Journal of Digital Media & Culture Technology Vol.1, No.2, December (2021), pp.77-84
ISSN 2983-0664(p) 2983-0850(e) *http://dx.doi.org/10.29056/jdmct.2021.12.02*

Enhancing Early Breast Cancer Detection Using Transfer Learning, Deep Feature Extraction and SVM Classification

G. Hemanth[1], N. Thirupathi Rao[2]*

Abstract

In recent years, breast cancer has emerged as one of the most common types of cancer among women globally. Late diagnosis often results in a higher mortality rate, underlining the crucial need for effective early detection systems, especially those leveraging personal imaging data. In this regard, this study focuses on the integration of transfer learning and deep feature extraction techniques to adapt pretrained CNN models to breast cancer detection. Specifically, AlexNet and VGG16 are employed for feature extraction, with further tuning conducted on AlexNet. The derived features are then classified using Support Vector Machines (SVM). A comprehensive evaluation is carried out using a publicly available breast cancer dataset based on surgical and cellular pathology. Accuracy scores serve as performance metrics. The findings underscore the superior performance of the transfer learning approach compared to the combination of deep feature extraction and SVM classification.

Keyword : Convolution neural network, breast cancer detection, image classification, feature extraction

1. Introduction

Breast cancer, the second most common cancer among women, results from uncontrolled cell growth in milk-producing glands and ducts. As per 2019 data, 268,676 new cases and 41,800 deaths were reported [1]. Early detection increases treatment effectiveness and reduces distress, made possible by non-invasive diagnostics like density-modified imaging, sonography, computed tomography (CT) and positron emission tomography (PET) scans. However, these methods carry radiation risks and cannot confirm malignancy so it requires a biopsy for confirmation before surgical intervention.

Biopsies, invasive diagnostic procedures, aid in identifying cancerous changes in breast cells. Surgical open biopsy (SOB) extracts significant suspect areas for microscopic cellular structure analysis, a process potentially time-consuming and reliant on a pathologist's expertise. In response, Computer-Aided Diagnosis (CAD) systems employing machine learning including deep learning have been introduced to

1 Department of Computer Science and Engineering, Vignan's Institute of Information Technology, India [Professor]
e-mail: goudahemanth21@gmail.com
2 Department of Computer Science and Engineering, Vignan's Institute of Information Technology, India [Professor]
e-mail: nakkathiru@gmail.com (Corresponding author)

Received(August 5, 2021), Review Result(1st: August 29, 2021), Accepted(December 3, 2021), Published(December 31, 2021)

streamline cell classification and reduce unnecessary biopsies and improve diagnostic accuracy [2][3]. Deep learning surpasses traditional artificial intelligence in image recognition with Convolutional Neural Networks (CNNs) being a common algorithm. Many breast cancer studies have utilized pretrained CNN models and achieved notable accuracy in cancer detection [4-6]. For example, Selvathi et al. achieved a 98.5% accuracy rate using an unsupervised deep learning approach with mammography [7].

In this study, the purpose is to optimize the classification process by integrating various image magnification rates and utilizing support vector machines for final classification. For this, this study used feature vectors extracted from the AlexNet and VGG16 models either independently or combined to enhance the result's effectiveness.

2. Related Studies

2.1 Convolutional neural networks

Convolutional Neural Networks, a neural network subset, are renowned for their impressive image recognition capabilities. They incorporate feature extraction and classification within their extensive architecture composed of convolutional, pooling, normalization and fully connected layers. The system's architecture is determined by sequentially arranging these layers. Conducting convolution and pooling successively allows high-level feature extraction used for classification that handled in the fully connected layers. CNNs require numerous parameters to be adjusted during learning and typically achieves via the standard backpropagation algorithm [8][9].

2.2 Transfer Learning

Transfer Learning (TL) involves applying knowledge from one domain to another for feature extraction and classification [10]. It commonly utilizes pretrained CNN models trained on large datasets, then applies this training to new data, including smaller image sets. TL has gained popularity as it's generally faster and easier than training a CNN model from scratch. Initial layers in CNN models learn low-level features (edges, corners, color blobs), while later layers capture abstract, specific features. Typically, the last three layers (fully connected, softmax, classification output) are discarded in new tasks to transfer the remaining layers.

