International Journal of Gender, Science and Technology
..ISSN: 2040-0748
UGC Care Group I Journal
Vol-12 Issue-02 DEC2023

DESIGN THINKING APPROACH FOR BREAST CANCER CLASSIFICATION USING RESNET MODEL IN ULTRASOUND IMAGES

Dr.M.PRAVEENA[1] Associate Professor,
praveenamarannan@gmail.com,
JISHOR. M[2], KALAIARASY.M[2], KARUPPUSAMY A[2].
Department of Computer Science,
Dr.SNS Rajalakshmi College of Arts and Science (Autonomous), Coimbatore - 49

Abstract—In terms of mortality, breast cancer is second only to lung cancer among female cancer patients. Many forms of genetic code contribute to the promotion of cancer in the context of breast cancer development. The subsequent steps in gene alterations that contribute to tumor development are poorly understood. Technology and techniques for detecting breast cancer have come a long way over the past few years.CAD systems have been developed to offer the radiologist with a neutral, algorithmic categorization of BUS pictures. Nevertheless, the vast majority of these methods rely on manually created characteristics to measure the tumor. As a result, the capacity of these CAD systems' handmade traits to distinguish between benign and malignant tumors is crucial to their efficacy. In order to detect breast cancer in mammography pictures, this research details an image processing method that makes use of the ResNet method. It explains the processes involved in finding breast cancer and describes the many ResNet method functions employed in doing so. This method aids the physician in making a correct diagnosis of breast cancer and keeping tabs on the progress of diagnosis. Experimental results show that pre-training on US pictures yielded the best results for the fine-tuned classifier (0.97 accuracy, 0.98 AUC). In order to boost the effectiveness of deep learning in biomedical field, it is recommended that pre-trained models be created utilizing medical imaging data.

***Index Terms*—Breast Cancer, Deep Learning Model, empathize, ResNet Model, design thinking, Computer-aided diagnosis (CAD).**

I. INTRODUCTION

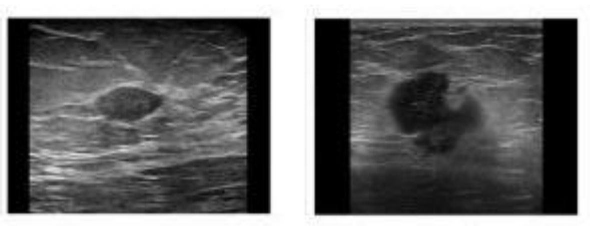
Worldwide, one in eight women may develop breast cancer sometime in her lifetime. It is why so many institutions and governments throughout the world are devoting resources to finding breast tumors early. Early detection of cancer improves treatment outcomes and lengthens the probability that a client will have a natural life span after treatment. Increased research into breast cancer's molecular pathways has been a major trend throughout the past few years. Many variables influence whether or not a woman may get breast cancer, including mass index, family history, age at delivery, duration of breastfeeding, alcohol intake, physical activity level, and more. There are certain things that have a major impact while others only have a little one. Certain risk factors, like being a woman or getting older, are unavoidable, while others, like living a healthy lifestyle, can help reduce the chance of breast cancer [1].

Invasive breast cancer develops when cancer cells originate in breast tissue and multiply uncontrollably. Variations in breast size, structure, and colour, as well as any new lumps or unusual discharge from the nipples, should all be noted. Regular self-examinations and mammograms are essential for spotting breast cancer early. Breast cancer is equally likely to affect men as women. It's important to keep in mind that not all breast tumors progress to malignancy [2]. Nonmalignant benign tumors also result from aberrant cell growth, however these tumors never spread outside of the breast. Nonetheless, having regular checkups with a medical expert is essential in order to detect cancer at an early stage.

A further diagnostic might be performed if a result is deemed questionable. Nonetheless, mammography occasionally reveals a worrisome region that is not cancer, which can lead to undue tension and, in rare cases, treatments [3]. In addition, an MRI scan can determine the cancer's extent by injecting a dye into the patient. A cyst filled with fluid can be distinguished from a solid mass with the use of an ultrasound. Figure 1 illustrates how certain characteristics of an ultrasound breast picture can be used to determine if a breast tumor, is cancerous or non-cancerous. In summary, benign breast ultrasonography findings include a brighter overall appearance, greater regularity in breast tissue, and the presence of two or three smooth lobulations. Yet, a malignant ultrasound breast imaging would typically show a vertically expanding mass with irregular margins and unclear mass borders or an increased number of blood vessels.

