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Breast Cancer Detection and Diagnosis Using Gabor Features and EfficientNetV2 Model

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ABSTRACT

Breast cancer is one of the most common diseases and the second most dangerous and fatal disease after skin cancer. The malignant masses begin to grow in the breast cells and develop in the breast tissue of women all over the world. Due to the necessity of early diagnosis to prevent the development of cancer and thus improve the chances of survival, many computer-aided methods are available to automate tissue classification to reduce the workload of the pathologist and improve accuracy. In this paper, a proposed method Gabor-EfficientNetV2 to extract deep features from a breast cancer dataset called “Breast cancer Histopathological dataset” (BreaKHis) to classify it as “benign” or “malignant” based on Gabor filter bank and EfficientNetV2 architecture. The proposed Gabor-EfficientNetV2 model offers significant advances in breast cancer detection and diagnosis by combining the texture analysis capabilities of Gabor filters with the efficiency and scalability of the EfficientNetV2 architecture. This hybrid approach enhances feature representation, resulting in improved classification accuracy and robustness compared to traditional models. Highest classification accuracy obtained with 400X magnification factor where the train accuracy of 97% and train loss of 0.13% while the test accuracy of 96.3% and the test loss of 0.135%, precision of 97.30% , recall of 90.30% , and F1-score obtained is 98.52%.

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1. Introduction

According to the World Health Organization, breast cancer is the second most common disease among women worldwide[1]. It is a malignant growth that begins in the tissues in the breast and then spreads to other parts of the body, causing the death of one in three women who have it, so research on it has increased in order to find the appropriate treatment and reduce the number of deaths before it is too late[2] .

Traditional methods of breast cancer diagnosis were very painful due to exposing the patient to ionizing radiation imaging, which usually fails due to the dense breast tissue.[3]. Then microwave imaging was used for diagnosis, but the image restoration process is inaccurate and susceptible to damage[4]. In the past few years, computer-aided diagnosis methods have emerged with the emergence of deep learning and medical image analysis, especially with

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the development of machine vision and digital microscopes that save slides in the form of digital images.[5]. With the progress made in the importance of deep learning in many fields such as object and speech recognition and its possible application to medical imaging, it is possible to use deep learning in the field of disease diagnosis[6]. In this research paper, we focus on detecting cancerous areas and then classifying them into benign and malignant based on tissue images.

The paper is organized as follows: Section 2 provides a review of related works. Section 3 explains the proposed method which includes preprocessing, feature extraction based on Gabor filter bank and efficientNetV2 deep learning classifier. Section 4 presents the experimental results including hyper-tuning, dataset and results. Section 5 concludes the paper. Finally, Section 6 suggests future work.

2. Related work

In the medical field, breast cancer detection by experts is a very important and sensitive process that requires a lot of time and effort. Therefore, the use of modern technology and artificial intelligence can increase the efficiency of diagnosis. In this regard, many studies have been conducted that use artificial intelligence in diagnosis [4]. One of these methods, which was done by T. Sharma et al. [7] deep learning (CNN) with transfer learning was used to diagnose breast cancer based on analysis of medical images in the database and the classification performance was better than most traditional algorithms with accuracy of 95%.

J. Maan and H. Maan [5] a system for detecting breast cancer with the help of deep learning techniques and using transfer learning techniques such as (VGG16) and (ResNet) is proposed. The proposed system is trained on the (BreakHis) dataset where images are classified into benign and malignant and the accuracy of the system was 90%.

G. Wadhwa and A. Kaur [8] Introduced CNN technology for breast cancer detection and diagnosis where DenseNet was used despite it being a memory-intensive neural network, as it was trained on the BreakHis dataset and the highest accuracy was 95.58% to classify images as benign and malignant.

H. Seo et al. [9] proposed a new approach called (pdMISVM) which is based on Primal-Dual Multi-Instance SVM and its related derivatives, where the method was trained on the (BreaKHis) dataset and the achieved classification accuracy was 0.858%.

D. M. Vo et al. [10] presented a new method called DCNN to extract useful features for classification and where data augmentation methods were used to improve classification and then Inception-ResNet-v2 was used for final classification and the method was trained on (BreaKHis) dataset and the classification accuracy was 92.2%.

