



## Prediction of Nephrolithiasis Based on Extracted Features of CT-Scan Images using Artificial Neural Networks

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**Abstract:** Nephrolithiasis or Renal calculi or Kidney stones transpire in 1 in 10 populace at some time in their life. Renal calculi are a general cause of bloody urine and stern pain in the abdomen, flank, or groin. To locate the position, size and number of stones in the renal structure the patient is recommended to take computed tomography (CT-scan). As there is rapid raise in population the necessitate of more nephrologists is essential. So, the most important objective of this paper is to afford a supportive diagnosis system to the physician using neural networks in order to envisage nephrolithiasis based on extracted features of CT-scan. The proposed system incriminates with pre-processing, segmentation, feature extraction by applying neural network techniques and finally prediction of kidney stone is done. Artificial Neural networks are intermittently used as a dominant distinctive classifier for errands in medical diagnosis for premature detection of diseases. Here we introduced a Feed-Forward Back propagation algorithm to lessen the diagnosis time and raise the accuracy of the system. The GLCM algorithm is introduced to extort the features which are used to train the network. The proposed system uses 22 input nodes, 10 hidden nodes and 1 output node. The network is trained until it targets its desired output. This trained network is used to cart out the classification automatically for a new model. The proposed system is tested with 50 real time samples, amid them 60% are used for training the network and 40% are used for testing the network. The intended system is implemented using MATLAB 8.5 software tool.

**Keywords:** Nephrolithiasis, CT-scan, pre-processing, Artificial Neural networks, Feed-Forward Back propagation algorithm, GLCM algorithm

### I. INTRODUCTION

Renal calculus, more commonly known as kidney stone formation, is characterized by the formation of crystals in the urine caused by substance concentration or genetic susceptibility. All persons are susceptible to kidney stones, even infants, and yet, the majority of kidney stone cases remain undetected except in cases where extreme abdominal pain is exhibited or abnormal urine color is observed. In addition, people with kidney stones exhibit common signs such as fever, pain and nausea that are easily associated to other conditions. Kidney stone detection is important particularly in its early stages to facilitate intervention or to receive proper medical treatment. The presence or the recurring presence of kidney stone decreases kidney functions and dilation of the kidney. It also has implications on the degrees of chronic kidney disease (CKD) or chronic renal failure (CRF) for people who have not been previously diagnosed with this condition. However, because of its asymptomatic nature, it is commonly diagnosed among patients who undergo medical examination for other diseases such as cardiovascular diseases (CVD), diabetes, and other medical conditions predispose to the urogenital apparatus [1]-[3]. Today, computer-assisted tools such as ultrasound imaging, computed tomography (CT), and Xrays that use intravenous pyelogram (IVP) provide the most accurate diagnostic tools for kidney stone screening and diagnosis. CT scans, which provide threedimensional views of the organ or region of interest is the most sought after kidney stone screening tool in hospitals. Its convenience and efficiency in kidney stone detection (including its pathology) for both asymptomatic and symptomatic patients make advances in CT technology extremely important for physicians and patients alike [4], [5]. Software programming, which has found current and potential

applications in technological advancements in the field of medicine, recognizes the need to contribute to CT screening development particularly in enhancing diagnosis of the kidney-urine-belly (KUB) region for kidney stone detection. This study developed a semiautomatic kidney screening program that integrated digital image processing and image analysis techniques in KUB CT images.

Nephrolithiasis [6], or renal calculi, are rigid masses formed of crystals. Kidney stones typically originate in kidneys, but can grow wherever alongside the urinary tract. The urinary tract consists of the kidneys, ureters, bladder, and urethra. Kidney stones are notorious to be one of the most painful medical conditions[7][8]. The origins of kidney stones vary according to the type of stone. The fig.1.1 shown below gives the kidney with stone and a healthy kidney.

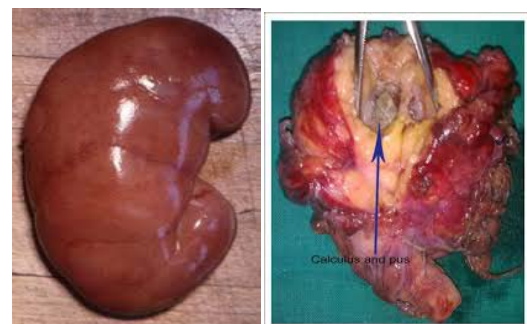


Fig:1.1. Healthy Kidney and Kidney with stone

#### 1.1. Types of kidney stones

There are four major types of kidney stones. The category of stone and its frequencies in the people is as shown in Table1.

