Detection of Breast Cancer using Convolutional Neural Networks with Learning Transfer Mechanisms

Victor Guevara-Ponce[1], Ofelia Roque-Paredes[2], Carlos Zerga-Morales[3], Andrea Flores-Huerta[4], Mario Aymerich-Lau[5], Orlando Iparraguirre-Villanueva[6]

Maestría Ciencia de los Datos-Escuela de Posgrado, Universidad Ricardo Palma, Lima, Perú[1,2,3,4,5]
Facultad de Ingeniería y Arquitectura, Universidad Autónoma del Perú, Lima, Perú[6]

***Abstract*—Breast cancer is the leading cause of mortality in women worldwide. One of the biggest challenges for physicians and technological support systems is early detection, because it is easier to treat and establish curative treatments. Currently, assistive technology systems use images to detect patterns of behavior with respect to patients who have been found to have some type of cancer. This work aims to identify and classify breast cancer using deep learning models and convolutional neural networks (CNN) with transfer learning. For the breast cancer detection process, 7803 real images with benign and malignant labels were used, which were provided by BreaKHis on the Kaggle platform. The convolutional basis (parameters) of pre-trained models VGG16, VGG19, Resnet-50 and Inception-V3 were used. The TensorFlow framework, keras and Python libraries were also used to retrain the parameters of the models proposed for this study. Metrics such as accuracy, error ratio, precision, recall and f1-score were used to evaluate the models. The results show that the models based on VGG16, VGG19 ResNet-50 and Inception-V3 obtain an accuracy of 88%, 86%, 97% and 96% respectively, recall of 84%, 82%, 96% and 96% respectively, in addition to f1-score of 86%, 83%, 96% and 95% respectively. It is concluded that the model that shows the best results is Resnet-50, obtaining high results in all the metrics considered, although it should be noted that the Inception-V3 model achieves very similar results in relation to Resnet-50, in all the metrics. In addition, these two models exceed the 95% threshold of correct results.**

Keywords*—Convolutional neural networks; transfer learning; deep learning; classification; breast cancer

I. Introduction

Breast cancer is the second most common cancer in women globally with more than 2.2 million cases in 2020. Breast cancer is the leading cause of mortality in women worldwide, as it is estimated that, in 2020, this carcinoma killed about 685 000 women [1]. This can be classified according to its histological basis into in situ and invasive carcinoma. Regarding the diagnosis of this disease, the evidence recommends that women over 40 years of age should undergo a screening mammogram every two years at the latest [2]. Mammography is the most used technique for the diagnosis of breast cancer; however, this test usually requires other ancillary tests to accurately determine the status of the tumor, among which are ultrasound [3] and tissue sampling [4]. Therapeutic treatment consists of debulking surgery, radiotherapy, endocrine targeted therapy and chemotherapy [5]. Among the surgical interventions, segmental mastectomy has proven to be effective in the treatment of tumors detected at early ages, especially when combined with the use of radiotherapy [6]. From these interventions, a sufficiently representative tissue sample is also obtained to perform the histopathological studies necessary for the determination of the benign or malignant nature of the tumor, which is why these images are used for the work. The main problem is how to identify and classify breast cancer using deep learning models. Also, as specific problems we have What kind of models can be applied? How to evaluate each of the models for the proposed case?

This paper presents four CNN models that can discover the features in the images, such as edges and corners to detect the type of breast cancer from biopsies, which can be used by medical centers to detect carcinoma in their patients. The four deep CNN models were programmed to classify the images into two types: benign and malignant. The CNN-based transfer learning models used for this research work are: VGG16, VGG19, ResNet50, and Inceptionv3, these models were programmed with the database hosted in Kaggle. The four CNN models seek to diagnose the type of breast carcinoma from histological breast images. It should be noted that the models used do not have the same number of depth layers, nor programming architecture, so the results are different in terms of accuracy. The objective of this work is to identify and classify breast cancer using Transfer Learning.

This paper is organized in the following order: In Section II a review of related works was performed, in Section III the methodology used for training the models is synthesized, in Section IV the results after experimentation are presented in addition to the discussion and in Section V the paper is concluded.

II. Related Work

In recent years, the concept of CNN has started to be used in fields such as medicine. This is because since their introduction they have presented very good results in image processing, as stated by LeCun in [7], [8].

