Al-Nahrain Journal for Engineering Sciences **NJES** 23(2)57-62, 2023
http://doi.org/10.29194/NJES.26020057

Convolutional Neural Network Deep Learning Model for Improved Ultrasound Breast Tumor Classification

Hiba Diaa AL-rubaie[1, 2], Hadeel K. Aljobouri[1*], Zainab J. AL-Jobawi[3], Ilyas Çankaya[4]

Authors affiliations:

1) Biomedical Engineering Department, College of Engineering, Al-Nahrain University, Baghdad, Iraq.

2) Ministry of Health, Babil Governorate Health Directorate, Babylon, Iraq
heba.mohammed5.9.91@gmail.com
* hadeel_bme77@yahoo.com

3) Ministry of Health, Babil Governorate Health Directorate, Imam Al-Sadiq Teaching Hospital, Babylon, Iraq.

4) Electrical and Electronics Engineering Department, Graduate School of Natural Science, Ankara Yıldırım Beyazıt University, 06010 Ankara, Turkey
icankaya@ybu.edu.tr

Paper History:

Received: 16th Dec. 2022

Revised: 21st Mar. 2023

Accepted: 15th May 2023

Abstract

Breast cancer is one of the greatest frequent tumours among females in Iraq. Medical ultrasound imaging has become a common modality for breast tumour imaging because of its ease of use, low cost, and safety. In the present study, Convolutional Neural Network (CNN) feature extraction approaches were used to classify breast ultrasound imaging. The CNN model used is composed of four-layer for breast cancer ultrasound image analysis. Two types of free datasets were used. These data were divided into groups A and B. Group A has three classes, namely benign, malignant and normal, while group B has two classes, namely, benign and malignant. The proposed technique was assessed based on its accuracy, precision, F1 score and recall. The model's classification accuracy for data A was 96%, whereas for data B was 100%.

Keywords: Breast Cancer, CNN, Ultrasound, Feature Extraction, Medical Imaging

تحسين تصنيف اورام الثدي بالموجات فوق الصوتية من خلال تصميم موديل للشبكة العصبية التلافيفية ذات التعلم العميق

هبة ضياء الربيعي, أم.د. هديل قاسم وادي, د. زينب الجوباوي, الياس جانكايا

الخلاصة

يعتبر سرطان الثدي من أكثر أنواع السرطانات انتشارا بين النساء العراقيات. أصبح التصوير الطبي بالموجات فوق الصوتية طريقة شائعة لتصوير سرطان الثدي بسبب سهولة استخدامه وانخفاض تكلفته وامانه. في هذه الدراسة تم استخدام طرق استخراج ميزة (CNN) لتصنيف صور الثدي بالموجات فوق الصوتية. يتكون نموذج CNN المستخدم من أربع طبقات لتحليل صور الموجات فوق الصوتية لسرطان الثدي. تم استخدام نوعين من مجموعة البيانات المجانية. تم تقسيم البيانات الى المجموعة (أ) و(ب). تتكون المجموعة (أ)من ثلاث فئات، حميدة وخبيثة وطبيعية بينما تتكون المجموعة (ب) من فئتين وهما حميدة وخبيثة. تم تقييم الطريقة المقترحة بناء على دقتها. حقق النموذج دقة بنسبة ٩٦% للبيانات (أ) و١٠٠% للبيانات (ب).

1. Introduction:

One of the most prevalent malignancies in females is breast cancer, which begins in the breast and spreads to other body areas[1][2][3][4]. It is the most common cancer in females, accounting for approximately 12% of new cases overall and 25% of all malignancies worldwide[5]. According to the Iraqi Ministry of Health statistics on cancer types for the year 2020, breast cancer is the most common tumour type among women, accounting for 7,515 (37.9%) cancer cases [6]. Medical ultrasound imaging offers some benefits, including being non-invasive, affordable, efficient, safe and adaptable. It also plays a vital part in the detection and treatment of breast tumours. It has emerged as the method of choice for the detection of superficial organ disorders early on[7][8][9][10]. A subfield of computer science known as Artificial Intelligence (AI) can be utilized to develop software that can perform tasks that were previously only achievable with human intelligence[11][12][13]. AI has been increasingly used in ultrasonography and has been shown to be a potent instrument for delivering trustworthy detection with greater accuracy and efficiency while minimising the effort of physicians[14][15][16].

