Early Detection of Breast Cancer using Pretrained AlexNet Convolutional Neural Network

1st Brenda Guanulema
School of Biological Sciences and Engineering, Universidad Yachay Tech
Urcuquí, Ecuador
brenda.guanulema@yachaytech.edu.ec

2nd Daniela Osorio-Ordóñez
School of Biological Sciences and Engineering, Universidad Yachay Tech
Urcuquí, Ecuador
daniela.osorio@yachaytech.edu.ec

3rd Helen Vaca-Farinango
School of Biological Sciences and Engineering, Universidad Yachay Tech
Urcuquí, Ecuador
helen.vaca@yachaytech.edu.ec

4th Ariana Mieles-Salazar
School of Biological Sciences and Engineering, Universidad Yachay Tech
Urcuquí, Ecuador
ariana.mieles@yachaytech.edu.ec

5th Fernando Villalba-Meneses
School of Biological Sciences and Engineering, Universidad Yachay Tech
Urcuquí, Ecuador
gvillalba@yachaytech.edu.ec

6th Gabriela Cevallos-Bermeo
School of Biological Sciences and Engineering, Universidad Yachay Tech
Urcuquí, Ecuador
gabriela.cevallos@yachaytech.edu.ec

7th Carolina Cadena-Morejon
School of Mathematical and Computational Sciences, Universidad Yachay Tech
Urcuquí, Ecuador
ccadena@yachaytech.edu.ec

8th Diego Almeida-Galárraga
School of Biological Sciences and Engineering, Universidad Yachay Tech
Urcuquí, Ecuador
Universidad de Otavalo
Otavalo, Ecuador
dalmeida@yachaytech.edu.ec

9th Andrés Tirado-Espín
School of Mathematical and Computational Sciences, Universidad Yachay Tech
Urcuquí, Ecuador
Universidad de Otavalo
Otavalo, Ecuador
ctirado@yachaytech.edu.ec

***Abstract*—Early detection of breast cancer is crucial in reducing mortality rates among women. Mammography imaging is an effective diagnostic technique, but it can be difficult to distinguish between healthy and cancerous tissue. Deep learning and convolutional neural networks (CNNs) have proven to be valuable tools in detecting breast cancer. In this study, we propose using a pre-trained CNN AlexNet to classify patients with breast cancer from healthy patients using digital imaging processing. The model was trained on a dataset of 1500 mammograms of healthy breasts and 1500 mammograms of breasts with malignant tumors and 720 images to validation. Additionally, data augmentation was performed to double the size of the training dataset to 6000. The proposed model showed a test accuracy of 98.9%, which is a higher accuracy value than the current state-of-the-art. This outcome underscores the potential of Alexnet as an effective tool for the early breast cancer detection through mammography images. This study highlights the potential of deep learning and CNNs in early breast cancer detection, therefore the exciting possibility for their real-world application can significantly improve the prognosis and quality of life for patients.**

Keywords*—*Breast cancer, deep learning, convolutional neural networks, CNN, digital image processing.

I. Introduction

Breast cancer is one of the most frequent types of cancer among women and has the highest incidence rate in patients worldwide as skin cancer [1]. In 2022, it was estimated that 287,850 new cases of invasive breast cancer and 51,400 cases of ductal cancer in situ DCIS would be diagnosed. Additionally, an estimated 43,250 women would die from breast cancer [2]. Although breast cancer has a higher incidence in women, men can also be diagnosed with it. According to the American Cancer Society, about 2700 men are diagnosed with breast cancer yearly, and approximately 530 men die because of it [3]. The World Health Organization (WHO) reported several new cases of breast cancer in females of all ages in Ecuador in 2020, of 3563 women [4].

For this reason, an early diagnosis is key to reducing the mortality rate since an immediate treatment can be applied. Therefore, some of the techniques that are usually used for its detection are digital mammography, considered one of the most effective methods in reducing breast cancer mortality, with a sensitivity rate of approximately 87% [5]. Additionally, techniques encompass bilateral ultrasound testing, magnetic resonance imaging (MRI), positron emission tomography (PET) and computed tomography [6], [7].

A digital mammogram is an X-Ray image of the breast; it is performed to check for breast cancer in both asymptomatic women/men and those with symptoms that could indicate cancer. The mammography is analyzed by a radiologist; during its interpretation, the doctor will be on the lookout for a variety of breast alterations, including tiny white spots known as calcifications, abnormal areas known as masses, and other suspicious findings that could be symptoms of cancer, however, when radiologist give their diagnostic it has high specificity indicates a low rate of false positives (accurately identifying non-cancerous cases), but it is lower in terms of sensitivity, which means that some cases of cancer will not be detected correctly [8].

To improve the quality of human life and use fewer resources in favor of conserving it, science advances by leaps and bounds; a clear example of it is artificial intelligence and Deep Learning, which have revolutionized the field of biomedicine, due to the development of algorithms that detect pathologies [9], such as in the glaucoma detection [10], skin lesion detection [11], cardiac diseases detection [12], among other uses such as neurorehabilitation [13] and protein identification [14].Therefore, deep learning has emerged as a support in medicine for analysis and clinical diagnosis instead of conventional methods for the detection and classification of objects because of its machine learning and optimization of time [15].

