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Transfer Learning with AlexNet and SqueezeNet for Enhanced Mammography Image Classification

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Abstract: Breast cancer is a leading cause of death among women worldwide. Early detection and appropriate treatment can significantly reduce death rates. The ability of Deep Convolutional Neural Networks (DCNNs) to achieve state-of-the-art accuracy in image classification tasks has made them a popular choice for researchers in disease diagnosis. This paper aims to use two different DCNN architectures, AlexNet and SqueezeNet, to classify mammography images using a transfer learning approach. It also highlights the impact of preprocessing of images and optimizer selection (ADAM: Adaptive Moment Estimation, SGDM: Stochastic Gradient Descent with Momentum) on identifying intricate features from mammography images, thereby improving classification accuracy. From the achieved simulation results, the combination of AlexNet with ADAM was found to perform better, with a classification accuracy of 84%, compared to other combinations such as AlexNet+SGDM (80%), SqueezeNet+ADAM(80%), and SqueezeNet+SGDM (71%). Various machine learning performance measures were evaluated and compared with existing research targeting similar problems with DCNNs. Overall, the use of DCNNs with more optimal hyperparameter values shows promise for further improvement in classification accuracy.

Keywords: *Breast Cancer (BC), Deep Learning (DL), Machine Learning (ML),Convolutional Neural Network (CNN), Transfer Learning (TL), Adaptive Moment Estimation (ADAM), Stochastic Gradient Descent with Momentum (SGDM)*

1. Introduction

Breast cancer (BC) is the most frequently diagnosed cancer among women globally, accounting for nearly one in four cancer cases, as highlighted in the Global Cancer Observatory (GLOBOCAN,2020) [1]. Detecting BC at an early stage and providing timely treatment can significantly enhance survival rates [2]. Digital mammography is widely considered as the most reliable and effective method for early detection, frequently used by radiologists [3]. However, challenges such as low-contrast mammogram images and differences in radiologists' expertise can lead to varying interpretations [4]. In recent years, Deep Convolutional Neural Networks (DCNNs) have emerged as a leading machine learning (ML) technology, excelling in computer vision and pattern recognition tasks. Their remarkable success has driven their adoption in medical imaging for disease diagnosis and prognosis. Depending on data availability, DCNNs can be utilized through scratch learning (SL) or transfer learning (TL) techniques. TL is particularly advantageous in scenarios where large datasets are unavailable, as it uses pretrained models to effectively adapt to task-specific challenges. This approach has proven highly efficient in achieving reliable diagnostic results for medical imaging applications. Some of the most relevant works pertaining to the proposed work are described here.

Al-masni et al. demonstrated the effectiveness of customized CNNs in distinguishing between benign and malignant mammograms. By combining preprocessing steps with fine-tuning strategies, they achieved notable classification accuracy, emphasizing the role of deep learning in mammographic analysis [5]. Ayan et al. employed pretrained models such as VGG16 and ResNet50 using TL techniques, which significantly improved performance, particularly for datasets with limited size [6].

.In 2019, Arevalo et al. created a deep learning-based model for mammogram analysis, focusing on learning both detailed and abstract features. Their system effectively addressed variability in mammogram interpretation among radiologists [7]. Similarly, Saha et al. investigated AlexNet with TL, incorporating hyperparameter optimization and data augmentation techniques to enhance classification accuracy [8]. Ragab et al. explored the integration of CNN- based deep learning with handcrafted features for breast cancer detection. Their hybrid approach improved diagnostic precision, combining traditional image analysis techniques with modern deep learning [9].

This paper aims to perform mammography image

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classification (MIC) with two different pretrained CNN architectures, namely AlexNet [10] and SqueezeNet [11]. The application of TL has been
applied to the pretrained models by customizing their architectures according to the problem of interest. DCNNs are trained and tested with open source Mini-DDSM (Digital Sataset for Screening Mammography) dataset [12]. The dataset contains mammography images of three different image categories: Normal, Malignant, Benign. The image enhancement algorithm has been applied to the raw mammogram to enhance the image quality. The preprocessed images are supplied to the modified AlexNet and Squeezenet architecture for network training. The final layers of the AlexNet and SqueezeNet are modified and required hyperparameter values are initialized before networks are trained. The trained model is evaluated by classification report consisting of different ML performance measures.The process workflow of MIC system is shown in the Fig. 1

FIGURE. 1: WORKFLOW OF MAMMOGRAPHY IMAGE CLASSIFICATION SYSTEM

2. Proposed Methodology

The proposed methodology used end to end CNN approach where CNNs are not only used as feature extractors from mammograms but also used as the classifer. The mammpgraphy images are preprocessed with steps such as: image resizing, image enhancement using Contrast Stretching & data augmentation. The methodological steps involved in the process workflow is described below.

