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Detection and classification of breast cancer using transfer learning

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ABSTRACT
Breast cancer is among the leading cause of mortality among women in developing as well as under-developing countries. The detection and classification of breast cancer in the early stages of its develop-ment may allow patients to have proper treatment. In this article, we proposed a novel deep learning framework for the detection and classification of breast cancer in breast cytology images using the con-cept of transfer learning. In general, deep learning architectures are modeled to be problem specific and is performed in isolation. Contrary to classical learning paradigms, which develop and yield in isolation, transfer learning is aimed to utilize the gained knowledge during the solution of one problem into an-other related problem. In the proposed framework, features from images are extracted using pre-trained CNN architectures, namely, GoogLeNet, Visual Geometry Group Network (VGGNet) and Residual Networks (ResNet), which are fed into a fully connected layer for classification of malignant and benign cells using average pooling classification. To evaluate the performance of the proposed framework, experiments are performed on standard benchmark data sets. It has been observed that the proposed framework outclass all the other deep learning architectures in terms of accuracy in detection and classification of breast tumor in cytology images.

Keywords:
Deep learning
Smart pattern recognition
Transfer learning
Breast cancer

I. INTRODUCTION

In biomedical research, analysis of microscopic images repre-senting different human organs and tissues play an important role in the understanding of different biological activities. Among mi-croscopic image examination assignments, classification of images (tissues, organs etc) is one of great significance. Different appli-cations identified with microscopic image classification have been developed. Breast cancer is the most common and a leading cause of death all over the world in women aged between 20 to 59 years [1]. If diagnosed in early stages, the survival rate from breast cancer may be increased up to 80% [2]. The two common diagnos-ing methods used for breast cancer detection are mammography and biopsy. In mammography, breast images of a specific type are used to detect early cancer symptoms in women by the radiolo-gist. It has been observed that due to the use of mammography for cancer detection, the death ratio has decreased [3]. A biopsy is another well efficient and accurate diagnosis method for breast cancer detection. In this approach, a tissue sample from an affected region of the breast is analyzed under a microscope by a pathol-ogist for the detection and classification of the tumor. Currently, biopsy plays a vital role in breast cancer as well as in other types of cancer diagnosis [4]. Through biopsy, pathologist can determine two types of lesion: benign and malignant. The benign lesion is not cancerous; it is indeed the abnormalities in the epithelial cells, and most of these abnormalities are unable to become a source of breast cancer. The malignant or cancerous cells are those types of cells, which start divisions abnormally and grows irregularly. It is a very complex and challenging task to analyze the microscopic images manually due to the irregular appearance of benign and malignant cells [5,6]

In the past few decades, numerous researchers have proposed different solutions for automated cells classifications for cancer de-tection in breast cytology images. In this regards, some researchers have worked on nuclei analysis by extracting features from nuclei to provide significant information for cell classification into benign and malignant [7]. Similarly, clustering based algorithms along with circular Hough Transform and

various statistical features are also exploited for nuclei segmentation and classification [8–10]. In the medical image analysis, algorithms for histopathological im-ages are developing rapidly but still, it is highly demanded to have an automatic system to get efficient and highly accurate re-sults [11–13]. Therefore, such types of techniques are required that gives the right direction towards qualitative products for diagnoses, to provide uniformity in the results during the observation process and improve the objectivity. The complex nature of tasks like pre-processing, segmentation, feature extraction, etc in classical ma-chine learning approaches degrades the performance of the system regarding efficiency and accuracy.

To overcome the problems of traditional machine learning tech-niques, the concept of deep learning has been introduced to ex-tract the relevant information from the raw images and use it effi-ciently for classifications process [14,15]. In deep learning, features are not adjusted manually instead the learning is performed from data sets with the help of general-purpose learning approach [14]. In the last few years, deep learning based on Convolution Neural Network (CNN) has achieved great success in the field of biomedi-cal image analysis like detection of mitosis cells from microscopic images [16,17] tumor detection [18], segmentation of neural mem-branes [19] skin disease and its classification [20], detection and classification of immune cells [21] and quantization of mass in mammograms [22]. Although, the CNN application works very well on large data sets, yet on small data sets it fails to achieve sig-nificant gains. In order to achieve higher recognition accuracy and reduce the computational costs, the concept of transfer learning can be exploited to improve the performance of individual CNN ar-chitectures by combining their knowledge [23,24]. In this regards, the set of features is extracted from generic image data sets us-ing pre-trained deep CNN and then directly applied for domain specific and smaller data sets [25]. The concept of context based learning gives a new direction to transfer learning in which CNN is trained in two phases both for single and overlapping patches and performed very well in breast cancer detection and classifica-tion [26]. The combination of multiple CNN architecture boosts up the performance of transfer learning and may replace the use of traditional single model CNN architecture. Similarly, the combina-tion of ResNet50, InceptionV2 and InceptionV3 are pre-trained on ImageNet which produced a fast and accurate model for cell based image classification [27,28].

