Improving Cervical Cancer Classification On MR images Using Texture Analysis And Probabilistic Neural Network

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Abstract— **The main theme of the project is to find-out the treatment output of cervical cancer patients could be obtained from the parameters of the pre-chemo radiotherapy Magnetic resonance images. It is automatic support system for stage classification using learning machine and to detect tumor through spatial fuzzy clustering methods This paper presents a segmentation method, spatial fuzzy clustering algorithm, for segmenting Magnetic Resonance images to detect the Cancer in its early stages anatomical structures. The neural network will be used to classify the stage of Tumor that is normal or abnormal. DTCWT texture features, fuzzy clustering segmentation is used as a explanatory variables for PNN classification, with treatment outcome as response The segmentation results will be used as a base for a Computer Aided Diagnosis (CAD) system for early detection of Tumor which will improves the chances of survival for the patient. Probabilistic Neural Network with radial basis function will be employed to implement an automated Tumor classification. Decision making was performed in two stages: feature extraction using GLCM and the classification using PNN-RBF network. The performance of this classifier was evaluated in terms of training performance and classification accuracies. The simulated results will be shown that classifier and segmentation algorithm provides better accuracy than previous method. while using PNN we get output with 90 percent accuracy than the previous method.**

*Index Terms— **MRI imaging, cervix, pattern recognition and classification, machine learning.***

I. Introduction

MR imaging[1] is very useful mechanism for initially monitoring and pre-planning for the cancer treatment. In DCE-MRI a drug agent is intravenously[2] injected in to the body, and its tissues internal operation is imaging as a function of space and time. the common malignancy observed in women is cervical cancer which is also called as gynacological malignancy, a frequent cause of death. the tumor size, histological grade, stage and nodal status altogether determines the patients survival time. the detection of exact stage of tumor is also an important strategy to make the decision regarding the treatment planning.The difference in the tumor sizes which vary from one patient to other patient is also responsible for planning strategies. for example a

patient may have a tumor in single slice while other patient may have its presence in all other nine slices. by combining the slices of tumor into an image of single slice. the tumor is accounted to be present in entire form than only as a specific size. texture is usually treated as a pattern with randomness and regularity. the radiologists use the technique of machine learning[3] in data intrepretation.The complex wavelet transform (CWT) is a complex-valued extension to the standard discrete wavelet transform (DWT). the multi resolution and sparse representation which is a useful characterization in the image structure is a 2D wavelet transform. DCTWT implementation is a straightforward process. decomposition of an input image is done as filter banks consisting of two sets namely horizontal and vertical. the horizontal filtering is done by (H0a,H1a) and (H0b,H1b) separately as a normal and conventional 2D DWT performs,. Probabilistic Neural Network gives fast and accurate classification and is a promising tool for classification of the tumors. The network classifies input vector into a specific class because that class has the maximum probability to be correct. In this paper, the PNN has three layers: the Input Layer, Radial Basis Layer and the Competitive layer the PNN networks are relatively insensitive to outliers the network generates accurate predicted target probability scores.After the classification of normal or abnormal image.The fuzzy clustering technique is used to locate the tumour area detection based on clusters and centroids and finally morphological operations has to perform and smoothen the tumour contour and background distortions.

II. EXISTING METHOD*:*

SVM:

Support Vector Machine (SVM) is one of the a classifier method that performs classification tasks by constructing hyper planes in a multidimensional space that separates cases of different class labels. SVM in which hyper-plane of separation takes place between the two classes .For regression problem SVMs can be applied by introducing alternative loss function.by including distance measure the loss function should be modified. The regression is two types linear and non-linear models.The Linear regression models

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having Huber and quadratic loss, e-intensive loss functions similar to classification problems .and non-linear regression it required adequate model data.SVM in which separating the hyper plane with maximum margin should be maintain. performance of this model was evaluated by finding the Accuracy, sensitivity, specificity.

III. PROPOSED METHOD

A. MR Images

Dynamic contrast enhanced (DCE) MRI, that provides insight into the vascular properties of the tissues linked to tumour features, increments chances for treatment outcome prediction. Cervical cancer is a common gynecological malignancy and a frequent cause of death. Patient outcome depends on tumor stage, size, nodal status, and histological grade. Correct tumor staging is important to decide the treatment strategy In DCE-MRI a paramagnetic contrast agent is intravenously administered, and its tissue distribution is imaged as a function of space and time.MR images can be useful tool for prediction of treatment response and for individualized treatment planning.

