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Enhanced Image Segmentation in Breast Cancer Classification Leveraging Deep learning

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Abstract:

In the recent years, the field of breast cancer research is using deep learning techniques to mitigate the problems of false positive and false negative cases caused by the breast cancer diagnosis done by the radiologist. Therefore, in this research we propose deep CNN (convolution neural networks) for classifying the mammogram image as cancerous or non-cancerous. However, it is observed that, merely using deep learning techniques also has some limitations such as, uncertainty in breast mass classification on the dense breast mammograms. Thus, in this research the images are preprocessed and segmented prior classification. In this research images are preprocessed using Rolling Ball algorithm for background removal and then compared CLAHE and Unsharp masking for improving image contrast and visibility of the images. The proposed work segmented MIAS preprocessed images using k-means algorithm. These enhanced images are provided to Deep CNN (Convolution Neural Networks) and its features extracted for classifying images as benign, malignant or normal. To improve the CNN's structure and lessen overfitting, dropout and zero-padding are employed. The proposed work is tested on mammography images from the databases of the Mammographic Image Analysis Society (mini-MIAS), Breast Cancer Digital Repository (BCDR). The proposed system has, Accuracy:0.89%, Precision: 0.91%, Recall: 0.90%, F1-score 0.88% and for the MIAS dataset, respectively.

Keywords: Deep CNN, background removal, rolling ball, segmentation, k-means, CLAHE, Unsharp

1. Introduction

According to worldwide research, breast cancer is one of the deadliest diseases. It is the second-most common cancer, leading to a high mortality rate among women across the world [1]. A study conducted by the Chinese National Institute of Cancer (NCI) found that 522,000 people died and 1.67 million incidences of breast cancer were reported between 2008 and 2012 [2]. Thankfully, research over the previous five years has also shown that the survival rate for breast cancer may exceed 90% if it is discovered in its early stages [3]. Diagnosis through breast screening examinations has to be encouraged among women for early detection, which can reduce the death rate [4]. However, if it is diagnosed too late, it may spread to other body areas, including lymph nodes, and the survival chance would be reduced by 27% [5]. The Breast Imaging-Reporting and Data System (BI-RADS) is a common system used to record mammography data. Due to the intricate structure of the breast, a specialist may occasionally be unable to recognize local lesions, and extensive reading procedures may also cause a false diagnosis [6]. Therefore, to overcome these challenges, automated techniques are used to assist radiologists in determining tumor detection with greater accuracy. The automated techniques are mainly performed in four stages: image preprocessing, lesion segmentation, feature extraction, and classification. The classification can be performed using machine learning approach, out of which the K-nearest neighbor (KNN), support vector machine (SVM), and sparse representation [7] are popular. But the typical machine learning algorithms require the feature extraction method to be manually built, it is challenging to create a highly effective feature extraction algorithm because of the diversity of the samples [8]. Deep learning has garnered a lot of attention in the last few years [9]. The CNN has been widely employed in the field of mammography processing because of its strong automatic image feature extraction capacity. Jaffar [10] retrieved features from a whole mammogram using CNN and then classified the features using SVM. Gardezi et al. [11] used VGG-16 to extract features from mammogram images. They also used standard machine learning algorithms, like SVM, logistic classifier, and KNN classifier, to classify the features as benign and malignant breast masses. A dataset of mammography images was enhanced by Chougrad et al. [12] by randomly rotating and warping the samples. When it comes to automatically extracting features from images, CNN performs admirably [13] [14]. Multi-view mammography and CNN are used to classify breast masses in order to solve the aforementioned issues [15]. Several Biomedical Image Processing (BIP) issues have been addressed with the CNN technique, with one of them including the segmentation of medical pictures [16]. Because convolutional calculations are made repeatedly during training and prediction, it results in significant capacity overhead and low estimate efficiency [17]. The accuracy of segmentation is decreased in this approach because large image blocks necessitate several pooling layers. Conversely, the use of a small picture block as input results in smaller receptive fields. With limited segmentation accuracy, these small-sized receptive fields only extract the local characteristics. A number of techniques, including the removal of the pectoral muscle and the background from images, have been previously proposed by researchers [18]. A critical stage in medical image processing is the extraction of the Region of Interest (ROI). The important or crucial areas of the picture are typically where ROI is most understood. ROI can typically be used to extract a quick image processing approach and to remove unnecessary portions of the image. Identifying the region of interest by segmentation is found to be a challenging task [19]. Therefore, a good segmentation is needed for mammographic images for accurate classification. This paper utilized k-means algorithm for segmentation.

However, there has been little research on pre-processing image enhancing methods. This research aims to propose effective approaches for image segmentation and enhancement. The processed images are examined to ensure that the suggested approaches do not negatively impact the region of interest (ROI) or pixel quality. Preprocessing techniques are applied to mammography pictures in order to minimize undesired areas and improve local details, hence facilitating the detection of ROIs and regions within ROIs. Thus, in this research images are preprocessed prior segmentation. The proposed work used rolling ball algorithm for background removal, and CLAHE for improving the contrast. Further the proposed system compares CLAHE and Unsharp for shading correction on MIAS images.

