

# Refine Observation of Kidney Stones using Neural Network

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**Abstract** – Back Propagation Network with image and data processing techniques was employed to implement an automated kidney stone classification. The conventional method for medical resonance kidney images classification and stone detection is by human inspection. Operator-assisted classified methods are impractical for large amounts of data. Medical Resonance images contain noises caused by operator performance which can lead to serious inaccuracy classifications. Artificial intelligent techniques through neural networks and feature extraction are shown great potential in this field. Hence, in this paper the Back Propagation Network was applied for the purposes. Decision making was performed in two stages: feature extraction using the principal component analysis and the classification using Back Propagation Network (BPN). This project presents a segmentation method, Fuzzy C-Mean (FCM) clustering algorithm, for segmenting computed tomography images to detect the lung cancer in its early stages. The performance of the BPN classifier was evaluated in terms of training performance and classification accuracies. Back Propagation Network gives fast and accurate classification than other neural networks and it is a promising tool for classification of the cancer.

**Keywords** – Neural Networks, Back Propagation Network, Kidney Stones, Grey-Level Co-Occurrence Matrix, Image Segmentation.

## I. INTRODUCTION

The automatic detection and classification of kidney stones in medical resonance image (MRI) had been widely studied in the previous years in order to detect kidney tumours. Although human inspection of operator-assisted images failed to detect the kidney stones due to the noises present in the MRI images and they were impractical for large amounts of data and non-reproducible.

In order to overcome this situation, a detection and classification of kidney stones using the neural network was implemented and a refined observation was carried out. Primarily the MRI images are processed to eliminate the noises produced by the operator which makes it easier for the detection and to extract the features such as energy, entropy, contrast, correlation coefficient, homogeneity. This helps to identify and detect the stones present.

Datasets containing a collection of similar or relevant MRI images are trained for an automatic classification of the processed image after pre-processing. This classification is carried out using the Back Propagation Network (BPN) algorithm. The performance of the BPN was evaluated in terms of training performance and classification accuracies. The Back Propagation learning rule can be used to adjust the weights and biases of networks to minimize the sum squared error of the

network. This project presents a segmentation method, K means clustering algorithm for segmenting kidney stones.

### • Related work:

Hyper vision net using coordinate convolutional layer for kidney tumour segmentation [1]. Kidney CT image segmentation using multi featured EM algorithm based on Gabor filters [2]. CorteXpert method for automatic renal cortex segmentation [3]. Detection of small renal masses in contrast enhanced CT images [4]. Automatic MRI segmentation based on adaptive feature learning probability boosting tree initialisation and CNN-ASM refinement [5]. Automatic segmentation of MR brain images with a CNN [6]. Interactive medical image segmentation using deep learning [7]. Monitoring kidney microanatomy changes using texture analysis of OCT images [8].

Combining fully convolutional network for automated segmentation of cervical cell nuclei [9]. Semi-automatic segmentation of prostate in CT images [10].

### • MRI data description:

The MRI data are used to visualize the functional activity of the Kidney. The datasets contains RF signal intensity, the tissue magnetisation, proton density image and the image brightness determined by proton. This database was developed by collecting data from the various experimental results. The datasets contains 1.5T and 3T scans. MRI data images are non-invasive and non

reproducible. These data sets contains MRI samples images, but we use only few samples for our experiments.

**Methodi:**

There are four main parts in kidney stone detection and classification containing Pre-processing, GLCM feature Extraction, Back propagation Network, K-Means Clustering Algorithm.

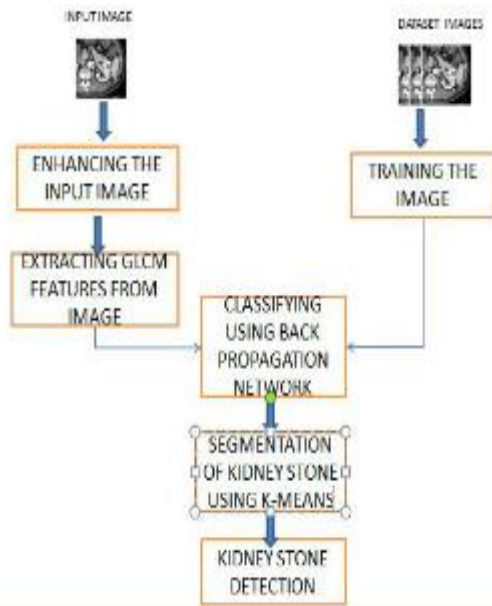


Fig.1.Architecture diagram of the proposed system.

**1. Pre-Processing**

In image processing, a Gaussian Blur is implemented to reduce the large amount of noise produced in an image. Gaussian Blur Parameters is increased to get the exact result in reducing noise in an image. Gaussian Blur is implemented in Python using Gaussian Blur function. A bilateral filter may be a non-linear, edge-preserving and noise-reducing smoothing filter for images. It replaces the intensity of every pixel with a weighted average of intensity values from nearby pixels. This weight are often supported a normal distribution. The weights depends on Euclidean distance of pixels and also the radiometric differences.

