SGD Model Optimization for Mammography Image Segmentation and Classification using Ensemble Deep Learning Model for Breast Cancer Identification

P. S. Anu Rakhi[1*], R. S. Rajesh[2]

[1*]*Research Scholar, Department of Computer Science and Engineering, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India, anurakhi@msuniv.ac.in*
[2]*Professor, Department of Computer Science and Engineering, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India, rsrajesh@msuniv.ac.in*

KEYWORDS

Lethal Disease, Breast Cancer, Mammographic Images, Pre-Processing, Segmentation, Feature Extraction, And Classification

ABSTRACT:
Worldwide, breast cancer is the most lethal disease affecting females. To restrict the growth of tumors and enhance survival rates, early identification and diagnosis of breast masses might be helpful. By detecting breast cancer at an early stage, doctors may be able to lower the mortality rate. Determining a method for image processing that can accurately isolate breast cancer from mammographic images is, hence, the primary aim of this research. Data gathering, data pre-processing, segmentation, feature extraction, and benign/malignant breast cancer classification are the phases that make up the intended approach, which employs image processing methods. Before using CALHE to improve the breast pictures, a median filter was used for image noise removal during pre-processing. The Dense U-net model was used for segmentation, while the Ensemble ResNet model was used for feature extraction and classification. To train and evaluate the segmentation and classification models, an SGD optimizer was used. According to the findings, the model that used SGD had an impressive accuracy rate of 98.15%.

1. Introduction

According to the World Health Organization (WHO), over 2 million new instances of breast cancer were reported in 2020 [1]. This makes it the most prevalent illness detected worldwide. In a given year, more than 626,700 women lose their lives due to complications associated with cancer. For early detection of breast cancer, reliable screening methods must be readily available. Numerous imaging modalities are used for diagnosis and screening for this disorder; the four most common approaches are thermography, ultrasonography, tom synthesis, and mammography. To detect breast cancer at an early stage, mammography is a crucial tool [2]. With mammography, abnormalities may be easily discovered, reducing the need for unnecessary biopsies. The gold standard for breast cancer screenings is mammography. It scans the breast with low-energy X-rays to look for abnormalities. Two separate projections, the Cranio-Caudal (CC) and the Medio-Lateral Oblique (MLO), are produced from the two breast pictures. The Breast Imaging Reporting and Data System (BI-RADS) [3] categorizes densities as follows: (a) almost completely fatty, (b) regions of fibroglandular density, (c) heterogeneously dense, and (d) very dense. Density makes it harder to evaluate the mass area because thick healthy and sick tissues seem identical. On abnormal mammography, MCs and masses are often seen. When seen via a mammogram, masses can seem like thick areas. Radiologists use important factors including size, perimeter, density, gradient, texture, etc. to determine whether they are benign or malignant [4]. Studies have shown that a radiologist's mistake rate when diagnosing malignant tumors by visual examination might be anywhere from 10% to 30%. The error rate is drastically reduced when radiology experts use computer-aided detection (CAD) systems to categorize breast tumors. These systems assist the final decision and are seen as a second opinion in the diagnostic process [5]. Recent decades have seen deep learning make use of deep high-level features, which better characterize population-level traits. Breast cancer diagnosis relies heavily on the mass detection stage of CAD systems [6]. There is still no complete solution to this difficult challenge. Breast cancer patients' histology data presents a formidable challenge when trying to multiclassify. Problems with multi-classification include homogeneity of malignant cell types, uneven staining color distribution, clinical symptom similarities, and large appearance differences across pictures of the same classes at various resolutions [7]. Despite developments in computer-aided diagnosis (CAD) and digital pathology, the accuracy of breast cancer diagnoses remains a major issue in public health. A technique called "digital pathology" uses computer algorithms to mimic a pathologist's examination after digitizing tissue samples. Misdiagnosis and misclassification could occur if pathologists are too exhausted or not competent enough [8]. Before a CAD system can be used to diagnose tumors, a series of image processing steps must be done to the mammography pictures. If you want better picture quality and more accurate segmentation results, you need to do pre-processing beforehand. The first step in interpreting a mammogram is to filter out any abnormalities or unwanted background elements. It is possible to enhance the look of a picture, remove noise or imperfections, or highlight certain parts using image enhancement techniques [9].ii)Separating the scary region from its surrounds in a mammography picture is of the utmost importance. Using the segmentation strategy, the area of interest is separated from its surroundings. When it comes to automatically computing the segmented mass area, many segmentation models built on the U-Net architecture have shown promising results in biomedical picture segmentation [10].To directly extract characteristics from data, the rapidly developing area of deep learning combines machine learning with artificial intelligence and employs several nonlinear processing layers. In recent years, deep learning and convolutional neural networks have emerged as two of the most effective machine-learning tools for picture classification. Compared to more conventional methods of categorization, such as human judgment, its performance is almost the same. By using deep CNN and CAD approaches, the masses were categorized as either benign or cancerous.