2. Parallel Research Work

This work tries to improve classification performance with mammographic imaging. This section highlights image preprocessing techniques, segmentation techniques and deep learning works, that were carried out for breast mass classification, in the past. The, preprocessing is crucial for improving the features of mammogram images in order to maximize ROI extraction. Past researchers have suggested a number of techniques [20-23],[24] to eliminate the background from mammograms and optimizing contrast enhancement in order to prevent artifacts and noise. But none of these techniques make an effort to provide an efficient image enhancement. For background removal, this study used "Rolling Ball Algorithm" and Contrast Limited Histogram Equalization (CLAHE) is used for improving the contrast of the image. The rolling ball technique [25] was able to recreate the lungs during the lung image segmentation stage, keeping the lung wall intact. They outperformed most of the other models with an accuracy of 89.89% using their convolutional neural network.

Recently the rolling ball approach was employed [26] to identify LED-induced electromagnetic interference in high-frequency radar range-doppler images. This approach detected and removed the background with a 91% probability when they employed a rolling ball to erase uneven backgrounds from photos. Basile et al. [27] made use of the rolling ball algorithm to mammography, to identify micro-calcifications in mammograms, and to highlight the main areas, and resulted with 91.78% true positive rate. And it is also used to eliminate noise and locate intensity level artifacts in the mammography image. The overfitting problems can be avoided by augmenting data by generating datasets by applying different transformations. The both local and global contrast normalization can shorten training times and increase performance [28], and it has resulted an 86% AUC. If at all a good preprocessing technique might have employed, the performance might have increased. The mathematical grey-scale morphology concepts were used for image segmentation, and to eliminate noise from images. A segmentation technique [29] that segments the image by using a convolutional neural network to identify the edges and the pectoral muscle boundary was proposed. The disadvantage is that, when applied in practice, creating and utilizing one CNN for the purpose of removing pectoral muscle and then creating a second CNN for detection and diagnosis may result in higher computational expenses and times. To address this, this research suggests that segmentation approach after the pre-processing stage itself. The local neighborhood approaches [30,31,32,33,34,35] are used extensively for texture and feature extraction. These approaches are based on a 3×3 window. The texton approaches are also used for the same [36,37,38,39,40]. These approaches are based on a 2×2 grid. For classification machine learning algorithms or distance functions are used [41]. By adjusting the magnification variables, a residual neural network model for breast cancer segmentation is proposed to compute the classification accuracy [42], [43]. Breast ultrasound (BUS) imaging is used to find abnormalities in the breast using diagnostic techniques. In [44] the breast tissues are categorized into two groups: dense and non-dense, and mass and non-mass. The segmentation and preprocessing, which are used to categorize the breast region into mass and non-mass categories [44]. For the non-dense and dense classes, the accuracy of the 95.6% and 97.72%, are reported respectively. In this research we have used CNN for feature extraction and classification of images.

3. PROPOSED METHOD

The proposed approach of this research is based on i) data acquisition, ii) image preprocessing, iii) breast region segmentation, iv) feature extraction and classification of images, and Figure 1. Depicts the same.

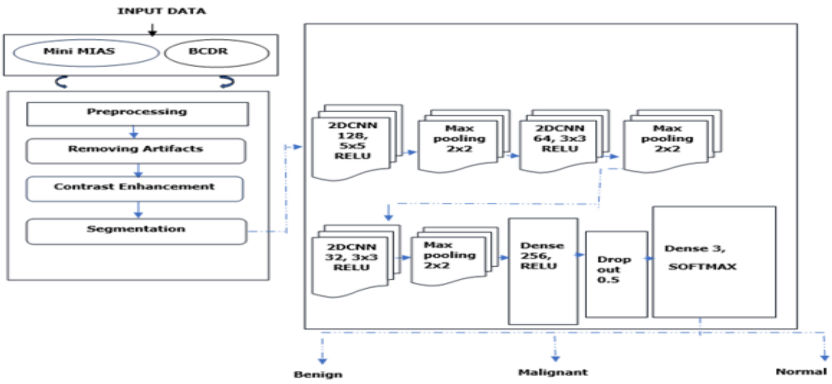


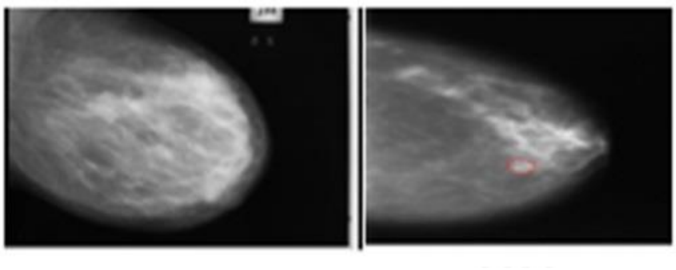
Figure 1. Proposed systems frame work

A. IMAGE ACQUISITION

The proposed method has collected Mammogram images from the MIAS [45] and BCDR database [46] to classify images as benign, malignant or normal. The Mammographic Image Analysis Society (MIAS) database is a consortium of UK research organization consisting of 322 digital gray scale images of size 1024×1024 pixels in Portable Gray Map (PGM) format [45]. It includes pictures of the patients' breasts, both normal and abnormal. The "truth" markings made by the radiologist on the locations of any irregularities could be included. MIAS images can be obtained at the website, and the dataset is available to the public [45].