Breast cancer detection has been the subject of numerous related works, and numerous methods have been proposed. In 2016, Nascimento et al. evaluated the classification of breast cancer nodules by using Support Vector Machines (SVM) with many kernel

NJES is an **open access Journal** with **ISSN 2521-9154** and **eISSN 2521-9162**

groupings and Neural Networks (NN) with numerous halt standards. A scalar feature selection method with the association was employed to decrease the feature images after 22 morphological characteristics from the contour of 100 breast ultrasound dataset were used as input for classifiers. The finest results got for accuracy were 96.98% [17]. In 2019, Hijab et al. conducted a CNN model design for the classification of 1,300 breast ultrasound images. A data augmentation step was performed before the implementation of three approaches. A CNN model was trained from zero, a pretrained VGG-16 model, and a fine-tuned version of a pretrained VGG-16 model. Stochastic gradient descent was used to update the weights of the network of the fine-tuned VGG16 model. The calibrated model attained 97% precision and 98% AUC [18].

In 2020, Wang et al. proposed a CNN model design for the classification of 316 breast cancers (135 malignant and 181 benign). Lesion features were extracted using a modified Inception-v3 model (CNN). Considering that automated breast ultrasound dataset can be seen in together crosswise and coronal views, CNN is an effective method for extracting multiview features from both views. By using multi-view plans, CNN can categorize breast tumours well with a sensitivity of 0.886 and a specificity of 0.876 [19]. In 2022, Jabeen et al. used 780 ultrasound images to classify breast tumours. The proposed technique is comprised of several successive stages. The breast images were first augmented and then retrained with a DarkNet-53 transfer-learning model. Following that, the features from the pooling layer were extracted, and the finest feature was identified using two distinct optimization techniques, such as the Reformed Gray Wolf (RGW) optimization algorithm and the Reformed Differential Evaluation algorithm (DE). The selected features were lastly merged using a proposed approach, and then classified by machine learning algorithms. The proposed technique attained the uppermost level of accuracy of 99.1%[20]. In 2023, Alnedawe and Aljobouri, proposed the convolutional neural network (CNN) model for feature extraction and the support vector machine (SVM) model for classifying axial lung CT scans into two groups (COVID-19 and NonCOVID-19) A dataset of 960 CT scan slices acquired from Iraqi patients at the Ibn Al-Nafis teaching hospital was employed. According to the results, the proposed method produced a high-quality model for the collected dataset, with an overall accuracy of 98.95% and an overall recall of 97%[21].

In the present work, a CNN model was used to classify breast cancer ultrasound images by extracting features from a convolution layer. The CNN model contains four convolution layers, two Max_Pooling2D layers, and four batch normalization layers. The model was applied to two different types of data to verify its performance and obtain the best results. According to experiment results, the proposed approach outperforms state-of-the-art algorithms in terms of accuracy. The aim of this work is to serve as a guide for us to apply the model to real data collected from a medical Iraqi center.

2. Methodology

The goal of this research is to appliance a CNN feature-based model that would assist radiologists in overloaded medical centers in the efficient detection of malignant and benign breast dataset using convolutional neural network dense layers.

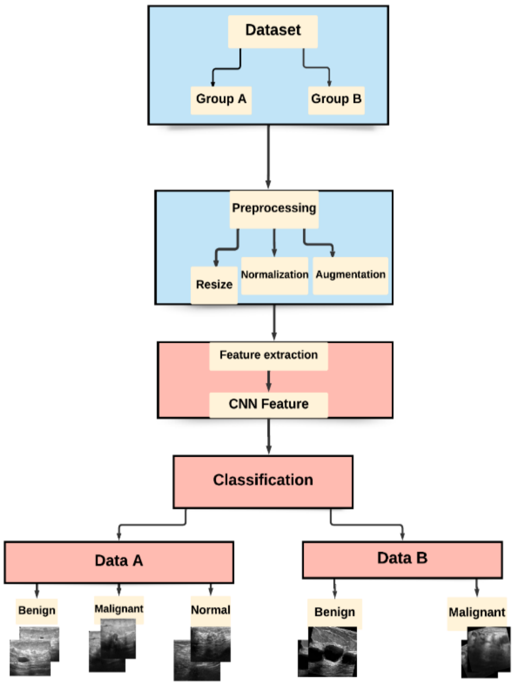
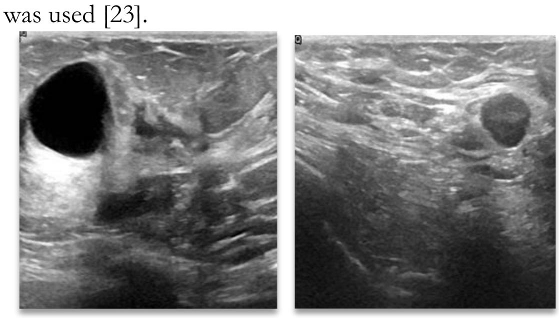


Figure (1): The proposed model.

