Deep CNN Model based on VGG16 for Breast Cancer Classification

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***Abstract*— Deep learning (DL) technologies are becoming a buzzword these days, especially for breast histopathology image tasks, such as diagnosing, due to the high performance obtained in image classification. Among deep learning types, Convolutional Neural Networks (CNN) are the most common types of DL models utilized for medical image diagnosis and analysis. However, CNN suffers from high computation cost to be implemented and may require to adapt huge number of parameters. Thus, and in order to address this issue; several pre-trained models have been established with the predefined network architecture. In this study, a transfer learning model based on Visual Geometry Group with 16-layer deep model architecture (VGG16) is utilized to extract high-level features from the BreaKHis benchmark histopathological images dataset. Then, multiple machine learning models (classifiers) are used to handle different Breast Cancer (BC) histopathological image classification tasks mainly: binary and multiclass with eight-class classifications. The experimental results on the public BreakHis benchmark dataset demonstrate that the proposed models are better than the previous works on the same dataset. Besides, the results show that the proposed models are able to outperform recent classical machine learning algorithms.**

Keywords*— *Deep learning, VGG16, BreaKHis histopathology dataset, feature extraction, pre-trained model.

I. Introduction

Breast cancer remains one of the most severe public health concerns, and it is the leading cause of cancer-related deaths in women around the world[1]. For example, in Jordan, breast cancer constitutes 19.7% of all diagnosed cancer[2]. Therefore, the early diagnosis of this disease is vital to avoid its progression consequences and reduce its morbidity rates in women. Breast cancer cells include numerous entities with distinctive clinical and histological attributes, this indicates that this disease is a heterogeneous one. Figure 1 shows two rows of images; the top row shows benign cells images while the bottom row show malignant cells ones. Unfortunately, this malignancy happens from the development of unusual breast cells and might conquer the close healthy tissues.

Clinical diagnosis of breast cancer is composed of numerous techniques. The first technique is clinical screening, which is performed by employing radiology images, e.g., Magnetic Resonance Imaging (MRI), Mammography and others. However, these non-invasive imaging may not be able to determine the cancerous area efficiently[3]. Thus, to analyze the malignancy professionally, biopsy images are used [4] with different stained to produce histopathology images. However, manual investigation of the histopathology images is tedious, time-consuming, and based on physician skills. Thus, manual diagnosing is subjective. To this end, Computer-Aided Diagnosis (CAD) plays a significant role in assisting pathologists in examining the histopathology images and finding the suspected area. Typically, it increases the diagnostic performance of BC by reducing the inter-and intra-pathologist variation in making a final decision[5].

Numerous machine learning techniques are often utilized to analyze the malignancy pathology images[4]. CAD systems are the most analysis models for digital histopathological image analysis. The previous studies on breast CADs can be divvied into shallow machine learning and deep learning. The shallow machine learning CADs mainly rely on features extraction from the input/ training images; then, these features are used to train a classifier (e.g. SVM) [6]. Therefore, these models are sometimes categorized as Handcrafted features based models[7] [8]. For example, the authors in [9] extracted six different types of features from input training images mainly: Gray Level Co-Occurrence Matrices (GLCM), Parameter-Free Threshold Adjacency Statistics (PFTAS), Local Binary Patterns (LBP), Local Phase Quantization (LPQ), Completed Local Binary Pattern (CLBP), Oriented FAST, and Rotated BRIEF (ORB). They achieved a classification accuracy of around 81% when using the 40x dataset from BreakHis. While the authors in [10] extracted different type of features from the input images, such as GLCM LBP, TWT , and PWT. They evaluated these features by k-nearest neighbors classifier(model) and achieved an accuracy range from 83% to 86%. In [11], the authors used an L1-norm sparse SVM (SSVM) as a feature selection method to select the essential handcraft features from BreakHis images.

Most of the previous studies on BreakHis used conventional handcrafted features that achieved acceptable results. Some drawbacks of these conventional CADs are that: first, the quality of the CADs depends on the extracted features, while acquiring representative features from the image is very complex issue. Second, using acquiring features may not be suitable for inter and intra-class variation in the histopathological images[4]. Third, most of the extracted features are based on class label information (supervised); thus, they can be lying to biased results[12].