D. Verma et al. [12] AlexNet transfer learning technique was used to classify breast cancer. The technique was trained on the BreaKHis dataset to classify cancer into malignant and benign, and the accuracy obtained from the channel was 95%. Table 1 show the summarizing of the related work and show the compare with proposed method.

Table 1 - summarizing the related work.

Author	Method	BreaKHis Dataset (Magnification)	Acc.	REC.	PRE.	F1-Score
T. Sharma et al. [7]	CNN	40x	-	-	-	-
		100x	-	-	-	-
		200x	-	-	-	-
		400x	95%	0.87%	0.95%	-
J. Maan and H. Maan [5]	VGG16, ResNet	40x	90%	-	-	-
		100x	87.9%	-	-	-

		200x	89.5%	-	-	-
		400x		-	-	-
G. Wadhwa and A. Kaur [8]	CNN & DenseNet	40x	-	-	-	-
		100x	-	-	-	-
		200x	95.58%	-	0.90%	0.89%
		400x	-	-	-	-
H. Seo et al. [9]	pdMISVM	40x	0.879%	0.894%	0.924%	0.903%
		100x	0.891%	0.923%		
		200x	0.875%	0.907%	0.891%	
		400x	85.8%	0.923	0.898	
D. M. Vo et al. [10]	ResNet-v2	40x	92.2%	-	-	-
		100x	91.3%	-	-	-
		200x	93.9%	-	-	-
		400x	94.8%	-	-	-
D. Verma et al. [12]	AlexNet	40x	95%	95.40%		
		100x	91.50%	91.40%	90.50%	
		200x	91.80%	94.90%	91.60%	
		400x	95.00%	97.70	91.71	
Proposed method	Gabor-EfficientNetV2	40x	87%	87.01%	85.6%	86.88%
		100x	93.5%	95%	90.30%	93.8%
		200x	94.1%	94.79%	92.40%	94.78%
		400x	96.3%	97.30%	92.90%	98.52%

3. Proposed Method

In this paper, we propose method to classification a breast cancer based on the fusion of Gabor features. Fig. 1 shows the block diagram of the proposed method in which consists of three main phases: In the first stage of the method, preprocessing will be used which will be applied to the dataset, while in the second stage of the method we will use Gabor bank to extract the features, and then in the final stage of the method apply classification by using the EfficientNetV2.