Convolutional neural networks (CNN) provide new techniques for solving problems in pattern recognition, data analysis, segmentation, and classification in images [16]. These methods of machine learning are useful and easy to manipulate according to the image development, training, and testing models that the user applies. Basically, they consist of a compound of layers of networks that learn through each layer, and the data extraction grows according to the layer level [17]. Therefore, the AlexNet structure can provide superior performance with fewer training factors for medical image applications [18]. AlexNet architecture consists of eight layers: five convolutional layers and three fully connected layers. AlexNet can recognize off-center objects, and most of its top five classes for each image are reasonable [19]. In this section, we delve into the mathematical model of Convolutional Neural Networks (CNNs), a key component of our research aimed at significantly improving breast cancer detection.

A. Mathematical model of CNN

An asterisk * symbol is frequently used in mathematics to denote convolution [14]. If we have an input image represented by X and a filter represented by f, as indicated by equation (1):

$$Z = X \times f \tag{1}$$

The architecture of a convolutional neural network is hierarchical. Each additional layer xj after the input signal x is calculated as equation (2):

$$x_j = \rho W_j x_{j-1} \tag{2}$$

Wj: a stack of convolutional filters

ρ: a rectifier max (x, 0) or sigmoid 1/1+exp(−x)

Each layer of a filter map can be expressed as the sum of the convolutions of the previous layer (3):

$$x_j\,(u, k_j) = \rho\,\left[\sum_k \left(x_{j-1}(.,k) * W_{j,k_j}(.,k)\right)(u)\right] \tag{3}$$

Convolutional neural networks' definition of optimization is a very non-convex problem. As a result, the weights Wj are often trained using stochastic gradient descent, which computes gradients using the backpropagation process [20].

The late diagnosis of breast cancer in women is the main cause of the increase in the mortality rate; consequently, the purpose of this research is to develop a detection model based on a pre-trained convolutional neural network AlexNet that can accurately classify patients with cancer from the healthy ones using digital mammograms of the right and left breast. To accomplish this purpose, it is necessary to obtain and perform a classification of mammograms of healthy and breast cancer patients. For patients with cancer, the Chinese Mammography Database (CMMD) [21] was used, and the Kaggle King Abdulaziz University [22] mammogram dataset was used for healthy patients.

B. *Literature Review*

In following Table 1, the literature review was carried out using the following descriptions: deep learning, convolutional neural networks, mammography, and breast cancer. This compendium of relevant articles that explore and evaluate various convolutional neural network architectures were taken as a reference for our project to help us to make a comparison and improve it.

Zhao et al. used the MIAS database and created a deep neural network classifier for the two-class categorization of benign and malignant mammograms. Their results revealed that their model's classification capability is more significant, with an accuracy of 97.57%. To address the issue of having a small dataset of only 115 ROI (Region of Interest) images for tuning a deep neural network model, data augmentation techniques were employed. These techniques involved creating new sample images by applying various transformations such as flipping, rotation, and others to the existing data [23]. Senan et al. used the BreaKHis dataset and proposed a convolutional neural network (AlexNet) method that extracts the most detailed features to classify breast cancer as benign or malignant. The study applied transfer learning and fine-tuned the AlexNet model pre-trained on the dataset for classifying breast histology images, they achieved an accuracy of 95% in the detection of breast lesions with their CNN. In the proposed system, data augmentation techniques were used to address the challenges of insufficient dataset size and overfitting in convolutional neural networks (CNNs) for histology image analysis [24]. Omonigho et al. used the MIAS database to classify breast cancer into benign and malignant tumors using a modified AlexNet. The deep convolutional neural network automatically learns and extracts information from mammographic pictures as a result, it reports an accuracy of 95.70%. In this study, original images from the MIAS database were initially in a large format, making training impractical. To address this, the images were downscaled by a factor of 16, reducing their dimensions to 64x64 for faster processing. These downscaled images were then augmented by horizontal flipping, resulting in different copies of each image. [25].

Xi et al. used the deep convolutional neural network VGGNet to locate masses and calcifications in mammography images without training on the entire images and presents an accuracy of 92.53% and demonstrate that they are the pioneers using a CBIS-DDSM dataset. To prevent overfitting, data augmentation techniques were applied to the training data, which included random rotations between zero and 360 degrees, as well as random X and Y reflections [26]. Hadush et al., their model is used to detect the mass region and classifies them into benign or malignant abnormality in mammogram (MG) images, the images were passed through different preprocessing stages such as gaussian filter, median filter, bilateral filters and extracted the region of the breast from the background of the MG image. The accuracy of the model is 91.86%. A dataset consisting of more than 5000 x-ray mammogram images collected from multiple hospitals between 2016 and 2018 was used in this study [27]. Guan et al., in their paper they firstly tested three training methods on the MIAS database and then they used method 2 to classify regions: benign vs. normal, malignant vs. normal and abnormal vs.

normal from the DDSM database and the average validation accuracy converged at about 90.5% for abnormal vs. normal cases. The study used region of interest (ROI) images for training neural networks, cropping them based on ground truth boundaries for abnormalities and averaging the size for normal ROIs. All ROIs were resized to a specific dimension and converted to RGB format for compatibility with CNN input requirements [28]. Characterization and classification model of microcalcification proposed by Cai et al. achieved an accuracy of 89.32%, he proposed a model based in AlexNet architecture to extract the deep features. The CNN architecture consisted of five convolutional layers with specific filter sizes and rectified linear unit activation, along with three max-pooling layers to reduce data dimension. To address overfitting, a dropout strategy was used [29].

