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RESEARCH ARTICLE

ENLARGEMENT OF EFFICIENT AUTOMATIC VOLUMETRIC MAMMOGRAPHIC IMAGE CLASSIFICATION BASED ON ROBUST FEATURES.

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Abstract

Image classification is always a supporting and difficult task for medical systems. Mammographic images contain various features like space, distance, circumscribed masses, speculated masses and micro calcification. This paper focuses on classifying mammographic images based on the region of interest. The images may be looking blurred due to the variation in illumination, intensity and contrast which cannot be directly processed. Hence, multilevel filters have been used to enhance the image. The integral images are generated from the input image to normalize the contrast of the image. Various filters and equalization techniques have been used to uniformly distribute the gray values in the image thereby the noise is eliminated to enhance the input image for further processing. The texture features, their shape, and spatial features are extracted to compute the growth of the anatomic features. Therefore, the quality of the image classification which is an ultimate aim of this paper is improved. Therefore, the quality of the image classification which is an ultimate aim of this proposed is improved. The result shows that the proposed method has increased the classification accuracy.

Introduction:-

The Breast cancer is one of the most emerging diseases which mainly affects woman between the ages 40-45. It is widely spread in developing nations when compared with the developed one. According to the survey results till 2014, about 59% of the women were affected with breast cancer during this age.

This paper addresses the volumetric mammographic image classification based on robust features and is common to randomly divide a set of statistics into a testing image and a training image. The testing image and training image have been deliberately chosen from DoD BCRP, MIAS, DDSM which ranges over accuracies in the training image that are distinct from the accuracies in the testing image.

Section 2 presents a precise -proposed method of system architecture. This section is divided into four subdivisions such as A.Integral Image Computation which is enabled for more advanced techniques and to find areas that match patterns corresponding with the region, B. Multilevel Filter that is consisting of Gray value, distribution filter, and histogram equalization. The image is implemented for the feature exaction by interest point feature extraction C. that is computed by interest points.

The volume of the region is given in section D. The volumetric feature for each testing image and trained images specified in section E. The classification algorithm has been used on the data are Mammographic Classifier in section E. The work presented here is compared with related work by other methods in section III. Finally, Section IV presents the conclusion. For five classification algorithms studied here, Automatic Volumetric Mammographic Image Classification Based on Robust Features information results in a significant increase in accuracy.

The work described here is most closely related to some related work such as histograms are compared for classification like a normalized histogram intersection and histogram intersection with support vector machine similarity K -nearest neighbour for galactographic image study[1,2].The classification of mammograms with benign, malignant and normal tissues using independent component has been studied in [3].In this paper ,two types of classifications support vector machine and linear discriminant analysis is used to analyse the mammographic images. The two classification methods are using the image pre-processing in wavelet decomposition and image enhancement [4]. In [5] has used some features (Fractal Dimension (FD) and Fractal Signature (FS)) and provide good descriptive values of the region. A trainable multilayer feed forward neural network has been designed for the classification purposes and compared with K-Means. Breast region is exacted from the decimated image which is divided into three partitioned regions, the fat, the glandular and the dense region [6]. The optimal set of features selected by the Genetic algorithm is fed as input to Adaptive Neuro- fuzzy inference system for classification of images into normal, suspect and abnormal categories[7].Breast cancer ultrasound images are approached to detect the breast cancer based on the fuzzy logic theory, transform into a fuzzy domain and focuses on discovery a reliable ROI instead of finding the precise tumor place at ROI generation phase[8,9].The parameters for shape and margin of masses10 such as lifetime risk, percentage density are computed which shows the experimental findings are matched with the breast image reporting and data system standardization. In a case of histogram intersection method, the textual shape of the dynamic region and quantitative measurements in [11,12].All these methods discussed above have the problem of classifying false positive classes of mammographic images. Hence, this proposed technique called a new volumetric classifier of mammographic images based on texture features helps to overcome the above -said problems.

Material and Methods:-

The proposed method has the following steps in Fig.1. Namely integral image computation, multilevel filter, edge detection, feature extraction, interest point computation, volume computation and mammogram classifier.

