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Breast Thermograms Analysis Using Deep Neural Network

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Abstract

Breast cancer is one of the leading causes of mortality among women globally. Early identification of this kind of cancer is important for a successful treatment outcome. A variety of screening techniques can be used to identify breast cancer. Thermography is possible for early diagnosis that uses thermal cameras with great resolution and sensitivity. The goal is to develop a system that automatically captures and classifies thermographic imaging of the breast as normal or abnormal. In this method,the detection and classification of breast cancer from thermography images usingadeeplearning-based convolution neural network using the VGG-19 algorithm. Breast cancer detection is performed using CNN with the help of Google collaboratory (Google Colab). Finally, as the result of experimental studies, the major focus is on the performance accuracy of the train and test dataset, and the graph is plotted between the training and validation accuracy.The VGG-19 network achieved the highesttestperformanceof 99.80% in breast cancer detection and to classify cancer using the DMR Mastology Research dataset.

Keywords: Breast cancer, Thermography, image processing, Convolutional Neural Networks, Deep Learning, VGG19, Thermal images.

1.INTRODUCTION

Breast cancer is one of the most severe cancers among women. Breast cancer is a difficult condition to understand. Breast cancer has various subtypes and several treatment options. While many patients have similar diagnoses or are given similar treatments, no two women's experiences are almost the same. More than 685,000 women will die each year from breast cancer, according to world health organization(WHO) information from 2020.Breast cancer wasdiagnosed in 7.8 million women in the previous five years, making it the most frequent cancer in the world by the end of 2020.Early identification of cancer detection focuses on recognizing symptomatic individuals as early as feasible so that they can receive a better treatment achievable. Breast thermography provides several benefits because it is non-invasive, safe, and painless. Thermographic images and the use of convolutional neural networks have improved the accuracy of thermography in the early detection of breast abnormalities. CNN can automatically extract features from images and then classify them. Convolutional neural networks have promising results when used to identify cancers using image datasets. The use of automated image processing algorithms based on deep learning has the potential to help in the early detection of breast cancer. Thermal imaging is being used to develop an innovative methodology that can be contacted immediately, inexpensively, and diagnoses patients earlier than previous procedures while causing no physical harm to them. Thermal imaging-based approaches have been

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demonstrated in studies to identify breast cancer at an early stage 8-10 years before mammography . Finding a data set that can be investigated is one of the most significant aspects of the research. The majority of the research in the literature has been conducted using thermal imaging obtained from local hospitals. Scholars at Federal Frequently Misdiagnosed University responded to the inquiry by providing the DMR (Database ForMastology Research) data set, which met the study's criteria. The DMR Mastology Research dataset is an online storage and management system for breast cancer screening diagnostic images.

2.DEEP LEARNING NETWORKS

Deep learning is a type of machine learning that uses many layers to extract higher-level facts from raw input.Lower layers may recognize boundaries in image processing, whereas higher layers may distinguish things significant to people, such as numerals, words, or faces. Between the input and output layers, a deep neural network (DNN) is a type of artificial neural network (ANN) having numerous layers . Although there are several types of neural networks, they always contain the same components: neurons, synapses,weights, biases, and functions. It is difficult to evaluate the performance of multiple architectures unless they are all the same. Unless alternative designs are evaluated on the same datasets, it might be difficult to compare their performance. In medical applications such as cancer cell classifications, lesion identification, organ segmentation, and image augmentation, deep learning has shown to be competitive.

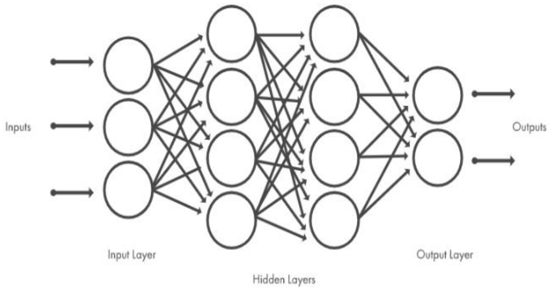

Fig. 1. Deep Learning Architecture

Since most deep learning approaches use neural network architectures, deep learning models are frequently referred to as deep neural networks.Fig.1 shows the DNN Architecture.