The capacity of CNNs in image processing has led researchers to start using them in the classification of histological images, as is the case of [9], where they carried out a work for the classification between benignity and malignancy of images obtained from breast tumors in a Brazilian laboratory, a model with AlexNet architecture was trained using four different strategies to deal with the high resolution of the images presented; obtaining results close to 85% in all strategies. Among the results of the work, an accuracy of 89.6

+/- 6.5% stands out. In a different work it can be observed that the applications expand to other medical fields, as is the case of [10] where a model based on the Inception V3 architecture is trained to detect the stress of a person based on thermal images of points of interest of the head. The results obtained were good, reaching an accuracy of 88% when 5 stress classes were used, but 97% when these 5 classes were divided into 2 with the labels "No stress" (classes 1 and 2) and "Stress" (classes 3, 4 and 5). The authors, in [11] developed a CNN model to segment the various types of breast abnormalities, based on the pretrained ResNet 50 model, achieving a recognition rate of 88%. Similarly, in [12] used 3 CNN models, Inception V3, Inception-ResNet V2 and ResNet-101, to predict whether patients with primary breast cancer will metastasize, based on their ultrasound images, the results were compared with the performance of 5 radiologists, having positive results in the two tests performed, in A and B with an area under the receiver operating characteristic curve (AUC) of 0. 9 and 0.89, a sensitivity of 82% and 85% and a specificity of 0.79% and 72%, respectively. Another study by in [13] implemented a method to classify breast cancer into benign and malignant based on a CNN, AlexNet. The results obtained show that AlexNet obtained an accuracy greater than 99%, superior to existing algorithms.

The following Table I summarizes the results obtained by the authors described in the previous points.

In [14] used a new advanced methodology that develops machine learning algorithms, such as deep learning algorithms, to accurately classify breast cancer. Deep learning algorithms are fully automatic in learning, feature extraction and classification and are suitable for all images, from natural images to medical images. The authors used a deep convolutional neural network, AlexNet, to classify breast cancer in mammography images. The performance of the proposed convolutional network structure they evaluated and compared with existing algorithms. In [15], four convolutional neural network (CNN) models were proposed for pneumonia detection in chest radio-graphs. They were trained to classify radiographs into two types: normal and pneumonia, using multiple convolutional layers. The models used in this work are pre-trained: VGG16, VGG19, ResNet50 and InceptionV3. The metrics used to evaluate the results are accuracy, recall and F1 score. The results showed that the Inceptionv3 model performed the best with 72.9% accuracy, 93.7% recall and 72.9% F1 score. 72.9% accuracy, 93.7% recall and 82% F1 score. This shows that CNN models are suitable for detecting pneumonia with high accuracy.

TABLE I. SUMMARY OF MODEL PERFORMANCE METRICS ACCORDING TO AUTHORS

Authors	Accuracy	Error rate	Other indicators
Fabiol, O. Luiz, P. Caroline and H. Laurent [10]	85% 88.9%	-+6.5	-
S. T. Ahmed and S. M. Kadhem [11]	88% - 97%	-	-
Maleika, B. Nazmeen, D. Wasiimah, N. .Shaista, G. Xiaohong, Sinha GR [12]	88%	-	-
Z. Li, W. Xing, H. Shu, W. Ge-Ge, Y. Hua, W. Qi [13]	82%- 85%	-	AUC: 0.8-0.9 sensitivity 82% specificity 79%

III. METHODOLOGY

This section details the procedure or methodology used for training and fitting CNN-based models from data acquisition to validation (evaluation) of results. Fig. 1 summarizes the 8-step process for model fitting, and subsequently the evaluation of the fit or generalization using data that the model has not seen (data test). This process starts with the data source, is ingested into the work environment for division into training and test data, followed by a normalization phase, then images are generated from the existing ones with the data augmentation technique, then transfer learning and fine tuning are applied to create models adapted to the case, then goes the training and adjustment, then metrics are used for model evaluation and model validation, if the model exceeds the threshold the final model is obtained otherwise it returns to the phase of pre-trained models for application of fine tuning until the model is valid.

A. Data Source

The breast cancer histopathology images acquired from patients have been obtained from the Kaggle platform, whose main source and original publication was provided by "Laboratory of Vision, Robotics and Imaging (VRI)" at the following link https://web.inf.ufpr.br/vri/databases/breast-cancer-histopathological-database-breakhis/, where there are two folders, one for each class, the first one for benign type images and the other one for malignant type images. The data source provides 7803 histopathology images obtained from the platform mentioned in the previous point, such images are provided in two types, 2479 images correspond to benign type and 5324 are of malignant type, in Fig. 2 a sample can be observed.

