Revue d'Intelligence Artificielle
Vol. 37, No. 5, October, 2023, pp. 1255-1261
Journal homepage: http://iieta.org/journals/ria

Efficient Feature Selection Using CNN, VGG16 and PCA for Breast Cancer Ultrasound Detection

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https://doi.org/10.18280/ria.370518

Received: 26 May 2023
Revised: 2 August 2023
Accepted: 8 August 2023
Available online: 31 October 2023

Keywords:
breast cancer, Convolutional Neural Network, deep learning, feature selection, ultrasound, PCA, Transfer Learning (VGG16)

ABSTRACT

Breast cancer frequently leads to fatalities among women worldwide and is the most commonly diagnosed form of cancer in this population. Ultrasound imaging, due to its versatility and non-invasive nature, serves as an auxiliary technique in breast cancer detection. Despite significant improvements in diagnostic methods, the precise and efficient classification of ultrasound images remains a challenge. This study proposes a novel approach to address this issue, employing an integration of deep learning and feature selection techniques aimed at enhancing the accuracy of breast ultrasound image classification. In the presented study, two primary models were proposed for the classification of real-world breast ultrasound images into three distinct categories: normal, benign, and malignant. The first model design leveraged Convolutional Neural Networks (CNN) and VGG16 for feature extraction. Subsequently, the second model incorporated Principal Component Analysis (PCA) into the framework of CNN and VGG16 for feature selection, aiming to reduce dataset dimensionality while preserving the maximum data variance before classification. The dataset used in this study, comprising 1059 breast ultrasound images, was obtained from the Breast Cancer Early Detection Clinic at Imam Al-Sadiq General Teaching Hospital in Babylon, Iraq. Images were categorized into normal, benign, and malignant based upon their respective characteristics. Evaluation of the proposed method was conducted based on accuracy, precision, F1 score, and recall. The classification accuracy for the models was as follows: 93% for CNN, 94% for CNN-PCA, 97% for VGG16, and 96% for VGG16-PCA. The findings of this study have considerable implications for breast cancer detection methodologies. The integration of deep learning techniques and feature selection strategies in our research offers a potentially more efficient and accurate diagnostic framework. Furthermore, this study provides a foundation for future development in ultrasound-based breast cancer detection, and it proposes a blueprint for enhanced diagnostic precision.

1. INTRODUCTION

Breast cancer, a malignant growth originating from breast cells, is the predominant cancer type among females in Iraq, with cases also reported in males [1-4]. It can develop in any region of the breast, encompassing the ducts that transport milk to the nipple, the lobules responsible for milk production, and the connective tissue enveloping the breast [5].

Breast ultrasound imaging, a diagnostic tool employing high-frequency sound waves to generate images of breast tissue, has become a crucial component in the detection of breast cancer. This imaging technique is often used in conjunction with mammography for women who present breast symptoms or are identified as having a higher risk of developing the disease.

Owing to its non-invasive nature and the absence of radioactivity, ultrasound imaging is considered a safe diagnostic tool. It has consequently been widely adopted for the identification and monitoring of a plethora of medical conditions [1, 6-8]. The non-radioactive attribute of ultrasound imaging makes it particularly suitable for frequent use, rendering it a vital instrument in medical diagnostics.

Deep learning is a subsection of machine learning that includes the use of deep neural networks, which are modeled after the construction of the human brain, to perform errands such as image recognition, natural language processing, and speech recognition [9-12]. Deep learning algorithms are able to learn from huge amounts of data and improve their performance over time, making them highly effective in a wide range of applications. Deep learning algorithms, inspired by the complex architecture of the human brain, can automatically learn and extract hierarchical features from these images, allowing them to discern subtle differences between normal, benign, and malignant cases. In the context of breast cancer, deep learning models can learn to identify irregular shapes, textures, and structural changes indicative of tumors. This ability to learn from vast amounts of data and adapt over time makes deep learning particularly suited for improving the accuracy and reliability of breast cancer detection compared to traditional methods [13-15]. Feature selection is an important step in the development of machine learning algorithms, including deep learning [16]. Feature selection involves identifying the most relevant features, or variables, in a dataset, and using only those features to train the algorithm. This can help to decrease the dimensionality of the data, making it easier for the algorithm to learn and improve its performance [17-19]. The research gap addressed in this study pertains to the limitations and gaps in current breast cancer detection techniques using ultrasound imaging. While various methods have been proposed, there is still a need for more accurate and efficient approaches to classifying breast ultrasound images. Many existing studies have explored the application of deep learning algorithms for this purpose, but few have extensively investigated the combined impact of deep learning models and principal component analysis (PCA) in enhancing the accuracy and interpretability of breast cancer detection. This study seeks to bridge this gap by proposing and evaluating different deep learning-based models, both with and without PCA, using a real dataset. By doing so, the study aims to contribute to a more precise and reliable means of classifying breast ultrasound images, ultimately improving the early detection of breast cancer and guiding more informed clinical decisions. The significance of this research lies in its potential to revolutionize the field of breast cancer detection through the fusion of advanced deep learning techniques and PCA. By utilizing these approaches, the study aims to achieve higher accuracy rates and more robust classifications of breast ultrasound images, ultimately enhancing early diagnosis and reducing false positives. This research is of paramount importance as it aligns with the broader goal of improving healthcare outcomes by providing clinicians with more reliable tools for detecting and diagnosing breast cancer at an early stage. Successful implementation of the proposed models could lead to more timely interventions, increased patient survival rates, and reduced healthcare costs associated with misdiagnoses. In this way, the study has the potential to significantly contribute to the ongoing efforts to combat breast cancer and improve the lives of affected individuals worldwide and particularly in Iraq because the data used are local.

