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# Tumor Detection and Classification in Breast Mammography-based on Fine-tuned Convolutional Neural Networks

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**Abstract**

***Breast cancer (BC) is one of the most dangerous diseases for women. Breast screening is a technique performed to discover BC at an early stage and reduce the mortality rate. Mammography, which allows patients to identify changes in their breasts before they feel them, is the primary screening tool for BC diagnosis. In this study, pretrained convolutional neural networks (CNNs) like visual geometry group (VGG) VGG-16 and VGG-19 are implemented to detect and classify breast tumors on the INbreast dataset. In the proposed model, breast images are initially preprocessed to improve image quality and reduce computation time. Then, the parameters learned in the networks are transferred to learn with the breast parameters to improve the classification results. Therefore, this work utilized to make an efficient manipulation for the obtained information from the large volume of data generated so that that correct classification may enhance the treatment options. Furthermore, in the evaluation stage, four metrics accuracy, sensitivity, specificity, and area under the ROC curve (AUC) were considered to measure the performance of the proposed model. It was found that the proposed model obtained accuracy, sensitivity, specificity, and AUC values of 97.1%, 96.3%, 97.9%, and 0.988%, respectively.***

*Keywords:* breast cancer; machine learning; segmentation; transfer learning; deep learning.

## 1. Introduction

The most common invasive cancer in women is breast cancer (BC). After lung tumors, BC is the second most prevalent risk factor for mortality. Early detection of BC can help the prognosis process by facilitating successful mitigation of serious complications and faster recovery [1].

BC accounts for approximately 15% of all cancers in women worldwide. In 2018, the rate of new patients with BC in the U.S. was predicted to reach 1,735,350, with 609,640 fatalities expected. Overall, women are expected to have 878,980 cancer cases, with 266,120 of those cases being BC with 40,920 deaths [2].

In Egypt, the total number of new cancer cases was predicted to reach 134,632 in 2020, with 22,038 cases of BC and 9,148 deaths [3]. Despite the fact that the number of occurrences of BC is increasing, the death rate is decreasing due to improved diagnostic capabilities and advancements in BC therapy [4].

Computer-aided diagnostic (CAD) techniques can help increasing diagnostic sensitivity. CAD techniques are used to aid doctors or acquire a second opinion [5]. Fig. 1 shows an overview of cancer cases in 2020. Several BC classifications approaches have been established; however, there is still room to develop an effective strategy to design and implement more effective BC diagnosis systems.

Various medical multi-imaging modalities are used for BC screening and classification. The automatic detection of lesions and their contours in breast mammography is the most important indicator when distinguishing malignant and benign tumors [6]. A critical issue in developing countries is the availability of a sufficient number of radiologists to process this work. In addition, precise image analysis of multiclass images depends on the radiologist's experience and knowledge [7] [8]. A diagnosis can be 91.1% accurate when using machine learning (ML) and deep learning (DL) technologies compared to just 79.9% when performed by a

qualified clinician [9]. However, an effective strategy is required to design and implement more effective BC diagnosis and classification systems.

CNNS are popular DL algorithms that have been modified for 2D image structures. However, CNNs require a large amount of data for training, which is lacking in the medical domain. To address this issue, transfer learning (TL) is used to improve performance by combining the knowledge of multiple networks.

Classification is a supervised ML process, where training data are required to construct a model that can classify new data. Here, the data are first split into a training set and a testing set. The training data are used to construct a learning model, and the testing data are used to evaluate the constructed model [10].

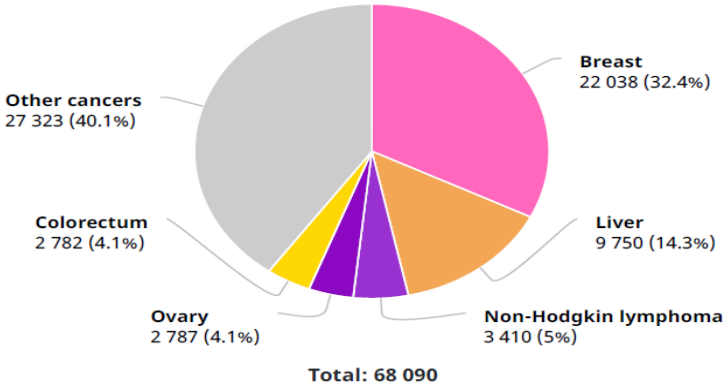


Fig. 1. Summary of cancer cases in 2020 (female) [3]

