Detection and classification of breast cancer types using VGG16 and ResNet50 deep learning techniques

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ABSTRACT

Breast cancer has become a major worldwide health issue, accounting for a large portion of the mortality rate among women. As a result, the need for early detection techniques to enhance prognosis is increasing. Many techniques are being used to detect breast cancer early, and treatment outcomes are frequently favorable when the disease is detected early. Mammography is a commonly used and very successful method for identifying breast cancer among these modalities. Through additional image processing operations like resizing and normalizing, this technology allows the detection of malignant spots from mammography pictures of the affected area. The goal of our research is to improve breast cancer detection and diagnosis speed and accuracy. In this study, we investigate the use of deep learning methods, particularly the visual geometry group (VGG16) and ResNet50 models, for mammography-based breast cancer detection. We assess the performance of the VGG16 and ResNet50 models by training and testing on a mammogram dataset that consists of 322 images from the mammographic image analysis society (MIAS) dataset. The suggested models aim to classify these images into normal, benign, and malignant groupings. Our results show better performance when compared to existing approaches. The proposed methods VGG16 and ResNet50 show promising results, achieving a classification accuracy of 91.23% and 99.01% respectively.

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1. INTRODUCTION

Breast cancer is a serious health issue in women worldwide and it causes high mortality. Cells inside the breast grow in an unrestricted manner which leads to a tumor mass. Due to abnormal lumps in breast, the size of breast increases and change in skin thickness can be observed. Research showed approaches using mammogram images to a quiet extent rendered early detection and it improves survival rate. Some risk factors that increase the cause of breast cancer are consumption of alcohol, shortage of exercise, reproducing history, obesity, dense breast, and genetic factors. Early-stage detection of breast cancer can increase many lives [1], [2]. Mammography is one of the efficient image techniques to detect tumor mass in the premature stage.

Lobular carcinoma in situ is a type of benign cancer that grows in milk glands. A malignant tumor called invasive lobular carcinoma starts in the lobules and spreads to the tissues around them. This kind of cancer affects 10% to 15% of the population. Ductal carcinoma in situ is a precancerous stage that starts in milk ducts and does not invade surrounding tissues [3], [4]. Invasive ductal carcinoma is a malignant cancer that grows in lactiferous ducts and spreads in fibrous tissue of ducts. In this paper, we have implemented a pre-trained deep neural network classifier based on the VGG16 and ResNet50 models for breast cancer classification [5].

Our approach involved amalgamating mammogram breast images from Kaggle repository to assess the network's generalization ability comprehensively. The classifier was meticulously trained, validated, and tested, with parameter tuning aimed at achieving superior performance. Ultimately, we compared our findings with those of related state-of-the-art studies to evaluate the efficacy of our approach. The major contributions of the research are as follows: i) innovative classification approach: presenting a new utilization of the VGG16 and ResNet50 model to classify various forms of breast cancer using mammogram images, and ii) elevated precision and productivity: Illustrating heightened accuracy in detecting and classifying breast cancer in contrast to conventional methodologies.