Breast cancer detection has been the subject of numerous related works, and numerous methods have been proposed. In 2019, Tanaka et al. collected ultrasound images of 1536 breast masses, with 897 of them classified as malignant and 639 as benign. The proposed method was CNN to classify ultrasound breast lesion data. An ensemble network was built by integrating two CNN models (VGG19 and ResNet152) that were fine-tuned with augmentation on a balanced training dataset. CNN was able to classify a specific mass based on all available views due to the mass-level classification technique. In an independent test set of 154 masses (77 malignant and 77 benign), the network outperformed the two CNN models with a sensitivity of 90.9%, a specificity of 87.0%, and an area under the curve (AUC) of 0.951 [20]. In 2019, Adel et al. collected elastography and ultrasound data to screen for breast cancer, then applied image processing techniques to extract features from the resulting images. used PCA to reduce the dimensions of a data set. This study used a support vector machine (SVM) learning algorithm to classify the combined elastic images and ultrasound images. K-fold validation was performed to confirm the generalizability of the algorithm. evaluated the accuracy and confusion matrix of the logistic loss algorithm and found that a maximum classification accuracy of 94.12% was achieved using an SVM kernel with a radial basis function (RBF) [21].

In 2022, Ragab et al. [22] identified 780 breast ultrasound images as having a tumor on them. Wiener filtering and contrast enhancement are the first two phases of pre-processing applied to ultrasound images. For the purpose of segmenting images, the Chaotic Krill Herd Algorithm (CKHA) and Kapur's entropy (KE) were used. For feature extraction, the VGG-16, VGG-19, and SqueezeNet ensemble of three deep learning models is also used. Lastly, Cat Swarm Optimization (CSO) with the Multilayer Perceptron (MLP) model is applied to categorize the images based on whether breast tumor exists or not. The optimal accuracy and area under the ROC curve were 98.08%. In 2022, Pramanik et al. the study suggests a technique based on deep learning to classify breast tumors in ultrasound images. This method incorporates Transfer Learning (TL) and a statistical approach involving three phases. Firstly, features are extracted from the ultrasound cancer images with a fine-tuned TL model. Following, these features are ranked based on their correlation coefficient values obtained from the Spearman Rank Correlation Coefficient method in the second stage. In the final phase, the most important and relevant top-ranked features are selected, and machine learning-based classifiers are employed to classify unseen breast ultrasound tumors. The proposed method achieves a classification accuracy of 98.72% [23].

In the present work, there are four models proposed (CNN, VGG16, CNN-PCA, and VGG16-PCA) for the classification of breast ultrasound images with and without PCA. A real dataset from Imam Al-Sadiq General Teaching Hospital (Breast Cancer Early Detection Clinic) in Babylon, Iraq was used to classify the ultrasound images of the Breast. In the first two models using CNN and VGG16 to extract features from the images and then categorize them. The second two models identified important features using PCA after extracting features with CNN and VGG16. The identified features were then used to classify the images as "normal," "benign," and "malignant".

2. MATERIAL AND METHODS

The presented work shown in Figure 1 in this section, involves several stages, beginning with ultrasound image acquisition and then moving on to image preprocessing, feature extraction, feature selection, and disorder classification.