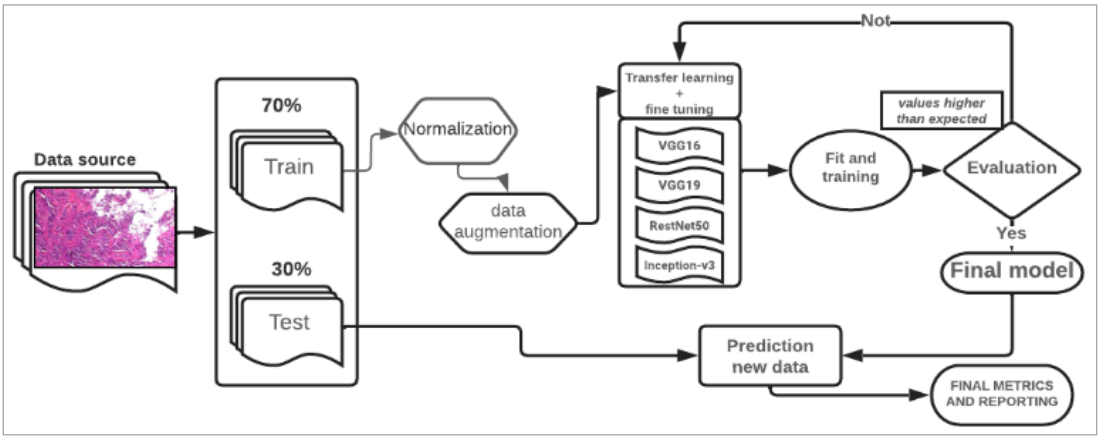

Fig. 1. Flow diagram corresponding to the phases of the silver-plated system.

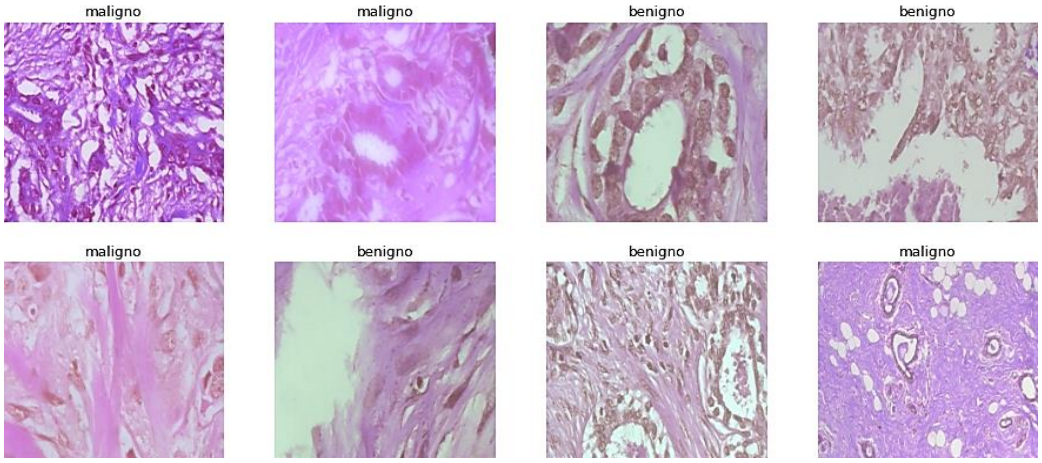

Fig. 2. Sample histopathology images obtained from the source.

B. Data Train and Test

Once the images have been ingested, they have been divided into training and test data, the criterion is 70% to train the models and 30% to evaluate results, this will allow determining the generalization of the models.

C. Normalization

The original images go through a normalization process, to avoid problems at the time of training [16][17], the criterion used is the division 1 between the maximum value of the pixels, for the case 1/255, which gives values between the range of 0 and 1.

D. Data Augmentation

The objective of data augmentation is to generate more images from the existing ones [18][19], the criteria used are: random rotations of 25 degrees, increase and decrease of width and height corresponding to 0.15 of the original size, random zoom of 20%, points outside the input limits by the "reflect" method and randomly flip the inputs horizontally, in Fig. 3 an example of a particular image and the result of five transformations can be observed.

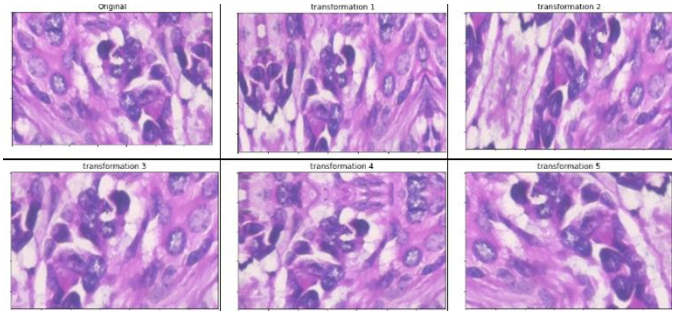

Fig. 3. Results of data augmentation transformation for the images under study.