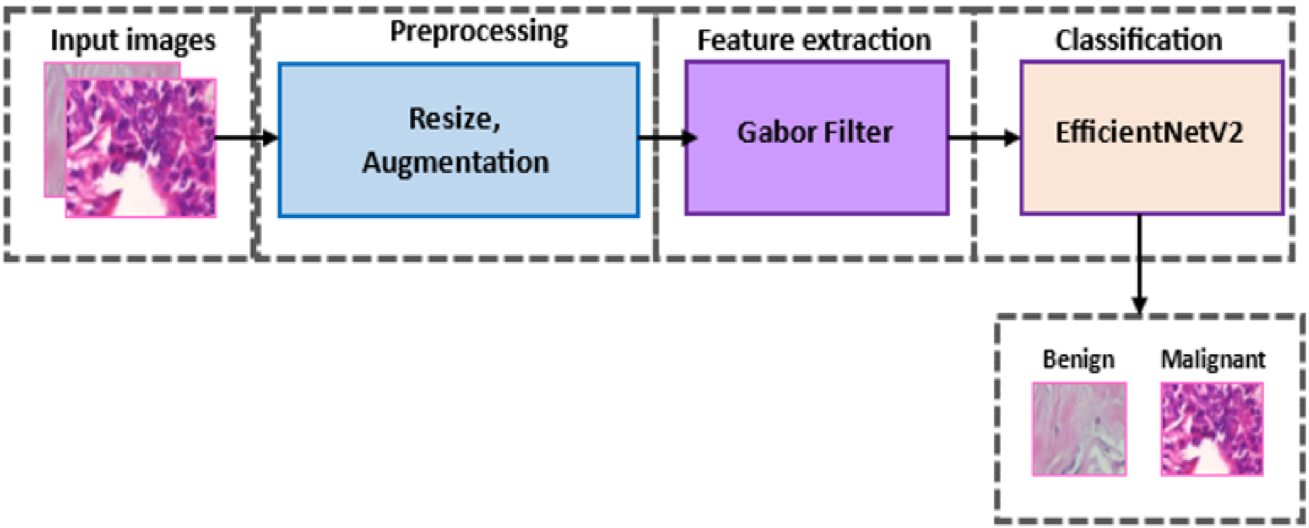

Fig. 1 - The Block Diagram Of The Proposed Method

3.1. preprocessing

The image size was changed to (300 × 300) to match the input requirements of the EfficientNetV2 model. Then, to increase the size of the data used and improve the accuracy of the model, data augmentation techniques were applied. Data augmentation is an important technique used in training deep learning models to improve performance and reduce overfitting. This technique relies on generating new and diverse images by applying simple transformations to the original data. In this study, the Keras library was used to implement data augmentation via the Image Data Generator function, which was applied to the original images[5] To increase the size of the data and improve accuracy, augmentation was applied using the following parameters: We used Parameters of augmented images are Zoom range of 0.2, Shear range of 0.2 Rotation range 0f 42 and Horizontal flip of True. This resulted in increasing the training set effectively without the need to collect additional data, improve overall performance and reduce overfitting.

3.2. Feature Extraction Based on Gabor Filter Bank

In this paper, the Gabor filter is used to extract the features of five scales and eight directions. Gabor filters are biologically inspired convolutional kernels that are widely used in digital image processing and computer vision applications [13] . It is used to extract spatial texture features, whether local or global, and can be adjusted in different directions and scales. It also has two very important properties, which are direction selectivity and site frequency, thus providing interesting and powerful statistics for cancer detection. Thus, it can be similar to the human visual system, as feature vectors will be normalized to zero mean and unit variance. [14] . The unitary form of the Gabor function was proposed in 1946 by the British physicist Gabor. Gabor filters are defined as follows [15] :

$$R = (x1, y1, \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x1^2+\gamma^2+y1^2}{2\times\sigma^2}\right) \times \exp\left(i(2x1\frac{x1'}{\lambda} + \psi\right) \qquad (1)$$

where

$$x1' = x1 \times cos\theta + y1 \times sin\theta \qquad (2)$$

$$y1' = -x1 \times sin\theta + y1 \times cos\theta \qquad (3)$$

Here in equations (1) to (3) x1 and y1 are the Cartesian coordinates in the spatial domain , the λ is the wavelength of the cosine factor in the Gabor function, θ mean the direction of the vertical to the parallel lines, (σ) is the standard deviation of the Gaussian function, (ψ) is the phase shift of the cosine, and (γ) is the spatial aspect ratio, the closer it is to one, the closer the Gabor kernel function is to the circle [16]. In order to extract features using Gabor filter, the first step is: generate Gabor filter array, set the number of scales u=5 (frequencies), and number of orientations v=8. Fig.2 show the Image Processed with Gabor Filters.

Algorithm Gabor Filter for Feature Extraction
Input: Breast Image **Output: Extracted Features from Breast Image** Step1: Convert image to double for processing Step2: Determine the Parameters for Gabor filter Number of scales=5, Number of orientations=8, Maximum frequency=0.25, Spatial aspect ratio=0.5, and Spatial frequency bandwidth=0.5. Step3: Determine the Initialize cell array to store Gabor filters Step4: Generate Gabor filters for each scale and orientation Step5: Calculate the wavelength and orientation by using $$\lambda = \max(2, \frac{f_{max}}{2(\mu - 1)/2})$$ Step6: Calculate the orientation by using $$\theta = \frac{(\mu - 1)\,.\,\pi}{numOrientations}$$ Step7: Create Gabor filter $$R = \exp(-\frac{x1^2 + \gamma^2 + y1^2}{2 \times \sigma^2}) \times \exp(i(2x1\frac{x1'}{\lambda} + \psi)$$ Step8: Apply Gabor filters to the image Step9: Display the final result.

