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DEEP LEARNING FOR THE RECOGNITION OF BENIGN AND MALIGNANT BREAST LESIONS IN MEDICAL IMAGES

Alio Boubacar Goga, Chaibou Kadri and Harouna Naroua
Département de Mathématiques et Informatique, Faculté des Sciences et Techniques, Université Abdou Moumouni, Niamey, Niger
E-Mail: gogaalioboubacar@gmail.com

ABSTRACT

The exploitation of medical imaging ("Big Data") is currently a task that healthcare professionals find very difficult to manage. However, the creation of Intelligent Systems (IS) is nowadays an effective mean for the detection and the recognition of most frequent diseases, in particular breast cancer. In this study, we propose a new deep learning (DL) architecture for the recognition of malignant and benign tumors on breast biopsy images. The experimental results show that the proposed method (IDenseNet-BCBC for Improvement of DenseNet for Binary Classification of Breast Cancer) achieved an accuracy of 99.17% and 100% on magnified level 40x, and 100x, respectively.

Keywords: intelligent system, deep learning, big data, medical imaging, breast cancer.

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1. INTRODUCTION

The capacity of rational exploitation of data particularly that of medical imaging, is at the heart of the challenges of tomorrow's medicine [1]. In reality, data exist in abundance. However, the exploitation of this "big data" is a very difficult task for doctors and other actors in their specific fields. Supervised machine learning, especially deep learning, requires a large amount of data [2]. This has prompted many researchers, from different specialties, to embark on the creation of Intelligent Systems in order to make their contributions in the detection of most frequent diseases, including breast cancer. Indeed, breast cancer is a malignant tumor that begins in the cells of the breast. Malignant tumor is a group of cancer cells that can destroy and invade nearby tissues. The benign tumor is harmless and it grows slowly without multiplying in other parts of the body. Moreover, the benign tumor is not considered as a cancer. Breast cancer is the most common type of cancer of women worldwide and has a very high mortality. Early detection and diagnosis can make treatment more effective and help improve survival rates for this disease [3].

Currently, Artificial Intelligence techniques are applied to medical images with the aim of detecting and classifying this global scourge. There are several studies that show the use of statistical learning methods on mammography [4], ultrasound [5], magnetic resonance imaging (MRI) [6].

Despite rapid progress in medical research, the reference for cancer diagnosis remains histopathological diagnosis (histopathology images) [7]. However, the robust properties of Convolutional Neural Network (CNN) and their major success in solving various computer vision problem tasks make it a plausible candidate among Artificial Intelligence methods for medical image classification [8].

Transfer learning is a better approach of using a pre-trained model to extract unique features from each medical image. In addition, the current performances of these models have attracted our attention because they have obtained better results in feature extraction and classification of breast cancer, particularly the DenseNet [9].

2. OVERVIEW OF EXISTING METHODS

The motivation of this state of the art is to present the application of deep learning and machine learning on medical images. Tables 1 and 2 show the binary classification (benign and malignant) of existing works that were carried out on the database of breast histopathology images called BreakHis.

Table-1. Binary classification of breast histopathology images.

Authors	Methods used	Accuracy
[10]	BiRNN and LSTM	91.90 %
[11]	Convolutional Neural Network (CNN) and Multilayer Perceptron (MP)	98.80 %
[12]	ResNet-50	99.10 %
[13]	DenseNet201	97.05 %
[14]	ResNet-18	92.03 %
[15]	DenseNet201 and XGBoost	97 %

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Table-2. Binary classification of breast histopathology images by magnification factor (40× and 100× respectively).

Authors	Methods used	Accuracy	
		40×	100×
[16]	CNN, SVM, LR, KNN and BG	97,01 %	96,25 %
[17]	CNN	80.97 %	80.92 %
[18]	ResNetV1 + GBT, InceptionV3 + GBT	93.50 %	95.30 %
[19]	IRRCNN + Aug.	97.95 %	97.57 %
[20]	AlexNet CNN	89.60 %	85.00 %
[21]	CSDCNN + Aug.	92.80 %	93.90 %
[22]	ResNet	95.60 %	94.89 %
[23]	CNN Hybride	85.7 %	84.2 %
[24]	VGG16 + SVM, VGG16 + RF	94.11 %	95.12 %
[25]	ASSVM	94.97 %	93.62 %
[26]	BiCNN	97.89 %	97.64 %
[27]	L-Isomap and SSAE	96.8 %	98.1 %
[28]	SVM	92.71 %	93.75 %
	CNN	94.65 %	94.07 %
	CNN+ DataAugmented	96.82 %	96.96 %
[29]	CNN+SE-ResNet	98.87 %	99.04 %