Mammographic screening has been proven to minimize the incidence of breast cancer in several investigations conducted over the past few decades [4]. Even though a lot of work has been done to combat it, breast cancer remains the most often disease in females and the top reason of cancer-related mortality globally. Mammographic screening is by far the most used. As this screening tool relies heavily on mammograms, it's crucial that they be interpreted correctly [5]. MATLAB makes it simple to investigate a wide range of breast attributes utilizing image processing methods, such as mass location, texture, border, and form.

Natural image categorization is one area where deep learning techniques, and in particular convolutional neural networks (CNNs), has been recently utilized with tremendous success. CNNs' strong picture classification ability stems largely from their capacity to learn from large-scale, diversified, and well-annotated datasets like ImageNet, which contains over 1.2 million tagged natural photos, and generate fair, precise, and generalizable visual features.



(a) (b)

Figure 1: (a) Benign (b) Malignant

Several studies have shown that CNNs can be useful in the realm of medical image analysis. For instance, convolutional neural networks (CNNs) have been used to the issue of tumor detection and delineation in BUS pictures. Also, some recent research have investigated the viability of using CNNs to solve the problem of benign/malignant picture classification for BUS. While it is possible to train CNNs from scratch to accomplish good BUS imaging techniques, the existing BUS image datasets are relatively lesser than the Imagenet dataset. The research presented here is meant to add to the work already being done to broaden the working of CNNs to the efficient analysis of BUS pictures. We are deploying CNNs to detect as benign or cancerous. As a means to this end, we have explored the transfer learning strategy, which makes it possible to employ a CNN, in this case the ResNet architecture that has been pre-trained with data from the Imagenet dataset to accomplish precise categorization of BUS photos. A popular deep learning model for computer vision tasks is the Residual Network (ResNet). Hundreds or even thousands of convolutional layers can be used in this CNN design.

II. Related Study

There has been a rise in interest in using AI to spot cancerous breast cancers in ultrasound scans. The author of article [6] suggests using deep learning to solve this issue. A deep convolutional neural network was trained with several hundred photos of benign and malignant patients that made up the training data (CNN). In order to combat overfitting, three distinct training methods are suggested: a baseline method in which the Neural Network Framework is trained from initial stage; a transfer-learning method in which the pre-trained model is further trained with the computed tomography; and a fine-tuned learning method in which the deep learning attributes are adjusted. Test outcomes indicate that pre-training on US pictures yielded the best results for the fine-tuned model (0.97 accuracy, 0.98 AUC). In order to boost the effectiveness of deep learning in biomedical applications, it is recommended that pre-trained algorithms be created utilizing medical imaging data.

Breast tumor digital image signatures may help in developing individualized breast cancer diagnosis and treatment plans. Tumor detection approaches leveraging transfer learning from DCNNs are now under research as an alternative to more conventional human-engineered computer vision techniques. In our recent study [7], we compare the performance of CNN-based transfer learning to that of human-engineered feature-based radiomics and fusion classifiers developed by combining such features in order to classify breast cancers for various diagnostic tasks across many imaging techniques. Second, a new work is given reporting on a detailed contrasting of the categorizingeffectiveness of attributes obtained from human-engineered radiomic characteristics, CNN transfer learning, and fusion classifiers for MRI-imaged breast lesions. These works show how transfer learning can be used in CADI, and they emphasize how fusion classifiers can be used to increase classification efficiency synergistically.