This research work has used 18 normal images, 27 clahe images and 20 malignant images of totally 65 MIAS images of patients. Figure 1 shows sample images from MIAS dataset of various categories of input images such as benign, malignant and normal. The dataset also consists of details of categories including glandular, fatty and dense. Images collected from database are low in resolution. This work has enhanced the artifacts present in the images, smoothed and segmented by eliminating the uneven background and breast tissue.

The BCDR database include 3703 mammography images from both the mediolateral oblique (MLO) and craniocaudal (CC) view perspectives. All of them are supplied as 720 x 1168-pixel resolution, 8-bit TIFF files. Working with the mammogram pictures in the BCDR database, which are in 8-bit TIFF format, is not too difficult. Expert radiologists manually created 1517 segmentations and classified them using Breast Imaging-Reporting and Data System (BI-RADS). A selection of sample mammography image from BCDR dataset is shown in Figure 2.



a) Mini mias b) BCDR

Fig 2: Sample images from the databases

B. IMAGE PREPROCESSING

Image preprocessing plays a critical role in medical image classification by boosting feature extraction, standardizing data from various sources, and guaranteeing accurate and efficient operation of classification algorithms on the data. It establishes the framework for trustworthy diagnosis and decision-making procedures in medical applications. This research has used rolling ball algorithm [47] correcting non-uniform brightness, particularly in medical images. In the event of uneven exposure, this technique calculates the gray scale image's background intensity. In this research MIAS and BCDR images plotted as a 3D surface, where the surface height is represented by the image's pixel value, have been successfully processed using this approach. The huge spatial variations in the background intensities are eliminated by subtracting the background surface from the original image, which is created by rolling ball (RB) with a user-defined radius over the rear of the surface. By using third-dimensional coordinate values for the intensity, the grayscale image is rendered as a three-dimensional surface using this method. Next, a set of tangent points is formed by rolling a 3D ball with a specific radius over the 3D surface; these tangent points are then interpolated and utilized as the backdrop map. Following that, the original image can have background noise removed.

Let $m(a, b)$ stand for the original image and n $n(a', b')$ for the rolling ball.

Background noise, then, $p(a_b, b_b)$, can be acquired using equations (1), (2), (3)

$$p = (m \ominus n) \oplus n \qquad (1)$$

Here $m \ominus n = min\,\{m(a + a', b + b') - n(a', b') | (a', b') \epsilon Dm\}$ (2)

$$m \oplus n = max\{m(a - a', b - b') + n(a', b') | (a', b') \epsilon Dm\} \qquad (3)$$

where Dm is the domain of the structuring element tm. we can get the updated image $t(a_t, b_t)$ using equation (4)

$$t = m - p \qquad (4)$$

Pre-smoothing increases the accuracy of background subtraction by reducing noise and homogenizing the background. If Gaussian smoothing is applied before to background subtraction, the parameter value is True; if not, it is False. The scale of the background changes that can be eliminated is determined by the parameter radius. A smoother background results from a broader radius.

The Figure 3. displays the mammography images after denoising using RB algorithm.

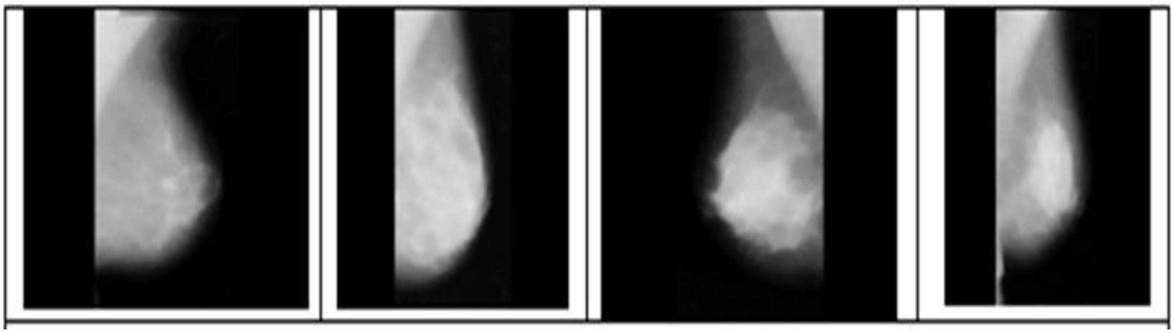


Fig 3: sample images after denoising using rolling ball algorithm

C. IMAGE ENHANCEMENT

When it comes to improving the quality of diagnostic data, boosting automated classification algorithm performance, contrast enhancement in medical image classification is essential. After background removal, the brightness of the image becomes low. Therefore, identifying the breast mass in low resolution images will give false positives and false negatives.

The existing works have used Adaptive Histogram Equalization (AHE) to improve the brightness of the image. But as the histograms in the near constant regions are highly concentrated, it over amplifies the contrast in those regions and causes noise to the images. For this, CLAHE and Unsharp masking methods are used by this paper and the results are compared between them.

D. Image enhancement using CLAHE

Histogram equalization (HE) [48] flattens and expands the dynamic range of the image's intensity levels, producing an output image with a uniform histogram that is effective and easier to use. It will also alter the brightness of the image and may lead to a rise in contrast. Equation (5) represents HE for an image.

$$T(i) = \left(\frac{I}{L}\right) * (P(j) <= i) \tag{5}$$

It determines the transfer function T, that converts the original intensity values to the new intensity values. I is an constant that regulates image contrast, L is the number of intensity levels, i is the intensity value and $p(j)$ is the probability density function of image intensity values.