**1.1.1 Calcium stones**

The majority kidney stones are formed of calcium composites, especially calcium oxalate [9]. Calcium phosphate and additional minerals as well may be present. The fig.1.2 shows the image of calcium stone.



**Fig.1.2: Calcium stones**

Circumstances that basis high calcium echelons in the body, such as hyperparathyroidism, enhance the risk of calcium stones. High levels of oxalate also raise the risk for calcium stones. Certain medicines might avert calcium stones.

**1.1.2 Uric acid stones**

A few of kidney stones are formed of uric acid, a devastate produce usually passed out of the body in the urine. The fig.1.3 shows the image of uric acid stone.



**Fig.1.3: Uric acid stone**

If anybody has uric acid stones they have:

- Squat urine output.
- A diet high in animal protein, such as red meat.
- A raise in how much alcohol you drink.
- Gout.
- Inflammatory bowel disease.
- Certain medicines may avoid or melt uric acid stones.

**1.1.3 Struvite stones**

Some kidney stones are struvite stones. They can also be called infection stones if they transpire with kidney or urinary tract infections (UTIs). These forms of kidney stones at times called as stag horn calculi if they develop hefty enough.



**Fig.1.4: Struvite stones**

Struvite stones shown in fig.1.4 can be somber, because they are frequently huge stones and may arise with an infection. Medical treatment, as well as antibiotics and exclusion of the stone, is usually considered necessary for struvite stones. Women are exaggerated other than men because of their higher peril of urinary tract infections.

**Table. 1 Kidney Stone Types and Frequencies**

Stone type	Adults			Children
	Males	Females	Both	
Calcium oxalate	82%	66%	76%	45–65%
Calcium phosphate	8%	19%	12%	14–30%
Uric acid	8%	6%	7%	4%
Cystine	1%	4%	2%	5%
Struvite	1%	5%	2%	13%

**1.1.4 Cystine stones**

Less familiar kidney stones are made of a chemical called cystine.



**Fig.1.5: Cystine stones**

Cystine stones shown in fig.1.5 are more likely to occur in populace whose families have a state that consequences in too much cystine in the urine (cystinuria).Cystine stones may be vetoed or liquefied with medicine. But this may be intricate and not very efficient. If a stone forms obstacle in the urinary tract or is too bulky, then it must be removed.

**1.2. Causes of kidney stones:**

**1.2.1 Heredity**

Some of the populace is more vulnerable to forming kidney stones, and inheritance may play a part. The majority of kidney stones are formed of calcium, and hypercalciuria (high levels of calcium in the urine) is one menace factor. The tendency to high levels of calcium in the urine may possibly be conceded on from generation to generation. Some infrequent hereditary diseases also incline some people to form kidney stones. Examples comprise people with renal tubular acidosis and people with tribulations of metabolizing an array of chemicals including cystine (an amino acid), oxalate, (a salt of an organic acid), and uric acid (as in gout).

**1.2.2 Geographical location**

There might be a geographic predilection to form kidney stones, so where a person lives may create it more liable for them to form kidney stones. There are regional "stone belts," with people living in the southern United States having an augmented menace of stone formation. The hot climate in this province shared with insufficient fluid ingestion may cause people to be relatively desiccated, with their urine becoming more rigorous and allowing chemicals to come in earlier contact to shape the nidus, or beginning, of a stone.

**1.2.3 Diet**

Diet may or may not be a concern. If a person is subjected to forming stones, then foods high in animal proteins and salt may enhance the peril; however, if a person isn't prone to forming stones, diet possibly will not amend that risk.

**1.2.4 Medications**

People taking diuretics (or "water pills") and those who guzzle surplus calcium-containing antacids can raise the quantity of calcium in their urine and potentially raise their risk of forming stones. Taking intemperance amounts of vitamins A and D are also related with high levels of calcium in the urine. Patients with HIV who take the medication indinavir (Crixivan) may form indinavir stones. Other frequently approved medications allied with stone structure consist of phenytoin (Dilantin) and antibiotics like ceftriaxone (Rocephin) and ciprofloxacin (Cipro).

**1.2.5 Underlying illnesses**

Some persistent illnesses are associated with kidney stone development, including cystic fibrosis, renal tubular acidosis, and inflammatory bowel disease.

