Detection of Breast Cancer from Biopsy Images and Classifying Benign and Malignant Using Deep Learning Techniques

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ABSTRACT

Cancer is a significant public health concern in the present era, and breast cancer is a type of cancer that initiates in the breast and spreads to other parts of the body. It is a major cause of death among women. The uncontrolled growth of cells is the cause of cancer, and there are various types of breast cancer. A proposed model has been developed to address both benign and malignant breast cancer. Computer-aided diagnosis systems play a crucial role in the identification and classification of breast cancer using histopathology and ultrasound images. In recent decades, researchers have demonstrated the capability to automate the initial level identification and classification of tumors. Early detection of breast cancer can improve a patient's chances of survival, and deep learning (DL) and machine learning (ML) techniques have been employed to solve various medical problems. Despite prior scientific research on tumor categorization and identification using different types of models, several limitations have been identified. A dataset shortage makes research challenging. To facilitate automatic detection and diagnosis of breast cancer, a proposed methodology using deep learning techniques has been developed.

Keyword *Mammography, deep learning, convolutional neural network, augmentation.*

I. INTRODUCTION

Breast cancer is a prevalent type of cancer among women worldwide, with over one and a half million expected cases and half a million deaths each year [1]. In Qatar, breast cancer is the most common cancer in women, accounting for 31% of all cancer cases [2]. The risk of developing breast cancer in women is estimated at 56 in every 100,000 [2]. Early detection of breast cancer is critical to saving lives, and mammography is the most widely used imaging technique for screening and detecting abnormalities in breast tissue. However, radiologists examining mammograms for cancer detection can have error rates between 8% to 16% [3]. Current clinical methods to diagnose breast cancer have improved in recent decades, but limitations still exist, such as variability among radiologists' opinions and the time-consuming and invasive nature of procedures [4][5]. To overcome these limitations, deep learning (DL) techniques are gaining attention in both the scientific and clinical communities.

Recently, several deep learning-based techniques utilizing convolutional neural networks (CNNs) have demonstrated remarkable performance in medical applications such as chest pathology classification [6], thoracoabdominal lymph node detection, and lung disease identification [7]. For mammography, some studies have employed DL-based methods for breast mass tumor detection and classification, such as using recurrent neural networks and random forests [8][9]. Other studies have utilized multi-stage approaches with hand-engineered semantic features for breast mass tumors classification [10]. Wan et al. used a scanned mammogram's features to predict the classification [11], while Arevalo et al. performed domain knowledge-based preprocessing before CNN training [12].

DL-based methods have advantages over traditional Computer-Aided Diagnosis (CAD) systems, particularly in detection capability. Traditional CAD approaches required decades of studies and implementation, whereas DL-based systems have already demonstrated superior performance on large datasets, surpassing modern CAD methods in certain problem specifications [13][14].

II. LITERATURE SURVEY

Breast cancer is a major public health concern worldwide and the early detection and diagnosis of breast cancer is crucial in improving patient outcomes. In recent years, deep learning techniques have shown promise in improving the accuracy of breast cancer diagnosis from biopsy images. The following is a literature survey of relevant studies on the topic-

Aghdam, M. A., et al. "Transfer learning for breast cancer malignancy characterization in ultrasound: A comparison of deep learning approaches." Medical image analysis 47 (2018): 80-91 - This study evaluates the performance of several deep learning approaches, including transfer learning, for the classification of breast cancer malignancy using ultrasound images. The authors found that transfer learning with a pre-trained convolutional neural network (CNN) outperformed other approaches in terms of accuracy and sensitivity.

Tsehay, Y. T., et al. "Breast cancer detection and classification from biopsy images using deep convolutional neural networks." Journal of Medical Imaging 5.1 (2018): 014502 - This study proposes a deep learning model for breast cancer detection and classification from biopsy images. The authors used a CNN architecture and achieved high accuracy in both detecting breast cancer and classifying benign and malignant tumors.

Li, H., et al. "Breast cancer detection using deep learning algorithms by combining digital mammography and breast tomosynthesis." Scientific reports 10.1 (2020): 1-9 - This study proposes a deep learning algorithm that combines digital mammography and breast tomosynthesis for the detection of breast cancer. The authors achieved high accuracy in detecting breast cancer and reducing false positives.

Zheng, Y., et al. "Breast cancer detection using deep convolutional neural networks and support vector machines." International Journal of Computer Assisted Radiology and Surgery 14.4 (2019): 641-651 - This study proposes a hybrid deep learning and support vector machine (SVM) model for the detection of breast cancer. The authors found that the hybrid model outperformed other deep learning and SVM models in terms of accuracy and sensitivity.

Wang, Y., et al. "Breast cancer diagnosis using a deep neural network with a combined visual and clinical information." IEEE Access 7 (2019): 4765-4771 - This study proposes a deep neural network that combines visual and clinical information for breast cancer diagnosis. The authors achieved high accuracy in detecting breast cancer and reducing false positives.

