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%,

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.

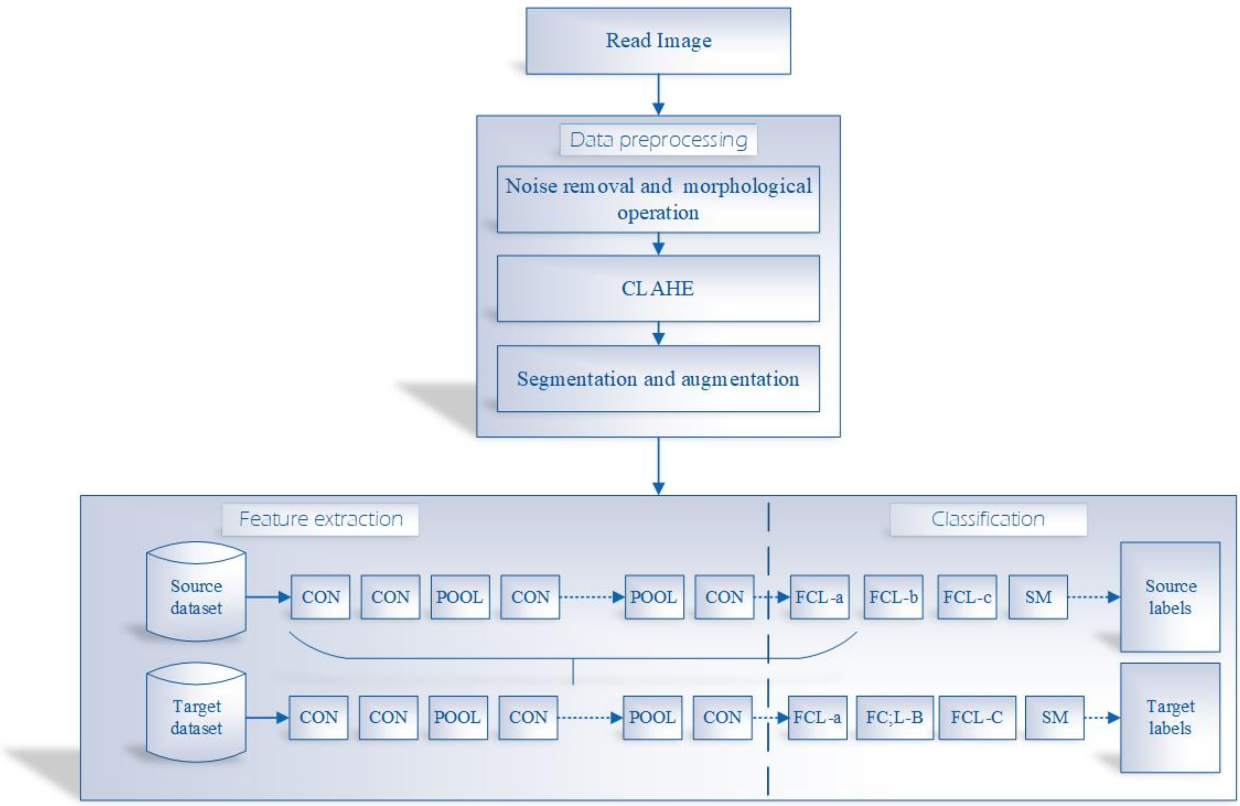

Fig. 2. Proposed model for breast tumor classification

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

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

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

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

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

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