The Gabor filter is effective in capturing the local spatial frequency features, as the larger the value of Scales (u), the finer details and wider texture are captured, and the direction v allows capturing the best features in different directions. In figure 2 u=5 and v=8 was chosen, which will include a set of Gabor filters for five different frequency scales and eight directions (extending from 0 degrees to 157.5 degrees with equal angular intervals). This creates a comprehensive set of filters to extract rich and diverse features of spatial and directional frequency at the same time, and thus the human visual perception system, which greatly improves classification performance.

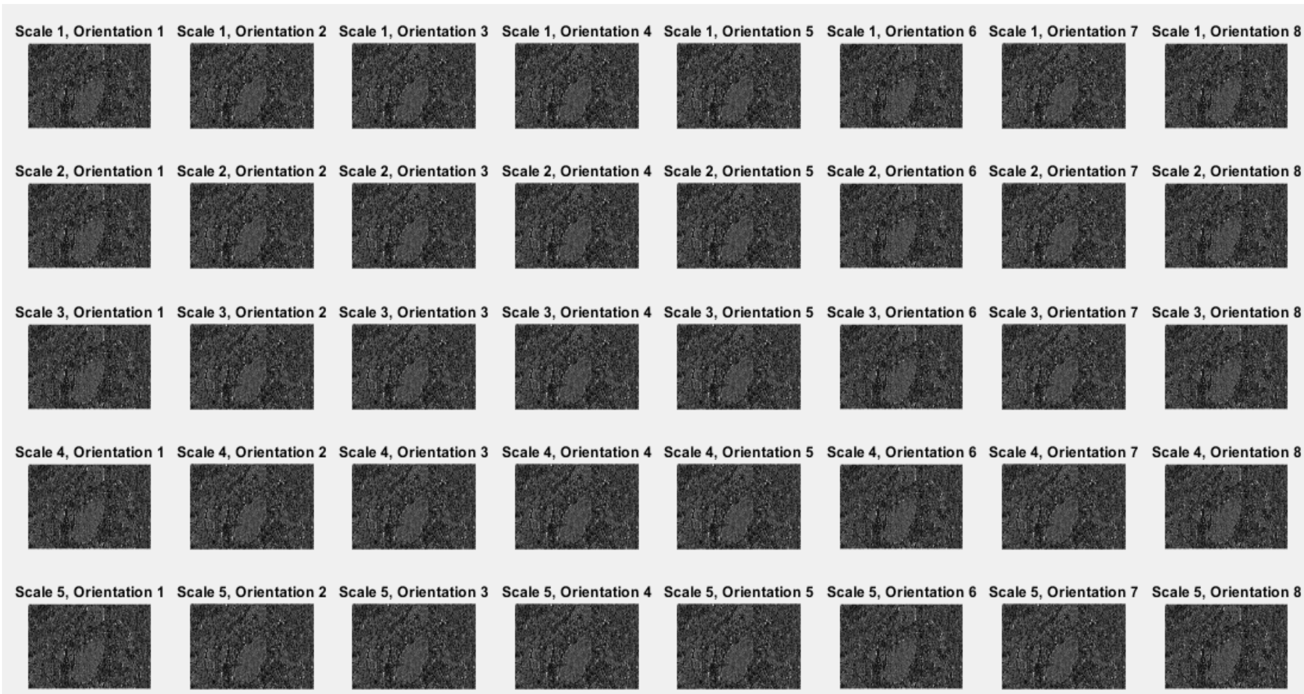

Fig. 2 – Breast Cancer Image Processed with Gabor Filters at 5 Scales and 8 Orientations

3.3. EfficientNetV2 deep learning classifier

EfficientNetV2 is a new family of deep learning models.[17]. It is considered one of the smallest and fastest models compared to previous models such as EfficientNet, ResNet, DenseNet and Inception [18], as it greatly speeds up the training process because it is a gradual learning model and adjusts the regularization value depending on the image size[19]. The EfficientNetV2 architecture is distinguished from EfficientNet in many aspects, the first of which is the increased use of both (fused-MBConv) and (MBConv) in the first layers of the architecture, the second is the use of smaller expansion coefficients, the third is the kernel size of (MBConv) is (3 × 3) Fourth, the removal of the last step from EfficientNet because it increases the time and thus it is possible to address the cost of memory access and the large parameter size[20]. All images are resized to 300 × 300 pixels to meet the input size requirements of the EfficientNetV2 model variant used. Image pixel values are scaled to the range [0,1] or normalized using the mean and standard deviation of ImageNet. The top (fully connected layers) is then replaced with a custom classifier for binary classification (benign vs. malignant). Finally, a global average pooling layer is used before the fully connected layers to reduce the dimensionality of the features.