E. Transfern Learning and Fine Tuning

Transfer learning is a method where previously trained models are used and applied to a particular case, for this study we have used models trained with a set of data provided by the "ImageNet" contests and that have been shared by the keras library [20][21], the models correspond to VGG16, VGG19, Resnet 50 and Inception V3. Such models were trained with 1.4 million photographs as input and 1000 image classes as output, among which vehicles, plants, animals, etc. stand out. The description of the models is detailed in the following points:

1) VGG16: The architecture of this neural network model stands out for using 3x3 convolution kernels, smaller than the previous models, in addition to max-pooling layers of a size of 2x2 [22]. The input size of the network is 224x224. At the output of the convolution layers, we have 3 layers of neurons formed by 4096 the first 2 and 1000 the last one, which presents a SoftMax activation function to determine the image class. Fig. 4 represents the architecture for this study.

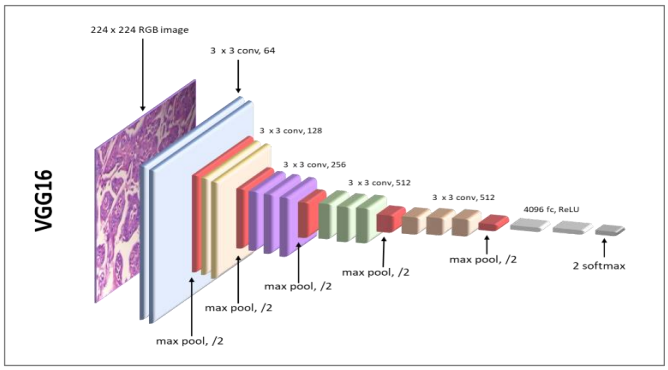

Fig. 4. VGG16-based model for breast cancer staging.

2) VGG19: The architecture of this neural network is like that of VGG16, where the difference in number represents the number of convolutional and dense layers in each model, which, in this case, would be 19 [23], Fig. 5 shows the architecture for this research.

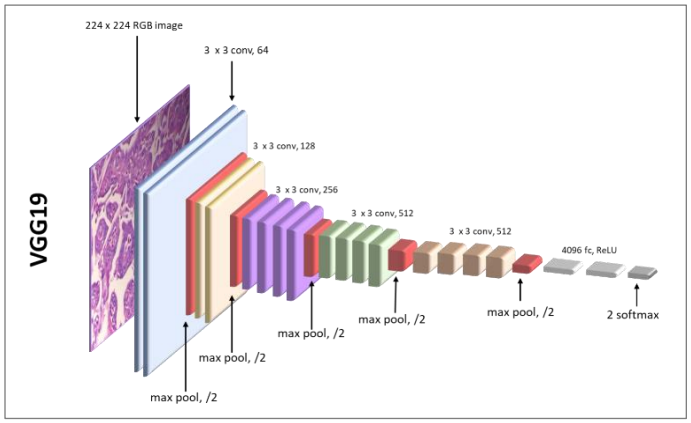

Fig. 5. VGG19-based model for breast cancer staging.

3) ResNet50: Convolutional neural network with 50 layers deep. These layers are ordered starting with one of a 7x7 convolution kernel, a 2x2 max-pooling [24], 9 layers repeating 3 times a sequence of 3x3. 64, 1x1,64 and 1×1,256, 12 layers repeating 4 times a sequence of 1×1,128, 3×3,128, and 1×1,512, 18 layers repeating 6 times a sequence consisting of 1×1,256, 3×3,256 and 1×1,1024 and completes the 50 layers with 3 repetitions of a sequence of 1×1,512, 3×3,512 and 1×1,2048. From this the average-pooling layers are used, in Fig. 6 the model used for the case is represented.

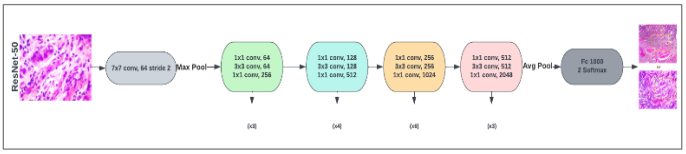

Fig. 6. ResNet 50-based model for breast cancer classification.

4) Inceptionv3: This is the third version of a neural network with 48 layers deep, unlike the VGG architectures, it requires considerably less computational power, but still provides reliable results. The size of the network image input is 299 x 299. Fig. 7 shows the synthesized process for the case.