In the proposed framework, transfer learning has been ex-ploited to overcome the deficiencies in existing systems for the de-tection and classification of cancer tumor. The main contribution in this paper can be summarized in the following:

- To provide a framework based on deep learning architecture for the detection and classification of breast cancer.
- To analyze the concept of transfer learning on three different deep learning architectures.
- To provide a comparative analysis of each deep learning ar-chitecture with respect to accuracy in the context of transfer learning.

The rest of the paper is organized as follows: Section. 2 pro-vides a detailed analysis of the proposed approach which in-clude subsections like data pre-processing and data augmenta-tion, pre-trained CNN architectures and transfer learning. Similarly, Section. 3 discuss the experimental results obtained after apply-ing the proposed approach along with its performance evaluation. Finally, Section. 4 gives the conclusion of the paper and provide future directions.

II. PROPOSED METHOD

In this section, the proposed framework based on CNN archi-tecture is explained for the detection and classification of malig-nant cells in breast cytology images. In the proposed framework different low level features are extracted separately by three well-known CNN architectures of GoogLeNet, VGGNet, and ResNet. The combined features are fed into a fully connected layer for the clas-sification task, as given in the block diagram shown in Fig. 1. The details about each step of the proposed architecture is given in the following subsections.

2.1. Data pre-Processing and augmentation processing

The pre-processing step is essential in tissue images to remove different types of noises. In the proposed approach, the micro-scopic H&E stain tissue images are normalized using the method proposed in [29]. To achieve higher performance in accuracy, CNN requires large data sets. Moreover, the performance of CNN deteri-orates with small data sets due to over-fitting. It means that the network performs very well on training data but under-perform on test data. In the proposed framework, data augmentation tech-nique is applied to increase the data set and reduce the over-fitting problems [30,31]. In the data augmentation method, the number of samples is increased by applying geometric transformations to the image data sets using simple image processing techniques. In this regards, the image data set is increased by color process-ing, transformation (translating, scaling, and rotation), flipping and noise perturbation. Since the microscopic images

are rotationally invariant, the pathologist can easily analyze the breast cancer mi-croscopic images from different angles without any variation in the diagnosis [32].

2.2. Pre-trained CNN architecture for feature extraction

In the beginning, separate CNN architectures are used for fea-ture extraction, which are combined into a fully connected layer for classification tasks. The combined features may contain multi-ple features extracted from single descriptor, these features may represent the shape descriptor like circularity, roundness, com-pactness, etc. In the proposed framework, three most recent and up-to-date deep CNN architectures: GoogLeNet [33], Visual Ge-ometry Group Network (VGGNet) [34] and Residual Networks (ResNet) [35] are adopted as a feature extractor for the classifica-tion of breast cancer in cytology images. These architectures are pre-trained for various generic image descriptors, followed by rel-evant feature extraction from microscopic images on the basis of transfer learning theory [36]. The basic structure of each adopted CNN architectures are described in the following sub-sections.

2.2.1. Googlenet

It is a small network consisting of three convolution layers, rec-tified linear operation layers, pooling layers, and two fully con-nected layers. Using the architecture of GoogLeNet, we proposed a model which combines various convolution filters of different sizes into a new single filter, which not only reduces the number of perimeters but also minimizes the computational complexity. The underlying architecture of GoogLeNet is illustrated in the Fig. 2.

2.2.2. VGGNet

VGGNet is similar to AlexNet except with additional convolution layers. VGGNet consists of 13 convolution, rectification, pooling and 3 fully connected layers [34]. The convolution network uses 3 × 3 windows size filter and 2 × 2 pooling network. VGGNet performs better as compared to AlexNet due to its simple architecture. The underlying architecture of VGGNet is illustrated in the Fig. 3.

