Breast cancer image classification using DenseNet201 and AlexNet based deep transfer learning

Nasser Edinne Benhassine[1,*], Abdelnour Boukaache[2], Djalil Boudjehem [2]

[1] University, Center of Aflou, Algeria.
[2] University, 8 Mai 1945, Guelma, Algeria
n.benhassine@cu-aflou.dz, boukaache.abdenour@univ-guelma.dz, boudjehem.djalil@univ-guelma.dz
* Corresponding author

Abstract. Breast cancer poses a significant risk to women, as it can advance silently during its initial phases without evident symptoms. Early detection is crucial in mitigating this potential threat to one's health. In the past several years, Convolutional Neural Networks (CNNs) have achieved notable progress in classifying breast cancer images. The accuracy and performance of automatically extracting complex features from images has improved, often surpassing previous advanced methods in this field. Furthermore, learning transfer facilitates the adaptation of complex models originally trained for one purpose to entirely new tasks. However, deep learning-based classification methods may have overfitting problems, particularly when the dataset is limited. This study uses a variety of convolutional models to examine how data augmentation methods, such as picture rotation or horizontal and vertical subject moving, affect transfer learning accuracy. For the DenseNet201 and AlexNet models, the experimental findings show a significant improvement in accuracy of around 3.5%.
Keywords: Ultrasound images, data augmentation, transfer learning, CNN, Alexnet, Densenet201.

1 Introduction

One of the leading causes of mortality for women globally is indeed breast cancer. A major factor in lowering the number of deaths related to this illness is early identification. Breast cancer detection and classification heavily depend on medical imaging. Breast ultrasonography is a commonly used tool in the identification of breast cancer. It is useful in helping to distinguish between benign and malignant lesions by producing images of the breast tissue. It is an effective imaging method for assessing anomalies in the breast [1-4]. Deep learning—specifically using Convolutional Neural Networks (CNNs)—has become an indispensable tool in medical image analysis, especially for problems like breast cancer classification [5, 6]. Researchers have created effective algorithms that reliably forecast cancer cell development using various medical imaging modalities, including tomosynthesis,

C. A. Kerrache et al. (eds.), *Proceedings of the International Conference on Emerging Intelligent Systems for Sustainable Development (ICEIS 2024)*, Advances in Intelligent Systems Research 184,
https://doi.org/10.2991/978-94-6463-496-9_11

