Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 23, Issues 3, pp. 115–127, DOI 10.12694/scpe.v23i3.1992

TRANSFER LEARNING ASSISTED CLASSIFICATION OF ARTEFACTS REMOVED AND CONTRAST IMPROVED DIGITAL MAMMOGRAMS

PARITA OZA*, PAAWAN SHARMA, AND SAMIR PATEL †

Abstract. Mammograms are essential radiological images used to diagnose breast cancer well in advance. However, an accurate diagnosis also depends on the quality of mammogram images. Therefore, removal of artefacts and mammogram enhancement are necessary pre-processing steps. Artefact removal helps exclude unsolicited regions in the mammograms and limits the search for suspicious regions without excessive impact from the background. Mammogram enhancements improve apparent visual details and improve some features of an image. In this paper, we propose a method for mammogram pre-processing. These pre-processed mammograms are then fed into Deep Convolutional Neural Network for the classification process. Two approaches are used and compared to classify mammograms; Training model from scratch and Transfer Learning. Transfer Learning is an excellent approach to dealing with the small-sized training set, allowing us to consume the extendibility of deep learning entirely. By employing VGG16 as a pre-trained network on the pre-processed MIAS dataset, we improved training accuracy (96.14%) compared to the model developed from scratch and other strategies described in the literature.

Key words: Mammogram, Artefacts,Thresholding, CLAHE, Classification, Deep CNN

AMS subject classifications. 68T05

1. Introduction. Among the female population worldwide, breast cancer is the most commonly diagnosed cancer [1, 2]. Breast cancer has become a widespread and significant health issue across Indian cities [3]. In the South-East Asia regions, Breast cancer ranks second as per the number of deaths by cancer site, and region [4]. A study [4] presented to estimate the burden of breast cancer in India using parameters like YLL (years of life lost), YLD (Years of healthy life lost due to disability), and DALY (Disability-adjusted life years) for the years 2016, 2021 and 2026. According to this study, breast cancer would increase total DALYs in India over the years. Hence, there is a need to initiate actions to control this disease in the country. Early detection of breast cancer can improve the chances of survival. A radiologist uses various imaging modalities to detect and diagnose this disease, including mammography, Breast MRI, Ultrasound, etc [5]. Out of all, mammography is the most traditional and successful imaging modality as it uses very low dose X-rays to capture the image and is easily affordable by people [6].

Mammogram pre-processing is an essential initial step for developing computer-aided breast cancer diagnosis. Lots of work have been done to process and analyze mammograms. A significant number of image processing techniques are used for processing mammograms, such as pixel-based transformation, edge-based transformations, and region-based transformation, and this field is still evolving [7]. Though mammography symbolizes a significant technological advancement in breast imaging, many artefacts and other noises are commonly perceived with this imaging modality [8]. Artefacts can be defined as any mammographic density variability. These artefacts may affect the accuracy rates and the inference knowledge capabilities of underlying techniques of breast cancer diagnosis. Hence artefact removal is an essential mammogram pre-processing task.

Sometimes mammograms have poor contrast. A large amount of stress exists on the eyes to achieve an appropriate focus due to poorly contrasted mammograms [9]. In addition, poor contrast may result in misdiagnosis if the breast region appears as almost monotonous grey [10]. This can slow down the learning process of the model.

The fields of Artificial Intelligence (AI), such as Machine Learning (ML) [11], [12] as well Deep Learning (DL), have also achieved tremendous success in various mammogram analysis tasks along with the detection and

*PhD Scholar at Pandit Deendayal Energy University, Gandhinagar, India, Nirma University, Ahmedabad, India
†Pandit Deendayal Energy University, Gandhinagar, India

classification [13] of breast abnormalities. Nowadays, the current research focus is on deep learning approaches due to the availability of a wide range of deep learning networks such as VGGnet [14], AlexNet [15], ResNet [16] etc. The research community of the domain widely adopts all these networks. VGGNet has many learnable parameters, but it is still most successful due to its uniform and simple architecture.

1.1. Research Contribution. The main scope of this paper is to develop a Deep convolutional neural network (Deep CNN) based model that can classify breast abnormalities. This model can serve as a second view tool to assist radiologists. The article also presents mammogram pre-processing techniques to eliminate unwanted mammogram regions and improve the mammogram's visual information contents. The main contribution of the paper is as follows:

- To provide a methodology for artefacts removal from the mammograms
- To perceive the effect of mammogram enhancement techniques
- To examine the power of the transfer learning approach for medical imaging data over CNN architecture implemented from scratch

1.2. Paper Organization. The paper is organized as follows: Section 2 presents existing literature in the domain. The proposed methodology is presented in section 3. Section 4 gives a detailed result analysis followed by conclusion in section 5. Figure 1.1 shows the taxonomy of the paper.