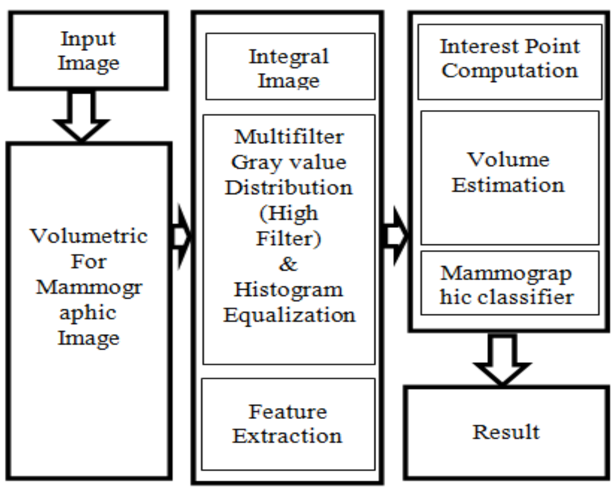


Fig.1:- System Architecture

Integral Image Computation:-

The input image is selected and a number of subs- images is created based on the parameters m and n. Here m and n specify the width and height of the integral image to be generated. The value of m and n is a multiple of width and height of the image. For example, for an image with size 300×300, the value of m and n will be 3×5 or 5×3 and so on. Fig.2shows the original image and Fig.3 shows the integral image generated with m×n values 20×35.

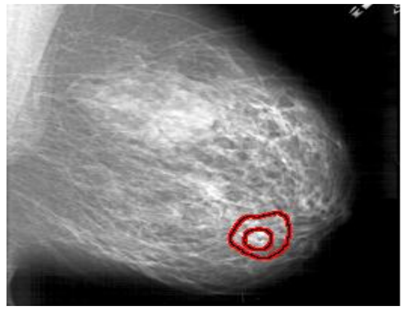


Fig.2:-Original image.

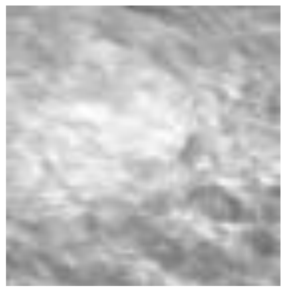


Fig.3:- Integral image generated with m×n values 20×35

Multilevel filter:-

The generated integral image is passed through a multilevel filter. The multilevel filter removes the noise present in the integral image. The convolution filter first sharpens the image; secondly, it enhances the image with histogram equalization technique. For each integral image Ini, the Gabor filter is applied and the result Ini is stored. Then the integral image Ini, is divided into boxes of size 3×3. For each box Bi in the integral image Ini, the frequency Fr of each pixel is computed. For each frequency ,Fr, the probability and cumulative distributional frequency (CDF) are computed. The cumulative distributional frequency represents the feature distribution around the region. Volumetric Estimation from a computed region and shape features the volume of the shape is calculated using multiple points of the region. Using the distance metrics we compute the overall volume of the component. The volume of the component is computed using different coordinate points. The boundary points are identified and we split the points into simple shapes less than a polygon. Based on the separated multidimensional space, for each shape volume will be computed..

Algorithm:-
Step1: Read input image img.
Step2: Generate Integral image set IImg.
Step3: Load possible intensity values
Ivset={0…256}.
Step4: For each image Ii in the set IImg
Select convolution matrix Cm,
divisor d, bios b.
For each pixel Pi in Ii
Compute convolution summation
CSumi = ∑Cm.
Compute Pi = CSumi+d+b.
Assign Pi = 255if(Pi>255)
Assign Pi = 0if(Pi<0)
End
End.
Step5: for each image Ii in the set IImg
For each value N in IvSet
Compute Frequency Fri = Pi/Ti.//compute the frequency of the value Pi in the integral image//
Pi= Number of pixel with intensity value N . Ti=total number of pixels in the box.

$Ii(j,k)=Floor((L-1)\times\sum_{n=0}^{fj.k} Fri)$.//assignthe frequency value//
End.
End.

Where L – is the possible intensity values from 0 to 256 and Fr is the normalized histogram which isrepresented as frequency.

Step6: stop.

The algorithm removes the noise present in the image and enhances its quality using a multilevel filter and histogram equalization technique. In the algorithm Step 1 reads the input image and in step 2 it generates the integral image from the input image which is a subset of small images with the size of box filter is used. In step 3 all the possible intensity values are loaded. In step4, for each integral image generated at step2, noise removal is applied using convolution filter. Then, histogram equalization technique at each integral image which enhances the image quality at step5 is implemented. To perform histogram equalization for each possible intensity values, the pixels are identified and then the possibility or frequency is computed. The calculated frequency value is used to work out the probability of distribution and round the value to which the pixel is restored. By performing histogram equalization, the pixels with similar intensity values are adjusted to a particular value that enhances the image quality.

The output of the multilevel filter with histogram equalization is shown in the Fig.4. It shows clearly that the image has been enhanced for its quality. It will be useful in identifying the cancer region.