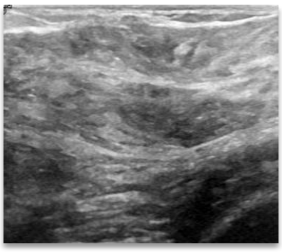
2.1 Dataset

The free breast ultrasound image data used in this work were divided into groups A and B. The dataset in group A includes 780 images with a mean image size of 500 pixels by 500 pixels. The dataset is in PNG format. The original images are shown with ground-truth images. They were categorised into 3 classes, namely, benign, malignant and normal. Data were collected at the baseline, and the total number of patients is 600, which were all womanly. The data include breast ultrasound dataset among females aged 25–75. The data were collected in 2018 [22].

The data in group B ultrasound images are related to benign and malignant breast cancers. The images have been augmented by rotation and sharpening to produce 9,016 images with an average image size of 256 pixels by 256 pixels. The images are in PNG and JPG format. In the present study, the PNG format was used [23].

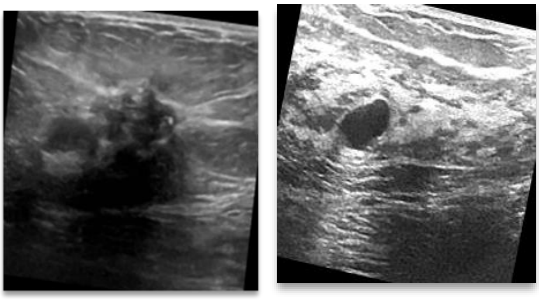


(1) (2)



(3)

Figure (2): Group A: 1) Benign, 2) Malignant and 3) Normal



(1) (2)

Figure (3): Group B: 1) Benign and 2) Malignant

2.2 Pre-processing

Number of pixels used to display an image. The ultrasound images of the breasts should be resized to 100 pixels ×100 pixels and 224 pixels ×224 pixels. Augmentation images were used in group (A) to obtain the best result by rotating left, rotating right, flipping vertically and flipping horizontally. Normalisation ensures that all variance values are between 0 and 1 by dividing the original data by 255. Normalisation may be quite useful for forecasting. Normalisation is extremely advantageous for neural network-based classification techniques.

3. Feature Extraction

Deep learning models were applied in medical imaging systems for extracting features routinely. In the present study, feature extractors were used in the proposed CNN model to categorize breast tumours. A convolutional neural network is a kind of deep learning that has many layer hierarchies. CNN translates the pixels in an image into features. Later, the features are employed for classification and detection. In the current work, the convolution layer was used to extract CNN features.

3.1 CNN Feature

Convolutional neural network was used to extract elevated features from the breast ultrasound images. The proposed CNN model layers are as follows:

1. Conv2D: filter size of layer the convolutional, 3×3; number of filters, 32; and padding = 'same'; and activation function, Relu.
2. Conv2D: filter size of layer the convolutional, 3×3, number of filters, 32; and activation function, Relu.
3. MaxPooling2D.
4. Conv2D. filter size of layer the convolutional, 3×3; number of filters, 64; and activation function, Relu.
5. Conv2D: filter size of layer the convolutional, 3×3; number of filters, 64; and activation function, Relu.
6. MaxPooling2D.
7. The flatten feature vector length for data A is 9,216, while that for data B is 50,176.

4. Classification

The fully connected layers were used to classify the images into three classes in group A and two classes in group B.

1. Dense unite (128), and Activation function is (Relu).
2. Dropout (0.2).
3. Dense activation function for multi-classification is ‘SoftMax’.