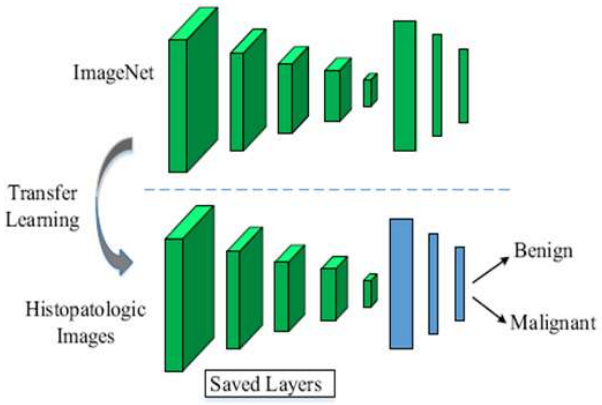
2.3 Feature Extraction in deep networks

Feature extraction in deep networks, a subset of TL, leverages CNN architecture to extract representative features without fine-tuning the model. Early layers capture basic image attributes while deeper layers extract high-level features crucial for image classification. For instance, in ImageNet, activations from initial and fully connected layers serve as feature descriptors [11][12].

3. Proposed Method

In this study, a pre-trained CNN model was adapted by using transfer learning and deep feature extract methods. After selecting a pre-trained CNN model of the AlexNet and VGG16, the final layers of the pre-trained model, usually the fully connected, softmax and classification output layers, are discarded. Subsequently, the weights of the remaining layers in the pretrained model are frozen. This prevents their alteration during further training to preserve their feature extraction capabilities [13]. The modified pre-trained model is then used to extract deep features from the new dataset. This transforms the input images into feature vectors based on what the model has learned, consequently changing the data's representation [14]. After feature extraction, new layers specific to the new task are added to the model. Depending on the data volume and available computational resources, some or all of the model layers can be unfrozen for further training. This could allow for slight weight adjustments, potentially enhancing performance on the new task.

3.1 Feature extraction using CNN models



[Fig. 1] Transfer Learning

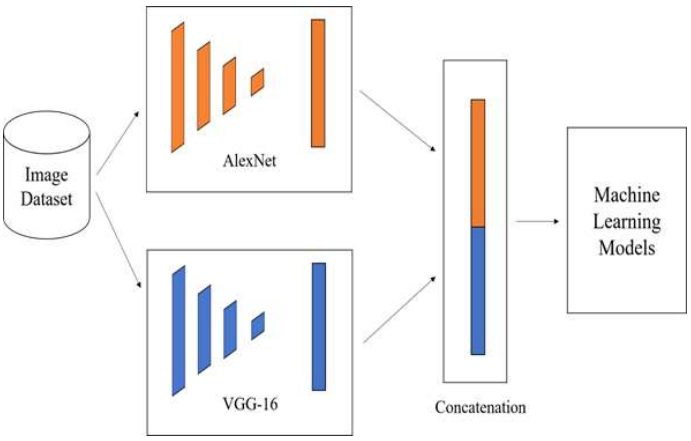
This proposed system and structure of this model are represented in [Fig. 1]. The process involves feeding breast cancer cell images from surgical and cellular pathology into the training phase of the CNN models. During this phase, feature extraction is conducted using the AlexNet and VGG16 models. The obtained feature vectors are then classified by a Support Vector Machine (SVM) classifier to determine the class label of the given images. For a detailed examination, the AlexNet model is considered as well.

3.2 Feature extraction using CNN models

For a detailed analysis, the pretrained AlexNet model was considered since it is the first comprehensive CNN architecture [15]. Comprising 30 layers, including 10 layers with adaptable parameters and 6 fully connected layers, AlexNet was a groundbreaking model in its time. Following each convolutional layer, the architecture includes rectified linear units, normalization, and pooling layers with different kernel sizes so that it can enhance its ability to extract diverse features.

Under the transfer learning approach, the final six layers of the AlexNet model were discarded as they were initially designed for the 1000-class ImageNet challenge and might not be suitable for the task in this study. Instead, the remaining layers for the breast cancer cell detection problem was focused. Specifically, the final layers was reconfigured to effectively distinguish between two classes: benign and malignant cells. This reconfiguration transforms the model to specifically cater to the given task, harnessing the complex feature extraction ability of the AlexNet model while ensuring compatibility with our binary classification problem. The newly designed class is illustrated in Figure.