**1.3. Symptoms of Nephrolithiasis**

A kidney stone may not cause signs till it travels around within the kidney or passes into ureter — the tube linking the kidney and bladder. At that point, the person may experience these signs and symptoms:

- relentless pain in the side and back, underneath the ribs
- Pain that spreads to the lower abdomen and groin
- Pain that comes in waves and changes in concentrations
- Pain on urination
- Pink, red or brown urine
- Cloudy or foul-smelling urine
- Nausea and vomiting
- Persistent need to urinate
- Urinating more often than usual
- Fever and chills if an infection is present
- Urinating small amounts of urine

Pain caused by a kidney stone may amend — for example, shifting to a diverse location or increasing in intensity — as the stone moves through urinary tract.

**1.4. Chemical Composition of the Urine in Nephrolithiasis**

Urine is the amalgamation of equally water and dissolved chemicals, such as sodium, calcium, potassium, urea, creatinine etc., usual persons urine consists precise amounts of chemical substances as shown in Table.2. If these amounts are not in typical ranges then the person is anguishing from the nephrolithiasis. Depends ahead the chemical material the nature of the stone produced is diagnosed.

**Table.2 chemical substances of Normal person urine**

ANALYTE	NORMAL VALUES (non-stone formers)	
	ADULTS	CHILDREN (< age 18)

ANALYTE	NORMAL VALUES (non-stone formers)	
	ADULTS	CHILDREN (< age 18)
VOLUME	> 1.5 L/day	25 ± 7 ml/kg/day
pH	5.8–6.2	5.85–7.05
CALCIUM mg	<250 (F), <300 (M),	<4 mg < 0.21 gm
OXALATE mg	30–50mg	0.56 mg/kg/day
CITRATE	>550 (F), >450 (M)	> 400 mg/g
URIC ACID	<750 (F), <800 (M)	< 815 mg
PHOSPHATE	500–1500	

**1.5. Imaging tests for prediction of kidney stone**

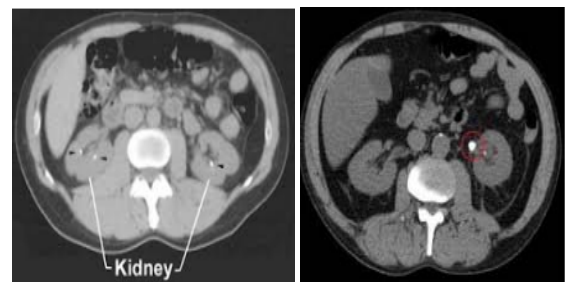
To check for kidney stones in urinary tract (kidneys, ureters, and bladder). Imaging analysis may consist of X-rays, a CT scan or an ultrasound [10]. If the first imaging test is not obvious, the patient needs to go for other two tests. These tests [11] include:

**1.5.1 X-Rays.**

A typical X-ray of the kidneys, ureters, and bladder may be a fine step for identifying stones, as several are observable on x-rays. Calcium stones can be recognized on x-rays by their white color.

**1.5.2 Spiral (or Helical) Computed Tomography.**

A sort of computed tomography (CT) scan called a spiral or helical CT scan is presently the finest method for diagnosing stones in either the kidneys or the ureters. This test is hasty, does not need devices or foreign chemicals to penetrate the body, and grants meticulous precise images of even very minute stones. If stones are absent, a spiral CT scan can frequently recognize other causes of pain in the kidney area. It is healthier than x-rays, ultrasound, and intravenous pyelogram -- the previous standard test for detecting kidney stones. Experts trust spiral CT will eventually be capable to spot the chemicals present in a stone. The CT-scan with and without stone is shown in fig.1.6.



**Fig.1.6: CT-scan with stone and without stone**

**1.5.3 Ultrasound.**

Ultrasound can detect apparent uric acid stones and obstacle in the urinary tract [12]. It is not helpful for pronouncement of extremely tiny stones, but some research specify that it may be a useful first diagnostic step in the urgent situation

to help envisage the likelihood of a stone, as well as suspected stones in children

## II. ARTIFICIAL NEURAL NETWORKS(ANN)

An artificial neural network (ANN) is a calculation model that challenges to account for the parallel nature of the human brain. An (ANN) is a network of vastly interrelating processing elements (neurons) working in parallel. These rudiments are stimulated by biological nervous structure. As in nature, the links between elements mostly verify the network task. A subgroup of dealing out element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be extra layer(s) of units, called hidden layer(s). Fig.1.7 signifies the typical neural network. One can train a neural network to execute an exact function by changing the values of the links (weights) between elements. Artificial Neural Network (ANN) is a data processing Technique based on the mode biological nervous systems, routes information [13]. Artificial Neural networks came into subsistence as a result of simulation of biological nervous system, such as the brain on a computer.