In contrast to the conventional CADs that was based on the extracted handcrafted features, DL plays a significant in multiple classification tasks and can achieve high performance and extract high-level features from histopathology images automatically. To mitigate conventional CADs practices limitations, numerous recent scholars thought of entrusting classification tasks to deep learning models, which can be adapted to select the most powerful features based on conventional and pooling layers.

Among DL models, CNN-based feature extraction models have received vast concern among scholars for the classification of histopathology breast images [13], [14], [15]. For example, authors in [13] employed ResNet50 as a feature extractor model from CNN architecture for the BreaKHis dataset. Then, they evaluated the extracted features using linear SVM and reported results for 40x around 88%.

The researchers of [14] introduced hybrid AlexNet and VGG16 models as feature extractor methods. In these hybrid methods, the BreaKHis dataset was classified, and the maximum accuracy reported was 90.96 %, while the VGG16 model achieved 90.96 % for 40x magnification. It has been observed that the AlexNet was better than VGG16 for feature extraction in this dataset. Besides, the performance has been increased as the number of training samples increases. Most of the above studies utilized different pre-trained models with a preprocess for the BreaKHis images. However, a little investigation has been done in previous studies for solving binary and multiclass tasks for the BreaKHis dataset using a different type of classifiers based on the features extracted from the VGG16 pre-trained model.

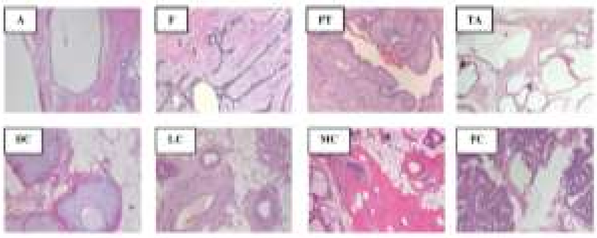

Figure 1: Breast histopathology images from BreaKHis dataset with 40× magnification factor, top row: benign, bottom row: malignant. All images include their class label for multiclass task [16].

This study has two main goals: first, to analyze pre-trained deep learning VGG16 [15] as a feature extractor for binary and multiclass breast cancer histopathological image classification tasks after fine-tuned VGG16 for these tasks. Second, this study investigates the capability of five different classifiers for classifying the extracted features of breast histopathology images. The five classifiers are RBF Support Vector Machine (SVM), Logistic Regression (LR), Poly SVM, K-Nearest neighbors (KNN), and Neural Network (NN). The breast cancer histopathology images are found from the publicly offered BreakHis 40x magnification dataset.

This manuscript is arranged as follows: the literature review is presented in Section 2, the methodology (Methods and Material) are presented in Section 3, the results and discussion are detailed in Section 4, and finally, the conclusions and future work are drawn in Section 5.

II. LITERATURE REVIEW

Deep learning models were used for breast cancer either as feature extraction models or classification models. In the former models, the transfer learning approaches are used from DL as feature extractors from images. Various researches have leveraged the pre-trained DL model to classify breast cancer related to the BreaKHis histopathology images. For instance, VGG16 and AlexNet as pre-trained DL models are used by authors in [14] to classify the Breakhis dataset. Authors in [17] introduced CNN as a feature extractor method for BreaKHis dataset. Then, they utilized data augmentation to reduce the imbalance between the class labels. The reported results for their method was varied from 88.3%- 94.1% based on the data augmentation. In other works in [18], the authors investigated the pre-trained inception-v3 with BLSTM to classify breast cancer histopathology images into three different classes: benign, normal, and carcinoma. Their experiment results showed that the proposed model achieved around 91.35 accuracy. In another study, the authors in [19] used AlexNet followed by SVM to classify the breast cancer images into 4-classes. The authors used BreaKHis dataset with 200x magnification and achieved an accuracy of 77% for 4-classes and 83.3% for binary classification.

The authors in [20], discriminate between benign and malignant cases in the BreaKHis dataset with various magnifications. They adapted AlexNet by changing the last layer to include two classes. Then used it as a feature extractor and classifier at the same time. They achieved an improved F-measure of 94.6 % for binary classification with 40 magnification. However, they ignore the multiclass task, which is a challenging task in this domain.