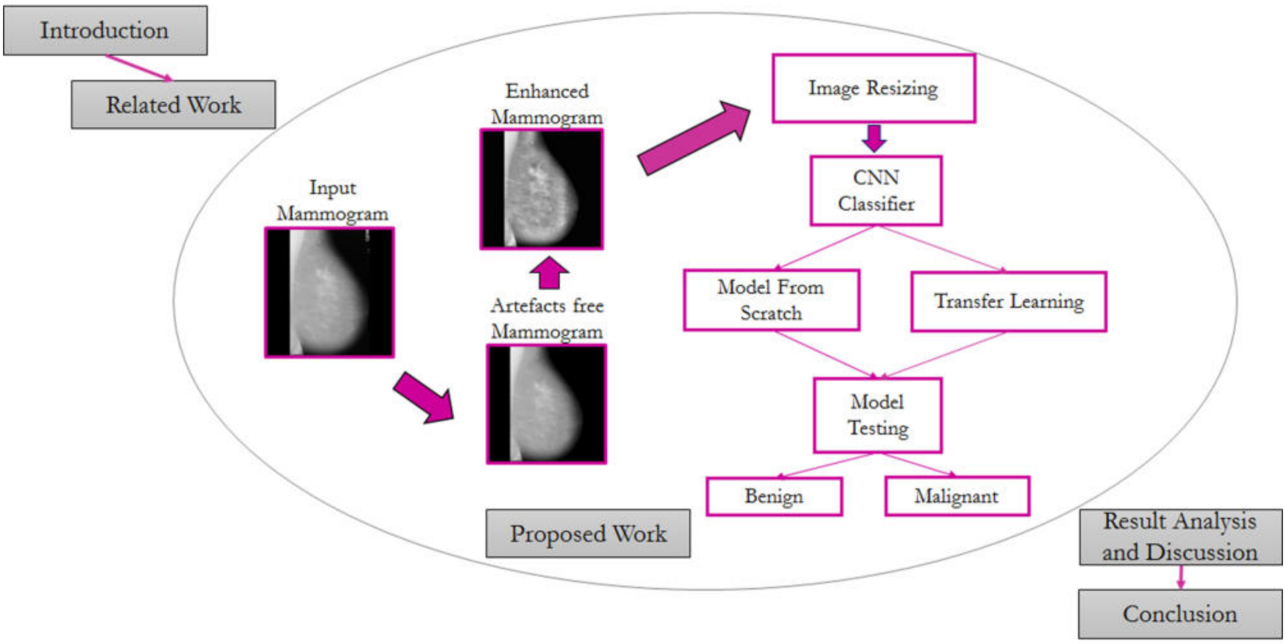


Fig. 1.1: Taxonomy of Paper

2. Previous Work. Deep learning techniques have been widely used in various application fields, including healthcare, personalization, fraud detection, image classification [30], pixel restoration, and many more. Moreover, this technique is also quite successful in various healthcare applications such as classification-Segmentation Pipeline for MRI [31], Retinal Blood Vessel Segmentation [33], abnormality detection, classification from medical images, and mammogram image analysis [34]. Dhivya et al. [17] proposed a model for enhanced tumor classification using pretrained neural network VGG16. The model is evaluated on various benchmark datasets. Authors could achieve an accuracy of 69.85% which was subsequently increased to 88% and 94% by conventional data augmentation and generative adversarial networks, respectively. Filtering techniques and morphological operations were applied on a mammogram as a part of pre-processing. Vaira et al. [6] developed a CNN model with eight convolutional, four max pool layers, and two fully connected layers. The model is compared with pre-trained nets such as AlexNet and VGG16. The proposed model achieved better results. Authors also have applied adaptive histogram equalization to improve the quality of mammograms. Sushreeta and Tripti [18] presented contrast enhancement techniques to detect the breast tumor boundaries from mammograms of the MIAS dataset. Authors have used thresholding and contrast limited adaptive histogram equalization (CLAHE) methods. Results were compared using the contrast improvement index (CII). It is concluded that the thresholding technique encouraged breast enhancement and segmentation results. Arefan et al. [19] presented a method to remove artefacts from a mammogram. Authors applied thresholding to get a binary image followed by connected component labeling to identify connected areas in an image. The largest connected areas in the image are identified, and the other regions are removed. Authors also have removed pectoral muscles from mammograms. Finally, breast tissues are extracted to classify mammograms such as Fatty, Glandular and Dense. Classification accuracy recorded was 97.66% with eight hidden layers neural network. Li et al. [20] presented a benign and malignant classification of a mammogram. Mammograms are pre-processed using zero-mean normalization, and data enhancement is used to prevent overfitting. The authors have modified DenseNet to replace the first convolutional layer with the Inception structure. Then, the pre-processed mammograms are trained and tested on various pre-trained CNN models and altered versions of DenseNet. Modified DenseNet could perform well as compared to other pre-trained models. The proposed work achieves 94% of overall classification accuracy. Another work is presented by Enas, and Nisreen [21] to classify malignant and nonmalignant mammograms. Pre-processing on mammograms was done using image filtration and CLAHE. The authors used two approaches to address the classification problem; using patches of ROI and whole images. The model is tested on different mammogram datasets. A model achieved higher performance on all the datasets.

3. Proposed Work. The focus of the proposed work is to classify breast abnormalities. Deep CNN model such as VGG16 is used as a classifier. The model is tested on the MIAS benchmark dataset. The initial step of the proposed work is to pre-process mammograms, which is a primary task for any medical imaging application. Pre-processing task includes artefact removal and mammogram enhancement. Thresholding transformations are used to remove artefacts such as high and low-intensity labels, markers, scratches, etc. Artefact removal is an essential pre-processing task that can limit the search for abnormal regions in the image without any impact from the background of the mammograms. The quality of mammograms is improved by applying the popular Contrast Limited AHE (CLAHE) method. Mammogram enhancement helps improve the visual quality and some features in the image. Figure 3.1 presents processing flow of proposed model. We present methodology of proposed model using activity diagram in figure 3.2.

