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Design and analysis performance of Kidney Stone Detection from Ultrasound Image by Level Set Segmentation and ANN Classification

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***Abstract*--The abnormalities of the kidney can be identified by ultrasound imaging. The kidney may have structural abnormalities like kidney swelling, change in its position and appearance. Kidney abnormality may also arise due to the formation of stones, cysts, cancerous cells, congenital anomalies, blockage of urine etc. For surgical operations it is very important to identify the exact and accurate location of stone in the kidney. The ultrasound images are of low contrast and contain speckle noise. This makes the detection of kidney abnormalities rather challenging task. Thus preprocessing of ultrasound images is carried out to remove speckle noise. In preprocessing, first image restoration is done to reduce speckle noise then it is applied to Gabor filter for smoothening. Next the resultant image is enhanced using histogram equalization. The preprocessed ultrasound image is segmented using level set segmentation, since it yields better results. In level set segmentation two terms are used in our work. First term is using a momentum term and second term is based on resilient propagation (R_{prop}). Extracted region of the kidney after segmentation is applied to Symlets, Biorthogonal (bio3.7, bio3.9 & bio4.4) and Daubechies wavelet subbands to extract energy levels. These energy level gives an indication about presence of stone in that particular location which significantly vary from that of normal energy level. These energy levels are trained by Multilayer Perceptron (MLP) and Back Propagation (BP) ANN to identify the type of stone with an accuracy of 98.8%.**

Keywords— Kidney Stone detection , Level Set Segmentation , Multilayer Perceptron (MLP) and Back Propagation (BP),Wavelet transform, and Ultrasound imaging.

I. INTRODUCTION

Kidney stone disease is one of the risks for the life in throughout the world, and majority people with stone formation in kidney initial do not notice it as disease and it damages the limb (organ) slowly. Before viewing symptoms, many people affected by continual kidney failure due to diabetes mellitus and hypertension, glomerulonephritis etc. Since kidney malfunctioning can be life threatening, diagnosis of diseases in the earlier stages is crucial. The currently available options include Ultrasound (US) image which is one of the non-invasive low cost, widely used imaging techniques for diagnosing kidney diseases [1]. Shock wave lithotripsy (SWL), percutaneous nephrolithotomy (PCNL), relative super saturation (RSS) are the techniques to test urine. The Robertson Risk Factor Algorithms (RRFA) are open and are used for laparoscopic surgery, these algorithms are reserved for uncommon [15].Special cases. Hyaluronan is a large (>106 Da) linear glycosaminoglycan composed of repeating units of glucuronic acid (GlcUA) and N-acetyl glucosamine (GlcNAc) disaccharides [16]. Hyaluronan has a central role in a number of processes that can ultimately lead to renal stone disease, including urine concentration, Uric acid, Salt form crystal, crystallization inhibition, crystal retention, Magnesium ammonium phosphate and amino acid.

Tanzila Rahman, Mohammad Shorif Uddin proposed reduction of speckle noise and segmentation from US image is discussed. It not only detect kidney region, but also enhance image quality [1]. The wan Mahani Hafizah proposed kidney US images were divided into four dissimilar categories: normal, bacterial infection, cystic disease, kidney stones, based on gray level co-occurrence matrix (GLCM). From these categories doctors identify that the kidney is normal or abnormal [2]. Gladis Pushpa had proposed Hierarchical Self Organizing Map (HSOM) for brain tumours using segmentation, wavelets packets, and the results were correct up to maximum 97% [3]. Norihiro Koizumi proposed high intensity focused ultrasound (HIFU) technique, used for destroying tumours and stones [4, 13]. Bommanna Raja proposed content descriptive multiple features for disorder identification and artificial neural network (ANN) for classification and the results says that the maximum efficiency is 90.47%, and accuracy 86.66% only [5]. The MLP- BP ANN is found as better performance in terms of accuracy having 92%, speed is 0.44 sec and sensitivity [8, 24]. The Non-invasive combination of renal using pulsed cavitation US therapy proposed shock wave lithotripsy (ESWL) has become a standard for the treatment of calculi located in the kidney and ureter [10]. Mohammad E. Abou EI-Ghar projected location of urinary stones with unenhanced computed tomography (CT) using half-radiation (low) dose compared with the standard dose and of the 50 patients, 35 patients had a single stone while the rest of them had multiple stones[11]. In order to solve the local minima and segmentation problem the thord Andersson, Gunnar Lathen proposed modified gradient search and level set segmentation [12]. For 3D detection of kidneys and their pathology in real time, the Emmanouil Skounakis proposed *templates based technique* with accuracy

of 97.2% and abnormalities in kidneys at an accuracy of 96.1% [13].

