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Deep Learning Implementation in The Classification of Breast Medical Images

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ABSTRACT **: Breast cancer is one of the prime purposes of ending women's life. For this purpose, mammogram analysis is an active manner that helps radiologists in the detection of breast cancer early. This paper uses deep learning models to classify mammographic images. The support vector machine (SVM) with deep learning features of a mammogram helps to classify breast tissue based on image processing techniques. Based on the values of these features of a digital mammogram, both deep learning models and SVM try to classify the breast tissue into basic categories normal, and abnormal given in the database (mini-MIAS database). Data augmentation mechanisms have been applied to increase the training set size to avoid overfitting. After making a comparison of some models, it became clear that the best result of the classification is 97.77 % by using the VGG model. These results will be useful in making medical classification images more accurate. By this method, a radiologist can detect if the breast has cancer or not.**

KEYWORDS: Image Classification, Medical Image, Deep Learning, Models, Breast Cancer

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I. INTRODUCTION

Breast cancer is more prevalent among women in poor and developing countries. The World Health Organization (WHO) said that by 2025, breast cancer will be diagnosed 19.3 million times**(Organization 2022)**. When breast cancer is classified early, patients will have a chance of recovering from the disease is great. Breast cancer is a type of disease in which cells grow and divide unorganized, causing a tumor breast. Lobules are the place where breast cancers develop. The serious symptoms of breast cancer are changes in breast skin color, the creation of a breast mass, and changes in breast shape and size. For breast imaging, several methods can be used, including X-rays, magnetic imaging, and ultrasound**(Bower 2008)**. Mammography using X-rays is one of the most common methods used in the diagnosis of this disease **(Shen et al. 2019)**.

Based on medical imaging, a lot of researchers are working on deep-learning models for breast cancer classification. Breast cancer imaging needs a visual check to recognize any cancer signs, such as lumps, that may signify disease. After determining these signs, relevant measurements were obtained to help doctors in determining the normal or abnormal tissue.

Calcifications and masses are among the most obvious signs in mammography, and from here specialists can locate the tumor. All suspicious areas are not malignant. To make it clear, we will give two examples. The first example is that a soft bulge is almost always benign. The second example is in the case of an irregular tumor, a biopsy is necessary, such as the shape of a starburst **(Rodriguez-Ruiz et al. 2019)**. An imbalance in the milk-producing ducts (invasive ducts) is the main cause of breast cancer. According to researchers in **(Rodríguez-Ruiz et al. 2019)**, lifestyle, hormonal and environmental factors may cause breast cancer. When radiologists examine these images, the diagnosis will be easy.

Radiologists' evaluations of breast cancer vary due to differences in their past experiences. As a result, from this point of view, deep learning (CNN)can be used to help doctors and confirm the correct opinion. The current study presented is one of the types of research that attempts to help clinicians evaluate this deadly disease.

Due to the remarkable scientific progress and development in which humanity lives, many researchers have created new technics. When the image classification problem appeared, Many or several methods have been used to solve this problem, such as Support Vector Machine (SVM), the K Nearest Neighbor algorithm (KNN), and the Artificial Neural Network (ANN). Convolutional Neural Networks (CNN), and Recurrent Neural networks (RNN) are important types of Artificial Neural Networks (ANN) **(Albahli et al. 2021)** . Simply, images problem needs Convolutional neural networks but trouble like analyzing text or videos needs RNN. CNNs use filters(kernels) and pooling layers, while RNNs results depend on feedback operation. CNN has fixed input sizes, but RNNs can use arbitrary lengths.

Since we are dealing with medical images in this research, it is appropriate to use Convolutional Neural Network. CNN has many advantages, for example, simplicity, independence of transformations, involving feeding segments of an image, reduced computation, better performance, great image classification, and finally reduced complexity and saving memory compared to other types. There are several models of deep learning like VGG16, VGG19, ResNet 50, inception v3, etc. Some of the disadvantages of CNNs are that they need a lot of training data, tend to be slow, the training process takes a long time, and finally have an overfitting problem **(network 2022)**.