The problems that exist in the literature are that they only detect the breast mass abnormality but no macro calcification abnormalities.

TABLE I. LITERATURE REVIEW FROM 2018 TO 2022

Model	**Database**		**Performance Measure**	**Ref.**
	Type	***Size (n)***	***Accuracy (%)***	
AlexNet	MIAS	4600	97.57	[23]
AlexNet	BreakHis	9109	95.00	[24]
AlexNet	MIAS	2576	95.70	[25]
VGG-Net	CBIS-DDSM	3103	92.53	[31]
VGG based R-CNN	MG	1588	91.86	[27]
VGG-16	MIAS-DDSM	2942	90.50	[28]
AlexNet	SYUCC	990	89.32	[29]

II. MATERIALS AND METHODS

A. Mammography dataset

The dataset was collected from two open access repositories: first, from the Kaggle King Abdulaziz University mammogram dataset, which depends on BI-RADS categories, where it was obtained 1800 mammography's images in jpg format of healthy patients of the right and left breast [22]. Second, in The Cancer Imaging Archive (TCIA) [32] provides Chinese Mammography Dataset (CMMD) [21] from the cancer imaging archive contains data from 3728 mammography images with benign and malign cases from the left and right sides of the breast; Although the last dataset would not be considered a current format, it allows the access to malignant mammography that, with an adequate image process, results in an optimal option for the neural network work.. As a result, from the two open data set a total of 3720 images were utilized for the networking.

The dataset used for AlexNet training comprised 1500 images of patients with breast cancer and 1500 images of healthy patients as shown in Fig. 1. On the other hand, for networking validation were used a total of 720 images were from breast cancer and normal breast. The data set was classified into two significant folders according to the BIRADS classification system. A BIRADS with a value of 1 corresponds to the category of negative or normal, and a BIRADS with a value of 5 means a malignant type. According to the information in the tables of the principal dataset, the images were divided into a folder named healthy breasts and a folder called breast cancer.

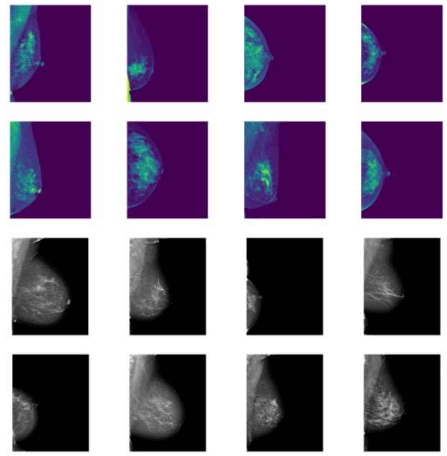

Fig. 1. Set and visualization of the dataset of mammographies images.

B. Image pre-processing

The first step is prepared data used in the train model, Fig. 2. shows the pre-processing of mammography images. Since these X-ray images are in different formats, it was necessary to preprocess the images to convert them to JPG format. The CMMD dataset was downloaded in TCIA format, so it was converted into DICOM format by NBIA Data Retriever in DICOM format; Then, this dataset was converted into JPEG format using DICOM Converted App (D2J).

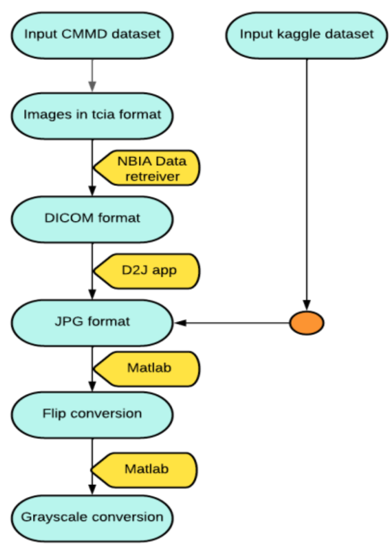

Fig. 2. Flowchart of image pre-processing.

In addition, it used the software tool MATLAB called Image Batch Processor, which allows the processing of multiple images in bulk. In this tool, the *flipr* function flips the array horizontally (left to right). It takes an input array and returns the same array with its columns flipped in the left-right direction, making it easier for AlexNet networking to identify and extract certain features from the images; its pre-processing was made with the code *B = fliplr(A)* [33]. In addition, to enhance the identification of the characteristics of breast cancer, the preprocessing of the complete dataset of 3720 x-ray images was made in MATLAB with *rgb2gray*, which converts an RGB image or colormap to grayscale with the code *I = rgb2gray (RGB)* [34].

C. Data augmentation

Data augmentation was selected as a method to improve the generalization ability of the neural network. For this reason, the training data was duplicated with different image enhancement techniques. From the original dataset for training, every 500 images were copied and applied gaussian noise, median filter, and erode image with image batch processor in MATLAB. Finally, the training and validation of the CNN model were carried out using the augmented image data containing 6,720 images, of which 3,360 mammograms are positive for breast cancer, and 3,360 are mammograms of healthy patients.