The paper proceeds as follows: In section II problem statement defined, section III describes proposed method, in section IV image segmentation to locate the kidney stone, in section V calculation of energy optimization for segmentation, in section VI wavelets based energy extraction, in section VII artificial neural networks classifiers used is described, in section VIII experiments results are discussion and in the last section we conclude the paper with future work.

II. PROBLEM STATEMENT

The kidney malfunctioning can be life threatening, thus detection of kidney stone in the earlier stages is crucial. In order to carry out surgical operation to remove kidney stone it is important to locate the kidney stone. The ultrasound images of kidney contain speckle noise and are of low contrast which makes the detection of kidney abnormalities a challenging task. As a result the doctors may have problem to identify the small kidney stones and their type properly. To address this issue a modified level set segmentation to identify location of the stone, Wavelets subbands to extract the energy levels of the stone and MLP-BP ANN algorithms for classification is proposed and analyzed [9].

III. METHODLOGY

Fig.1. shows the overall block diagram of proposed method. It consists of the following blocks Kidney Image Database, Image Pre-processing, Image Segmentation, Wavelet processing and ANN Classification.

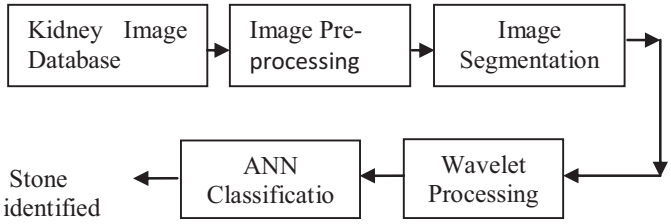

Fig.1. Block Diagram of proposed method

A. Kidney Image Database

The 500 US kidney images of both normal and abnormal kidney are collected from different hospitals of different patients and are stored in database. One of the image is taken from the database and subjected to stone detection.

B. Image Pre-Processing

The acquired ultrasound (US) image consists of speckle noise and is of low contrast. Due to this, the image quality is may not be good for analyzing. For surgical operations it is very important to identify the location of kidney stone. To overcome speckle noise and low contrast, pre-processing of US image needs to be done. Fig.2. shows pre-processing of US image, which consists of the following steps:

1. Image restoration
2. Smoothing and sharpening
3. Contrast enhancement

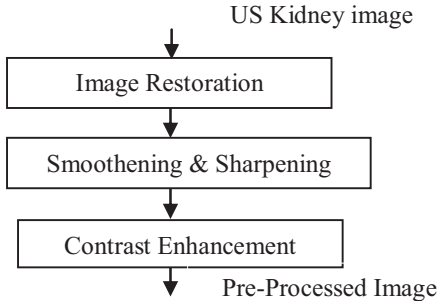

Fig.2. Pre-processing of kidney image

1. Image Restoration

The very purpose of image restoration is to reduce the degradations that are caused during acquisition of US scanning. In this system for proper orientation, level set function is used. By the use of plan curve motion, curve smoothers, shrinks are eventually disappeared [1].

2. Smoothing and Sharpening

To obtained optimal resolution in both spatial and frequency domains, Gabor filter is used which act as band pass filter for the local spatial frequency distribution [4]. The standard deviation of the Gaussian function can be varied to adjust degree of smoothening.

3. Contrast Enhancement

To improve contrast and to obtain uniform intensity histogram equalization is used. This approach can be used on whole image or part of an image. In this system, enhancing the contrast of images is done by transforming the values in an intensity image, such that the histogram of the output image approximately matches a specified histogram. The output signal is of same data type as the input signal.

IV. IMAGE SEGMENTATION

Fig.3. shows the level set segmentation method used to segment the location of kidney stone. Proposed work consists of two modified gradient descent methods. First is using a momentum term and second is based on resilient propagation (R_{prop}) term. The intention of the segmentation is to overcome difficulties involved in energy function. The energy function depends on properties of the image such as gradients, curvatures, intensities and regularization terms, e.g. smoothing constraints. These are simple, but effective modifications of the basic method are directly compatible with any type of level set implementation. The first proposed method is based on a modification which essentially adds a momentum to the

motion in solution space [15, 19]. This simulates the physical properties of momentum and often allows the search to disregard local optima and take larger steps in positive directions. In order to avoid the typical problems of gradient descent search, R_{prop} provides a modification which uses individual adaptive step sizes and the signs of the gradient components.

1. Momentum term

Spinning to gradient descent with Momentum will adopt the machine learning community and choose a search vector according to:

$$a_l = -\eta(1-w)\nabla f_l + w a_{l-1} \quad ------(1)$$

Where η is the *learning rate* and $\omega \in [0, 1]$ is the *momentum*. Note that $w = 0$ gives standard gradient descent $\boldsymbol{a}_l = -\eta\nabla f_l$, while $w = 1$ gives "infinite momentum" $\boldsymbol{a}_l = \boldsymbol{a}_{l-1}$.

