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Deep learning for cancer tumor classification using transfer learning and feature concatenation

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ABSTRACT

Deep convolutional neural networks (CNNs) represent one of the state-of-the-art methods for image classification in a variety of fields. Because the number of training dataset images in biomedical image classification is limited, transfer learning with CNNs is frequently applied. Breast cancer is one of most common types of cancer that causes death in women. Early detection and treatment of breast cancer are vital for improving survival rates. In this paper, we propose a deep neural network framework based on the transfer learning concept for detecting and classifying breast cancer histopathology images. In the proposed framework, we extract features from images using three pre-trained CNN architectures: VGG-16, ResNet50, and Inception-v3, and concatenate their extracted features, and then feed them into a fully connected (FC) layer to classify benign and malignant tumor cells in the histopathology images of the breast cancer. In comparison to the other CNN architectures that use a single CNN and many conventional classification methods, the proposed framework outperformed all other deep learning architectures and achieved an average accuracy of 98.76%.

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1. INTRODUCTION

Analysis of the microscopic images that represent various human tissues has developed as one of the most vital fields of biomedical research, as it aids in the understanding of a variety of biological processes. Different applications of microscopic images classification have been developed, which include identifying simple patient conditions and studying complex cell processes. Tissue image classification is extremely important. After lung cancer, breast cancer is considering the most frequent cancer type studied and the most prevalent type of cancer in women has the highest death rate in the world [1]. The radiologist uses microscopic images of the breast to detect cancer indications in women at an early stage, and the rate of survival will be increased if detected early. Pathologists use a microscope to analyze a sample of microscopic images of breast tissue to detect and classify the types of cancer tumors, which are categorized into benign and malignant tumor. The benign tumor is harmless, and the majority of this type is unable to become a breast cancer source, while the malignant tumor is characterized by abnormal divisions and irregular growth.

Because manual classification of microscopic images is time-consuming and expensive, there is a growing demand for automated systems as the rate of breast cancer rises and diagnosis differs. As a result, computer-aided-diagnosis (CAD) system is required to decrease a specialist's workload by increasing the efficiency of diagnostic and reducing classification subjectivity. Various applications have been developed

for microscopic image classification. Traditional automated classification techniques such as local binary patterns (LBP) [2] that use hand-crafted features extractors, support vector machines (SVM) [3] as a linear classifier, clustering-based algorithms segmentation and classification of nuclei [4], [5], hybrid SVM-ANN [6]. Although these methods produced some acceptable results in classification, the accuracy might be improved.

Deep convolutional neural networks were used to overcome the accuracy limits in traditional machine learning techniques and have developed as one of the most advanced methods in the classification process [7]. Deep CNN systems as nuclei detection and classification [8], tumor detection [9], skin disease classification [10], detection and classification of lymph nodes metastasis [11]. On large datasets, CNN systems perform well, but it fails on small datasets to achieve high gains.

The principle of transfer learning is used to exploit deep neural networks in small datasets to enhance the CNN structure's performance by combining their knowledge to reduce computing costs and achieve high accuracy. CNN architecture is learned on a generic large dataset of nature images and then employed as a features extractor using the pre-trained CNN structure in transfer learning. The generic features extracted from the CNN can apply to various datasets [12], [13]. To improve transfer learning performance, the use of a combination of multiple CNNs structures has been introduced and could eventually replace the usage of a single CNN model. VGG16, ResNet50, and Inception-v3 networks have developed an accurate and fast model for image classification [14]–[16], which are pre-trained on ImageNet.

In the suggested framework, we use transfer learning and a combination of extracted from multiple CNN architectures to overcome the shortcomings in cancer tumor detection and classification in existing systems. We can summarize the contributions in this research in the following: i) provide a framework for detecting and classifying breast cancer tumor that use CNN architectures, ii) apply the transfer learning concept and provide a comparative analysis of accuracy for three different deep CNN architectures, and iii) using a combination of extracted features from various networks to improve classification accuracy.