Overfitting occurs when the model has a high variance, the training data size is not enough, and fails to generalize to unseen examples. Data augmentation techniques consider one of the best solutions that can help accomplish this mission. Data augmentation techniques apply modifications to increase training data samples. The main purpose of augmented data is to reduce the distance among training and validation data. Such as binary classification has two classes called minority class and majority class, and misclassification problems occur when one class contains fewer samples than the other class. Data augmentation is not the only way to reduce the impact of the over-fitting problem. **Figure 1** shows how to overcome overfitting. By using transfer learning, this problem can also be overcome. To save time and costs used, transfer learning and deep learning have been combined, especially in the classification of medical images. Obtaining important features using deep learning is called feature extraction. Another method uses machine learning models (Inception) as pre-trained.

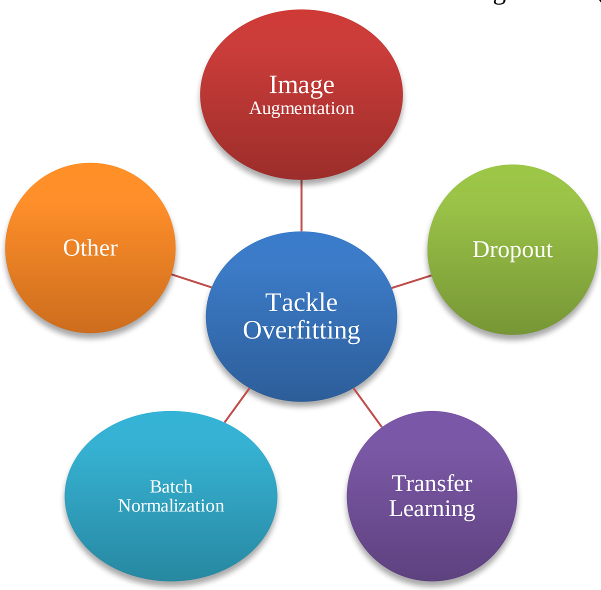

Figure 1. Overcome overfitting.

II. PROBLEM FORMULATION

Our study compares the result of two popular models VGG16 and inception. All used models are executed on breast data. The purpose of the models in this paper is to perform binary classification on medical image data. In fact, many researchers have used DL models to classify medical images. An important part of breast cancer classification is breast intensity classification. Mammographic breast density is divided into four famous classes: fatty, dense, fibroglandular, heterogeneously, and extremely dense. The tumor may hide in the latter two types. Breast images can be viewed from a more angle such as Left Cranial Caudal=L-CC, Left Medio Lateral Oblique= L-MLO, Right Cranial Caudal=R-CC, and Right Medio Lateral Oblique=R-MLO **(Han et al. 2017)**. Over 300 images are used in the proposed models. Data augmentation will be used to cancel overfitting. The proposed method used the geometric transformations technique in **figure 2**.

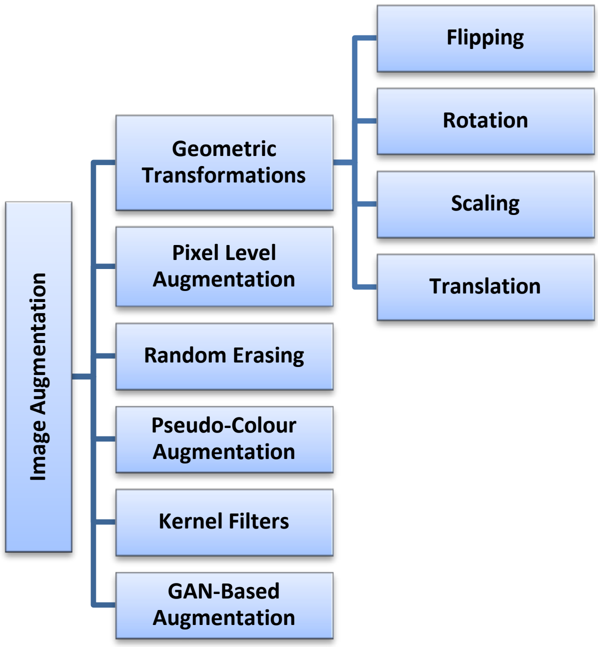

Figure 2. Basic image augmentation techniques.