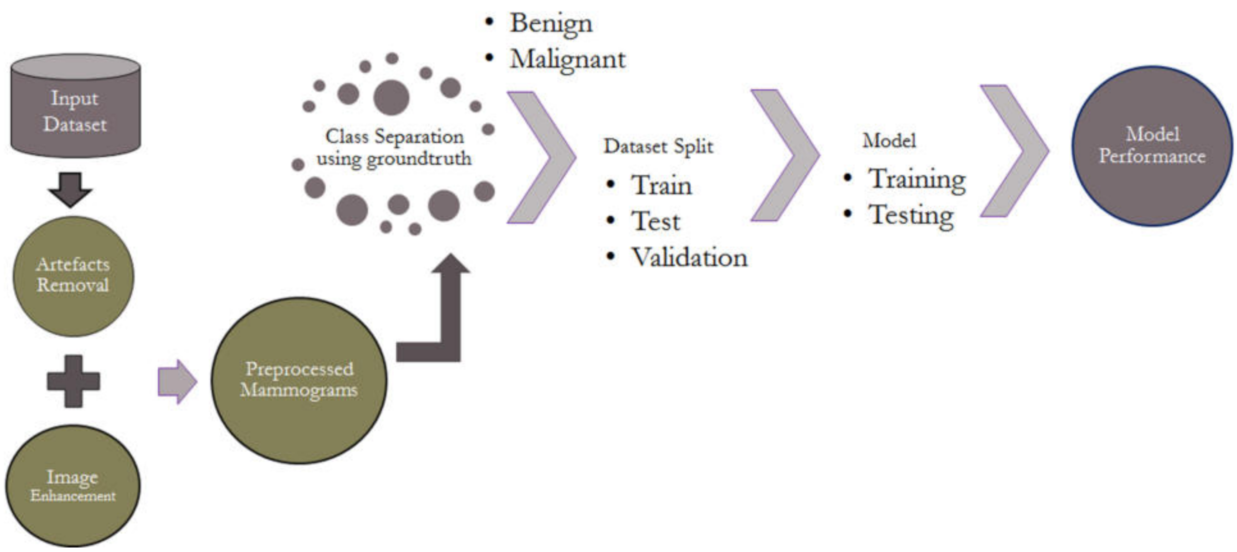


Fig. 3.1: Processing Pipeline of Proposed Model

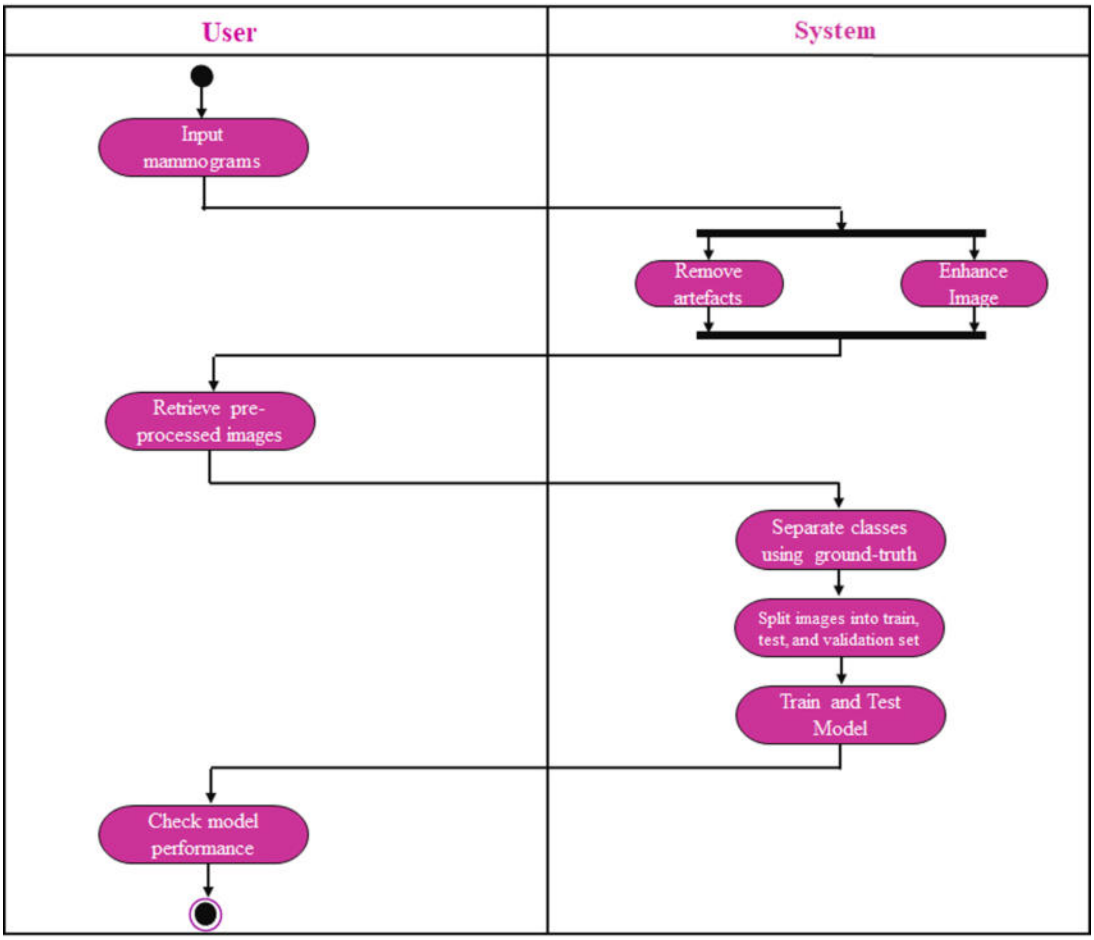


Fig. 3.2: Activity diagram of proposed model

3.1. Material and Methods.

3.1.1. Dataset. An organization of the UK research community, The Mammographic Image Analysis Society (MIAS [22]), has developed a mammogram repository. MIAS is one of the old benchmark mammogram datasets. Due to the dataset's widespread use among academics and researchers studying breast cancer, we employed MIAS in our research. Moreover, in comparison to other datasets like DDSM [27], CBIS-DDSM [28], and INbreast [29], which have very high-resolution images and are also accessible with variable sizes, all the images in the MIAS are the same size, 1024×1024, which will minimize the processing time to a higher extent. The dataset comprises 322 images categorized into three classes; Normal, Benign, and Malignant. Dataset also presents abnormality types such as microcalcifications, architectural distortion, circumscribed masses, speculated masses, ill-defined masses, and bilateral asymmetries. Details of all the images are given in a separate file. Ground truth is available as x, y image coordinates of the center of abnormality and approximate radius (in pixels) of a circle enclosing the abnormality. Table 3.1 shows classification of abnormalities of MIAS dataset.

3.1.2. Mammogram Pre-processing.
Why preprocessing?: Pre-processing is the first and essential step for any detection or classification process. It improves the quality of input data and makes it easier for the classifier to learn patterns and features from the processed information.

Table 3.1: MIAS Dataset

Types of Abnormaly	Total Images
Spiculated Mass	19
Circumscribed Mass	24
Microcalcification	25
Breast Asymmetry	15
Architectural distortion	19
Ill-defined mass	15
Class of Abnormality	**Total Images**
Benign	64
Malignant	51
Normal	207

Common problems with raw mammography images:

- Mammograms come with floating artefacts in the background. The other noise observed in mammograms is low and high-intensity labels, markers, and other tape artefacts.
- Some mammograms come with extra boundaries, which may create ambiguous features in the mammogram that the classifier might learn.
- Mammograms may have poor contrast. Small-sized lesions or calcifications may be obscured by the poor contrast and complex structure of density variations in the breast tissues.
- Low contrast abnormal regions may cause marginal visual threshold between suspicious and normal breast tissues.