Currently, Deep Learning (DL) has reached the peak performance in many artificial vision (or computer vision) tasks as in [30] and in the studies presented above (Tables 1 and 2). Convolutional Neural Networks (CNN) has become the dominant statistical learning approach for medical image recognition, specifically mammography and breast histopathology images.

To solve the leakage gradient problem, DenseNet was created. The architecture of this method consists in modifying the standard CNN architecture as shown in the following figure:

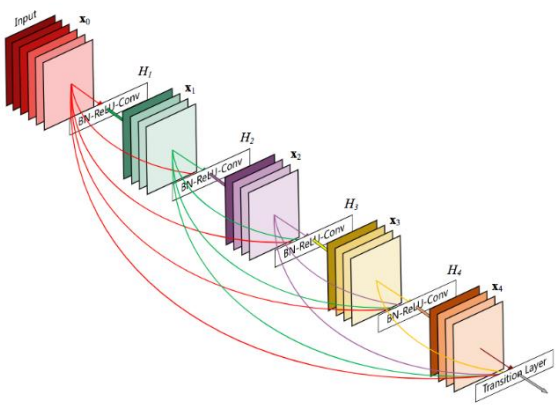

Figure-1. DenseNet Architecture [31].

In a DenseNet architecture, each layer is connected to all other layers using a feedforward approach, hence the name Densely Connected Convolutional Network. For L connections between the previous layer and the next layer in traditional CNNs, there are $\frac{L(L+1)}{2}$ direct connections in a DenseNet. Therefore, the network gains the ability to classify the added and retained information, since it concatenates features from previous layers rather than adding them [31].

3. DEEP LEARNING IDENSENET-BCBC MODEL FOR THE RECOGNITION OF MALIGNANT AND BENIGN TUMORS ON BREAST BIOPSY IMAGES

In this study, we used images from the BreakHis dataset (biopsy images) publicly available from [32]. The dataset contains 7909 breast histopathology images acquired from 82 patients. The BreaKHis dataset (BDB) contains microscopic biopsy images of benign and malignant breast tumors and all data have been anonymized. We considered the same magnification levels as in [16] and others. Table-3 shows the details of the dataset in terms of magnification and lesion types.

Table-3. Distribution of images by magnification factor and class.

Magnification	Benign	malignant	Total
40 x	625	1370	1995
100 x	644	1437	2081

For the detection and recognition of malignant and benign tumors on breast biopsy images, the IDenseNet-BCBC architecture in Figure-2 was used. This method is based on the DenseNet architecture which has been widely used or modified in many studies because of its ability to extract features; thus, improving the classification of medical images in particular.

The proposed approach is created from the combination of improved DenseNet (we modified DenseNet by adding a dense layer of 512 perceptron) and convolutional neural networks. Data augmentation was used and brought an improvement in accuracy (accuracy increase of 0.42 for 40 x magnification level and 0.79 for 100 x magnification level). Therefore, the proposed method improves the accuracy compared to existing studies of the literature.

The image augmentation parameter details are as follows:

- Horizontal flip
- Vertical flip
- Rotation range
- Zoom range
- Height shift range
- Width shift range

For more details on the proposed architecture, the IDenseNet-BCBC algorithm is depicted in Figure-2, giving the essential steps:

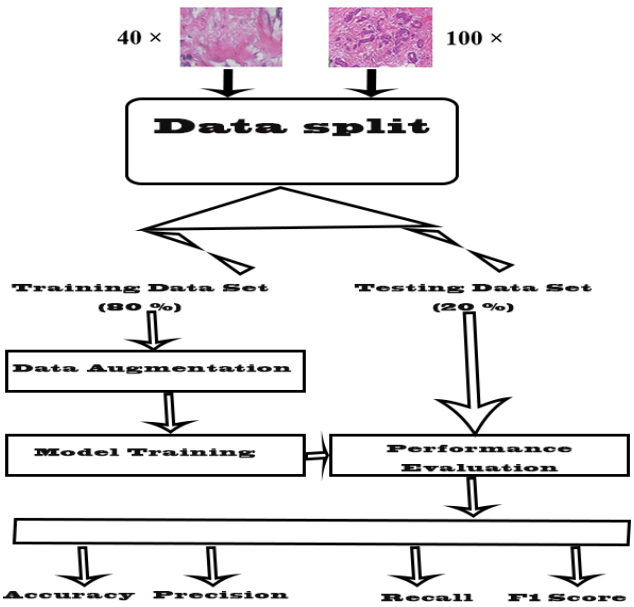

Figure-2. The architecture of IDenseNet-BCBC.

The following algorithm describes all the steps for the detection and recognition of malignant and benign tumors on breast biopsy images.

Algorithm: IDenseNet-BCBC
input:
D_1← set of training images
D_2← set of test images
A← learning rate
B← epochs
C← Batch size
D← Number of images covered in one batch size.
output:
E← the weights of the pre-trained model of the convolutional neural network
begin:
1:Convert each biopsy image to a 224x224 training set.
2:Perform data augmentation with the goal of increasing the size of the training set.
3: Extract features from each biopsy image using only the DenseNet.
4:Set Thin Layers CNN_{dense}, $CNN_{globalAveragePooling}$, CNN_{dense}, $CNN_{dropout}$, $CNN_{batchNormalization}$, $CNN_{softmax}$.
5:Initialize the parameters of the pre-trained model of the convolutional neural network: A, B, C and D.
6:Train the IDenseNet-BCBC approach and determine the initial weights.
7: for B going from 1 to epochs do
7.1:Select a mini-batch size (size: D) for Trainingset D1
7.2:Propagate forward and determine the loss function
7.3:Back-propagate and update E-weights
8: end for
end IDenseNet-BCBC

Data augmentation focuses on improving image recognition models. So, to augment the dataset to improve the performance of this model, thereby obtaining a robust model, we performed the following augmentations: random horizontal flipping, random vertical flipping and random rotation.

To assess the performance of the model, we considered the following criteria:

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \times 100$$

$$Precision = \frac{TP}{TP+FP} \times 100$$

$$Recall = \frac{TP}{TP+FN} \times 100$$

$$F1-Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where:

- **TN:** True Negatives (i.e., patients who do not actually have breast cancer). So that is a true statement. For example, a woman does not have breast cancer, and the model predicted the same.
- **FN:** False Negatives (this is not a true statement). For example, a woman has breast cancer, but the model predicted that she does have breast cancer. This prediction is a type 2 error.
- **TP:** True Positives (i.e., patients who actually have breast cancer). So that is a true statement. For example, a woman has breast cancer, and the model predicted the same.
- **FP:** False Positives (this is not a true statement). For example, a woman does not have breast cancer, but the model predicted that she has breast cancer. This prediction is a type 1 error.

Note that, the actual values are true and false and the predicted values are positive and negative.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

For the purposes of the experiment and to study the performance of the proposed model, we used 80% of the data for training and 20% for testing. Containing a magnification factor (40x, 100x), all images are organized into two classes namely, benign and malignant.

Figures 3 and 4 show Receiver Operating Characteristic (ROC) curves by a magnification factor (40x, 100x). An AUC (Area under the Curve) with a value of 50% indicates that the model is non-informative. An increase in AUC indicates an improvement in discriminatory abilities, with a maximum of 100%.

In summary, AUC is an effective way to summarize the overall diagnostic accuracy of the model on test dataset. It takes values from 0 to 1, where a value of 0 indicates a perfectly inaccurate test and a value of 1 reflects a perfectly accurate test. AUC can be calculated using the trapezoidal rule.

In general, an AUC of 0.5 suggests no discrimination (i.e., the ability to diagnose benign and malignant patients), 0.7 to 0.8 is considered acceptable, 0.8 to 0.9 is considered excellent and more than 0.9 is considered exceptional [33].