Fig. 1: 3D-to-2D converted tumour slices

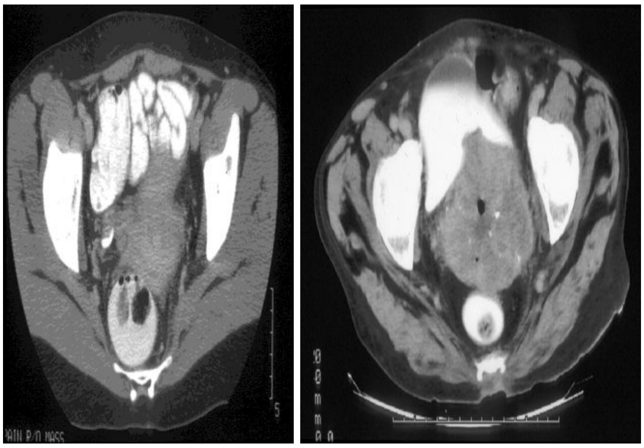

Fig. 2: Cervical Cancer MR Images

B. Dual Tree Complex Wavelet Transform

The complex wavelet transform (CWT)[4] is a complex valued extension to the standard discrete wavelet transform (DWT). It is a two-dimensional wavelet transform which provides multi resolution, sparse representation, and useful characterization of the structure of an image. Further, it purveys a high degree of shift-invariance in its magnitude. The complex transform of the signal can be calculating from dual tree complex wavelet transform using two DWT separate decompositions tree a and tree b. In this decomposition filters used one are specially designed different those from the other.DWT possible to produce real and the imaginary co-efficients.

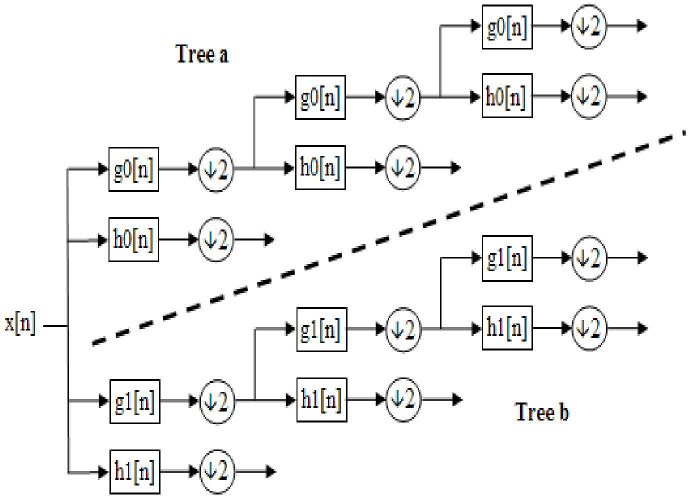

Fig. 3: DTCWT Blocks Representation

The filters design is mainly significant for the transform to occurs correctly and essential characteristics are:

- The two trees a and b in the low pass filter has a half sample period difference.
- Reconstruction filters are overturn of analysis.
- Filters all are from same orthonormal set
- Frequency responses of the tree a and tree b are same

The advantage in the dual-tree complex wavelet transform which is used to implement 2D wavelet transforms. There are two types of the 2-D dual-tree wavelet transforms one is real 2-D dual-tree DWT and another one is complex 2-D dual tree DWT. here the real one is 2 times expensive and complex one is 4-times expansive. Straight forward implementation should be possible with DDWT. Here the input image is seperated into two set of the filter banks they are H0a,H1a and H0b,H1b separately. the image can be filtered horizontally and then vertically as conventional as 2D DWT does.