4. Experimental Results

4.1. Hyper-tuning

The proposed method was developed using “Python” , and the implementation experiments were conducted on Google Colaboratory (Colab) . Table 2 summarizes the parameters used in this method.

Table 2 - Hyperparameter Tuning.

Hyper parameter	Setting
Dropout	0.5
Epochs	20
Optimizer	Adam
Learning rate	10−3
Batch size	50
Image size	128 x 128

The proposed method was evaluated by accuracy (ACC), Recall, precision(PRE) and F1-score. They have the formulas

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$RECALL. = \frac{TP}{TP + FN} \quad (5)$$

$$PRE . = \frac{TN}{FP + TN} \quad (6)$$

$$F1 - Score = 2.\frac{PRE \times Recall}{(PRE + Recall)} \quad (7)$$

4.2. BreakHis Dataset

In this proposed method, the BreakHis dataset will be used to measure the performance, which is an open source and available dataset built in Brazil in collaboration with P&D Laboratory in 2016 [5]. which contains general breast cancer histological data. This database contains 7909 images obtained from 82 patients, classified into 2480 benign tissue samples and 5429 malignant tissue samples as shown in Fig 3.[21], The images were collected at different magnification factors (40x, 100x, 200x, and 400x). Table 3 shows the dataset [5], [9], [22] .

Table 3 - BreakHis Dataset 1.0

Magnification	Benign	Malignant	Total
40X	652	1370	1995
100x	644	1437	2081
200x	625	1390	2013
400x	588	1232	1820
Total of images	2480	5429	7909

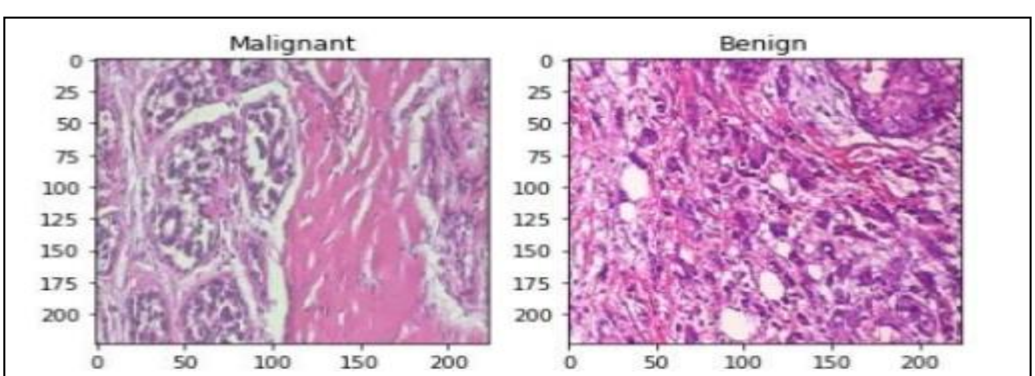

Fig. 3 - Malignant and benign images from the BreakHis dataset.

This method was trained to perform cancer diagnosis and classification and the results are shown in Table 4 where the accuracy was 87% with a test loss of 0.150 when 40x magnification was used, when 100x magnification was used the accuracy was 93.55% with a test loss of 0.13, the accuracy for 200x magnification was 88% with a test loss of 0.21 and finally at 400x magnification the accuracy was 96.3% with a test loss of 0.135.

Table 4 - Results for Breast Lesion Diagnosis Using Gabor-EfficientNetV2.