VGG16 used by [21] for BreakHis classification with 40X magnification. They achieved 89.6% on multiclass classification. One reason for these low results is both of them used CNN as a classifier model, which may require a sharp fine-tuning for its parameters. Thus, feeding the features to the classifiers may produce good results.

In view of the previous studies, some points are observed: first, using pre-trained CNN as a feature extraction method is better than merging the extraction and classification in one model. Second, the multiclass classification task in BreaKHis is a challenging task and needs more attention from scholars. Third, to reduce the imbalance in the dataset, a data augmentation strategy is needed

III. METHODS AND MATERIAL

A. Proposed Approach

1) Deep Convolutional Neural Network (CNN)

Among deep learning approaches, CNN is considered a dominant technique from deep learning approaches. It has been used in various data science tasks such as medical image classification and feature extraction from the input training images using a pre-trained CNN model.

Practically, CNN tries to learn and extract high-level features which able to discriminate between different class labels in a classification task. In most cases, the extracted features from CNN outperform the handcrafted features.

The main components of the CNN are stack of input, multiple hidden, and output layers. The foremost work is in the hidden layers, which are typically comprised of several convolutional layers (CL), pooling layers, and the last layer is set of the fully connected layers (FC). Extra layers can be added to build a complex model, which allows the model to learn more complicated features towards superior decision-making[22]. Figure 2 shows the typical CNN architecture, where the convolutional and pooling layers are used to extract features from the input training set by using a small filter (e.g., 5x5) which is sliding on the image. In CNN, each CL is used to extract the distinct set of features from an image set. For example, one CL is responsible for edges, bright spots, dark spots, shapes. In contrast, other is responsible for shapes and objects relating to the image which are recognizable. The next main layer is the pooling, which is responsible for reducing the feature map's dimensionality while preserving the most vital information, such as max and average pooling. The FC layer is called the classifier layer. After passing through the FC layers, the output layer(final layer) produces probabilities of the input based on the softmax activation function.

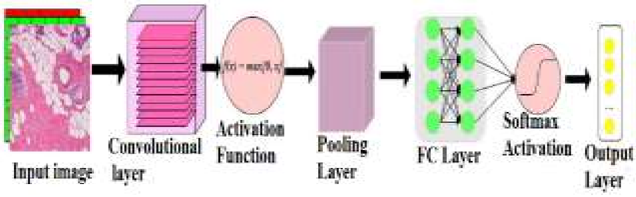

Figure 2: Typical CNN architecture

In recent years, CNN is growing fast, and various architectures have been introduced. One of the famous CNN is VGG16[15]. It has less filter size comparing to AlexNet and simple layer architecture. VGG16, like other CNN models, pre-trained on a vast size dataset, i.e., ImageNet, and proved to be valuable for various image classification tasks, such as breast cancer classification [14, 21].

2) VGG16

VGG16 is one of the most common deep learning architectures introduced by Oxford University [17]. The prominent architecture for VGG16 is presented in Figure 3. It includes 41 layers disturbed as the following: 16 weight layers, 13 convolutional layers (Conv.), and 3 FC layers. VGG16 employs a small 3x3 kernel(filter) on all Conv Layers with stride one. Max pooling layers always follow Conv. Layers. The input for VGG16 is fixed 224x224 three channels images. In VGG16, the three FC layers have different depths. The first two have the same channel size (4096), while the last FC has 1000 channel size, representing the number of the class label in the imageNet dataset. The output layer is the soft-max layer which is responsible for the given probability for the input image.

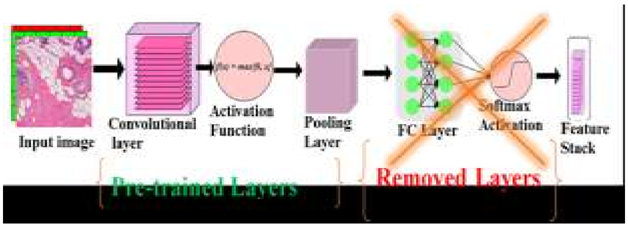

Figure 3:The VGG16 Model for feature extraction, which includes frozen 16 Convolutional with their Max Pooling layers, three Dense layers for FC layer, and an output layer of 1,000 nodes(for 1000 classes).in this study, the top layers(FC and output layers) are deleted.