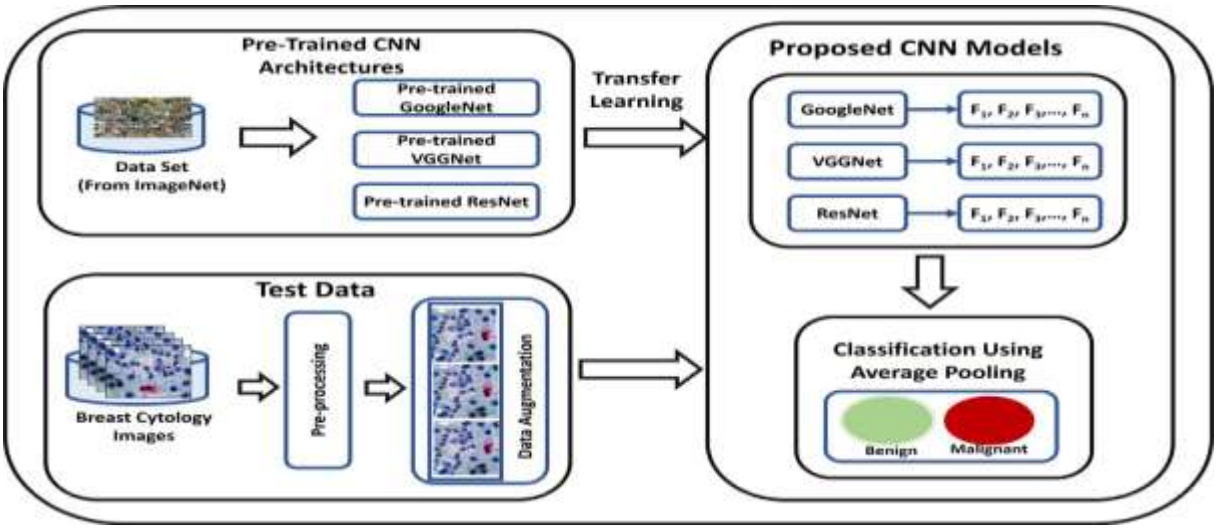

Fig. 1. Block Diagram of the Proposed Deep Learning Framework.

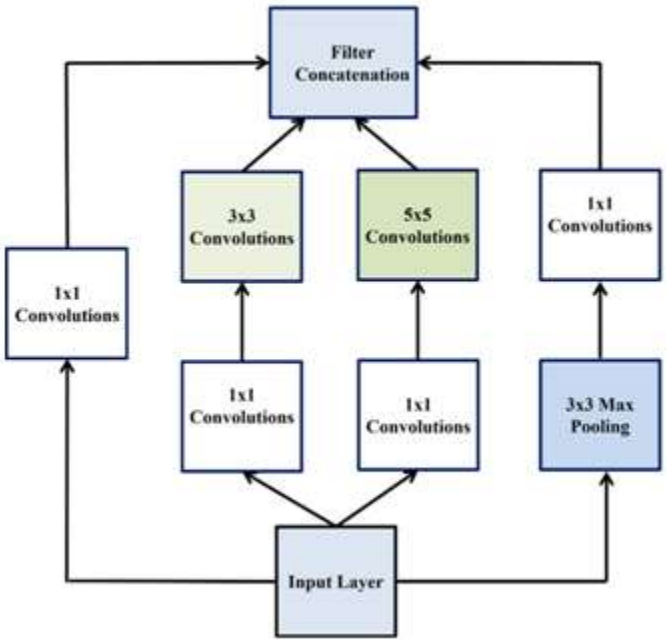

Fig. 2. Basic Architecture of GoogLeNet [33].

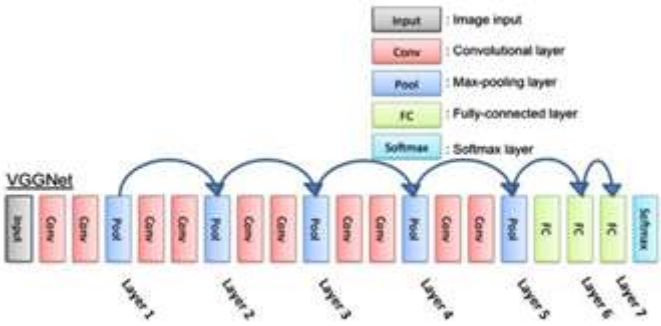

Fig. 3. Basic Architecture of VGGNet [34].