MRIs, ultrasounds, and mammograms [7]. However, most medical datasets have drawbacks like tiny sample sizes. Transfer learning involves moving learned information from the source domain to the target domain, which is a workable and efficient method for resolving these issues and enhancing the performance of machine learning models (such as Alexnet, and Densenet-201) in such situations [8]. To improve the performance of deep learning models, particularly in situations when datasets are few, data augmentation and transfer learning are essential. By extending datasets through changes, data augmentation reduces overfitting and enhances generalization abilities [9–12]. Contrarily, transfer learning speeds up the process of teaching new models by utilizing the information from previously taught models [13]. Recent studies indicate that the accuracy of breast cancer detection and classification can be improved by combining data augmentation and transfer learning. A computer-aided diagnosis (CAD) system for classifying breast tumours as benign or malignant on mammograms was proposed by Asmaa et al [14]. The system achieved an accuracy of 0.91 using AlexNet and 0.84 using ResNet-50 models. Nadra et al. [15] developed a hybrid CNN-SVM model to detect early breast cancer in ultrasound images. The model outperformed AlexNet with 91% accuracy, demonstrating the potential for improved medical image analysis. Shi et al. [16] produced a deep learning technique for breast cancer detection and classification utilizing Efficient-Net employing mammography images, and they were successful in achieving a 75% accuracy rate. In literature, [17] transfer learning was used using CNNs such as MobileNet, DenseNet121, and others to detect breast cancer in ultrasound images. This demonstrates the potential for automated diagnosis while emphasizing the importance of professional confirmation. Furthermore, the author in [17] looked at the viability of employing transfer learning techniques for breast cancer detection and discovered that transfer learning models could identify breast cancer in ultrasound pictures. Thus, these methods show how transformer learning may be used to enhance ultrasound image classification for breast tumours. Mohamed et al. [18] implemented a custom CNN and transfer learning approach on ultrasound breast cancer images, achieving high accuracy (up to 92.53%) for early identification. Reusing previously trained models for novel tasks is made possible by the machine learning approach known as transfer learning. Here, it has been used to use ultrasound images for the diagnosis of breast cancer [19]. Convolutional neural networks (CNNs), one type of deep learning algorithm, have been investigated in several studies for the early detection of breast cancer using ultrasound pictures. CNNs have been trained using transfer learning approaches to automatically diagnose breast cancer from ultrasound images [20]. Using a collection of histopathology images, the authors in Ref [21] examined pre-trained deep transfer learning models for breast cancer detection, including ResNet50, ResNetl01, VGG16, and VGG19. They discovered that ResNet50 performed better than the other models, obtaining 90.2% accuracy rates. Deniz, et al. [22] Developed a CAD system based on deep convolutional neural networks (CNN) to classify the histopathological breast cancer images as benign and malignant. the combination of pre-trained AlexNet and VGG16 models used for deep feature extraction and classification with a support vector machine (SVM) has been completed. The authors [23] combine three CNNs (VGG16, Densenet201, and Resnet50) with transfer learning to distinguish between ill and healthy static thermography images. The Densenet used 38 static photos per class in its experiments, yielding the greatest accuracy results of 91.67%. Many researchers use data augmentation approaches to increase the number of samples in the dataset and avoid overfitting, which is a typical occurrence while training on a model with a small sample size [24, 25]. In [26], researchers used a Deep Convolution Generative Adversarial Network (DCGAN) and the pre-trained DenseNet201 model with feature concatenation to identify breast cancer histopathology pictures, obtaining good accuracy at various magnification levels. This work compares several models' effectiveness in identifying breast cancers in ultrasound pictures and looks at transfer learning strategies utilizing pre-trained models. This paper examines how data augmentation could affect how well transfer learning models work in medical imaging. Moreover, the effectiveness of data augmentation has been confirmed, improving the model's performance in two- and three-class tasks for classification. The proposed network architecture yielded % overall accuracy of 94.5% for the two and three tumor classification lessons, respectively. Alexnet's accuracy increased by approximately 2.2% and Densenet201's by approximately 3.5% after image augmentation was implemented in our proposed network architecture. The following structure is employed in the paper: a summary of the evaluation procedure is presented in Section II, while the experimental findings and comments are presented in Section III. Finally, the article is concluded in Section IV.

2 Methodology Description

The data preparation processes, and classification approach used are described in this section. Figure 1 depicts the flow chart for the suggested method. After pre-processing, two previously trained convolutional neural networks (DenseNet201 and AlexNet) were used to modify the images and generate feature vectors.
The Support Vector Machine (SVM) classifier was then used to classify these vectors. Subsequently, these vectors were classified using the Support Vector Machine (SVM) classifier. An overview of two commonly used convolutional neural network (CNN) models is given in the following subsections.