2. R_{prop} term

The disadvantages of standard gradient descent (SGD) is overcome by incorporating adaptive step-sizes ∇_l called *update-values* in which each dimension will have one update value i.e. dim (∇_l) = dim $(\boldsymbol{x}_l)$. The gradient size is never used in R_{prop}. The update rule considers only the signs of the partial derivatives. Another advantage of R_{prop}, which is very important in practical use, is the stoutness of its parameters; R_{prop} will work out of the box in many applications using only the standard values of its parameters [18, 20].

We will now describe the R_{prop} algorithm briefly, but for implementation details of R_{prop} we refer to [23. 21]. For R_{prop}, we choose a search vector $\boldsymbol{s}_l$ according to:

$$s_l = -sign(\nabla f_l) * \nabla_l \quad ------(2)$$

Where ∇_l is a vector containing the current update-values and sign $(\cdot)$ the element wise sign function.

V. Energy Optimization for Segmentation

The segmentation problems can be approached by using the calculus of variations where energy functions is defined representing the objective of the difficulty. The extreme to the functional are found using the Euler-Lagrange equation [10, 22] which is used to derive equations of motion, and the corresponding energy gradients, for the contour [17]. Using these gradients, a gradient descent search in contour space is performed to find a solution to the segmentation problems. Consider, for instance, the derivation of the *weighted region* described by the following functional:

$$f(p) = \iint_{\Omega_p} g(x, y)\,dxdy \quad -----(3)$$

Where p is a 1D curve embedded in a 2D space, $\boldsymbol{\Omega}_p$ is the region inside of p, and $g(x, y)$ is a scalar function. This functional is used to maximize some quantity given by $g(x, y)$ inside p. If $g(x, y) = 1$ for instance, the area will be maximized. Calculating the first variation of Eq. 1 yields the evolution equation:

$$\frac{\partial p}{\partial t} = -g(x, y)\eta \quad ------(4)$$

Where η is the curve normal. Using $g(x, y) = 1$ which is constant flow in the negative normal direction. The contour is often implicitly represented by the zero level of a time dependent signed distance function, known as the level set function. The *level set method* was introduced by Osher and Sethian [6]. Formally, a contour p is described by $p = \{\boldsymbol{x}: \varphi(\boldsymbol{x}, t) = 0\}$. The contour p is evolved in time using a set of partial differential equations (PDEs). A motion equation for a parameterized curve $\frac{\partial p}{\partial t} = \gamma\eta$ is in general translated into the level set equation $\frac{\partial \varphi}{\partial t} = \gamma|\nabla\varphi|$ Eq. 2 gives the familiar level set equation:

$$\frac{\partial \varphi}{\partial t} = -g(x, y)|\nabla\varphi| \quad ------(5)$$

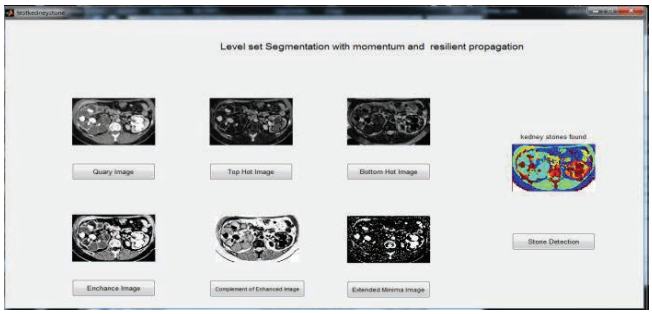

Fig.3. Level set segmentation of kidney stone detection

VI. Wavelet Processing

The segmented image which has got from previous block is applied to wavelet processing block. It consists of Daubechies filter (Db12), Symlets filter (sym12) and Biorthogonal filter (bio3.7, bio3.9 & bio4.3). *Daubechies filter (Db12)* in this the number 12 refers to the number of vanishing moments. Basically, the higher the number of vanishing moments, the smoother the wavelet (and longer the wavelet filter) and the length of the wavelet (and scaling) filter is two times that number [3]. *Symlets filter (sym12)* extract features of kidney image and analyse discontinuities and abrupt changes contained in signals, one of the 12^{th} - order Symlets wavelets is used. *Biorthogonal filter (bio3.7, bio3.9 & bio4.4)* filter's wavelet energy signatures were considered and averages of horizontal and vertical coefficients details were calculated. Each filter will give different energy levels or energy features. These energy features will show significant difference, if there is any stone is present in the particular region or location. The identification of type of stone is described in next section.

VII. ANN CLASSIFICATION

In ANN Classification two architectures are used namely, Multilayer Perceptron and back propagation which are described in detail in the following sections.