Figure 3.3 shows a labeled mammogram with artefacts and other breast tissue.

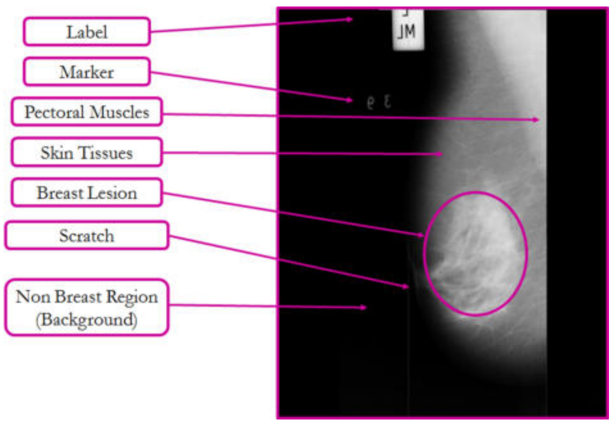


Fig. 3.3: Mammogram with Artefacts and Other Breast Tissues

Artefacts removal from mammograms: Lots of techniques are used to remove artefacts from mammograms. More broadly, these techniques are categorized as Region Segmentation and Edge-based Segmentation. In Edge-based Segmentation, edge pixels are detected and linked to form a contour. Edges do not completely enclose the entire object; it also needs post-processing to link all the detected edges that belong to the same boundary. As compared to edges, regions cover more image pixels; hence, we can have more detailed information to characterize those regions. Further, this region segmentation can be categorized as region-based and thresholding (also known as pixel-based segmentation). Region-based segmentation is an iterative and computationally expensive task. Hence, we have used thresholding transformations to remove artefacts, which is computationally very fast and simple [23],[24]. These methods achieve better results for images with uniform intensity and contrasting backgrounds. We applied two methods of thresholding; Global and OTSU [25]. Global thresholding is manual. This method selects an initial threshold value T to create clusters of classes for extracting the object from the image background. For a given image $f(a,b)$, the thresholded image can be defined by the following equation,

$$G(a,b) = \left\{ \begin{array}{ll} 1, & if(a,b) > T \\ 0, & if(a,b) \leq T \end{array} \right\} \tag{3.1}$$

The output of thresholding transformation is a binary image with a pixel value of 1 (object) and 0 (background).

OTSU is auto thresholding. It separates two clusters by the threshold calculated as an outcome of minimization of the weighted variance of those classes, which can be defined as $\sigma_w^2(t)$. The following equation can describe this computation.

$$\sigma_b^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \tag{3.2}$$

Here $w_1(t)$ and $w_2(t)$ are the class probabilities divided by the threshold T. The initial threshold can be defined in varieties of ways. As per [25] there are two ways; minimize the intra-class variance, $\sigma_w^2(t)$, and maximize the inter-class variance,

$$\sigma_b^2(t) = w_1(t)w_2(t)[\mu_1(t) - \mu_1(t)]^2 \tag{3.3}$$

where μ_i is a mean of class. The methodology adopted to get artefacts free mammograms is shown in algorithm 1.

Algorithm 1: Algorithm 1

Input: Mammograms
Output: Artefacts free mammograms
for *all mammograms* **do**
    `Convert image to grayscale and median blur`
    Function `Thresholding Transformation(`*Grayscaled and Blurred Image*`):`
        Apply thresholding transformation and get the threshold
        Get a binary image with the threshold
        return Binary Image

    Function `Morphological Operations(`*Binary Image*`):`
        Morph close to get a smooth image
        Dilate to enhance contour
        return Smooth Image

    Function `Generating Mask(`*Smooth Image*`):`
        Extract convex regions
        Find the largest convex region and eliminate other components; this largest object is breast contour
        Generate mask using this largest convex region
        return Binary Mask

    `Perform bitwise AND operation between input mammogram and generated mask`

Why should pectoral muscle not be removed while pre-processing mammograms?: In a mammogram, the pectoral muscle looks like a triangular opacity across the upper posterior border of the breast region. Detection and removal of pectoral muscle is per se a research theme with many publications. However, removing the pectoral muscle is medically incorrect as this region might have an abnormality. This argument is supported by figure 3.4 labeled with pectoral muscle and associated abnormality.

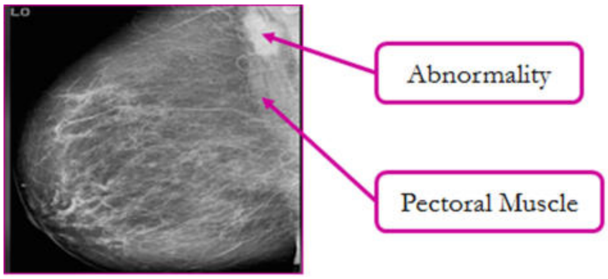


Fig. 3.4: Mammogram with Abnormality in Pectoral Muscle

Mammogram Enhancement: Image enhancement is an essential pre-processing step that allows changing the visual features of an image. A lack of good contrast in an image puts lots of strain on the eyes to get proper focus [9]. Various operations like Histogram Equalization, Image smoothing, Image sharpening, and Greyscale Multiplication are used to improve the contrast of an image. In our work, we used histogram-based methods to get enhanced mammograms. We applied both global histogram and CLAHE on mammograms and recorded the results.