2. PROPOSED METHOD

In this paper, we suggest a framework by using three different deep CNN architectures: VGG16, ResNet50, and Inception, these CNNs were pre-trained on ImageNet dataset [17]. We used them for the breast cancer tumor detection and classification in histopathology images. The suggested model combined various low-level features that were separately extracted from various CNN architectures, and then fed it into a fully connected (FC) layer to classify the benign and malignant tumor.

2.1. Pre-trained CNN architectures for features extraction

In this section, three different CNN models are used for feature extraction of the proposed method, VGG-16 [18], ResNet50 [19], and Inception-v3 [20]. These models are concatenated into the FC layer which is used to classify breast cancer tumor. The ImageNet dataset, which contains multiple generic image descriptors, was used to pre-train these CNNs [21], and then feature extraction is performed using transfer learning concept. The structures for each CNN architectures are described briefly:

2.1.1. VGG-16 architecture

VGG-16 is made up of 16 layers, containing 13 convolution layers, pooling layers, and three FC layers [18]. The number of channels in convolution layers is 64 channels in the first layer and rises after each pooling layer by a factor of two until it reaches 512. A 3x3 window size filter and a 2x2 pooling network are used in the convolution network. VGG-16 is a convolutional network similar to the model AlexNet but contains more convolution layers. Because of its simple architecture, it outperforms AlexNet. VGG-16's basic architecture is shown in Figure 1.

2.1.2. ResNet50 architecture

Residual networks (ResNet) [19] are a group of deep neural networks that have architectures that are similar but varying depths that perform well at classification tasks on ImageNet [22]. To deal with the degradation problem of deep neural networks, the residual learning unit is a structure introduced by ResNet [19]. The merit of this structure is it enhances classification accuracy without raising model complexity. ResNet50's basic architecture is depicted in Figure 2.

2.1.3. Inception-v3 architecture

Inception-v3 [20] is an enhanced version of the GoogLeNet architecture [23], which uses transfer learning in biomedical applications to achieve high classification performance [24], [25]. Inception suggested a model that combines many convolutional filters of varying sizes into a single one. As a result of this design,

the computational complexity and the number of trained parameters are reduced. Inception-v3's basic architecture is depicted in Figure 3.

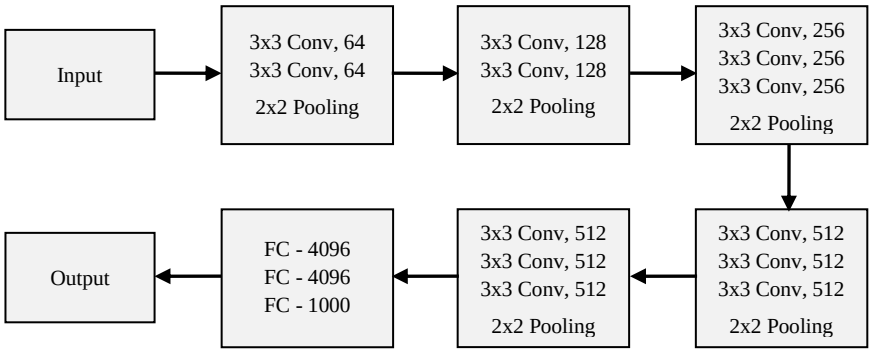

Figure 1. The VGG-16 CNN architecture [18]

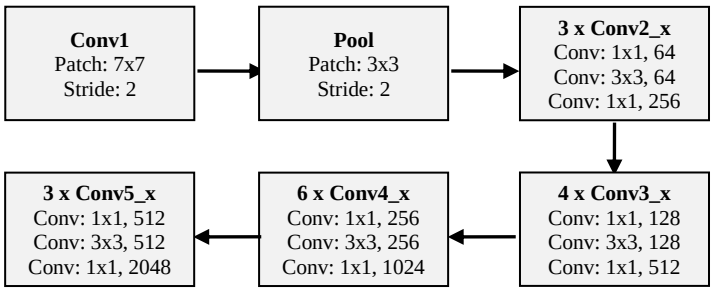

Figure 2. The ResNet50 CNN architecture [19]