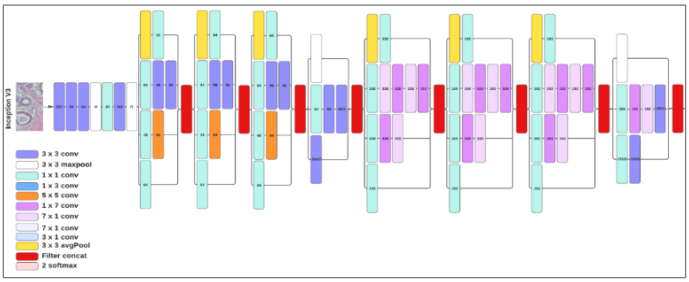

Fig. 7. Inception V3 model for breast cancer staging.

Fine tuning is the method that allows to adapt the results when using a pre-trained model, since such models had a different or similar task to the one being studied. For this case of this study whose output is of two classes, in which you want to evaluate whether an image corresponds to benign or malignant type, it is used import the original models without considering the fully connected layer, then the convolutional layer is retrained, the fully connected layer is added and the output of two classes.

A convolutional neural network model has the first layer corresponding to the convolutional layer, it is a block where most of the computations occur, given by a set of convolutional filters each of which allows to detect certain characteristics of the images. For example, 1) Pooling operation: it allows to simplify the output of the results of the convolution operation by decreasing the subsampling rate, thus reducing the number of parameters that the network needs to learn. There are several types of subsampling, for this study Max-Pooling is used; 2) Flatten layer: allows to add a flat layer where the spatial dimensions of the input collapse in the dimension of the channel, this procedure is used in this pooling and prior to the fully connected layer; 3) Fully connected: in this stage all the input neurons (flattened) are connected to each neuron of the output layer. The main objective of this fully connected layer is to carry out a kind of clustering of the information that has been obtained so far, which will be used in subsequent calculations for the final classification; 4) Evaluation: for the evaluation of the different models, multiple evaluation measures are used to assess the performance of a Deep learning model. Its objective is to verify the accuracy of the generalization of a model on new data. Different metrics such

as confusion matrix, accuracy, precision, recall, F1-Score, etc. are used to evaluate the models.

F. Evaluation Model

Multiple evaluation measures are used to assess the performance of a deep learning model for the evaluation of different models. Their objective is to verify the accuracy of the generalization of a model on new data.

G. Matriz De Confusión

The confusion matrix is a matrix representation that allows to compare the results of the predictions and the actual data of the target class. Each predicted value gives as correct or incorrect result, this depends on the coincidence with the correct value:

True Positive (TP): The predicted value when compared to the stored value is correct.

True Negative (TN): The predicted value when compared to the stored value is not correct.

False Positive (FP): Predicted value is positive when compared to the stored value is negative.

False Negative (FN): The predicted value is negative and when compared to the stored value is positive.

H. Accuracy

This is the total percentage of items correctly classified [25].

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

a) Error Rate

This is the total percentage of incorrectly classified items.

$$Error\ rate = \frac{FP + FN}{TP + FP + FN + TN}$$

b) Precision

The number of items that have been properly recognized as positive out of a total number of items recognized as positive [25].

$$Precision = \frac{TP}{TP\ +\ FP}$$

c) Recall

The metric allows reporting on the rate of true positives [25].

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

d) F1-Score

This metric combines precision and recall obtaining a much more objective value.

$$F1 = 1 * \frac{(Recall * presicion)}{Recall + presicion}$$

IV. Results and Discussion

The results obtained following the proposed methodology are synthesized in this section, from the division between training data (70%) and test data (30%) of the 7803 original images. The number of epochs for each of the models was a maximum of 20 and the parameters for the activation function "relu" for the hidden layers and for the output "Sigmoid" were used, to reduce the overfitting restricted to the deactivation of 30% of neurons in each layer (dropoud=0.30), the learning rate of 0.001 and the stochastic downward gradient optimizer with momentum, for the training of the models with the adaptation detailed in the previous point, GPU was used for the processing and adjustment of the model. Fig. 8 shows the results and the evolution of the Loss and accuracy for the VGG16 model, clearly there is a significant change in the first epochs of the training process, in relation to the Loss, this decreases drastically in the first two epochs, from then on there is a slow decrease, with respect to the accuracy, until epoch 10 there was a good increase and from then on there is no significant improvement and even has to fall into a problem of overfitting.

From the model fit, the test data was used to predict using the model and make a comparison between the expected output results and the given prediction, a summary through the confusion matrix is shown in Fig. 9.