1. *Multilayer Perceptron (MLP)*

A multilayer perceptron is a feed forward artificial neural network algorithm that maps sets of energy values obtained from wavelets subbands energy extraction shown in the table1. These energy values are fed to input layer and multiplied with initial weights as in equation (6). The back propagation is modified version of linear perceptron in which it uses three or more hidden layers with nonlinear activation function. The back propagation is the most widely applied learning algorithm for multilayer perceptron in neural networks and it employs gradient descent to minimize the squared error between the network output value and desired output value as in equation (7). These error signals are used to calculate the weight updates which represent power of knowledge learnt in the network [7]. Multilayer Perceptron with Back Propagation (MLP-BP) are the main algorithms. Based on the literature survey, MLP-BP algorithm was found to be better than the others in terms of accuracy, speed and performance [14].

The phases involved in ANN are forward phase and backward phase as shown in fig4. In back propagation, weights are updated after each pattern and by taking one pattern m at a time as follows:

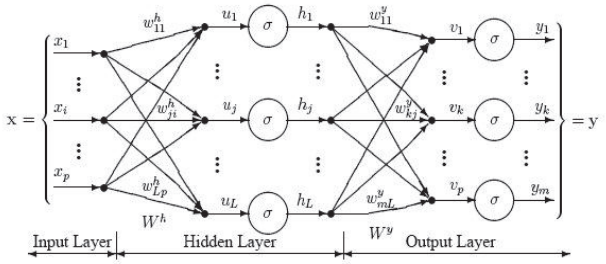

Fig.4. Multilayer Perceptron architecture

A. *Forward Phase*

Apply the pattern $X_j^{(l)}$ to the input layer and propagate the signal forward through the network until the final outputs X_j^L have been calculated for each i and L

$$X_j^{(l)} = \theta\left(s_j^{(l)}\right) = \theta\left(\sum_{i=0}^{D(L-1)} x_j^{(l)} w_j^{(l)} + w_j^{(l)}\right) \quad ------(6)$$

Where D (L-1) is the number of neurons in layer (L-1), $X_i^{(l-1)}$ output of the j[th] neuron in the (l-1) [th] layer, $W_{ij}(i)$ synaptic weight contained in the current neuron, $W_{ij}(i)$ current neuron's bias weight, $X_j^{(l)}$ output of the current neuron.

B. *Backward Phase*

In this phase, the weights and biases are updated according to the error gradient-descent vector. After an input vector is applied during the forward computation phase, a network output vector is obtained. A target vector t is provided to the network, to drive the network's output toward the expected targeted value [10, 14].

Starting with the output layer, and moving back towards the input layer, calculates the error terms and gradient as follows:

$$e_j^{(l)} = \begin{cases} \left(u - x_j^{(l)}\right) & for \quad l = L \\ \sum w_{ij}^{(l+1)} s_j^{(l+1)} & for \quad l = 1,2,3, \ldots\ldots L-1 \end{cases} \quad ------(7)$$

where e_j^l is the error term for j[th] neuron in the l[th] layer

$$s_j^{(l-1)} = e_j^{(l+1)} \theta(s_j^{(l)}) \quad for \quad l = 1,2,\ldots\ldots \quad ----(8)$$

where $\theta(s_j^{(l)})$ is the derivative if the activation function.

Calculate the changes for all the weights as follows:

$$\Delta w_{ij}^{(l)} = \eta\, s_j^{(l)} x_j^{(l-1)} \ldots\ldots\ldots l = 1,2,\ldots\ldots\ldots L \quad ------(9)$$

where η is the learning rate. Update all the weights as follows:

$$w_{ij}^{(l)}(L+1) = w_{ij}^{(l)}(L) + \Delta w_{ij}^{(l)}(L) \quad ------(10)$$

Where l=1, 2...L [(l)] and j=0, 1 ...L [(l-1)], W_{ij} [(l)] (L) is the current synaptic weight.

W_{ij} [(l)] (L+1) is the updated synaptic weights to be used in the next feed forward iteration. The Fig.4 show the complete cycle of period, in neural networks training the term period is used to describe a complete pass through all of the training patterns. The weight in the neural net may be updated after each pattern is presented to the net, or they may be updated just once at the end of the period.