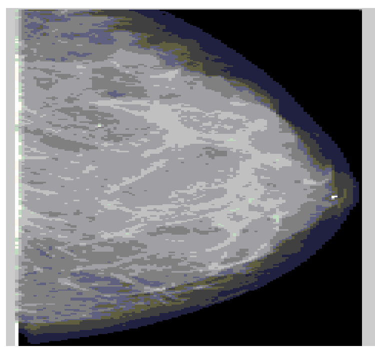


Fig.4:- Output of image enhancement using multilevel filtering

Feature Extraction:-

The mammogram templates are matched to identify the affected regions. The identified and marked components are read to extract the features. The robust features are used to extract the feature of the image. The features are extracted from the marked components and it will generate interest points where the important features are present. The computed interest points are stored for further usage.

Volume Computation:-

With the extracted interest points, the coordinate points and the distance metrics are computed. Using the distance metrics, the overall volume of the component is computed. The volume of the component is computed using different coordinate points and interest points.

Algorithm:-
Step1: start
Step2: initialize volume feature Vs.
Step3: for each Interest point Inti
Compute boundary points Bi = ß(Inti). // we compute the boundary or edge points.
Compute volume Vs = Vs+Vi. // we compute the volume of the region.
End
Step4: stop.

In the algorithm, step 1 and 2 is to start the process and to initialize the volume features Vs respectively. Step 3 computes the boundary of coordinate points from the interesting point and also it calculates the area and volume which are affected by the interesting point. The pixel that comes into the region of interest point is identified along with the edges. Based on the edges, the area of accumulation is recognized to compute the volume. Hence, each interest point will be having different volume because the number of coordinates covered by the interesting point will differ between them.

Mammographic Classifier:-

The mammographic classifier computes the volumetric feature for each testing image and trained images. The interesting point has 124 features, while the volumetric feature has 125 features which are used for the classification purpose. The Euclidean distance measure of the input feature vector with other feature vectors of trained images is computed to classify the mammographic image.

Algorithm:-
Step1: start
Step2: read feature vectors computed Ints, Vs, TInt.
Step3: initialize distance vector Dv.
Step3: for each vector v from Ints
Dv(Ints(i)) = Σni=1 (Ints(i)-TInts(i+1)).//compute the distance between the interest points//
End
Step4: select minimum distanced feature vector and class.
Step5: Assign class label to the mammographic image.
Step6: stop.

The algorithm computes the distance between the feature extracted from the input image and the feature set available as the trained image. It also processes the distance between each feature vector i.e., it calculates the volumetric distance between each feature vector and selects the least distance vector. In algorithm step, 2 reads the feature vectors i.e., computed Ints, Vs and Tint. In step,3 it initializes the distance vector Dv while step4 is used to compute distance vector Dv for each vector v from Ints. Step5 reckons the distance between two interest points of the input and target feature vector. The process will be repeated with the feature vector of each class and finally a single class with least distance will be assigned as the classified labels.

Result and Discussion:-

The proposed methodology has been evaluated with various data sets of mammographic images. The proposed method uses different data set and various numbers of classes namely classification, circumscribed masses, speculated masses, ill-defined masses, architectural distortion, and asymmetry. A Number of samples have been used for each class. The following Table.1 shows the data set used for the evaluation of the proposed method. The Department of Defence (DoD) database for breast cancer research program of Standford School of medicine, California ,and Mammographic Image Analysis Society (MIAS) data set and Digital Dataset et for Screening Mammography (DDSM) for the evaluation of the proposed method.

Table .1:-Usage of dataset

Database	Number of samples	Number of Testing images
DoD BCRP	750	18
MIAS	322	12
DDSM	2640	41

The Fig.5shows the snapshot of interest points identified using the proposed method and it shows that there are many points has been identified as feature places and the Fig.6shows the cancer identified image and it shows clearly that the proposed method has identified the presence of cancer

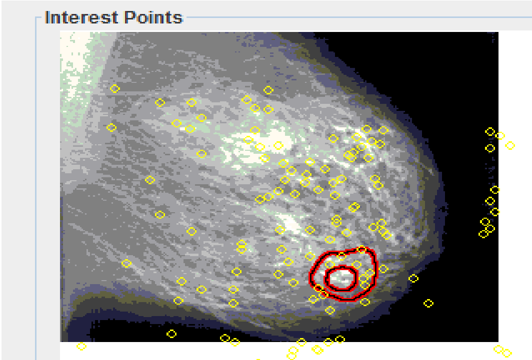


Fig.5:- Snapshot of interest points identified.