2.1 Dataset:

The proposed work used Mini-DDSM [14] with three different image categories. The sample distribution considered for model training is shown in TABLE 1.

TABLE 1 Mini-DDSM Dataset image samples

Image Categories	Total Training Samples	Total Testing Samples
Normal	1964	1937 (Randomly selected)
Benign	2419	
Cancer	2589	

2.2. Image Preprocessing:

The different preprocessing steps applied to mammography images are described below.

2.2.1 Resizing of Mammography Images: The mammography image samples are resized to 227x227x3 to suit the input dimensions required by AlexNet and SqeezeNet.

2.2.2 Contrast Enhancement: The contrast stretching algorithm is applied to mammography images for contrast enhancement [13]. The algorithm is shown in Fig 2. Where the input image is rescled between o to maximum pixel intensity value of L.

2.2.3 Data Augmentation: To increase the number of images the augmentation by random rotation technique is applied on the resized and enhanced images.

2.3. Pre-trained CNN models:

DCNN, consists of multiple layers such as Convolutional layer (to perform convolution operation between input image and filter), Pooling Layer (to reduce the spatial dimensions of the feature map created after convolution operation) and fully connected layer (to perform the classification score). The pretrained models utilized here for the MIC include AlexNet and Squeezenet. The AlexNet comprises of five convolutional layers for extracting spatial and feature-based information and three fully connected layers for classification. The final layer uses a softmax function to predict output probabilities. The AlexNet uses Rectification Linear Unit (ReLU) activations for faster training, dropout to mitigate overfitting, and overlapping max-pooling for better feature retention. It processes RGB images of size 227x227 and is designed for largescale image datasets like ImageNet. Squeezenet is a lightweight neural network that achieves accuracy comparable to AlexNet while drastically reducing the number of parameters. It starts with a standalone convolutional layer (conv1), followed by eight Fire modules (Fire2 to Fire9). Each Fire module consists of a squeeze layer, which uses 1x1 convolutions to compress input channels, and an expand layer, which uses both 1x1 and 3x3 convolutions to process features. The model concludes with a final convolutional layer (conv10) for classification. By optimizing parameter efficiency, SqueezeNet uses approximately 50 times fewer parameters than AlexNet, making it ideal for resource-constrained environments.

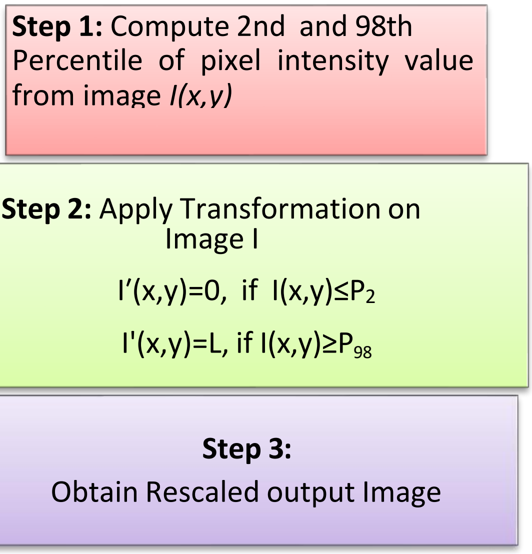

Figure. 2: contrast stretching algorithm

2.4. Layer customization with Transfer Learning approach:

The CNN architectures used in the proposed work are intended to be used in end to end way, where they not only extract the features from the mammography images but also perform classification for the prediction of categories that an image belongs to. Since the pretrained models are assumed to initialize with Imagenet weights, the final layers are customized and network hyperparameters are selected with appropriate values in the MIC. The layer customization and hyperparameter selection are elaborated in the next section. After the necessary amendments in the network architecture, the final layers are trained with training mammography image samples to obtain the trained model to predict the final class of mammography image (Normal, Benign or Malignant). In the proposed work, the network ability has been examined with unbalanced dataset with unequal distribution of training samples in mammography images of each class. The impact of ADAM & SGDM optimizers is also observed in evaluating the model efficacy in terms of machine learning performance measures.