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

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

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**

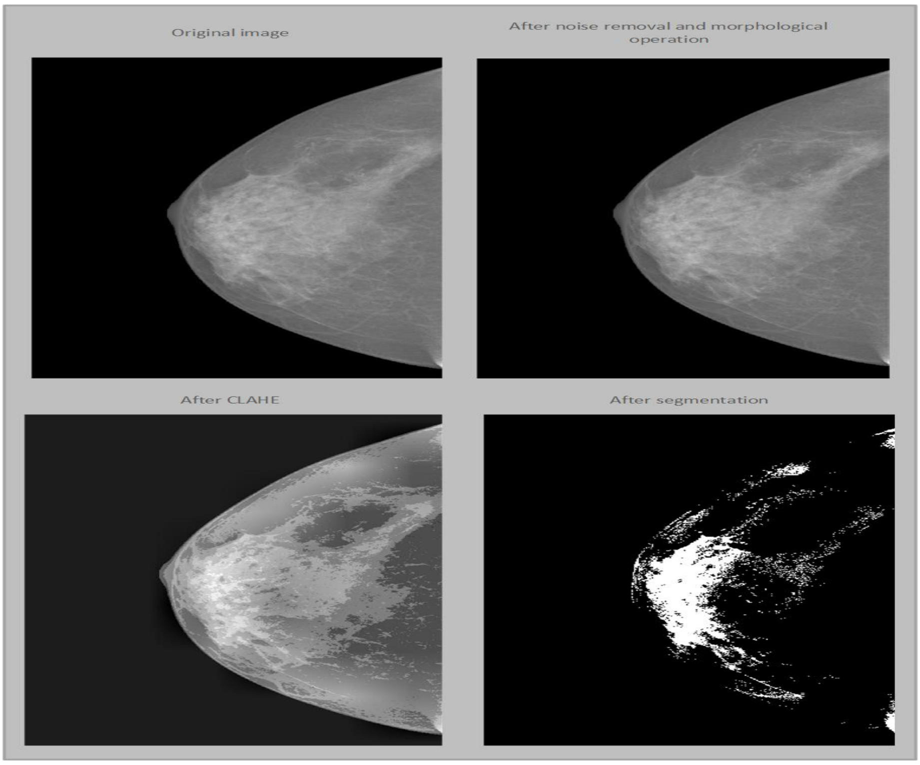

Fig. 4. Preprocessing steps results

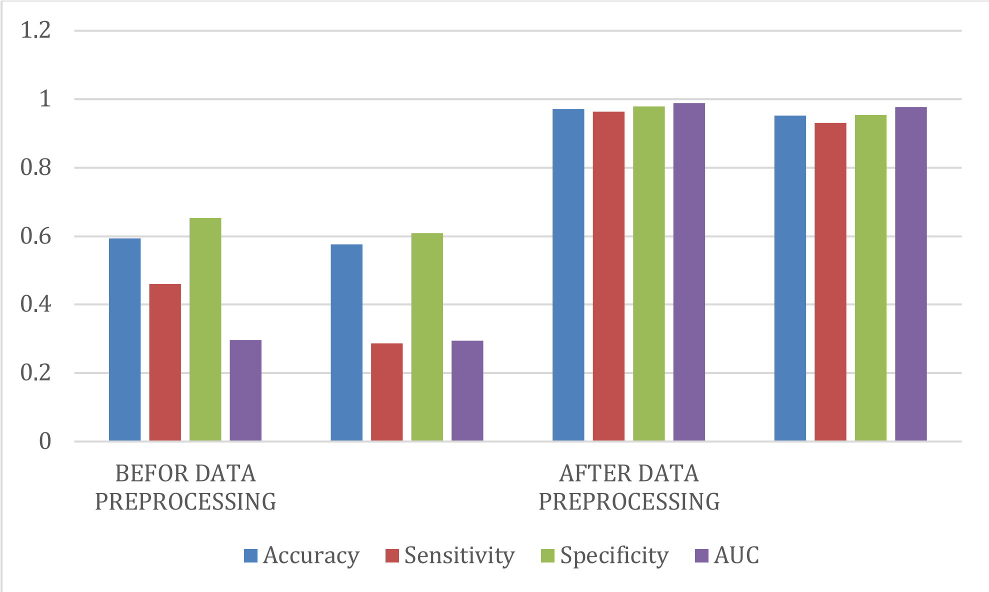

Fig. 5. Comparison of results before and after preprocessing

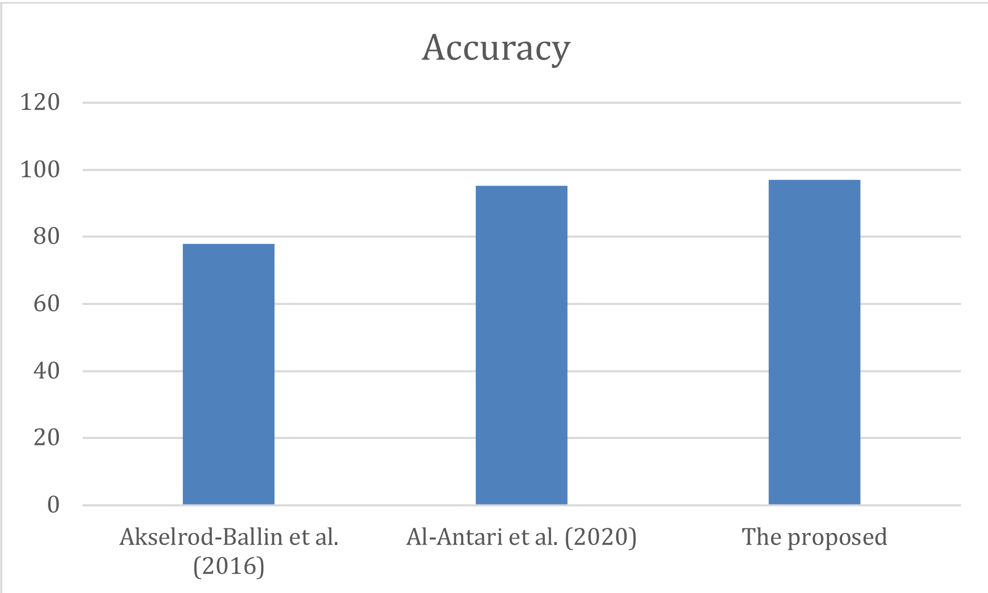

Fig. 6. Comparison between existing methods and proposed model

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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