The results show that of the correct or positive true predictions, 1487 correspond to 63.52% of the total and 569 true negative predictions, representing 24.31% of the total; the incorrect predictions, with respect to false positives, were 201 images and false negatives correspond to 84 images.

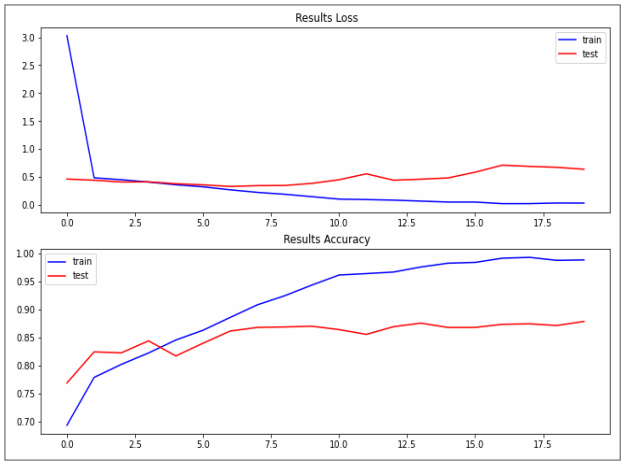

Fig. 8. Evolution of results loss and accuracy of the training process - Model VGG16.

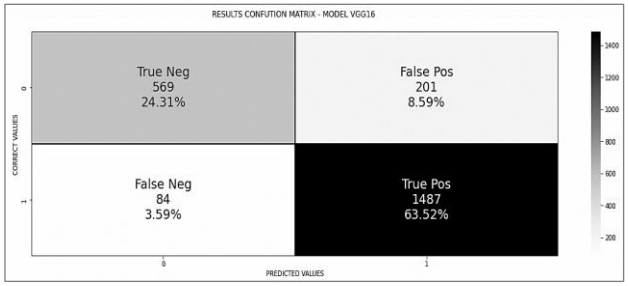

Fig. 9. Confusion matrix of the VGG16 model.

With respect to the training results of the VGG19 model, they show that as the number of epochs increases the error decreases and the accuracy increases, this change can be seen with greater force until the second epoch, in advance the change is slow and even approaching epoch 20 the values begin to differ between the training and test data. Once the model has been fitted with the training data, the test data is used to predict and evaluate how well it generalizes to new cases.

Regarding the third model RestNet50, it shows the evolution of the error function during the training process, the model starts with high variability between the training versus test data, from the eighth epoch the process stabilizes; regarding the accuracy it increases significantly until the eighth epoch, thereafter no significant change is observed.

Finally, the Inception V3 model shows the improvement in the two metrics clearly distinguished, regarding Loss in the first epochs decreases drastically and even in the fifth epoch the results are more stable or homogeneous, as you in-crease the epochs these results improve the accuracy between training and test data is very close, the model fit metrics finally corroborate this perspective (further shown below).

After fitting the models and using the prediction test data to evaluate the accuracy of each model, Table II summarizes the performance measures for each model, with the metrics accuracy, error-rate, precision, recall and f1-score.

TABLE II. SUMMARY PERFORMANCE METRICS OF THE MODELS PROPOSED FOR BREAST CANCER PREDICTION

Modelo	Accuracy	Error rate	Presicion	Recall	f1-score
VGG16	0.88	0.12	0.88	0.84	0.86
VGG19	0.86	0.14	0.86	0.82	0.83
ResNet 50	0.97	0.03	0.96	0.96	0.96
Inception V3	0.96	0.04	0.96	0.95	0.95

The results indicate that there is a significant correlation with related work, the findings of this paper are discussed below with relevant research highlighting similarities and differences. For example, the ResNet-50 model achieved an accuracy of 97%, this result is consistent with that achieved in papers [9] and [12], in which CNN was used to classify breast cancer abnormalities, achieving a performance of 75% and 83%, respectively. Also, the Inception-v3 model achieved a very significant performance of 96%, higher than that achieved in the work [13], where they used this model to predict lymph node metastasis from images, achieving an accuracy of 85%, 73% specificity and 73% sensitivity. The VGG16 model also achieved satisfactory results in terms of 88% accuracy. However, this model, achieved a better performance in [14], reaching 95.70% accuracy in tumor detection in monograph images and the VGG19 model in this work achieved a performance of 86% accuracy, higher than that achieved in [15], where it reached 72% pressure in pneumonia detection through transfer learning with CNN. Artificial intelligence, specifically neural networks, have contributed significantly to the clinical field, models such as ResNet50 and Inception-v3, are great and efficient predictors in this field of health, and in this work have been classified as the best models in performance and accuracy, to identify and classify breast cancer using transfer learning page.

