Indonesian Journal of Electrical Engineering and Computer Science
Vol. 37, No. 3, March 2025, pp. 1927~1935
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v37.i3.pp1927-1935

Empower BreastNet: breast cancer detection with transfer learning VGG Net-19

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Article Info

Article history:

Received Jul 1, 2024
Revised Sep 26, 2024
Accepted Oct 7, 2024

Keywords:

Breast cancer
Deep learning
Transfer learning
Convolutional neural networks
VGG-19

ABSTRACT

Breast cancer is a major cause of death among women globally, making early detection crucial for effective treatment. This study introduces a new deep learning (DL) method using transfer learning (TL) to automatically detect and diagnose breast cancer. TL improves performance on new tasks by using knowledge from previous tasks. In this study, we use pre-trained convolutional neural networks (CNNs) like AlexNet, ResNet50, visual geometry group (VGG)-16, and VGG-19 to extract features from the breast cancer wisconsin (BCW) diagnostic dataset. We measure the model's success with accuracy, sensitivity, specificity, precision, and F-score. The results show that the VGG-19 model, when applied with TL, performs best for diagnosing breast cancer, achieving an overall accuracy of 98.75%, sensitivity of 97.38%, specificity of 98.35%, precision of 97.35%, and an F-score of 97.66%.

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1. INTRODUCTION

Breast cancer continues to pose a significant health challenge globally, representing a substantial portion of cancer diagnoses and mortality rates, particularly among women. Despite notable progress in screening programs and treatment strategies, the timely detection and accurate diagnosis of breast cancer remain pivotal for improving patient outcomes and survival rates [1]. However, existing diagnostic methods face inherent limitations stemming from the complexity and variability of breast cancer manifestations, compounded by the subjective nature of interpretation in traditional approaches. These challenges contribute to diagnostic errors, treatment delays, and suboptimal patient care.

In this context, the emergence of deep learning (DL), a subset of artificial intelligence (AI) that excels in learning intricate patterns and features from vast amounts of data, offers new avenues to enhance breast cancer detection and diagnosis [2], [3]. Convolutional neural networks (CNNs), a prominent DL architecture, have demonstrated remarkable capabilities in automatically extracting relevant features from medical images, including mammograms. By leveraging DL, researchers and clinicians can potentially overcome the limitations of conventional diagnostic methods. DL models trained on large datasets of mammogram images can learn to recognize subtle patterns indicative of breast cancer, enabling earlier detection and intervention. Moreover, DL facilitates the development of automated systems capable of triaging images, prioritizing cases for further review, and assisting radiologists in interpreting complex findings, thereby improving workflow efficiency and diagnostic accuracy.

Despite the promising prospects offered by DL, its effective application in breast cancer diagnosis faces several challenges. One significant hurdle is the requirement for large annotated datasets, which are often scarce and costly to obtain in medical imaging domains. Additionally, DL models must demonstrate robustness, generalizability, and interpretability to gain acceptance and trust among healthcare professionals and regulatory bodies.

In response to these challenges, researchers are exploring innovative approaches to harness the potential of DL in breast cancer diagnosis. Transfer learning (TL) has emerged as a valuable technique to address the data scarcity issue by transferring knowledge learned from pre-trained models on large non-medical datasets to specific medical imaging tasks. TL enables DL models to leverage features learned from diverse datasets, enhancing their performance on tasks with limited data availability.

In addition to DL techniques, various machine learning (ML) methodologies have been investigated for cancer detection, particularly in breast cancer diagnosis [4]-[6]. These methods encompass a spectrum from conventional ML algorithms to sophisticated DL architectures. Conventional ML techniques like support vector machines (SVM), random forests, and logistic regression have found extensive application in tasks such as classification and pattern recognition within medical imaging datasets [7], [8]. However, while these ML techniques have shown promise, they often require handcrafted feature extraction and selection, which can be time-consuming and may not fully capture the complexity of medical images. Furthermore, the performance of traditional ML algorithms is highly dependent on the quality and relevance of the features provided as input. Conversely, DL methodologies, notably CNNs, have garnered considerable attention in recent times due to their capacity to autonomously acquire hierarchical representations directly from unprocessed data, such as mammogram images. CNNs can effectively capture intricate patterns and features at different levels of abstraction, making them well-suited for medical image analysis tasks, including cancer detection. TL emerges as a powerful approach to enhance the performance of DL models, especially in scenarios where labeled data is limited [9], [10]. TL leverages knowledge learned from pre-trained models on large datasets (e.g., ImageNet) and applies it to related tasks with smaller datasets, such as medical image analysis. By initializing DL models with weights learned from pre-trained networks, TL enables the transfer of knowledge about low-level features, edge detection, and texture recognition, which are often transferrable across domains. In the context of breast cancer detection, TL allows DL models to leverage the representations learned from non-medical image datasets to improve the performance of cancer detection models. This approach addresses the challenge of data scarcity in medical imaging by providing a means to transfer knowledge from domains with abundant data to domains with limited data availability. By fine-tuning pre-trained CNN architectures on specific medical imaging datasets, TL enables DL models to adapt to the intricacies of breast cancer detection tasks while benefiting from the generalization capabilities learned from diverse datasets. As a result, TL serves as a valuable tool for improving the accuracy, efficiency, and robustness of DL-based cancer detection systems, ultimately advancing the field of medical image analysis and contributing to improved patient outcomes.