In the field of deep feature extraction, both the AlexNet and VGG16 models was used. The VGG16 model is an advanced CNN model composed of 43 layers, 19 of which possess adjustable parameters. These adjustable layers consist of 16 convolutional layers and three fully connected layers. Unique to the VGG16 model is its exclusive use of small 3x3 kernels across all convolutional layers. Like AlexNet, max pooling layers follow the convolutional layers in the VGG16 model. The first and second fully connected layers, referred to as fc6 and fc7, are employed for the extraction of feature representations. These representations known as feature probabilities offer an informative overview of the input image. These feature vectors can then be used for various tasks including image classification, image retrieval and object detection.



[Fig. 2] Feature Extraction

4. Results

The performance of various configurations of AlexNet is summarized in [Table 1]. Alterations in AlexNet's structure yield the desired outcomes with most accuracy scores surpassing 90%. The maximum accuracy of 93.5% was achieved at Layer 3 with a 40X magnification, closely followed by an accuracy of 93.2% in Layer 5 at a 200X magnification. For a 400X magnification, Folds 2 and 4 attained the highest accuracies and yielded 90.7% and 91.8%, respectively. Layer 1 scored an accuracy of 91.37% at a 40X magnification.

The results from [Table 1] indicate that the performance of the AlexNet model, as demonstrated by accuracy scores, is influenced by alterations in the model's structure and the chosen level of image magnification. The 93.5% accuracy score achieved at Layer 3 with a 40X magnification is significant as it suggests that lower levels of the AlexNet model, paired with moderate magnification, can effectively classify breast cancer cell images. This is further emphasized by the strong performance at Layer 5 with a 200X magnification where an accuracy of 93.2% was achieved.

[Table 1] AlexNet accuracy scores with fine tuning

Folding Number	40 X	100 X	200 X	400 X
Fold-1	92	91	88	90
Fold-2	88	89	89	91
Fold-3	94	93	93	91
Fold-4	91	88	92	92
Fold-5	90	91	93	92

Further comparison was conducted among the results as shown in [Table 2], with the average accuracy across folds and their standard deviation serving as the metrics. Each column signifies a different level of magnification. As per the table, the enhanced AlexNet configuration had the highest average accuracy scores across all magnification levels, recording a 91.96% average. Conversely, the lowest average accuracy was achieved with the feature set combining AlexNet and VGG16 at the sixth fully connected layer.

[Table 2] AlexNet accuracy scores with fine tuning

Hybrid model	40 X	100 X	200 X	400 X
AlexNet + VGG16 With FC-6	85.87	90.21	89.65	87.75
AlexNet + VGG16 With FC-7	85.58	90.03	89.31	87.00
AlexNet with fine tuning	91.96	91.58	92.37	92.30

[Table 2] results provide insight into the comparison between different combinations of AlexNet and other architectures (VGG16 and VGG18), using different levels of magnification and different layers for feature extraction. This might suggest that integrating these specific layers from different architectures does not yield significant improvements possibly due to the inherent differences in these models or the complexity added by merging features from different layers and architectures.

5. Conclusion

This study examines the efficacy of transfer learning and deep feature extraction techniques in the identification of breast tumor cells through the analysis of surgical and cellular pathology images. The study primarily revolved around the use of two advanced deep convolutional neural networks (CNNs), AlexNet and VGG16. The extensive dataset which contains a large collection of sample images, was employed for experimental tasks.

The experiment was conducted in three stages. The initial stage involved extracting feature vectors from the fully connected layer (fc7) of both AlexNet and VGG16 models which were then combined. In the second stage, similar feature extraction was carried out from the fc6 layer of both models and the extracted feature vectors were subsequently merged. For both of these stages, a Support Vector Machine (SVM) classifier was deployed to classify the images into benign and malignant categories. The final stage of the experiment entailed fine-tuning the pretrained AlexNet model using the breast cancer images from our dataset. The results suggested that the fine-tuned AlexNet model outperformed the other

models. Moreover, it was observed that the results from the initial experimental phase were more advantageous than those from the second phase. The results of this study have demonstrated the potential of deep learning techniques in diagnosing breast cancer through the analysis of pathology images. Further studies can be done to utilize diverse CNN models to further enhance classification accuracy and another area is data augmentation as a strategy for enhancing the effectiveness of transfer learning as well.