V. CONCLUSIONS

This work by using deep learning models allowed retraining and adaptation for the correct classification of benign or malignant cancer from real histopathology images, four models based on VGG16, VGG19, ResNet 50 and Inception V3 were considered, and a retraining process was carried out using GPU for faster convergence, once the models were adjusted, the result evaluation process was carried out with test data. The model that achieves the best performance is ResNet 50, with 97% of correctly classified cases, although the model based on Inception V3 has a value of 96%, statistically there would be no significant difference (at 95% confidence), the model that has the lowest performance is based on VGG19 with 86%. Individually for the prediction of the positive classes that are positive, the models based on ResNet 50 and Inception v3 obtain equal scores with 96% of the cases. Regarding the positive values that have been correctly classified the model based on ResNet 50 obtains the highest value corresponding to 96 % equal to the f1-score. It is followed by the Inception v3 model with 1% below these results; statistically there would be no significant difference. The work shows a suitable methodology for the retraining of Deep learning models, the results are encouraging, the model based on ResNet 50 and Inception v3 exceeds the threshold of 90% for the classification of breast cancer of the case raised.

REFERENCES

[1] World Health Organization, "Breast cancer", 2021. https://www.who.int/es

[2] H. T. H. S. ALRikabi, I. A. Aljazaery, J. S. Qateef, A. H. M. Alaidi, and R. M. Al_airaji, "Face Patterns Analysis and Recognition System Based on Quantum Neural Network QNN," International Journal of Interactive Mobile Technologies, vol. 16, no. 8, pp. 34–48, 2022, doi: 10.3991/IJIM.V16I08.30107.

[3] M. Fahad Ullah, "Breast Cancer: Current Perspectives on the Disease Status," Adv Exp Med Biol, vol. 1152, pp. 51–64, 2019, doi: 10.1007/978-3-030-20301-6_4/COVER.

[4] X. Wenbin, W. Chaoyan, W. Huachao, F. Sha, L. Nuomin, Y. Haijun. "Survival Comparisons between Breast Conservation Surgery and Mastectomy Followed by Postoperative Radiotherapy in Stage I-III Breast Cancer Patients: Analysis of the Surveillance, Epidemiology, and End Results (Seer) Program Database," Curr Oncol. 2022 Aug 15;29(8):5731-5747. doi: 10.3390/curroncol29080452. PMID: 36005190; PMCID: PMC9406949

[5] E. Ernest A. Maram, B. Patrick. "Errors in Mammography Cannot be Solved Through Technology Alone," Asian Pac J Cancer Prev. 2018 Feb 26;19(2):291-301. doi: 10.22034/APJCP.2018.19.2.291. PMID: 29479948; PMCID: PMC5980911.

[6] N. Heidi, T. Kari, N. Arpana, B. Christina, C. Benjamin, H. Linda; "Screening for breast cancer: an update for the U.S. Preventive Services Task Force," Ann Intern Med. 2009 Nov 17;151(10):727-37, W237-42. doi: 10.7326/0003-4819-151-10-200911170-00009. PMID: 19920273; PMCID: PMC2972726.

[7] Karin, B. Anne, K. Alfons, et al. “The additional diagnostic value of ultrasonography in the diagnosis of breast cancer,” Arch Intern Med. 2003 May 26;163(10):1194-9.

[8] O. Iparraguirre-Villanueva et al., “Text prediction recurrent neural networks using long short-term memory-dropout,” Indonesian Journal of Electrical Engineering and Computer Science, vol. 29, no. 3, pp. 1758–1768, Mar. 2023, doi: 10.11591/IJEECS.V29. I3. PP1758-1768.

[9] L. Yann, B. Yoshua, y H. Geoffrey, “Deep learning”, Nature, vol. 521, núm. 7553, pp. 436–444, 2015 May 27. doi: 10.1038/nature14539

[10] S. Fabiol, O. Luiz, P. Caroline and H. Laurent, "Breast cancer histopathological image classification using Convolutional Neural Networks," 2016 International Joint Conference on Neural Networks (IJCNN), 2016, pp. 2560-2567, doi: 10.1109/IJCNN.2016.7727519.