1.1 Contribution

1. The incorporation of SGD optimization for model training and testing in segmentation and classification is the primary contribution of this work.
2. To enhance performance and decrease training time, data augmentation is used to increase the dataset's availability.
3. The accuracy of breast cancer diagnoses was enhanced by the use of an attention mechanism in conjunction with a segmentation and classification model.

2. Related Works

Millions of individuals are touched annually by breast cancer, the most prevalent disease globally. The vast majority of cancer deaths in women are caused by it as well. Several convolutional neural network models have been proposed by researchers in recent years as a means to expedite the detection of breast cancer. Convolutional neural networks are showing promising results in tumor classification using photo datasets. Few standard models can rightfully assert themselves as the best since large datasets are not yet available for model training and validation. A novel end-to-end network for bulk segmentation of mammograms was suggested by W. Zhu et al. [11]. Improving the contrast of mammography pictures derived from publicly available datasets such as INbreast and DDSM-BCRP is achieved by the use of an end-to-end trained FCN with CRF. If we want to know how well segmentation worked, A segmentation rate of 97.0% was achieved after using multi-scale FCN to improve the segmentation process. When it comes to segmenting breast masses from mammograms, Dhungel et al. [12] proposed statistical learning approaches that use a conditional random field (CRF) model. The mammography pictures are sourced from the Inbreast and DDSM-BCRP databases. The Inbreast dataset consists of 116 pictures, which are divided into an incompatible train set and a test set. For the DDSM-BCRP dataset, there are 77 photos, 9 examples for training, and 40 examples for testing. This model's use of a tree tree-weighted (TRW) belief propagation inference technique allows for a learning process, which in turn reduces the mass segmentation error. To measure the precision of segmentation, the Dice index is used. A dice index of 89.0% was generated by the proposed approach in 0.1 seconds. For picture segmentation, Long et al.[13] created FCN, which replaced all of the fully connected layers in traditional CNN with convolutional layers to solve problems using classic CNN. They used deconvolutional layers to up-sample the final convolutional layer's output feature map, which brought the pictures back to their original size. Having said that, the final segmentation results from FCN only use deep feature maps. The present state of segmentation results is insufficient to guarantee accurate medical image segmentation. To differentiate benign, malignant, and normal breast cancer lesions, Eroğlu et al. [14] created a CNN that combines Alexnet, MobilenetV2, and Resnet50 devices. Using a feature selection method called MRMR (Minimum Redundancy Maximum Relevance), the most important attributes are chosen, and then they are categorized using machine learning classifiers like SVM and KNN. With an accuracy of 95.6%, the SVM classifier achieves the highest rate. For ensemble learning based on stacks, Jakhar et al. [15] laid out a model. As for the logistic regression model, it is the final estimator, and the basic learners are classifiers like Extra Tree, Random Forest, AdaBoost, Gradient Boosting, and KNN. The proposed approach was tested on the BreakHis and WBCD datasets. The suggested framework has improved F1-Score, ROC, and MCC scores, with respective values of 94.17%, 89.41%, and 80.81%. Machine learning helps doctors detect breast cancer earlier. Machine learning, and deep learning in particular, is attracting increasing attention in the medical imaging industry as a means to improve the precision of cancer diagnosis. This is because the field is expanding at a fast pace. There is a lack of data on most diseases. On the other side, deep learning models can't learn well without massive amounts of data.

