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BREAST CANCER DETECTION USING SOFT COMPUTING TECHNIQUE

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ABSTRACT

During a decade ago breast cancer is perceived as significant reason for death among ladies and the quantity of breast cancer disease patients is expanding. Mammography is the best technique for the early discovery of breast diseases. Finding a precise and powerful computer supported determination framework for arrangement of the variations from the norm in the mammograms as threatening or considerate still stays a test in the advanced mammography. The present work focus around the extraction of the element without expelling pectoral muscle in pre-processing stage utilizing another effective strategy and distinguish unusual region utilizing division and edge location. Database of MIAS mammography images was used to classify normal/ abnormal individuals and benign/ malignant cancer patients and the KNN classifier. Training on an enormous number of information offers a significant level of exactness. Be that as it may, because of the constrained volume of patients, the biomedical datasets contain a moderately modest number of tests. Information growth is along these lines a technique to expand the size of info information by creating new information from the previous information. The information increment has numerous structures; the one utilized here is the pivot. When manually cropping the ROI from the mammogram, the reliability of the newly trained DCNN design is 71.01 percent. Segmentation methods, the average region under the curve (AUC) attained was 0.88 (88%). In contrast, when using the CBISDDSM specimens, the DCNN reliability is improved to 73.6%. The accuracy of the KNN thus becomes 87.2% with an AUC equal to 0.94 (94%). Compared to previous work, this is the largest AUC value using the similar conditions.

Keywords—CNN, Mammography

1. INTRODUCTION

Breast cancer is caused by an abnormal breast cell growth. These cells are rapidly growing in benign and malignant tumours. Increasing number of cells in benign tumours stop at a defined stage, but in malignant tumours it continues to grow until all parts of the body are affected. The risk of breast cancer increased with early menstruation in younger age, menopause in older age and late marriage. Nutrition and lifestyle are important factors in breast cancer, in addition to contraceptive drugs and hormone. Image processing is one of the key concepts in the fields of medical and biotechnology.

The purpose of these mechanisms is to enhance the relative quality of information

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to be interpreted by the doctor. The photo processing is used for diagnosing unusual events, analysing images and collecting useful information. Since cancers can be correctly diagnosed in the short term, the image processing system is a quick and non-invasive tool for diagnosing cancer cells to improve earlier diagnosis and increase the rate of survival. Particularly in earlier stages of disease, mammography is the most important and effective tool for diagnosing breast cancer. Throughout mammography, tissue receives part of x-ray radiation and moves another section.

Tissue naturally absorbs some heat. The level of the cancer tissue output signal is different from normal. Input level to output signal loss can be used to diagnose tissue cancer. X-ray mammography is the most common technique for radiologists to detect and monitor breast cancer. This approach is used for early diagnosis of illness and decreases the rate of death. Nonetheless, mammography images are difficult to interpret and clarify; there are many research studies to identify tumours from mammography images. The purpose of this study is to obtain texture-based images from mammography without extracting pectoral muscle.

Most mammographic images contain pectoral muscles and they cause error for tissue diagnosis. Therefore, different processing methods are attempting to remove them. High-accuracy detection is possible without removing pectoral muscles by using strong pre-processing and extraction the powerful features. Therefore, the diagnosis for physicians must be accelerated. After enhancing the image quality and eliminating potential noises, a new method for extracting the function is provided by 1-D transformation and extracting non-stationary features.

2. EXISTING SYSTEM

The existing system uses techniques DCNN and SVM classifier. These techniques introduce problems is that it uses global thresholding method .This is done by setting an appropriate threshold value (T). This value of (T) will be constant for the whole image. The other problem is that SVM is not suitable for large datasets and provides less accuracy when the dataset has more noise. In cases where number of features for each data point exceeds the number of training data sample, the SVM will underperform

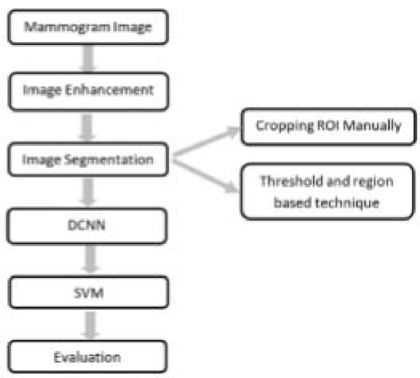

Fig: process diagram for existing model

IMAGE SEGMENTATION:

Image segmentation Image segmentation is used to divide an image into parts having similar features and properties. The main aim of segmentation is to simplify the image by presenting in an easily analysable way. Some of the most popular image segmentation methodologies are edge, fuzzy theory, partial differential equation (PDE), artificial neural network

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(ANN), threshold, and region-based segmentation.