3.1 Mammography Image Preprocessing: As described in the previous section the effect of preprocessing steps such as image resizing and contrast stretching algorithm for image enhancement is shown in Fig 3 where the first row shows the raw mammography images of each class with different sizes and the second row shows the images after resizing and contrast stretching algorithm is applied on the. The data augmentation techniques such as random rotation, X-axis reflection, and random translation is employed to enhance the robustness and generalization of the proposed model. The mammography images are subjected to random rotations within the range of 0 to 360 degrees to ensure the model's invariance to orientation, which is particularly important for medical imaging data where abnormalities can appear at arbitrary angles. Additionally, X-axis reflections were applied to introduce symmetry, enabling the model to effectively learn from mirrored variations of the input data. Furthermore, random translations along the X and Y axes within a range of [-30, 30] pixels were utilized to simulate positional variability. The application of data augmentation techniques is visulalized in Fig 4.

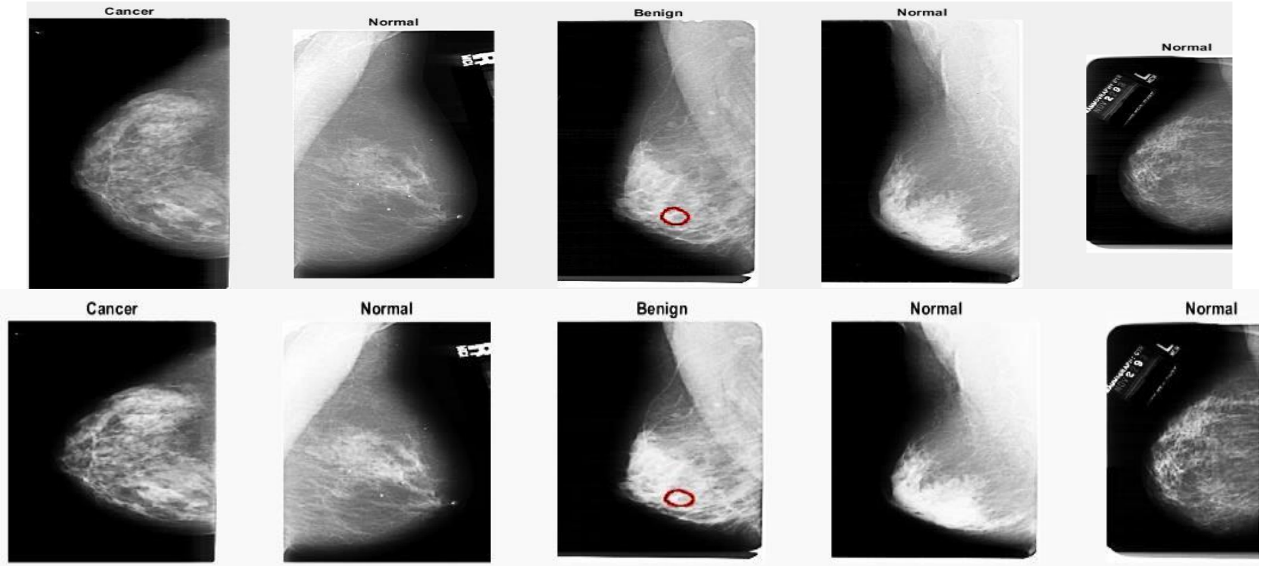

Fig. 3: Image enhancement with contrast stretching

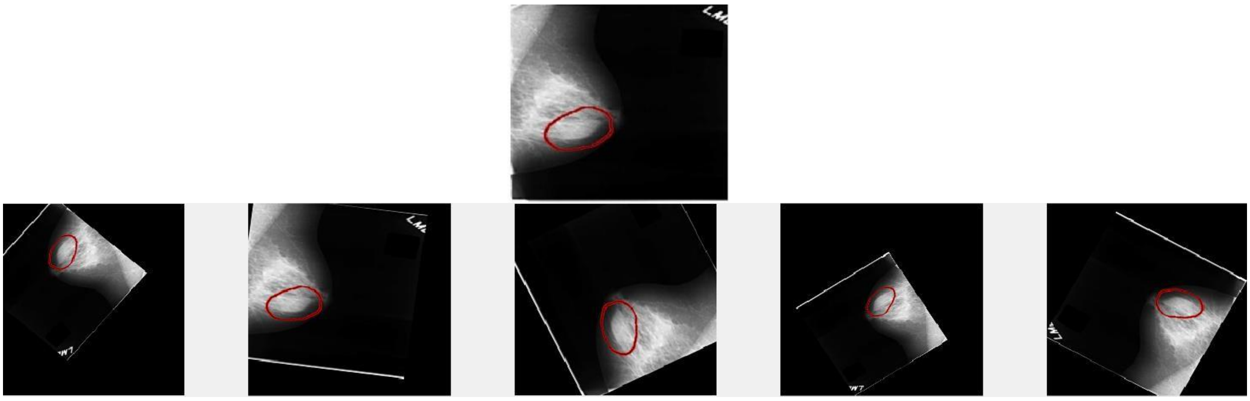

Figure 4: data augmentation results with random rotation at angles between [0 360]

3. RESULTS

This section demonstrates the associated results with each step involved in MIC.

To train the pretrained models, the required changes are made in the network architecture and hyperparameter values. As shown in table 2, the pretrained models are customized by making the necessary changes in final layers of the network and hyperparameter values such as learning rate, batch size, epochs etc.

TABLE 2: The network customization and hyperparameter values