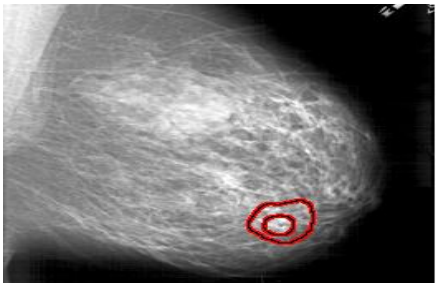
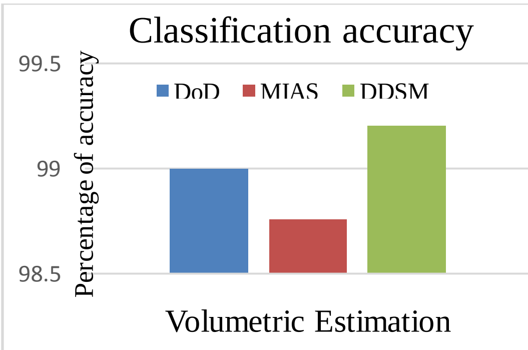


Fig.6:- Final result of breast cancer identified.

Table 2:-Comparison of classification accuracy

Algorithm	Classification Accuracy		
	DOD	MIAS	DDSM
Volumetric Estimation	99	98.7577	99.2045

The Table .2 shows the comparison of classification accuracy produced by different databases. It shows clearly that the proposed volumetric estimation based mammogram classification approach has produced more accuracy in mammogram classification.



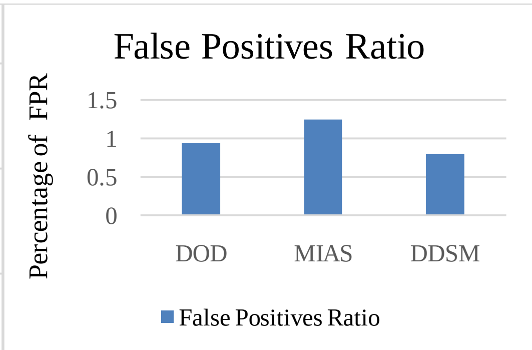


Fig.7:- Comparison of classification accuracyFig.8 Volumetric Estimation of false positives classification ratio

The Fig.7 shows the classification accuracy produced by different methods and the efficient results of proposed volumetric approach compared to others.

The Fig.8 shows the Volumetric Estimation of false classification ratio produced by different methods and declared that the proposed method has produced less false ratio than other methods. It also shows the Volumetric Estimation of false classification ratio produced by different samples and from this, it is clear that the proposed approach has produced less time complexity than other approaches.

The proposed method uses less number of samples, i.e. less than 10% of training samples. Also it takes less time for training and testing, because unlike other methods, only few stages are used to identify the mammogram and image classification. The proposed method has classified the test images accurately up to 99 % with the less number of input samples. Hence, it is proved that the prospect method has produced the efficient results with minimum time complexity.

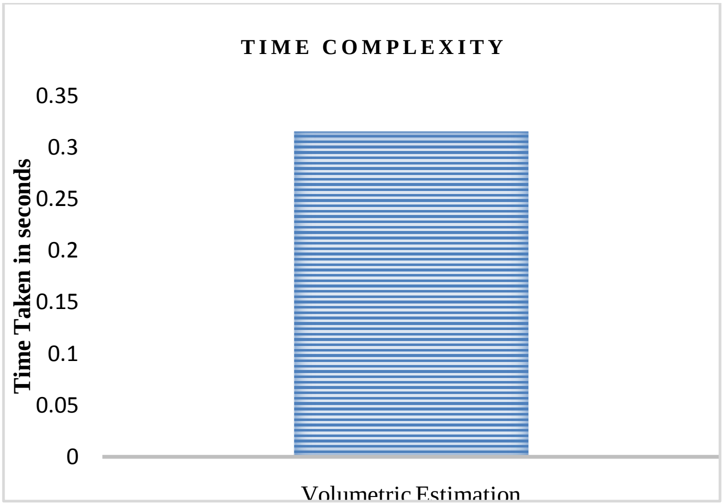


Fig.9:- Volumetric Estimation of Time Complexity

Conclusion:-

The proposed method called a new volumetric classifier for the mammographic image has produced efficient results. The integral image was generated for the computation of the interest point which represents the texture features of the region and the volumetric feature. The computed feature vector is used to compute the distance of the image with other feature set of the trained images. Finally, the volumetric classifier assigns a label to the input image based on the distance computed. Thus the proposed technique bent good results by reducing the FPs and time complexity.

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