THRESHOULD METHOD:
Thresholding methods are the simplest methods for image segmentation. The image pixels are divided with respect to their intensity level. The most common type of thresholding method is the global threshold (Kaur&Kaur, 2014).This is done by setting an appropriate threshold value (T). This value of (T) will be constant for the whole image.

REGION BASED SEGMENTATION: Region based segmentation divides the image into different regions based on predefined criteria (Khan, 2013). There are two main types for the region-based segmentation; (1) region growing and (2) region splitting and merging.

CLASSIFICATION: In this step, the ROI is classified as either benign or malignant according to the features. There are lots of classifier technique**s:** such as linear discriminate analysis (LDA), artificial neural networks (ANN), binary decision tree, and support vector machines (SVM).

3. PROPOSED SYSTEM
Proposed system uses OTSU thresholding method which returns a single intensity threshold that separate pixels into two classes, foreground and background. These filtered images are given as input to Adaptive Median Filtering to gain more accuracy .We used KNN algorithm which is a simple technique that stores all available instances and classifies based on a similarity measure. It has been used in statistical estimation. For each row of the test set, the K nearest training set vectors are found and the classification is decided by majority vote, with ties broken at random. If there are ties for the kth nearest vector, all candidates are included in the vote. The data from KNN goes to GMM Segmentation and fit the data accordingly to classify the classes.

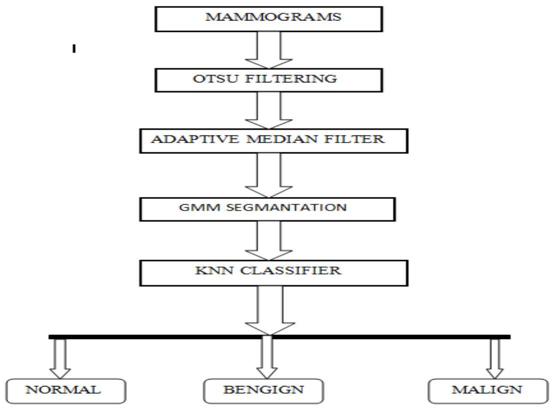

Fig: Steps of Proposed System

OTSU is used to perform automatic image thresholding. In the simplest form, the algorithm returns a single intensity threshold that separate pixels into two classes, foreground and background.

ADAPTIVE MEDIAN FILTERING 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 neighbour pixels.

K-MEANS clustering is used as a pre-processing step for the GMM segmentation where the breast images are partitioned into three clusters.

A **GMM** (Gaussian mixture model) is used for modelling data which comes from one of the numerous groups, the groups might be different from each other, but

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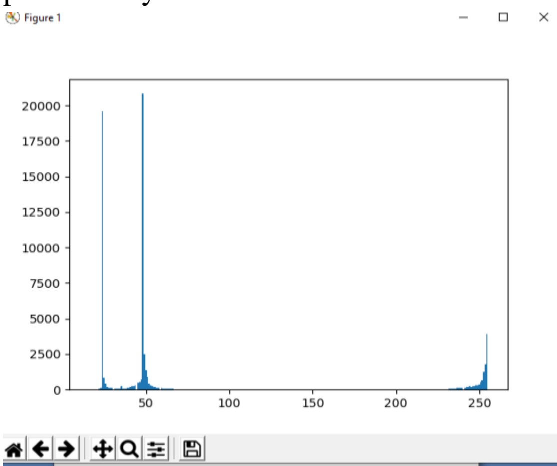
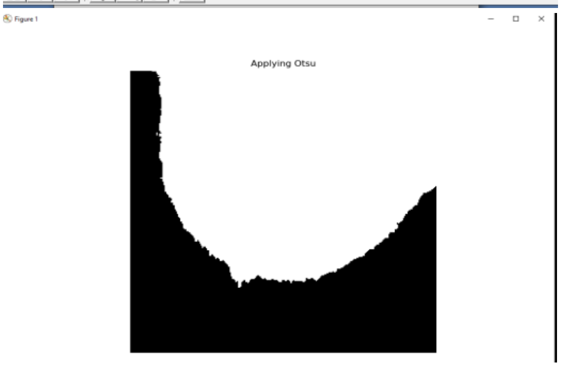
data points within the same group can be modelled by a Gaussian distribution. The image is a matrix in which each element is a pixel. The value of the pixel is nothing but a number that shows intensity or colour of the input image.