Deep neural networks have a large number of hidden layers. Deep networks can have up to 150 hidden layers, whereas traditional neural networks only have 2-3. Deep learning models are trained using large amounts of labeled data and neural network topologies that learn features directly from the data instead of requiring human feature extraction. One of the most prevalent forms of deep neural networks is convolutional neural networks (CNN or ConvNet).A CNN employs 2D convolutional layers to convolve learned features with incoming data, making it ideally suited to processing 2D data such as images. CNN eliminates the need for manual feature extraction, so we need not identify features that are used to classify images. The CNN operates by extracting characteristics from images directly. Because of this automated feature extraction, deep learning models are highly accurate for computer vision applications such as object categorization. CNN’s learn to detect unique parts of an image by using tens or hundreds of hidden layers. Every hidden layer raises the complexity of the previously learned visual elements.

3.PROPOSED METHODOLOGY

A deep convolutional neural network was used in this study to detect breast cancer using thermographic images.The DMR Mastology Research dataset is a platform for storing the data online and a management system for mastological images used in breast cancer screening. The DMR data set was the most extensively used dataset in the research. "Banco de Imagens Mastológicas - Visual Lab"; Figure [3] shows an example of images.

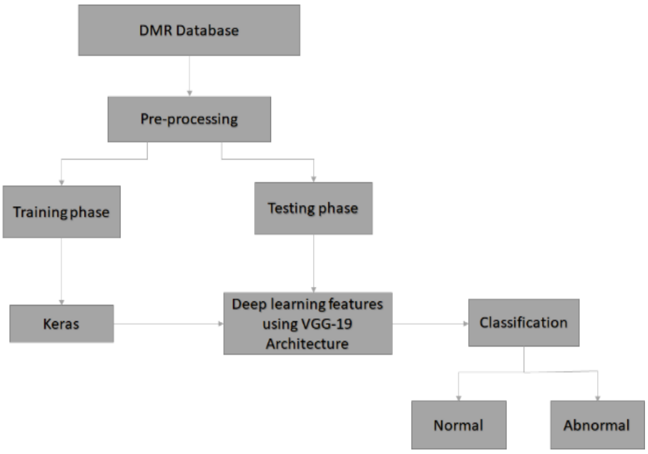

Fig. 2. Flow diagram of the proposed model

The framework, which is shown in the above figure, consists of various steps for accurately detecting breast cancer.The mechanism operates in four phases, as shown below.
Step 1: For analytical purposes, the dataset "DMR-Database" is uploaded into the database.
Step 2: The database is pre-processed for image reshaping, rescaling, and conversion to an array format when it is uploaded.
Step 3: The dataset is divided into two parts: training and testing.
Step 4: Building a CNN model is the fourth step. The training dataset is given to CNN, and the weights are fine-tuned to properly detect breast cancer.

3.1 Database

Researchers can use infrared breast images from the database for Mastology Research with Infrared Image—DMR-IR . The FLIR SC 620 thermal camera, which has a high resolution of 480*640 pixels, great sensitivity of 0.04, and a capture temperature range of 40 C to 500 C, was used to collect these photographs. This data collection has been used in a vast number of studies to compare performance. The DMR data set may be accessible on the internet for free. Thermographic pictures from this data set were utilized in this study. Figure [3] depicts the DMR-Mastology Research dataset.