### *1.1. Open challenges for BC in ML, DL, and TL [11-13]:*

- Standard ML methods employ constrained techniques that are restricted to certain density types or datasets.
- Traditional techniques for ML use domain experts to manually extract and select features, which is time consuming.
- Cancer cells exhibit a variety of positions, shapes, and sizes; thus, automatic detection of cancer tissues in breast images is a significant problem. Here, no adequate scale has been defined for a variety of people; thus, mass analysis is not performed.
- DL techniques require huge amounts of data; however, data availability is a serious issue.
- The computational cost required to train deep CNNs is extremely high.
- Good layers are required in deep networks for feature extraction due to the complexity of BC images and other abnormalities, e.g., granuloma, adenopathy, and mastitis.
- The generalizability of a network's structure is reduced with increasing depth.

Thus, in this current study, BC detection and categorization strategy was proposed that is based on fine-tuning the VGG-16 and VGG-19 networks. The proposed model comprises two primary components. First, image preprocessing is applied to enhance image contrast depending on various operations, e.g., noise removal, morphological analysis, contrast limited adaptive histogram equalization (CLAHE), segmentation, and augmentation. Then, pretrained DL models, e.g., VGG-16 and VGG-19, are applied to transfer parameters to train the BC classification task and improve network performance. The major objectives of in this study are extracting the affected regions automatically using segmentation, reducing training time, and improving classification performance.

The remainder of this work is organized as follows. Sections II and III introduce related work and present the proposed model for breast tumor diagnostics, respectively. Experimental results obtained on real-world data are described in Section IV. Finally, the paper is concluded in Section V.