The HE might not work well with many kinds of images, particularly ones that have a limited range of pixel values or sharp fluctuations in brightness or contrast. To address this, the present research used CLAHE for image enhancing.

Low contrast image enhancement has been successfully achieved with CLAHE, which was initially developed for medical image analysis. Comparing with the typical equalization of histograms techniques, CLAHE makes two significant advances. i) CLAHE has the potential to more evenly improve each pixel's contrast. ii) the range of the histogram widens and the image's gray value distribution becomes more uniform in the conventional histogram equalization methods after the histogram is equalized.

The local mapping function of CLAHE may be found in equation (6), where the gray values before and after the conversion are denoted by Da and D_b, respectively, and the number of pixels in the ith gray level is represented by $H(i)$. Every area of the image has its contrast optimized using CLAHE, which raises contrast overall.

$$D_b = \frac{255}{8\times 8}\sum_{i=0}^{Da} H(i) \tag{6}$$

By minimizing contrast enhancement, CLAHE could also lessen the issue of noise enhancement. Most pixels will peak in these regions of the histogram, if they fall within the same gray range.

Since the slope of the local mapping function will be quite great, the areas are pretty high. High gray values will be transferred to low gray values in this case, such as the original background or noise. Limiting contrast enhancement is how CLAHE addresses the noise issue. A certain gray value is used to determine the maximum number of pixels $(Hmax)$. If more pixels are used than $(Hmax)$, the extra gray values are clipped. After the histogram is clipped, the distribution of pixel values becomes more uniform as in (7).

$$H(I)' = \{ H(i) + L, \quad H(i) < Hmax \; Hmax + L \quad H(i) \geq Hmax \tag{7}$$

The CLAHE technique includes Pixels-based division sub-class. The specific purpose of its creation was to enhance low-contrast medical images [49].

A stepwise procedure used for image enhancement using CLAHE:

Step-1 1) The first step is to gather previously processed images that have had the
2) Background elimination. The images are divided into a number of small non overlapping contextual regions called tiles or blocks.

Step-2 3) The contrast of the images is controlled by the two main parameters of this method, tile size (TS) and clip limit (CL).
This paper has used 8x8 sized contextual regions (Tiles) and applied histogram equalization with a clip limit 3 as a threshold limit to avoid oversaturation of images (in homogeneous regions).

Step-3 4) The image histogram is calculated for each sub-image using the CLAHE approach. The resulting histograms are then clipped for each contextual region, distributing the clipped pixels over all gray levels.

Step-4 5) Since the intensity of picture pixels is restricted to the value of CL for all gray levels, the newly generated histograms are different from the original ones. While determining the normalized CL, the tile histogram is computed. The normalized CL is then used to get the true CL, which is subsequently used to assess the standard for the sub-image's histogram clipping.

Step-5 The CLAHE method determines how many pixels each sub-image has for its intensity, which is then equated with CL. The value of CL sets a limit on the number of pixels that correspond to each intensity value. The leftover pixels (above CL value) are spread out to cover the sub-images. The output is then subjected to a transform function to adjust the resulting image so that it looks more realistic. Ultimately, the combined final image with improved quality is created by combining all of the improved sub-images.

6) Figure4. Shows sample images after image enhancement using clahe.

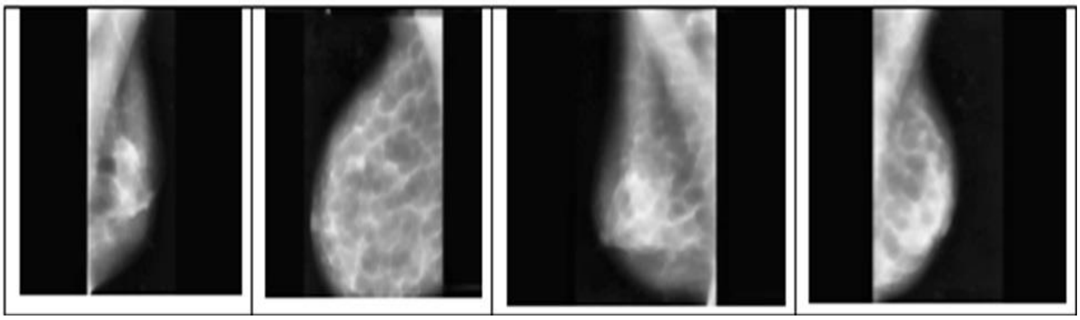


Fig 4: Sample Images after enhancement using Clahe

E. Image enhancement using Unsharp Masking

This paper used Unsharp masking also to improve the image's sharpness. By suppressing the low-frequency components while high-frequency components are amplified. The unsharp masking algorithm is described in detail below:

1. Read the image

2. Blur the image:

Blur the image using smoothing filters (Gaussian noise). This stage requires convolution based smoothing filters. Let smooth or blurred image taken as $f'(x, y)$

3. Construct the Mask:

To get the "mask", subtract the original image from the blurred one. The high-frequency elements (edges and fine features) that are present in the original image but not in the blurred image are represented by this mask. i.e., original image $f(x, y)$ is subtracted from blurred image $f'(x, y)$

The equation (8) is Sharper image fs

$$Mask = f(x, y) - f'(x, y). \quad (8)$$

4. To the original image, add the mask.

Multiply the mask by a gain factor (usually represented by the letter k) to make it more amplified. To create the sharper image g, add this amplified mask back to the original using equation (9).

$$g(x, y) = f(x, y) + k * Mask \quad (9)$$

The Figure 5. Shows sample images after enhancement using clahe and unsharp masking. Figure 5. shows sample images after enhancement using unsharp.