Based on previous studies in computer science and previous research, a new method for classifying images based on deep learning has been developed. The main motive of this study is to assist clinicians in diagnosing and detecting patients in a correct, safe, and rapid manner. Finally, medical imaging models have a major role in spontaneous diagnosis and classification. The following **table 1** illustrates important papers in the classification of breast image cancer.

Table 1. previous researches.

Field	Authors	Method	Accuracy
Breast	**(Shi et al. 2019)**	CNN	83%
	(Lopez-Almazan et al. 2022)	Confusion Matrix Convolutional Neural Network (CM-CNN)	85%
	(Raj et al. 2022)	VGG-16/19	85.7%
	(Ting et al. 2019)	CNNI-BCC	90%
	(Sadad et al. 2021)	DenseNet201, ResNet50	90.47%
	(Guan and Loew 2017)	CNN (VGG-16) with a one FC NN-classifier	91%
	(Gao et al. 2018)	Shallow-Deep Convolutional Neural Network (SD-CNN)	92%
	(Oyelade et al. 2021)	Deep CNN	93.75%
	(Dhivya et al. 2020)	DCNN	94%
	(Omonigho et al. 2020)	Modified AlexNet	95.70%
	(Muduli et al. 2022)	Deep CNN	96.6|%
	This work	VGG 16, Inception + SVM	Up 97 %
	(Thomaz et al. 2017)	CNN and MLP-NN	98 %
	(Desai and Shah 2021)	CNN	98.06 %

III. PROPOSED METHODOLOGY

The human brain structure is the inspiration for an artificial neural network. All input layers, hidden layers, and output layers are the main blocks of artificial neural networks. Consider that the hidden layer uses activation functions (AFs) to do calculations that think like a human brain and then show the result in the output layer **(Nwankpa et al. 2018)**. There are three types of activation functions. The proposed approach was used to classify medical images using deep learning. In this section, we propose the architecture and detailed learning of the CNN model due to medical image classification. In addition, we describe image augmentation. This study aims to perform the automatic classification of medical images based on the CNN model and SVM. **Figure 3** illustrates framework of the proposed model.

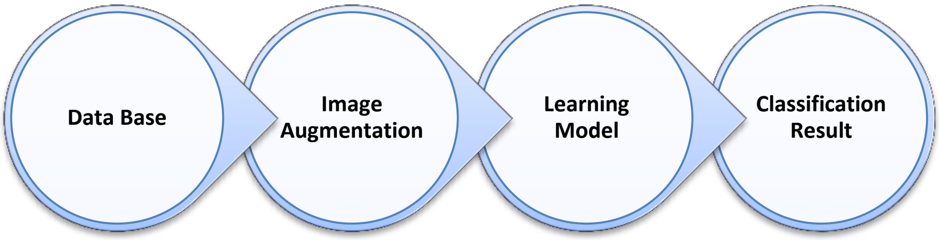

Figure 3. Design of the proposed computer-aided diagnosis model.

DL methods have been successful in classifying images, the details of which will be discussed next.

3.1. Data Preparing

This step involves converting the raw data images to an appropriate format. Some images were sent to training after we labeled them. **Table 2** gives information number about the breast cancer BC data used.

Table 2. Datasets information.

Dataset	Training data		Test data	
	Normal	**Abnormal**	**Normal**	**Abnormal**
Breast **(cancer 2021)**	54	43	153	72
Breast after augmentation	324	258	153	72

3.2. Data preprocessing

It largely involves normalization, resizing, feature extraction, and transformation. We normalize and resize our dataset images. The meaning of normalization is that the pixel values in magicians are scaled before they are implemented in deep learning. Many ways and techniques are used also like segmentation and noise removal. The image data source has different sizes, so we had to resize it before being used in most of the neural network models such as Inception, and VGG16 we use. Depending to **figure 2**, there are a lot of ways to augment the data. Geometric transformation is the best and easy way to augment training data and the random transformations we used are rotation, permutation, etc. Then, the new images will be used in the model form. **Figure 4** gives information about the data augmentation type.