The use of convolutional neural networks (CNNs) has proven effective in breast cancer detection using a computer-assisted ultrasound. Many other CNN-based approaches have been presented thus far. The majority of these methods, however, treat tumor location and classification as two distinct processes rather than one. In addition, the diagnostic information available in B-mode ultrasonography (BUS) pictures is inadequate. Author created a unique network, ResNet-GAP, in paper [8], which combines localization and classification into a single process. We use stiffness information from the elastography ultrasound (EUS) modality and apply collaborative learning to ResNet-training GAP's phase to improve its performance. To be more specific, a ResNet-GAP network with two independent channels—one for BUS and one for EUS—is created. Several class activity maps (CAMs) are created in each channel by applying a sequence of convolutional kernels of varying sizes to the input data. Network optimization also takes into account whether or not the CAMs in both channels are consistent across scales. In this study, 264 patients were used to demonstrate that the newly created ResNet-GAP outperforms certain state-of-the-art methods.

Cancer of the breast is the worst form of cancer in women and has rapidly risen to epidemic proportions worldwide. Ultrasonography, a type of non-invasive imaging, can detect and grade breast lesions, making it useful for both routine and mass screening. Nevertheless, BUS picture identification confronts higher hurdles than natural photos because of the morphological diversity of lesions in BUS images, together with relatively low contrast and varied textures. The research [9] presents a new network design that integrates a CNN with a vision transformer (ViT) to jointly learn both keypoints features and long-range feature relationships. Moreover, we incorporate cross attentiveness among the feature space map and the weak feature space in the network block to perform out the relationship among the deep feature and the weak feature data in order to conduct multi-scale feature fusion. We built a massive dataset and ran a battery of tests to ensure the model's accuracy. In comparison to other CNNs and vision transformers, our technique obtains an accuracy of 85.33 percent with the same number of parameters.

Inexpensive and radiation-free ultrasound (US) imaging has proven effective in detecting breast cancer at an early stage. Classifiers trained with deep learning are now being employed in the breast cancer classification process. While training a deep neural network, a sizable data collection is essential. Nevertheless, existing breast cancer US imaging collections are tiny, and the tumor sizes shown in the photos vary widely. This means that classifiers based on deep learning cannot give adequate generalization. To overcome these difficulties, we suggest combining multiple models. To deal with the problem of insufficient data, a transfer learning model built on top of VGG16 is employed. The features extracted by convolutional autoencoders can be used to accurately represent pictures with significant noise. To deal with the challenge of learning from ultrasound pictures that may contain tumors of varying sizes and forms, author [10] suggests a unique multi-scale deep learning approach. The three models undergo separate training phases before being combined using a differential evolution (DE) method to get anend categorization outcome. Two public U.S. datasets are utilized to test the innovative fused ensemble of deep learning-based classifiers that was presented. Multi-scale models are 89% accurate, whereas transfer learning models are 88% accurate and autoencoder models are 85% accurate. When the outcomes from these three methods are combined using the DE method, the resulting classification accuracy is 93%.

III. METHODOLOGY

Pre-trained ResNet CNN model is described here. In addition, we describe two methods for using the pre-trained ResNet method for BUS image classification.

The ResNet model is a type of CNNmethod that has already been trained; after part of the convolution layers, it uses max pooling and three fully connected layers. The ResNet model has already been pre-trained on the Imagenet dataset, which consists of lot of images organized into 1000 categories. Pretrained as it is to effectively represent a broad variety of real-time pictures, the ResNet technique cannot be easily used to classifying the breast cancer images into two classifications. Moreover, it is not possible to train the ResNet method, which has more than 50 million attributes, from start using the limited collections of BUS pictures now accessible. Because to this restriction, we have looked into a transfer learning strategy that would allow us to use a previously trained ResNet model to categories BUS photos. These two methods are discussed in detail below. Figure 2 shows the ResNet architecture.