C. *Naive Bayes classification*

Naive Bayes classifiers can handle an arbitrary number of independent variables whether continuous or categorical. Given a set of variables, X = $\{x_1,x_2...,x_d\}$, to construct the posterior probability for the event Cj among a set of possible outcomes C = $\{c_1,c_2...,c_d\}$ where X is the predictors of energy values of kidney and C is the set of categorical levels present in the dependent variable. Using Bayes' rule:

$$P(c_J \mid x_1, x_2, \ldots, d_d) \propto P(x_1, x_2, \ldots, d_d \mid c_j) P(c_j) \quad --(11)$$

Where p (C_j | x_1, x_2, ...,x_d) is the posterior probability of class membership , i.e., the probability that X belongs to C_j. Since Naive Bayes assumes that the conditional probabilities of the independent variables are statistically independent we can decompose the likelihood to a product of terms:

$$P(x \mid c_j) \propto \prod_{k=1}^{d} P(x_k \mid c_j) \quad ----------(12)$$

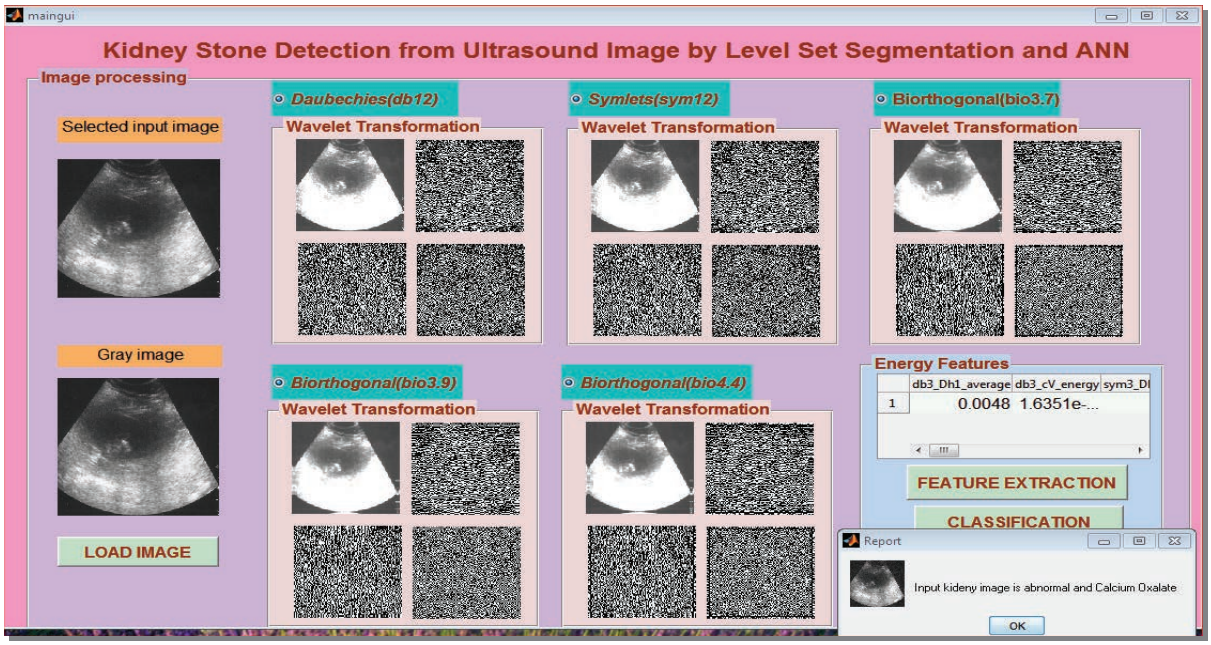

Fig.5. Wavelets subbands energy extraction

VIII. Implementation and Results

The implementation is done using Matlab 2012a. The Graphical User Interface (GUI) is created and as shown in the Fig.5. From the database of the US kidney images, one kidney image is loaded through the GUI. The loaded image pre-processed and is shown in the GUI. The image segmentation option given in the GUI is selected next to get segmented image. The segmented image is applied for Wavelet processing by selecting one of the wavelet filters shown in the GUI. After selecting the particular filter, that particular wavelet code will be invoked to get resultant image. Then the feature extraction option is selected to get list of energy levels extracted from the segmented image.

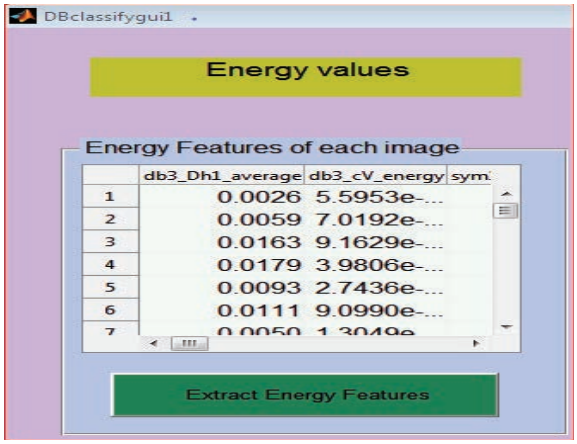

Fig.6. Wavelets subbands energy extracted values

In the GUI shown in the Fig.6 there is another table which lists energy levels of all the kidney images present in the database. This is done to test the accuracy of MLP-BP ANN system in identifying the kidney images as normal or abnormal and the stone type. Essentially in the database we have both normal and abnormal images which we already know how many of them are normal and abnormal. During the test it is found that our system can classify the kidney images as normal and abnormal almost with accuracy of 98.8%.