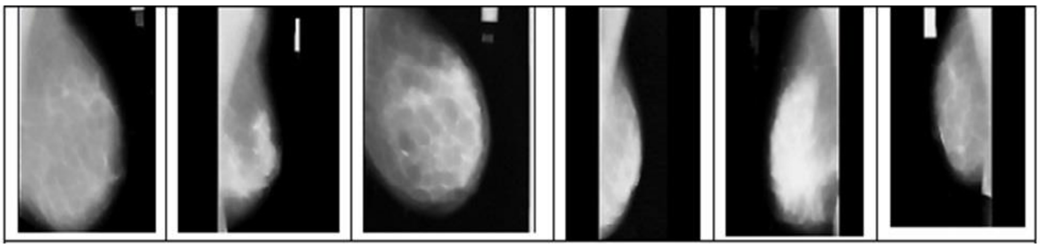


Fig 5: Sample images after enhancement using unsharp

When working with images that need for precise local contrast enhancement, CLAHE is quite helpful, especially in domains such as medical imaging or scenarios were maintaining natural appearance and minimizing noise enhancement are crucial. Conversely, Unsharp Masking is better suited for broad edge enhancement in photography but does not have the contrast limiting features and adaptable capabilities of CLAHE.

F. Image segmentation

To address this in mammogram images this present paper employed a segmentation process to identify and extract particular areas or features from an image that enhances classification accuracy by enabling classifiers to concentrate exclusively on features inside the tumor boundary in the context of tumor identification. The image is segmented into regions of interest (ROI), which helps to focus the subsequent classification effort on smaller, easier-to-manage sections. As a result, the classification algorithms analyze the divided sections more quickly and efficiently due to a decrease in computing complexity. To implement the above precisely and accurately, this paper used k-means algorithms for segmenting the images prior feature extraction and classification of images.

G. Segmentation using k-means algorithm

To increase the classification accuracy the proposed work used k-means for segmenting significant regions (disordered portions) in an image. K-means used to estimate the number of clusters that depended on the values of pixels. This work has used 3 clusters and divides pixels into homogeneous clusters for segregating normal and abnormal tissues.

The proposed k-means algorithms procedure is described as follows:

Input: preprocessed mammogram input images

Output: Segmented image

Begin

Step1 Initialize the k number of clusters in the given data. (k=3).

Step2 Select the data points randomly and assign each to a cluster.

Step3 Compute Cluster centroids are calculated

Step4 Repeat the steps until an optimal centroid is found which remain unchanged

4.1 – The distance between data and centroid with a minimal distance is assigned to nearest cluster centroid using equation (10)

4.2 − At last compute the centroids for the clusters by taking the average of all data points of that cluster.

$$D = \sqrt{(m2 - m1)^{2} + (n2 - n1)^{2}} \qquad (10)$$

Where D is the distance. $m1, m2, n1, n2$ are coordinates.

4.3 At final step centroids are calculated by taking the average of all data points of that cluster.

The Figure 6. Shows images after segmenting using k-means clustering algorithm.

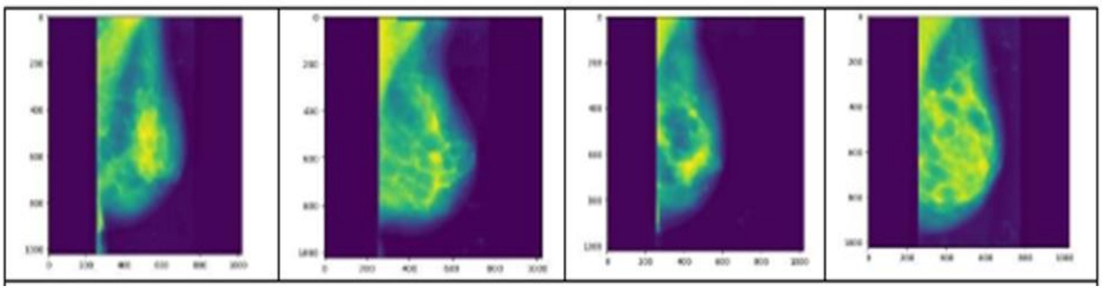


Fig 6: Segmented images using k-means

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H. Image Feature Extraction and Classification technique

Feature extraction is done automatically in CNN. However, to shorten the feature learning process in this research we have used a simple CNN with adequate layers and good kernels to accelerate convolution computation.