## *2.* Related work

Chaurasia and Pal [14] examined three BC detection and classification approaches. They concluded that sequential minimal optimization (SMO) outperforms the KNN and best first decision tree techniques in terms of classification accuracy. PATR´ICIO et al. [9] proposed a model to confirm the presence of BC using ML algorithms, and they proved that a support vector machine (SVM) was achieved the best results in terms of specificity and sensitivity. In addition, Agrawal et al. [15] compared bioinspired algorithms, and the results demonstrated that the accuracy of the directed bee colony (DBC) algorithm was the second highest among the compared algorithms. Jain et al. [16] integrated CFS for cancer classification, where correlation-based feature extraction techniques and the improved binary particle swarm optimization (iBPSO) algorithm were used. They compared their results to seven common methods and demonstrated that their model exhibited the best performance. Mahmood et al. [17] implemented the K-Star algorithm for traffic classification and obtained high accuracy (99.47%) using the NSL-KDD dataset. To identify the presence of liver disease, Thangaraju et al. [18] proposed a practical swarm optimization (PSO) technique that used the K-Star classifier, and they reported an accuracy rate of 100%. Sakr et al. [19] introduced a model for BC classification based on the K-Star, clonal selection (CLONALG), artificial immune recognition system (AIRS), and Naïve Bayes (NB) algorithms. They found that the K-Star-based model obtained best results in terms of accuracy, sensitivity, specificity, precision, and AUC values (97.142%, 100.00%, 95.24%, 93.3%, and 0.998%, respectively). Zheng et al. [20] presented a hybrid framework that combined the K-means and SVM algorithms (K-SVM). Here, hidden tumor patterns (either benign or malignant) are determined using the K-means algorithm, and then the SVM uses the updated classifier to classify incoming tumors. In an evaluation on a BC dataset, they found that their technique was 97.38% accurate using 10-fold cross-validation. The adaptive neuro-fuzzy inference system (ANFIS) and information gain (IG) were used as a feature selection strategy by Ashraf et al. [21] to develop a BC diagnosis model. Here, IG is applied to reduce the number of features to the optimal number, and then the dataset is passed to the ANFIS classifier. Compared to other methods, the proposed model was achieved the best results with overall accuracy of 98.24%. Dheeba et al. [22] proposed a model to detect breast anomalies-based PSO wavelet neural network in breast images. The proposed model achieved specificity, sensitivity, and accuracy values of 92.105%, 94.167%, and 93.671%, respectively. Abeer et al. [23] proposed a TL model to detect and classify BC in mammography images. This model extracts breast features by transferring learned parameters from pretrained (e.g., VGG-16, VGG-19, and Inception V3) and training the MIAS dataset. They concluded that VGG-16 is effective in terms of detecting and classifying BC, showing an overall accuracy of 96.8%. Charan et al. [24] proposed a model to classify breast images into seven classes (six for abnormal types and one for normal type). Here the first morphological operation is used to extract the region of interest, and then they designed and trained a CNN to extract images features. They found that their model achieved 65% accuracy on the MIAS dataset. Ting et al. [25] developed and implemented a CNN with a single input layer, 28 hidden layers, are a single output layer. Their model was trained and tested on a shuffled dataset that contains malignant, benign, and normal breast images. In addition, a data augmentation