- Gaussian Noise Filter removes noise by smoothing each pixel of the mammography. This filter convolves each pixel with a Gaussian kernel. This results in the output pixel being calculated by summing the convolution of all pixels[35]. Subsequently, the equation (4) carried out on every input pixel can be determined as:

  $$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{4}$$

  where (x,y) are the distances from the origin in the horizontal and vertical axis, respectively. And σ is the standard deviation of the Gaussian distribution.
  The function used to perform the Median filter is *imgaussfilt()*.
-
- Median Blur Filter replaces the values of a pixel with the median of the neighbor pixel's spectrum level. It decreases the noise by calculating pixel by pixel, going through all the neighborhoods. This filter substitutes each pixel within the original image with the median value derived from the neighboring pixels encompassed within a square area centered on the pixel under consideration The output pixel g(x,y) is computed as the weighted sum of the input pixel f(i+k, j+l), so in equation (5):

  $$g(i,j) = \sum_{k,l} f(i+k, j+l) h(k,l) \tag{5}$$

  where h(k,l) is the kernel.
  The function used to perform the Median filter is *medfilt2()*.
- Erode filter it is a morphological filter that reduces the noise and shrink the boundaries of foreground objects in binary or grayscale image. The mathematical model of an erosion filter involves the use of a structuring element (also known as a kernel) that defines the neighborhood around each pixel in the input image. The mathematical representation of this filters follows in equation (6):

  $$I_{eroded}(x) = \min_{p \epsilon B} I(x+p) \tag{6}$$

  Where I_{eroded} (x) represents the pixel value at position x in the eroded image, and I(x+p) represent the pixel value in the input image at position x+p (where p is the relative position defined by the kernel B).
  The function used to perform the erode filter is *imerode()*.

Fig 3. shows the process of applying filters and image enhancement techniques, which helps to improve the model's robustness by introducing variability in the training data and reducing the risk of overfitting. In addition, data augmentation allows the model to generalize better to new images that it has not seen before.

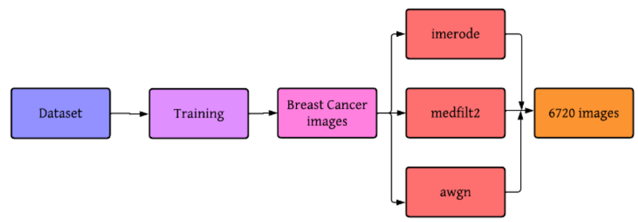

Fig. 3. Image enhancenment techniques and filters application process to input images in MATLAB.

D. AlexNet architecture

The AlexNet architecture used on the presented study is shown in Fig. 4. It consists of eight layers, including five convolutional layers and three fully connected layers. It also uses ReLU activations, dropout regularization, and data augmentation techniques. In addition, the input size of the structure is 227x227 pixels and a depth of 3 channels. The use of TensorFlow and Keras to implement AlexNet provides a high-performance interface that simplifies the creation and training of models of this architecture, allowing for easy image classification.

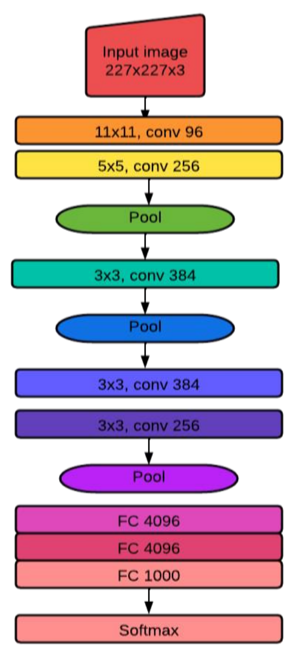

Fig. 4. AlexNet architecture.

E. *Model training*

The training model was performed in Google Colab to develop code in Python format. It uses the kernel matrix, which refers to the collection of 2D convolutional filters used in the convolutional layers of the network. It has been appreciated in the literature that it plays a crucial role in extracting meaningful features from the input image and enabling the network to perform accurate image classification tasks. In addition, it used a categorical class mode and the parameter used in training model is shown in Table 2. The criteria for selecting these parameters are based on the best results of the AlexNet training. In addition, the batch size of 128 was chosen so as not to take up too many graphics card resources.

TABLE II. PARAMETERS USED IN MODEL TRAINING

Parameters	Value
Learning rate	0.0001
Rotation range	10
Shear range	0.02
Zoom range	0.2
Batch size	128
Target size	227x227
Epoch	10

III. RESULTS

After the training and validating the 3,720 images database with the previously described parameters, almost 100% accuracy was obtained, suggesting a possible over-training of the deep convolutional neural network [36]. Consequently, a data augmentation was realized to apply noise addition and other image enhancement techniques for an improvement in the generalization ability of the model. Therefore, the results are divided into two phases: breast cancer identification without augmentation and with augmentation of the KAU-CMMD training dataset. Is important to remark that in both cases, the parameters used in both models were the same.

In Table 3, the accuracy and loss values obtained during the training and validation of images were summarized and compared.

TABLE III. ACCURACY AND LOSS VALUES BEFORE AND AFTER DATA AUGMENTATION IN 10 EPOCHS

Description	Size of Database	Performance Measurement			
	(n)	*Accuracy (%)*	*Loss (%)*	*Validation Accuracy*	*Validation loss (%)*
Data	3000	98.90	2.90	99.60	0.58
Data augmentation	6000	99.50	1.40	99.80	2.30

These values exhibit that the data augmentation and the image enhancement techniques applied to the original database were not adequate solutions for getting a lower accuracy. On the other hand, the accuracy percentages increased after the application of all the enhancements techniques and data augmentation.