Evaluation	Magnification			
	40X	**100x**	**200x**	**400x**
Train-Acc	87.92	94	88.9	97
Train-Loss	0.153	0.12	0.20	0.13
Test- Acc	87	93.5	94.1	96.3
Test-Loss	0.150	0.13	0.21	0.135
Precision	87.01	95	94.79	97.30
Recall	85.6	90.30	92.40	92.90
F1-score	86.88	93.8	94.78	98.52

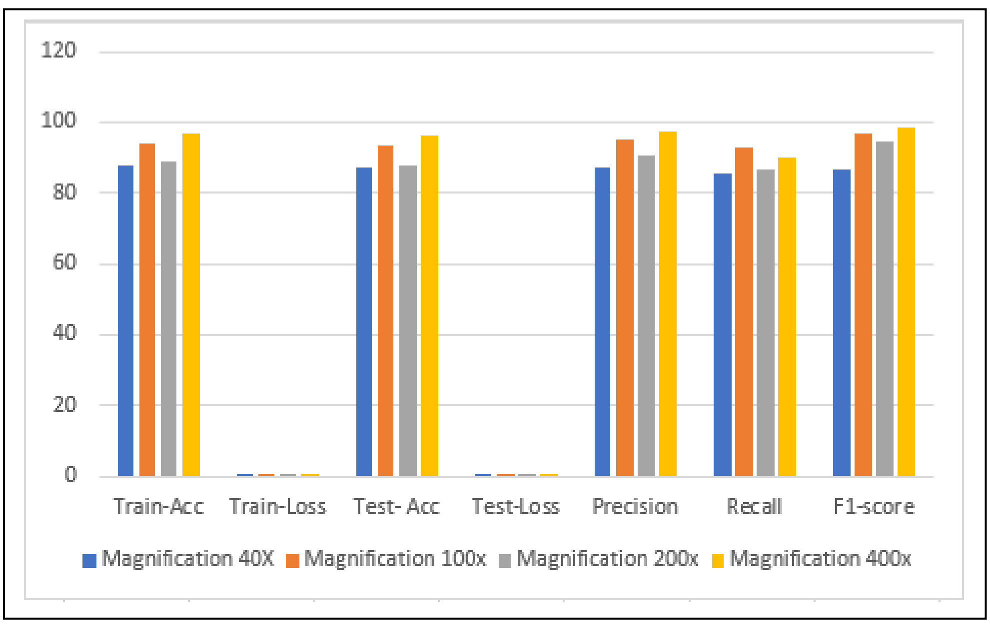

Fig. 4 - Display Performance of Gabor-EfficientNetV2 for Detection of Breast Lesion.

Fig.4 shows the performance of Gabor-EfficientNetV2 on the (BreaKHis) dataset for all four zoom factors (40, 100, 200, and 400). The graph shows that when images were used at 40x zoom factor, the accuracy, recall, and F1 score were 87%, 87.01%, 85.6%, and 86.88%, respectively, for the proposed method. When using 100x zoom factor, the accuracy, precision, recall, and F1 score were 93.5%, 95%, 92.90%, and 96.8%, respectively, for the proposed method. When using 200x zoom factor, the proposed method obtained accuracy, precision, recall, and F1 score of 88%, 90.79%, 86.40%, and 94.78%, respectively. When 400x magnification was used, we observed that the system obtained the best performance for use with precision, recall and F1 score of 96.3%, 997.30%, 90.30% and 98.52% respectively.

By relying on multiple evaluation metrics, the study ensures a comprehensive and accurate assessment of the model's performance, addressing the unique challenges and priorities of medical imaging tasks.

5. Conclusion

In this paper, we proposed an efficient method for the diagnosis and detection of breast cancer called Gabor-EfficientNetV2 where used the Gabor filter to features extraction and used the EfficientNetV2 model for classification the breast cancer to malignant and benign. This proposed method gives the efficiently diagnose and detect breast cancer at an early stage where the method achieves high accuracy with 96.3 %, precision of 97.30%, recall of 90.30% and F1-score of 98.52% for 400X magnification factor.

6. Future Work

1. Integration of public datasets such as the Breast Cancer Histological Database (BreakHis) and the Cancer Imaging Archive (TCIA).

2. The combined approach of Gabor filters and EfficientNetV2 is not limited to breast cancer. It can be adapted to detect other types of cancer that exhibit distinct tissue patterns.

3. Real-time implementation where real-time cancer detection tools integrated into clinical workflows can provide immediate diagnostic support to radiologists and clinicians.

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