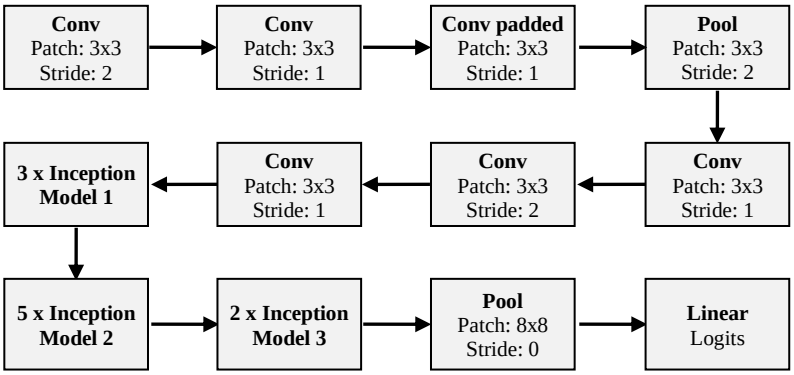

Figure 3. Inception-v3 CNN architecture [20]

2.2. Data augmentation

Because CNN's performance weakens when used with small datasets due to overfitting [26], which gives unwell results on test data despite it achieving good performance in the training data, it requires large data sets to attain higher accuracy. In this paper, to reduce overfitting issues and expand the dataset, a data augmentation technique is used [26]. The number of data at training is increased by using image processing methods to apply geometric transformations to image datasets at data augmentation technique. During the training stage, using flipping samples vertical and horizontal, scaling, translation, and rotation, the training data is increased. Because microscopic images rotationally are invariant, cancer tumor microscopic images can be easily analyzed from various positions without affecting the diagnosis [27].

2.3. Transfer learning

To achieve high accuracy and train a model from scratch, it needs a large amount of data, but getting a large dataset of relevant problems can be difficult in some cases. As a result, the term "transfer learning" has been introduced. The CNN model structure is first trained for a task using a large image dataset related to that task and then transferred to a wanted task which is trained on a small dataset [28].

The similarity between the source training dataset and the target dataset and selection of pre-trained model are two steps in the process of transfer learning process. If the size of the used dataset is small and related to the original training dataset, there is high overfitting probability. If the target dataset size is large and different from the source training dataset, there is low overfitting probability [16], and in this case all that is required for the pre-trained model is fine-tuning.

2.4. The proposed network structure

First, the three CNN architectures VGG16, ResNet50, and Inception-v3 are trained on a dataset of general images from 1,000 categories using ImageNet dataset [17], after which a transfer learning method can be used, allowing CNN architectures to learn generic characteristics from other image datasets without the need to train models from scratch. The CNN model's transfer learning architecture is shown in Figure 4, the pre-trained network acts as a features extractor for general features of image, and add FC layers for classification. The details of the extracted features from the CNN architecture can be summarized as the following: i) VGG-16: 512 feature is extracted from the last layer as shown in Figure 1; ii) ResNet50: 2048 feature is extracted from the last layer as shown in Figure 2; iii) Inception-v3: 2048 feature is extracted from the last logits layer as shown in Figure 3.

The extracted features from the per-trained models are concatenated to form 4,612-dimensional feature. The concatenated features are then fed into the FC layer using average pooling for classification of the benign and malignant tumor. Figure 5 shows the structure of the proposed feature concatenation scheme.