3.1.3. Breast Abnormality Classification. In the last several decades, deep convolution neural networks (DCNNs)-based computer-aided diagnostic (CAD) systems for breast cancer have operated as a decision-making system [32]. Many pre-trained deep CNNs have been utilized in the literature to diagnose breast cancer. All these models, along with their parameter-based comparison, strength, and limitations, are covered in one of our prior works [26]. We used VGG16 as a base architecture to categorize breast anomalies as benign or malignant based on comparisons from our earlier research. The model was first proposed by Simonyan, and Zisserman [14] in 2014. The authors have made this model uniform by using the same kernels throughout the network, consisting of 13 convolutional layers, each with 3×3 filters. The model has 2×2 max pooling layers following every convolutional layer. It is practically demonstrated in a model that multiple small-sized filters can perform better than a single large kernel. This increased network depth can learn more intricate features nicely. To further explore the efficacy of transfer representation learning, we utilized VGG16 in two ways; implementation from scratch and transfer learning. To implement from scratch, we used five blocks (convolutional followed by max pool layer) of VGG16, two fully connected layers of 4096 units followed by one dense softmax layer with two units (to classify mammogram as benign or malignant). RELU activation is used for the dense layer with 4096 units to add non-linearity to the network. The model was trained with 100 epochs and optimized with an Adam optimizer using a learning rate of 0.001. The ”ImageDataGenerator” class of Keras pre-processing is used for loading data. We also used Transfer Learning on VGG16 to deal with a small-sized training set and used pre-trained weights of VGG16 (trained on ImageNet). We created a base model and populated it with pre-trained weights. All the layers in the base model are then frozen by setting trainable = False. A new model is then created on top of the output of the base model. Figure 3.5 presents a process of TL used in our work. We show hyperparameters used to train the models in table 3.2.

The dataset we used (MIAS) has all the images of size 1024×1024. As per the input layer of VGG16, these images are resized to 224×224 before training. We also used the early stopping method from Keras. Early stopping is essential to stop the model's training if there is no improvement in the learning or no increment in the parameters. Therefore, we monitored validation accuracy to do early stopping.

4. Results and Discussion. We used two methods to remove artefacts from mammograms and compared their results; Global thresholding and OTSU Binarization. OTSU binarization is auto thresholding and is

Table 3.2: Hyper Parameters for Training

Hyper Parameters for Model Training	
Epoch	100
Activation Function	RELU
Learning Rate	0.001
Batch Size	64
Optimizer	Adam
Loss Function	Binary Cross Entropy

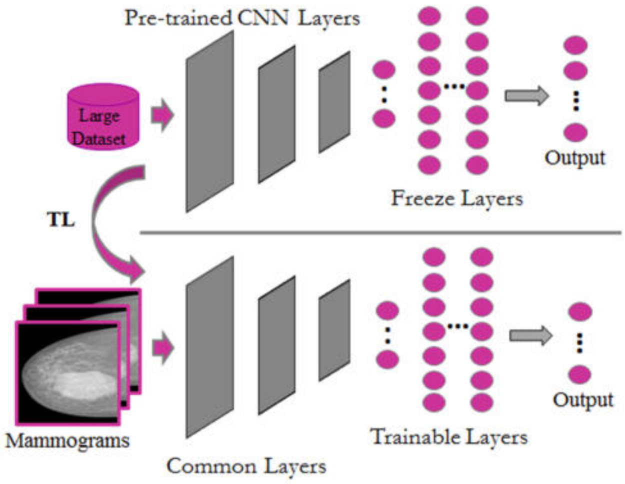


Fig. 3.5: Transfer Learning based training process

usually operated on grayscale images. The technique works by minimizing within-class variance and maximizing between-class variance. OTSU finds a threshold that keeps class clusters as tight as possible. In addition, it tries to reduce the overlap between two class clusters. Figure 4.1 presents the results obtained by OTSU thresholding as per the steps mentioned in the algorithm 1.

Global thresholding is manual, where the initial threshold (T) is selected; it then segments the image using the specified threshold and creates two-pixel groups. Finally, the average of pixels in both groups is computed to find a new threshold. This process repeats till there is no change in the threshold value. Figure 4.2 presents results obtained by Global thresholding as per the steps mentioned in the algorithm 1.

We have compared (see fig. 4.1 and 4.2) these two methods for two images of the MIAS dataset (mdb163 and mdb174) to showcase both the worst case and best case. As can be seen from image 4.1, there is a lot of pixel loss in the final processed image (mdb163) when applied OTSU binarization. On the other hand, from figure 4.2, We can see that global thresholding performs better as far as it concerns pixel loss. The detailed analysis of the thresholding technique is presented in table 4.1.

We applied histogram-based techniques to improve the quality of the mammogram. Figure 4.3 shows the performance comparison of the global histogram and CLAHE. Global histogram can enhance image contrast, but sometimes we may lose important details and features due to over brightness. The reason is that histograms do not restrict to a particular region. CLAHE can do better here; images are divided into small chunks known as "tiles ."Each of these tiles is then histogram equalized. With the help of contrast limiting, for any histogram bin above a specified contrast limit, those pixels will be clipped and scattered uniformly to other bins. Then, histogram equalization is applied. Finally, bilinear interpolation is used to remove artefacts in the borders of tiles. We noticed that over brightness due to global histogram for some images has resulted in the loss