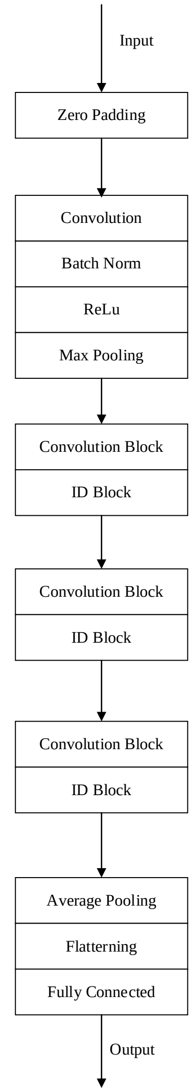


Figure 2. ResNet Architecture

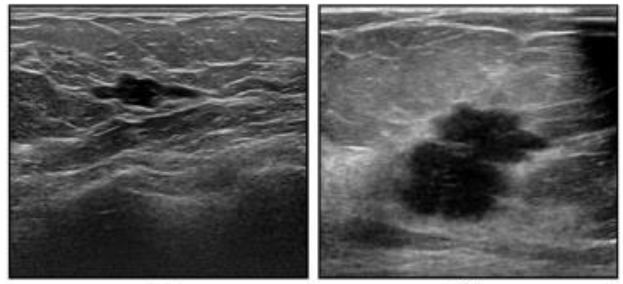
It's easy to see how components like convolution and pooling may be used in any of these designs. There are notable topological distinctions in contemporary deep learning systems, though. AlexNet, VGG, GoogLeNet, Dense CNN, and FractalNet are among the most widely-used DCNN architectures due of their superior performance on a variety of object classification evaluations. Some of these designs (like GoogLeNet and ResNet) were designed with massive data sets in mind, while others (like the VGG network) are more general purpose. The widely used ResNet50 network included 49 convolution layers and 1 fully linked layer. Both the network's weights and MACs add up to a whopping 25.5M and 3.9M, respectively. Several simple residual nodes make up the residual network. However various residual network architectures allow for distinct processes to take place in the residual block. In 2016, the integrated residual transformation was suggested as a new and enhanced residual network technique. There have been several new proposals for Residual Network-based variations of residual models.

Image preprocessing methods employ a number of filtering procedures to avoid the background noise and enhance the quality of the images. The segmentation process determines the image's edges and removes the surrounding pixels using a binary filter and edge detection. When the image has been separated, a standard deviation filter is used to increase contrast, and the Region of Interest (ROI) is retrieved by establishing a threshold.

It is predicted that the ResNet model's extraction of deep features would result in features that are both redundant and unrelated to the BUS image classification task. To find maximize subsets of deep attributes that optimize classification accuracy, features selection is applied independently to the four groups of deep features retrieved. To find the ideal combination of features that optimizes the classification accuracy for a given deep features group, one must undertake an exhaustive search, which is computationally and time-intensive. Instead, we've used a custom-built, three-stage algorithm based on the features selection approach to pick the feature-set that yields the highest classification accuracy for a given set of deep data. The minimal-redundancy-maximal-relevance (mRMR) criterion is used to rank the features in the initial stage of the features selection algorithm. To lessen the burden on the computer, just the top 100 features from the collection of deep features are chosen as potential candidates. The top m features are then sorted into m subgroups, and the classification accuracy of each subset is calculated in the second phase. For further optimization, we choose the smallest features subset that yields the maximum classification accuracy as the candidate features combination. A backward elimination method is used to refine the features combination chosen in the second phase into a minimal set that maximizes classification accuracy in the third and final stage.

IV. RESULTS AND IMPLEMENTATION

We have compiled a collection of 1300 high-resolution JPEG ultrasound pictures, each measuring 960 by 720 pixels. A training set of 1,000 images (of which 600 were considered Non-cancerous and 400 were considered Cancerous) and a test set of 300 images were created (165 benign and 135 malignant). At the initial stage of our process, we perform transformations on the dataset such as rotation, width shift, height shift, resampling, splitting, magnification, horizontal tilting, and refilling in order to make it bigger and more evenly distributed throughout classes. This is a crucial stage since it allows us to boost our sample size by 24 times, to a total of 21,600 photos, which in turn boosts our generalization performance. Seventy percent of the expanded dataset was used for training, while thirty percent was used for testing. It is possible to use this augmentation method to get around the overfitting that the drop-out layers assist to mitigate. Figure 3 shows the cancerous and non-cancerous images from dataset.



(a) (b)

Figure3. (a) Non- Cancerous and (b) Cancerous breast cancer images from dataset.