Hameed *et al.* [6] introduces an ensemble deep learning method designed to accurately classify histopathology images of non-carcinoma and carcinoma breast cancer, utilizing a dataset curated by the authors. The researchers developed four distinct models employing pre-trained VGG16 and VGG19 architectures. By combining the fine-tuned VGG16 and VGG19 models, the ensemble achieved a carcinoma sensitivity of 97.73% and an overall accuracy of 95.29%. Furthermore, it yielded an F1-score of 95.29% Seemendra *et al.* [7] conducted experiments using the VGG, ResNet, DenseNet, MobileNet, and EfficientNet designs to determine the best configuration. The most favorable result achieved was by optimizing the VGG19 architecture in conjunction with careful image enhancement. The precision and sensitivity of this method were 94.46% and 93.05%, respectively. Cruz *et al.* [8] assessed the effectiveness of the VGG16 and VGG19 convolutional neural network architectures for the classification of breast density in three different scenarios. For analysis, the authors used a portion of the ABC-digital mammography dataset. VGG16 attained accuracies of 93.33% and 90.00% for two-class and four-class classification, respectively. Behar and Shrivastava [9] presented a robust convolutional neural network (CNN) model leveraging transfer learning for automatic classification of histopathology images into malignant and benign tumor categories. Kumar *et al.* [10] aims to define and predict labels for breast cancer classes. Regions of mass are detected by the ResNet50, which then classifies them as invasive, triple negative, ductal carcinoma, or inflammatory cancer. A dataset related to breast cancer is used for experimentation, and 90.6% accuracy in classification and prediction is obtained. Elkorany *et al.* [11] examine the performance of three different CNN models for deep learning (DL) as feature extractors: Inception-V3, ResNet50, and AlexNet. Term variance (TV) feature selection algorithm is used in this method to extract useful features from each CNN model. The performance of the average classification accuracy (CA) is noteworthy. More specifically, the CA reaches 91.81% for 70% of the training data. For 80% of the training data, this accuracy increases to 96%, and for 90% of the training data, it reaches its ideal value. Hekal *et al.* [12] presented a new computer-aided detection (CAD) and classification system intended to identify and categorize mammography cancers as either benign or malignant based on their difference between two types: mass and calcification. Tumor-like regions (TLRs) in this CAD system are detected by use of the automated optimal Otsu thresholding technique. Deep convolutional neural networks (DCNNs) next analyze the retrieved TLRs to extract relevant mammography features, the suggested CAD system classifies areas of interest (ROIs) into one of the four classes with an accuracy of 0.91. Goncalves *et al.* [13] developed three state-of-the-art CNN models (VGG-16, DenseNet201, and ResNet50) to categorize static thermography images into categories for the sick and well, using transfer learning. These experiments yield excellent results, with the DenseNet model performing at the best level. DenseNet model trained on 38 static images for each class and obtain an F1-score of 0.92, accuracy of 91.67%, 100% sensitivity, and 83.3% specificity.

2. PROPOSED METHOD

This study aims to create a classification framework to discern various types of breast cancer utilizing VGG16, and ResNet50 architectures. The system is designed to identify tumor cells present in the mammogram. The training dataset comprises 70% images, while 30% images are reserved for testing. The procedural steps entail dataset collection, preprocessing and training of the VGG16, and ResNet50, followed by testing with diverse normal and abnormal cells [14]. The overall flow of proposed method is shown in Figure 1.

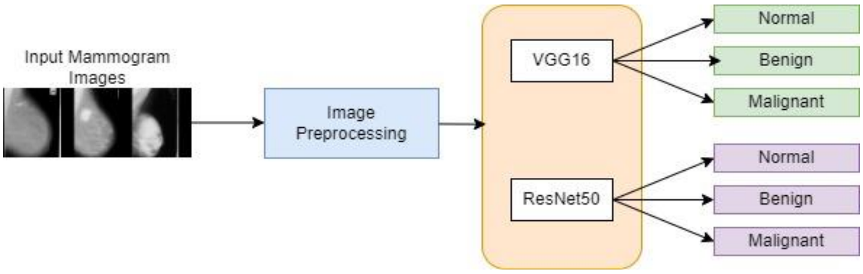

Figure 1. Block diagram of proposed model for Breast cancer (BC) classification using deep learning

2.1. Image preprocessing

Resizing and normalizing breast mammogram images is a critical preprocessing step for many medical image analysis tasks. Smaller images require less computational power and memory to process. By resizing images to an optimal size, processing tasks such as filtering, feature extraction, and object detection can be performed more quickly and efficiently [15]. After resizing, it may be beneficial to normalize the pixel values to a standard range (e.g., 0-1 or 0-255) to ensure consistency in further processing steps. Algorithm 1 show the detailed algorithm steps for resizing and normalizing mammogram images.