Unlike Neural Networks, CNN is not only used for recognizing and detecting objects in image input data, consisting of weight, bias, and the activation function when processing inputs but also enable feature extraction to learn patterns from high-dimensional inputs. This process is termed convolution and is executed in a convolutional layer (feature extraction layer). As shown in Figure 7, CNN has two major layers: feature extraction and fully connected. This section describes the structure of the proposed CNN (Figure 4). The convolutional neural network classifies an input image into categories: benign, malignant and normal. The details of the modified CNN are described below:

input_shape = (100,100,3)

Conv2D (128, kernel_size= (5,5), activation=relu, pool_size = (2,2), padding='same', Batch normalization ())

Conv2D (64, kernel_size= (3,3), activation=relu, pool_size = (2,2), padding='same', Batch normalization ())

Conv2D (32, kernel_size= (3,3), activation=relu, pool_size = (2,2), padding='same', Batch normalization ())

Flatten ()

Dense (units=256, activation =" relu")

Dropout (0.5)

Dense (units=3, activation = "softmax")

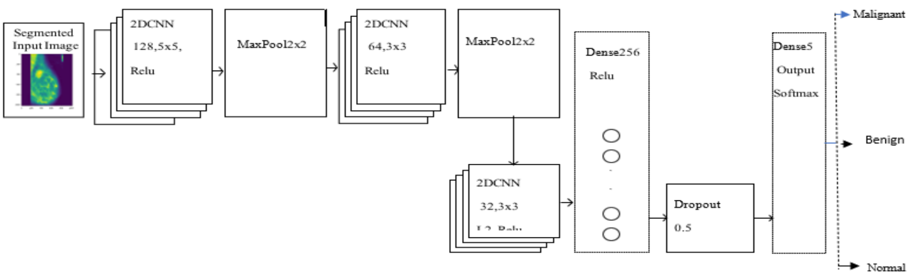

Fig: 7 The block diagram of the modified convolutional neural network (CNN).

Convolution layer, Rectified Linear Activation Function (RELU) layer, max pooling layer, fully connected layer, and dropout layer are the five parts of a CNN model. The CNN consists of trainable filters and updates its parameters at each iteration. RELU layer is the most preferred layer in CNN architectures as it speeds up the training process. Max pooling layer is used to reduce parameter size and control overfitting. Neurons in fully connected layer are a regular neural network. Dropout layer is used to prevent overfitting. The step-by-step process of the proposed work is described below:

1. Input images are transformed into vectors.
2. The next layer is Conv 2D layer. It consists of 128 feature maps with 5 x 5 kernel dimension. This layer creates a feature map to predict the class probabilities for each feature by applying a filter(kernel). The activation function uses the Rectified Linear Unit.
3. The proposed work used, Max Pooling layer with a size of 2 x2 was used. These layers are inserted between the individual convolution layers to reduce the computation time.
4. This block uses the Conv2D with the same parameters as in step 2, but the number of feature maps used are 64.
5. The Max Pooling layer with a size of 2x 2 was used. The output from the feature map of the last convolution layer or subsampling layer (Max Pooling layer) is transformed into a one-dimensional vector.
6. In the block6, the Conv2D with same 32 parameters are used.
7. In this step, dense layer with non-linearity activation function (ReLU) was used.
8. In this step, the drop out layer with a probability of 0.5 was added to prevent over training.
9. The last layer is the SoftMax function. The goal of this layer is to normalize the output of individual neurons to match the obtained probabilities (validation of the training progress).

Drop out

The issue of overfitting is frequently seen in CNN training. In order to enhance the performance of a neural network, overfitting can be avoided by minimizing the interaction between feature detectors. Dropout is a technique for training deep neural networks in which the overfitting phenomena can be greatly minimized in each training batch by disregarding half of the feature detectors, meaning that half of the hidden layer nodes' weights are set to 0 during dropout. Dropout is a useful tool in this study to effectively prevent overfitting. Every neuron in every layer produced zero with a probability of 0.5 since we had set the retention probability for dropout to p = 0.5.

Zero Padding

When employing a CNN to process image data, the convolutional kernel will often only operate on the majority of the edge pixels in the input image once, while the middle pixels will be scanned multiple times. This somewhat lowers the border information's reference degree. However, following the use of zero-padding, the new boundary affects a specific portion of the processing itself. To some extent, this difficulty can be resolved by introducing zero padding. It is possible to complement input images of varied sizes so sizes such that they are the same size at the same time. Consider the output size is(OX, OY), the input size is (X, Y), the filter size is(FX, FY), and the stride is S. The output size formula then looks like this:

$$OX = \frac{X + 2P - FX}{S} + 1$$

$$OY = \frac{Y + 2P - FY}{S} + 1$$

I. EXPERIMENT RESULTS AND DISCUSSIONS

The proposed work used rolling ball algorithm for background removal on MIAS images in initial step. Then CLAHE and Unsharp methods are applied on the back ground removed images for optimizing contrast enhancement and this research has compared both and found CLAHE has provided effective image enhancement. The proposed work has performed image segmentation using K-means algorithms on the enhanced images generated by CLAHE and Unsharp. After preprocessing the images using proposed methods, these preprocessed images are provided to deep CNN model for feature extraction and classification. The experimental results of the suggested system are described in this section. The suggested approach is applied to two publicly available datasets, namely MIAS and BCDR. The proposed system performance is evaluated using F-metrics, recall, precision, and accuracy. While accuracy is a commonly used metric to assess classifier performance, it only considers the impact of classes on the total number of instances. In summary, in an unbalanced dataset, classifiers typically exhibit a bias towards the majority class. Therefore, other metrics that are frequently used for classification with imbalanced datasets will also be taken into account for a more thorough analysis as shown in Table 1. These metrics include specificity, sensitivity, precision, F1-score, recall.