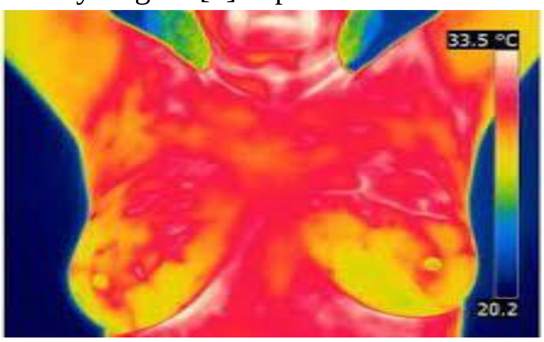

Fig. 3. An example of the DMR-Mastology Research dataset

The photographs were classified into three categories:

• Training and testing decided to take 80% of the work (400 Healthy and 400 Sick), which included obtaining characteristics and modifying filter weights. Training (320 thermography in each) and testing (320 thermography in each) were the two categories for this set (80 thermography in each class).

• 20% of the thermography (100 in each class) was set aside for blind validation and assessing the overall prediction accuracy of these structures using a non-learning image database (training and testing).

3.2 Thermography

Thermography, also known as thermal imaging, uses a specific camera to monitor the temperature of the skin on the surface of the breast.It is a non-invasive test that does not use radiation. Lawson published a revolutionary method of thermography for the analysis of breast lesions in 1957, and it was authorized and recognized as an effective tool for breast cancer diagnosis by the US Food and Drug Administration (FDA). Although thermography has been used for decades, there is limited evidence that it is a useful screening method for detecting breast cancer early on when it is most treatable."There is no reliable scientific evidence that thermography devices, used alone or in combination with another diagnostic test, are a helpful screening tool for any medical condition, including early detection of breast cancer or other diseases and health issues," the FDA said in the research. "The most effective breast cancer screening approach and the only one shown to enhance survival through early diagnosis is mammography (the process of acquiring x-ray images of the breast)."

Future studies will focus on designing and testing additional thermography versions that will improve the test's accuracy and use in the future. Thermography may also be used to identify breast cancer in its early stages, and it is a safe and rapid procedure. Finally, there is no need for ionization, high pressure, or breast compression with thermography.

Ekici et al [18], the camera will display variations in body temperature using a variety of colors to accentuate an increase or decrease in the quantity of infrared radiation emitted from the surface of the breast. This investigation resulted in the finding of anomalous temperature symmetry.In normal tissues, there is a minimum of high degree symmetry. Figure 4 depicts the technique and the equipment utilized.

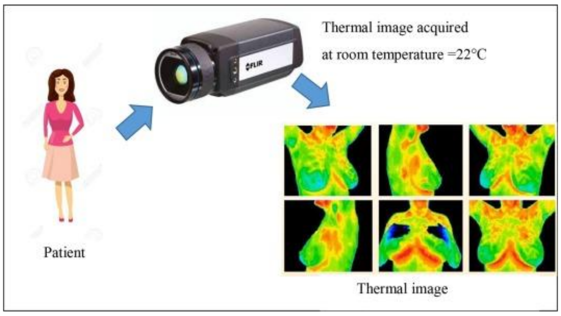

Fig. 4. Breast cancer detection using thermography

3.3 VGG-19

The VGG-19 model (also known as VGGNet-19) has the same principle as the VGG16 model, with the exception that it supports 19 layers. The number "19" refers to the model's number of weight layers (convolutional layers). There are 19 layers all in VGG19 (16 convolution layers, 3 fully connected layers, 5 MaxPool layers, and 1 SoftMax layer). VGG11, VGG16, and more VGG versions exist as well. The total number of FLOPs in VGG19 is 19.6 billion. The VGG-19 network, as the name implies, is made up of 19 CNN layers and three fully-connected layers. The VGG-19 network's architecture is shown in figure [5].

Filter sizes for the first and second convolutional layers are 64 pixels. The third and fourth filters have 128 pixels, the fifth and eighth have 256 pixels, while the ninth and sixteenth have 512 pixels. The only pre-processing was a reduction in the mean RGB value of each pixel, which was determined throughout the whole training set.Spatial padding was used in order to retain the image's spatial resolution. While previous studies focused on tanh or sigmoid functions, the Rectified linear unit (ReLu) was employed to introduce non-linearity into the model in order to enhance classification and speed up processing.