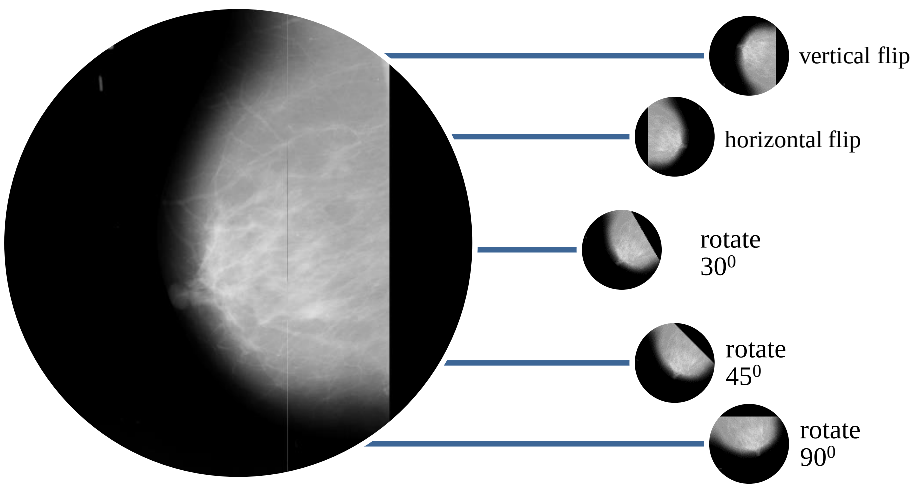

Figure 4. Data augmentation (geometric transformations technique).

3.3. Deep learning model

All of the convolutional layer, the fully connected layer, and the pooling layer are the main factors that build A CNN. **Figure 5** gives a general overview of deep learning models.

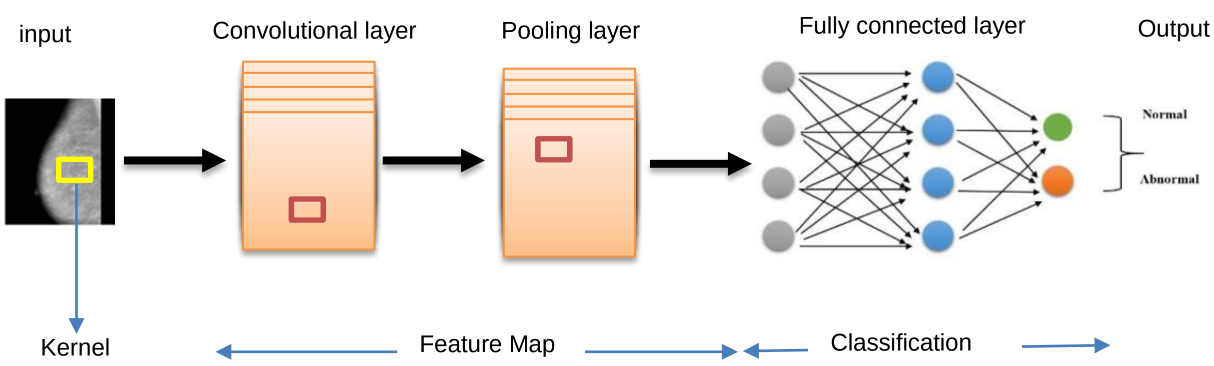

Figure 5. Proposed convolutional neural network architecture.

The next part will explain the most important CNN concepts used in the classification process.
Input layer: It was used to perform a set of pixels that belong to the input data of the image.
Convolutional layer: The convolution process uses the image input to the filter and passes toon the image pixels to extract the features to create the output function as a feature map for this image, thus reducing the storage space in which each image is stored. The convolution layer performs convolution operations with the output of the previous layer as the input to the current layer.