The training and validation of the CNN model was carried out using the original image data containing 3,720 images, of which 1,860 mammograms are positive for breast cancer, and 1,860 are mammograms of healthy patients.

The training and validation curves presented below were obtained from the AlexNet neural network for the detection of healthy and cancer patients, these graphs help us to understand how a neural network behaves in the training process and how it generalizes to unseen data. The vertical axis shows the accuracy of the model, i.e., its ability to correctly classify samples. The horizontal axis shows the number of iterations or epochs the model performed during training. In general, what we want to achieve is that both curves increase over time. If the training curve continues to improve while the validation curve stops or decreases, this could indicate overfitting, which means that the model is memorizing the training data but not generalizing them well. On the other hand, if both curves are low, the model may be underfit. What is necessary is to find a balance between both curves, where high accuracy rates are achieved in both the training set and the validation set. These curves help us make decisions on how to adjust and improve the model to obtain more reliable cancer detection results.

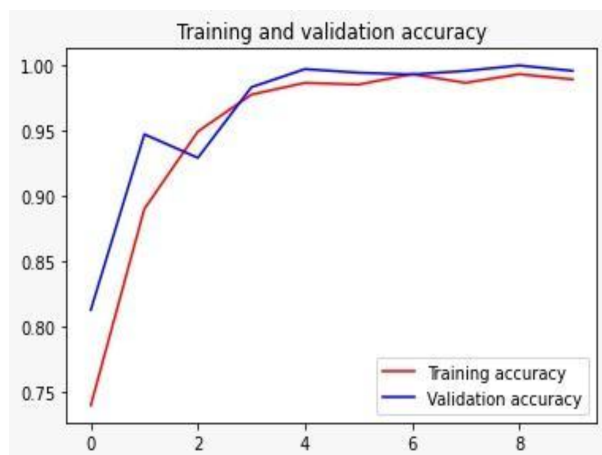

Fig. 5. Training and validation accuracy values of AlexNet with the 3720 image database.

In addition, Fig. 5. represents the plot of all the accuracy values obtained during the training and validation processes with 10 epochs. The curve seems to display a normalized behavior without any overfitting or underfitting. Also, the training and validation accuracy values have similar increasing behavior, meaning their values increase almost at the same ratio during the different epochs. Moreover, the accuracy values achieve a plateau or become constant around the third epoch.

In Fig. 6., the curve for training and validation loss values during the training and validation processes. Similar to the accuracy plot, these values exhibit normal behavior, and the loss values during the training and validation decrease at the same ratio.

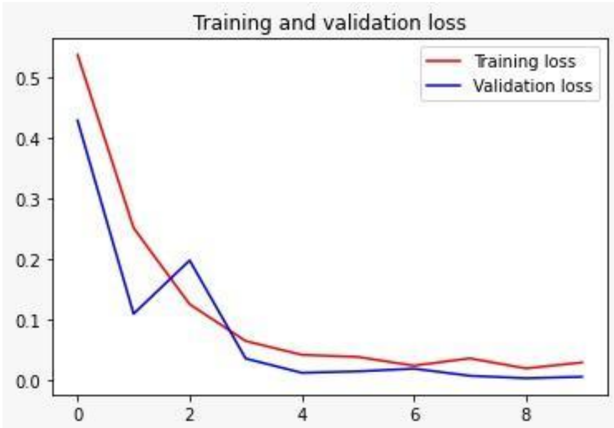

Fig. 6. Training and validation loss values of AlexNet with the 3720 image database.

In Fig. 7., the plot of all the accuracy values obtained during the training and validation processes with 10 epochs follows the previous normalized behavior with a similar increasing ratio. Moreover, the accuracy values achieve a plateau or become constant around the third epoch.

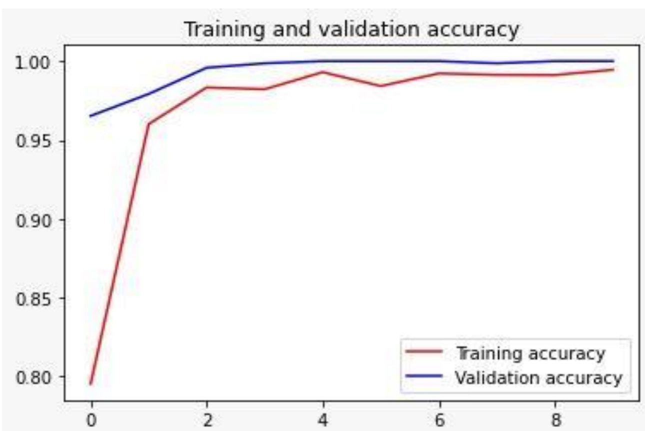

Fig. 7. Training and validation accuracy values of AlexNet with the 6720 image database.

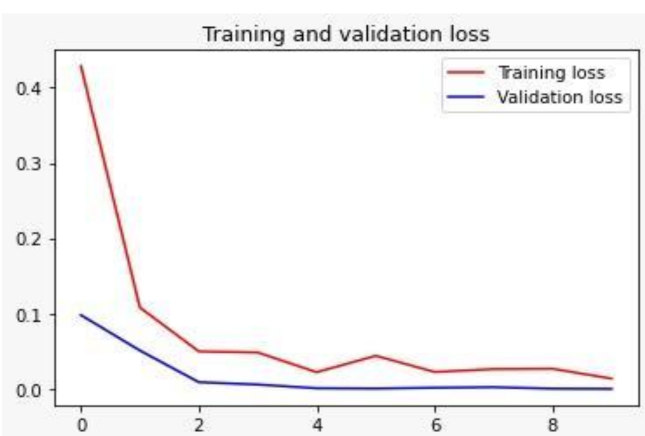

Fig. 8. Training and validation accuracy loss of AlexNet with the 6720 image database.