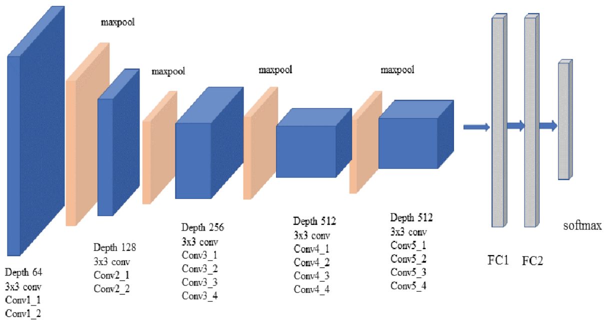

Fig. 5. The architecture of VGG19 CNN

3.4 Convolutional Neural Network (CNN)

Convolutional neural networks (CNNs, or ConvNets) are a type of artificial neural network widely employed in deep learning to analyze visual information. In 1998, Yann LeCun et al. proposed Convolutional Neural Networks (ConvNets or CNNs). A CNN is made up of convolutional and fully connected layers that are combined in a multi-stage process.In general, a convolution method is utilized to reduce the amount of memory required, and it is computed on confined regions to improve performance.

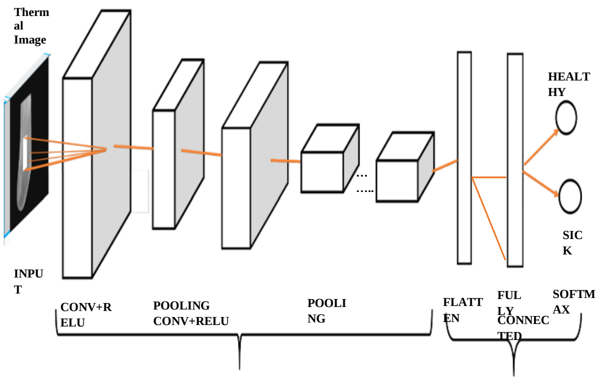

Fig. 6. Convolutional Neural Networks (CNN)

Convolutional neural networks (CNNs) are a type of feed-forward artificial neural network that employs multilayer perceptron variants to minimize pre-processing. CNN's design consists of a convolutional layer, a pooling layer, and a fully connected layer.Convolution means a filtering process, Pooling layer ensures non-linearity otherwise the data will lose dimensionality, and the fully connected layer allows classification of the dataset.

3.5 Convolution Layer

The layers in a deep CNN where filters are applied to the original image or other feature maps are known as convolutional layers. To find most of the network's user-defined variables. The number of kernels and their size are the most important qualities.In the reference section [18], the convolutional layer of CNN [Fig.7] on the other hand, is used for image classification andidentification. The Convolution layer parameters are made up of K learnable filters (also known as "kernels"), each of which has a width and height and is almost usually square. These filters are minimal, but cover the full depth of the volume.

Edge detection, blurring, and sharpening may all be accomplished by convolutions an image with many filters. The filter may not always properly suit the input image. In such instances, you have two choices: 1. Fill in the gaps with zeros to make the image fit (zero padding). 2. Cut off the part of the image where the filter didn't work. Because it only keeps a piece of the picture that is genuine, this is referred to as valid padding.

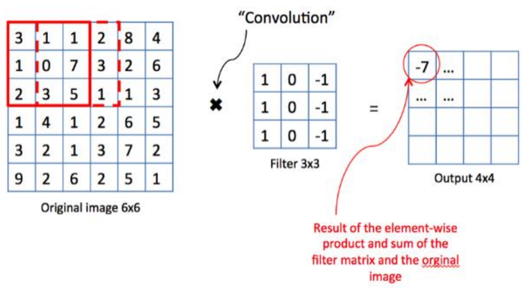

Fig. 7.A convolutional layer of CNN.