Algorithm 1. Steps for resizing and normalizing mammogram images
1. Let I represent the input mammogram image.
2. Convert the input image to Grayscale: $I = Grayscale\ (I)$
3. Resize the Image to optimal size: $I\ resized = Resize\ (I, 224 * 224)$
4. Normalize the resized Image: $I\ normalized = I\ resized/255$

2.2. VGG 16

A convolutional neural network (CNN), often referred to as ConvNet, is a type of artificial neural network specifically designed for processing and analyzing visual data. It comprises an input layer, an output layer, and multiple hidden layers. VGG16 stands as a prominent example of a CNN, renowned for its exceptional performance in computer vision tasks. The term "16" in VGG16 signifies the presence of 16 layers with learnable weights. Despite the network containing a total of 21 layers, including convolutional, max-pooling, and dense layers, it has only 16 layers with trainable parameters. VGG16 architecture consists of thirteen convolutional layers, five max-pooling layers, and three dense layers [16]. Remarkably, the architecture predominantly employs convolutional layers with 3×3 filters, a stride of 1, and maintains consistent padding. Additionally, max-pooling layers with 2×2 filters and a stride of 2 are utilized. VGG16 accepts input tensors of size 224×224 with three RGB channels. The Conv-1 layer is equipped with 64 filters, Conv-2 boasts 128 filters, while Conv-3 showcases 256 filters. Notably, both Conv-4 and Conv-5 boast 512 filters each. Following this convolutional cascade, the architecture proceeds with three fully connected (FC) layers [17]. The VGG16 architecture for breast mass detection and classification is shown in Figure 2. Mathematically, the operations performed by VGG16 can be represented as follows: Let X be the input image with dimensions $W_{in} \times H_{in} \times C_{in}$ where W_{in} is the width, H_{in} is the height, and H_{in} is the number of channels. Each convolutional layer applies a set of filters to the input image to extract features. Let K be the number of filters in the convolutional layer and Let F be the filter size (e.g., 3×3).

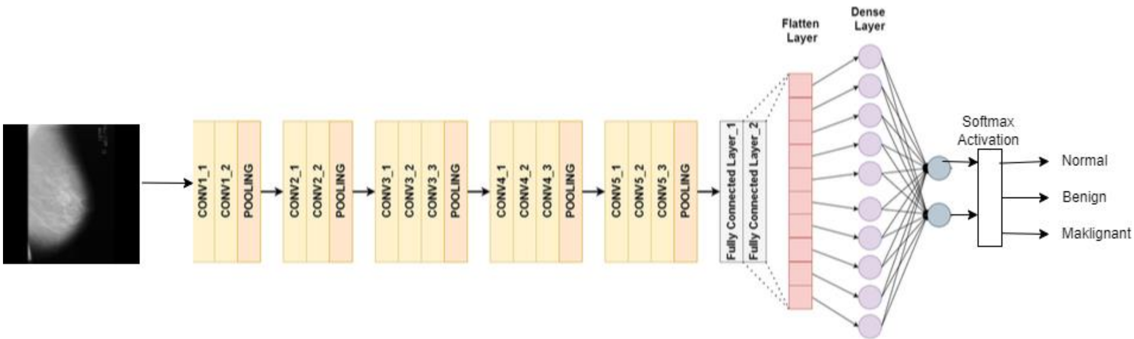

Figure 2. VGG16 architecture for breast cancer classification

The output feature map Y of a convolutional layer can be computed as (1):

$$Y = ReLU(W * X + b) \tag{1}$$

where W is the set of convolutional filters with dimensions $F \times F \times C_{in} \times K, b$ is the bias term, $*$ denotes the convolution operation, and $ReLU(\cdot)$ is the rectified linear unit activation function. Max pooling layers downsample the feature maps by selecting the maximum value from each local region. Let S be the stride (e.g., 2×2). The output of a max pooling layer is computed as (2).

$$Y = MaxPool\ (X, S) \tag{2}$$

The feature maps are flattened and passed through one or more fully connected layers for classification. Let N be the number of neurons in the fully connected layer. The output of the fully connected layer is computed as (3).

$$Y = ReLU(W \cdot X + b) \tag{3}$$

where W is the weight matrix with dimensions $M \times N$ (where M is the number of neurons in the previous layer), b is the bias term, and "·" denotes matrix multiplication.