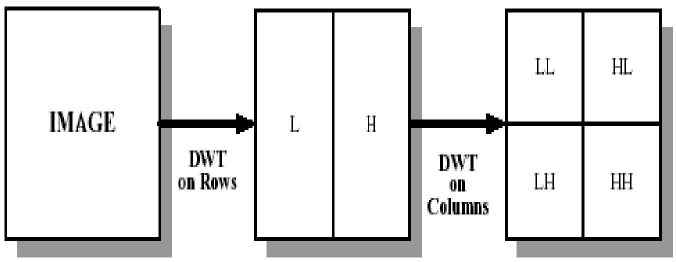

Fig. 4: Block diagram of DWT

The image from which sub bands can be obtained as LLa, LHa, HLa, HHa, LLb, LHb, HLb, HHb. By simple linear operations from which highpass subband of one filter bank combines with corresponding other filter banks sub band. The linear operations are averaging or differencing. Each DDWT functional[5] basis includes at a following directions

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are ±75º, ±15º, and ±45º. However, 2DDWT basis function of the HH sub band mixes with directions of ±45º together. The DTCWT from which image can be sub divided into four sub parts and analyze the image with clarity.

C. GLCM

Gray level co-occurance matrix gives the relation between two pixels they are reference and neighbour pixels at a time. The reference and neighbour pixels are at side by side. The reference pixel is present at the left of the neighbouring pixel this relation can be expressed as (1,0) here the pixel '1' direction should be in x-axis and pixel '0' direction should be in y-axis. Here the pixel of cells are filled repeatedly no. of times the same combination occurs. GLCM in which the number of columns and rows to the original image gray levels.it is a square matrix .A Co-occurrence matrix (CCM) by calculating how often a pixel with the intensity (gray-level) value '1' occurs in a specific spatial relationship to a pixel with the value '0'. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right(horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (i,j) in the resultant CCM is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image. The number of gray levels in the image determines the size[5] of the CCM.

Energy: Energy measures sameness in the image it is calculated from normalized co-occurance matrix and disorderness in the image texture[6] can also be detected with help of this.its ranging from zero to unity for uniform images.

$$E = \sum_{i,j} p(i,j)^2$$

Homogeneity: H is a measure of the nearness of the elements in the GLCM to the diagonal. It ranges from zero to one. Homogeneity is unity for a diagonal GLCM, that is, if all pixels in the original image have the same value as their neighbor.

$$H = \sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$

Contrast: It measures the contrast in gray level from reference pixel to its neighboring pixel. contrast range is from zero for a constant image to (G-1)2, where G is number of gray levels.

$$K = \sum_{i,j} (i-j)^2 p(i,j)$$

Correlation Coefficient: R measures the relationship between intensities in neighboring pixels. μi is the row average and μj is the column average of the GLCM. σi and σj are the standard deviations of row i and column j in the GLCM

$$R = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)\,p(i,j)}{\sigma_i \sigma_j}$$

D. Probabilistic Neural Network

A probabilistic neural network (PNN) is a feed forward network, which is derived from the Bayesian network and a statistical algorithm called Kernel Fisher discriminant analysis. Performance of the PNN classifier was evaluated in terms of training performance and classification accuracies.Probabilistic Neural Network gives fast and accurate classification and is a promising tool for classification of the tumour. Since the training and running procedure can be implemented by matrix manipulation, the speed of PNN is very fast. The network classifies[7] input vector into a specific class because that class has the maximum probability to be correct. In this paper, the PNN has three layers: the Input Layer, Radial Basis Layer and the Competitive layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly.Competitive Layer finds the shortest distance among them, and thus finds the training pattern closest to the input pattern based on their distance.Tthe problem of classifying can be treated using a three layer PNN structure. An input to be compared and a training set for comparison is present. a distance calculation between given input and existing training set is performed in first layer to evaluate the closeness. The probability vector set is produces for all input classes a 1 is produced for targetted class and 0 is produced for non targetted class using the above information and a complete transfer function this helps to find the outcome of treatment the performance measure of the PNN model can be examined in terms of Accuracy, Sensitivity and Specificity.

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FN+FP}$$

$$\text{Sensitivity}=\frac{TP}{TP+FN}$$

$$\text{Specificity}=\frac{TN}{TN+FN}$$

where *TP* is the number of true positives, *TN* is the number of true negatives, *FP* is the number of false positives, and *FN* is the number of false negatives.

IV. RESULTS

The result explains that spatial relations with in the tumour quantified by texture features related to tumour heterogeneity were more useful for treatment outcome prediction than previous model While using probabilistic neural network model the classification should be performed on MRI cervical cancer images we can obtain the result normal or abnormal with accuracy 92.8%.while using PNN model we can identify the tumour location and stage and outcome of cervical cancer with better accuracy than compared to the SVM model.so pnn model can be very useful and more accurate.