3.6 Pooling Layers

A Pooling Layer is typically used after a Convolutional Layer.Fig [8] shows the max-pooling and average pooling. The pooling layer component reduced the number of parameters when the images were too huge. Spatial pooling, also known as sub-sampling or down-sampling, reduces the dimensionality of each map while keeping important information. Maximum, average, and sum pooling are the three different types of spatial pooling. The corrected feature map's biggest element is used in max pooling. By picking the largest element, the average pooling can be computed. The total of all the components in a feature map is referred to as sum pooling.

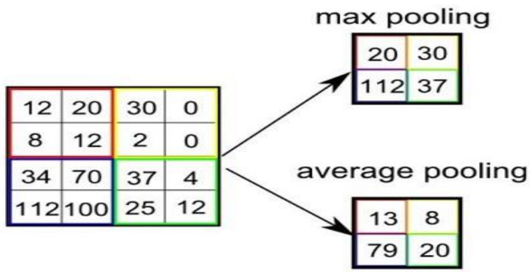

Fig. 8. Pooling Layer

3.7. ReLU Layers

ReLU stands for Rectified Linear Unit, which is a non-linear operation. The solution (x) = max is (0, x). The purpose of ReLU is to make our ConvNet more non-linear. In order to operate with real-world data, our ConvNet has learned non-negative linear values. In order to operate with real-world data, our ConvNet has learned non-negative linear values.

3.8 Fully-Connected Layers

A fully connected neural network is made up of a sequence of fully interconnected layers that connect each neuron in one layer to the next. Fully linked networks offer the advantage of being "structure agnostic," meaning that no special input assumptions are required.The Fully-Connected Layer is shown in Figure [9]. These properties, when combined with completely linked layers, form a model. Finally, to categorize the outputs, an activation function such as softmax or sigmoid is used.

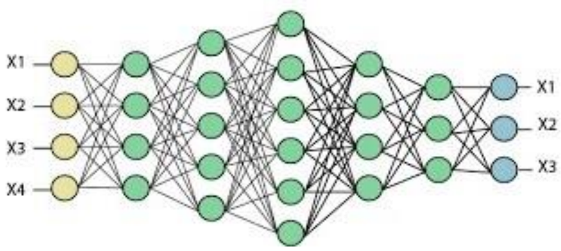

Fig. 9. Fully-Connected Layer.

4.PERFORMANCE METRICS

a) Accuracy: Accuracy is defined as the ratio of correctpredictions to total predictions produced by the model. Its mathematical definition is as follows:

$$\text{Accuracy} = \frac{TN+TP}{TP+FP+TN+FN}$$

Where, TP = True positive, FP = False Positive, TN = True Negative, FN = False Negative.

The number of pixels accurately recognized is known as True Positive. The number of healthy pixels identified as sick is known as a False Positive. The number of pixels accurately categorized as unhealthy is known as True Negative. The number ofpixels designated as healthy is measured by False Negative.

b) Precision: Precision measures the ability of the system's capacity to properly identify the kind of breast cancer in terms of true negative (TN) and false positive (FP).

$$\text{Precision} = \frac{TN}{FP+TN}$$

c) Recall: The performance of classification is measured by a recallsystem to classifybreast cancers according to terms of true positive (TP) and false-negative (FN).

$$\text{Recall} = \frac{TP}{TP+FN}$$

d) F1-score: Precision and Recall are weighted averages. As a result, this metric takes into account both types of false values. When the F1 score is 1, it is ideal; when it is 0, it is a complete failure.