Type of Pretrained Model	**Solver Used**	**New Layers after layer transfer**	**New Layers parameters**
Alexnet	ADAM SGDM	New Fully connected Layer New Softmax Layer New Classification Layer	Number of new classes=3 Weight Learn Rate Factor=20, Bias Learn Rate Factor=20 Learning rate=0.0001 Batch size=128 Epochs=10 Total iterations=540 Validation frequency=50 iterations Environment=Single GPU
Squeezenet	ADAM SGDM	New Conv Layer New Classificaton Layer	

3.2 Evaluation of Performance Measures: The amendments in final layers of pretrained models and hyperparameter values chosen are illustrated in Table 2. After these amendments and hyperparameter value settings, both pretrained DCNNs are retrained with preprocessed mammography images training samples. Once training is performed, the evaluation of each trained model is performed by examining the machine learning performance measures such as (TP (True Positive), TN (True Negative), FP (False Positive), FN (False Negative), accuracy=(TP+TN)/(TP+TN+FP+FN),precision=TP/(TP+ FP), True positive rate (TPR)/Recall=TP/TP+FN, False Positive rate (FPR), F1-score=2* (Precision*Recall/Precision+Recall)). Table 3 shows the obtained machine learning performance measures when a trained model is subjected to unforeseen mammography image from testing samples.

TABLE 3: Performances metrices summary obtained with mini-ddsm dataset

Pretrained Model	Optimizer	TPR	Precision	Accuracy	F1-Score
AlexNet	ADAM	0.77	0.77	0.84	0.76
AlexNet	SGDM	0.70	0.71	0.80	0.71
SqueezeNet	ADAM	0.70	0.70	0.80	0.70
SqueezeNet	SGDM	0.57	0.59	0.71	0.56

3.3 Confusion Matrix: The confusion matrix and AUC are fundamental tools for evaluating the performance of MIC models, especially for detecting BC. Figure 5,6,7 and 8 shows the confusion matrix for the model combination of AlexNet+ADAM, Alexnet+SGDM, SqueezeNet+ADAM, and SqueezeNet+SGDM respectively.