2.3. ResNet50

ResNet50, also referred to as the deep residual network, stands out among pre-trained models trained on ImageNet. It tackles the gradient vanishing issue by skipping one or more layers, enabling efficient optimization. Its depth can be increased to enhance sample accuracy. In ResNet50, two or three layers are directly connected to another layer, skipping over adjacent layers, enabled by the rectified linear unit (ReLU) nonlinear activation function. Both forward and backward propagation methods are employed in ResNet50 [18], [19]. The ResNet50 model for breast anomaly prediction and classification is shown in Figure 3.

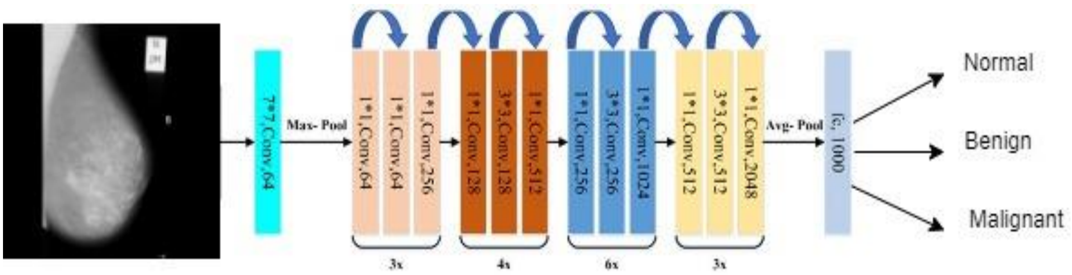

Figure 3. ResNet50 architecture for BC classification

A skip connection directly connects to the output after bypassing several training stages. ResNet serves as a potent tool extensively utilized in various computer vision tasks. It incorporates skip connections, which append the output of the previous layer to the next layer, mitigating the vanishing gradient issue [20], [21]. The first layer of ResNet50 is a convolutional layer with 64 distinct kernels, each with a stride of 2 and a kernel size of 7×7. This is followed by a max pooling layer, also with a stride of 2. The next set of convolutions includes three layers: 1×1 with 64 kernels, 3×3 with 64 kernels, and 1×1 with 256 kernels. These three layers are repeated three times, resulting in nine layers. Next, a convolutional block is applied, consisting of a 1×1 kernel with 128 filters, a 3×3 kernel with 128 filters, and a 1×1 kernel with 512 filters [22]. This block is repeated four times, totaling 12 layers. Following this, there is a convolutional block with a 1×1 kernel with 256 filters, two 3×3 kernels with 256 filters, and a 1×1 kernel with 1,024 filters. This sequence is repeated six times, adding up to 18 layers. Subsequently, a block with a 1×1 kernel with 512 filters, a 3×3 kernel with 512 filters, and a 1×1 kernel with 2,048 filters is used. This is repeated three times, contributing nine layers. Finally, an average pooling layer is added, followed by a fully connected layer with three nodes, and concluded with a SoftMax function, resulting in one final layer [23], [24]. In ResNet-50, there are two types of blocks: Identity block, the value of '*x*' (the input) is added to the output of the block only if the input size is equal to the output size. Convolutional block: if the input size is not equal to the output size, a convolutional layer is added in the shortcut path to adjust the input size to match the output size. There are two methods to adjust the input size to match the output size: Apply 1×1 Convolution to the input 'x' to change its dimensions to match the output size. Using striding adjust the stride of the convolutional layer in the shortcut path to match the spatial dimensions of the output size [25]. The typical form of a skip connection in ResNet involves adding the input of a layer to its output before applying the activation function. Mathematically, the operations performed by ResNet50 can be represented as follows: Let X be the input to the residual block with dimensions $W_{in} \times H_{in} \times C_{in}$, where W_{in} is the width, H_{in} is the height, and C_{in} is the number of input channels [26].