The convolutional layer is the core building block. Used to reduce complexity. There are three hyper parameters: depth, stride, and setting zero padding. Overview of these important parameters.
Pooling layer: The pooling layer is another building block of CNN. It is executed after each convolutional layer. The aggregation process involves moving a 2D filter over each channel in the feature map as it summarizes the features within the area covered by the filter to reduce the dimensions of the feature map. This reduces the number of tasks that have to be learned and the number of operations performed in the network. Pooling layer types are max pooling and average pooling.
Fully connected layer: A fully connected layer can be called an assembler, and it can connect and connect all the features in the layers together so that the classification operation can be performed. The fully connected layer is the last layer and takes a long time, the reason is that it collects the data from the previous layers and gives it to the final layer (the output layer). It should be borne in mind, that batch normalization is used to standardize the inputs to the convolutions by calculating the mean and standard deviation across the minimum batch, dropout can also help reduce overfitting.

IV. NUMERICAL RESULTS

Our model uses Keras and TensorFlow libraries. Keras is a deep learning API written in Python that runs on top of the machine learning platform Tensor Flow **(Brownlee 2016).** It was developed with a focus on enabling rapid experimentation. Being able to go from an idea to results as fast as possible is the key to doing good research. TensorFlow is an open-source software library developed by the Google Brain team. Computing using tensor flow can be executed on a variety of systems **(Abadi et al. 2016).**

4.1. Pre-trained models

This paper used two famous models that achieve good results. These models are inception and VGG.

Inception: The inception-v3 model has two parts. The first part is featuring extraction using a convolutional neural network. The second part, called the classification part, uses fully connected layers and the SoftMax activation function. The inception model used these parts to do its job **(Szegedy et al. 2016)**.

VGG: The model used was a visual geometric group (VGG16). In 2014, the convolutional neural network (CNN) architecture won the ImageNet competition **(Simonyan and Zisserman 2014)**. It is an excellent vision model architecture to date. The most unique feature of the visual geometric group (VGG16) is that instead of having many hyper-parameters, they focused on having convolution layers of 3 × 3 filters with a stride of 1 and always used the same padding and max -pool layer of a 2 × 2 filter of stride 2. Follows this arrangement of convolution and max pool layers consistently throughout the architecture (**Khan et al. 2020**).

SVM: Support Vector Machine (SVM) is used for classification and regression processes. The goal of the SVM algorithm is to discover a hyperplane in an N-dimensional space. Features number responsible for hyperplane dimension. When the number of input features takes two, then the hyperplane is a line. If the number of input features is three, then the hyperplane becomes a 2-D plane. The SVM has a kernel called a function that takes low-dimensional input space and transforms it into higher-dimensional space. After features appear from CNN, they will pass through the SVM classifier **(Shima 2018).**

Five evaluation metrics were applied to assess the performance of the proposed method. These metrics were sensitivity (tell us about the percentage of total results which had been truly classified by model), specificity (SPE), accuracy (proportion of correct predication among the total number of cases), precision (tell us about the proportion of input data that are true), and F-score (is the harmonic average of precision and recall). Mathematic representations are:

$$\text{Accuracy} = \text{ACC} = \frac{\text{TP+TN}}{\text{TP+TN+FN+FP}} \text{ X } 100 \tag{1}$$

$$\text{Sensitivity} = \text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \text{ X } 100 \tag{2}$$

$$\text{Specificity} = \text{SPE} = \frac{\text{TN}}{\text{TN+FP}} \text{ X } 100 \tag{3}$$

$$\text{Precision} = \text{PPV} = \frac{\text{TP}}{\text{TP+FP}} \text{ X } 100 \tag{4}$$

$$\text{F} - \text{score} = \frac{\text{2TP}}{\text{2TP+FP+FN}} \text{ X } 100 \tag{5}$$

Where these metrics are evaluated in the terms:
TP=True Positive=both actual data and predicated data are true.
FP=False Positive=actual data is false but class predicated data is true.
FN=False Negative= actual data is true but class predicated data is false.
TN=True Negative= both actual and predicated data are false.
After using Python code with keras library with CNN model (VGG16), we get the following good results:

4.2. VGG results

Figure 6 shows the performance matrix for the breast data set.

Actual label			
	Cancer	69	3
	Normal	2	151
		Cancer	Normal
		Predicated label	

Figure 6. Confusion Matrix from the breast cancer dataset by VGG.