This preserves sharp edges. An RGB to Grey Conversion is also used. A greyscale Image is digital image in which the value of every pixel is a single sample. Greyscale images are often the results of measuring the pixel of intensity of light in a single band of the electromagnetic spectrum. In some cases they are monochromatic proper when a given frequency is captured.

The bilateral Filter is defined as

$$I^{bilateral}(x) = \frac{1}{W_p} \sum_{t_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

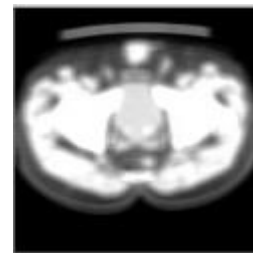


Fig 1.1 Gaussian Blurring.

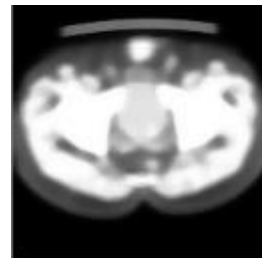


Fig 1.2 Bilateral Filters.

**GLCM Feature Extraction**

The co-occurrence is constructed first, by the orientation and distance between image pixels. Then the information are extracted from the matrix as the texture representation. Grey-level-co-matrix uses scaling to reduce the number of intensity values in gray scale image from 256 to 8. The GLCM Features are:1.Energy 2.Contrast 3.Correlation 4.Homogeneity.

**Energy:**

It is a measure of homogeneity changing by gray-scale image texture.Itreflects the distribution of image gray-scale uniformity of texture and weight.

$$E = \sum_x \sum_y p(x, y)^2$$

p(x , y) is the GLCM

**Contrast:**

Main crossways near the moment of inertia is contrast, contrast measures the value of the distributed matrix and images of local changes in number. It reflects the texture of shadow depth and image clarity.

$$I = \sum \sum (x-y)^2 p(x, y)$$

**Correlation Coefficient:**

The correlation is a analytical measure of the joint probability occurrence of the specified pixel pairs.

Correlation:  $\frac{\sum (\sum ((x-\mu_x) (y-\mu_y) p(x, y)/\sigma_x \sigma_y))}{\sigma_x \sigma_y}$

**Homogeneity:**

Homogeneity measures the closeness of the allocation of elements within the GLCM to the GLCM diagonal.

Homogeneity =  $\frac{\sum (\sum (p(x, y) / (1 + |x-y|)))}{\sum \sum p(x, y)}$

## 2. Back Propagation Network

This classification is carried out using the Back Propagation Network (BPN) algorithm. The performance of the BPN was evaluated in terms of training performance and classification accuracies. The Back Propagation learning rule can be used to adjust the weights and biases of networks to minimize the sum squared error of the network. Widrow-Hoff delta learning in which the load adjustment is completed through a mean square error of the output response to the sample input. The set of those sample patterns are repeatedly presented to the network until the error value is minimized.

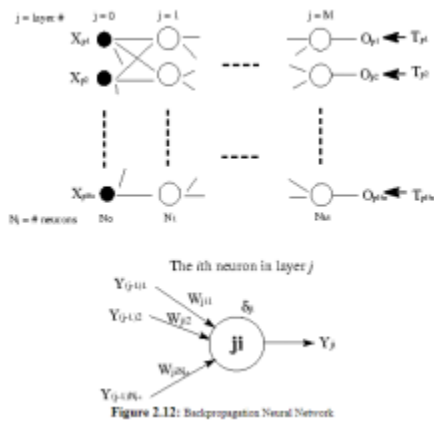


Fig: 1.2 Back propagation Neural Network.

The following is the outline of the back propagation learning algorithm:

- Initialize connection weights into small random values.
- Present the  $p$ th sample input vector of pattern.  $\mathbf{X}_p = (X_{p1}, X_{p2}, \dots, X_{pN_0})$  and the corresponding output target to the network.  $\mathbf{T}_p = (T_{p1}, T_{p2}, \dots, T_{pN_M})$
- Pass the given values to the first layer. For every input Node  $i$  in layer  $0$ , perform:

$$Y_{0i} = X_{pi}$$

- For every neuron  $i$  in every layer  $j$ , from input to output layer  $j = 1, 2, \dots, M$ , find the output from the neuron:

$$Y_{ji} = f \left( \sum_{k=1}^{N_{j-1}} Y_{(j-1)k} W_{jik} \right),$$

Where

$$f(x) = \frac{1}{1 + \exp(-x)}$$

Obtain output Values. For every output node  $i$  in layer

$$O_{pi} = Y_{Mi}$$

,perform:

Calculate error value  $\delta_{ji}$  for every neuron  $i$  in every layer  $j = M, M - 1, \dots, 2, 1$

in backward order, from output to input layer, followed by weight adjustments. For the output layer, the error value is:

$$\delta_{Mi} = Y_{Mi}(1 - Y_{Mi})(T_{pi} - Y_{Mi}),$$

And

for

hidden

$$\delta_{ji} = Y_{ji}(1 - Y_{ji}) \sum_{k=1}^{N_{j+1}} \delta_{(j+1)k} W_{(j+1)ki}$$

layers

The weight adjustment can be done for every connection

$$(i - 1)$$

from neuron  $k$  in layer  $(i - 1)$  to every neuron  $i$  in every layer  $i$ :

$$W_{jik}^+ = W_{jik} + \beta \delta_{ji} Y_{ji},$$

$\beta$

Where  $\beta$  represents weight adjustment factor normalized between 0 and 1. The derivation of the equations above will be discussed soon.