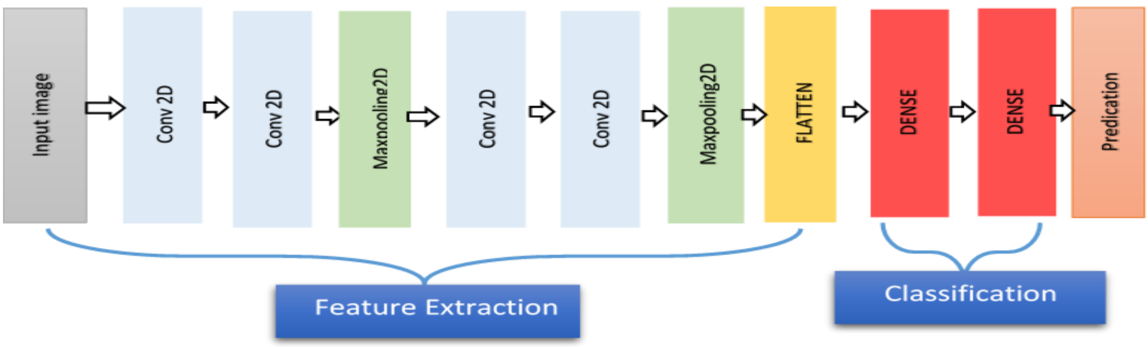


Figure (4): the structure of the CNN architecture

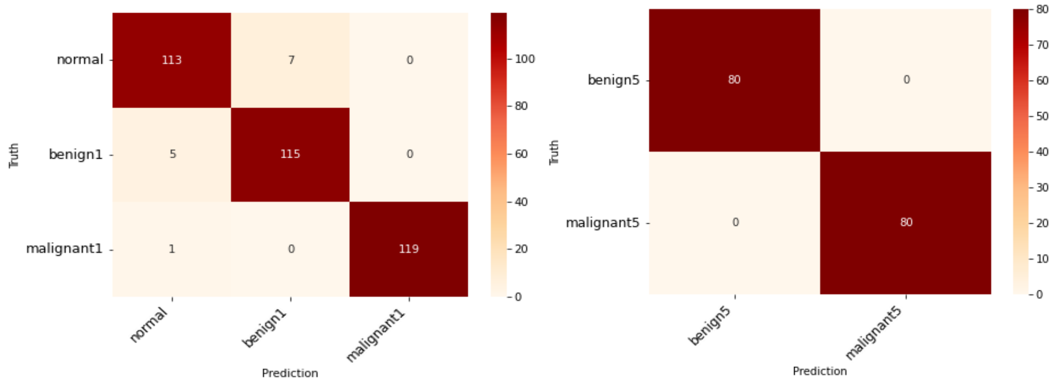
5. Results

This study proposed the use of CNN features to classify the images into group A as normal, benign and malignant and group B as benign and malignant. The confusion matrix was used to calculate the model accuracy, precision, F1 score and recall. Figure 5 displays confusion matrices obtained during the model construction in this research, where the x-axis represents predicted labels, and the y-axis shows real labels.

The following formulas have used false negative (FN), false positive (FP), true negative (TN), and true positive (TP) values:

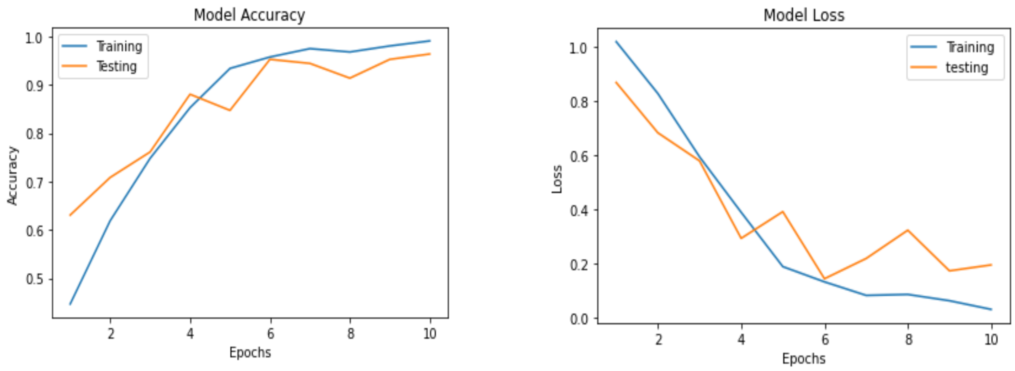
$$\boldsymbol{Accuracy} = ((\boldsymbol{TP} + \boldsymbol{TN}) / (\boldsymbol{TP} + \boldsymbol{FP} + \boldsymbol{FN} + \boldsymbol{TN})) * \mathbf{100\%} \quad \dots 1$$
$$\boldsymbol{Precision} = (\boldsymbol{TP} / (\boldsymbol{TP} + \boldsymbol{FP})) * \mathbf{100\%} \quad \dots 2$$
$$\boldsymbol{Recall} = (\boldsymbol{TP} / (\boldsymbol{TP} + \boldsymbol{FN})) * \mathbf{100\%} \quad \dots 3$$
$$\boldsymbol{F1\,Score} = (\mathbf{2} * (\boldsymbol{Recall} * \boldsymbol{Precision}) / (\boldsymbol{Recall} + \boldsymbol{Precision})) * \mathbf{100\%} \quad \dots 4$$