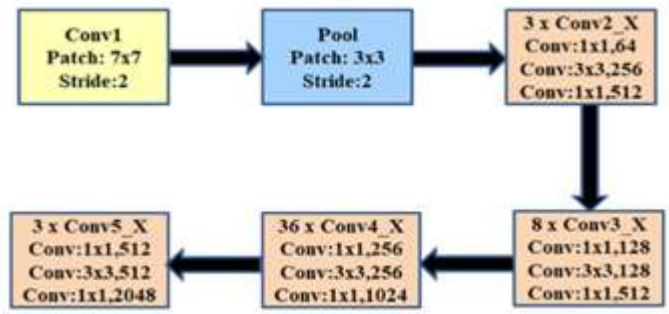

Fig. 4. Basic Architecture of ResNet [35].

2.2.3. Resnet

ResNet is a very deep residual network and it achieves good re-sults in classification task on the ImageNet [37]. ResNet combined multiple sized convolution filters which manage the degradation problem and

reduces the training time that occurs due to its deep structures. The underlying architecture of ResNet is illustrated in the Fig. 4.

2.3. Transfer learning

In practices, large size of data is required to train a CNN from scratch but in some cases, it is very difficult to arrange a big data set of relevant problems. Contrary to an ideal situation, in most of the real world applications, it is not the case, or it is a complicated task to gain matching training and testing data. Therefore, the con-cept of transfer learning has been introduced. Transfer learning is one of the most well-known methods of machine learning which learned the background knowledge applied for solving one prob- lem and reused on the other relevant problems. Initially, the base network is trained for a specific task on their relevant data set and then transfer to the target task trained by target data set [38].

The transfer learning process can be divided into two main steps: selection of the pre-trained model, problem size and simi- larity. The selection of the pre-trained model is made on the basis

Table 1
Magnification based Comparative Analysis of the Proposed Framework with other CNN Architec-
tures.

CNN Architectures	Lens Magnification				Average Accuracies	Classification
	100X	140X	200X	500X		
GoogLeNet	90.4	93.7	95.3	94.6	93.5%	
VGGNet	90.8	94.8	96.7	94.2	94.15%	
ResNet	91.5	93.3	95.4	97.2	94.35%	
Proposed Framework	96.8	96.9	97.8	98.6	97.525%	

of the associated problem which is relevant to the target problem. If the size of the target data set is smaller (i.e., less then 1000 im-ages) and similar to the source training data set (medical data sets, hand-written character data sets, vehicles data sets or biometric related data sets etc.) then the chance of over fitting is high. Simi-larly, if the size of the target data is larger and similar to the source data sets then the chance of over fitting is low and it requires only the fine tuning of the pre-trained model.

In the proposed framework, three CNN architectures (GoogLeNet, VGGNet, and ResNet) are used to share their prop-erties on transfer learning and fine-tuning. These three CNN architectures are trained by the sample images from ImageNet data set and transfer learning has been adopted. This makes the ar-chitecture capable of learning the generic features from other data sets without the need for new training. The number of features extracted independently from the respective CNN architecture is combined into the fully connected layer for classification of the malignant and benign cell using average pooling classification.

III. EXPERIMENTAL RESULTS AND DISCUSSION

3.1. Dataset

To evaluate the performance of the proposed framework two breast microscopic image data sets are used: the first one is a stan-dard benchmark data set [39], and the other is developed locally at LRH hospital Peshawar, Pakistan. For both data sets, first aug-mentation technique is applied by scaling, rotation, translation and colors modeling to produce a total of 8000 images. In these 8000 images, 6000 images are used for training the architecture while 2000 images are used for testing the trained model. In both data sets, images are captured by microscope with various magnifica-tions (the enlargement process of images seen by microscopic lens known as lens magnification). In the proposed framework various magnified images (100X, 140X, 200X and 500X) are used for accu-rate evaluation. During the execution of the proposed framework, 75% of data set is

used for training purpose while 25% of data set is used for testing the accuracy of the proposed architecture. More-over, to control the over-fitting issues, the initial stopping criteria is designed which is based on the performance validation, i.e., to stop the training process when the system shows no or less im-provement after 1000 iterations.

3.2. Results and analysis

The proposed framework is trained on three different CNN ar-chitectures, i.e., GoogLeNet, VGGNet, and ResNet, individually and then transferred the learning data into combined features extrac-tion using transfer learning. The obtained results from single CNN is compared with combined features set along with different ex-isting techniques. Table. 1 show the result of each architecture in-dividually in different magnification sizes as well as the proposed transfer learning approach.