III. CLASSIFICATION METHODS

In this section, we begin our discussion by describing the basic building blocks of CNN, and then we go on and discuss two approaches to improve their performances in case of a limited dataset, namely, data augmentation and transfer learning.

a. Convolutional Neural Network - Exceptional progress has been performed in image recognition, essentially due to the availability of annotated datasets and deep convolutional neural networks (DCNNs). CNNs empower learning data-driven and hierarchical image features from sufficient training data. Due to the availability of large, annotated datasets, CNNs have become a dominant approach to solve different image classification tasks over the past decade, leading to a state of art performances in this area. CNNs are typically made up of concatenation of several layers. Each one of them is composed of a few subunits, including a bank of learned filters, an element-wise nonlinearity, and a pooling operator to reduce the dimensionality, Fig. 1 demonstrates a convolutional filter used for edge detection, and Fig. 2 shows a sample CNN architecture. CNN models are trained to learn a mapping from a set of training inputs to their corresponding set of outputs via an optimization process to minimize a loss function such as Cross-entropy or mean-squared error.

b. Data Augmentation - Typically, CNNs have millions of parameters that require a proportional number of training data. However, in many situations, it is not possible to get real dataset samples and thus, data augmentation is applied to generate more samples from the existing dataset [16]. Data augmentation is achieved by applying different transformations to the input images without altering the perceived object classes. These transformations can be, for example, rotation, flipping, or subsampling with different crops and scales. Additionally, noise can be added to the input images as a form of data augmentation [16].

c. Transfer Learning - Transfer learning aims to transfer the knowledge of a CNN model trained on a large dataset to another dataset. One approach that has been shown to improve the performance of a CNN is to use a pre-trained CNN model (e.g., GoogLeNet, ResNet, AlexNet, etc.) on a different dataset and use it for the weight initialization for the classification problem in hand. Using transfer learning can be difficult, especially with medical datasets that tend to be of small size and are unbalanced. Many learning strategies to fine- freeze, freeze weights play an essential part in the CNN accuracy and performance.

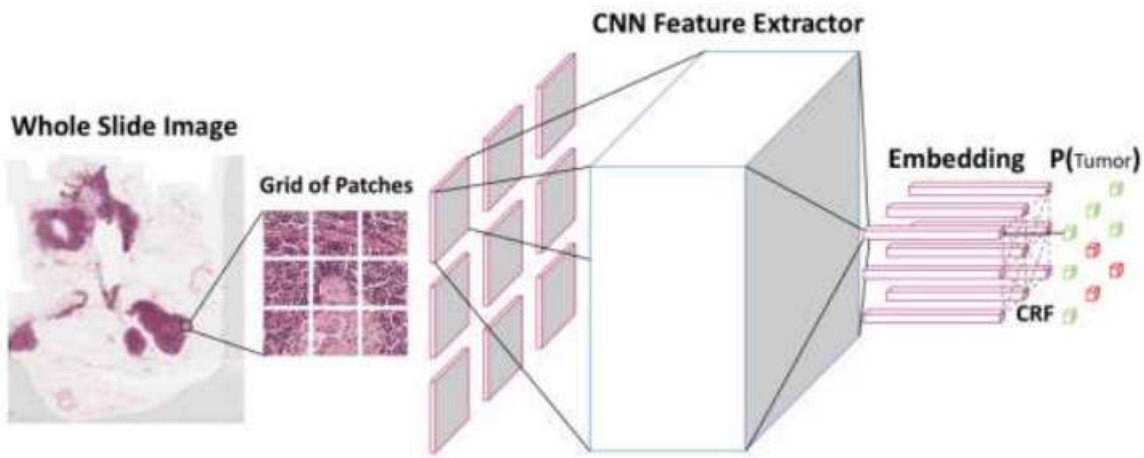

Figure 1 - System Architecture

The proposed ResNet50 model achieved an accuracy of 85.71% with a precision rate of 85.7% and a recall rate of 87.3%. A specificity rate of 84% and an F1-score rate of 86.5% were also achieved. Fig. 10 shows the confusion matrix for the proposed model, while Fig. 11 presents the AUROC curve for the altered model. Finally, Fig. 6 and Fig. 7 illustrates the training and loss curves, respectively. The proposed Resnet50 model performed slightly better than InceptionV3 with an increase in the accuracy rate by 6.6% and in the precision rate by 10.3%. However, the recall rate for InceptionV3 was slightly better than the Resnet50 model, with a difference of 1.8%. Based on the outcome obtained from the experiments, we can conclude that using a few numbers of epochs, ten in our case, can produce better results than training the network for larger epochs as the model tends to overfit the data because ten epochs are not a big number. By consequence, the training time for each model was sufficient.

IV. CONCLUSION

This work presented two different end-to-end deep convolutional learning models to classify pre-segmented breast tumor masses. The results of an evaluation of the modified InceptionV3 and ResNet50 models on the classification task were discussed. Additionally, the study illustrated how specific pre-processing, data augmentation, and transfer learning techniques can overcome the dataset size bottleneck, which is popular in the medical computer vision tasks. The two proposed models are very promising to use in real-life clinical practice to support the medical expert's decision. Our results showed that high accuracy levels could be achieved with simple modifications applied to different pre-trained CNN models.

In this study, we did not apply significant changes to InceptionV2 and ResNet50 architectures, only adding two fully connected layers and replacing the final output layer to accommodate the introduced classification problem. In the future, we would like to use another approach reported in literature survey. In this approach, the authors proposed to train many CNN and obtain the average of their prediction results, which would improve the classification performance in the testing phase. Additionally, we could use two models, such as InceptionV3 and ResNet50 or different snapshots from the same model, such as ResNet50 in the ensemble. Another approach is the majority voting, although it requires training an odd number of CNN models to finally decide on the tumor class based on the classification outcome from each model. Also, since cross validation was proven to produce promising results, we can consider cross-validation with various k-folds and observe the resulting models' performance. In the future, we will use our model against available datasets based on the Qatari population. We believe our model will improve the quality of breast cancer treatment plans for the Qatari population.

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