This study endeavors to construct a robust DL framework for the automatic detection and diagnosis of breast cancer through the utilization of TL methodologies. Our strategy entails harnessing the capabilities of pre-trained CNN architectures, encompassing renowned models such as AlexNet, ResNet50, visual geometry group (VGG)-16, and VGG-19 [11]. The use of TL in this research enables us to overcome data scarcity, leverage pre-learned features, improve generalization, and enhance computational efficiency. These advantages collectively contribute to the development of more accurate, efficient, and scalable DL-based solutions for breast cancer detection, ultimately benefiting patients, clinicians, and healthcare systems. By fine-tuning these pre-trained models on a specific medical imaging dataset, such as the breast cancer wisconsin (BCW) diagnostic dataset, we seek to improve the accuracy, efficiency, and generalization capabilities of our DL framework for breast cancer detection [12]. The primary objective of this study is to evaluate the efficacy of TL in enhancing breast cancer diagnosis by addressing the challenges of data scarcity, feature learning, generalization, and computational efficiency. Through comprehensive experimentation and evaluation using established performance metrics such as accuracy, sensitivity, specificity, precision, and F-score, we aim to demonstrate the superiority of our proposed DL framework over traditional methods in breast cancer detection. Through advancing the frontiers of DL and TL within breast cancer detection, this investigation seeks to make significant contributions to the continuous endeavors directed towards enhancing early diagnosis, treatment efficacy, and patient survival rates. Ultimately, the refinement of more precise and effective DL-driven solutions for breast cancer detection harbors the potential to transform healthcare delivery profoundly and bring about positive changes in the lives of countless individuals afflicted by this ailment.

In order to enhance the identification, localization, risk assessment, and categorization of breast lesions, Mahmood *et al.* [13] have created sophisticated DL algorithms, with a focus on reducing false positives and resolving problems associated with slow convergence rates. They use a combination of advanced filtering techniques, preprocessing approaches, and data augmentation tactics to improve model performance and prevent both underfitting and overfitting. One significant breakthrough in their research is the efficient detection of dense breast lesions with the application of chaotic leader selective filler swarm optimization (cLSFSO). Furthermore, they enhance the capacity of DL models such modified VGGNet and SE-ResNet152 to distinguish between normal and questionable regions in mammograms by utilizing TL. Further improving the analysis, the study suggests hybrid deep neural network methods for identifying and classifying malignant polyps using pre-segmented regions of interest (ROIs), such as CNN+LSTM and CNN+SVM. Breast abnormalities can now be diagnosed more accurately thanks to the application of grad-CAM techniques. Analyses on public and private datasets demonstrate remarkable improvements in mammography analysis, with remarkable sensitivity (0.99) and an overall area under the curve (AUC) of 0.99.

With multiple noteworthy advances, Sahu *et al.* [14] have proposed an inventive DL based ensemble classifier specifically designed for breast cancer diagnosis. Results from experiments show that their suggested strategy produces remarkable categorization outcomes. On the mini-DDSM and ultrasound dataset (BUSI) dataset, it specifically achieves an accuracy of 99.17% for abnormality detection and 97.75% for malignancy detection and 96.92%, and 94.62% accuracy for abnormality and malignancy diagnosis, respectively. Furthermore, it achieves 97.50% accuracy on the BUS2 ultrasound dataset. The suggested approach shows potential for breast cancer diagnosis across multimodal datasets due to its adaptability and dependability.

Abunasser *et al.* [15] proposed a strategy for classifying breast cancer MRI pictures into eight groups. Their approach combines a unique DL model with five fine-tuned models, all of which were trained on the ImageNet database. They used a generative adversarial network (GAN) to enhance the dataset. The authors methodically analyzed the performance of their proposed DL model and the five pre-trained models on each dataset separately. The classification accuracies for their proposed model (BCCNN) were 98.28%.