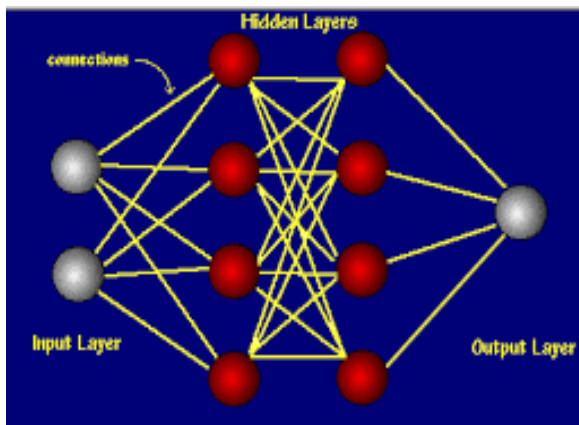


Fig.1.7. A typical neural network

Neural networks are specified as a cluster of nodes called neurons and links between them. The links have weights related with them, representing the —power of those links. Currently neural networks can be useful to troubles that do not have algorithmic clarifications or problems for which algorithmic solutions are too intricate to be found. In other words the type of tribulations in which inputs and outputs variables does not have a obvious relationship between them, a neural networks is a proficient approach in such problems [14].

Mainly neural network architecture has three layers in its structure. First layer is input layer which affords an interface with the environment, second layer is hidden layer where calculation is made and last layer is output layer where output is hoard. Data is promulgated through successive layers, with the absolute result accessible at the —output layer. Many dissimilar types of neural networks are obtainable and multi layer neural networks are the trendiest.

### 2.1 Advantages of Neural Networks

- Can be useful to many tribulations, as long as there is some information.

- Can be applied to problems, for which logical methods do not yet subsist
- Can be used to mold non-linear dependencies.
- If there is a model, then neural networks should swiftly work it out, even if the information is ‘noisy’.
- At all times offers some answer even when the input information is not inclusive.
- Networks are effortless to retain

### 2.2 Review of Literature:

The most recurrent problem in the Field of usual diagnostic is the diagnostics using rapid and precise algorithm which doesn’t need lengthy time to run and confer accurate and correct results [15]. To diminish the diagnosis time and progress the diagnosis accuracy, it has develop into more of a demanding topic to build up consistent and powerful medical diagnosis system to maintain the physician and tranquil increasingly problematical diagnosis procedure. The medical diagnosis by nature is a difficult and fuzzy cognitive Process hence flexible computing methods, such as neural networks, have shown immense potential to be applied in the enlargement of medical diagnosis[16][17].

Dr. S. Vijavarani et al. envisaged kidney diseases by using Support Vector Machine (SVM) and Artificial Neural Network (ANN). The objective of research is to evaluate recital of these two algorithms on the origins of its accuracy and execution time by balancing these two algorithms. The outcomes it shows that the performance of the neural network is superior to the any other algorithm [18].

Lara Dantas et al. [19] studied to utilize neural networks such as Multi-layer Perceptron, Extreme learning Machine and Reservoir computing to performing early on diagnosis of a patient with or without AD and Mild Cognitive Impairment (MCI), and for a further common type of disease. This paper also presents detail to consume the Random Forest Algorithm and the feature assortment method obtainable on Weak called Info Gain Attribute Eval to choose proteins from the original set and, thus, build a new protein signature. Through experiments end result show that the greatest performance was obtained with the MLP and the novel signatures created with the Random Forest attained better results than any other system.

Koushal Kumar Abhishek diagnoses kidney stone disease by using three different neural network algorithms which have diverse structural design and distinctiveness. The intend of his work is to evaluate the performance of all three neural networks on the basis of its accuracy, time taken to build model, and training data set size [20].

Tijjani and Sani[21] presented an outline of the ANN based approaches to predicting kidney predicament through comparing mental conduct of the patient using matlab software. Hafizah, Supriyanto, and Yunus extracted a feature of kidney from ultrasound image based on intensity histogram [22].