The output of the residual block is defined as (4):

$$Y = F(X) + X \tag{4}$$

where $F(X)$ is the residual function that represents the transformation applied to the input X to learn the residual mapping, $+$ denotes element-wise addition and Y is the output of the residual block with dimensions $W_{out} \times H_{out} \times C_{out}$, where W_{out}, H_{out}, and C_{out} are the width, height, and number of output channels, respectively. The residual function $F(X)$ typically consists of a sequence of convolutional layers followed by batch normalization and ReLU activation. The input X is also optionally passed through a convolutional layer to match the dimensions of $F(X)$ if needed. The convolution block and identity block of ResNet50 are shown in Figures 4 and 5.

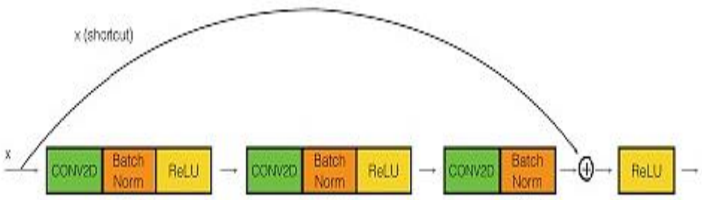

Figure 4. Convolution bock

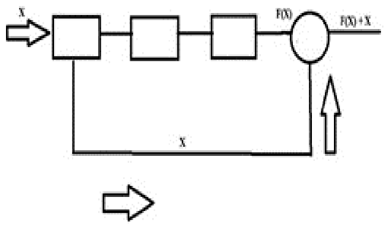

Figure 5. Identity Block

3. RESULTS AND DISCUSSION

3.1. Dataset description

This section tests the proposed approaches using mammographic image analysis society (MIAS)-mammography dataset taken from Kaggle repository. The dataset contains a total of 319 samples which are grouped into 207 normal images, 63 benign images and 49 malignant images. 80% of images are considered for training and 20% of images are used for testing.

3.2. Performance of breast cancer classification with VGG-16

As previously mentioned, VGG-16 is a 16-layer neural network consisting of 13 convolutional layers, five max pooling layers, and three fully connected layers. The input dimensions for the first convolutional layer are 224×224×64, for the second convolutional layer are 224×224×64, and for the first max pooling layer are 112×112×64. The Figure 6 outlines the structure and dimensions of all 16 layers and also provides the network parameters of VGG16 model.

3.3. Performance of breast cancer classification with ResNet50

Here, the backpropagation technique is applied. As the network depth increases, convergence becomes more challenging. As previously discussed, ResNet-50 is trained with 50 layers, including convolutional layers with zero padding, max pooling layers, activation functions, batch normalization layers, average pooling layers, and fully connected layers. The input dimensions for the first convolutional layer are 224×224×64, for the second convolutional layer are 224×224×64, and for the first max pooling layer are 55×55×64. Figure 7 presents the structure and dimensions of the 50 layers. Figures 8 and 9 show the performance of breast cancer classification using VGG16 and ResNet50 model. The comparative analysis of breast cancer classification using VGG16 and ResNet50 are shown in Table 1.

Even with small datasets, an interpretable integrated diagnostic strategy has been developed and demonstrated to be accurate and effective. Various transfer learning models have been explored and compared, showing superior performance relative to previous studies. Table 2 presents a comparison of various existing models with our proposed model, highlighting that our methods have achieved notable accuracy. The comparison of existing models with proposed methods is shown in Table 3.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_2 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 112, 112, 64)	0
conv2d_3 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_4 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 56, 56, 128)	0
conv2d_5 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_6 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_7 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_3 (MaxPooling2	(None, 28, 28, 256)	0
conv2d_8 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_9 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_10 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_4 (MaxPooling2	(None, 14, 14, 512)	0
conv2d_11 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_12 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_13 (Conv2D)	(None, 14, 14, 512)	2359808
max_pooling2d_5 (MaxPooling2	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 4096)	102764544
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 4096)	16781312
dropout_2 (Dropout)	(None, 4096)	0
dense_3 (Dense)	(None, 2)	8194