The actions in steps 2 through 6 will be repeated for every

$p$

training sample pattern, and repeated for these sets until the root mean square (RMS) of output errors is minimized.

## 3. K Means Clustering

Clustering is employed to arrange data for efficient retrieval. One of the issues in clustering is that the identification of clusters in given data. A well-liked technique for clustering is predicated on K-means such that the info is partitioned into K clusters. During this method, the amount of clusters is predefined and therefore the technique is very looked into the initial identification of elements that represent the clusters well. An outsized area of research in clustering has focused on improving the clustering process such as the clusters aren't hooked into the initial identification of cluster representation. The technique can identify K clusters in an input file by merging previous clusters and by creating new ones while keeping the number of clusters constant. The technique has not been able to achieve a powerful speed-up of an inquiry process when other efficient search techniques might not be available. The purpose of clustering is to perform an efficient search of elements in a data set. Clustering is mainly effective in multi-dimensional data that may be otherwise difficult to organize efficiently.

One of the earliest clustering techniques within the literature is that the K-means clustering method. In this, clustering is predicated on the identification of K elements within the data set which will not create an initial representation of clusters. These K elements forming the cluster seeds. The leftover elements of the data set are then assigned to one of these clusters. Even though the tactic seems to be simple, it bears from the very fact that it's going to not be easy to identify the initial K elements of the seeds for the clusters. This shortcoming led the researchers to look into alternative methods that provide an improvement over K means. Some of these techniques include genetic algorithm-based clustering and fuzzy clustering.

The adaptive K means clustering algorithm starts with the choice of K elements from the input file set. These K elements form the clusters and are randomly selected. The properties of every element also form the properties of the cluster that's constituted by the element. The algorithm is predicated on the power to compute the distance between a given element and cluster. This function is additionally applied to compute the distance between two elements. An important consideration for this function is that it should be ready to account for the space supported properties that are normalized so that space is not dominated by one property or some property is not ignored while distancing computation. In most cases, the Euclidean distance could also be sufficient. For example, in the case of spectral data given by 'n' dimensions, the distance between two data elements E1 and E2, is equal to

$$\sqrt{(E_{11} - E_{21})^2 + (E_{12} - E_{22})^2 + (E_{1n} - E_{2n})^2}$$

Where  $E_1 = \{E_{11}, E_{12}, \dots, E_{1n}\}$  and  $E_2 = \{E_{21}, E_{22}, \dots, E_{2n}\}$

## II. EXPERIMENT RESULTS

In this experiment, the results were based on using different MRI Images. Sensitivity, specificity, accuracy are the parameters which are used to calculate the result efficiency of the classifier. Here we increased the efficiency of the system compares to the previous works. Results produced by this project are verified with the experts. The sample signals are collected from the Openfmri, they provide exact results. These datasets are trained during the development phase for producing the accurate results.

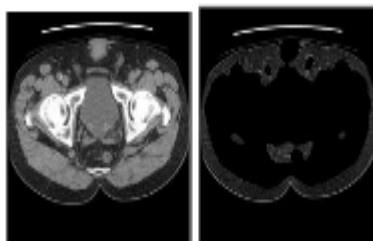


Fig 3.1:Input Image Fig 3.2:Extracting feature.



Fig 3.2:Segmentation.

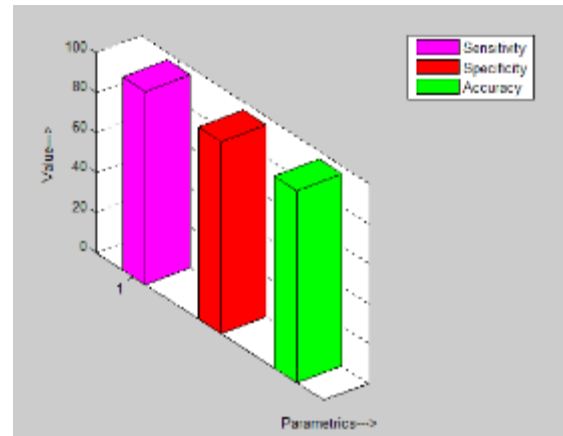


Fig 2 :It shows Performance Metrics of Sensitivity, Specificity and Accuracy.

## III. CONCLUSION

The experiments show that the suggested algorithm has performed more accurate results in compared to the previous implemented algorithm. The specificity and sensitivity of a Kidney Stone detection obtained by the suggested algorithm is better. The proposed method can be used for other application for comparing the MRI images. Here experimental results produce the accuracy level of 96 % for the implemented algorithm. These results are improved compared to existing systems.

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