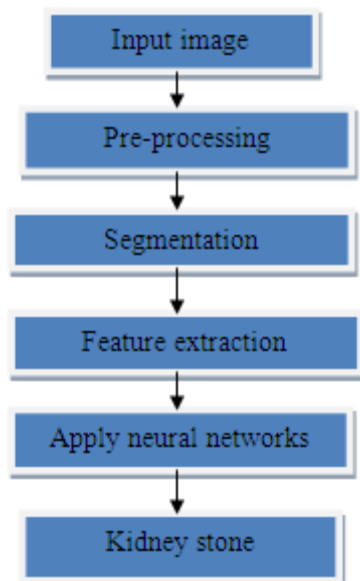
HasanTemurtas et al., efforted on a comparative Pima diabetes disease diagnosis. For this reason, a multilayer neural network composition which was trained by Levenberg–Marquardt (LM) algorithm and a probabilistic neural network system were employed by them. The outcomes of this research compared with the results of the earlier studies reported focusing on diabetes disease diagnosis and utilizing the same UCI database [23].

In this paper a supportive diagnosis system is developed using neural networks [24][25] in order to present a sustain for the physician in the prediction of nephrolithiasis[26][27][28]. This is extremely helpful in plummeting the diagnosis time and to augment the accuracy. The proposed system is executed through 5 stages. They are pre-processing, feature extraction, neural networks and final segmentation. The process is done based on the CT-scan. The section II is about the ANN and its applications, III describes the proposed methodology. Conclusion is described in Section IV.

### III. PROPOSED METHODOLOGY

Computed tomography (CT) is an imaging procedure that utilizes special x-ray equipment to make meticulous pictures, or scans, of areas inside the body. It is also called computerized tomography and computerized axial tomography (CAT). The word tomography comes from the Greek words tomos (a cut, a slice, or a section) and graphein (to write or record). Each image created for the duration of a CT process shows the organs, bones, and other tissues in a slight "slice" of the body.

CT-scan is a fast, 5-20 minute painless exam that combines the rule of X-rays with computers to generate 360 degree, cross-sectional views of body. CT is capable to image bone, soft tissue and blood vessels all at the similar time. Therefore in the current study, the procedure is done according to the flowchart given below in fig.3.1. Here the process is done in a systematic procedure in sort to envisage the renal calculi or kidney stone. This method utilizes artificial neural networks for the prediction of nephrolithiasis alongside with diminution of diagnose time and elevate in accuracy [29][30]. The GLCM algorithm is utilized for the extraction of features which are very strong to transforms and orientations. Then these features are used to train the artificial neural network.



**Fig.2.1: The Flow Diagram of Proposed System**

The information utilized for the current study is the CT-scans, which are composed from different hospitals of

diverse patients. In order to develop these CT-scans, the images are accumulated in JPG format as shown in fig.2.2 which is an input image.

#### 3.1. Pre-processing

Pre-processing repress the undesired buckles and improves certain image features important for further processing and stone detection. Devoid of preprocessing, the CT-scan image quality may not be superior for examine. For surgical procedures, it is necessary to recognize the locality of kidney stone accurately. Pre-processing assists to trounce the issue of squat contrast and noise lessening.



**Fig.2.2: Input image**

For pre-processing first the input image is transformed to gray scale image and then the image is resized. Then the resized image is attuned in order to improve the contrast of the image. The contrast can be represented as given in equ.2.1.

$$f(x) = \begin{cases} \max(k, 0), & \text{if } a(x, y) < G(x, y) \\ \min(k, 0), & \text{otherwise} \end{cases} \dots\dots(2.1)$$

Where  $a(x, y)$  is average intensity petite neighborhood and  $G(x, y)$  is mean in the equal neighborhood.

Therefore, the foremost step is preprocessing, which is done by padding the noisy image. Image padding commences new pixels approximately the edges of an image. The border affords space for annotations or proceeds as a boundary when using advanced filtering techniques. This is an iteration process in which the accumulated denoised pixels are spawned to renew the accumulated weights.



**Fig.2.3: kidney segmentation at 500<sup>th</sup> iteration**

Digital images are subjected to diversity types of noise. Noisy images creates difficult to clinically diagnosis. A mask is functioned to the improved image in order to

eliminate noise from the image. Then the denoised image is attained.

**3.2. Segmentation**

Segmentation is naturally utilized to trace objects and boundaries (lines, curves, etc.) in images. If the domain of the image is given by 'I', then the segmentation quandary is to verify the sets  $S_K \subset I$  whose unification is the whole image I. Thus, the sets that formulate up segmentation must gratify equ.(2.2)

$$I = \cup_{k=1}^K S_K \dots\dots\dots (2.2)$$

Where  $S_K = S_j = \emptyset$  for  $k \neq j$ , and each  $S_k$  is connected. Preferably, a segmentation method locates those sets that keep up a correspondence to distinctive anatomical structures or regions of interest in the image.