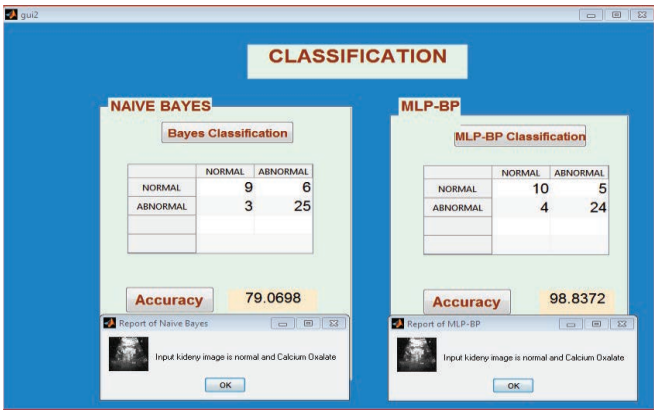

Fig.7. Naive bayes and MLP-BP Classifications for normal

The energy levels of kidney image are applied for classifications to classify the image which is found to be normal is shown in Fig.7 and Fig.8. shows the abnormality of another kidney image.

Db12 Dh1 average	Db12 cV energy	Sym12 Dh1 average	Sym12 cV energy	rbio3.7 Dh1 average	rbio3.7 cD energy	rbio3.7 cV energy	rbio3.7 Dh1 average	rbio3.9 cD energy	rbio3.9 cV energy	rbio3.9 cV average	rbio4.4 Dh1 average	rbio4.4 cH energy	rbio4.4 cV energy
0.0026	5.5953e-05	0.0026	5.5953e-05	0.0052	1.3895e-04	1.6450e-04	0.0043	1.0764e-04	1.0719e-04	0.0039	1.7720e-04	9.9153e-05	9.0838e-05
0.0059	7.0192e-05	0.0059	7.0192e-05	0.0127	2.2286e-04	1.8849e-04	0.0128	1.7324e-04	1.5039e-04	0.0129	3.9994e-04	1.6002e-04	1.3280e-04
0.0163	9.1629e-04	0.0163	9.1629e-04	0.0316	0.0010	0.0021	0.0306	7.6544e-04	0.0023	0.0303	0.0051	6.9376e-04	0.0022
0.0179	3.9806e-04	0.0179	3.9806e-04	0.0255	5.4659e-04	4.8874e-04	0.0263	3.9515e-04	5.3478e-04	0.0267	0.0051	3.5862e-04	5.7644e-04
0.0093	2.7436e-04	0.0093	2.7436e-04	0.0249	6.8200e-04	9.5594e-04	0.0214	5.2108e-04	8.9330e-04	0.0198	0.0031	4.9557e-04	9.0662e-04
0.0111	9.0990e-04	0.0111	9.0990e-04	0.0239	5.5269e-04	0.0033	0.0197	4.1572e-04	0.0023	0.0179	0.0031	3.8182e-04	0.0019
0.0050	1.3049e-04	0.0050	1.3049e-04	0.0094	5.6388e-04	3.4976e-04	0.0087	3.9534e-04	2.5024e-04	0.0085	7.2749e-04	3.4186e-04	2.1581e-04
0.0073	7.8642e-05	0.0073	7.8642e-05	0.0136	2.6317e-04	2.4022e-04	0.0132	1.8109e-04	1.5338e-04	0.0133	8.1203e-04	1.5963e-04	1.2771e-04
0.0105	2.3515e-04	0.0105	2.3515e-04	0.0137	7.1012e-04	4.0684e-04	0.0131	5.2176e-04	3.7809e-04	0.0133	0.0013	4.5959e-04	4.0670e-04
0.0145	1.3983e-04	0.0145	1.3983e-04	0.0154	6.6207e-04	3.3536e-04	0.0144	4.8498e-04	2.4507e-04	0.0184	0.0018	4.3049e-04	2.1859e-04
0.0173	2.1550e-04	0.0173	2.1550e-04	0.0278	6.2009e-04	4.9155e-04	0.0262	4.7615e-04	4.1534e-04	0.0260	0.0042	4.4141e-04	4.0481e-04
0.0128	3.7797e-04	0.0128	3.7797e-04	0.0256	5.8045e-04	5.3523e-04	0.0234	4.5160e-04	5.7497e-04	0.0238	0.0038	4.1888e-04	6.8299e-04
0.0074	0.0018	0.0074	0.0018	0.0132	8.6715e-04	0.0043	0.0133	6.7642e-04	0.0040	0.0140	8.5301e-04	6.2365e-04	0.0040
0.0043	2.0368e-04	0.0043	2.0368e-04	0.0072	6.4413e-04	4.8808e-04	0.0066	5.2519e-04	3.7235e-04	0.0065	4.2114e-04	4.8302e-04	3.3005e-04
0.0204	3.3482e-04	0.0204	3.3482e-04	0.0379	7.3661e-04	9.6556e-04	0.0353	5.1190e-04	8.2002e-04	0.0344	0.0043	4.3896e-04	7.5465e-04
0.0077	0.0012	0.0077	0.0012	0.0169	5.8343e-04	0.0030	0.0158	4.5069e-04	0.0028	0.0153	6.8829e-04	4.1780e-04	0.0027
0.0080	1.7951e-04	0.0080	1.7951e-04	0.0161	5.8455e-04	3.1453e-04	0.0155	4.8010e-04	2.9501e-04	0.0154	0.0017	4.4850e-04	3.1878e-04
0.0079	2.9445e-04	0.0079	2.9445e-04	0.0151	4.5209e-04	0.0010	0.0134	3.6543e-04	9.2231e-04	0.0126	0.0011	3.3598e-04	8.9855e-04
0.0171	5.9446e-04	0.0171	5.9446e-04	0.0325	0.0010	8.2026e-04	0.0214	8.0706e-04	8.5152e-04	0.0180	0.0016	7.2994e-04	9.7450e-04