In Fig. 8., the curve for training and validation loss values during the training and validation processes. Similar to the accuracy plot and the results of the previous model, these values exhibit normal behavior, and the loss values during the training and validation decrease at the same ratio.

IV. DISCUSSION

In the present study, the AlexNet pre-trained convolutional neural network was used for breast cancer detection using mammograms. Three filters, Gaussian, median filter and erode, were applied to the mammograms in order to enhance the contrast enhancement and edges of the mammogram, to reduce noise and to facilitate the visualization of tumors and relevant features of the breast tissue, so that the network can detect patterns and determine the presence of cancer accurately.

In comparison with similar studies in Table 4. it is presented that the AlexNet network outperformed architectures such as VGG-Net, VGG-16, VGG based R-CNN which show an accuracy of 92.53%, 90.50%, 91.86% respectively. In contrast with those that employed AlexNet for network training shows a high accuracy, [23] presents an accuracy of 97.57% with a training of 95 epochs, followed by [25] with 95.70% with 100 epochs, [24] with 95% and 89.32% [29], this last one is the lowest with respect to all architectures, which is used for detection of microcalcifications. Respect to the filters applied in the different architectures, it should be considered whether their presence improved the accuracy, and the use of filters will depend on the quality of the images used for training [37].

The proposed model presented an accuracy higher than 98.90% without filters, and when the data augmentation was performed together with the application of filters, the accuracy of the network improved to 99.50%. This remarkable performance underscores the efficacy of Alexnet architecture in cancer detection. However, its essential to exercise caution in interpreting these results, as the high accuracy achieved could potentially be attributed to data overfitting. Compared to related works, our model's exceptional performance is particularly striking when considering the minimal training time. With only 10 epochs, we achieve noteworthy results, as evidenced by the stabilization of loss and accuracy values after this point. This observation suggests that further training epochs may not yield significant improvements, making the model's efficiency even more noteworthy.

To ensure the robustness of our findings and guard against overfitting, we recommend employing additional techniques such as cross-validation, exploring hyperparameter adjustments, and augmenting the database. These steps will help validate the model's performance and ensure its applicability in real-world scenarios [38].

TABLE IV. COMPARISON BETWEEN THE MODELS OF THE LITERATUE AND THE PRESENT WORK.

Model	**Performance Measure**	**Epochs**	**Data information**		**Ref**
	Accuracy (%)		***Filter***	***Data augmentation***	
AlexNet	97.57	95	Kernel	Yes	[23]
AlexNet	95.00	-	Kernel	Yes	[24]

Model	Performance Measure	Epochs	Data information		Ref
	Accuracy (%)		***Filter***	***Data augmentation***	
AlexNet	95.70	100	Gaussian	Yes	[25]
VGG-Net	92.53	200	Banks	Yes	[31]
VGG based R-CNN	91.86	500	Gaussian, median & bilateral	No	[27]
VGG-16	90.50	500	Gabor	No	[28]
AlexNet	89.32	300	Morphological	Yes	[29]
Present work AlexNet	98.90	10	-	No	-
Present work AlexNet	99.50	10	Gaussian, Median Erode	Yes	-

V. Conclusion

The presented study addresses the critical need for early breast cancer detection, recognizing the challenges in accurately distinguishing between healthy and cancerous tissue through mammography imaging. Moreover, the research of neural networks has increased in recent years due to their advantages in the detection and study of diseases of high mortality rates. Leveraging the power of convolutional neural networks (CNNs), we proposed a novel approach utilizing the pre-trained CNN model, AlexNet, to classify patients with breast cancer from healthy individuals using image enhancement techniques and only 10 epochs for training.

Initially, the model demonstrated a remarkable performance, achieving an accuracy rate of 98.90% without the application of filters or data augmentation procedures. Besides, data augmentation was introduced alongside filter application, to analyze if their application settles a possible overfitting in the model. Furthermore, the network's accuracy soared to an impressive 99.50%, highlighting the potential and effectiveness of AlexNet in early breast cancer detection, and presenting a substantial advancement compared to the current state-of-the-art methods.

It is crucial to acknowledge that while these results are promising, they also raise concerns of potential data overfitting, which can affect the reliability of our model. To address this, we recommend the implementation of rigorous techniques such as cross-validation, exploration of hyperparameter adjustments, and database augmentation to ensure the model's robustness and reliability.

On the other hand, our research demonstrates that with just 10 epochs of training, we attain exceptional results, as evidenced by the convergence of loss and accuracy values. This observation suggests that extended training may not be necessary, underscoring the efficiency of our approach. Overall, this study offers a contribution to the early detection of breast cancer, highlighting the transformative potential of deep learning and CNNs in improving the prognosis and quality of life for patients. Our findings not only align with the objectives outlined but also pave the way for future advancements in the realm of medical imaging and cancer diagnosis.

