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RADIAL BASIS FUNCTIONS BASED KIDNEY ABNORMALITY DETECTION AND CLASSIFICATION IN ULTRASOUND IMAGE

[1]Anisha.A.S, [2]Dr.R.Kavitha Jaba Malar

[1]M.Phil Research Scholar, Department of Computer Science, Nanjil catholic college of arts and science, Kaliyakkavilai, India
[2]Assistant Professor, Department of Computer Science, Nanjil catholic college of arts and science, Kaliyakkavilai, India

Abstract: *Image processing is the advancement in the medical field. This research aims at classification of abdominal ultrasound images of kidney as normal and abnormal kidney images. The wiener filter is used to reduce the noise present in the image. The gray-level co-occurrence matrix (GLCM) is used for examining the texture. In this research the Back-propagation Neural Network (BPNN) and Radial Basis Function (RBF) is used to classify the images as normal or abnormal kidney images. We got a better accuracy of 99% for BPNN and 96% for RBF. The obtained result is then compared and justified that the BPNN method is more efficient in the classification of US kidney Image.*

Key words – *Abnormal, Feature Extraction, Pixel, Speckle noise, Texture.*

I. INTRODUCTION

With the growth of technology, a lot of computer aided system has been developed for detecting the presence of disease with a significant emphasis on systems accuracy. Today most of the population is fastly suffering from various kidney diseases. Lot of the people do not notice symptoms in its initial stage but it begins to spoil the kidney slowly. Hence, early detection and prevention is become need of such patients. Recently many diagnosis techniques are available in the medical field. Every technique has importance according to severity of disease at correct time. But Ultrasound imaging technique is extensively used as an initial evaluation or as primary diagnosis aid. In Ultrasound imaging, image is obtained by passing high frequency sound waves through the human body. The echoes of reflected sound wave are recorded and displayed as a real time visual image. Ultrasound imaging is radiation free and portable. Today great achievements have been made in automated systems for detecting kidney abnormalities which allow a larger rate and quality of information to be extracted during imaging the patients. The ultrasound (US) imaging uses the quicker and more absolute nature in medical diagnosis. It has various virtues like non-invasive, non-radioactive and inexpensive. US has wide spread applications as a primary diagnostic aid the quality of the US image depends on combination of many factors originating from the imaging system and the knowledge level or experience of the operator. The image may contain speckle noise due to loss of proper contact or air gap between transducer and body part. The speckle noise can also be formed during beam forming process or signal processing. The speckle may cause the image to be blurred. Hence despeckling is performed prior to the texture feature extraction.

II RELATED WORK

In [1], authors have proposed an automatic region of interest (ROI) generation for kidney ultrasound images. Firstly, the speckle noise reduction was carried out using median filter, Wiener filter and Gaussian low-pass filter. Then texture analysis was performed by calculating the local entropy of the image, continued with the threshold selection, morphological operations, object windowing, determination of seed point and lastly the ROI generation is carried out after removing unwanted background from the US images. In [2], authors have proposed a method based on the scale space representation of the evaluation of multi-scale differential principal curvature features which, can be used to determine and measure the extent of isolation between the features of different kidney categories. In [3], authors have used Laws' micro-texture energies and maximum a posterior (MAP) estimation to construct a probabilistic deformable model for kidney segmentation. Using texture image features and MAP estimation, each image pixel is classified as inside or outside the boundary. Texture and shape based method is used for kidney segmentation in ultrasound (US) images. In [4], authors have discussed a higher order interpolated contour obtained with up-sampling of homogenously distributed coordinates for segmentation of kidney region in different classes of ultrasound images.

III. ARCHITECTURE

The main aim of this research is to classify the kidney as normal/Abnormal from the ultrasonic kidney images using RBF. Ultrasound medical images are produced in large number because of their availability in all hospitals. The image sets consists of normal and abnormal kidney images. The images were obtained from a Scan centre at Marthandam, India. The data file consist of 25 US kidney images. In which 15 are normal kidney image and 10 are abnormal kidney image with multiple kinds of diseases.