For the model, loss and accuracy curves were plotted. Figure 5 shows the model accuracy schemes, in which the x-axis signifies the number of epochs, and the y-axis signifies the accuracy over the identical epoch and the loss schemes with the x-axis representing the number of epochs and the y-axis representing the loss over the identical epoch. The schemes show the model's performance throughout ten epochs during the training and testing stages. The data was split into two parts with 80% for training and 20% for testing.

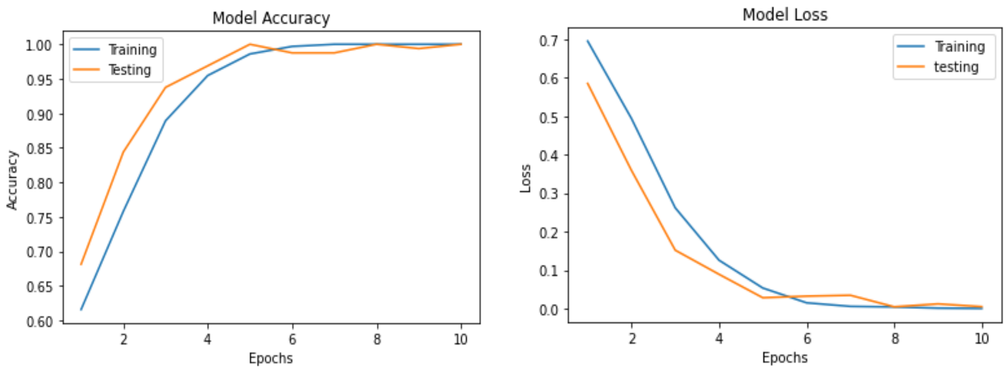


a) CNN Group A b) CNN group B

Figure (5): Confusion matrix of the true positive (TP), true negative (TN), false negative (FN), false positive (FP) values for CNN feature model (a) and (b)



a) CNN Group A



b) CNN Group B

Figure (6): Representative schemes of model accuracy and model loss schemes. The schemes signify the model performance for ten epochs during training and testing phases. (a), (b) the performance of the model depending on CNN features

The CNN-based model when using data (A) achieved an accuracy of (96%), while the accuracy is (100%) when data (B) was used. Tables 1 and 2 below detail the model's performance in terms of precision, recall, F1-score, and accuracy.

Table (1): Results of the CNN model of data A

Classes	Precision	Recall	F1-score	Accuracy
Normal	95%	94%	95%	96%
Benign	94%	96%	95%	
Malignant	100%	99%	100%	

Table (2). Results of the CNN model of data B

Classes	Precision	Recall	F1-score	Accuracy
Benign	100%	100%	100%	100%
Malignant	100%	100%	100%	

6. Discussion

In the present study article, a classification model was implemented to classify two group of breast ultrasound images into group A (437 benign, 210 malignant and 133 normal) and group B (400 benign and 400 malignant). Convolutional neural network was used to extract elevated features from the breast ultrasound images. Then, CNN features were employed to detect relevant texture features in the images for classification. In 2022, Ragab et al. used data A and employed the transfer learning (VGG-16, VGG-19 and Squeeze Net) method for feature extraction [24]. Jabeen et al. used data A to classify breast tumours by using the DarkNet-53 transfer learning model [18]. In the proposed work, the CNN model with data A achieved 96% accuracy 96%, while the best accuracy of 100% was obtained when using data (B) with the CNN model.