Total params: 134,268,738
Trainable params: 134,268,738
Non-trainable params: 0

Figure 6. Network parameters of VGG-16

Layers	50 Layers
"Conv1 "	"7x7, 64, stride 2"
	"3x3 x max pool with stride 2"
"Conv2_x"	"[1 x 1,64 3 x 3,64 1 x 1,256] x 3"
"Conv3_x"	"[1 x 1,128 3 x 3,128 1 x 1,512] x 4"
"Conv4_x"	"[1 x 1,256 3 x 3,256 1 x 1, 1,1024] x 6"
"Conv5_x"	"[1 x 1,512 3 x 3,512 1 x 1,1024] x 3"
	Average pool

Figure 7. Network parameters of ResNet50

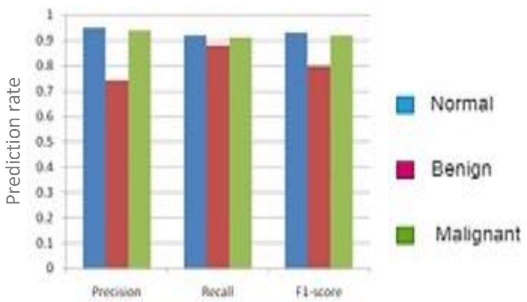

Figure 8. Performance of breast cancer classification with VGG16

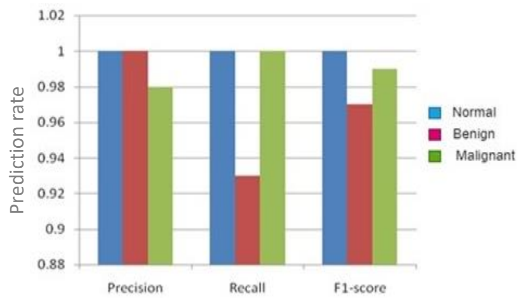

Figure 9. Performance of breast cancer classification with ResNet50

Table 1. Comparative performance of classification of breast cancer with MIAS dataset using VGG16 and ResNet50

	VGG16			ResNet50		
Breast cancer classification	Precision	Recall	F1-score	Precision	Recall	F1-score
Normal	0.95	0.92	0.93	1.00	1.00	1.00
Benign	0.74	0.88	0.80	1.00	0.93	0.97
Malignant	0.94	0.91	0.92	0.98	1.00	0.99

Table 2. Comparative performance of breast cancer classification accuracy with MIAS dataset using VGG16 and ResNet50

Model	Accuracy
VGG16	91.23%
ResNet50	99.01%

Table 3. Comparative performance of breast cancer classification using VGG16 and ResNet50 with existing work

Existing Methods	Methods	Accuracy
Elkorany *et al.* [11]	CNN	91.81%
Hekal *et al.* [12]	AlexNet	91%
Gonçalves *et al.* [13]	DenseNet201	91.67%
Proposed method	VGG16	91.23%
Proposed method	ResNet50	99.01%

4. CONCLUSION

Breast cancer poses a significant global challenge for women, with more than 2.1 million new cases diagnosed annually. This disease affects women of all ages, races, and ethnicities, making no group immune to its impact. Despite extensive research, a permanent cure remains elusive. Early-stage prediction and classification of breast cancer is the crucial task for radiologists. There is a need for more precise methods capable of diagnosing any abnormalities in women's breasts autonomously, achieving high accuracy rates without human intervention. Various machine learning models are implemented on feature-based datasets for detection and classification of cancerous and non-cancerous mass but did not give an efficient accuracy. Our proposed research uses VGG16 and ResNet50 pre trained methods to build a model that recognizes and classifies breast cancer types as normal, benign, and malignant. Our model achieves an improved accuracy of 91.23% and 99.01% by utilizing VGG16 and ResNet respectively. Compare to the state-of-art models we got an impressive accuracy. In future we want to apply VGG16 and ResNet50 models on different datasets contain more images.

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