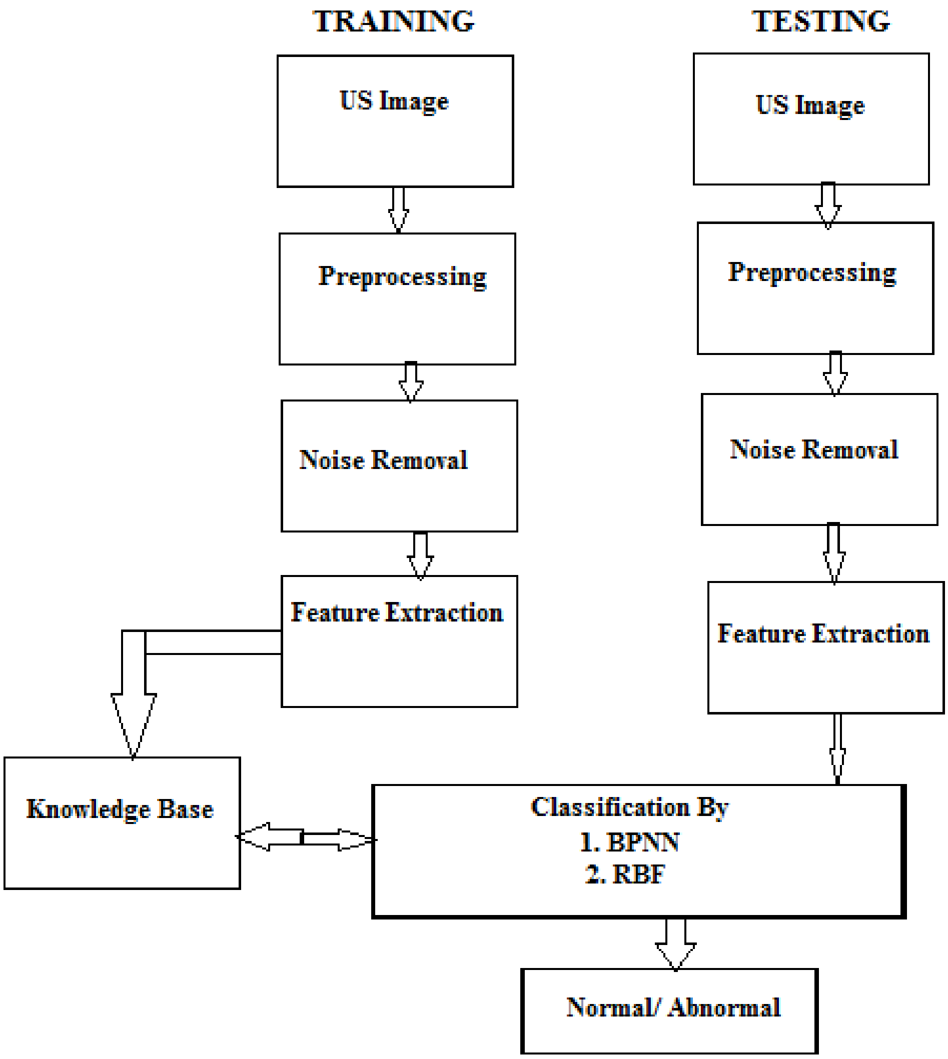

Fig.1. Proposed Methodology

Initially, we have to remove the speckle noise from the image. In the research, the wiener filter is used to reduce the noise present in the image. Wiener filter inverts the blurring and removes the additive noise simultaneously by performing an optimal trade off between inverse filtering and noise smoothing.

