithm, since several false positive things are unclear. The best settings are chosen to perform. The best configuration will be selected to effectuate the validation and comparison with other methods.

C. *Experimental setup*

DeepLesion[10] is the largest data sets in the field of medical CT scanning published in the Journal of Medical Imaging by the National Institute of Health (NIH) aiming to enhance machine learning in CAD. There are in the hospital image archive and contact system 4,427 specific patients collected from 2010. (PACS). We concentrate only on detecting the kidney lesion and then we collect 956 kidney images from the Deep Lesion and form a kidney data set after we have discarded some noise samples. The Network has been trained with 80% of the available examples, while the Network has been tested with 20%.

D. *Validation*

The last step is the method introduced in this thesis to be validated. Validation is carried out by checking the CNN in the configuration selected, which was previously trained in the training set (input images of 9 pixels, 10 filters size 7, and the pool size one). The procedure consists of taking the CT scans from various patients and verifying the number of items as stones. The CNN classifies and includes all associated components defined for each patient fulfilling the size conditions. The preprocessing steps have been performed to detect the components. There are null or one stones and thousands of connected components on each CT scan, which are not stones, but this unbalance is not significant since the CNN is already qualified.

The sensitivity observed was 97.8 percent and the accuracy 98.1 percent of all CT scans used for validation. Each CT scan contains an average of 92 false positives. This is because the accuracy is minimal, though the sensitivity is great, and the false positive must be tailored in a different way.

IV. Discussion

This method is implemented in MATLAB R2014a.Thus classification of kidney stone using GLCM feature extraction and neural network is successfully achieved. Comparing with Gabor filters, Canny Edge Detection and Daubechies lifting schemes GLCM has shown great potential for recognizing the significant features for accurate classification of kidney lesion. Others lead to feature reduction which may probably remove some significant features. GLCM feature extraction is a statistical approach. GLCM has great potential in feature extraction leading to higher accuracy of 98.8 % of classification rate. K-means algorithm performs better in overlapped data. In K-means clustering data point may belong to more than one cluster.

In short, the developed algorithm is useful for analysing and determining their position by analysing the data from the CT scans. Once the CNN has been trained, it takes.

*A. **Future Work***

The work of the future classification of stones based on CT scans should concentrate on finding other CNN composition that exceeds what was conceived in this work. This includes change of architecture, several layers of convolution and bundling, or the activation or error functions used even if their properties are selected. For the future, the search process should not focus only on changing hyperparameters using the same structure.

The position of the regions that will be classified as this is usefully information and the urethral stones are located in a specific region of the body would be another field of further research. The amount of input data could be reduced much more. The major problem when using such techniques is to refer to the position of a specific body part or organ, such as the spine, rather than the position of the CT scan as the start and end positions of the CT scans can vary according to the variables of the body. Then, the position and region of the stones of the all CT scans used in the training can be saved.

V. Conclusion

In sum, lesion detection shows advantages and time saving in locating analyzing lesion. Some algorithm proves deep learning are practically possible in CAD, but they are not meet the accuracy and comprehensiveness. We proposed and algorithm that has high precession to detect the kidney lesion in the CT scan image. In our system we have morphological operation for preprocessing to make the system detect easier. We modify the layers into FPN to generate into different sizes. The validation experiments were conducted on a CT images that proves that cascaded RCNN has greater performance in detecting lesions.

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