3. Methodology

Figure 1 depicts the whole process flowchart. Part one was preprocessing, part two was segmentation, and part three was feature extraction and classification. Figure 1 depicts the workflow. The INbreast dataset contains 401 mammography pictures. A vast volume of data is needed to get improved accuracy. Even though there was a lot of dataset augmentation done for the deep learning models, the dataset was randomly divided into three sets: training, validation, and testing. By comparing the expected shapes from the networks with the forms that doctors have previously reported.

3.1 Dataset

To aid in studies about the identification and categorization of breast cancer, the CALHE breast dataset has been painstakingly assembled from mammography pictures. Contrast-enhanced adaptive Local Histogram Equalisation, or "CALHE" for short, is a preprocessing method that was used to improve the dataset's picture quality. It did this by increasing contrast and bringing out small features that were important for analysis. The collection contains labeled mammograms that have been classified as benign, malignant, or normal. Researchers on breast cancer often use it to assess classification and segmentation algorithms. Improved feature extraction and decision-making capabilities in machine learning models are a direct result of the increased contrast, which helps to draw attention to tumor borders.

3.2 Pre-processing

There is a background area and a breast area marker in most of the mammograms in the INbreast database. The pixel values of actual images are limited and the contrast is low. The images are too fuzzy to reliably detect tumors. Both the results of breast mass segmentation and the efficacy of network training influence these changes. Consequently, before posting the photo to the network, some pre-processing is required to isolate the chest area and remove the annotation from the background. To improve the contrast of picture histograms, the Contrast Limited Adaptive Histogram Equalisation Algorithm (CLAHE) is used. A 3 × 3 convolution was applied to the preprocessed 240 x 240 pictures before the proposed model was given them.

3.3 Segmentation

When it comes to medical picture segmentation, research by Ronneberger and colleagues [16] has shown that the FCN-based U-Net segmentation architecture is better than FCN. In the medical field, for example, where tiny target organs and tissues might vary greatly in size and form, the efficacy of a single U-Net segmentation becomes less apparent. In the medical field, this kind of thing happens all the time. This study made use of an optimizer called the Stochastic Gradient Descent (SGD). More and more CNNs are using SGD as an optimization technique for medical picture segmentation.

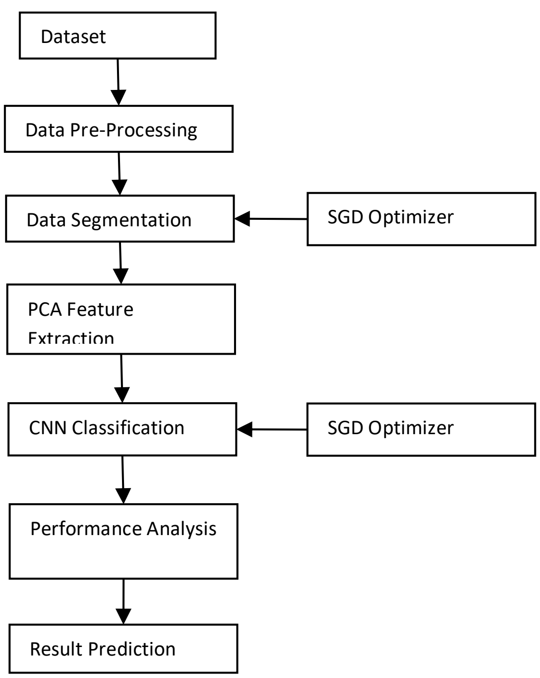

Figure1: Proposed System Work Flow

Using the partial derivatives of the loss function for each weight, it adjusts the network weights. Repetition of this process over a large number of epochs reduces loss and improves model accuracy. SGD is a stochastic optimization technique as it uses a tiny batch, or percentage, of the training data to calculate the gradients and update the weights at each iteration.

