ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 7, Issue 3, March 2019

Breast Cancer Detection and Classification Using PNN

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ABSTRACT: Breast Cancer is a serious threat and one of the largest causes of death of women throughout the world. Analyzing histopathological images is a non-trivial task, and decisions from investigation of these kinds of images always require specialized knowledge. Deep Neural Network (DNN) has been recently introduced for biomedical image analysis. This project presents a variation of fuzzy c-means (FCM) algorithm that provides image clustering. The proposed algorithm incorporates the local spatial information and gray level information in a novel fuzzy way. The new algorithm is called fuzzy local information C-Means (FLICM). FLICM can overcome the disadvantages of the known fuzzy c-means (FCM) algorithms and at the same time enhances the clustering performance. Experiments performed on synthetic and real-world images show that FLICM algorithm is effective and efficient, providing robustness to noisy images classification using Multi SVM.

KEYWORDS: DNN, FCM, FLICM, Multi SVM

I. INTRODUCTION

Cancer is the utmost precarious and foremost source of death in the entire world. It can affect different organs of human very badly and very fast. It is possible and very important to diagnose at initial stages otherwise it is very to handle it. Breast cancer is one of the conspicuous causes for deaths of women, and according to a survey and report published in 2016 statistics shows, that 61,000 new circumstances of breast cancer are prophesied. It has been well established and well reported in the literature that if breast cancer is perceived at early stages by mammographic screening process then there are many chances to survive for these types of cancerous patients and even survival rate can be increased more than 90%. Mammography is a proven method for the detection of breast cancer at any early stage. Approximately 10-30% of patients with breast cancer are misdiagnosed by mammography (have the cancer missed or not detected on their mammograms). The classification of microcalcifications for the diagnosis of breast cancer has been important and yet difficult task in mammography. Microcalcifications occur in malignant and benign conditions. This paper proposes optimized detection and classification of breast cancer using PNN.

II. NEURAL NETWORK

A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. Neural networks can adapt to changing input so the network generates the best possible result without needing to redesign the output criteria.

2.1. DEEP NEURAL NETWORK

A deep neural network is an artificial neural network (ANN) with multiple layers between the input and output layers. The DNN finds the correct mathematical manipulation to turn the input into the output, whether it be a linear relationship or a non-linear relationship. Complex DNN have many layers such as input layer, output layer and almost one hidden layer in between, hence the name “DEEP” networks.

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2.2. PROBABILISTIC NEURAL NETWORK

A probabilistic neural network (PNN) is a feed forward neural network, which is widely used in classification and pattern recognition problems. In the PNN algorithm, the parent probability distribution function (PDF) of each class is approximated by a Parzen window and a non-parametric function. Then, using PDF of each class, the class probability of a new input data is estimated and Bayes's rule is then employed to allocate the class with highest posterior probability to new input data. By this method, the probability of mis-classification is minimized. This type of ANN was derived from the Bayesian network and a statistical algorithm called Kernel Fisher discriminant analysis. In a PNN, the operations are organized into multi-layered feed forward network with four layers: 1.Input layer 2. Pattern Layer 3. Summation layer 4. Output layer.

III. GAUSSIAN MIXTURE MODEL

A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian component densities. It is the fastest models of the mixture models. GMMs are commonly used as a parametric model of the probability distribution of continuous measurements or features in a biometric system, such as vocal-tract related spectral features in a speaker recognition system. GMM parameters are estimated from training data using the iterative Expectation-Maximization (EM) algorithm or Maximum A Posteriori (MAP) estimation from a well-trained prior model.

IV. FUZZY C MEAN CLUSTERING ALGORITHM

Fuzzy Clustering plays an important role in solving problems in the areas of pattern recognition and fuzzy model identification. In fuzzy clustering, data points can potentially belong to multiple clusters. A variety of graph clustering methods have been proposed and most of them are based upon distance criteria. One widely used algorithm is the Fuzzy C-Mean Clustering (FCM) algorithm. It uses reciprocal distance to compute graph weights. The idea of FCM (FCM) is using the weights that minimize the total weighted mean-square error.

V. FUZZY LOCAL INFORMATION C MEAN CLUSTERING

To overcome the drawbacks of FCM such as for noisy images it does not take into account spatial information, which makes it sensitive to noise & other image artifacts, fuzzy local information C-means clustering algorithm (FLICM) is used for image segmentation. FLICM incorporates local spatial information and grey level information in a novel fuzzy way. FLICM is completely free of any parameter determination, while balance between the noise and image details is automatically achieved by the fuzzy local constraints, enhancing concurrently the clustering performance. Its characteristics include it provide noise immunity, it preserves image details and it is free of any parameter selection.