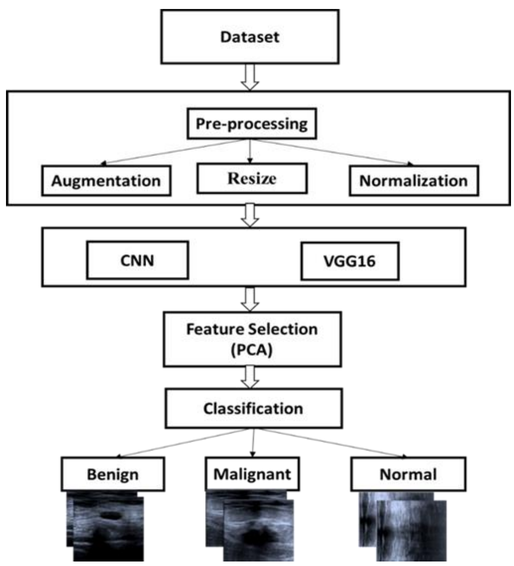
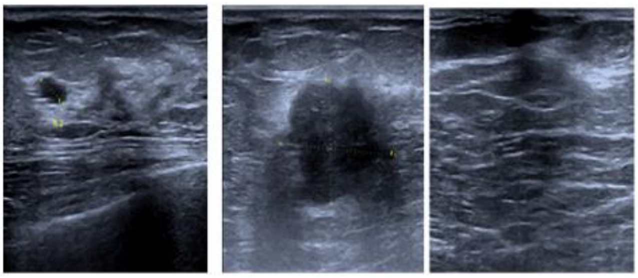


Figure 1. Represents the proposed models

2.1 Dataset

Real data of breast ultrasound images were collected from the Breast Cancer Early Detection Clinic in Imam Al-Sadiq General Teaching Hospital in Babylon, Iraq, using a device called the GE Voluson S8. The real dataset is composed of 1059 breast ultrasound images from 235 patients (723 benign, 132 malignant, and 204 normal) were selected at random from the general community to participate in this study after giving their informed consent in accordance with the ethical approval obtained from Al-Nahrain University's College of Engineering (02/2020) as shown in Figure 2. The real data set is unbalanced in the number of images; therefore, use the augmentation process to obtain 800 images for each class. Three radiologists examined images of each healthy and sick breast in women and made a diagnosis. The images are in DICOM format with a size of 806×838.



a) Benign b) Malignant c) Normal

Figure 2. Breast ultrasound images

2.2 Pre-processing

The images were pre-processed as preparation for the feature extraction step because the feature extraction step is greatly affected by the pre-processing operations. Pre-processing can contribute to model performance when suitable pre-processing steps are implemented. The steps of pre-processing are:

• Breast tumours ultrasound images converted from DICOM to BITMAP format. Then the files were arranged and randomly separated into 70% for training 30% for testing. DICOM is a standard format for storing and transmitting medical images. However, for the purpose of this task, the images needed to be converted to the BITMAP format, which is a commonly used image format for training machine learning models.

The conversion process involves extracting the ultrasound images from the DICOM files and saving them in the BITMAP format. This can be achieved using appropriate software libraries or tools that support DICOM image processing and conversion.

• Region of Interest (ROI) refers to a specific area or region within an image that is considered important or relevant for a particular analysis or task. In the context of ultrasound images, ROI is the process of selecting and cropping out unwanted areas or unnecessary information from the images, such as patient names, scan details, or irrelevant background.

The purpose of using ROI in this work was to eliminate the extraneous information from breast ultrasound images. By removing non-diagnostic regions or irrelevant elements, the focus was narrowed down to the critical parts of the image that contain the necessary features for classification. The elimination of unnecessary information through ROI can reduce the computational load and processing time required for analysing the images.

• Augmentation images were used with real data to obtain the best result by rotating left, rotating right, flipping vertically, and flipping horizontally.

• Image resizing is a technique used in image processing to rise and reduction the size of an image in pixel format. Resize the breast ultrasound images to 224×224. Adjust the image size without altering the amount of information in the image.

• Normalization divisions the original data by 255 to confirm that all change values fall between 0 and 1. Normalization can be quite useful for forecasting. Normalization is extremely advantageous for neural network-based classification techniques.

2.3 Feature extraction

Feature extraction is a key technique in deep learning that involves automatically learning a set of representative features from raw data. In deep learning, this is typically achieved through the use of neural networks, which are designed to automatically learn features that are useful for a given task.

2.3.1 CNN model

Convolutional Neural Networks (CNNs) are a class of neural networks that are particularly suited for image classification tasks [24]. They contain numerous layers, including convolutional layers, pooling layers, and dense layers. CNNs work by learning a set of filters that are applied to the input image, with the goal of identifying important features in the image [25-28].

The CNN used in this research consists of four convolutional layers followed by dual MaxPooling2D layers and four batch normalization layers. Each convolutional layer is designed to learn specific features from the input image. The activation functions used in the convolutional layers are typically ReLU (Rectified Linear Unit), which helps introduce non-linearity to the model. The sizes of the convolutional kernels and the number of filters in each layer will also be outlined. This information will be crucial for understanding the architecture's depth and complexity. The dense layers are totally detached, as exposed in Figure 3.