Method	Data	Author	Accuracy
CNN, VGG19 and ResNet152	ultrasound images of 1536 breast masses	2019, Tanaka et al.[25]	95%
CNN, VGGNet, ResNet, and DenseNet	1687 tumors in the dataset	2020, Moon et al.[26]	94%
CNN	Breast ultrasound images	Proposed model	96%,100%

7. Conclusion

The breast cancer ranking model was established using a convolutional neural network for feature extraction and classification. The CNN model used is composed of four-layer for breast cancer ultrasound image analysis. Two datasets were used, namely, datasets A and B. The data augmentation method was used to obtain the best performance. The proposed model was trained on breast ultrasound image datasets to classify cancerous, non-cancerous and normal images. The model provided the best classification accuracy for data B from data A. This model could be a viable solution for Iraq's challenging clinical environment. Considering the lack in terms of medical study and diagnosis possibilities, this model was created to assist the radiologist in the diagnosis process as well as to increase the number of patients receiving medical care by diminishing the time consumed on normal breast images.

8. References

[1] A. Jalalian, S. B. T. Mashohor, H. R. Mahmud, M. I. B. Saripan, A. R. B. Ramli, and B. Karasfi, "Computer-aided detection/diagnosis of breast cancer in mammography and ultrasound: A review," *Clinical Imaging*, vol. 37, no. 3, pp. 420–426, 2013, doi: 10.1016/j.clinimag.2012.09.024.

[2] F. Sadoughi, Z. Kazemy, F. Hamedan, L. Owji, M. Rahmanikatigari, and T. T. Azadboni, "Artificial intelligence methods for the diagnosis of breast cancer by image processing: A review," *Breast Cancer: Targets and Therapy*, vol. 10, pp. 219–230, 2018, doi: 10.2147/BCTT.S175311.

[3] T. Pang, J. H. D. Wong, W. L. Ng, and C. S. Chan, "Semi-supervised GAN-based Radiomics Model for Data Augmentation in Breast Ultrasound Mass Classification," *Computer Methods and Programs in Biomedicine*, vol. 203, p. 106018, 2021, doi: 10.1016/j.cmpb.2021.106018.

[4] K. Yu, S. Chen, and Y. Chen, "Tumor segmentation in breast ultrasound image by means of res path combined with dense connection neural network," *Diagnostics*, vol. 11, no. 9, 2021, doi: 10.3390/diagnostics11091565.

[5] J. Alawa, F. Alhalabi, and K. Khoshnood, "Breast Cancer Management Among Refugees and Forcibly Displaced Populations: a Call to Action," *Current Breast Cancer Reports 2019 11:3*, vol. 11, no. 3, pp. 129–135, Jun. 2019, doi: 10.1007/S12609-019-00314-6.

[6] World Health Organization. "Iraq Source: Globocan 2020." Iraq-international agency for research on cancer. https://gco.iarc.fr/today/data/factsheets/populations/368-iraq-fact-sheets.pdf. html (2020).

[7] Z. Zhuang, Z. Yang, A. N. J. Raj, C. Wei, P. Jin, and S. Zhuang, "Breast ultrasound tumor image classification using image decomposition and fusion based on adaptive multi-model spatial feature fusion," *Computer Methods and Programs in Biomedicine*, vol. 208, p. 106221, 2021, doi: 10.1016/j.cmpb.2021.106221.

[8] L. Bing and W. Wang, "Sparse Representation Based Multi-Instance Learning for Breast Ultrasound Image Classification," *Computational and Mathematical Methods in Medicine*, vol. 2017, 2017, doi: 10.1155/2017/7894705.

[9] J. Ding, H. D. Cheng, J. Huang, J. Liu, and Y. Zhang, "Breast ultrasound image classification based on multiple-instance learning," *Journal of Digital Imaging*, vol. 25, no. 5, pp. 620–627, 2012, doi: 10.1007/s10278-012-9499-x.

[10] G. Ayana, J. Park, J. W. Jeong, and S. W. Choe, "A Novel Multistage Transfer Learning for Ultrasound Breast Cancer Image Classification," *Diagnostics*, vol. 12, no. 1, pp. 1–14, 2022, doi: 10.3390/diagnostics12010135.

[11] N. H. Alkordy, H. K. Aljobouri, and Z. K. Wadi, "Feature Extraction and Selection of Kidney Ultrasound Images Using a Deep CNN and PCA," in *Software Engineering Application in Systems Design*, 2023, pp. 104–114.