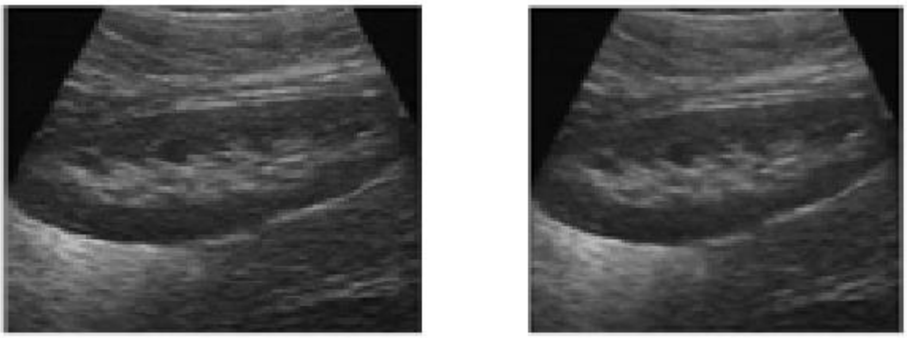

Image Before Filtering

Image After Filtering

Fig.2. Filtered Image

A texture is a set of metrics, calculated in image. It gives us information about the spatial arrangement of color or intensities in an image. The gray-level co-occurrence matrix (GLCM) is used in the research for examining the texture. In GLCM, there is only one instance in the image. Two horizontally adjacent pixels have the values 1 and 1.

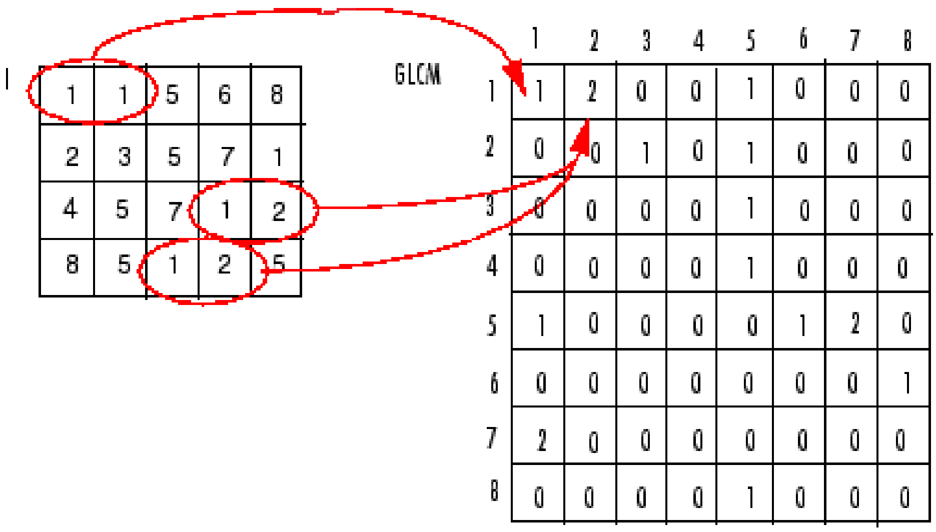

Fig.3. Gray-Level Co-occurrence Matrix

The resultant square matrix has the size of the largest pixel value in the image. Here the features such as contrast, correlation, energy and homogeneity are calculated. Here the classification of the US kidney image is done by two methods namely BPNN and RBF method. Back Propagation networks are fully connected, layered, feed forward networks, in which activations flow from the input layer through the hidden layer(s) and then to the output layer. Back propagation uses supervised learning in which the network is trained using data for which inputs as well as desired outputs are known. In order to train a neural network to perform some task, the weight of each unit must be adjusted, in such a way that the error between the desired output and the actual output is reduced. The learning process of a BP network structure consists of two parts positive dissemination and propagation. In the BP network the error correction with weight and threshold of each layer.