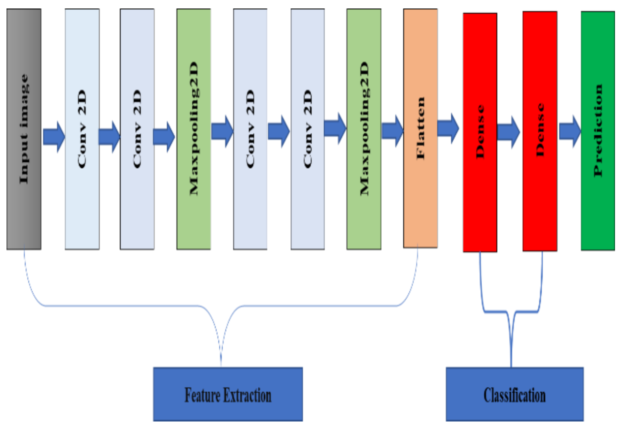


Figure 3. The proposed model of the CNN

2.4 VGG16 model

VGG16 is a specific CNN architecture that was advance by the Visual Geometry Group at the University of Oxford. It consists of 16 layers, with 13 convolutional layers and 3 fully connected layers [29]. The model's architecture of stacking multiple convolutional layers with small 3x3 filters followed by MaxPooling layers contributes to its ability to capture intricate features at different scales. This makes VGG16 a reliable benchmark for image classification tasks, and the decision to use it can be supported by referencing its success in various competitions and research endeavors. VGG16 is known for its simplicity and high accuracy in image classification tasks. Feature extraction in VGG16, the convolutional layers learn a set of filters that are used to extract increasingly abstract features from the input image. The output of the final convolutional layer in VGG16 is a tensor that contains the learned features. This tensor can be flattened and fed into the fully connected layers to produce a final output. Following that, as seen in Figure 4, features are taken from ImageNet weights and fed into classifier for prediction.

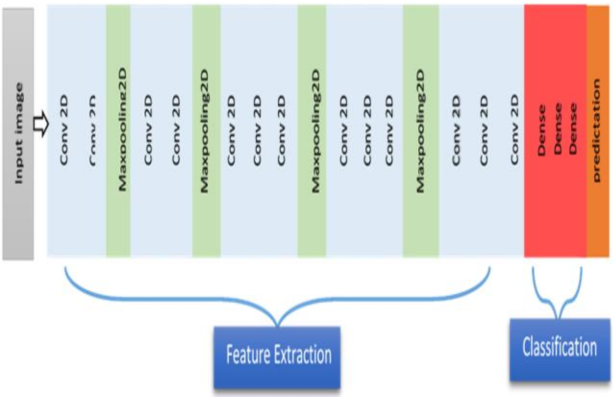


Figure 4. The proposed model of the VGG16

3. FEATURE SELECTION (PCA)

Feature selection is the method of identifying and selecting a subsection of relevant features from a greater set of features that are used to build a predictive model or analyze a dataset [30]. The aim of feature selection is to improve the performance of a model by dipping the number of features used while retaining the most important and informative ones. PCA is a statistical technique that transforms a dataset into a new coordinate system in order to reduce its dimensionality while preserving the maximum variance among the original features [31, 32]. In the context of our study, PCA is used as a feature selection method to identify and retain the most relevant features from the original dataset of breast ultrasound images. Regarding our choice of using PCA over other feature selection methods, we opted for PCA due to its specific advantages that align well with our research objectives. PCA is particularly effective when dealing with high-dimensional datasets, which is common in medical imaging tasks like ours. It helps in removing multicollinearity and noise, leading to a more efficient model with reduced overfitting risks. In our analysis, we found that certain principal components exhibited significantly higher eigenvalues, indicating that they capture the most variance in the dataset. These components corresponded to patterns and structures in the ultrasound images that are crucial for distinguishing between different classes. This research used the PCA with CNN and VGG16 models for feature selection after feature extraction and to classify the breast ultrasound images as shown in Figures 5 and 6.