References

[1] "Breast Cancer Histopathological Database(BreakHis)", http://web.inf.ufpr.br/vri/breas t-cance r-database, (accessed July 25, 2021).

[2] C. Pearce, "Convolutional neural networks and the analysis of cancer imagery", Stanford University, 2017.

[3] K. Simonyan and A. Zisserman, "Very deep convolutional networks for largescale image recognition", Computing research repository (CoRR), vol. 1, April 2015, doi: 10.48550/arXiv.1409.1556.

[4] N. Bayramoglu, J. Kannala and J. Heikkilä, "Deep learning for magnification independent breast cancer histopathology image classification", 2016 23rd International Conference on Pattern Recognition (ICPR), Cancun, Mexico, 2016, pp. 2440-2445, doi: 10.1109/ICPR.2016.7900002.

[5] Z. Sha, L. Hu and B. D. Rouyendegh, "Deep learning and optimization algorithms for automatic breast cancer detection", International Journal of Imaging Systems and Technology, vol. 30, no. 2, 2020, pp. 495-506, doi: 10.1002/ima.22400.

[6] R. S. Patil and N. Biradar, "Automated mammogram breast cancer detection using the optimized combination of convolutional and recurrent neural network", Evolutionary Intelligence, April 2020, pp. 1-16, doi: 10.1007/s12065-020-00403-x.

[7] D. Selvathi D, A. Poornila, "Breast cancer detection in mammogram images using deep learning technique", middle-east. J Sci Res, vol. 25, no. 2, 2017, pp. 417-26.

[8] F. A. Spanhol, L. Oliveira, C. Petitjean and L. Heutte, "Breast cancer histopathological image classification using Convolutional Neural Networks", 2016 International Joint Conference on Neural Networks (IJCNN), Vancouver, Canada, 2016.

[9] S. Hadush, Y. Girmay, A. Sinamo and G. Hagos, "Breast cancer detection using convolutional neural networks", arXiv preprint, vol. abs/2003.07911, 2020.

[10] E. Deniz, A. Şengür, Z. Kadiroğlu, Y. Guo, V. Bajaj, Ü. Budak, "Transfer learning based histopathologic image classification for breast cancer detection", Health Inf Sci Syst, vol. 6, no. 1, Sep 2018, pp. 18, doi: 10.1007/s13755-018-0057-x.

[11] J. G. Melekoodappattu and P. S. Subbian, "Automated breast cancer detection using hybrid extreme learning machine classifier", Journal of Ambient Intelligence and Humanized Computing, vol. 14, 2020, pp. 5489-5498, doi: 10.1007/s12652-020-02359-3.

[12] A. H. Shayma, M. S. Sayed, M. I. Abdalla and M. A.Rashwan, "Breast cancer masses classification using

deep convolutional neural networks and transfer learning", Multimedia Tools and Applications, vol. 79, no. 41, November 2020, pp. 30735-30768, doi: 10.1007/s11042-020-09518-w.

[13] L. Ahmed, M. M. Iqbal, H. Aldabbas, S. Khalid, Y. Saleem and S. Saeed, "Images data practices for semantic segmentation of breast cancer using deep neural network", Journal of Ambient Intelligence and Humanized Computing, 2020, pp. 1-17, doi: 10.1007/s12652-020-01680-1.

[14] R. Platania, S. Shams, S. Yang, J. Zhang, K. Lee and S. J. Park, "Automated breast cancer diagnosis using deep learning and region of interest detection (bc-droid)", the 8th ACM international conference on bioinformatics, computational biology and health informatics, August 2017, pp. 536-543, doi: 10.1145/3107411.3107484.

[15] G. Hamed, M. A. E. R. Marey, S. E. S. Amin and M. F. Tolba, "Deep learning in breast cancer detection and classification", In Joint European-US Workshop on Applications of Invariance in Computer Vision, Springer, Cham, April 2020, pp. 322-333, doi: 10.1007/978-3-030-44289-7_30.