VI. ADAPTIVE MEDIAN FILTER

Adaptive median filtering has been applied widely as an advanced method compared with standard median filtering. The Adaptive Median Filter performs spatial processing to determine which pixels in an image have been affected by impulse noise. The Adaptive Median Filter classifies pixels as noise by comparing each pixel in the image to its surrounding neighbor pixels. The size of the neighborhood is adjustable, as well as the threshold for the comparison. A pixel that is different from a majority of its neighbors, as well as being not structurally aligned with those pixels to which it is similar, is labeled as impulse noise. These noise pixels are then replaced by the median pixel value of the pixels in the neighborhood that have passed the noise labeling test.

VII. SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data

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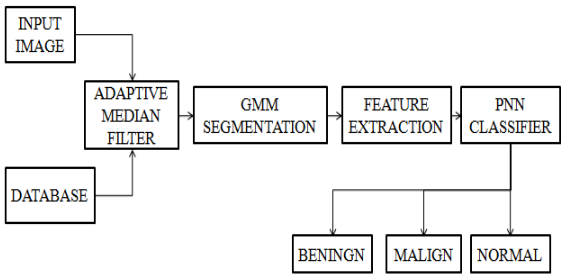
item as a point in n-dimensional space (where n is number of features we have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well.

VIII. PROPOSED MODEL

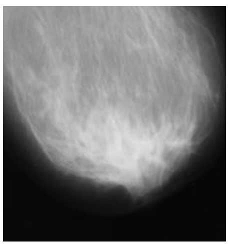
The block diagram of the proposed system is given below:



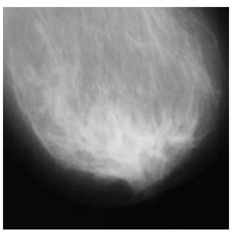
The input image is browsed from the data set images. AMF is applied on the input image to remove noise. The filtered image is segmented using GMM segmentation. The features of the filtered are extracted using FLICM. The segmented image is classified using PNN classifier. We can observe the results as Benign, Malign and Normal.

IX. SIMULATION RESULTS

1) BENIGN

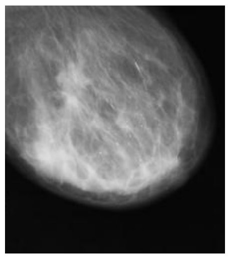


INPUT IMAGE

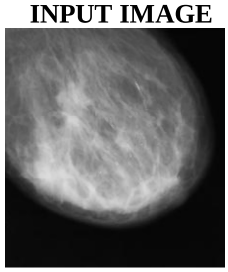


FILTERED IMAGE

2) MALIGN



INPUT IMAGE



FILTERED IMAGE

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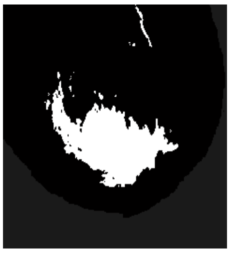
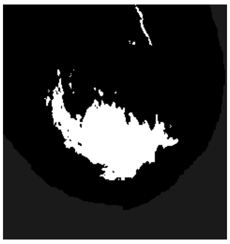


GMM SEGMENTATION

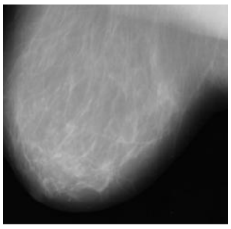


CLASSIFIED USING PNN

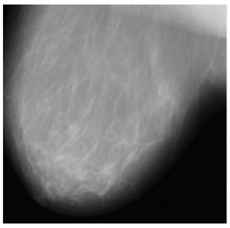
GMM SEGMENTATION

CLASSIFIED USING PNN

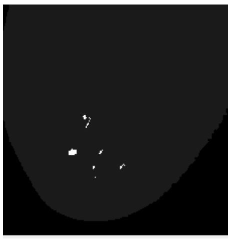
3) NORMAL



INPUT IMAGE



FILTERED IMAGE



GMM SEGMENTATION

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CLASSIFIED USING PNN

X. CONCLUSION

Hence, the whole image is taken as the input, filtered, segmented and classified. The input is not filtered for better classification. We used the Adaptive Median Filter to remove noise from the image. There is no feature selection process in the existing paper. But, this paper uses the Gabor feature selection. Multi SVM is used. It gives output as 3 stages. They are:

1) Benign - Affected
2) Malign - Severely Affected
3) Normal - Not Affected

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