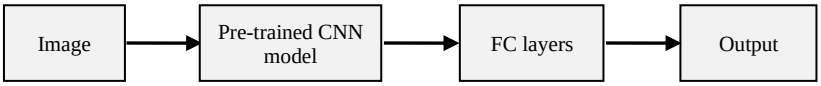

Figure 4. The CNN model's transfer learning architecture

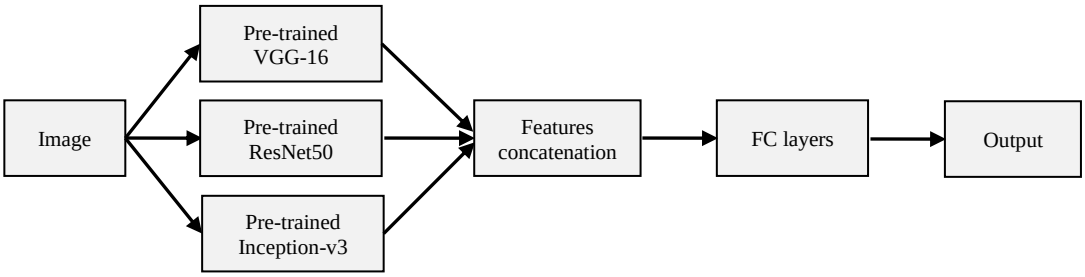

Figure 5. The proposed feature concatenation structure

3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1. Dataset description

The proposed framework is evaluated using the breast cancer histopathology images (BreakHis) dataset [29]. The dataset consists of 7,909 breast cancer histopathology images using various factors of magnification (40X, 100X, 200X, and 400X) which were collected from patients and contain 5,429 malignant and 2,480 benign samples. The details of the dataset used are illustrated in Table 1.

Table 1. The breast cancer histopathological images dataset

Magnification	Malignant	Benign	Total
40X	1,370	625	1,995
100X	1,437	644	2,081
200X	1,390	623	2,013
400X	1,232	588	1,820
Total	5,429	2480	7,909

3.2. Results and discussion

We split the dataset into two parts: the first one contains 80% of the dataset as a training set (6,328 image) for training the models and the other contains 20% as a testing set (1,581 image) for testing the models. The accuracy of classification for the proposed architecture is compared to three single transfer learning network architectures: VGG16, ResNet50, and Inception individually. Table 2 displays the classification accuracy results obtained by the proposed model and other used architectures in different magnification factor and then the average magnification accuracy is calculated for each model.

As the results shown in Table 2, it can be noticed that the proposed framework achieved the highest accuracy of 99.732%, 98.947%, 99.328%, and 98.626% at magnification factor 40X, 100X, 200X, and 400X respectively. The VGG-16, ResNet50, and Inception-v3 architectures give an average magnification accuracy of 95.25%, 90.19%, and 97.02%, respectively. Meanwhile the suggested model achieves 99.16% as an average accuracy. The results shown indicate that the suggested architecture outperforms the three single architectures and achieves high accuracy in the cancer tumor classification.

Table 2. The accuracy of the proposed model and other CNN models based on different magnification factor

CNN model	Magnification accuracy (%)				Average magnification accuracy (%)
	40X	100X	200X	400X	
VGG-16	96.242	96.447	96.102	92.214	95.25
ResNet50	89.262	92.368	88.441	90.687	90.19
Inception-v3	97.572	96.586	97.172	96.748	97.02
Proposed Framework	99.732	98.947	99.328	98.626	99.16

In this situation, to get more accurate results for the different models, the entire dataset is divided using multiple splitting ratio procedures into training and testing parts, such as 90-10%, 80-20%, and 70-30% ratios. The 90-10% splitting ratio indicates that 90% of the data are used when train the model, while the remaining 10% are used to test the model. Table 3 and Figure 6 compare the proposed framework architecture to the other CNN models based on different splitting ratios. The "Class Type" represents the type of tumor, where B denotes benign and M is malignant cancer in Table 3. It shows the precision of each class type and the accuracy of each splitting ratio. In addition, it provides the average accuracy based on splitting ratios of each CNN models. Figure 6 shows the accuracy of CNN architectures at different splitting ratios and an average accuracy for the architectures. As shown in Table 3 and Figure 6, the proposed framework architecture achieves the highest accuracy compared to single architectures in the classification of the cancer tumor. The VGG-16, ResNet50, and Inception-v3 architectures achieve an average accuracy 95.68%, 88.43%, and 96.49% respectively, while the suggested model achieves an average accuracy 98.76%.