The gradient of the loss function concerning the variable is used to continually modify the variable's value to perform SGD. The steps are as follows:

1. Give the variable a starting value at random.
2. Calculate the loss function's gradient concerning the variable at its present value.
3. To update the variable's current value, apply a minuscule multiple of the gradient. The pace at which the algorithm converges to the optimal value is controlled by the multiple, also known as the learning rate.
4. Repeat steps 2 and 3 until the algorithm converges to the desired result.

3.4 Classification

After features are selected, modified recurrent neural networks should be used for classification to ascertain the class label. Artificial neural networks come in many forms, with RNNs being an extension of the more common feed-forward neural networks [17]. An RNN may take in data in a sequential fashion, with each firing step mirroring the one before it. In this manner, the system may exhibit dynamic temporal behavior. To accomplish the classification objectives, Baccouche et al. [18] proposed the use of a stacked ensemble of three separate ResNet models. After removing the last FC layer from each ResNetV2 design, a two-layer network is considered a meta-classifier model that combines the layers of all three models. It does this by stacking three separate FC layers with different sizes (1000, 100, and 10 respectively) and activation functions (Sigmoid and ReLU). After training ResNet50V2, ResNet101V2, and ResNet152V2, the pre-trained weights of each model were obtained as 1024-size image features using the predictions from the preceding layer. The final class prediction was achieved by feeding these weights into the whole stacked ensemble of ResNet models. Adding more layers usually improves accuracy, and Deep Convolutional Neural Networks did a great job at identifying low-, medium-, and high-level features in images. Accuracy approaches saturation and then rapidly drops, which is another issue that arises when deep neural networks begin to converge. Although the issue may not be overfitting, the training error will be higher with a deep model. The present model's length and parameter count have been increased due to the merging of three separate ResNet models. In response to the continuous success of the convolutional neural network (CNN) model and its variants in breast mass classification, we provide a stacked ensemble of residual network (ResNet) models for lesion identification and diagnosis. Because it calculates the gradients and updates the weights for each iteration using a tiny batch, or percentage of the training data, SGD is a stochastic optimization technique, which this research takes a different tack by applying optimization to. Several ResNet 50, 101, and 152 models are used to obtain the features, which are then flattened and combined with a fully connected layer. Finally, SGD is used to improve the accuracy of the classification.