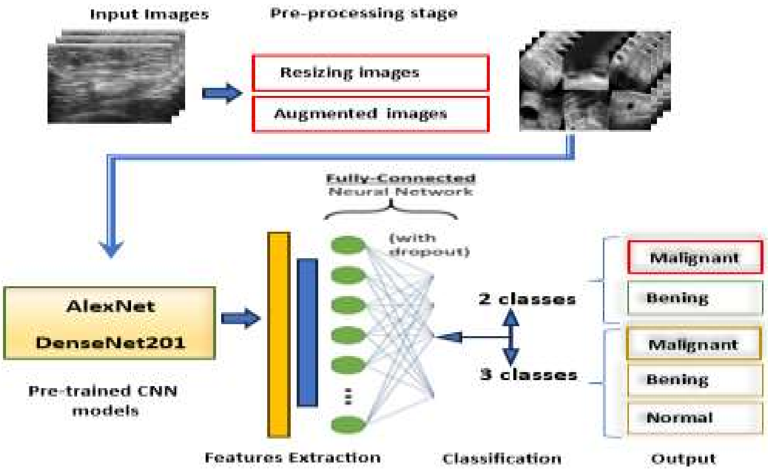

Fig. 1. Flow diagram for the suggested approach.

2.1 Using CNNs to Transfer Learning

To improve accuracy and efficiency, transfer learning with (CNNs) is a technique that uses pre-trained models on a big dataset and adapts them to different tasks or datasets [27, 28]. Rather than starting from begin to train a (CNN), the later layers are optimized for the specific task, while the earlier layers that learned generic properties like edges and forms are reused.

2.2 Pre-trained AlexNet Model

One of the most basic convolutional neural networks is AlexNet, developed in 2012 by Krizhevsky et al. ReLU activates twenty-five levels in the model, including three fully connected layers, three overlapping max-pooling layers, and five cross-correlated convolutional layers. The output is a 1000-way SoftMax, with one for each ImageNet class [29]. Details of the design can be seen in Fig. 2, which depicts the AlexNet architecture. The selection of AlexNet CNN was based on its thorough investigation. Furthermore, it is the first notably successful CNN architecture in the 2012 ImageNet large-scale visual recognition challenge (LSVRC) [30], and it has rekindled significant research interests in CNN.

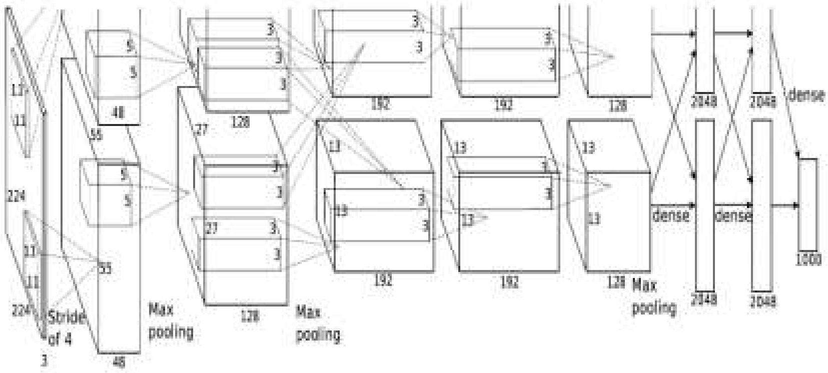

Fig. 2. AlexNet architecture [29].

2.3 Pre-trained DenseNets

The DenseNet (Densely Connected Convolutional Networks) architecture densely connects all layers to address redundancy, providing direct information flow from every layer, resulting in superior image representation [31]. DenseNet outperforms other structures in ImageNet and is more parameter efficient, making it easier to train. It also has competitive training times compared to lower-layer networks [31].

2.4 Pre-trained DenseNet-201

DenseNet201 represents a popular variant of the DenseNet architecture. The network comprises 201 layers, as illustrated in Figure 3. The process that produced the model's h5 format was dense block 1, transition layer 1, dense block 2, transition layer 3, transition layer 4, and classification layer [32]. The network accepts an input image of size 224×224, with the capacity to learn a diverse range of feature representations applicable to a multitude of image types. The principal architecture of the DenseNet201 model is illustrated in Figure 3.