Table 3. Comparative analysis of accuracy based on different splitting ratios for proposed model with other CNN models

CNN model	Splitting ratio	Class type	Precision	Accuracy of splitting ratio (%)	Average accuracy (%)
VGG-16	90%-10%	B	95.05	96.20	
		M	96.73		
	80%-20%	B	93.72	95.44	95.68
		M	96.22		
	70%-30%	B	95.82	95.40	
		M	95.20		
ResNet50	90%-10%	B	84.55	90.60	
		M	93.35		
	80%-20%	B	72.87	88.22	88.43
		M	95.20		
	70%-30%	B	79.92	86.49	
		M	89.49		
Inception-v3	90%-10%	B	98.37	96.95	
		M	96.31		
	80%-20%	B	94.94	96.32	96.49
		M	96.96		
	70%-30%	B	97.77	96.2	
		M	95.48		
Proposed Framework	90%-10%	B	97.96	99.23	
		M	99.81		
	80%-20%	B	97.58	98.67	98.76
		M	99.17		
	70%-30%	B	97.98	98.39	
		M	98.58		

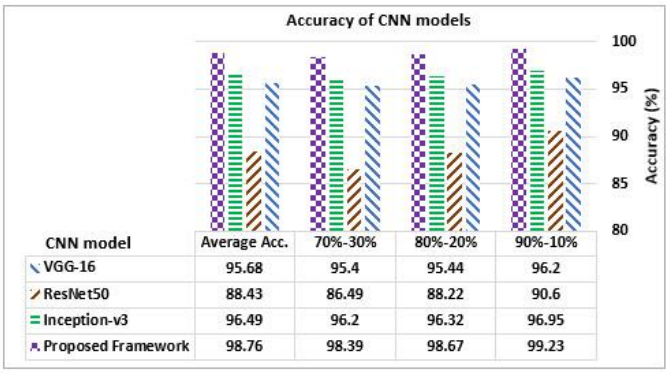

Figure 6. Comparative analysis of accuracy for CNN models

3.3. Comparison between the proposed framework and other methods

In this section, it is preferable to compare the results achieved from our proposed framework technique with those achieved using various conventional classification methods as indicated in Table 4. It can be indicated that the performed structures in [13]–[16] have an accuracy 92.63%, 97%, 97.08%, and 97.52% respectively, while our proposed scenario has the highest accuracy of all four procedures at 98.76%. These results demonstrate the suggested framework's superiority over other similar methodologies.

Table 4. Comparison between the proposed framework and other methods

Method	Accuracy (%)
Nguyen [13]	92.63
Kensert [14]	97.00
Vesal [15]	97.08
Khan [16]	97.52
Proposed Framework	98.76

4. CONCLUSION

In this study, we suggest a deep learning framework based on the transfer learning principle for detection and classification of breast cancer Histopathological images. In this framework, by using three different deep CNN models (VGG-16, ResNet50, and Inception-v3), the features from breast cancer images are extracted, and then concatenated to improve classification accuracy. Data augmentation is a method for increasing the dataset size to minimize over-fitting issues and improve the efficiency of CNN architecture. The work presented here shows how transfer learning and features concatenation of multiple CNN architectures can improve classification accuracy when compared to single CNN networks and achieves excellent classification accuracy. It is also compared the proposed framework's performance to that of different existing classification methods, and it is found that the proposed model achieves 98.76% as an average accuracy.

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