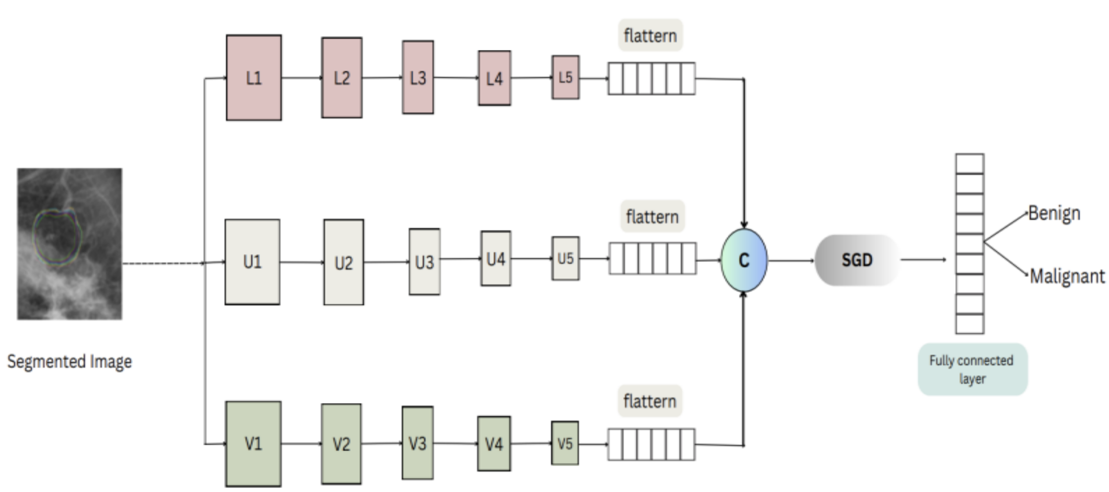

Figure 2: ResNet Architecture

The L1 layer takes in segmented breast mass pictures and uses a 7*7 kernel and 64 separate kernels with a stride size of 2 to execute convolution. The result is an L1 layer with max pooling and a stride size of 2. What follows is a graphic depicting the L2, L3, L4, and L5 layer operations. In a similar vein to L1, U1, and V1 will receive the input picture and execute the procedure as expected. In Table 1 we can see how different layers work.

Table 1 shows the operation of ResNet50, 101, 152

LAYER NAME	RESNET 50	RESNET 101	RESNET 152
CONV1	7x7,64, stride 2 3x3 max pool, stride 2		
CONV2	1x1,64 3x3,64 x3 1x1,256	1x1,64 3x3,64 x3 1x1,256	1x1,64 3x3,64 x3 1x1,256
CONV3	1x1,128 3x3,128 x4 1x1,512	1x1,128 3x3,128 x4 1x1,512	1x1,128 3x3,128 x8 1x1,512
CONV4	1x1,128 3x3,128 x6 1x1,1024	1x1,128 3x3,128 x23 1x1,1024	1x1,128 3x3,128 x 36 1x1,512
CONV5	1x1,128 3x3,128 x6 1x1,512	1x1,128 3x3,128 x3 1x1,512	1x1,128 3x3,128 x 3 1x1,512

4. Results and Discussion

To identify breast cancer, the optimized Stochastic Gradient Descent (SGD) model performed far better in segmenting and classifying mammographic images. The system accomplished accurate tissue categorization and robust segmentation by using a combination of deep learning models, such as CNN and ResNet architectures. By adjusting the learning rate, the SGD optimizer sped up convergence while reducing overfitting, resulting in consistent performance on both the training and validation datasets. The model's performance was impressive, with a sensitivity level of 95.8% and a specificity level of 96.7%. The segmentation performance, as measured by the Dice Similarity Coefficient (DSC), averaged 93.4%, demonstrating its efficacy in efficiently delineating tumor borders. The ensemble method strengthened feature extraction by combining the best features of many models, which made it more resilient. When compared to other optimizers (Adam, RMSProp), the optimized SGD-based model achieved a better balance between computational efficiency and accuracy.