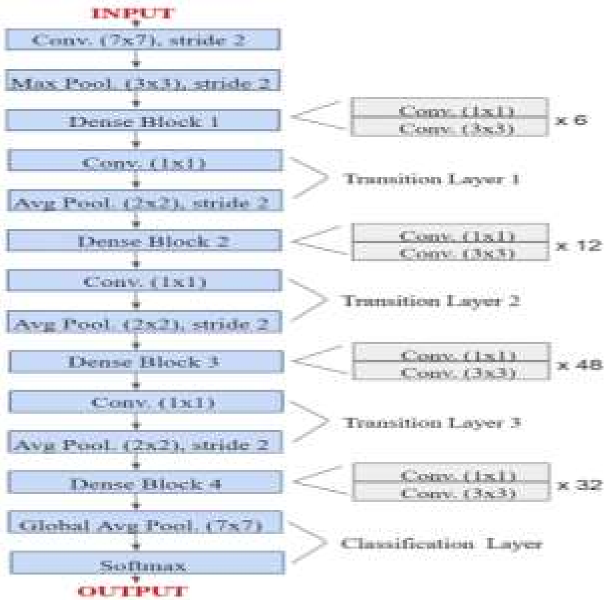

Fig. 3. Structure of DenseNet201 [33].

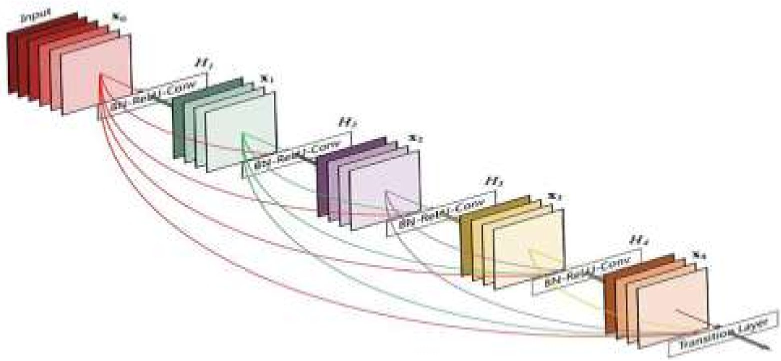

Fig. 4. The direct connections between layers are represented by a 5-layered dense block [33].

2.5 Image Data Augmentation [34-36]

For deep neural networks to function at their best, a sizable training set is required. Furthermore, increased data availability improves the quality of the outcomes obtained. Most datasets provided only contain a limited quantity of data. An image augmentation approach can help decrease the risk of overfitting by creating novel data sets from the current data collection. In the field of data augmentation, two main categories of techniques can be distinguished: geometric transformations and colour alterations. Geometric augmentation affects only the pixel location, as illustrated in Fig. 5, through the application of techniques such as flipping, shifting, and resizing.

In this work, we used geometric augmentation to increase the size of the training set while preserving the pixel values in the images. Images were randomly translated, flipped horizontally or vertically, and rotated randomly between 0 and 60 degrees as part of the augmentation process. Scaling was also used to change the pictures' dimensions.

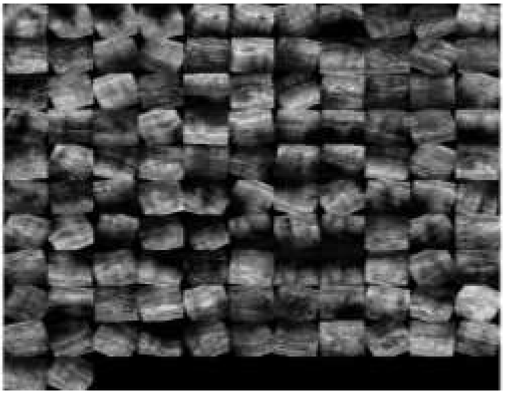

Fig. 5. Samples of augmented images.

3 Experimental results

3.1 Database

This study employed the Breast Ultrasound Images Dataset (BUSI) to classify breast cancer [37]. This dataset was collected from six hundred female participants who ranged in age from 25 to 75. It has 780 images divided into three categories: 210 malignant, 487 benign, and 133 normal photos. Figure 6 displays samples of images from the data.