The classification performance of the Convolutional layers and fully connected layers are measured using a ten-fold cross-validation process. The BUS pictures in the dataset are initially aligned at random as part of the cross-validation method. Eighty percent of the BUS pictures in the database are utilized as a training set, while the remaining twenty percent are used as a testing set in the first phase of the operation. The four classes of deep characteristics are determined from the training set Containing pictures using a pre-trained ResNet framework. A SVM classifier is trained with the selection of features that is most representative of each of the four classes of deep features. The BUS pictures are used to assess the trained SVM model linked with the four classes of feature representation. In order to test all of the BUS photos in the database, we repeat the procedure of choosing 80% of the images for training and 20% for testing 10 times. The effectiveness of the transfer learning strategy has also been assessed using a ten-fold cross-validation process. However, the Breast cancerimages in the training dataset are employed to fine tune the ResNet network, and the photos in the testing set are utilized for testing, in each cycle of this approach. Table 1 and 2 shows the performance of various models. Figure 4 and 5 shows the accuracy and AUC performance of various models.

Model	Accuracy
VGG-Net	0.91
MG-Net	0.93
Baseline method	0.80
Proposed model	0.98

Table 1. Accuracy performance of various models.

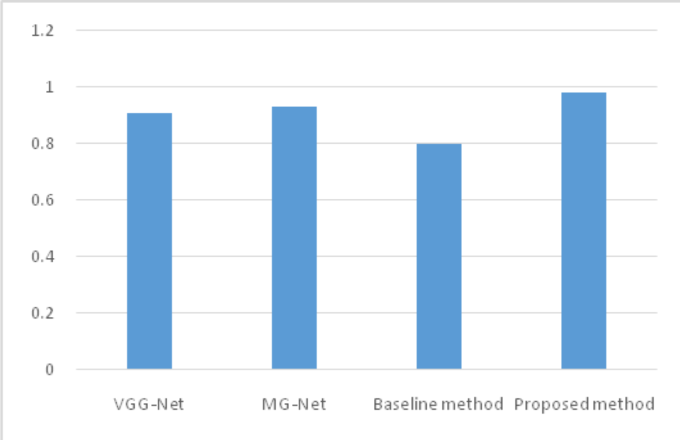


Figure 4. Accuracy performance.

Models	AUC
VGG-Net	0.96
MG-Net	0.98
Baseline method	0.98
Proposed model	0.99

Table 2. AUC performance of various models

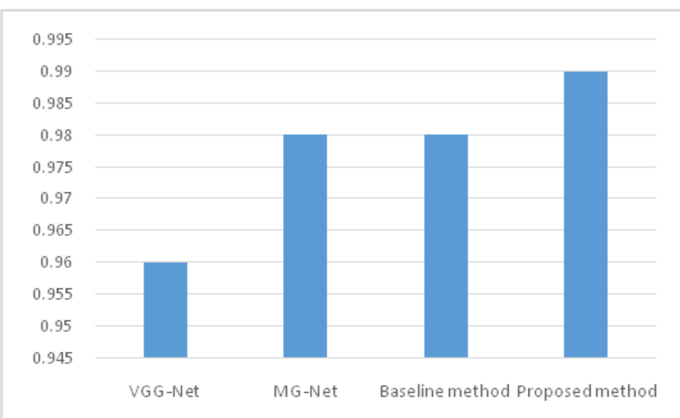


Figure 5. AUC performance

Figure 6 and Figure 7 displays the time series of accuracy gains for the baseline technique, in which the deep structure is built from beginning, while detecting benign and malignant breast tumors. Last but not least, results after further tweaking the deep learning settings are displayed in Figure 8 and Figure 9. In the long run, the US image-based fine-tuned learning method beats the transfer-learning and benchmark methods, as well as the MG and MR fine-tuned learning methods. Table displays the results of a trained MR-based breast cancer classification algorithm prior to fine-tuning, showing an accuracy of 0.93 and an AUC of 0.98. Comparatively, a detector trained from scratch in the United States achieves an effectiveness of 0.80 and an AUC of 0.82, therefore this efficiency is superior. Accuracy and AUC for a ResNet-based model developed in the United States are both 0.96 and 0.98, respectively. Its effectiveness is comparable to that of a freshly trained MR-based detector. Fine-tuning, however, improves accuracy, with the US-based model achieving 0.99 and the AUC reaching 0.99. That's better than the 0.93 efficiency and 0.98 AUC of the mammogram-based fine-tuned detector.