As shown in Table. 1, the GoogLeNet, VGGNet and ResNet archi-tecture individually gives average classification accuracy of 93.5%, 94.15%, and 94.35% respectively, while the proposed framework gives an accuracy of 97.525%. These results show that the proposed framework achieve high performance in terms of accuracy in de-tection and classification of breast cancer tumor as compared to the other three architectures.

Moreover, during experimentation of the proposed approach, the data is splatted into training and testing data sets. The splat-ting is performed using three different procedures:90%-10%, 80%-20%, 70%-30%. The 90%-10% splatting means that 90% data is used for training while the rest of 10% is used for testing the CNN archi-tectures. A comparative analysis of the proposed approach based on data splatting is performed with other CNN architectures given in Table. 2. In Table. 2, 'Class Type' represent the type of cancer (B or M), where B represent benign and M represent malignant and their respective Precision, Recall, F1 Score and Accuracy. It also provides an average accuracy of each architecture on the basis of splatting procedures. It can be noted that the proposed framework gives higher accuracy in the classification of cancer cells in breast cytology images as compare to individual architectures.

3.3. Comparative analysis of accuracy with other methods

Similarly, a comparative analysis of the results obtained using the proposed framework with four well-known methods is carried out to relates the strength of the proposed architecture as given in Table. 3. It can be observed from Table. 3 that the methods in [25– 28] give an accuracy of 92.63%, 90.0%, 97.0%, and 97.5% respectively, whereas, the results obtained using the proposed framework gives an accuracy of 97.52%, which is higher than all the four methods. These results show the strength in terms of accuracy of the pro-posed approach as compare to other similar methods.

IV. CONCLUSION

In this article, we proposed a novel deep learning framework for the detection and classification of breast cancer using the con-cept of transfer learning. In this framework, features are extracting from breast cytology images using three different CNN architec-tures (GoogLeNet, VGGNet, and ResNet) which are combined using the concept of transfer learning for improving the accuracy of clas-sification. Similarly, we also proposed the concept of data augmen-tation to increase the size of a data set to improve the efficiency of CNN structure. Finally, the performance of the proposed frame-work is compared with different CNN architectures independently and also compared with other existent methods. It has been ob-served that the proposed framework gives excellent results regard-ing accuracy without training from scratch which improves classi-fication efficiency. In future, both hand-crafted features along with CNN features will be used to further improve the classification ac-curacy.

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Table 2

Splatting based comparative analysis of proposed framework with other CNN architecture.

Classifier	Training-testing data splitting	Class type	Precision	Recall	F1 score	Accuracy	Average Accuracy
GoogLeNet	90%–10%	B	0.93	0.94	0.94	93.67%	93.22%
		M	0.96	0.94	0.95		
	80%–20%	B	0.93	0.93	0.93	93.00%	
		M	0.93	0.94	0.93		

	70%–30%	B	0.96	0.9	0.93	93.00%	
		M	0.92	0.98	0.95		
VGGNet	90%–10%	B	0.9	0.97	0.94	93.67%	94.00%
		M	0.9	0.91	0.92		
	80%–20%	B	0.97	0.96	0.95	96.00%	
		M	0.95	0.93	0.92		
	70%–30%	B	0.91	0.92	0.94	92.33%	
		M	0.9	0.99	0.96		
ResNet	90%–10%	B	0.97	0.98	0.99	98.00%	94.89%
		M	0.99	0.98	0.99		
	80%–20%	B	0.99	0.9	0.99	96.00%	
		M	0.9	0.98	0.99		
	70%–30%	B	0.9	0.92	0.9	90.67%	
		M	0.91	0.98	0.99		
Proposed Framwork	90%–10%	B	0.96	0.97	0.98	97.00%	97.67%
		M	0.95	0.96	0.98		
	80%–20%	B	0.97	0.99	0.97	97.67%	
		M	0.96	0.97	0.98		
	70%–30%	B	0.98	0.98	0.99	98.33%	
		M	0.97	0.96	0.98		

Table 3

Comparative Analysis with other Methods.

Methods	Accuracy
Nguyen [25]	92.63%
Awan [26]	90.00%
Kensert [27]	97.00%
Vesal [28]	97.50%
Proposed Framework	97.52%

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