[12] A. A. Almindelawy and M. H. Ali, "Improvement of Eye Tracking Based on Deep Learning Model for General Purpose Applications," *Al-Nahrain Journal for Engineering Sciences*, vol. 25, no. 1, pp. 13–19, 2022, doi: 10.29194/njes.25010012.

[13] A. A. Alsalihi, H. K. Aljobouri, and E. A. K. ALTameemi, "GLCM and CNN Deep Learning Model for Improved MRI Breast Tumors Detection," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 18, no. 12, pp. 123–137, Sep. 2022, doi: 10.3991/IJOE.V18I12.31897.

[14] G.-G. Wu *et al.*, "Artificial intelligence in breast ultrasound," *World Journal of Radiology*, vol. 11, no. 2, pp. 19–26, 2019, doi: 10.4329/wjr.v11.i2.19.

[15] Z. A. Magnuska *et al.*, "Influence of the Computer-Aided Decision Support System Design on Ultrasound-Based Breast Cancer Classification," *Cancers*, vol. 14, no. 2, 2022, doi: 10.3390/cancers14020277.

[16] Y. Jiang, A. V. Edwards, and G. M. Newstead, "Artificial intelligence applied to breast MRI for improved diagnosis," *Radiology*, vol. 298, no. 1, pp. 38–46, 2021, doi: 10.1148/RADIOL.2020200292.

[17] C. D. L. Nascimento, S. D. D. S. Silva, T. A. da Silva, W. C. D. A. Pereira, M. G. F. Costa, and C. F. F. Costa Filho, "Breast tumor classification in ultrasound images using support vector machines and neural networks," *Revista Brasileira de Engenharia Biomedica*, vol. 32, no. 3, pp. 283–292, 2016, doi: 10.1590/2446-4740.04915.

[18] A. Hijab, M. A. Rushdi, M. M. Gomaa, and A. Eldeib, "Breast Cancer Classification in Ultrasound Images using Transfer Learning," *International Conference on Advances in Biomedical Engineering, ICABME*, vol. 2019-Octob, pp. 1–4, 2019, doi: 10.1109/ICABME47164.2019.8940291.

[19] Y. Wang, E. J. Choi, Y. Choi, H. Zhang, G. Y. Jin, and S. B. Ko, "Breast Cancer Classification in Automated Breast Ultrasound Using Multiview Convolutional Neural Network with Transfer Learning," *Ultrasound in Medicine and Biology*, vol. 46, no. 5, pp. 1119–1132, 2020, doi: 10.1016/j.ultrasmedbio.2020.01.001.

[20] K. Jabeen *et al.*, "Breast Cancer Classification from Ultrasound Images Using Probability-Based Optimal Deep Learning Feature Fusion," *Sensors*, vol. 22, no. 3, 2022, doi: 10.3390/s22030807.

[21] S. M. Alnedawe and H. K. Aljobouri, "A New Model Design for Combating COVID -19 Pandemic Based on SVM and CNN Approaches," *Baghdad Science Journal*, 2023, doi: 10.21123/bsj.2023.7403.

[22] "Breast Ultrasound Images Dataset | Kaggle." https://www.kaggle.com/datasets/aryashah2k/breast-ultrasound-images-dataset (accessed Dec. 02, 2022).

[23] "Ultrasound Breast Images for Breast Cancer | Kaggle." https://www.kaggle.com/datasets/vuppalaadithyasairam/ultrasound-breast-images-for-breast-cancer (accessed Dec. 02, 2022).

[24] M. Ragab, A. Albukhari, J. Alyami, and R. Mansour, "Ensemble Deep-Learning-Enabled Clinical Decision Support Ultrasound Images," *Biology*, vol. 11, no. 439, 2022.

[25] H. Tanaka, S. W. Chiu, T. Watanabe, S. Kaoku, and T. Yamaguchi, "Computer-aided diagnosis system for breast ultrasound images using deep learning," *Physics in Medicine and Biology*, vol. 64, no. 23, 2019, doi: 10.1088/1361-6560/ab5093.

[26] W. K. Moon, Y. W. Lee, H. H. Ke, S. H. Lee, C. S. Huang, and R. F. Chang, "Computer-aided diagnosis of breast ultrasound images using ensemble learning from convolutional neural networks," *Computer Methods and Programs in Biomedicine*, vol. 190, 2020, doi: 10.1016/j.cmpb.2020.105361.