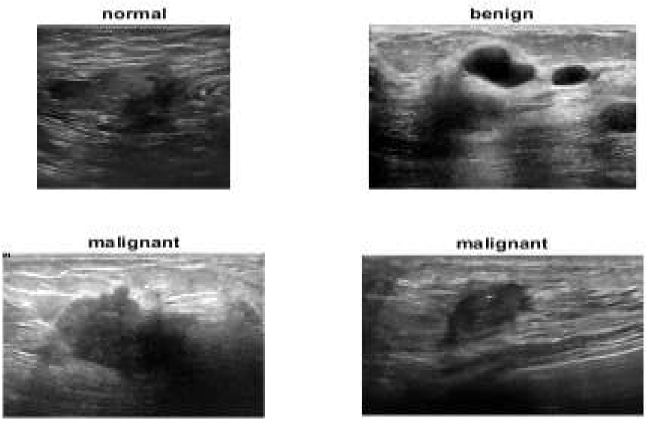

Fig. 6. Examples of images from the BUSI collection.

3.2 Image preprocessing

This paper aims to evaluate the accuracy of various CNN types for tumor classification and the effects of data augmentation on network performance. The following preprocessing steps were carried out before loading the data into the networks:

• applying the data augmentation approach to the training images (see Fig. 5).
• resizing all input images to 224x224 for the AlexNet and DenseNet201 networks.

The assessment results of DenseNet201 and AlexNet for the previously mentioned dataset are shown in this section. Four performance measures form the basis of the evaluation: recall (Rc), precision (Pr), accuracy (Ac), and F1 score. The given expressions are used to compute these measures.

$$\mathrm{Rc} = \frac{\sum \mathrm{TP}}{\sum(\mathrm{TP+FN})} \times 100\ \% \tag{1}$$

$$\mathrm{Pr} = \frac{\sum \mathrm{TP}}{\sum(\mathrm{TP+FP})} \times 100\ (\%) \tag{2}$$

$$\mathrm{Ac} = \frac{\sum \mathrm{TN} + \sum \mathrm{TP}}{\sum(\mathrm{TN+FN+FP+TP})} \times 100\ (\%) \tag{3}$$

$$\mathrm{F1score} = \frac{2 * \mathrm{Pr} * \mathrm{Rc}}{Pr + Rc} \times 100\ (\%) \tag{4}$$

Where:
True Negative, or TN, represents the measure of correctly categorizing benign cases as benign. We use the term "True Positive" (TP) to represent the number of cases where we correctly diagnose malignant patients as malignant. FN (denotes the number of benign cases that are mistakenly labeled as False Negative). We refer to the number of malignant cases mistakenly labeled as benign as False Positives or FP. The percentage of successfully detected positive instances is called recall (sensitivity). However, accuracy evaluates the frequency with which the classifier produces accurate predictions. The accuracy and recall metrics' harmonic average is known as the F1-score. It shows how reliable the classifier is. The study presents the findings for the two-class (benign and malignant) and three-class (normal, benign, and malignant) classification problems.

Table 1. Dataset evaluation results (2 classes).

Model	Rc (%)	Pr (%)	F1 score	Ac (%)
AlexNet	88,5	90	89,24	85,6
DenseNet20	95,4	90,2	92,74	89,9

To classify the dataset without augmentation into benign or malignant images, Table 1 displays the accuracy, recall, precision, and F1-score of the AlexNet and

DenseNet201 models. The confusion matrix of the two classes is displayed in Figure 7, where DenseNet201 attained an accuracy of 89.9%.