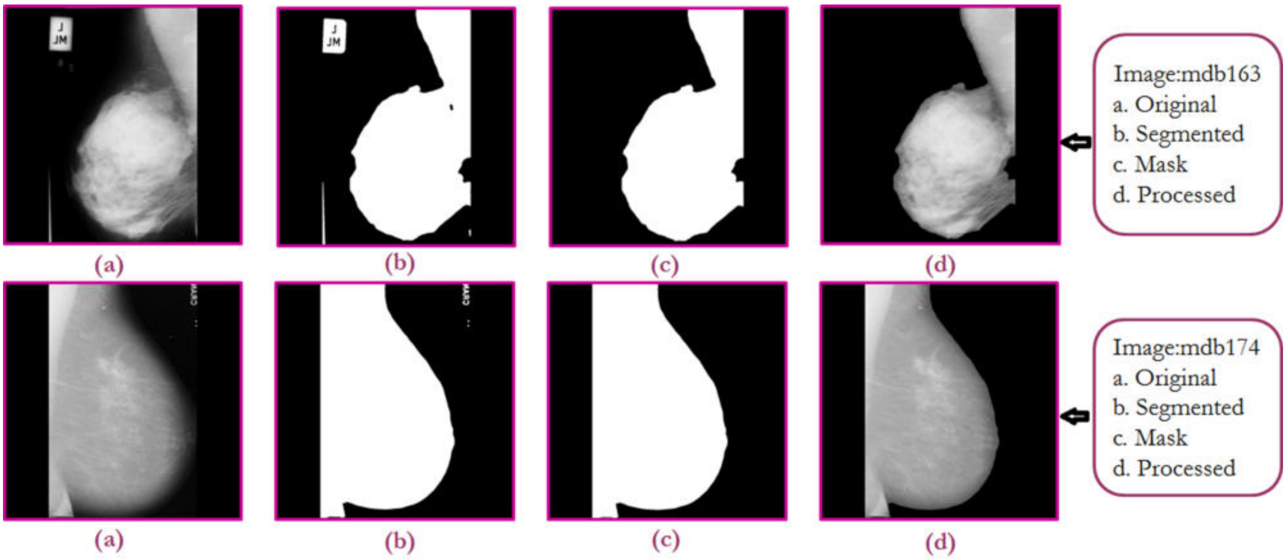


Fig. 4.1: Artefacts removal: OTSU Binarization

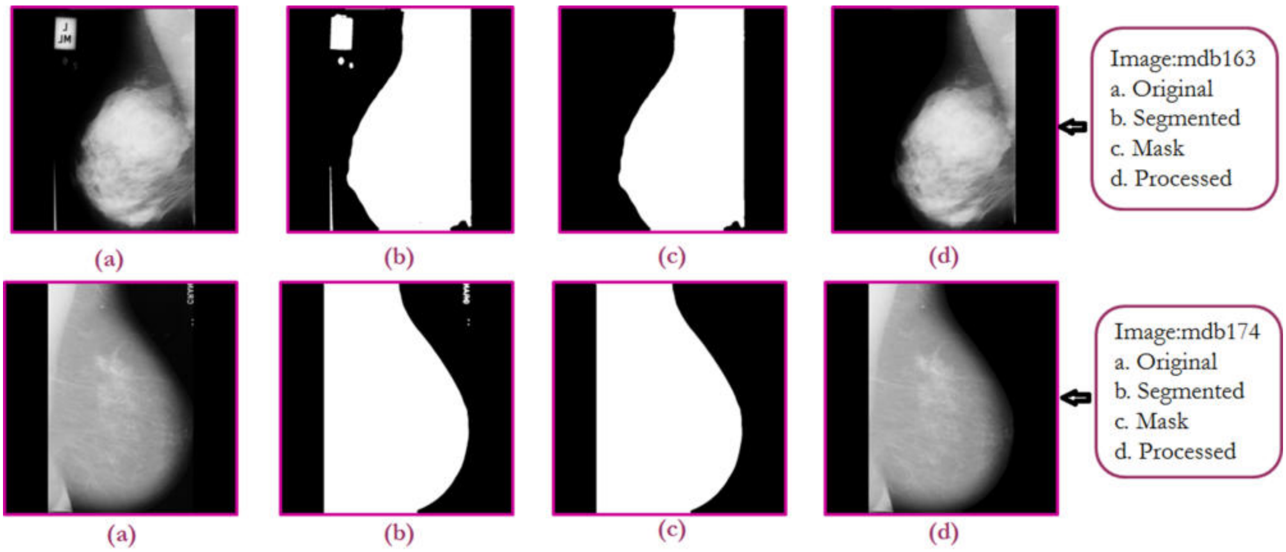


Fig. 4.2: Artefacts removal: Global Thresholding

of scattered benign calcifications. However, these calcifications were very well seen after applying CLAHE to enhance the mammogram.

Finally, these pre-processed mammograms are used to train the models. We have trained two models on the pre-processed MIAS dataset and recorded their results; the first model was built from scratch (based on VGG16 block structure), and the second model was built using Transfer Learning (Using pre-trained VGG-16). We evaluated the two models on the test dataset using precision, recall, sensitivity, specificity, and F1-score as performance indicators. We also provide validation and training accuracy and loss outcomes to clearly understand the model performance. The F1 score reflects the classifier's performance better than the traditional

Table 4.1: Result Analysis: Thresholding Techniques

Method	**Threshold Value**	**Acceptable**	**Unacceptable**
	10	306	16
	15	314	8
	20	317	5
	26	318	4
	28	319	3
	30	321	1
Global	Exceptional Case : mdb274 (T value 69)		
Otsu	-	322	0

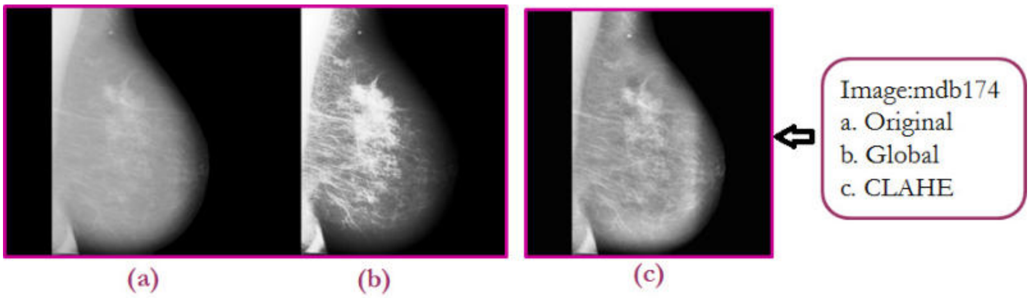


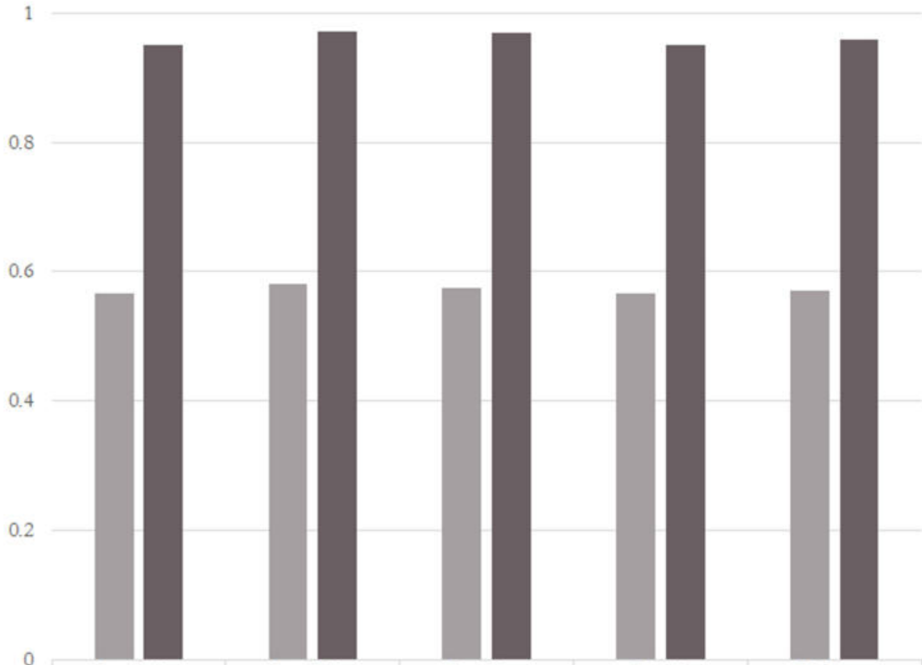
Fig. 4.3: Results: Mammogram Enhancements. (a) Artefact free mammogram (b) shows over brightness as compared to (c).