approach was employed to address overfitting. This CNN obtained an overall accuracy of 90.5% on the MIAS dataset. Abeer et al. [26] introduced a DL technique based on TL. This technique involves two main components. The first component comprises seven data preprocessing steps. Here, parameters learned from the Inception-V3, VGG-16, ResNet50, VGG-19, and Inception-V2 ResNet networks were frozen and then passed to the BC classification task in the second component. Note that SoftMax and a multiclass SVM (MSVM) were used in the classification process. The overall model accuracy was 98.87% for BC diagnosis with the TL of the VGG-16 model and MSVM classifier. Akselrod-Ballin et al. [27] proposed a BC classification framework based on segmentation and a region-based CNN. The proposed model was evaluated on the INbreast dataset and achieved an accuracy rate of 78%. Al-Antari et al. [28] discussed a DL model that contains two stages to detect and classify BC. In the first stage, an improved YOLO network was used for tumor detection. Then, feedforward CNN, ResNet 50, and Inception ResNet-V2 networks were employed to classify the tumors. The proposed model achieved an overall accuracy of 94.50%, 95.83%, and 97.50%, respectively, on the DDSM dataset. In addition, this model achieved 88.74%,

92.55%, and 95.32% accuracy on the INbreast dataset with the three classification networks, respectively. Table 1 compares the above methods in chronological order.

Table 1. *Comparison between the related works*

| Author/Year | Model performance | | | |
|---|---|---|---|---|
| | Purpose | Field | Technique | Results |
| Chaurasia and Pal (2017) [14] | Prediction | BC | Compares three ML classification techniques (SMO, KNN, and best first decision tree) | SMO showed higher prediction accuracy (96.2%) |
| PATR´ICIO et al. (2018) [9] | Classification | BC | LR, RF, SVM | Specificity: 85% to 90%<br>Sensitivity: 82% to 88% |
| Jain et al (2018) [16] | Classification | Colon Tumor, Leukemia, Breast, Lung, Ovarian, Lymphoma | SVM, CFS-iBPSO | CFS-iBPSO showed the highest average classification accuracy of (98.28%) |
| Agrawal et al. (2019) [15] | Classification | diabetes, cancer, and heart disease | Artificial Neural Network, DBC | DBC's overall accuracy is good and the best for diabetes |
| Mahmood et al. (2013) [17] | Classification | Traffics classification | K-Star | Accuracy: 99.47% |
| Thangaraju et al. (2016) [18] | Classification | Liver disease | PSO and K-Star algorithms | Accuracy: 100% |
| Zheng et al [20] | Classification | BC | K-SVM | Accuracy: 97.38% |
| Ashraf et al [21] | Classification | BC | ANFIS and Information gain | Accuracy: 98.24% |
| Dheeba et al [22] | Classification | BC | Particle Swarm Optimized Wavelet Neural Network | Specificity: 92.105%<br>Sensitivity: 94.167%<br>Accuracy: 93.671% |
| Sakr et al [19] | Classification | BC | K-star, NB, AIRS, and CLONALG | Accuracy: 97.142%<br>Specificity: 95.24%<br>Sensitivity: 100%<br>AUC: 0.998 |
| Abeer et al. [23] | Classification | BC | A novel TL model based on VGG-16, VGG-19, and Inception V3 | Accuracy: 96.8%. |
| Charan et al [24] | Classification | BC | A novel CNN | Accuracy: 65%. |
| Ting et al. [25] | Classification | BC | A novel CNN | Accuracy: 90.5%. |
| Abeer et al. [26] | Classification | BC | A novel TL model based on inception-V3, ResNet50, VGG-16, VGG-19, and Inception-V2 ResNet | Accuracy: 98.87%. |
| Akselrod-Ballin et al. [27] | Classification | BC | segmentation and region-based CNN. | Accuracy: 78%. |
| Al-Antari et al. [28] | Detection Classification | BC | YOLO, feedforward CNN, ResNet 50, and Inception ResNet-V2 | Accuracy<br>Feedforward CNN: 88.74%<br>ResNet 50: 92.55%<br>Inception ResNet-V2: 95.32% |