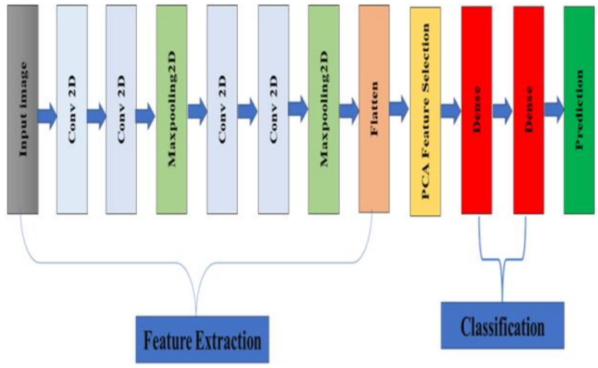


Figure 5. The structure of the CNN-PCA model architecture

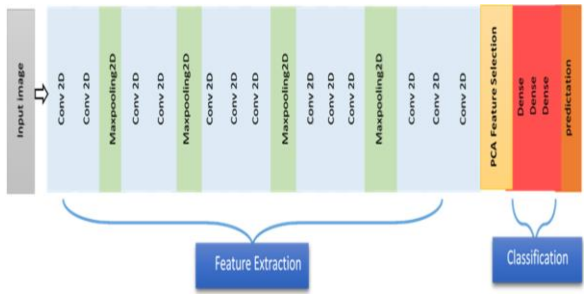


Figure 6. The structure of the VGG16-PCA model architecture

4. RESULTS

The suggested method's applicability is measured using accuracy, precision, specificity, sensitivity, and the F1-score.

A confusion matrix is a table that is often used to assess the performance of a classification model. It compares the predicted labels of the model with the real labels and displays the number of true positives, true negatives, false positives, and false negatives. Figure 7 displays confusion matrices obtained during the (CNN, CNN-PCA, VGG16, and VGG16-PCA) model's construction in this research, where the x-axis represents predicted labels, and the y-axis shows real labels.

The equations for calculating accuracy, precision, recall, and F1 score using the parameters from the confusion matrix:

Accuracy: The proportion of properly classified instances out of the total number of instances.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

Precision: The proportion of true positive predictions out of all positive predictions.

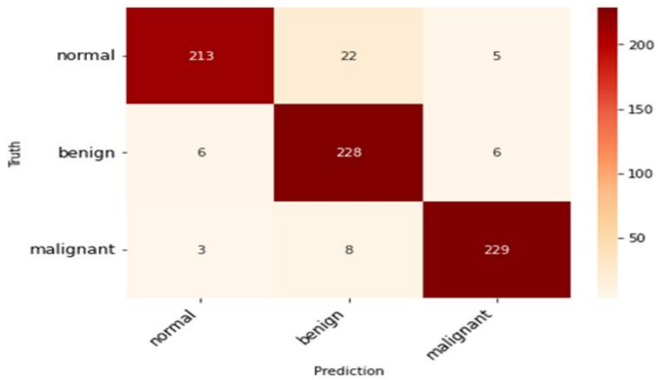
$$Precision = TP / (TP + FP)$$

Recall (also known as sensitivity or true positive rate): The proportion of true positive predictions out of all actual positive instances.

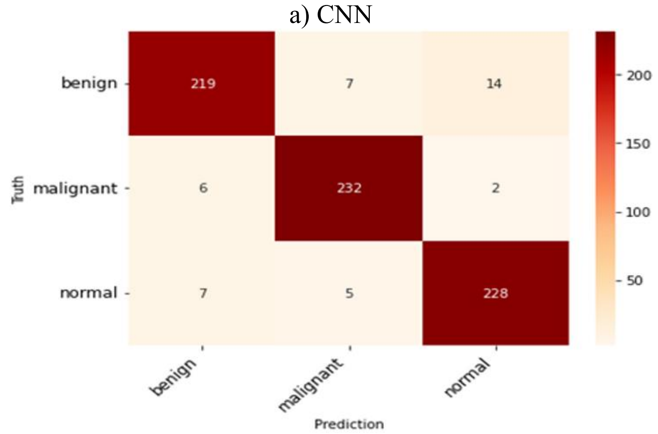
$$Recall = TP / (TP + FN)$$

F1 score: A harmonic mean of precision and recall that balances the trade-off between them.

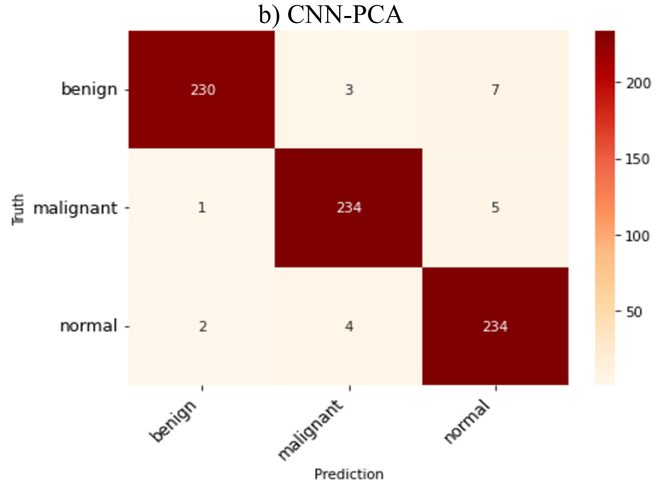
$$F1\,score = 2 * Precision * Recall / (Precision + Recall)$$