As any pre-trained models, VGG16 [17] requires heavy training if the weights are initialized randomly. So, in general, CCN models utilize transfer learning (TL) techniques. TL refers to a mechanism in which a model trained on one task is utilized in some way on a second similar task. I.e., we train a CNN model on a similar problem to the problem that is being addressed, where the input is the same, but the output may be of a different in nature. In this case, the VGG 6 model [17] is trained using the ImageNet dataset, which contains many real-world object images.

Then, the weights of layers migrate to a BC classification task/ feature extraction. Thus, the training time is reduced. Besides, TL is a more powerful classification technique when a small dataset is evaluated [23]. TL can be used either for classification or feature extraction after the adaptation of some layers from the pre-trained model. In this study, the capability of the VGG16 with transfer learning is utilized to extract high-level features from the input images.

Algorithm 1: Extract features from input images using VGG16

Input *A set of Training images N with their label L, pre-trained VGG16.*

Output *Extracted features for all images.*

1. *Prepare the VGG16 to do feature extraction by removing the FC layers from VGG16*
   - *Model_VGG16=VGG16-FC layers*
2. *For i=1 to N do:*
3. *Read image i*
4. *Resize the image i to 224x224x3*
5. *Extracted_features(i)= model_VGG16(i)*
6. *Flatten(i): convert the Extracted_features(i) from the 3-D feature stack into a one-D array, see Figure 2*
7. *Features(i)= Flatten(i)*

End for

3) Proposed Feature Extraction Algorithm

The nature of breast histopathological images carry many textures, shape, and histological structure such as nuclei, cytoplasm. Thus, the proposed method utilizes VGG16 to extract deep representative features of the input histopathological images. The main steps of the proposed method, as presented in Algorithm 1, are:

First, the input training images are resized to consist of the size of the input layer of the VGG16. Second, the VGG16 is adapted for the histopathological images by removing the last three layers (FC) layers (Top layers of the stack),as illustrated in Figure 3, which represent the classifier. Thus, the leaving layers are convolutional and pooling layers. The input image is passed through the model to extract 4096 features.

After preparing the data by extract the features from all input images, we divide the data into training 90% and testing (10%) to be used with a set of classifiers. Then, we trained five diverse classifiers, namely, RBF Support Vector Machine (SVM), Logistic Regression (LR), Poly SVM, K-Nearest neighbors (KNN), and Neural Network (NN).

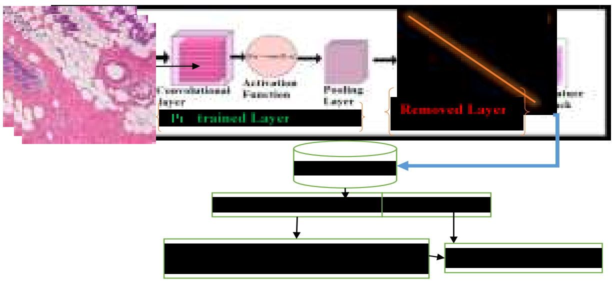

Figure 4: The proposed Model for Breast Histopathological Image Classification

4) Material

In the implementation of the present study, the BreaKHis[9] benchmark dataset for breast cancer histopathology images with 40X magnification is used. The 40x dataset is divided into benign lesions, consisting of 625 images, and malignant lesions, which cosset 1370 images. Each of the malignant and benign cases is divided into 4-subclasses. Thus, in multiclass classification, eight different classes are handled. We balanced the dataset to reduce the bias in the classifiers.

IV. Results and Discussion

1) Experiment Setup

This study conveyed two main experiments with images of 40x magnification from BreaKHis dataset. For each image, the VGG16 is used to extract 4096 features. These features with class labels for the images is used to construct the dataset. This dataset is divided into 90% training and 10% testing, as in [24]. Then, we trained five diverse classifiers, particularly, RBF SVM, LR, Poly SVM, KNN with k=1, and NN with 300 iterations.

2) Evaluation Methods

In this study, various metrics such as accuracy, sensitivity, and Specificity are applied to measure the image diagnosis performance for binary and multiclass classification tasks[25]. All of these metrics are averaged over 30 runs as in [20].