$$F1 = 2 * \frac{(Precision*Recall)}{(Precision+Recall)}$$

5.RESULTS AND DISCUSSION

I.Datasets

In ordertopredictbreast cancer over 30,000 images from 2 classes have been evaluated.The DMR-Mastology Research dataset was selected to recognize breast cancer using the Google Colab environment. The dataset was customized to train and test. Initially, there are 84 images in the training dataset and 22 images in the testing dataset. The training dataset was split up into train_set and test_set. In the train_set 21,367 images were used for training processes and in test_set 10,335 images were used for validation processes.Theentiredataset was divided into training and testing sets at random. The model was instructed using the training set. The best accurate results maybeobtainedbyincludingmoreimagesinthetrainingdataset.Inthismodel, 80% ofthedataset wasusedfortraining andtheremaining 20% fortesting.

(a) (b)

Fig. 10. DMR-Mastology Research dataset images.

(a) Thermographic breast images without cancer. (b) Thermographic breast images with cancer.

The importance of deep learning networks in breast cancer diagnosis was established in this study. The model summary has been obtained using binary-cross-entropy with Adam as an optimizer. From the Tensorflow, the normalization layer and convolution layers are used and the epochs were determined. The epochs are calculated for 20 and obtained the Maximum Validation accuracy of 100% as shown in figure [11]. The loss values are less for this dataset which is an advantage.

```
10/10 [==============================] - 31s 3s/step - loss: 0.3956 - accuracy: 0.9875 - val_loss: 521.4713 - val_accuracy: 0.9316
Epoch 4/20
10/10 [==============================] - ETA: 0s - loss: 0.1844 - accuracy: 0.9875
Epoch 4: val_accuracy did not improve from 0.99609
10/10 [==============================] - 34s 3s/step - loss: 0.1844 - accuracy: 0.9875 - val_loss: 424.3519 - val_accuracy: 0.9375
Epoch 5/20
10/10 [==============================] - ETA: 0s - loss: 0.0945 - accuracy: 0.9937
Epoch 5: val_accuracy did not improve from 0.99609
10/10 [==============================] - 34s 3s/step - loss: 0.0945 - accuracy: 0.9937 - val_loss: 105.0653 - val_accuracy: 0.9707
Epoch 6/20
10/10 [==============================] - ETA: 0s - loss: 0.6547 - accuracy: 0.9875
Epoch 6: val_accuracy did not improve from 0.99609
10/10 [==============================] - 31s 3s/step - loss: 0.6547 - accuracy: 0.9875 - val_loss: 59.8509 - val_accuracy: 0.9863
Epoch 7/20
10/10 [==============================] - ETA: 0s - loss: 0.0986 - accuracy: 0.9937
Epoch 7: val_accuracy did not improve from 0.99609
10/10 [==============================] - 34s 3s/step - loss: 0.0986 - accuracy: 0.9937 - val_loss: 814.2450 - val_accuracy: 0.9082
Epoch 8/20
10/10 [==============================] - ETA: 0s - loss: 0.2299 - accuracy: 0.9937
Epoch 8: val_accuracy did not improve from 0.99609
10/10 [==============================] - 31s 3s/step - loss: 0.2299 - accuracy: 0.9937 - val_loss: 18.1649 - val_accuracy: 0.9961
Epoch 9/20
10/10 [==============================] - ETA: 0s - loss: 3.7241e-10 - accuracy: 1.0000
Epoch 9: val_accuracy improved from 0.99609 to 1.00000, saving model to /bestmodel.h5
10/10 [==============================] - 38s 4s/step - loss: 3.7241e-10 - accuracy: 1.0000 - val_loss: 0.0000e+00 - val_accuracy: 1.0000
Epoch 10/20
10/10 [==============================] - ETA: 0s - loss: 4.3835e-12 - accuracy: 1.0000
Epoch 10: val_accuracy did not improve from 1.00000
10/10 [==============================] - 36s 3s/step - loss: 4.3835e-12 - accuracy: 1.0000 - val_loss: 0.0000e+00 - val_accuracy: 1.0000
Epoch 11/20
10/10 [==============================] - ETA: 0s - loss: 0.2818 - accuracy: 0.9875
Epoch 11: val_accuracy did not improve from 1.00000
10/10 [==============================] - 31s 3s/step - loss: 0.2818 - accuracy: 0.9875 - val_loss: 133.9139 - val_accuracy: 0.9551
Epoch 12/20
10/10 [==============================] - ETA: 0s - loss: 0.0768 - accuracy: 0.9969
Epoch 12: val_accuracy did not improve from 1.00000
10/10 [==============================] - 31s 3s/step - loss: 0.0768 - accuracy: 0.9969 - val_loss: 0.4024 - val_accuracy: 0.9980
Epoch 12: early stopping
```