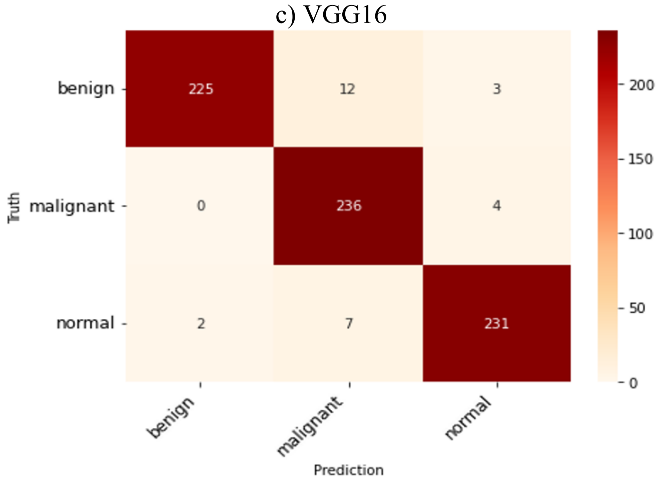
a) CNN



b) CNN-PCA



c) VGG16



d) VGG16-PCA

Figure 7. Confusion matrix of the true positive (TP), true negative (TN), false negative (FN), and false positive (FP) values for CNN feature model (a), CNN-PCA model (b), VGG16 model (C), and VGG16-PCA model (d)

Tables 1, 2, 3 and 4 detail the model's performance in terms of precision, recall, F1-score, and accuracy.

Table 1. Results of the CNN model

Classes	Precision	Recall	F1-Score	Accuracy
Benign	96%	89%	92%	
Malignant	88%	95%	92%	93%
Normal	95%	95%	95%	

Table 2. Results of the CNN-PCA model

Classes	Precision	Recall	F1-Score	Accuracy
Benign	94%	93%	93%	
Malignant	94%	95%	94%	94%
Normal	95%	95%	95%	

Table 3. Results of the VGG16 model

Classes	Precision	Recall	F1-Score	Accuracy
Benign	99%	964%	97%	
Malignant	97%	97%	97%	97%
Normal	95%	97%	96%	

Table 4. Results of the VGG16-PCA model

Classes	Precision	Recall	F1-Score	Accuracy
Benign	99%	93%	96%	
Malignant	94%	98%	96%	96%
Normal	96%	97%	96%	

In this study, four models were employed, including CNN, CNN-PCA, VGG16, and VGG16-PCA. These models attained notable levels of accuracy, with percentages of 93%, 94%, 97%, and 96%, respectively.

5. DISCUSSION

The study presented aims to classify breast ultrasound images as benign, malignant, or normal using CNN and VGG16 feature extraction methods. Feature selection using Principal Components Analysis is also applied to reduce the dimensions of the dataset while retaining as much variance as possible in the data. The study is evaluated based on its accuracy, precision, F1 score, and recall. The real dataset used comprises 1059 breast ultrasound images, augmented for better performance and accuracy. The proposed technique's classification accuracy ranges from 93% to 97%. Table 5 shows previous work in comparison to the proposed method.

Table 5. Previous work in comparison to the proposed method

Method	Data	Author	Accuracy
CNN, VGG19 and ResNet152	ultrasound images of 1536 breast masses	In 2019, Tanaka et al. [20]	95%
SVM, PCA	elastography and ultrasound data	In 2019, Adel et al. [21]	94.12%
ResNet101, NB, PCA, and SVM	Breast ultrasound images	In 2022, Liu et al. [1]	89%
CNN, VGG16, CNN-PCA and VGG16-PCA	Breast ultrasound images	Proposed model	93%, 97%,94% and 96%

6. CONCLUSIONS

In conclusion, this study proposed a breast cancer automatic detection tool using real ultrasound images and deep learning algorithms. Specifically, Convolutional Neural Network and VGG16 feature extraction methods were used to classify ultrasound images as benign, malignant, or normal. Furthermore, Principal Components Analysis was used as a feature selection technique to decrease the dimensions of the dataset while retentive the relevant features. The proposed techniques were evaluated based on their accuracy, precision, F1 score, and recall. The results demonstrate high classification accuracy for both the CNN and VGG16 models, with and without PCA feature selection. The study contributes to the growing body of research on breast cancer detection and validates the potential of deep learning and feature selection methods in medical imaging. The findings of this study could have significant implications for improving the accuracy and effectiveness of breast cancer diagnosis and treatment. These models could be a viable solution for Iraq's challenging clinical environment. Considering the lack of medical study and identification possibilities, this model was created to assist the radiologist in the analysis procedure and to rise the number of patients receiving medical care by diminishing the time expended on breast images.