## *3.* Proposed model

The presented model for BC detection and classification contains three major components. The first component is used for data preprocessing, the second is used for extracting and transferring the features, and the third is for the classification task, as shown in Fig. 2.

### *3.1 Data preprocessing*

1) Noise removal and morphological operation

We use a 3 × 3 medium filter and morphological analysis operations to remove noise and ensure that no breast regions are present in the images.

2) CLAHE

The CLAHE technique is applied to improve image contrast. This approach generates numerous histograms, each of which corresponds to a different portion of the image. The generated histograms are then used to redistribute the image's lightness values.

3) Segmentation and augmentation

To speed up the computing process, affected breast tissues are extracted during the segmentation phase. Here, data augmentation is applied to address overfitting, which occurs in the training process due to a lack of data. The most common data augmentation techniques are translation, rotation, flipping, color shifting, intensity fluctuation, and random cropping. Here, rotation and flipping procedures are used to increase the amount of data.

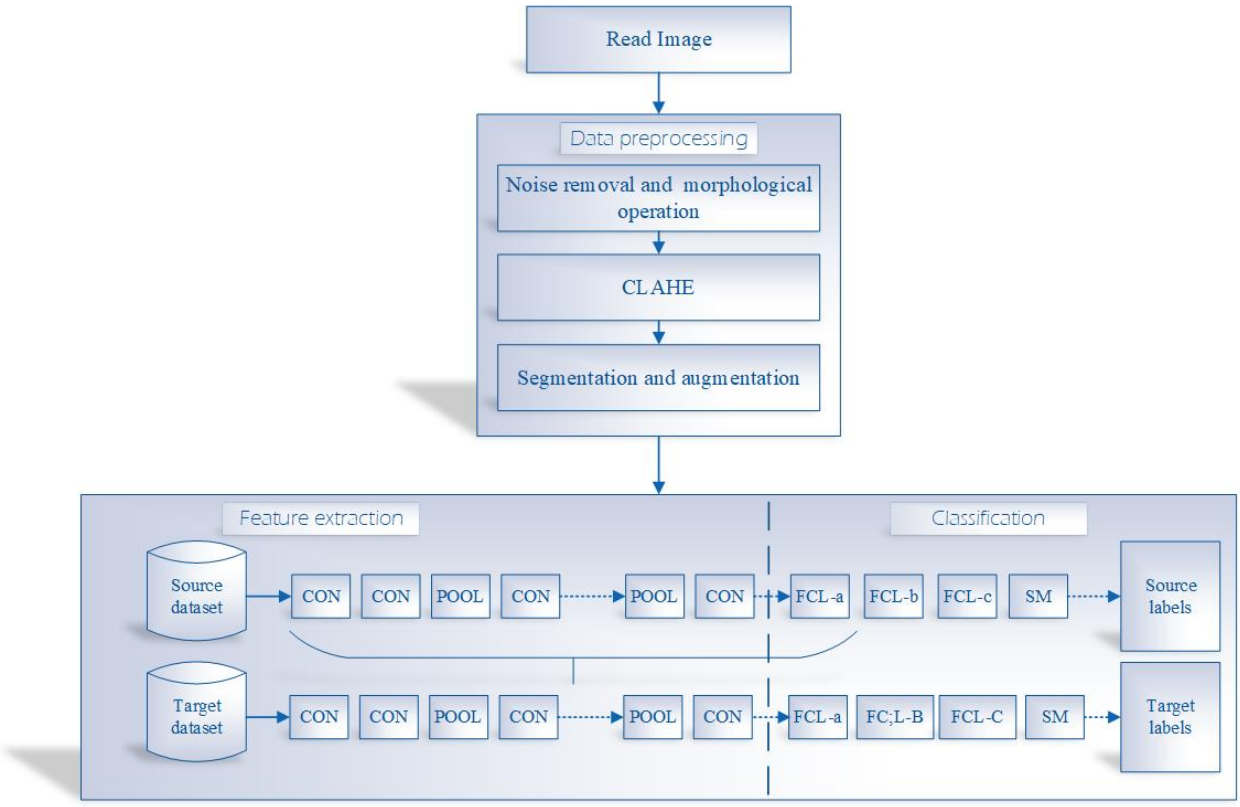


*Fig. 2. Proposed model for breast tumor classification*

### *3.2 Feature extraction*

In the proposed model, feature extraction is performed using the VGG-16 and VGG-19 networks, which are trained over the ImageNet database. The network layers are applied to extract features from the input images, e.g., the horizontal lines, vertical lines, and colors, to recognize objects. The VGG-16 and VGG-16 architectures are described in the literature [29]. VGG-16 is a deep CNN that contains 13 convolution layers and three FCLs. Here, the size of input image is 224 × 224-RGB The filter size in VGG-16 is 3 × 3 with a stride value of 1 [30]. VGG-19 contains 16 convolution layers and three FCLs with an input size of 224 × 224-RGB. The filter size is 3 × 3 with stride equal 1.

### *3.3 Classification*

Here, SoftMax is employed for multiclass classification. The output layer comprises three classes (i.e., normal, benign, and malignant).

## *4.* Results

### *4.1 Dataset*

As shown in Fig. 3, the INbreast dataset is one of the most popular datasets used for breast tumors classification. For 115 instances, this dataset provides 410 images in the digital imaging and communications in medicine format. In addition, data are provided for the benign, malignant, and normal classes. The class value is defined by the Breast Imaging-Reporting and Data System (BI-RADS) value. If the BI-RADS value is 1, the class is normal. If the BI-RADS value is 2 or 3, the class is benign. Otherwise, the class is malignant [31].