Performance of classifier and confusion matrix operators can be shown in **table 3.**

Table 3. Performance matrices after training on BC data set by VGG.

Data	TP	TN	FP	FN	ACC	RECALL	SPE	PPV	F
Cancer	69	151	2	3	97.77	95.83	98.69	97.18	96.5
Normal	151	69	3	2	97.77	98.69	95.83	98.05	98.37

The accuracy of the proposed method through fine-tuning process is illustrated in **figure 7.**

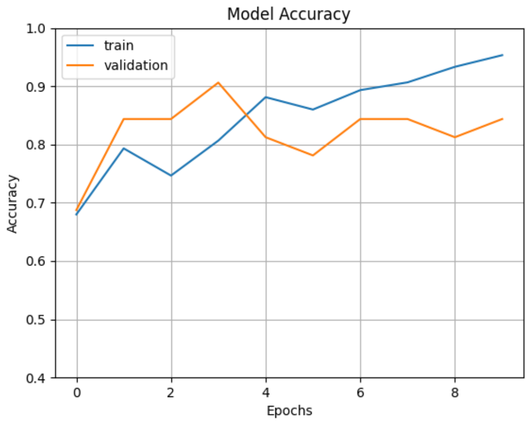

Figure 7. The model accuracy of breast cancer dataset by VGG.

4.3. Inception results

Figure 8 shows the performance matrix for the breast data set.

Actual label		Cancer	Normal
	Cancer	63	9
	Normal	7	146

Predicated label

Figure 8. Confusion Matrix from the breast cancer dataset by inception.

Performance of classifier and confusion matrix operators can be shown in **table 4.**

Table 4. Performance matrices after training on BC data set by inception.

Data	TP	TN	FP	FN	ACC	RECALL	SPE	PPV	F
Cancer	63	146	7	9	92.88	87.5	95.42	90	88.73
Normal	146	63	9	7	92.88	95.42	87.5	94.19	94.8

The accuracy of the proposed method through fine-tuning process is illustrated in **figure 9**.

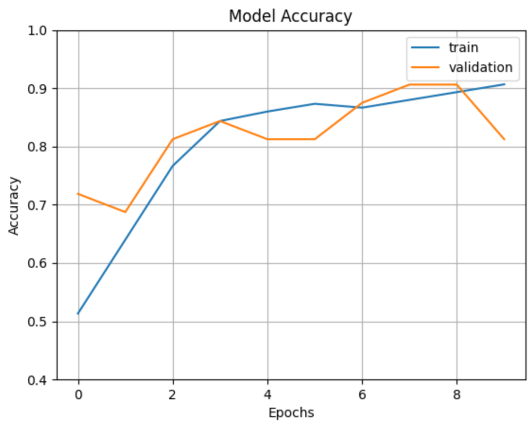

Figure 9. The model accuracy of breast cancer dataset by inception.

From the previous results, it is clear that, when using the VGG model, it gave good results, while the Inception model gave satisfactory results. The benefit of applying the models to data for the purpose of generalization. This study and previous research show that the concept of deep learning is very important in the process of classifying medical images, provided that the model and homogeneous tools are used together. Also, how used augmentation process.

V. CONCLUSION

A new area of research is the automatic diagnosis of the disease from medical images based on DL. The reasons for choosing DL in medical image classification are access to the high structure of data, availability of GPU performing, and advanced algorithms. In the present paper, we have a summary of the CNN architecture with its concepts for classifying medical images. This paper discusses the solution to overcome obstacles in the classification process **(Malhotra et al. 2022)**.

The proposed model uses CNN models and SVM for reducing the classification error and high accuracy compared with other models. Previous results show us VGG is more accurate than inception. Accuracy is 97.77 % of breast image classification. These results will be helpful for clinicians in making more accurate classifications of medical images. In future works, it is possible to use other models and new and more numerous databases, to make a generalization that includes the classification process of medical images. The segmentation process may be an extension of this work to enable doctors to identify diseases. Implementation of this strategy may benefit society.

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