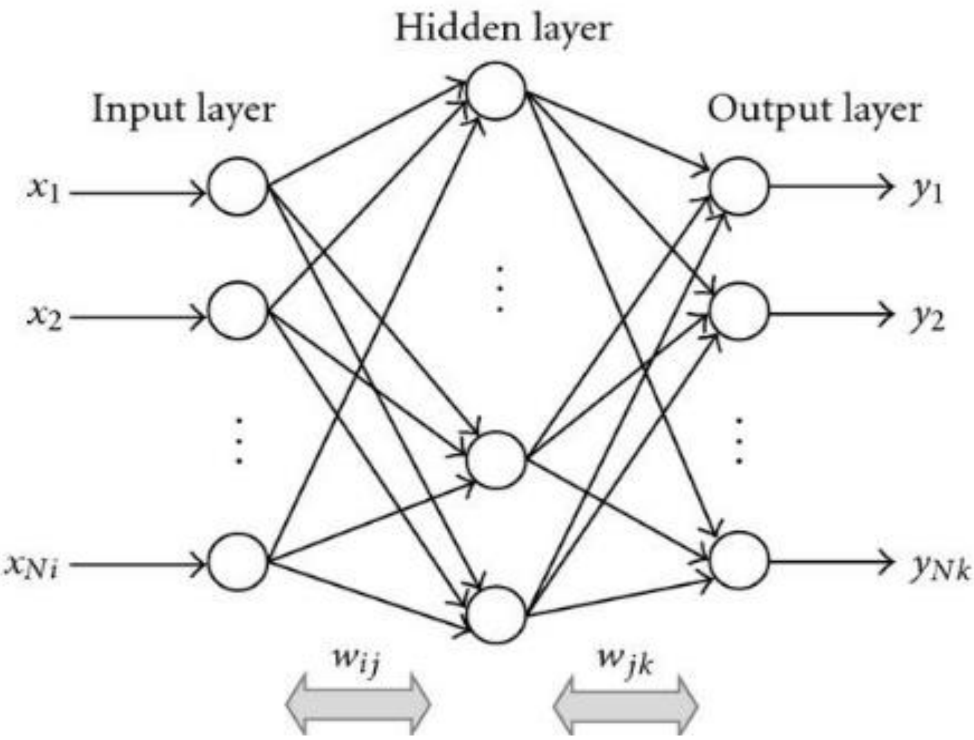

Fig.4. BPNN Architecture

The RBF Mapping can be cast into a form that resembles a neural network. A RBFN classify by calculating the input's similarity from the training set. Each neuron saves a prototype, which the training set. If one needs to classify a new input, each neuron computes the Euclidean distance between the input and its prototype.