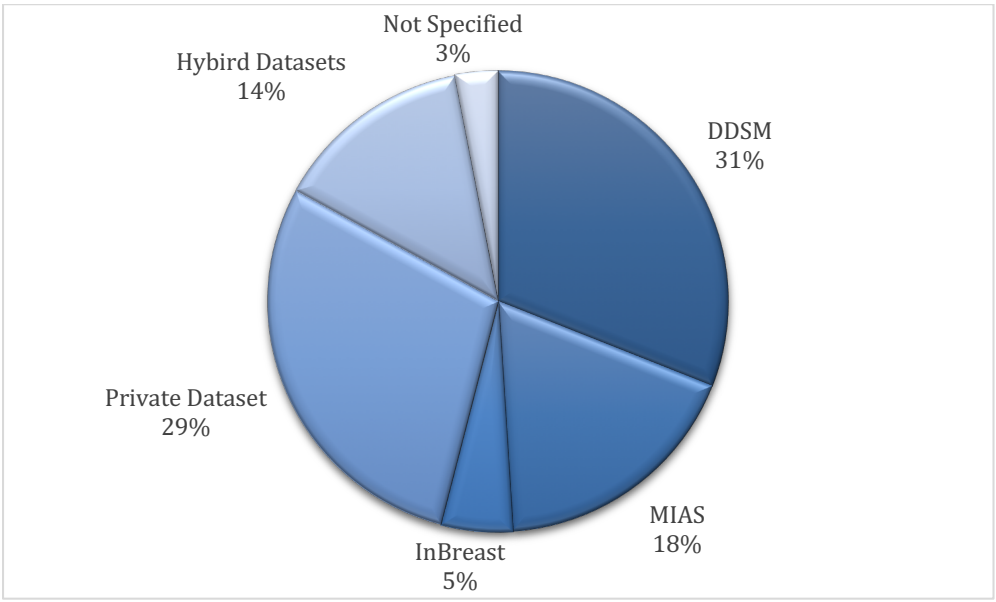


Fig. 3. Breast tumor dataset

### *4.2 Experimental analysis*

The preprocessing steps results in the proposed model are shown in Fig. 4. The original data are enhanced to improve the classification results. The breast images are segmented to improve the performance and reduce the computation cost in the training process. The segmented data are augmented and used to train the model. Each breast image is rotated at 45°, 90°, 180°, and 27°, and then all images are flipped to improve classification accuracy and prevent overfitting. The TL models using VGG-16 and VGG-19 are used to train the presented model. Here, the stochastic gradient descent method with the momentum (SGDM) optimizer is applied for the fine-tuning task to maximize the performance of the network.

The proposed model was evaluated using a three-class confusion matrix in terms of accuracy, sensitivity, specificity, and AUC, as shown in Table 2 and Eq. (1) to Eq. (7). The INbreast data were divided into three classes, 80% of the data was for training and 20% was used for testing. Prior to preprocessing, the highest accuracy (59.3%) was achieved by VGG16, as shown in Table 3. After preprocessing, VGG-16 achieved the best results in almost value, as shown in Table 4. Note that the accuracy and specificity results for VGG-16 were the best in all three classes. In addition, VGG-19 obtained the best sensitivity for the malignant class.

Fig. 5 compares the results of the VGG-16 and VGG-19 networks before and after data preprocessing. In addition, Fig. 6 compares the accuracy of existing methods on a similar dataset (the suggested model is also identified). For tables 3 and 4, the results are increased after the preprocessing stage by increasing the number of input data generated from the augmentation process. We utilized geometry transformation based on rotation and flipping which slightly improved the results obtained. Hence the gap between the results reduced due to augmentation process.

Table 2. *Confusion matrix*

| **Classes** | | **Predicted** | | |
|---|---|---|---|---|
| | | **Benign (B)** | **Malignant (M)** | **Normal (N)** |
| **Actual** | **Benign (B)** | BB | BM | BN |
| | **Malignant (M)** | MB | MM | MN |
| | **Normal (N)** | NB | NM | NN |

$$\text{Accuracy} = \text{BB+MM+NN} / \text{BB+MB+NB+BM+MM+NM+BN+MN+NN} \quad (1)$$

$$\text{Sensitivity B} = \text{BB} / \text{BB+BM+BN} \quad (2)$$

$$\text{Specificity B} = \text{MM+MN+NM+NN} / \text{MM+NM+MN+NN+MB+NB} \quad (3)$$

$$\text{Sensitivity M} = \text{MM} / \text{MB+MM+MN} \quad (4)$$

$$\text{Specificity M} = \text{BB+BN+NB+NN} / \text{BB+BN+NB+NN+BM+NM} \quad (5)$$

$$\text{Sensitivity N} = \text{NN} / \text{NB+NM+NN} \quad (6)$$

$$\text{Specificity N} = \text{BB+BM+MB+MM} / \text{BB+BM+MB+MM+BN+MN} \quad (7)$$

Table 3. *Classification performance of proposed model before data preprocessing*

| Deep Network | Class | Deep Network Classifier Performance | | | |
|---|---|---|---|---|---|
| | | ***Accuracy*** | ***Sensitivity*** | ***Specificity*** | ***AUC*** |
| VGG-16 | Benign | 0.57 | 0.51 | 0.69 | 0.30 |
| | Malignant | 0.62 | 0.43 | 0.59 | 0.30 |
| | Normal | 0.59 | 0.44 | 0.68 | 0.29 |
| | **Average** | **0.593** | **0.46** | **0.653** | **0.297** |
| VGG-19 | Benign | 0.58 | 0.30 | 0.62 | 0.299 |
| | Malignant | 0.60 | 0.27 | 0.58 | 0.291 |
| | Normal | 0.55 | 0.292 | 0.628 | 0.293 |
| | Average | **0.577** | **0.287** | **0.609** | **0.294** |