Table: 1. Evaluation metrics description

Evaluation metric	To determine	Formula	Preferred value
Accuracy	Overall, how often result is true	TP + TN / T	High (≈1)
True positive rate (TPR) Recall or sensitivity	When it is actually true, how often does it predict true	TP / FN + TP	High (≈1)
Precision	When it predicts true, how often it is correct	TP / FP + TN	High (≈1)
F1-Score	Harmonic mean of precision and recall	2 x precision x TPR / precision + TPR	High (≈1)

where TP, TN, FP and FN are true positives, true negatives, false positives and false negatives respectively. The harmonic mean of the precision and recall is known as the F1-score among those evaluation measures. Within positive predictions, precision is defined as the percentage of accurate positive predictions. Sensitivity, another name for recall, is the true positive rate among the class instances. The term "specificity" refers to the actual negative rate, which can be seen as the classifier's capacity to appropriately reject individuals who are healthy and free of conditions. The trade-off between recall and precision is shown by the F1-score. In the case of imbalanced dataset categorization, the F1-score can offer more insights than accuracy.

This paper compared the two different image enhancement methods with k means segmentation approach for classification of images and the results are presented in Table 2. The Table 2 summarizes the preprocessing by CLAHE exhibited better results than unsharp masking.

TABLE 2. Classification results of CNN using clahe for image enhancement and k-means for segmentation on MIAS dataset.

	CNN Classifier on segmented images with k means	
Image Enhancement Technique used	CLAHE	Unsharp
Precision	0.91	0.82
Recall	0.89	0.83
F1 Score	0.90	0.83
Accuracy	88	82

4. COMPARATIVE ANALYSIS

The proposed method is compared with existing methods [20,21,22,50,15] as shown in Table 7. The S. J. Malebary et al. [20] have not used any preprocessing and used k-means for segmentation and finally RNN approach for classification. The wang et al. [22] used window sliding and adaptive mass region techniques for preprocessing and segmentation respectively and finally used CNN for classification. R. Beeravolu[50] used RB and canny edge detection by employing CNN and sun et al. [15] interestingly not used any preprocessing and segmentation and directly given images to Multiview convolution neural networks.

Authors	Preprocessing approach	Segmentation approach	Breast mass Classification approach	Dataset Used	Total number of images	Accuracy	Sensitivity	Precision	F-measure
S. J. Malebary et al., (2021) [20]	**-**	**K-means**	**Long Short-Term Memory network of Recurrent Neural Network (RNN), CNN, boosting techniques**	**MIAS** **DDSM**	**322 Digital mammogram images** **2620 Digital mammogram images**	**0.95** **0.96**	**0.97** **0.97**	**-**	**0.98** **0.97**
Z. Wang *et al.* (2019) [22]	**Window sliding**	**Adaptive Mass Region Detection**	**Convolution Neural Networks-Extreme Learning Machine**	**Image dataset**	**400 mammogram images**	**86.50**	**85.10**	**-**	**-**
P. E. Jebarani et al., (2021) [21]	**Adaptive Median Filter**	**K-means and GMM**	**-**	**MIAS**	**322 Digital mammogram images**	**95.50**	**-**	**-**	
R. Beeravolu et al., (2021) [50]	**Rolling Ball Algorithm, Huang's Fuzzy Thresholding**	**Canny Edge Detection, Hough's Line Transform**	**Convolution Neural Networks**	**MIAS**	**322 Digital mammogram images**	**-**	**-**	**--**	**-**

Sun et al., (2019) [15]	**-**	**-**	**Muti view Convolution Neural Network**	**MIAS** **DDSM**	**322 Digital mammogram images** **1445 images**	**0.63**	**-**	**-**	**-**
proposed	**Rolling ball with Unsharp**	**K-means**	**Convolution Neural Networks**	**MIAS**	**322 Digital mammogram images**	**82**	**0.83**	**0.82**	**0.83**
	Rolling ball with CLAHE	**K-means**	**Convolution Neural Networks**	**MIAS**	**322 Digital mammogram images**	**88**	**0.89**	**0.91**	**0.90**

Table 7. Comparison of Breast Mass Classification Accuracy (in %) based on combination of preprocessing approach, segmentation approach by various classification methods

The graphical representation of the performance metrics of existing and proposed systems is shown in Figure 8.

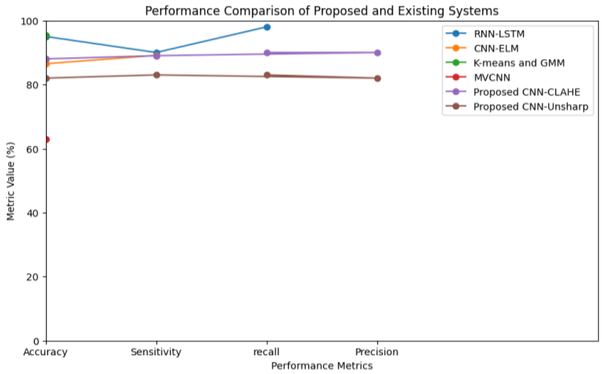

Figure 8. performance metrics comparison of proposed and existing systems.