For the identification and classification of breast cancer, Raza *et al.* [16] presented deep breast CancerNet, an innovative DL model. As its two normalization processes, the model combines the clipped rectified linear unit (ReLU) activation function, the leaky ReLU activation function, batch normalization, and cross-channel normalization. Their testing revealed that the suggested model has an astounding 99.35% classification accuracy. Two extremely successful deep TL based models are presented by Yari *et al.* [17] in an effort to enhance the state-of-the-art methods that are currently in use for the detection of breast cancer in both binary and multiclass classification. These models make use of deep convolutional neural networks (DCNN) that have already been trained using a sizable image dataset from the ImageNet dataset. Regarding multiclass classification tasks, the accuracy of the proposed system is impressive. The current status of DL research in breast cancer imaging is thoroughly reviewed by Balkenende *et al.* [18]. They emphasize how important breast imaging is for early breast cancer detection, monitoring, and assessment during therapy.

The integration of DL, a subset of AI, becomes possible with the automation of various imaging techniques. In breast imaging, DL is being used for a variety of tasks, including cancer risk prediction, therapeutic response prediction and evaluation, lesion classification and segmentation, and picture reconstruction and generation. Studies show that DL algorithms perform as well as or better than radiologists on a few tasks. However, larger studies are required to properly determine the added value of DL in breast cancer imaging, especially in ultrasound and MRI.

The literature review highlights the vital role that TL plays in improving breast cancer detection by leveraging DL models' enhanced accuracy, efficiency, and generalization capacities. TL, in the fight against breast cancer, provides a realistic technique to improve patient care by leveraging knowledge learned from pre-trained models to improve diagnostic outcomes.

2. METHOD

In this paper, we explored various classification models for the diagnosis of breast cancer, including AlexNet, ResNet50, VGG-16, and VGG-19. Our proposed methodology is illustrated in Figure 1. This figure depicts the process starting from data acquisition from the dataset. The data preparation step involves loading the breast cancer dataset and ensuring the features are normalized or standardized to maintain uniform influence across the algorithms. Next, a training set and a test set are created from the dataset, usually with a 70-30 split for each. Using predetermined criteria, we evaluated each model's performance using AlexNet, ResNet50, VGG-16, and VGG-19 for training. The best algorithm for identifying breast cancer was to be found.

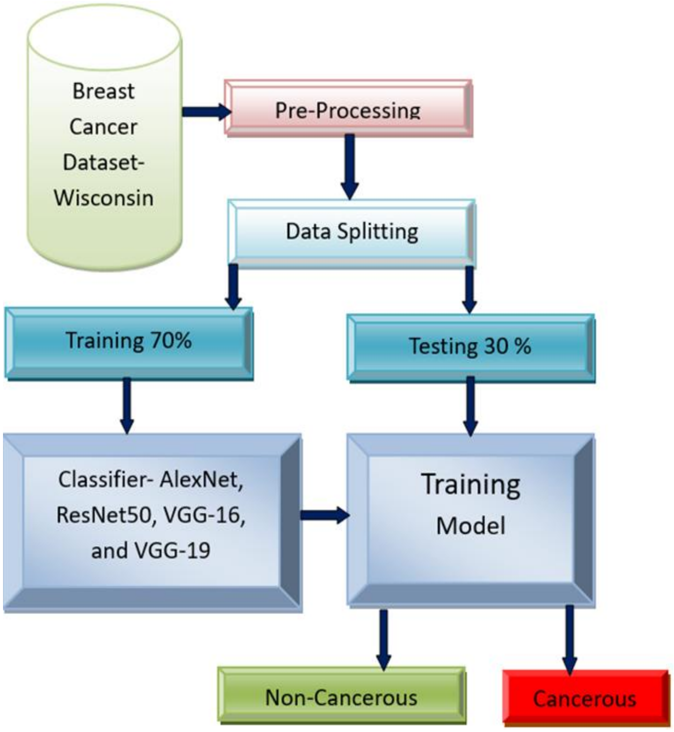

Figure 1. Block diagram of breast cancer detection

2.1. Dataset

The wisconsin breast cancer dataset (diagnosis), which we downloaded from the Kaggle ML and data science community website, https://archive.ics.uci.edu/dataset/17/breast+cancer+wisconsin+ diagnostic [19] was used in this study. There are 569 instances in this collection, and each instance has 30 properties. 357 of them are benign, and 212 are malignant. Below are the features of the dataset. Ten real-valued characteristics are used to evaluate each cell nucleus:

- Radius (mean of distances from center to points on the perimeter).
- Texture (standard deviation of gray-scale values).
- Perimeter.
- Area.
- Smoothness (local variation in radius lengths).
- Compactness (perimeter^2 / area - 1.0).
- Concavity (severity of concave portions of the contour).
- Concave points (number of concave portions of the contour).
- Symmetry.
- Fractal dimension ("coastline approximation" - 1).