CLASSIFICATION: The images are accurately segmented to separate out the tumour region from Benign, Malignant and Normal Images.

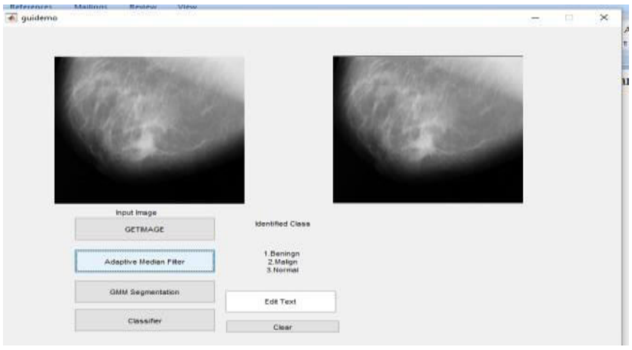
4. SOFTWARE DEPLOYMENTS

1) PYTHON: This proposed model uses python for initial filtering where it apply otsu filtering to the image as mentioned above to the pixels of image are made into classes with their single intensity values provided by OTSU





2)MATLAB: MATLAB does all the mathematical calculations where it takes the OTSU filtered image as input and then apply Adaptive Median filtering,GMM segmentation and compare the treshold values to the already existing training data and classify the class.



3.Accuracy: The proposed model provides an average accuracy of 94 percentage and can be improvise the mammo grams is more noise free .

5. RESULTS

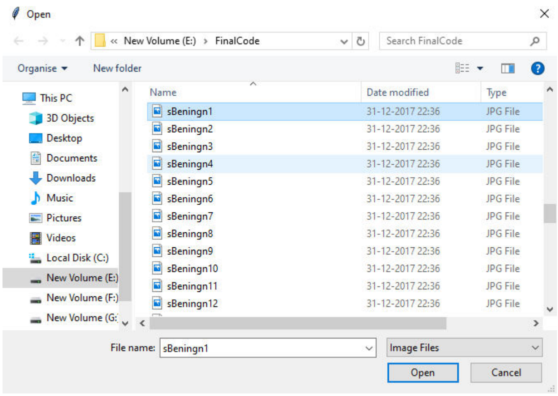
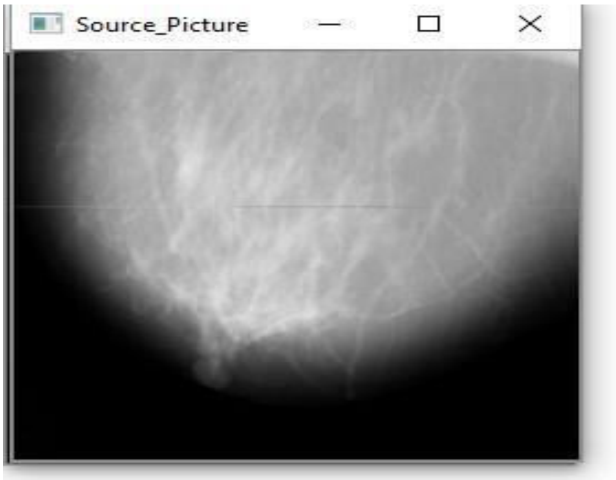


Fig: choosing an image

STEPS OF PREPROCESSING:

Source picture:



Final picture

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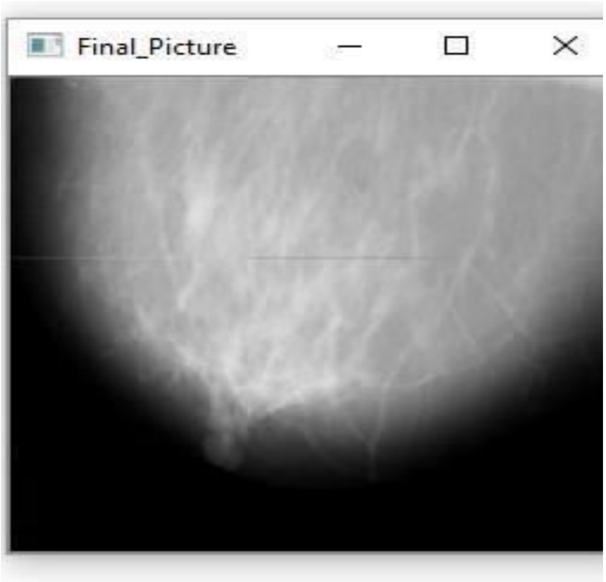
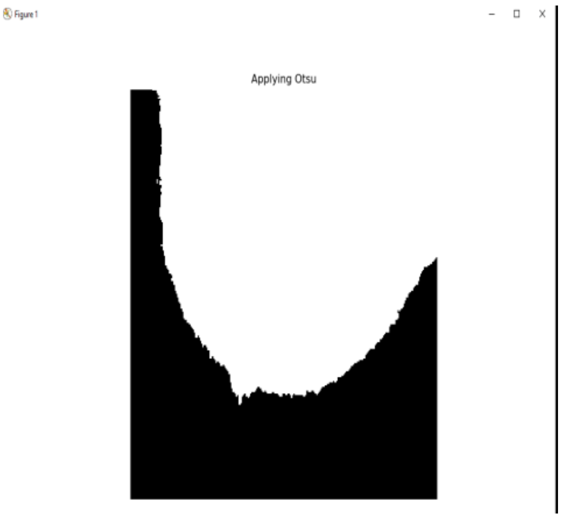


Applying OTSU



OTSU Graph

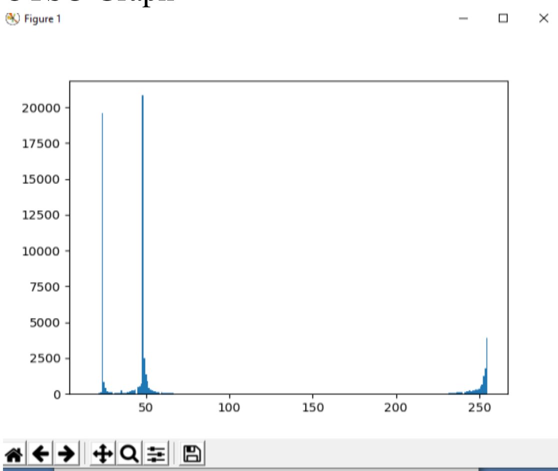


Fig: AutomaticThreshold graph

Adaptive Median filtering

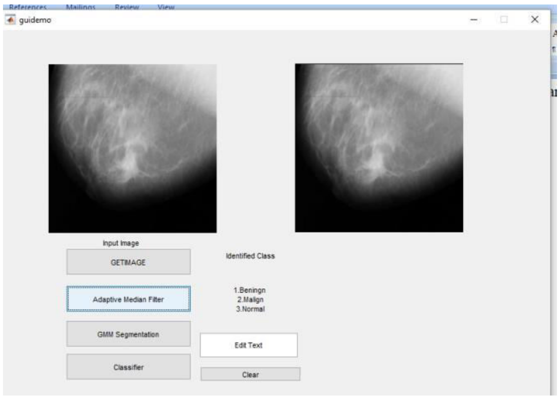


Fig: Applying adaptive medina filtering

GMM Segmentation

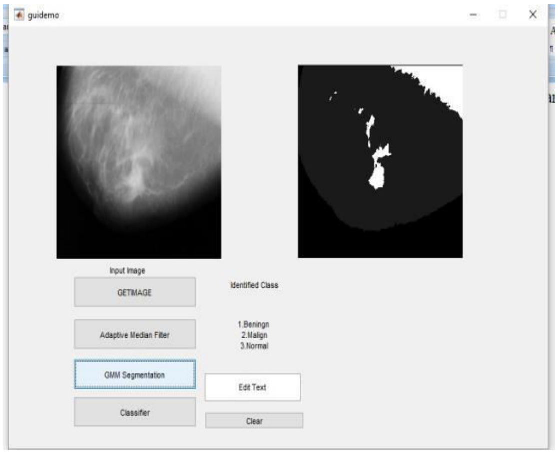
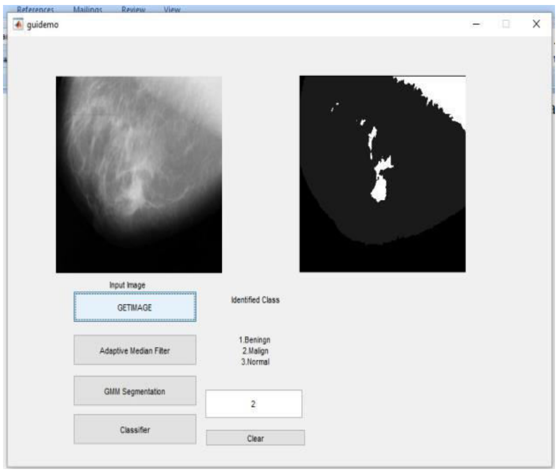