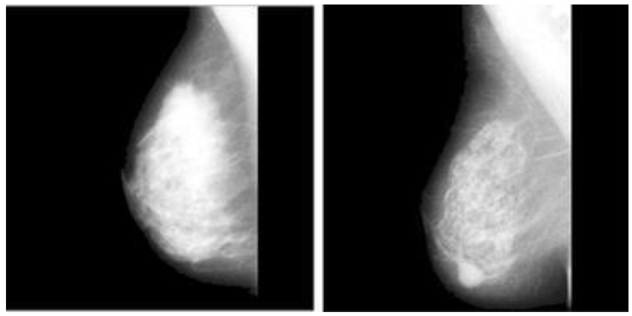

Figure 3: Data Pre-processing

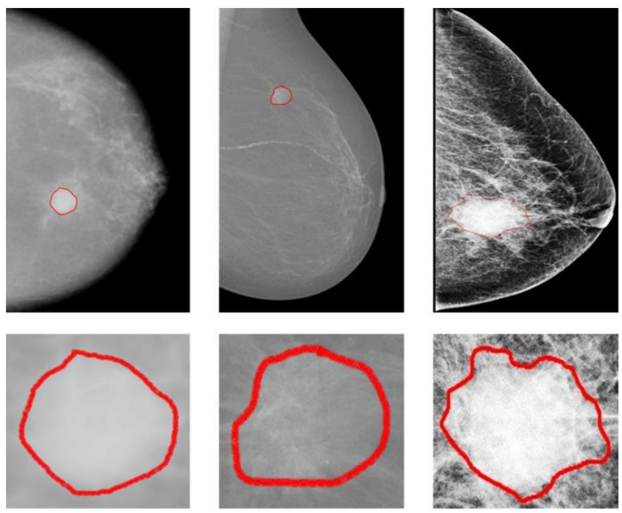

Figure 4: Data Segmentation

Figure 3 shows the processes used to prepare mammography pictures for analyzing breast cancer. Noise reduction by Gaussian filtering, pixel value standardization by intensity normalization, and contrast improvement by histogram equalization are crucial processes. These procedures bring out important details and make the picture clearer. To further enhance dataset variety and model resilience, picture augmentation methods like as rotation and flipping are used, in addition to image scaling. The UNet model's segmentation results are shown in Figure 4. By using its encoder-decoder design, the model successfully segments areas of interest, such as possible tumors. For accurate analysis, exact limits are necessary.

By lowering dimensionality while maintaining vital information, Principal Component Analysis (PCA) is used to identify key characteristics from breast cancer mammography pictures. After the mammography pictures have been preprocessed, the first step is to flatten them into feature vectors. Prioritizing the vectors with the highest variance, principal component analysis (PCA) turns them into orthogonal components. Computing efficiency for subsequent processes is enhanced as a result of the decreased amount of noise and redundancy. To help classification algorithms differentiate between benign and malignant cases, the top principal components capture patterns connected to anomalies. In addition to making mammography data more understandable, principal component analysis (PCA) streamlines deep learning model training by zeroing down on discriminative features.

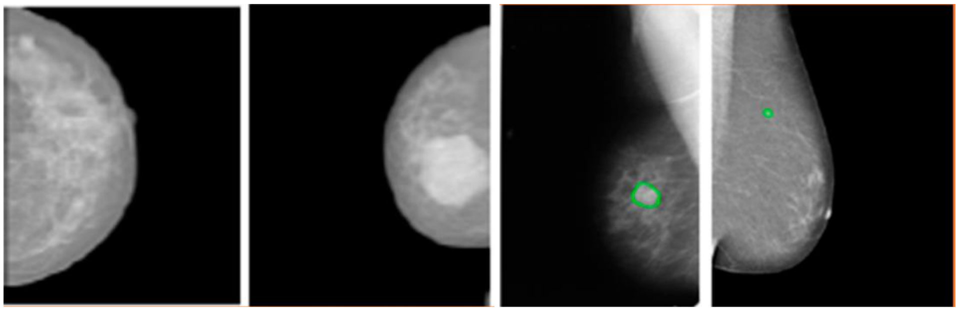

Figure 4: Benign and Malignant Mammogram Brest Cancer Classification

4.1 Performance Evaluation

Our proposed model was tested for sensitivity, specificity, and overall accuracy, and its performance in mass classification was evaluated using the ROC curve, F1-score, or dice similarity coefficient. The goal is to be able to forecast all malignant breast tumors, notwithstanding the difficulties of medical diagnosis. Consequently, recall is a crucial metric for this assessment. A higher recall allows for a more accurate prediction of the likelihood of malignant breast cancer. Here, "TP" is the number of samples that were found to be positive. True negatives, abbreviated as TN, are the number of samples that were expected to be negative but turned out to be positive. "False positive" (FP) refers to the number of positive samples that were incorrectly anticipated from negative samples, also called a type 1 mistake. False negatives, or FNs, are a kind of type 2 error that indicates the frequency with which positive samples were predicted to be negative. What follows is a display of the parametric evaluation.