0.0111	1.3944e-04	0.0111	1.3944e-04	0.0224	4.9967e-04	3.9034e-04	0.0211	3.9642e-04	3.4776e-04	0.0202	0.0021	3.7177e-04	3.4225e-04
0.0074	2.6753e-04	0.0074	2.6753e-04	0.0153	3.5545e-04	8.2306e-04	0.0141	2.8304e-04	7.1102e-04	0.0136	0.0011	2.7166e-04	8.4002e-04
0.0036	2.0845e-04	0.0036	2.0845e-04	0.0065	5.9565e-04	5.5595e-04	0.0061	4.5940e-04	4.5326e-04	0.0061	4.0954e-04	4.1321e-04	4.4339e-04
0.0048	1.6351e-04	0.0048	1.6351e-04	0.0083	6.4050e-04	4.1405e-04	0.0086	5.0618e-04	3.0850e-04	0.0085	5.2424e-04	4.5489e-04	2.7296e-04
0.0056	8.0388e-05	0.0056	8.0388e-05	0.0106	1.5185e-04	2.4317e-04	0.0115	9.1844e-05	1.8853e-04	0.0139	6.2159e-04	7.8351e-05	1.7249e-04
0.0128	2.9260e-04	0.0128	2.9260e-04	0.0255	2.4498e-05	0.0019	0.0272	1.0831e-05	0.0024	0.0258	7.3530e-04	7.3841e-06	0.0022
0.0087	6.3554e-04	0.0087	6.3554e-04	0.0157	0.0013	0.0021	0.0143	5.8765e-04	0.0014	0.0146	0.0018	3.7878e-04	0.0012
0.0099	8.3973e-04	0.0099	8.3973e-04	0.0123	3.7739e-04	7.3807e-04	0.0163	1.9745e-04	9.0590e-04	0.0189	7.7251e-04	1.4336e-04	0.0010
0.0094	0.0011	0.0094	0.0011	0.0219	0.0015	0.0028	0.0239	0.0010	0.0024	0.0247	0.0015	8.7336e-04	0.0024
0.0059	2.5405e-04	0.0059	2.5405e-04	0.0112	4.3833e-04	7.4134e-04	0.0105	2.6179e-04	6.1060e-04	0.0105	6.9152e-04	2.1206e-04	5.9138e-04
0.0063	7.7728e-04	0.0063	7.7728e-04	0.0124	6.3668e-04	0.0024	0.0112	4.0345e-04	0.0020	0.0109	0.0011	3.3200e-04	0.0019
0.0074	8.2789e-04	0.0074	8.2789e-04	0.0152	8.4256e-04	0.0020	0.0128	6.0219e-04	0.0019	0.0118	0.0011	5.2250e-04	0.0018
0.0167	4.1325e-04	0.0167	4.1325e-04	0.0156	5.3976e-04	4.7820e-04	0.0140	2.9495e-04	4.2729e-04	0.0136	0.0018	2.1938e-04	5.2332e-04
0.0069	5.5092e-04	0.0069	5.5092e-04	0.0122	0.0010	0.0018	0.0113	6.9704e-04	0.0016	0.0119	0.0012	5.8484e-04	0.0014
0.0148	9.2528e-04	0.0148	9.2528e-04	0.0298	8.8080e-04	0.0017	0.0214	5.8155e-04	0.0015	0.0163	0.0011	4.8485e-04	0.0016
0.0045	2.3998e-04	0.0045	2.3998e-04	0.0080	3.3799e-04	6.2947e-04	0.0069	2.5098e-04	5.5864e-04	0.0065	4.1366e-04	2.1907e-04	5.0073e-04
0.0169	0.0011	0.0169	0.0011	0.0336	5.8337e-04	0.0016	0.0241	3.8469e-04	0.0016	0.0182	8.5080e-04	3.4381e-04	0.0018
0.0056	8.0388e-05	0.0056	8.0388e-05	0.0106	1.5185e-04	2.4317e-04	0.0115	9.1844e-05	1.8853e-04	0.0139	6.2159e-04	7.8351e-05	1.7249e-04
0.0128	2.9260e-04	0.0128	2.9260e-04	0.0255	2.4498e-05	0.0019	0.0272	1.0831e-05	0.0024	0.0258	7.3530e-04	7.3841e-06	0.0022
0.0087	6.3554e-04	0.0087	6.3554e-04	0.0157	0.0013	0.0021	0.0143	5.8765e-04	0.0014	0.0146	0.0018	3.7878e-04	0.0012
0.0099	8.3973e-04	0.0099	8.3973e-04	0.0123	3.7739e-04	7.3807e-04	0.0163	1.9745e-04	9.0590e-04	0.0189	7.7251e-04	1.4336e-04	0.0010
0.0094	0.0011	0.0094	0.0011	0.0219	0.0015	0.0028	0.0239	0.0010	0.0024	0.0247	0.0015	8.7336e-04	0.0024
0.0059	2.5405e-04	0.0059	2.5405e-04	0.0112	4.3833e-04	7.4134e-04	0.0105	2.6179e-04	6.1060e-04	0.0105	6.9152e-04	2.1206e-04	5.9138e-04
0.0063	7.7728e-04	0.0063	7.7728e-04	0.0124	6.3668e-04	0.0024	0.0112	4.0345e-04	0.0020	0.0109	0.0011	3.3200e-04	0.0019