Fig. 11. Epochs values for DMR-Mastology Research dataset.

The model VGG-19 was constructed using a convolutional neural network model with a learning rate of 0.001. The weights and biases were changed using the Adam optimizer, and the momentum of 0.9 was adjusted. The batch size is fixed to 32, and the number of epochs was set to 10. The accuracy of this model was tested using 20% of the images from the DMR-Mastology Research dataset.

In each class, 20% of the images were chosen at random for testing. For the DMR-Mastology Research dataset, a graph was plotted between Training and Validation Accuracy, as well as Training and Validation Loss, as illustrated in Figs. [12] and [13]. From the graph, the training accuracy increased by 100% and the Validation Accuracy has increased gradually increased.

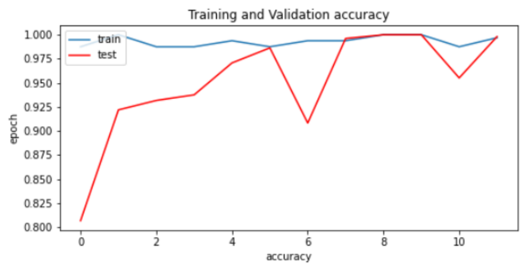

Fig. 12. Training accuracy vs Validation accuracy

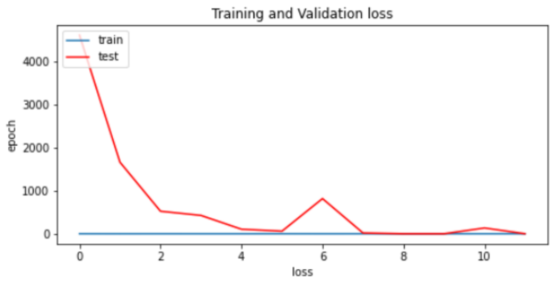

Fig. 13. Training loss vs Validation loss

The model's accuracy and loss for both training and validation graphs are presented above. When the training dataset and epoch are raised, so does the accuracy is also increased. The accuracy of the model achieves the best accuracy of 99.80% at the epoch and classifies the test images.

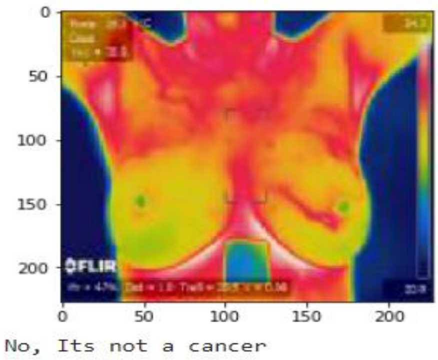

Fig.14. ClassificationResult.

6.CONCLUSION

A deep neural network is used to detect breast cancer using thermographic images. The findings of the experiments show that the training process is uninterrupted. It achieved a maximum training accuracy of 100% for the DMR-Mastology Research dataset. The studies achieved the highest accuracy performance with 99.05% using the VGG-19 algorithm. As a result of these findings, the DMR-Mastology Research dataset is more stable and provides high accuracy values.

These accuracies of the proposed model can be enhanced in the future. Furthermore, the proposed system can be implemented on hardware processors.

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