Discussion

The goal of this work is to address the classification challenge on breast mammography image datasets by investigating ways to improve image quality.

Expanding upon research [21], a K-means and a Gaussian mixture model (GMM) are suggested to acquire more detailed image characteristics, hence exhibiting enhanced efficacy in the classification of benign, normal and malignant tumors. The MIAS dataset was used to assess and validate these benefits.

The impulse noise and speckle were eliminated from the images using an adaptive median filter technique. The region or seed points are effectively divided into several sub-instances using the labeled characteristics of both k-means and GMM in the suggested hybrid technique. Breast tumors are segmented by the K-means and GMM models, which also classify the images into benign, normal, and malignant groups. However, there is not as much of a performance gain in the classification accuracy, which is probably because of the low image quality, because in the adaptive median filter, the median value within variously sized windows for every pixel, it adjusts to the local noise level. Particularly when working with large images, this can take a while and to get a suitable median value in images with extremely high noise density and the filter may need to greatly enlarge the window size. This may result in blurring that resembles the effect of a typical median filter with a large window size, decreasing the filter's ability to preserve edges and fine details. Therefore, to overcome these problems, our suggested model is purposefully made to improve the quality of images on two distinct datasets of mammography images. The rolling ball method was utilized to eliminate uneven lighting and background noise, while CLAHE was employed to improve local contrast. The resulting design is extremely competitive, outperforming other classifiers on various image enhancement techniques in terms of classification performance. Although adaptive median filtering works well for reducing noise, it is not as effective for correcting illumination, handling large-scale artifacts, or background subtraction. Sensitivity and Precision are not considered which is significant to reduce false negative and false positive.

As Fig. 1 shows, the original mammography images which are of low resolution, uneven illumination and also containing noise. The images denoised with rolling ball algorithm displayed in Fig. 2, shows that the situation is significantly better.

We also compared and assessed the contrast enhancement performance of the CLAHE and unsharp methods. This research found CLAHE has outperformed unsharp method.

The proposed work used CLAHE with the tile size 8 x 8 and clip limit 3. This research has shown sharp improvements in the image contrast using CLAHE on denoised images which are generated by rolling ball method and quantitatively demonstrate the improvement in contrast as shown in Fig. 3.

Tables 2 to 6 further demonstrate that the suggested system performs better on both datasets in terms of accuracy, sensitivity, precision, and F-measure.

SHARAF J. MALEBARY et al. [1] achieved a performance improvement of on their CNN-RNN-LSTM model through a k-means data segmentation approach to overcome the drawbacks of ignoring semantic features. The model demonstrated exceptional classification abilities, highlighting the substantial influence of the BMC system's performance. However, there are certain drawbacks in using data segmentation techniques on a dataset. For example, better image enhancement techniques are needed to provide prior segmenting the images and to improve the performance.

Auto encoders are used to extract the features which prone to over fitting. Convolution Neural Network with an Extreme Learning Machine (CNN-ELM) classifier has been employed by the researchers and window sliding method has been used for denoising [22]. They combined morphological, texture, and deep characteristics from image datasets to strategically design. But combining multiple feature types can lead to very high-dimensional data, making the model more complex and potentially leading to overfitting. The suggested method has given classification accuracy of 88% which can be further improved by CNN classifier which is proved in our work. And also, the image quality can be improved further, because the window sliding method used in the research, applies the same processing over overlapping regions, it induces edge distortion or blurriness. This might result in artifacts at the edges and the constant window size requirement may hinder its ability to accommodate different image scales or forms. Therefore, the proposed work has used the rolling ball technique which is specifically made to simulate and remove intricate backdrop structures, whereas the window sliding method might not be as good at capturing the subtle changes in the background.

R. Beeravolu et al. [50] Used Huang’s Fuzzy Thresholding technique and the rolling ball algorithm are to eliminate background from images. Hough's Line Transform with Canny edge detection is used to eliminate pectoral muscle. However the CNN architecture has not been explicitly defined.

Sun et al. [15] has proposed multi-dilated CNNs with varying dilation rates to gather data at different scales. They employed a multi-dilated CNN to categorize mammograms using features taken from the craniocaudal (CC) and mediolateral oblique (MLO) views. Although this can aid in the detection of more extensive contextual features, it also makes the model more complex, which raises the computing costs. Instead, the process of feature extraction can be improved using preprocessing prior classification which has been proved in our proposed model which has achieved classification accuracy, precision, recall and F-measure for MIAS dataset as 0.88%, 0.91%, 0.89% and 0.90% respectively with CNN for BMC comparatively.

CONCLUSION

In this study, the mammography pictures are classified as normal, benign, or malignant using the CNN model. The techniques for image segmentation, image enhancement, and background removal are considered in this approach. Images with noise and artifacts are cleaned up using the "Rolling ball algorithm" during the background removal phase. K-means is the segmentation method utilized to segment the breast region, while the "CLAHE" method is used for image enhancement by raising the contrast level. The performance of the classification techniques has improved with the CLAHE algorithm by improving image contrast. The neural network's performance was enhanced by these previously processed images. It has been demonstrated that, in comparison to other current methods, the suggested method performs better on performance metrics. This intelligent health care paradigm, which solves social issues and helps detect breast cancer in women at an early stage, will revolutionize the medical field.

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