FIGURE. 5: CONFUSION MATRIX: ALEXNET+ADAM

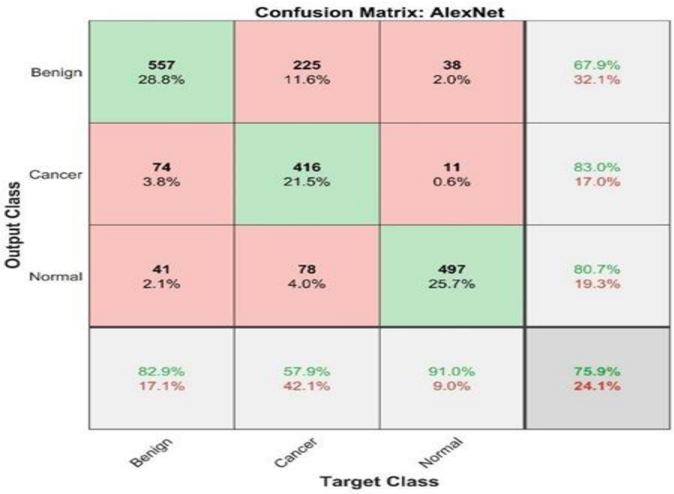

FIGURE 6: CONFUSION MATRIX: ALEXNET+SGDM

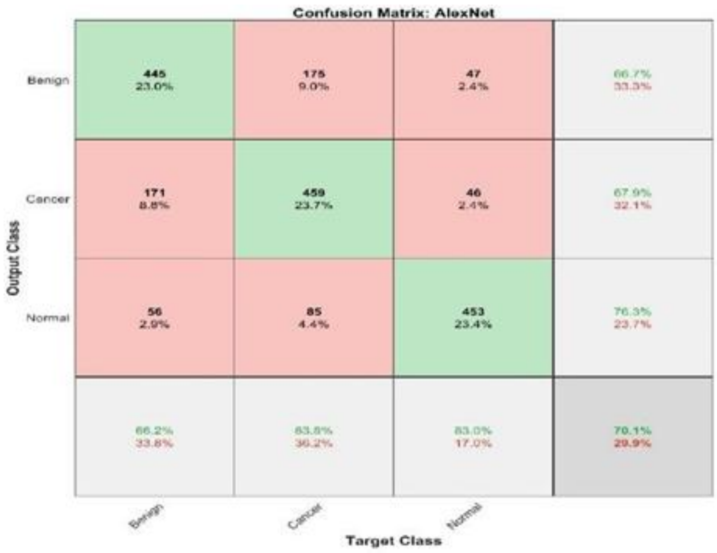

FIGURE. 7: CONFUSION MATRIX: SQUEEZENET+ADAM

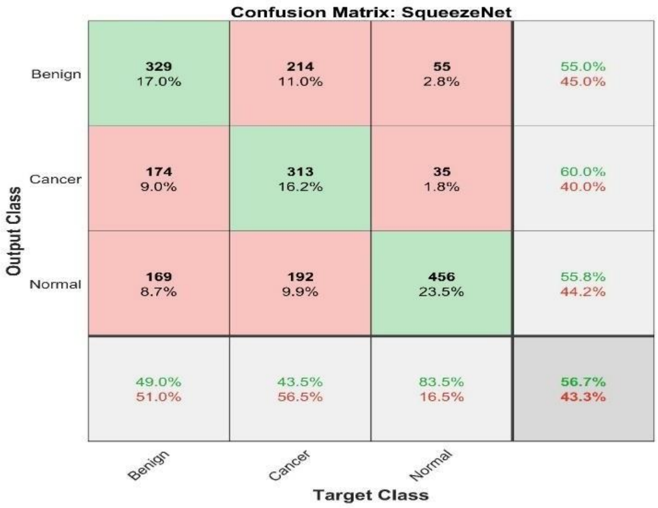

FIGURE. 8: CONFUSION MATRIX: SQUEEZENET+SGDM

4. CONCLUSION:

The proposed work highlights the use of AlexNet and SqueezeNet in MIC. The combination of AlexNet with the ADAM optimizer performs better than other combinations, achieving an overall classification accuracy of 84%. SqueezeNet, with lower MIC accuracy, shows the potential for further improvement through adjustments in model hyperparameters to achieve more accurate results. Being lightweight in structure, SqueezeNet can be an impactful choice for optimizing memory load on hardware resources and reducing training time. The selection of an appropriate image preprocessing algorithm can also improve network performance in accurately classifying mammographic masses. A balanced dataset should always be the preferred choice when training a CNN with any imaging modality, as it enables the model to learn intricate features more effectively compared to an unbalanced dataset, as used in the proposed method

Conflicts of interest

The authors declare no conflicts of interest.

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