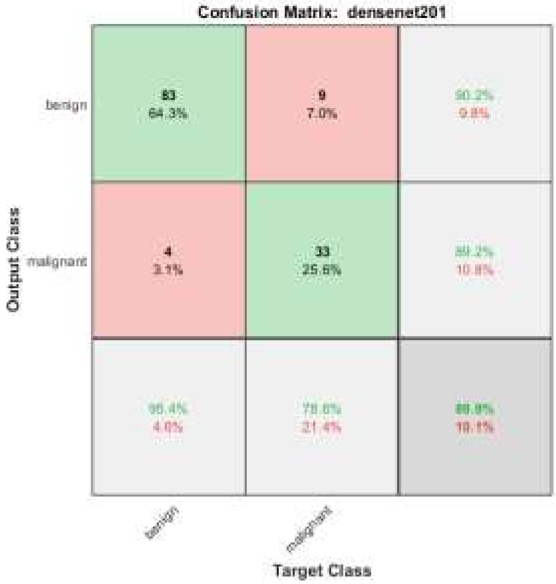

Fig. 7. DenseNet201's confusion matrix (2 classes).

The results of the second experiment, where the models were tested on a dataset with three classes, are presented in the following section. Fig. 8 displays the three classes' confusion matrix, and DenseNet201 achieved an accuracy of 91.0%.

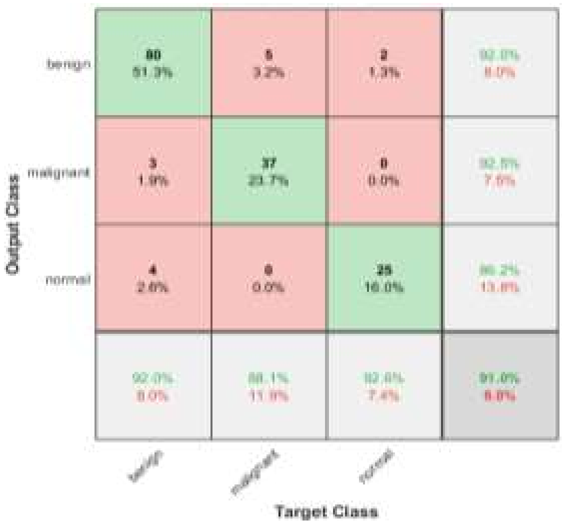

Fig. 8. DenseNet201's confusion matrix (3 classes).

Table 2 displays outcomes from the evaluation of the AlexNet network using data augmentation for the same dataset.

Table 2. Alexnet accuracy results.

Number of Classes	Accuracy (%)	
	Absent data augmentation	**With the addition of data**
2 classes	85,6	87,6
3 classes	86,3	88,5

Regarding the subsequent assessment phase, we evaluated the AlexNet network and obtained 85.6% accuracy for 2 classes and 86.3% for 3 classes (see Fig .9).

Fig. 9. AlexNet's confusion matrix (3 classes).

Table 3 presents the DenseNet201 network's performance dependent on the number of classes employed and the data augmentation method. It is worth noting that the technique improves the network's performance in both cases (2 or 3 classes). We achieved an accuracy of 92.5% with two classes and 94.5% with 3 classes, representing a 2.6% and 3.5% increase in accuracy, respectively.

Table 3. Results for densenet201 accuracy.

Number of Classes	Accuracy (%)	
	Absent data augmentation	**With the addition of data**
two classes	89,9	92,5
three classes	91	94,5

The study's examination has led to the conclusion that, in situations when the data is enough and properly pre-processed, deep learning and transfer learning approaches can perform well in the classification of breast cancer. But when the dataset is small, the outcomes don't seem as good. These factors lead to the data augmentation technique's goal of rotating and translating further images. The image's rotation is randomly chosen, and it may be moved in either the x- or y-axes. This step improves classification performance as well as the training process. The ROC curves and the AUC values are displayed in Figures 9 and 10 for each class. Figure 10 shows the AUC values obtained for benign and malignant, which were 0.94 and 0.94, respectively. However, as shown in Figure 11, the AUC values obtained for benign, malignant, and normal were 0.931, 0.935, and 0.981, respectively. The relationship between the true positive rate (TPR) and the false positive rate (FPR) at various cut-off criteria was shown by the receiver operating characteristic's area under the curve (ROC-AUC), where:

$$TPR = \sum TP / \sum (TP+FN) \quad (5)$$

$$FPR = \sum FP / \sum (FP+TN) \quad (6)$$

AUC is a measure of separability, while ROC is a probability curve that is inside the ROC-AUC curve. On the other hand, the AUC represents the area under the whole ROC curve. It can be demonstrated that the performance of the model in question improves as the AUC increases.