3) Results

Two major experiments on the 40X magnification Breakhis have been conducted to evaluate the performance of the VGG16 for feature extraction. The first experiment is used to solve the binary classification task (benign vs. malignant), as shown in Table 1. While the second experiment handles the multiclass task (8-subclasses), as shown in Table 2. In each experiment, the results of the five different classifiers are collected. It is worth mentioning that all of the reported results are for the test dataset.

Table 1: Average performance of the proposed VGG16 model (%) for binary classification task with standard deviation

Classifier	Accuracy	Sensitivity	Specificity
RBF-SVM	95.1± 4.47	95.1± 4.40	93.9± 4.42
LR	88.8± 4.42	88.8± 4.44	84.8± 2.20
Poly-SVM	**96.0± 2.20**	**96.0± 2.22**	**93.9± 4.41**
KNN	87.9± 2.24	87.9± 2.21	77.2± 2.26
NN	90.4± 0.0	90.4± 0.0	86.36± 1.11

As illustrated in Table1, the proposed model obtained the following accuracies: 96% and 95.1 using polynomial SVM and RBF SVM, respectively. These values confirm that the SVMs have the highest average accuracy scores for 40x magnification. In comparison, the proposed model outperforms the previous studies on 40X. For examples, in [9], the author achieved 88% for 40x magnification using the combination of CNNs trained from scratch. It is worth mentioning that the proposed method outperforms the works in [14], which combine the features of VGG16 and AlexNet. We can see from Table 1 that the worst classifier was Knn which achieved around 87% accuracy for binary classification. One reason for this result is choosing the k value for this classifier.

Table 2: Average performance of the proposed VGG16 model (%) for Multiclass classification task with standard deviation

Classifier	Accuracy	Sensitivity	Specificity
RBF SVM	**89.83± 0.005**	**89.83± 0.005**	**100± 0.0**
LR	87.2± 2.27	87.2± 2.23	100± 0.0
Poly SVM	88.1± 0.007	88.1± 0.007	100± 0.0
KNN	87.2± 2.24	87.2± 2.28	100± 0.0
NN	87.2± 2.32	87.2± 2.83	100± 0.0

The results for the eight-class classification are reported in Table2. As stated in Table2, the proposed model based on RBF SVM gained the highest score, where the average accuracy, sensitivity, and specificity of the proposed model are 88.1%, 88.1%, and 100%, respectively. Specificity (true negative rate) in the experiments means the number of negative samples that were correctly classified divided by all negative samples. The high specificity in this study implies that the proposed method able to predict the true negative cases accurately.

Table 3: Comparison of the performance of the proposed model with previous deep learning approaches on the same dataset with 40X magnification.

Previous studies	Classification type	Type of classifier	Accuracy
VGG16[26]	Binary	VGG16	86.2±2.0
AlexNet [20]	Binary	AlexNet	94.6%
AlexNet and VGG16 [14]	Binary	SVM	84.87± 1.14
VGG16 [21]	Multi-class (8-classes)	SVM +NN + KNN	89.6±4.0
Proposed for binary	**Binary**	**RBF-SVM**	**96.0± 2.20**
Proposed for multiclass	**Multi-class (8-classes)**	**RBF-SVM**	**89.83± 0.005**

Overall, from the obtained results in Table 1,Table 2, and Table 3 we noticed that the proposed model with SVM classifiers provide superior performance in binary and multiclass classification tasks. We also observed that the performance of the specificity is increased remarkably in multiclass classification, which intimates that the extracted features from VGG16 able to discriminate between the complex cases in the breast cancer domain.

V. CONCLUSIONS AND FUTURE WORK

Extracting high-level features from breast histopathological images assists in improving the effectiveness of the diagnostic process. Thus, the main objective of this study is to utilize VGG16, a pre-trained model from CCN deep learning, to extract the high-level features from breast images. To do that, we removed the last fully connected layers in VGG16. Then, the obtained features were classified using a set of heterogeneity classifiers. Extensive experiments on Breakhis dataset (public dataset) were carried out, and a set of performance metrics was calculated for performance evaluation (on test data portion). The experimental results outperformed various techniques in the state-of-the-art. This is demonstrate the effectiveness of the extracted features using VGG16 with polynomial and RBF SVMs classifiers. In the future, further investigation for an ensemble of different classifiers and pre-trained models to deliver high performance for this complex domain will be addressed.

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