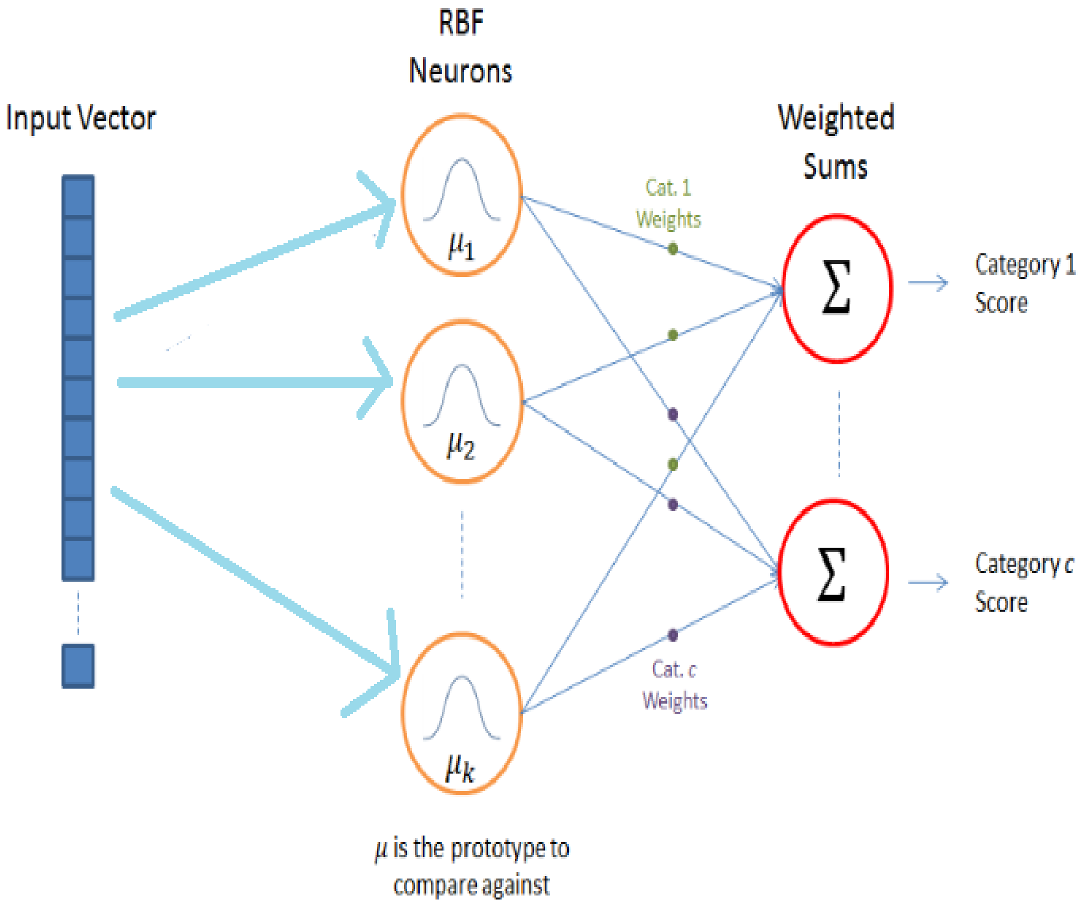

Fig.5. RBF Architecture

The hidden to output layer part works with the sum of the weighted hidden unit activations giving the output unit activations. The hidden unit activations are given by the basic functions $\varphi_j(x,\mu_j,\sigma_j)$, which depend on the "weights" $\{\mu_{ij},\sigma_j\}$ and input activations $\{x_i\}$ in a non-standard manner. It gives the give the error function

$$E = \sum_p \sum_k (t_k^p - y_k(\mathbf{x}^p))^2 = \sum_p \sum_k (t_k^p - \sum_{j=0}^{M} w_{kj}\phi_j(\mathbf{x}^p, \boldsymbol{\mu}_j, \sigma_j))^2$$

One could iteratively update the weights/basis function parameters using

$$\Delta w_{jk} = -\eta_w \frac{\partial E}{\partial w_{jk}} \qquad \Delta \mu_{ij} = -\eta_\mu \frac{\partial E}{\partial \mu_{ij}} \qquad \Delta \sigma_j = -\eta_\sigma \frac{\partial E}{\partial \sigma_j}$$

IV. EXPERIMENTAL RESULTS

We have tested our work with the ultra sound kidney images obtained from a scan centre at Nagercoil; India. We used various types of US kidney images such as normal, cyst, renal diseases for experimentation. The research work is implemented on Intel core i3 processor using Dotnet2012. The work is done using two algorithms BPNN and RBF. We got a better accuracy of 99% for BPNN and 96% for RBF.

Table 1. Comparison of Accuracy

Method	**Accuracy**
BPNN	99%
RBF	96%

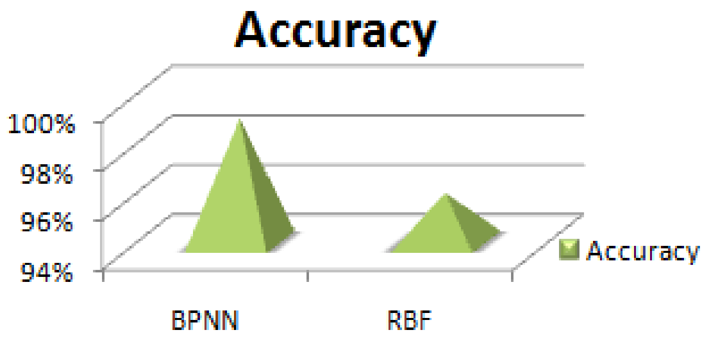

Fig.6: Comparison of Accuracy

V. CONCLUSION

An efficient ultrasound kidney image classification system using ANN classifiers is presented. Texture features are extracted and put in a training database. An efficient method gray-level co-occurrence matrix (GLCM) is applied for analyzing the texture.. The back-propagation algorithm and RBF algorithms are used to classify the kidney image into normal and abnormal kidney image. We achieved a better accuracy of 99% for BPNN and 96% for RBF. The comparison of BPNN and RBF in kidney image classification shows that the BPNN method is more suitable for US kidney image classification.

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