Table 4. *Classification performance of proposed model after data preprocessing*

| Deep Network | Class | Deep Network Classifier Performance | | | |
|---|---|---|---|---|---|
| | | ***Accuracy*** | ***Sensitivity*** | ***Specificity*** | ***AUC*** |
| VGG-16 | Benign | 0.968 | 0.985 | 0.98 | 0.99 |
| | Malignant | 0.981 | 0.943 | 0.974 | 0.982 |
| | Normal | 0.965 | 0.961 | 0.982 | 0.991 |
| | **Average** | **0.971** | **0.963** | **0.979** | **0.988** |
| VGG-19 | Benign | 0.952 | 0.89 | 0.97 | 0.98 |
| | Malignant | 0.96 | 0.96 | 0.952 | 0.974 |
| | Normal | 0.947 | 0.94 | 0.943 | 0.981 |
| | Average | **0.953** | **0.93** | **0.955** | **0.978** |

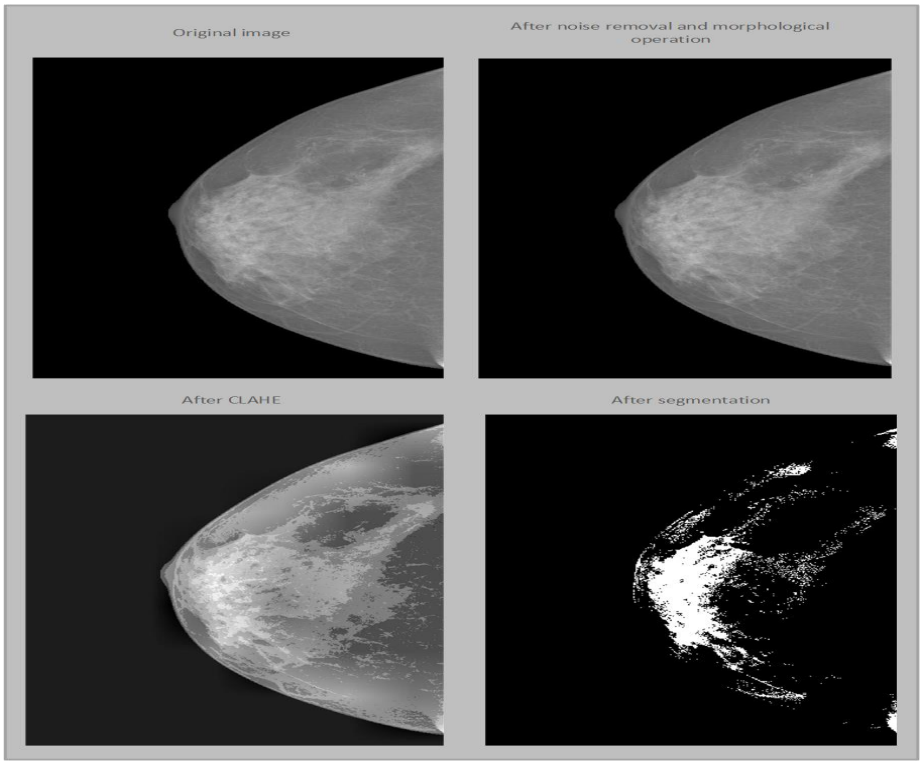


Fig. 4. Preprocessing steps results

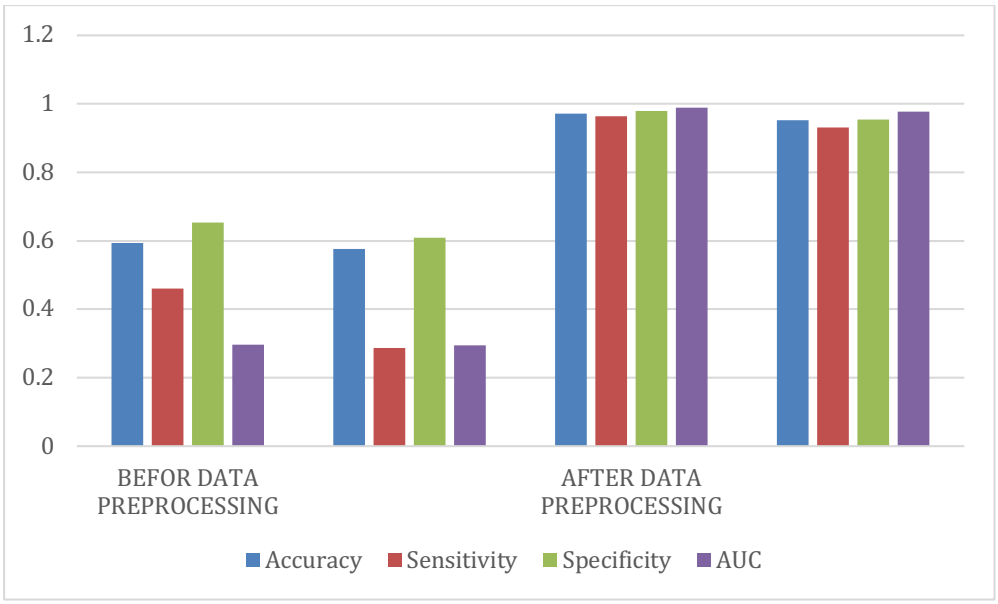


Fig. 5. Comparison of results before and after preprocessing

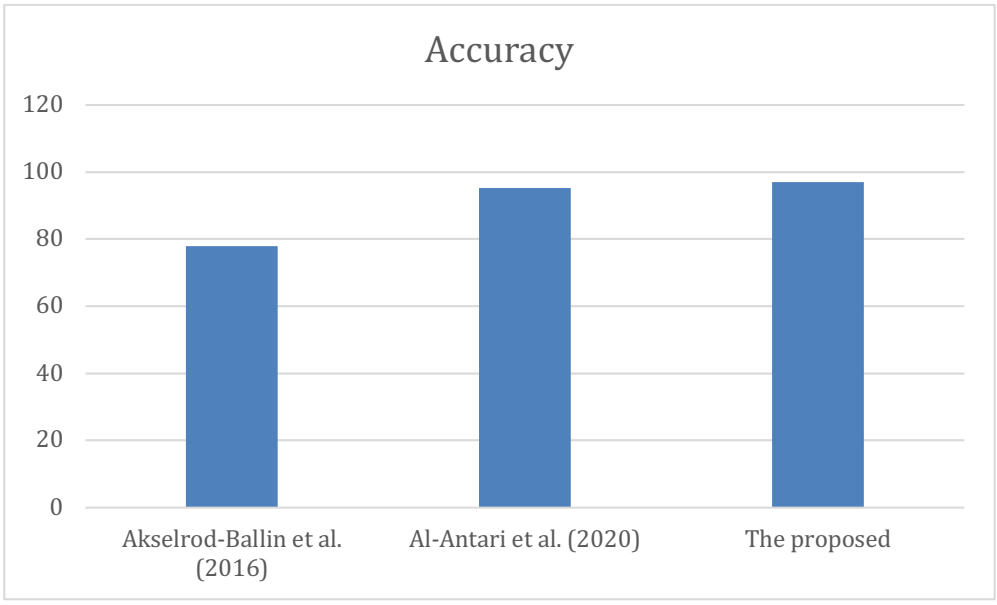


Fig. 6. Comparison between existing methods and proposed model

## 5. Conclusion

This paper has proposed a model to detect and classify breast tumors from mammography images. In the first phase of the proposed model, original images in the INbreast dataset are first preprocessed to remove noise and improve image contrast. Then, data augmentation techniques are applied to increase the amount of available data because the INbreast dataset only contains 410 images. In the second process, features are extracted from the input images and improved using the features transferred from the VGG-16 and VGG-19 networks. Finally, the SoftMax classifier is employed for data classification. The experimental results demonstrate that VGG-16 achieved the best accuracy, sensitivity, specificity, and AUC values of 97.1%, 96.3%, 97.9%, and 0.988%,

respectively. Overall, the experimental results indicate that a model's generalizability is reduced as network depth increases.

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