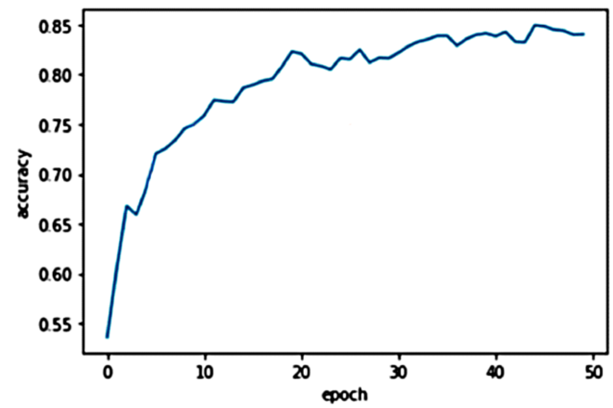


Figure 6. Training accuracy of baseline method.

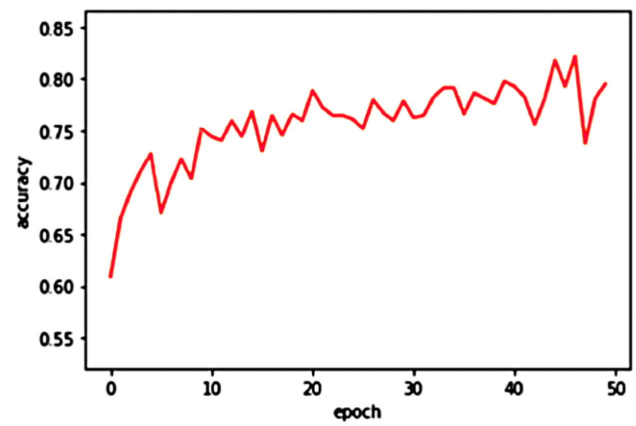


Figure 7. Testing accuracy of baseline method.

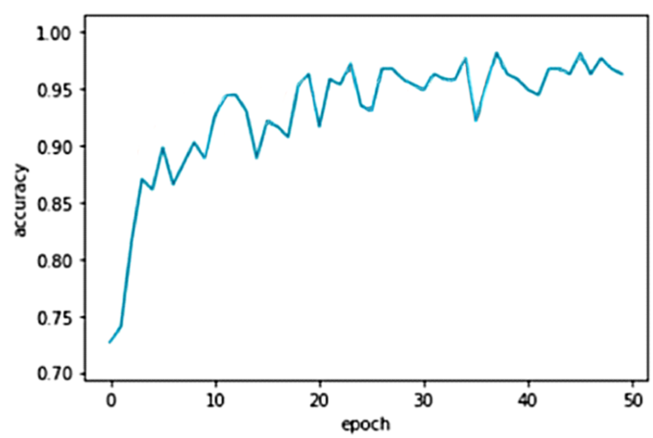


Figure 8. Training accuracy of proposed model

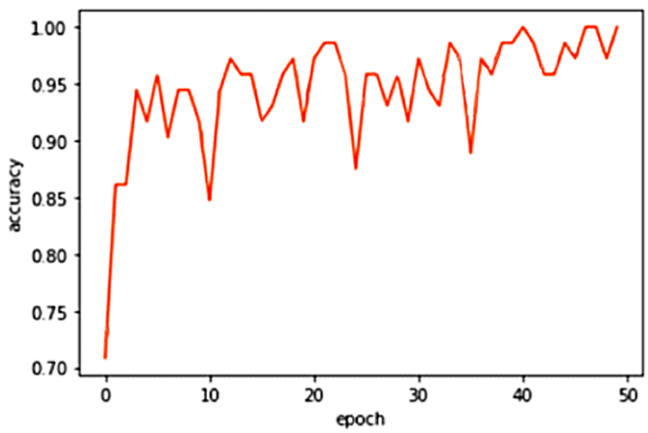


Figure 9. Testing accuracy of proposed model.