**Fig.2.4: Detection of stone in kidney image**

Then final segmentation of the kidney stone is done with a bounding box represented with a green color as shown in fig.2.4. By this the ordinary people also can spot the kidney stone very simply.

**3.3. Feature extraction**

In order to extort the requisite features from the segmented image, Gray level co-occurrence matrix (GLCM) feature extraction method is proposed which is very strong. GLCM approximates image characteristics related to second-order statistics.

Every entry (x,y) in GLCM keep up a correspondence to the number of occurrences of the brace of gray levels i and j which are a distance d apart in original image. Presume I(i,j) is an image with size P×Q and a set of  $N_g$  gray levels co-occurrence matrix  $F(x,y,d,\theta)$  is defined in eq.(2.3) as follows:

$$F(x,y,d,\theta) = \aleph\{(i_1,j_1), (i_2,j_2) \in (P \times Q) \times (P \times Q) | (i_2,j_2) = i, I(i_2,j_2) = j, 1 \leq x,y < N_g\} \dots\dots (2.3)$$

$\aleph$  Denotes the number of elements in the set. Here we computed 22 features which were used as input parameters to train the network. Some of these are energy, contrast, correlation and homogeneity etc.

**2.3.1Energy**

Energy offers the sum of squared elements in the GLCM, also known as regularity or the angular second moment. Energy is 1 for a constant image. Here, the distance d is set to 50 and  $\theta$  varies in 4 directions 0, 45, 90,135 degree. Precisely the energy is defined in eq.2.4.

$$\text{Energy}(d, \theta) = \sum_{x=1}^{N_g} \sum_{y=1}^{N_g} F(x,y,d,\theta)^2 \dots\dots\dots (2.4)$$

**2.3.2: Contrast**

Contrast measures the local variations in the gray-level co-occurrence matrix. This defined in eq.2.5 as follows.

Contrast is 0 for a constant image.

$$\text{Contrast}(d, \theta) = \sum_{x=1}^{N_g} \sum_{y=1}^{N_g} (i - j)^2 F(x,y,d,\theta) \dots\dots (2.5)$$

**2.3.3: Correlation**

Correlation measures the joint probability occurrence of the specified pixel pairs. Correlation is defined in eq.2.6

$$\text{Correlation}(d, \theta) = \frac{\sum_{x=1}^{N_g} \sum_{y=1}^{N_g} (x-m_i)(y-m_j) F(x,y,d,\theta)}{\sigma_i \sigma_j} \dots\dots (2.6)$$

**2.3.4: Homogeneity**

Homogeneity measures the proximity of the circulation of elements in the GLCM to the GLCM diagonal. This represented in eq.2.7mathematically.

$$\text{Homogeneity}(d, \theta) = \sum_{x=1}^{N_g} \sum_{y=1}^{N_g} \frac{1}{1+|x-y|} F(x,y,d,\theta) \dots\dots (2.7)$$

The GLCM features extracted from the segmented image are used for training the neural network. The allowable values of these features are shown in the below table 3. There are 22 features some of them are represented in the table.3.

**Table.3: GLCM features and their allowed values**

Features	Allowed values
Energy	4.1636e-04
Contrast	378.7012
Correlation	0.0666
Homogeneity	0.1316

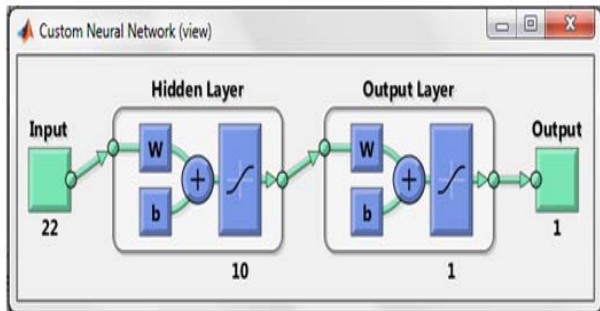
**3.4. Neural network techniques**

Although the features are extracted automatically from CT-scan by the developed algorithm, still it is complicated for a physician to analyze nephrolithiasis. Because the extracted feature values will not be similar for all the patients as an alternative they differ from person to person based on age, sex, weight, and height. This may because the inaccuracy of the diagnosis and raises the time delays of the diagnosis. Since Neural Networks have shown immense potential to be applied in the development of medical System for diagnosis of renal syndromes.