ACKNOWLEDGMENT

The author would like to acknowledge all the participants who volunteered in this study as without their cooperation, this research work would not have been possible to conduct.

REFERENCES

[1] Liu, W., Guo, M., Liu, P., Du, Y. (2022). Mfdcmodel: A novel classification model for classification of benign and malignant breast tumors in ultrasound images. Electronics, 11(16): 2583. https://doi.org/10.3390/ELECTRONICS11162583

[2] Jabeen, K., Khan, M.A., Alhaisoni, M., Tariq, U., Zhang, Y.D., Hamza, A., Damaševičius, R. (2022). Breast cancer classification from ultrasound images using probability-based optimal deep learning feature fusion. Sensors, 22(3): 807. https://doi.org/10.3390/s22030807

[3] Hasan, A.M., Al-Waely, N.K., Ajobouri, H.K., Ibrahim, R.W., Jalab, H.A., Meziane, F. (2023). A classification model of breast masses in DCE-MRI using kinetic curves features with quantum-Raina's polynomial based fusion. Biomedical Signal Processing and Control, 84: 105002. https://doi.org/10.1016/J.BSPC.2023.105002

[4] Alsalihi, A.A., Aljobouri, H.K., ALTameemi, E.A.K. (2022). GLCM and CNN deep learning model for improved MRI breast tumors detection. International Journal of Online & Biomedical Engineering, 18(12): 123-137. https://doi.org/10.3991/IJOE.V18I12.31897

[5] Sharma, G.N., Dave, R., Sanadya, J., Sharma, P., Sharma, K. (2010). Various types and management of breast cancer: An overview. Journal of Advanced Pharmaceutical Technology & Research, 1(2): 109.

[6] Ding, J., Cheng, H.D., Huang, J., Liu, J., Zhang, Y. (2012). Breast ultrasound image classification based on multiple-instance learning. Journal of Digital Imaging, 25: 620-627. https://doi.org/10.1007/s10278-012-9499-x

[7] Nothacker, M., Duda, V., Hahn, M., Warm, M., Degenhardt, F., Madjar, H., Albert, U.S. (2009). Early detection of breast cancer: benefits and risks of supplemental breast ultrasound in asymptomatic women with mammographically dense breast tissue. A systematic review. BMC Cancer, 9: 1-9. https://doi.org/10.1186/1471-2407-9-335

[8] Alzubaidi, L., Zhang, J., Humaidi, A.J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data, 8: 1-74. https://doi.org/10.1186/s40537-021-00444-8

[9] Yamashita, R., Nishio, M., Do, R.K.G., Togashi, K. (2018). Convolutional Neural Networks: An overview and application in radiology. Insights Into Imaging, 9: 611-629. https://doi.org/10.1007/S13244-018-0639-9

[10] Al-Dhabyani, W., Gomaa, M., Khaled, H., Aly, F. (2019). Deep learning approaches for data augmentation and classification of breast masses using ultrasound images. International Journal of Advanced Computer Science and Applications, 10(5): 1-11.

[11] Sun, Q., Lin, X., Zhao, Y., Li, L., Yan, K., Liang, D., Li, Z.C. (2020). Deep learning vs. radiomics for predicting axillary lymph node metastasis of breast cancer using ultrasound images: Don't forget the peritumoral region. Frontiers in Oncology, 10: 53. https://doi.org/10.3389/fonc.2020.00053

[12] Almindelawy, A.A., Ali, M.H. (2022). Improvement of eye tracking based on deep learning model for general purpose applications. Al-Nahrain Journal for Engineering Sciences, 25(1): 12-19. https://doi.org/10.29194/njes.25010012

[13] Daoud, M.I., Abdel-Rahman, S., Bdair, T.M., Al-Najar, M.S., Al-Hawari, F.H., Alazrai, R. (2020). Breast tumor classification in ultrasound images using combined deep and handcrafted features. Sensors, 20(23): 6838. https://doi.org/10.3390/s20236838

[14] LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. Nature, 521(7553): 436-444. https://doi.org/10.1038/nature14539

[15] Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., Chen, T. (2018). Recent advances in Convolutional Neural Networks. Pattern Recognition, 77: 354-377. https://doi.org/10.1016/J.PATCOG.2017.10.013

[16] Nayeem, M.A.R., Joadder, M.A.M., Shetu, S.A., Jamil, F.R., Al Helal, A. (2014). Feature selection for breast cancer detection from ultrasound images. In 2014 International Conference on Informatics, Electronics & Vision (ICIEV), Dhaka, Bangladesh, pp. 1-6. https://doi.org/10.1109/ICIEV.2014.6850813