Fig : Applying GMM segmentation

Identified Class



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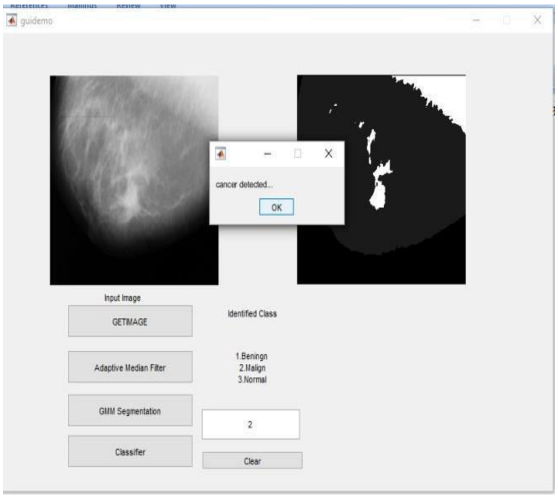
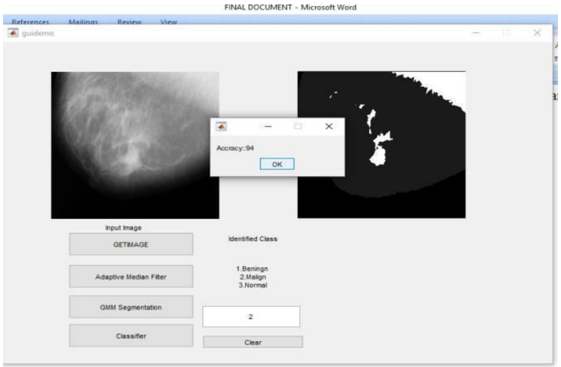
Cancer detection

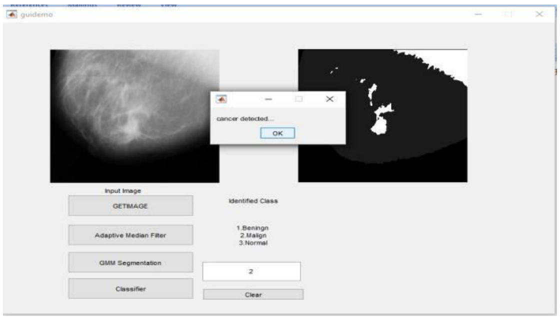


Accuracy

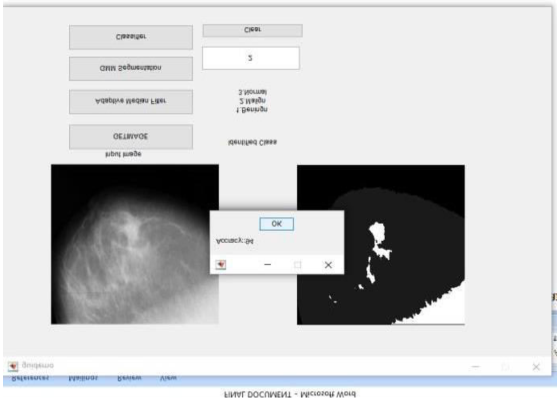


6. CONCLUSION

We introduced OTSU filtering as pre-processing step for Adaptive median filtering for early BREAST CANCER DETECTION USING SOFT COMPUTING TECHNIQUES system feature extraction and DCNN classifier. The identification of (CNN) is a very basic classifier that works well on issues of recognition. The KNN algorithm can be compared to other classifiers as it makes predictions that are highly accurate. Therefore, for our BREAST CANCER DETECTION USING SOFT COMPUTING TECHNIQUES system, we use the KNN algorithm which provides high precision.



We use the MIAS image in our work with the types of "Portable Gray Map" (PGM) format. The experimental results revealed that the system has a 94 percent reliability rating. We segmented the abnormal regions using GMM segmentation. We have intended to improve the identification accuracy in the future work by using other forms for classification. We plan to add more derived features and extend the selection of features to get more accurate diagnosis and identification of breast cancer.



7. FUTURE ENHANCEMENT

This project can be enhanced better in both medical and technical fields as of now the data sets are very limited and rare for future purpose there should be more datasets to analyze to obtain more accurate result. Our system only takes mammograms that are in size of 256*256 in future we will upgrade our system so that it can take input of mammogram having any size and provide more accurate output.

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