The strictures that are utilized to execute Diagnosis classification of nephrolithiasis based on CT-scan are age, gender, weight, height, and the GLCM features extracted from the CT-scan. In the current study, to train and test the network, an overall number of 50 samples are utilized then one output parameter is exhibited. Then, a feed-forward Backpropagation Neural Network is build by taking 22 input parameters of the extracted features and the essential information.

In order to realize Backpropagation Network Model, primarily a Feed Forward Neural Network is build with 22

input nodes, 10 hidden nodes and one output node as shown in the fig.2.5.



**Fig 2.5: Feed Forward Neural Network with 22 input nodes, 10 hidden nodes and one output node**

The training is completed by using the extracted GLCM features. The Algorithms mentioned in the nntaintool shown below in Fig.2.6. Here the information which is unruflled is alienated randomly. Then that random information is used for training by using a learning method called Levenberg-Marquardt Method. The Levenberg-Marquardt algorithm adaptively differs the parameter updates between the gradient descent update and the Gauss-Newton update is in equ.2.8.

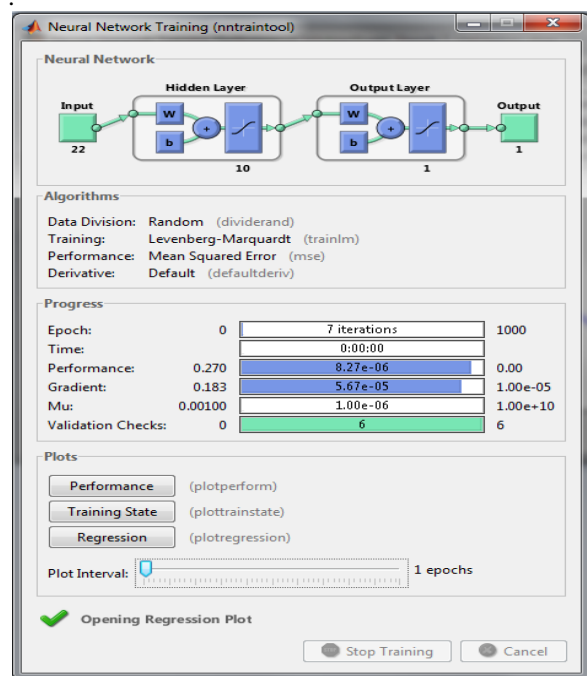
$$[J^T W J + \lambda I] h_{lm} = J^T W (y - \hat{y}) \dots\dots (2.8)$$

Where petite values of the algorithmic parameter  $\lambda$  answers in a Gauss-Newton update and huge values of  $\lambda$  result in a gradient descent update. The parameter  $\lambda$  is initialized to be large so that first updates are small steps in the steepest-descent direction. If any iteration happens to result in a poorer estimate ( $x^2(p + h_{lm}) > x^2(p)$ ), then  $\lambda$  is improved. Otherwise, as the result improves,  $\lambda$  is diminished, the Levenberg-Marquardt technique move towards the Gauss-Newton method, and the result usually hastens to the local bare minimum.

In Marquardt's update relationship is defined in equ.2.9 as

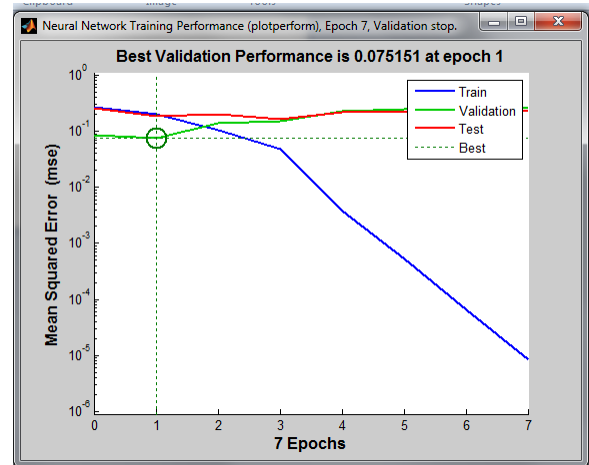
$$[J^T W J + \lambda \text{diag}(J^T W J)] h_{lm} = J^T w (y - \hat{y}) \dots (2.9)$$