[11] S. T. Ahmed and S. M. Kadhem, “Using Machine Learning via Deep Learning Algorithms to Diagnose the Lung Disease Based on Chest Imaging: A Survey,” International Journal of Interactive Mobile Technologies, vol. 15, no. 16, pp. 95–112, 2021, doi: 10.3991/IJIM.V15I16.24191

[12] Maleika, B. Nazmeen, D. Wasiimah, N. .Shaista, G. Xiaohong, Sinha GR, et al. “Multi- class classification of breast cancer abnormalities using Deep Convolutional Neural Network (CNN)”, https://doi.org/10.1371/journal.pone.0256500

[13] Z. Li, W. Xing, H. Shu, W. Ge-Ge, Y. Hua, W. Qi, et al. “Lymph Node Metastasis Prediction from Primary Breast Cancer US Images Using Deep Learning,” Radiology. enero de 2020;294(1):19-28, doi: 10.1148/radiol.2019190372

[14] Ulagamuthalvi V, Kulanthaivel G, Balasundaram A, Sivaraman A. “Breast Mammogram Analysis and Classification Using Deep Convolution Neural Network,” Comput Syst Sci Eng. 2022;43(1):275-89, doi: 10.32604/csse.2022.023737

[15] O. Iparraguirre-Villanueva et al., “Convolutional Neural Networks with Transfer Learning for Pneumonia Detection,” IJACSA) International Journal of Advanced Computer Science and Applications, vol. 13, no. 9, p. 2022, https://dx.doi.org/10.14569/IJACSA.2022.0130963

[16] M. Imane, C. Rahmoune, M. Zair, and D. Benazzouz, “Bearing fault detection under time-varying speed based on empirical wavelet transform, cultural clan-based optimization algorithm, and random forest classifier,” JVC/Journal of Vibration and Control, Jan. 2021, doi: 10.1177/10775463211047034

[17] U. M. Haque, E. Kabir, and R. Khanam, “Detection of child depression using machine learning methods,” PLoS One, vol. 16, no. 12, p. e0261131, Dec. 2021, doi: 10.1371/JOURNAL.PONE.0261131.

[18] L. Han and Z. Yin, “A hybrid breast cancer classification algorithm based on meta-learning and artificial neural networks,” Front Oncol, vol. 12, Nov. 2022, doi: 10.3389/fonc.2022.1042964.

[19] B. S. Abunasser, M. R. J. Al-Hiealy, I. S. Zaqout, and S. S. Abu-Naser, “Breast Cancer Detection and Classification using Deep Learning Xception Algorithm,” International Journal of Advanced Computer Science and Applications, vol. 13, no. 7, pp. 223–228, 2022, doi: 10.14569/IJACSA.2022.0130729.

[20] E. Taghizadeh, S. Heydarheydari, A. Saberi, S. JafarpoorNesheli, and S. M. Rezaeijo, “Breast cancer prediction with transcriptome profiling using feature selection and machine learning methods,” BMC Bioinformatics, vol. 23, no. 1, Dec. 2022, doi: 10.1186/S12859-022-04965-8.

[21] S. S. Yadav and S. M. Jadhav, “Thermal infrared imaging-based breast cancer diagnosis using machine learning techniques,” Multimed Tools Appl, vol. 81, no. 10, pp. 13139–13157, Apr. 2022, doi: 10.1007/S11042-020-09600-3/METRICS.

[22] P. Sudhakaran, S. Swaminathan, D. Yuvaraj, and S. S. Priya, “Load predicting model of mobile cloud computing based on glowworm swarm optimization LSTM network,” International Journal of Interactive Mobile Technologies, vol. 14, no. 5, pp. 150–163, 2020, doi: 10.3991/IJIM.V14I05.13361

[23] I. Ullah, F. Ali, B. Shah, S. El-Sappagh, T. Abuhmed, and S. H. Park, “A deep learning based dual encoder–decoder framework for anatomical structure segmentation in chest X-ray images,” Sci Rep, vol. 13, no. 1, Dec. 2023, doi: 10.1038/S41598-023-27815-W.

[24] M. M. Srikantamurthy, V. P. S. Rallabandi, D. B. Dudekula, S. Natarajan, and J. Park, “Classification of benign and malignant subtypes of breast cancer histopathology imaging using hybrid CNN-LSTM based transfer learning,” BMC Med Imaging, vol. 23, no. 1, Dec. 2023, doi: 10.1186/S12880-023-00964-0.

[25] S. Han, J. Liu, G. Zhou, Y. Jin, M. Zhang, and S. Xu, “InceptionV3-LSTM: A Deep Learning Net for the Intelligent Prediction of Rapeseed Harvest Time,” Agronomy, vol. 12, no. 12, Dec. 2022, doi: 10.3390/AGRONOMY12123046.