V. Conclusion and Future Scope

In this research, we explore the pre-trained ResNet CNN model's potential for effective BUS image categorization with the use of deep features extraction and transfer learning. Results showed that the deep features method of extraction, when coupled with a powerful features selection algorithm, may achieve better results than the transfer learning method alone. Although our database is modest, our results suggest that the fine-tuned model incorporating medical data for pre-training has increased accuracy rate. In the long run, this research will help develop deep learning algorithms that are both flexible and usable for the categorization of breast cancer. Clinical evaluation and treatment plans should benefit from these technologies. While much progress has been made with ultrasound-based approaches in the pursuit of high-performance breast cancer diagnosis, many questions remain unanswered. To be more specific, the lack of racial and cultural diversity in the training data can have a detrimental effect on detection and survival rates for underserved patient groups. Our long-term goal is to compile pre-training data from several imaging modalities to use in designing a deep learning architecture for use in our future research. When creating new medical image-based automated detection methods, this pre-trained model might be helpful.

REFERENCES

[1] B. Gheflati and H. Rivaz, "Vision Transformers for Classification of Breast Ultrasound Images," 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Glasgow, Scotland, United Kingdom, 2022, pp. 480-483, doi: 10.1109/EMBC48229.2022.9871809.

[2] K. Wei, B. Wang and J. Saniie, "Faster Region Convolutional Neural Networks Applied to Ultrasonic Images for Breast Lesion Detection and Classification," 2020 IEEE International Conference on Electro Information Technology (EIT), Chicago, IL, USA, 2020, pp. 171-174, doi: 10.1109/EIT48999.2020.9208264.

[3] T. -C. Chiang, Y. -S. Huang, R. -T. Chen, C. -S. Huang and R. -F. Chang, "Tumor Detection in Automated Breast Ultrasound Using 3-D CNN and Prioritized Candidate Aggregation," in IEEE Transactions on Medical Imaging, vol. 38, no. 1, pp. 240-249, Jan. 2019, doi: 10.1109/TMI.2018.2860257.

[4] S. M. Badawy, A. E. -N. A. Mohamed, A. A. Hefnawy, H. E. Zidan, M. T. GadAllah and G. M. El-Banby, "Classification of Breast Ultrasound Images Based on Convolutional Neural Networks - A Comparative Study," 2021 International Telecommunications Conference (ITC-Egypt), Alexandria, Egypt, 2021, pp. 1-8, doi: 10.1109/ITC-Egypt52936.2021.9513972.

[5] A. K. Aggarwal, Alpana and M. Pandey, "Deep Learning based Breast Cancer Classification on Thermogram," 2022 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), Greater Noida, India, 2022, pp. 769-774, doi: 10.1109/ICCCIS56430.2022.10037624.

[6] A. Hijab, M. A. Rushdi, M. M. Gomaa and A. Eldeib, "Breast Cancer Classification in Ultrasound Images using Transfer Learning," 2019 Fifth International Conference on Advances in Biomedical Engineering (ICABME), Tripoli, Lebanon, 2019, pp. 1-4, doi: 10.1109/ICABME47164.2019.8940291.

[7] H. M. Whitney, H. Li, Y. Ji, P. Liu and M. L. Giger, "Comparison of Breast MRI Tumor Classification Using Human-Engineered Radiomics, Transfer Learning From Deep Convolutional Neural Networks, and Fusion Methods," in Proceedings of the IEEE, vol. 108, no. 1, pp. 163-177, Jan. 2020, doi: 10.1109/JPROC.2019.2950187.

[8] W. Ding, J. Wang, W. Zhou, S. Zhou, C. Chang and J. Shi, "Joint Localization and Classification of Breast Cancer in B-Mode Ultrasound Imaging via Collaborative Learning With Elastography," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 9, pp. 4474-4485, Sept. 2022, doi: 10.1109/JBHI.2022.3186933.

[9] L. Li et al., "Cross-Attention Based Multi-Scale Feature Fusion Vision Transformer For Breast Ultrasound Image Classification," 2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Las Vegas, NV, USA, 2022, pp. 1616-1619, doi: 10.1109/BIBM55620.2022.9994966.

[10] E. A. Nehary and S. Rajan, "Classification of Ultrasound Breast Images Using Fused Ensemble of Deep Learning Classifiers," 2022 IEEE International Symposium on Medical Measurements and Applications (MeMeA), Messina, Italy, 2022, pp. 1-6, doi: 10.1109/MeMeA54994.2022.9856496.