2.2. Data pre-processing

To ensure proper relevance assignment [20], the dataset underwent standardization using in the (1).

$$z - \frac{x-\mu}{\delta} \quad (1)$$

The standard deviation of the normalization feature is given by and the mean by δ.

Preprocessing aimed to replace duplicate values and balance the dataset using a data balancer, followed by feature extraction. The processed data was then partitioned into training and testing sets, with a 70-30 split. Several ML classifiers, including AlexNet, ResNet50, VGG-16, and VGG-19, were used to assess how accurate they were at detecting and preventing breast cancer [21]. CNNs were particularly leveraged due to their adeptness in learning significant features from input data, making them highly effective for image-related applications.

2.3. Classification

Classifiers are algorithms that learn to assign class labels to input data based on patterns learned from labeled training data. In the context of image classification, classifiers analyze the features extracted from images and make predictions about their class labels. These predictions help in tasks such as identifying objects, recognizing patterns, and detecting anomalies within images.

In this research, classifiers such as AlexNet, ResNet50, VGG-16, and VGG-19 are employed to classify images of breast tissue as either benign or malignant. Each classifier offers unique architectural characteristics and capabilities, making them suitable for analyzing medical images and assisting in the diagnosis of breast cancer. AlexNet, ResNet50, VGG-16, and VGG-19 are advanced DL models that play a crucial role in breast cancer detection by analyzing medical images to identify cancerous cells. AlexNet, ResNet50, VGG-16, and VGG-19 are sophisticated DL models that have been adapted for breast cancer detection through the analysis of medical images. Here's a detailed look at each model and its application in this context:

- AlexNet
  a) Structure: AlexNet comprises 8 layers, including 5 convolutional layers followed by 3 fully connected layers. It utilizes ReLU activation functions to introduce non-linearity, making the model more capable of capturing complex patterns.
  b) Application in breast cancer detection: AlexNet can process large medical images and identify features indicative of cancerous changes in breast tissue. Its architecture allows it to detect varying textures and shapes associated with malignant tumors, providing a robust initial framework for medical image analysis.
- ResNet50
  a) Structure: AlexNet comprises 8 layers, including 5 convolutional layers followed by 3 fully connected layers. It utilizes ReLU activation functions to introduce non-linearity, making the model more capable of capturing complex patterns.
  b) Application in breast cancer detection: AlexNet can process large medical images and identify features indicative of cancerous changes in breast tissue. Its architecture allows it to detect varying textures and shapes associated with malignant tumors, providing a robust initial framework for medical image analysis.
- VGG-16 and VGG-19
  a) Structure: VGG-16 and VGG-19 are known for their simplicity and depth, with 16 and 19 layers, respectively. Both models use small (3×3) convolution filters throughout their architecture, which helps in capturing detailed and localized features within images.
  b) Application in breast cancer detection: these models excel in identifying fine-grained patterns in breast tissue images. VGG-16 and VGG-19 are useful diagnostic tools because of their depth, which enables them to distinguish between benign and malignant lesions with extreme precision.
- Use of pre-trained models and TL
  a) Pre-training: all these models are initially trained on large datasets like ImageNet, which consists of millions of diverse images. This pre-training allows the models to learn a broad set of features useful for various image recognition tasks.
  b) TL: for breast cancer detection, these pre-trained models are fine-tuned on specific medical image datasets, such as the BCW diagnostic dataset. This process involves retraining the models on breast cancer images so they can adapt their learned features to the specific task of identifying cancerous cells.

These models are often pre-trained on large datasets, such as ImageNet, which helps them learn a wide range of features. For breast cancer detection, these pre-trained models are fine-tuned using medical image datasets like the BCW diagnostic dataset. This fine-tuning process helps the models to better recognize patterns specific to breast cancer, leading to higher accuracy, sensitivity, and specificity in diagnosis.

3. RESULTS AND DISCUSSION

The proposed classifiers were evaluated using standard validation metrics like accuracy, recall, precision, and F-measure. Performance metrics

– Accuracy: measures the proportion of correctly identified cases (both positive and negative) out of the total cases.
– Sensitivity (recall): indicates the model's ability to correctly identify patients with breast cancer (true positive rate).

- Specificity: measures the model's ability to correctly identify patients without breast cancer (true negative rate).
- Precision: reflects the accuracy of positive predictions, showing how many of the positively identified cases are actually correct.
- F-Score: a harmonic mean of precision and recall, providing a single metric that balances both false positives and false negatives.