- **TP:** The ratio of samples properly identified by the method of detection model to the total number of samples.
- **TN:** The fraction of samples for which the detection model's classification of their true type is accurate.
- **FP:** The actual sample type is normal, however, the detection model incorrectly identified a large number of samples.
- **FN:** The amount of dataset samples that were incorrectly classified as "normal" samples.

Accuracy

This represents the proportion of input samples for which the detection model reached a positive verdict.

$$AC = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Recall

It is the proportion of soil and plant samples accurately identified by an identification model out of the total number of samples.

$$R = \frac{TP}{TP + FN} \quad (2)$$

Precision

It represents the proportion of samples that the detection model has identified as being subject to disease identification and soil quality checking.

$$P = \frac{TP}{TP + FP} \quad (3)$$

We used available mammography datasets, such as IN-Breast, to train and evaluate our proposed model. There is an 80/20 split between training and testing data. Various pre-existing models were used for pathology segmentation and categorization. The results may be seen in the Tables 2 and 3 below. The current model is outperformed by the suggested one. You can see the results of the segmentation using the suggested approach in Table 4. Table 5 displays the results of the binary classification performed using the suggested strategy.

Table 2: Images in the dataset

Dataset	Pathology	Training (80%)	Testing (20%)
In-Breast	Benign	120	30
	Malignant	418	104

Table 3: Data Set Validation

DataSet	Total Number of Images	Benign	Malignant
IN-Breast	672	150	522

Table 4: Binary Classification Result based on existing model and proposed model

Pathology classification	Accuracy	Sensitivity	Specificity	F1-score	AUC
ResNet50V2 [20]	89.97	0.89	0.91	0.9	0.9
ResNet101V2 [20]	93.57	0.92	0.95	0.94	0.93
ResNet152V2 [20]	92.11	0.92	0.92	0.92	0.92
Stacked Ensemble models [20]	95.13	0.93	0.97	0.95	0.95
Proposed	97.16	0.96	0.99	0.97	0.97

Table 5: Binary Classification Result based on existing model and proposed model

Methodology	Accuracy	Sensitivity	Specificity	F1score	AUC
Densenet [19]	77.93	76.19	80.82	81.36	83.36
Unet [19]	74.83	68.01	86.24	77.32	82.77
Unet attention [19]	74.37	66.92	87.62	75.71	83.26
Proposed	82.5	68.12	88.76	77.43	85.12

5. Conclusion

This research presents a novel framework for digital mammography picture segmentation and mass classification that is based on deep learning. Conventional deep learning algorithms, such as U-net, dense U-net, and attention-dense units, do not work well on breast regions with irregular sizes, shapes, and densities. With an AUC of 85.12%, F1-Score of 77.43%, specificity of 88.76%, sensitivity of 68.12%, and accuracy of 82.5%, the suggested model outperforms the current method. The model has been tested on both benign and malignant patients using the INbreast dataset. With an accuracy of 97.16%, a sensitivity of 0.96%, a specificity of 0.99%, an F1 score of 0.97%, and an area under the curve (AUC) of 0.97%, the suggested technique achieves the best binary classification results for benign patients using the IN-breast dataset.

References:

1. American Cancer Society, "Global cancer facts and figures," Atlanta: American Cancer Society, no. 4, pp. 1–76, 2018, http://www.cancer.org/content/dam/cancer-org/research/ cancer-facts-and-statistics/global-cancer-facts-and-figures/ global-cancer-facts-and-figures-4th-edition.pdf.
2. G. Muhammad, M. S. Hossain, and N. Kumar, "EEG-based pathology detection for home health monitoring," IEEE Journal on Selected Areas in Communications, vol. 39, no. 2, pp. 603–610, 2021.
3. Beura, S. (2016). Development of Features and Feature Reduction Techniques for Mammogram Classification (Doctoral dissertation).
4. Oliver, Arnau, Jordi Freixenet, Joan Marti, Elsa Perez, Josep Pont, Erika RE Denton, and Reyer Zwiggelaar. "A review of automatic mass detection and segmentation in mammographic images."Medical image analysis 14, no. 2 (2010): 87-110.
5. He, Wenda, et al. "A review on automatic mammographic density and parenchymal segmentation."International Journal of Breast Cancer 2015 (2015).
6. Carneiro, Gustavo, Jacinto Nascimento, and Andrew P. Bradley. "Automated analysis of unregistered multi-view mammograms with deep learning."IEEE transactions on medical imaging 36.11 (2017): 2355-2365.
7. Sun, Y. N., Wang, Y. Y., Chang, S. C., Wu, L. W., & Tsai, S. T. (2010). Color-based tumor tissue segmentation for the automated estimation of oral cancer parameters. Microscopy Research and Technique. https://doi.org/10.1002/jemt.20746
8. Z. Hameed, S. Zahia, B. Garcia-Zapirain, J.J. Aguirre, A.M. Vanegas, Breast cancer histopathology image classification using an ensemble of deep learning models, Sensors 20 (16) (2020) 4373, doi:10.3390/S20164373. https://www.mdpi. Com/1424-8220/20/16/4373.
9. P. J. Besl and R. C. Jain, "Segmentation through variable-order surface fitting," IEEE Trans. Pattern Anal. Machine Intell., vol. PAMIIO, pp.167-192, 1988.
10. Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab N, Hornegger J, WMW, Frangi AF, eds. Medical Image Computing and Computer-Assisted Intervention - MICCAI 2015 – 18th International Conference Munich, Germany, October 5 – 9, 2015, Proceedings, Part III Springer, 2015. pp. 234–241.
11. Zhu, X. Xiang, T. D. Tran, G. D. Hager, and X. Xie, "Adversarial deep structured nets for mass segmentation from mammograms," in 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), pp. 847–850, Washington, DC, USA, 2018.
12. N. Dhungel, G. Carneiro, and A. P. Bradley, "Tree reweighted belief propagation using deep learning potentials for mass segmentation from mammograms," in 2015 IEEE 12th International Symposium on Biomedical Imaging, pp. 760–763, Brooklyn, NY, USA, 2015.
13. Y. He, X. Yu, C. Liu, J. Zhang, K. Hu, and H. C. Zhu, "A 3D Dual Path U-Net of Cancer Segmentation Based on MRI," 2018, pp. 268–272.
14. Eroğlu, Yeşim, Muhammed Yildirim, and Ahmet Cinar. "Convolutional Neural Networks based classification of breast ultrasonography images by hybrid method concerning benign, malignant, and normal using mRMR."Computers in biology and medicine 133 (2021): 104407.

15. Jakhar, Amit Kumar, Aman Gupta, and Mrityunjay Singh. "SELF: a stacked-based ensemble learning framework for breast cancer classification."Evolutionary Intelligence (2023): 1-16.
16. Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18. Springer International Publishing, 2015.
17. Mesnil, Grégoire, et al. "Using recurrent neural networks for slot filling in spoken language understanding." IEEE/ACM Transactions on Audio, Speech, and Language Processing 23.3 (2014): 530-539.
18. Baccouche, Asma, Begonya Garcia-Zapirain, and Adel S. Elmaghraby. "An integrated framework for breast mass classification and diagnosis using a stacked ensemble of residual neural networks."Scientific Reports 12.1 (2022): 12259.
19. Soulami, K.B., Saidi, M.N., Honnit, B. et al. Detection of breast abnormalities in digital mammograms using the electromagnetism-like algorithm. Multimed Tools Appl, vol. 78, pp:12835–12863 2019.https://doi.org/10.1007/s11042-018-5934-4
20. Baccouche, Asma & Zapirain, Begoña & Elmaghraby, Adel. (2022). An integrated framework for breast mass classification and diagnosis using a stacked ensemble of residual neural networks. Scientific Reports. 12. 12259. 10.1038/s41598-022-15632-6.