References

[1] WCRF International, “Breast Cancer Statistics,” Mar. 23, 2022.

[2] A. N. Giaquinto *et al.*, “Breast Cancer Statistics, 2022,” *CA Cancer J Clin*, vol. 72, no. 6, pp. 524–541, Nov. 2022, doi: 10.3322/caac.21754.

[3] R. A. Smith *et al.*, “Cancer screening in the United States, 2017: A review of current American Cancer Society guidelines and current issues in cancer screening,” *CA Cancer J Clin*, vol. 67, no. 2, pp. 100–121, Mar. 2017, doi: 10.3322/caac.21392.

[4] International Agency for Reseach on Cancer (IARC), “Ecuador Fact Sheets,” *Globocan 2020*, 2020.

[5] C. D. Lehman *et al.*, “National Performance Benchmarks for Modern Screening Digital Mammography: Update from the Breast Cancer Surveillance Consortium,” *Radiology*, vol. 283, no. 1, pp. 49–58, Apr. 2017, doi: 10.1148/radiol.2016161174.

[6] M. Broeders *et al.*, “The Impact of Mammographic Screening on Breast Cancer Mortality in Europe: A Review of Observational Studies,” *J Med Screen*, vol. 19, no. 1_suppl, pp. 14–25, Sep. 2012, doi: 10.1258/jms.2012.012078.

[7] D. Barba *et al.*, “Breast cancer, screening and diagnostic tools: All you need to know,” *Crit Rev Oncol Hematol*, vol. 157, p. 103174, Jan. 2021, doi: 10.1016/j.critrevonc.2020.103174.

[8] P. Taylor, J. Champness, R. Given-Wilson, K. Johnston, and H. Potts, “Impact of computer-aided detection prompts on the sensitivity and specificity of screening mammography,” *Health Technol Assess (Rockv)*, vol. 9, no. 6, Feb. 2005, doi: 10.3310/hta9060.

[9] A. Rodríguez-Ruiz *et al.*, “Detection of breast cancer with mammography: Effect of an artificial intelligence support system,” *Radiology*, vol. 290, no. 3, pp. 305–314, Mar. 2019, doi: 10.1148/radiol.2018181371.

[10] D. Almeida-Galarraga *et al.*, “Glaucoma detection through digital processing from fundus images using MATLAB,” in *Proceedings - 2021 2nd International Conference on Information Systems and Software Technologies, ICI2ST 2021*, Institute of Electrical and Electronics Engineers Inc., Mar. 2021, pp. 39–45. doi: 10.1109/ICI2ST51859.2021.00014.

[11] O. P. Yanchatuña *et al.*, “Skin Lesion Detection and Classification Using Convolutional Neural Network for Deep Feature Extraction and Support Vector Machine,” vol. 11, no. 3, 2021.

[12] E. Aguiar-Salazar, F. Villalba-Meneses, A. Tirado-Espín, D. Amaguaña-Marmol, and D. Almeida-Galárraga, “Rapid Detection of Cardiac Pathologies by Neural Networks Using ECG Signals (1D) and sECG Images (3D),” *Computation*, vol. 10, no. 7, Jul. 2022, doi: 10.3390/computation10070112.

[13] M. G. Gualsaquí *et al.*, “Convolutional Neural Network for Imagine Movement Classification for Neurorehabilitation of Upper Extremities Using Low-Frequency EEG Signals for Spinal Cord Injury,” in *Communications in Computer and Information Science*, Springer Science and Business Media Deutschland GmbH, 2022, pp. 272–287. doi: 10.1007/978-3-030-99170-8_20.

[14] J. D. Suquilanda-Pesántez, E. D. Aguiar Salazar, D. Almeida-Galárraga, G. Salum, F. Villalba-Meneses, and M. E. Gudiño Gomezjurado, “NIFtHool: an informatics program for identification of NifH proteins using deep neural networks,” *F1000Res*, vol. 11, p. 164, 2022, doi: 10.12688/f1000research.107925.1.

[15] K. Yasaka, H. Akai, A. Kunimatsu, S. Kiryu, and O. Abe, “Deep learning with convolutional neural network in radiology,” *Jpn J Radiol*, vol. 36, no. 4, pp. 257–272, Apr. 2018, doi: 10.1007/s11604-018-0726-3.

[16] M. M. Taye, “Theoretical Understanding of Convolutional Neural Network: Concepts, Architectures, Applications, Future Directions,” *Computation*, vol. 11, no. 3, p. 52, Mar. 2023, doi: 10.3390/computation11030052.

[17] A. A. Almisreb, N. Jamil, and N. M. Din, “Utilizing AlexNet Deep Transfer Learning for Ear Recognition,” in *2018 Fourth International Conference on Information Retrieval and Knowledge Management (CAMP)*, IEEE, Mar. 2018, pp. 1–5. doi: 10.1109/INFRKM.2018.8464769.

[18] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.

[19] S. Sengan, L. Arokia Jesu Prabhu, V. Ramachandran, V. Priya, L. Ravi, and V. Subramaniyaswamy, "Images super-resolution by optimal deep AlexNet architecture for medical application: A novel DOCALN1," *Journal of Intelligent & Fuzzy Systems*, vol. 39, no. 6, pp. 8259–8272, Dec. 2020, doi: 10.3233/JIFS-189146.

[20] J. Koushik, "Understanding Convolutional Neural Networks," May 2016.