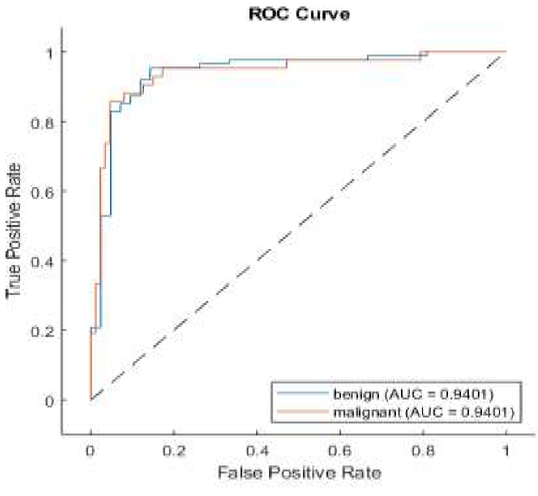

Fig. 10. ROC Curve of densenet201 for 2 classes.

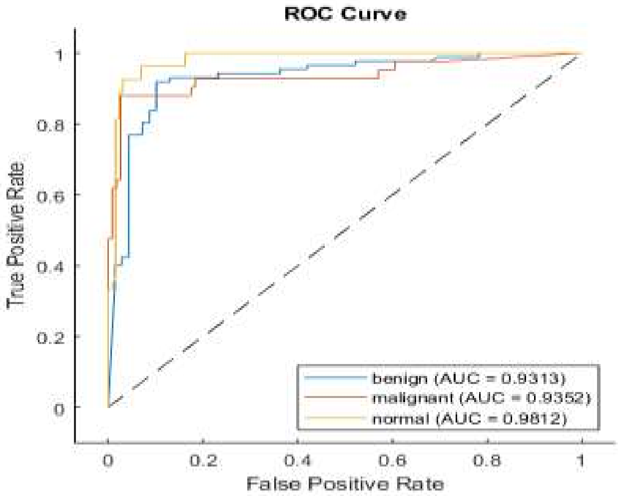

Fig. 11. ROC Curve of densenet201 for 3 classes.

To illustrate the efficacy of this approach, a comparative analysis was conducted with other existing publications. A comparison between the outcomes from our suggested strategy and those from published research is shown in Table 4.

Table 4. Results Comparison results of the proposed with current approaches

Author	Classification methods	Accuracy%
Guizani et al. [15]	Alexnet	91
Shi et al. [16]	EfficientNet	75
Md Ishtyaq et al. [21]	Resnet50	90.2
Jiang et al [22]	DSCNN	91.6
Gonçalves et al. [23]	Dense-Net	91.6
The proposed	AlexNet	86.3
	DenseNet201	**94.5**

4 Conclusion

Treatment success depends on early detection and diagnosis of breast cancer. This study utilized Convolutional Neural Network (CNN) models, specifically AlexNet and DenseNet201, to classify breast cancer using the BUSI dataset. To overcome the issue of data limitation, data augmentation methods were used to address overfitting. The outcomes show how transfer learning using deep learning models is beneficial. Moreover, the application of data augmentation generates more data, which helps to construct more accurate models. Therefore, better performance is shown with a bigger picture collection, while worse performance is seen with a smaller dataset.

DenseNet201 showed an improvement in accuracy of 3.5%, while AlexNet showed an improvement of 2.2%.

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