The values of  $\lambda$  are regularized to the values of  $J^T W J$



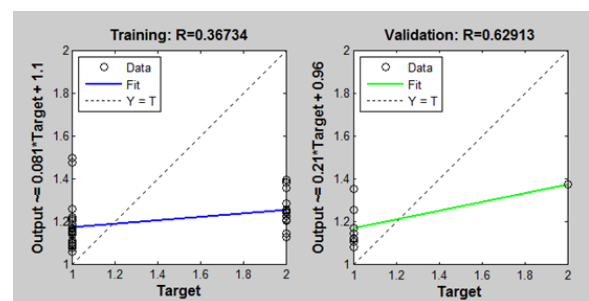
**Fig.2.6. Nntaintool**

Then the concert is evaluated after the training is finished. Then the values are evaluated. The performance is evaluated by taking epochs and mean square error is shown in Fig.2.7. The graph shown below describes the performance of error at 7 epochs. The train data is indicated with a blue line, the test data with a red line. The best validation is taken at the point where both train and test are alike. Here the best validation is at epoch1 and the value of validation performance is 0.075151.

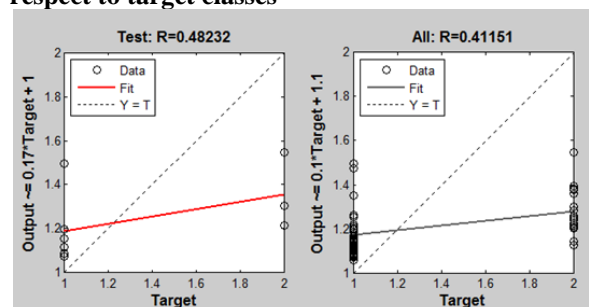


**Fig.2.7. Best validation performance at epoch1**

The performance of the system can be evaluated using the regression models. The plots shown in fig.2.8 reveal the information of training and the validation of target and output classes. In the graph the input is represented as data denoted by 'o'. Then the dotted line represents the linearity of output and the target. The fit value starts at 1.2 and it is a straight line throughout the training. The fit value doesn't change even the target classes increased. The validation graph shows the fit value linearly increases along with the target and output classes. Then for test data the plots are represented below in fig.2.9.



**Fig.2.8. Plot of training and validation for output with respect to target classes**



### Fig.2.9.Plot of testing data for output with respect to target classes

The fig.3 reveals the information of gradient, mu and validation fail at 7 epochs. The gradient value decreases and the value becomes 5.6739e-005 at the 6<sup>th</sup> epoch. Then the mu value also decreases and at the 6<sup>th</sup> epoch the value is 1e-006. The validation checks increases along with the increase in the epochs i.e. the validation checks and the epochs are linear and the validation check value at the 7<sup>th</sup> epoch is 6.

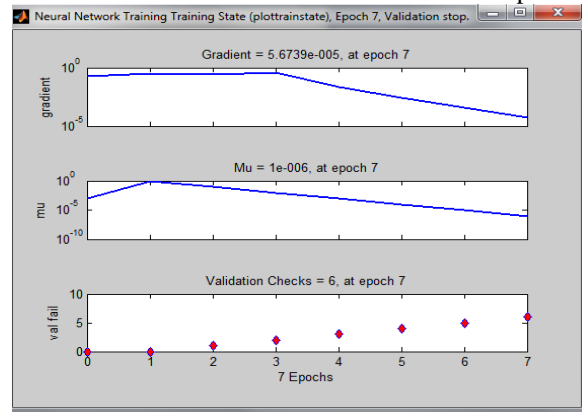


Fig.3.Gradient, mu and validation fail at 7<sup>th</sup> epoch

### 3.1: Result

The input parameters used in this system are the age, gender, weight, height and the GLCM features extracted from the CT-scan and the output parameter indicates result of the diagnosis in terms of either normal or suffering from nephrolithiasis i.e. if the CT-scan of the kidney doesn't have any stone then the condition is normal if the kidney consists of a stone then the result is finding the number of stones.

## IV. CONCLUSIONS

The diagnosis of nephrolithiasis is based on CT-scan features is a complex task for physicians due to the cause that the CT-scan images will not be alike for all populace instead it varies from person to person. Therefore, the Systems can be used by a physician to automatically extract CT-scan features and to perform the prediction of stone automatically based on the extracted features. The developed System decreases the diagnosis time and improves the accuracy of the diagnosis. The extracted features are from a normal person then the result as normal otherwise it gives the result with the final segmented image with a bounding box accurately.

As the future work the technique of combining both Artificial Neural Networks and Fuzzy Logics may be used to increase the sensitivity.

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