accuracy metric. We tried to examine the power of the transfer learning approach for medical imaging data over CNN architecture implemented from scratch. The results are presented in figure 4.4 and 4.5 respectively.

It can be seen that the use of transfer learning for the small-sized dataset can indeed help to improve the model performance and also help to mitigate the effect of overfitting. Table 4.2 shows a comparative analysis of methods available in the literature for pre-processing mammograms and abnormality classification with the proposed work. The result indicates that Transfer Learning improves accuracy rates because the model has already learned a lot and trained to find some patterns and features.

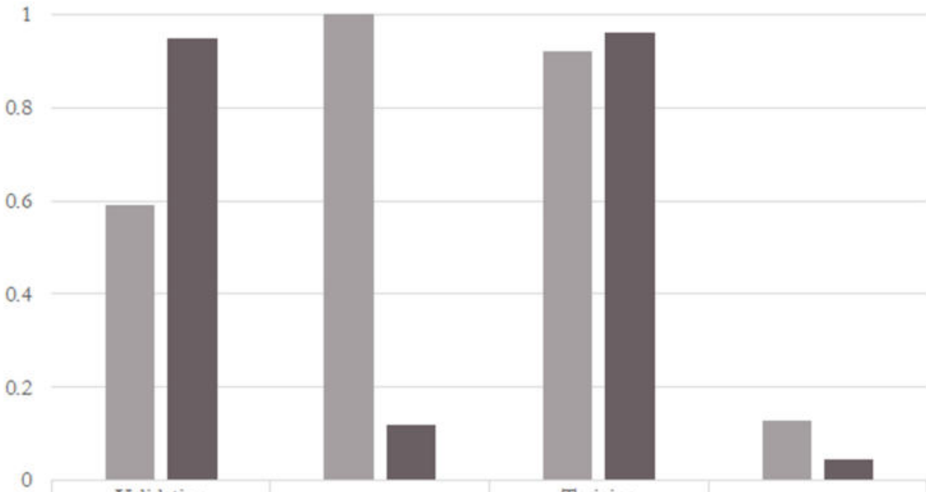
5. Conclusion. Artefacts may affect deep learning techniques' accuracy rates and inference knowledge capabilities. So, having artefact-free mammograms can improve the model's extendibility onto a wide range of datasets. We presented a methodology to pre-process images of MIAS to remove artefacts. First, two thresholding techniques are implemented for image binarization, and their results are compared. Global thresholding could do better if it concerns pixel loss in the image. Next, images of the datasets are enhanced using histogram-based methods. We implemented two techniques; global histogram and CLAHE. CLAHE could properly enhance the mammogram without obscuring small-sized lesions and benign calcifications. This work also presents a CNN-based abnormality classification from mammograms, where the abnormalities are classified as benign and malignant. The model was trained and tested on the pre-processed MIAS images. We used two versions of VGG16 to classify the mammograms, VGG16 trained from scratch and Transfer Learning. Due to a small-sized training set, the first model started to overfit after certain epochs. We achieved better results using Transfer Learning for the performance measures like precision (96.83%), sensitivity (95.11%), specificity (97.09%), recall (95.11%), F1-score (95.96%), and accuracy (96.14%).

Acknowledgements. The authors like to thank Dr. Rajiv Oza (Consultant Radiologist) for providing them with medical advice on radiological imaging techniques.



	Sensitivity	Specificity	Precision	Recall	F1-Score
VGG 16 (From Scratch)	0.5667	0.5812	0.5737	0.5667	0.5701
VGG 16 (TF)	0.9511	0.9709	0.9683	0.9511	0.9596

Fig. 4.4: Model comparison based on various Performance Measures



	Validation Accuracy	Validation Loss	Training Accuracy	Training Loss
VGG-16 (From Scratch)	0.59	1.69	0.92	0.13
VGG-16 (TF)	0.9469	0.1189	0.9614	0.047

Fig. 4.5: Accuracy and Loss measures of the models

Table 4.2: Comparison with other Work

Work	**Pre-processing Technique**	**Model**	**Task Performed**	**Dataset**	**Training Accuracy**
[6]	Adaptive histogram equalization	VGG 16	Mass Classification	MIAS	48.67%
[6]	Adaptive histogram equalization	Proposed CNN	Mass Classification	MIAS	92.54%
[17]	Filter Techniques and Morphological Operations	VGG 16	Mass Classification	MIAS	69.85%
[17]	Filter Techniques and Morphological Operations	VGG 16	Mass Classification	MIAS (Augmented)	94%
Our Work (1)	Thresholding, CLAHE and Morphological Operation	VGG 16 (From Scratch)	Mass Classification	MIAS	92%
Our Work (2)	Thresholding, CLAHE and Morphological Operation	VGG 16 (Transfer Learning)	Mass Classification	MIAS	96.14%

REFERENCES

[1] Bray, Freddie, et al. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians. 68.6 (2018): 394-424.

[2] Viale, Pamela Hallquist. The American Cancer Society's facts & figures: 2020 edition. Journal of the Advanced Practitioner in Oncology. 11.2 (2020): 135.

[3] Mathur, Prashant, et al. Cancer statistics, 2020: report from national cancer registry programme, India. JCO Global Oncology. 6 (2020): 1063-1075.