Figures and Tables

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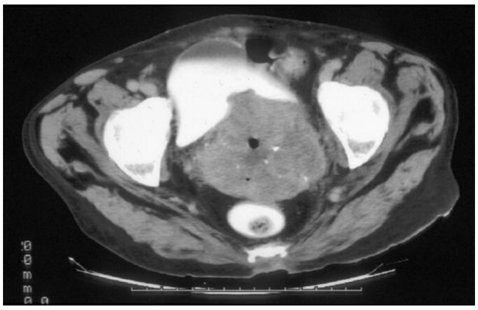


Fig a:Input MR Image Of Cervical Cancer

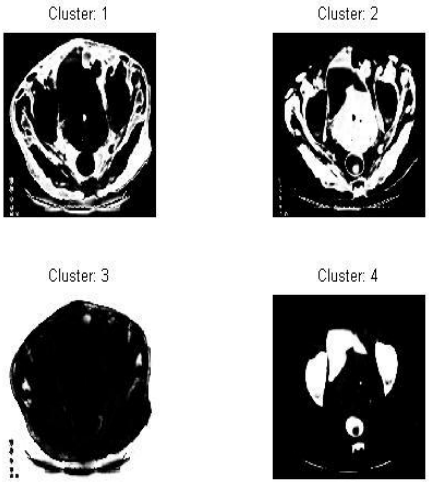


Fig b:Segmented Fuzzy Clustering Images

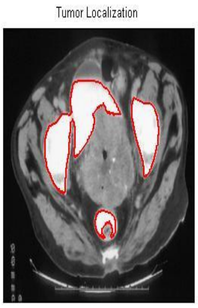


Fig c:Segmented Area Fig d:Tumor Located Area

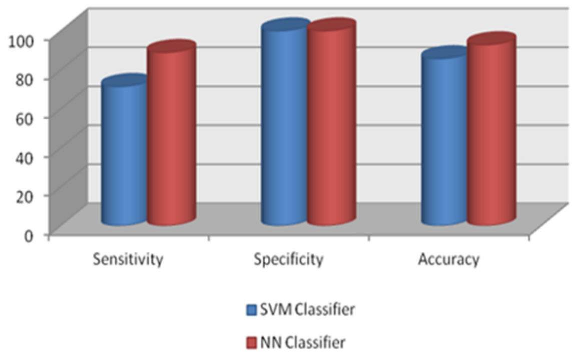
Table 1:
Texture Features Of Normal And Abnormal images

Features	Abnormal	Normal
K	22.1955	17.4055
R	-0.2471	-0.1328
E	0.1164	0.1054
H	0.4182	0.4609
K	15.0177	14.5841
R	-0.1859	0.2460
E	0.0950	0.1553
H	0.4673	0.5879

K	21.7860	14.5784
R	-0.2784	0.2507
E	0.1107	0.1569
H	0.4108	0.5902

Table 2: Comparisons between SVM and PNN Classifier

	SVM Classifier	PNN Classifier
Sensitivity	71.4286	88.8889
Specificity	100	100
Accuracy	85.7143	92.8571



V. CONCLUSION

This paper proposes a method for classification of tumor through Cervical cancer image. The main objective of this step is to differentiate the different abnormal cervical cancer images based on the optimal feature set. This classification is performed on Magnetic Resonance images. But the classification[8] accuracy results are different for different datasets which is one of the drawbacks of this approach. Experiments are conducted on various real-world datasets and the results concluded that the proposed algorithm yield good results when compared with the other classifiers. The results revealed that the proposed method approach is accurate, fast and robust. In this paper, we proposed two approaches for cancer detection, i.e identification and classification. The first approach is based on an integrated set of image processing algorithms, while the other is based on a modified and improved probabilistic neural network structure. However, simulation results using this algorithm showed its ability and accurately detect and identify the contour of the tumor, its computational time and accuracy were much less than its corresponding algorithms that use the parallel distributed processing nature of neural networks

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to reduce computing time and enhance the classification accuracy. This leaded us to propose a modified and improved probabilistic artificial neural networks structure. The modification is based on automatic utilization of specified regions of interest (ROIs) within the tumor area in the MRI images. Form each ROI, set of extracted features include tumor shape and intensity characteristics are extracted and normalized. In future using this PNN classifier we have also implement it on brain tumor and bone cancer also.

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