[21] C. C. H. F. Z. Z. L. D. T. L. J. W. Jinghua. Cui *et al.*, "The Chinese Mammography Database (CMMD): An online mammography database with biosy confirmed types for machine diagnosis of breast. ," *The Cancer Imaging Archive*, 2021.

[22] A. S. Alsolami, W. Shalash, W. Alsaggaf, S. Ashoor, H. Refaat, and M. Elmogy, "King Abdulaziz University Breast Cancer Mammogram Dataset (KAU-BCMD)," *Data (Basel)*, vol. 6, no. 11, p. 111, Oct. 2021, doi: 10.3390/data6110111.

[23] X. Zhao, X. Wang, and H. Wang, "Classification of Benign and Malignant Breast Mass in Digital Mammograms with Convolutional Neural Networks," in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Oct. 2018, pp. 47–50. doi: 10.1145/3285996.3286006.

[24] E. M. Senan, F. W. Alsaade, M. I. A. Al-Mashhadani, T. H. H. Aldhyani, and M. H. Al-Adhaileh, "Classification of histopathological images for early detection of breast cancer using deep learning," *Journal of Applied Science and Engineering (Taiwan)*, vol. 24, no. 3, pp. 323–329, 2021, doi: 10.6180/jase.202106_24(3).0007.

[25] E. L. Omonigho, M. David, A. Adejo, and S. Aliyu, "Breast Cancer:Tumor Detection in Mammogram Images Using Modified AlexNet Deep Convolution Neural Network," in *2020 International Conference in Mathematics, Computer Engineering and Computer Science, ICMCECS 2020*, Institute of Electrical and Electronics Engineers Inc., Mar. 2020. doi: 10.1109/ICMCECS47690.2020.240870.

[26] IEEE Instrumentation and Measurement Society and Institute of Electrical and Electronics Engineers, *MeMeA 2018 Rome : 2018 IEEE International Symposium on Medical Measurements & Applications : 2018 symposium proceedings : June 11-13, 2018*.

[27] S. Hadush, Y. Girmay, A. Sinamo, and G. Hagos, "Breast Cancer Detection Using Convolutional Neural Networks," Mar. 2020, [Online]. Available: http://arxiv.org/abs/2003.07911

[28] S. Guan and M. Loew, "Breast Cancer Detection Using Transfer Learning in Convolutional Neural Networks," in *2017 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*, IEEE, Oct. 2017, pp. 1–8. doi: 10.1109/AIPR.2017.8457948.

[29] H. Cai *et al.*, "Breast Microcalcification Diagnosis Using Deep Convolutional Neural Network from Digital Mammograms," *Comput Math Methods Med*, vol. 2019, pp. 1–10, Mar. 2019, doi: 10.1155/2019/2717454.

[30] J. Pereira-Carrillo, D. Suntaxi-Dominguez, O. Guarnizo-Cabezas, G. Villalba-Meneses, A. Tirado-Espín, and D. Almeida-Galárraga, "Comparison Between Two Novel Approaches in Automatic Breast Cancer Detection and Diagnosis and Its Contribution in Military Defense," in *Smart Innovation, Systems and Technologies*, Springer Science and Business Media Deutschland GmbH, 2022, pp. 189–201. doi: 10.1007/978-981-16-4884-7_15.

[31] P. Xi, C. Shu, and R. Goubran, "Abnormality Detection in Mammography using Deep Convolutional Neural Networks," in *2018 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, IEEE, Jun. 2018, pp. 1–6. doi: 10.1109/MeMeA.2018.8438639.

[32] K. Clark *et al.*, "The Cancer Imaging Archive (TCIA): Maintaining and Operating a Public Information Repository," *J Digit Imaging*, vol. 26, no. 6, pp. 1045–1057, Dec. 2013, doi: 10.1007/s10278-013-9622-7.

[33] R. C. Gonzalez, R. E. Woods, and S. L. Eddins, *Digital Image Processing using MATLAB*, 3rd ed. Gatesmark Publishing, 2020.

[34] J. S. Lim, *Two-Dimensional Signal Processing*. Englewood Cliffs, NJ: Prentice Hall, 1990.

[35] N. Kumar and M. Nachamai, "Noise Removal and Filtering Techniques used in Medical Images," *Oriental journal of computer science and technology*, vol. 10, no. 1, pp. 103–113, Mar. 2017, doi: 10.13005/ojcst/10.01.14.

[36] S. Shafique and S. Tehsin, "Acute Lymphoblastic Leukemia Detection and Classification of Its Subtypes Using Pretrained Deep Convolutional Neural Networks," *Technol Cancer Res Treat*, vol. 17, p. 153303381880278, Jan. 2018, doi: 10.1177/1533033818802789.

[37] D. A. Ragab, M. Sharkas, S. Marshall, and J. Ren, "Breast cancer detection using deep convolutional neural networks and support vector machines," *PeerJ*, vol. 7, p. e6201, Jan. 2019, doi: 10.7717/peerj.6201.

[38] A. D. Gavrilov, A. Jordache, M. Vasdani, and J. Deng, "Preventing Model Overfitting and Underfitting in Convolutional Neural Networks," *International Journal of Software Science and Computational Intelligence*, vol. 10, no. 4, pp. 19–28, Oct. 2018, doi: 10.4018/IJSSCI.2018100102.