[4] Kunnavil, Radhika, et al. Estimation of burden of female breast cancer in India for the year 2016, 2021 and 2026 using disability adjusted life years. Int J Community Med Public Health. 3 (2016): 1135-40.

[5] Oza, Parita, et al. A bottom-up review of image analysis methods for suspicious region detection in mammograms. Journal of Imaging. 7.9 (2021): 190.

[6] Gnanasekaran, Vaira Suganthi, et al. Deep learning algorithm for breast masses classification in mammograms. IET Image Processing. 14.12 (2020): 2860-2868.

[7] Bhateja, Vikrant, Mukul Misra, and Shabana Urooj. Non-Linear Enhancement Techniques for Mammograms.Non-Linear Filters for Mammogram Enhancement. Springer, Singapore, 2020. 55-62.

[8] Chaloeykitti, L., M. Muttarak, and K. H. Ng. Artifacts in mammography: ways to identify and overcome them. Singapore medical journal. 47.7 (2006): 634.

[9] Gu, Ke, et al. The analysis of image contrast: From quality assessment to automatic enhancement. IEEE transactions on cybernetics. 46.1 (2015): 284-297.

[10] Moradmand, Hajar, et al. Comparing the performance of image enhancement methods to detect microcalcification clusters in digital mammography. Iranian journal of cancer prevention. 5.2 (2012): 61.

[11] Pillai, Rohan, Parita Oza, and Priyanka Sharma. Review of machine learning techniques in health care. Proceedings of ICRIC 2019. Springer, Cham, 2020. 103-111.

[12] Oza, Parita, Paawan Sharma, and Samir Patel. Machine learning applications for computer-aided medical diagnostics. Proceedings of Second International Conference on Computing, Communications, and Cyber-Security. Springer, Singapore, 2021.

[13] Oza, Parita, Yash Shah, and Marsha Vegda. A Comprehensive Study of Mammogram Classification Techniques. Tracking and Preventing Diseases with Artificial Intelligence. Springer, Cham, 2022. 217-238.

[14] Simonyan, Karen, and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint. arXiv:1409.1556 (2014).

[15] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems. 25 (2012).

[16] He, Kaiming, et al. Deep residual learning for image recognition. Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

[17] Dhivya, S., et al. GAN based Data Augmentation for Enhanced Tumor Classification. 2020 4th International Conference on Computer, Communication and Signal Processing (ICCCSP). IEEE, 2020.

[18] Tripathy, Sushreeta, and Tripti Swarnkar. Unified preprocessing and enhancement technique for mammogram images. Procedia Computer Science. 167 (2020): 285-292.

[19] Arefan, D., et al. Automatic breast density classification using neural network. Journal of Instrumentation. 10.12 (2015): T12002.

[20] Li, Hua, et al. Benign and malignant classification of mammogram images based on deep learning. Biomedical Signal

Processing and Control. 51 (2019): 347-354.

[21] El Houby, Enas MF, and Nisreen IR Yassin. Malignant and nonmalignant classification of breast lesions in mammograms using convolutional neural networks. Biomedical Signal Processing and Control. 70 (2021): 102954.

[22] Suckling, J., et al. Mammographic Image Analysis Society (MIAS) database.v1.21 [Dataset]. (2015) https://www.repository.cam.ac.uk/handle/1810/250394

[23] Bhateja, Vikrant, Mukul Misra, and Shabana Urooj. Non-Linear Enhancement Techniques for Mammograms. Non-Linear Filters for Mammogram Enhancement. Springer, Singapore, 2020. 55-62.

[24] Al-Bayati, Moumena, and Ali El-Zaart. Mammogram images thresholding for breast cancer detection using different thresholding methods. Scientific Research Publishing. (2013).

[25] Otsu, Nobuyuki. A threshold selection method from gray-level histograms. IEEE transactions on systems, man, and cybernetics. 9.1 (1979): 62-66.

[26] Oza, Parita, et al. Deep convolutional neural networks for computer-aided breast cancer diagnostic: a survey. Neural Computing and Applications. (2022): 1-22.

[27] M. Heath, K. Bowyer, D. Kopans, P. Kegelmeyer, R. Moore, K. Chang, and S. Munishkumaran, "Current status of the digital database for screening mammography," in Digital mammography, pp. 457–460 , Springer, 1998.

[28] R. S. Lee, F. Gimenez, A. Hoogi, K. K. Miyake, M. Gorovoy, and D. L. Rubin, "A curated mammography data set for use in computer-aided detection and diagnosis research," Scientific data, vol. 4, no. 1, pp. 1–9, 2017.

[29] I. C. Moreira, I. Amaral, I. Domingues, A. Cardoso, M. J. Cardoso, and J. S. Cardoso, "Inbreast: toward a full-field digital mammographic database," Academic radiology, vol. 19, no. 2, pp. 236–248, 2012.

[30] Leppioja, Markus, Pasi Luukka, and Christoph Lohrmann. "Image based classification of shipments using transfer learning." In KNOWCON, pp. 37-44. 2021.

[31] Duong-Trung, Nghia, Dung Ngoc Le Ha, and Hiep Xuan Huynh. "Classification-Segmentation Pipeline for MRI via Transfer Learning and Residual Networks." In RICE, pp. 39-43. 2021.

[32] Oza, P., Sharma, P., Patel, S. (2022). A Drive Through Computer-Aided Diagnosis of Breast Cancer: A Comprehensive Study of Clinical and Technical Aspects. In:Recent Innovations in Computing. Lecture Notes in Electrical Engineering, vol 832. Springer, Singapore. https://doi.org/10.1007/978-981-16-8248-3_19

[33] Li, Ming, Qingbo Yin, and Mingyu Lu. "Retinal blood vessel segmentation based on multi-scale deep learning." In 2018 Federated Conference on Computer Science and Information Systems (FedCSIS), pp. 1-7. IEEE, 2018.

[34] Oza, P.; Sharma, P.; Patel, S.; Adedoyin, F.; Bruno, A. Image Augmentation Techniques for Mammogram Analysis, J. Imaging 2022, 8, 141. https://doi.org/10.3390/jimaging8050141

Edited by: Luciano Caroprese
Received: Apr 5, 2022
Accepted: Aug 31, 2022