[17] Ng, S.C. (2017). Principal component analysis to reduce dimension on digital image. Procedia Computer Science, 111: 113-119. https://doi.org/10.1016/j.procs.2017.06.017

[18] Alkordy, N.H., Aljobouri, H.K., Wadi, Z.K. (2022). Feature extraction and selection of kidney ultrasound images using a deep CNN and PCA. In Proceedings of the Computational Methods in Systems and Software, Cham: Springer International Publishing, pp. 104-114. https://doi.org/10.1007/978-3-031-21435-6_10

[19] Muñoz-Meza, C., Gómez, W. (2013). A feature selection methodology for breast ultrasound classification. In 2013 10th International Conference on Electrical Engineering,

Computing Science and Automatic Control (CCE), Mexico City, Mexico, pp. 245-249. https://doi.org/10.1109/ICEEE.2013.6676056
[20] Tanaka, H., Chiu, S.W., Watanabe, T., Kaoku, S., Yamaguchi, T. (2019). Computer-aided diagnosis system for breast ultrasound images using deep learning. Physics in Medicine & Biology, 64(23): 235013. https://doi.org/10.1088/1361-6560/ab5093
[21] Adel, M., Kotb, A., Farag, O., Darweesh, M.S., Mostafa, H. (2019). Breast cancer diagnosis using image processing and machine learning for elastography images. In 2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST), Thessaloniki, Greece, pp. 1-4. https://doi.org/10.1109/MOCAST.2019.8741846
[22] Ragab, M., Albukhari, A., Alyami, J., Mansour, R.F. (2022). Ensemble deep-learning-enabled clinical decision support system for breast cancer diagnosis and classification on ultrasound images. Biology, 11(3): 439. https://doi.org/10.3390/biology11030439
[23] Pramanik, P., Mukhopadhyay, S., Kaplun, D., Sarkar, R. (2021). A deep feature selection method for tumor classification in breast ultrasound images. In International Conference on Mathematics and Its Applications in New Computer Systems, Stavropol, Russia, pp. 241-252. https://doi.org/10.1007/978-3-030-97020-8_22/COVER
[24] Spanhol, F.A., Oliveira, L.S., Cavalin, P.R., Petitjean, C., Heutte, L. (2017). Deep features for breast cancer histopathological image classification. In 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Banff, AB, Canada, pp. 1868-1873. https://doi.org/10.1109/SMC.2017.8122889
[25] Alrubaie, H., Aljobouri, H.K., AL-Jobawi, Z.J., Çankaya, I. (2023). Convolutional neural network deep learning model for improved ultrasound breast tumor classification. Al-Nahrain Journal for Engineering Sciences, 26(2): 57-62. https://doi.org/10.29194/NJES.26020057
[26] Chirra, V.R.R., Uyyala, S.R., Kolli, V.K.K. (2019). Deep CNN: A machine learning approach for driver drowsiness detection based on eye state. Revue d'Intelligence Artificielle, 33(6): 461-466. https://doi.org/10.18280/ria.330609
[27] Mukkapati, N., Anbarasi, M.S. (2022). Brain tumor classification based on enhanced CNN model. Revue d'Intelligence Artificielle, 36(1): 125. https://doi.org/10.18280/ria.360114
[28] Hijab, A., Rushdi, M.A., Gomaa, M.M., Eldeib, A. (2019). Breast cancer classification in ultrasound images using Transfer Learning. In 2019 Fifth international conference on advances in biomedical engineering (ICABME), Tripoli, Lebanon, pp. 1-4. https://doi.org/10.1109/ICABME47164.2019.8940291
[29] Collins, R.T., Liu, Y., Leordeanu, M. (2005). Online selection of discriminative tracking features. IEEE Transactions on Pattern Analysis and Machine Intelligence, 27(10): 1631-1643. https://doi.org/10.1109/TPAMI.2005.205
[30] Balasubramanian, D., Srinivasan, P., Gurupatham, R. (2007). Automatic classification of focal lesions in ultrasound liver images using principal component analysis and neural networks. In 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, France, pp. 2134-2137. https://doi.org/10.1109/IEMBS.2007.4352744
[31] Sheela, N., Basavaraj, L. (2018). Analysis of gabor filter based features with PCA and GA for the detection of drusen in fundus images. International Journal of Engineering and Technology (UAE), 7(1): 115-120, https://doi.org/10.14419/ijet.v7i1.8969
[32] Howley, T., Madden, M.G., O'Connell, M.L., Ryder, A.G. (2005). The effect of principal component analysis on machine learning accuracy with high dimensional spectral data. In International Conference on Innovative Techniques and Applications of Artificial Intelligence, Cambridge, United Kingdom, pp. 209-222. https://doi.org/10.1016/j.knosys.2005.11.014