Table 1Enlarged table of the table in the GUI of Fig.6

Table1 shows the lists of energy levels extracted from segmented image. This table is the enlarged version of the table shown in the GUI. The rows of the table are individual energy level of each kidney images of database. The Columns of the table shows energy level extracted from the images of

database with respect to each wavelet filter. First two columns are corresponding to Daubechies filter, the third and fourth columns are corresponding to symlets12. The fifth, sixth and seventh columns are corresponding to Biorthogonal filter (Bio3.7). The eighth, ninth and tenth columns are corresponding to Biorthogonal filter (Bio3.9). The eleventh twelfth and thirty columns are corresponding to Biorthogonal filter (Bio4.4).

The Bayes and MLP-BP classifications have given type of stone with maximum accuracy of 79.1% and 98.8% respectively.

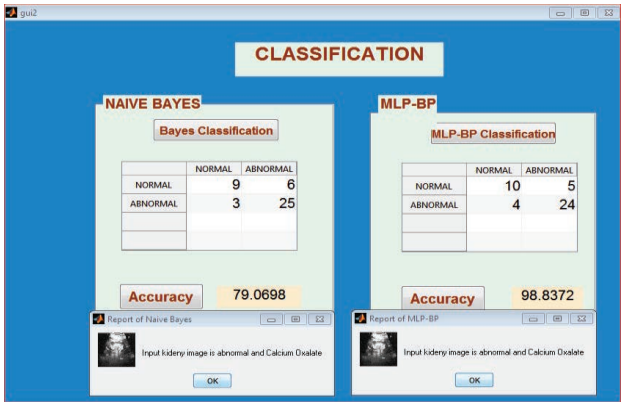

Fig.8. Naive bayes and MLP-BP for abnormal and identifying type of stone

IX. Conclusion and Future Work

The level set segmentation with momentum and resilient propagation are very effective in identifying the region of stones in the US kidney image. The energy levels extracted from the wavelet subbands i.e. Daubechies (Db12), Symlets (sym12) and Biorthogonal filterers (bio3.7, bio3.9 & bio4.4), gives the clear indication of difference in the energy levels compared to that of normal kidney image if there is stone. The ANN trained with normal kidney image and classified image input into normal or abnormal by considering extracted energy levels from wavelets filters. The system is tested with different kidney images from database and has classified successfully with the accuracy of 98.8%. So this system can be readily used in the hospitals for detecting abnormality of individuals US kidney image. Thus in this work it is proved that the combination level set segmentation, wavelet filters, multilayer Perceptron with back propagation the better approach for the detection of stones in the kidney In the future work the system will be designed and implement on FPGA using hardware description language (HDL) to display kidney image and stone with colour for easily identification and visibility of stone on monitor.

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