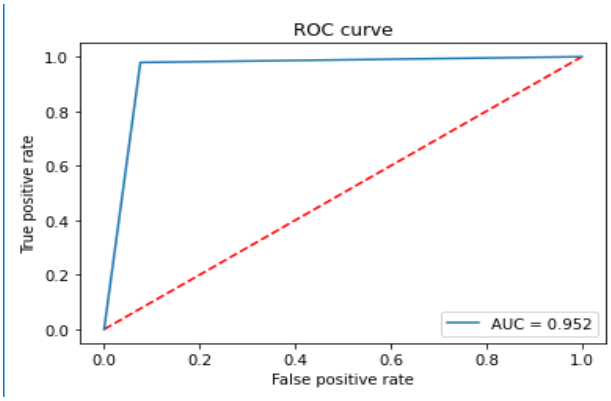

Figure-3. ROC curve for breast cancer classification 40×.

The proposed model recorded an AUC of 95.20% for the 40× magnification factor and this value is considered exceptional.

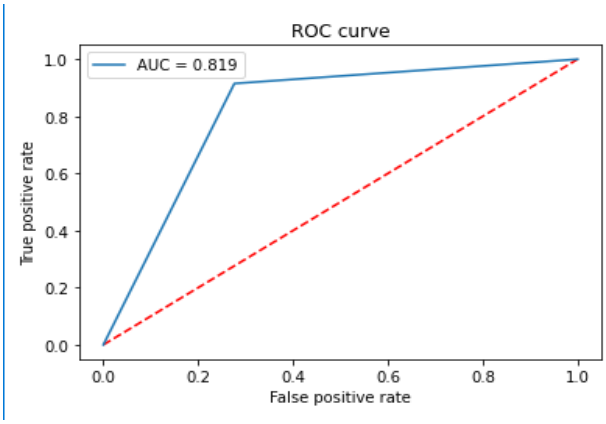

Figure-4. ROC curve for breast cancer classification 100×.

For the 100× magnification factor, the new model achieved an AUC of 81.9%. An AUC of this value is considered excellent.

Table-4 also shows the final performance results of the IDenseNet-BCBC model by magnification factors (40x, 100x).

Table-4. Performance by evaluation criteria.

	IDenseNet-BCBC (Proposed method)	
Evaluation criteria	**Magnification factors**	
	40 x	**100 x**
Accuracy	99.17 %	100 %
Precision	97 %	90 %
Recall	98 %	92 %
F1-Score	97 %	91 %

Given that Accuracy is the most common metric used to evaluate the performance of a model, we found it useful to compare this performance indicator with those of the literature.

With IDenseNet-BCBC, values of 99.17% and 100% were obtained at magnification levels of 40× and 100×, respectively, for the Accuracy indicator. The experimental results show that this model obtained better Accuracy values compared to the best study presented in the literature (see tables 2 and 3) as shown in Table-5 below:

Table-5. Comparative study between IDenseNet-BCBC and the best method of our literature review.

	40 x	**100 x**
IDenseNet-BCBC	99.17 %	100 %
SE-ResNet [29]	98.87 %	99.04 %

5. CONCLUSION AND PERSPECTIVES

In this study, we proposed the IDenseNet-BCBC approach with the objective of classifying breast cancer into two (2) categories, i.e., normal (benign breast cancer) and abnormal (malignant breast cancer) patients. This approach is based on transfer learning and the convolutional neural network. Experimental results on the same dataset of breast histopathology images demonstrated that the proposed method outperforms the existing approaches in terms of accuracy. Indeed, the new method achieved an accuracy of 99.17% and 100% by magnification levels (40x, 100x), respectively.

For future work, it would be useful to:

- Test or configure IDenseNet-BCBC on local mammographic images, in particular those from the Magori Polyclinic in Niamey, Niger Republic.
- Test the performance of the model on small medical imaging databases.
- Classify breast cancer into eight (8) classes (adenosis, fibroadenoma, tubular adenoma, phyllodes tumor, ductal carcinoma, lobular carcinoma, mucinous carcinoma (colloid) and papillary carcinoma) using mammography or biopsy images.
- Incorporate the model on wearable devices to facilitate breast cancer recognition in rural areas.

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