The experiment used the BCW diagnostic dataset to diagnose breast cancer using several classifiers, including AlexNet, ResNet50, VGG-16, and VGG-19. As shown in Figure 2, the outcomes of different classifiers differed. VGG-19 had the best classification accuracy of 97.95%, while ResNet50 had the lowest, at 94%. The F1-score, which is a combination of precision and recall ratios, is indicative of a model's classification performance. Surprisingly, all four classifiers (AlexNet, ResNet50, VGG-16, and VGG-19) produced equal F1-score values of 96.66%.

It's noteworthy that although VGG-16 and VGG-19 showed superior sensitivity and accuracy in Figure 2, VGG-19 outperformed in terms of F1-score and precision. Consequently, both VGG-16 and VGG-19 classifiers, having been trained on the dataset, emerged as the top-performing classifiers for predicting new cases among all models considered in this comparison. Table 1 shows proposed result with state of are methods.

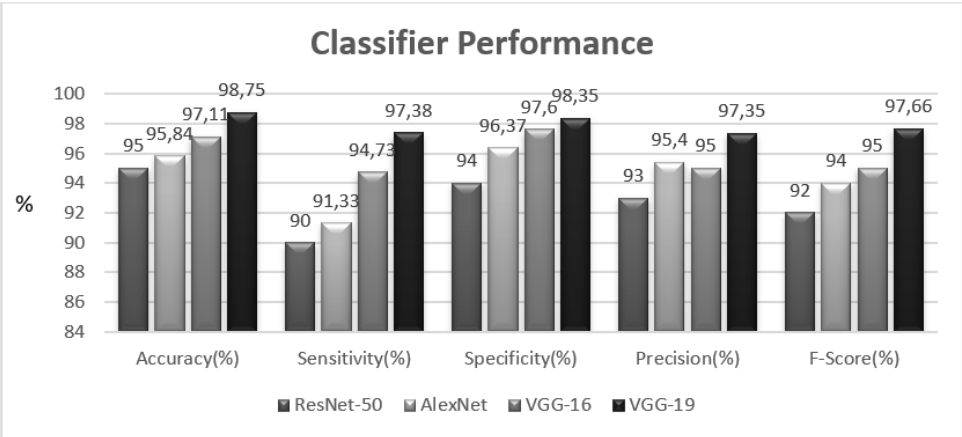

Figure 2. Performance evaluation of classifiers

Table 1. Comparison of the proposed work with state-of-the-art works

Author	Method	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F-score (%)
Magboo *et al.* [22]	Logistic regression	80	80	-	--	76
Naji *et al*. [23]	SVM	97.2	97.5	-	-	-
Alwohaibi *et al.* [24]	Multi-stage learning technique	82	81	82	96	--
Sahoo *et al.* [25]	SVM	84.85	90.59	84.81	84.93	84.81
Alsudani *et al*. [26]	SVM	98.6	97.5	96.9	-	-
Proposed	VGGNet-19	98.75	97.35	97.38	98.35	97.66

4. CONCLUSION

One major global health concern is cancer, a disease with terrible implications. Of all the cancers, breast cancer is the most well-known. Not only may early identification of cancer save lives, but it also lowers the cost of treatment. Therefore, it is crucial to design a trustworthy prediction system. This study evaluated four distinct ML algorithms in terms of F1-score, recall (sensitivity), accuracy, and precision to find the best model for predicting breast cancer disease (BCD). The results of the analysis conducted on the BCW diagnostic dataset indicated that the perceptron and VGG-19 methods had superior sensitivity and accuracy. On the other hand, ResNet50 showed lesser sensitivity and accuracy, whereas VGG-16 showed better precision and F1-score.

Our findings align with previous research highlighting the potential of DL models in medical diagnostics. However, our study specifically focuses on breast cancer detection and provides a comparative analysis of different ML models, adding to the existing body of knowledge by highlighting the specific strengths and weaknesses of each model in this context.

Future research should explore the integration of these ML models with other diagnostic tools to enhance their predictive power. Additionally, examining the performance of these models on larger and more diverse datasets could provide further insights into their generalizability. Investigating the combination of different ML models through ensemble methods might also improve prediction accuracy and reliability. Moreover, incorporating patient demographics and genetic information could lead to more personalized and precise breast cancer detection systems.

In summary, our study underscores the importance of using advanced DL models, particularly VGG-19, for the early and accurate detection of breast cancer. By leveraging these models, medical professionals can significantly improve diagnosis accuracy and efficiency, ultimately leading to better patient outcomes through earlier and more reliable detection.

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